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Development of Empirical Models to Predict Gap Acceptance Parameter Based on the Geometrical and Operational Parameters of Different Roundabouts

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Abstract

This paper develops a mathematical formula that accounts the influence of roundabout's design and performance parameters to predict the gap acceptance parameter "Critical gap". Thirteen roundabouts in Hungary having different geometric and operational parameters were selected. The geometrical and operational data of each roundabout's leg was collected. Raff's method was used to estimate the critical gap for each roundabout leg. Firstly, the collinearity analysis was carried out to identify independent parameters to avoid any possible negative impact on the developed predictive models. Nine out of ten parameters passed the collinearity test. These nine parameters are the main parameters used in the model development. Three models were developed. The first model (M1) is based on Multivariate Adaptive Regression Spline (MARS) algorithm. The second model (M2) is based on Pearson correlation. The last model (M3) was based on Spearman correlation. Linear regression models were constructed using the retained parameters of the M2 and M3 models. Subsequently a comparison of the three developed models is done based on R2 and RMSE values. Based on the results obtained from the comparison, the MARS model (M1) is the best predictive model of the critical gap. According to the results of the MARS model, the most important parameters for predicting critical gap value are circulating traffic flow and the distance between neighboring legs.

Keywords

linear regression, critical gap, gap acceptance, roundabouts, geometric elements, Raff's method, MARS algorithm

1 Introduction

Gap acceptance parameters are important in determining capacities, delays, queue length, and performance of roundabouts [1]. In terms of safety, gap acceptance parameters may be utilized to predict the risk associated with small gaps, which indicate a higher risk of accidents [2]. Gap is defined as the time between two consecutive vehicles passing through a reference line [3]. Driver at roundabout entry observes all available gaps, and accept any gap he/she thinks is sufficient to merge into the mainstream [4]. Several definitions have been given to "Critical" gap. Greenshields et al. [5] referred to it as the accepted average minimum time gap and defined it as the gap accepted by 50 percent of the drivers. The idea of "critical gap" was used by raff, who defined it as the gap for which the number of accepted gaps shorter than it is equal to the number of rejected gaps longer than it [6]. Another definition is the minimum gap that the driver at the roundabout entry accepts to join safely the mainstream [7]. Raff's method also known as the graphical method. Two cumulative distribution curves are drawn, one is for number of accepted gaps less than t and the other one is for the number of rejected gaps greater than t. The intersection point of these two curves gives the value t of the critical gap [8]. Critical gap cannot be evaluated on site. Hence, several methods developed to evaluate the critical gap value at a certain location after some observations of the rejected and accepted gaps of each driver. The most famous methods for critical gap estimation are Raff's method [6], Maximum likelihood method [9], and Ashworth's method [10]. In this research, Raff's method was implemented to find the critical gaps values for the forty-one legs of the thirteen roundabouts. The critical gap depends on several parameters: (1) geometric design elements of roundabout (central island diameter D_{Island}, inscribed diameter $D_{Inscribed}$, width of

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circulatory carriageway $W_{circulatory}$, entry angle E_{Angle}, splitter island width $W_{Splitter}$, distance between neighboring legs $Distance_{Legs}$, entry width W_{Entry}, and approach entry width $W_{Approach}$) [11]; and (2) Traffic volume at the circulatory roadway [12, 13]. It's very important to know how the critical gap might vary based on various traffic and geometry conditions. Haitham and Schuchmann [11] studied the relationship between the geometric elements of ten roundabouts and the critical gaps in Hungary. They found that approach entry width ($W_{Approach}$), distance between neighboring legs ($Distance_{Legs}$), splitter island width ($W_{Splitter}$), and entry width (W_{Entry}) have the highest correlation with critical gap for the selected roundabouts. Accurate estimation of critical gap value is of a high importance for an accurate roundabout capacity or performance calculations. For example, in Highway capacity manual [1], the capacity of roundabouts formula can be calibrated using the critical gap value and follow-up headway. There are several studies of critical gaps estimation at roundabouts in several countries, as efforts to develop new methods for roundabout capacity estimation. This research deals only with critical gaps values. In this paper, new mathematical models are developed to estimate the critical gap value using the geometric and traffic parameters based on the available data. The developed models were generated using some statistical methods. Therefore, the model with the highest Coefficient of determination R^2 value and the lowest root squared mean error RMSE will be considered as the best predictive model of critical gap.

Hagring [14] found that the critical gap is different in the inner and outer lanes. According to Hagring the inner lane critical gap is longer than the outer lane by 0.4 seconds. Hagring [15] developed a model for estimating the critical gap as a function of the waving section, width of the weaving section, and inner – outer entry lanes. It is descried in the following Eq. (1).

$$T = 3.91 - 0.0278 \times L + 0.121 \times W + 0.592 \times \left(N_L - 1\right) \tag{1}$$

Where,

T = critical gap (s),

L = length of the weaving section (m),

W = width of the weaving section (m),

N_L = lane number (Inner = 2, Outer = 1).

In 2005, Chodur [16] studied the critical gaps and follow up times of fourteen roundabouts in Poland and developed an equation for these parameters. The developed equation (Eq. (2)) of the critical gaps is:

$$t_c = 1.92 \times t_f + 0.316 \times b_e - 0.427 \times w_i - 0.126 \times D_{ex} \tag{2}$$

Where,

t_f = follow-up time (s),

t_c = critical gap (s),

D_{ex} = external roundabout diameter (28–44 m),

w_i = Width of apporch lane (3.0–5.0 m),

v_{ce} = circulating flow at entry e (134–481 veh/h),

b_e = distance between the collision point of entering stream and circulating flow and the point where the vehicles diverge (16.2–23.0 m).

While in 2020, Macioszek [17] studied a total of six roundabouts to calculate the entry capacity as a case study in Tokyo and Tokyo surrounding. According to Macioszek, the dependence of the critical gap on the outer diameter of the roundabout and width of roadway can be expressed in the following form (Eq. (3)).

$$t_g = 12.80 - 0.19 \times D_i - 0.56 \times w_c \tag{3}$$

for 24 m ≤≤ 37 m, 4.0 m ≤≤ 5.0 m,

where,

t_g = critical gap (s),

D_i = external diameter of the roundabout (m),

w_c = width of the circulatory roadway (m).

However, some researchers developed mathematical models to estimate the critical gap using the driver socio-economic characteristics, the expected waiting time, time of day, and trip purpose [18]. Others tried to investigate the influence of geometric and traffic parameters on critical gap based on the interaction between the driver and vehicle [19]. Tian et al. [20] conducted a research using linear regression analysis on microscopic level of 40 intersection throughout the United States. They Intended to address the detailed analysis of various factors that might affect critical gap and follow-up time. These factors include geographical region, intersection geometry, traffic movements, vehicle type, speed, delay, etc.

This paper introduces the development of mathematical models of gap acceptance parameter (critical gap) at thirteen roundabouts in Hungary. The results include the estimated critical gaps for each entry, geometric parameters of the selected roundabouts, traffic volumes (circulating and entry flows) of each leg. The objective of the study was to find the best predictive mathematical model of the critical gaps based on geometric and operational parameters and identify the parameters that have the highest impact on critical gap value. The practical application of this research is to help traffic engineers as well as traffic surveyor in finding the critical gap value without the need of conducting a big study of the rejecting and accepting gaps of each driver. Since this process is very time consuming.

The results and methodology of this research can be transferable to similar driving cultures.

2 Methodolgy

The study is divided into five parts. The first part deals with the study area and data collection process. Critical gaps estimation using Raff's method. Obtaining the Geometric parameters of the selected roundabouts. Extracting the circulating and entry flows from the recorded videos. All the videos were recorded during the morning and evening peak hour. Developing predictive models for critical gaps using the geometric and operational parameters of the roundabouts by using some statistical methods. Nine of the thirteen selected roundabouts exist in urban settings inside built up areas and the other four roundabouts exist in rural settings outside built-up areas.

In this paper, the critical gaps values of the thirteen roundabouts were estimated manually using Raff's method. Some of the geometrical data of the roundabouts was taken from vector maps provided by Hungarian Public Roads, and the others were obtained using google maps. The traffic volumes were extracted manually from the recorded videos of selected roundabouts. The influence of pedestrian and cyclists is neglected in this research.

After obtaining all the necessary data, some statistical methods were implemented to find the best predictive model. Statistical packages in Python were used for the statistical analysis purposes.

For the development of the predictive model three statistical Models were created (Model 1 (M1), Model 2(M2), and Model 3 (M3))

- Multivariate adaptive regression spline (MARS) as M1,
- linear regression model based on Pearson correlation coefficient as M2, and
- linear regression model based on Spearman correlation coefficient as M3

Finally, a comparison between all three models. The comparison is done by reporting the model with highest coefficient of determination R^2 and the lowest root mean squared error (RMSE) as the best predictive model of the critical gap.

3 Models development

Building a Linear regression model to predict the critical gap is done by selecting the most influential parameters. The research data contained 26 parameters for each roundabout see Table 1.

To identify the most influential parameters for the regression models, fifteen variables have no impact or meaningful relationship with critical gaps value were excluded. Thus, the most influential parameters are divided into two groups Geometric parameters and Operational parameters. tabulated in Table 2.

3.1 Collinearity analysis

Collinearity analysis, checking any possible high correlation between the parameters since the model cannot attribute the shared variance with the response to either of the predictors because they basically contain the same information. Since there are high probabilities of significant collinearity among the parameters. Collinearity analysis was

Table 1 All available data for all roundabouts

No.	All Parameters
1	Roundabout ID
2	Roundabout
3	Latitude
4	Longitude
5	Day/night recording
6	Length of recording
7	Data of recording
8	No. of observation
9	Peak hour recorded (Morning, afternoon, or evening)
10	Critical gap
11	Leg
12	Central island diameter (D_{Island})
13	Inscribed diameter ($D_{Inscribed}$)
14	Width of circulatory carriageway ($W_{Circulatory}$)
15	Entry angle (E_{Angle})
16	Splitter island width ($W_{Splitter}$)
17	Distance between neighboring legs ($Distanc_{eLegs}$)
18	Entry width (W_{Entry})
19	Approach entry width ($W_{Approach}$)
20	Entry volume (pcu/h) (v_e)
21	Circulating volume (pcu/h) (v_c)
22	No. of circulatory lanes
23	No. of entry lanes
24	No. of exit lanes
25	Urban/Rural
26	No. of legs

Table 2 List of metadata parameters with a meaningful relationship with observed gaps at roundabouts

1	Central island diameter (D_{Island})	Geometric parameters
2	Inscribed diameter ($D_{Inscribed}$)	
3	Width of circulatory carriageway ($W_{Circulatory}$)	
4	Entry angle (E_{Angle})	
5	Splitter island width ($W_{Splitter}$)	
6	Distance between neighboring legs ($Distance_{Legs}$)	
7	Entry width (W_{Entry})	
8	Approach entry width ($W_{Approach}$)	
9	Entry volume (pcu/h) (v_e)	Operational parameters
10	Circulating volume (pcu/h) (v_c)	

carried out. The reason of collinearity analysis is to avoid any possible correlation within the parameters which will affect the results of the linear regression.

The researcher performed an analysis for possible correlation between the selected parameters. Coefficients of the parameters were computed to have broader idea which parameters have the highest collinearity among them Table 3. In the beginning of the performed analysis $D_{Inscribed}$ is excluded automatically due to 0 tolerance. In the Collinearity Statistics column of Table 3 both D_{Island} and $W_{Splitter}$ have the lowest tolerance. While the conventional threshold is based on the variance inflation factor VIF > 10 [21].

In this case all the parameters except the $D_{Inscribed}$ are independent. Henceforward, the nine parameters listed in Table 4 forms the basis parameters used for the development of the next three models.

Table 4 The retained parameters of the collinearity analysis

1	Central island diameter (D_{Island})
2	Width of circulatory carriageway ($W_{Circulatory}$)
3	Entry angle (E_{Angle})
4	Splitter island width ($W_{Splitter}$)
5	Distance between neighboring legs ($Distance_{Legs}$)
6	Entry width (W_{Entry})
7	Approach entry width ($W_{Approach}$)
8	Entry volume (pcu/hr) (v_e)
9	Circulating volume (pcu/hr) (v_c)

3.2 Multivariate Adaptive Regression Spline (MARS) Model 1 (M1)

Multivariate adaptive regression spline is an artificial intelligence (AI) algorithm. This algorithm was used to develop the first regression model for the available set of parameters. This method is well suited for high-dimensional issues such as a large number of inputs. MARS algorithm operate by using the trained data then the process is done either by forward pass FP or backward pass BP computation method. After implementing all the parameters retained from collinearity analysis, the MARS retained functions as shown in Table 5.

Then the two functions obtained from MARs model as expressed in Eqs. (4) and (5).

$$t_c = 3.27263 - 0.0389436 \times BF1 - 3.5 \times 10^{-5} \times vc \quad (4)$$

$$BF1 = max\left(0,\ 25.81 - Distance_{Legs}\right) \quad (5)$$

The R^2 of the MARS model is 0.54 and mean squared error RMSE = 0.0237.

Table 3 Collinearity Statistics of all important parameters

Model		Coefficients						
		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
	(Constant)	2.964	0.376		7.891	0.000		
	D_{Island}	-0.001	0.004	-0.064	-0.217	0.830	0.133	7.546
	$W_{Circulatory}$	0.045	0.025	0.259	1.809	0.080	0.556	1.798
	E_{Angle}	-0.001	0.004	-0.044	-0.290	0.774	0.495	2.019
	$W_{Splitter}$	-0.039	0.023	-0.542	-1.681	0.103	0.110	9.105
	$Distance_{Legs}$	0.013	0.004	0.622	3.316	0.002	0.325	3.078
	W_{Entry}	0.099	0.061	0.200	1.622	0.115	0.754	1.326
	$W_{Approach}$	-0.086	0.030	-0.371	-2.852	0.008	0.673	1.485
	v_e (pcu/h)	-0.465	0.434	-0.123	-1.071	0.293	0.868	1.152
1	v_c (pcu/h)	-1.526	0.400	-0.458	-3.818	0.001	0.792	1.262

Table 5 MARS retained functions summary

Basic Function	Pruned	Coefficient
(Intercept)	No	3.27263
h ($Distance_{Legs}$ -25.81)	Yes	None
h (25.81 - $Distance_{Legs}$)	No	-0.0389436
v_c	No	-0.000358345
$W_{Splitter}$	Yes	None
h (v_c -659.88)	Yes	None
h (659.88- v_c)	Yes	None
W_{Entry}	Yes	None
E_{Angle}	Yes	None
$W_{Approach}$	Yes	None
h (E_{Angle} -63)	Yes	None
h (63- E_{Angle})	Yes	None
$W_{Circulatory}$	Yes	None
h (W_{Entry} - 4.75)	Yes	None
h (4.75- W_{Entry})	Yes	None

3.3 Second linear model (M2) based on Pearson correlation

Pearson correlation coefficient is a statistical measure of the linear correlation between two variables. The collected data of the variables met the assumption of continuity to perform the Pearson correlation. The correlation conducted for pair of variables in this case critical gap t_c with one variable of retained nine parameters [22].

Table 6 Second regression model based on Pearson correlation

Model 2 Summary				
Model	R	R Square	Adjusted R Square	RMSE
2	.688	0.473	0.430	0.17358

The retained nine parameters from collinearity test was examined and their relationship with the critical gap was analyzed see Fig. 1. The threshold of selecting the highest correlation parameters with the t_c is based on significance level $p < 0.05$. The highly correlated parameters with the p smaller than 0.05 were used to develop the second regression model. The returned parameters after Pearson correlation are $Distance_{Legs}$, $W_{Approach}$, and v_c.

The result of the linear regression analysis of the retained parameters of the second model are as shown in Table 6.

3.4 Third linear model (M3) based on Spearman correlation

In this model, Spearman correlation in Fig. 2 was used to find the highest correlated parameters with the t_c for the regression analysis. The selection threshold for this model is similar to the one in Pearson correlation $p < 0.05$.

The returned parameters from Spearman correlation matrix are $W_{Approach}$ and v_c where $p < 0.05$. according to Spearman correlation matrix, the retained parameters are the same as Pearson correlation matrix except for $Distance_{Leg}$.

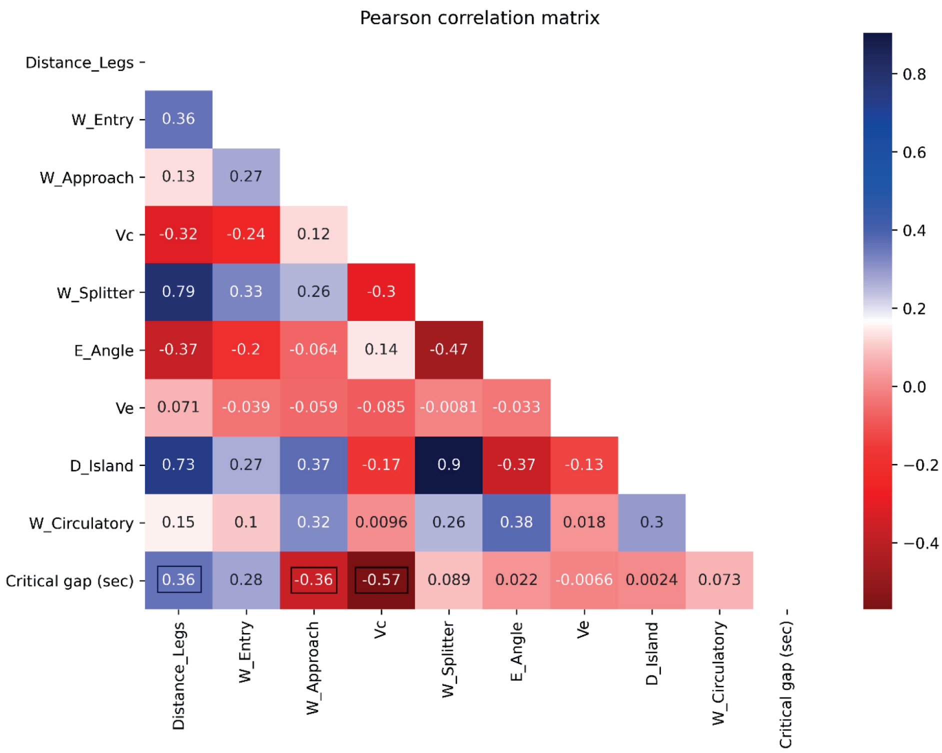

Fig. 1 Pearson correlation matrix heatmap

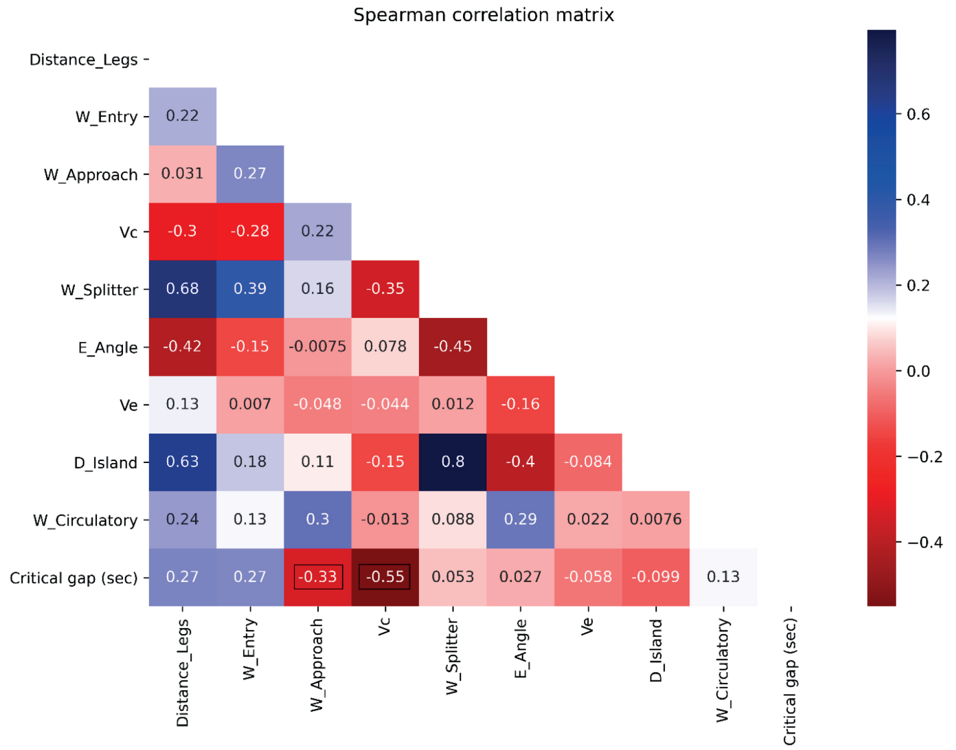

Fig. 2 Spearman correlation matrix heatmap

Table 7 Third regression model based on Spearman correlation

M3 Summary				
Model	R	R Square	Adjusted R Square	RMSE
1	.642a	0.413	0.382	0.18080

The results of the regression model of the Spearman retained parameters are as shown in the Table 7.

4 Models comparison

As discussed in the previous section, the model with the highest coefficient of determination R^2 and the lowest RMSE is considered as the best t_c predictive model. The comparison of the three models is as illustrated in Table 8.

It has been found that M1 model generated by MARS algorithm gives the best R^2 among the other models with the lowest RMSE. Therefore, the critical gap value can be predicted using Eqs. (4) and (5), where, v_c is circulating flow in PCU/h and $Distance_{Legs}$ is the distance between neighboring legs in (m).

The percentage difference between estimated t_c and predicted t_c generated by MARS model for each roundabout leg is shown in Fig. 3. The percentage difference between the estimated and predicted t_c is in range of 0.2%–14.3%. In Fig. 4, the linear model's regression line passes through the origin accurately describing the relationship between the estimated and predicted t_c values with $R^2 = 0.9975$.

Table 8 comparison of the developed models

Models Summary						
Model	R	R Square	1st Rank	RMSE	2nd Rank	Final Rank
M1	.735	0.54	1	0.0237	1	1
M2	.688	0.473	2	0.17358	2	2
M3	.642	0.413	3	0.18080	3	3

A 3D colormap illustration of the selected MARS function is shown in Fig. 5.

5 Conclusions

Critical gap value is very important in determining the capacity and performance of the roundabouts. An accurate estimation of the critical gap value gives an accurate estimation of the capacity as well as the performance of the desired roundabout. There are many methods in the literature proposing an approach for the critical gap estimation. In this research, Raff's method was used to estimate the critical gap for all the roundabout's entries. Using any method found in the literature for critical gap analysis is very time consuming and needs a lot of efforts. This was the motivation of conducting this study to find a mathematical model to ease the task for traffic engineers. In the beginning there were 26 collected parameters for each roundabout. After dropping off unnecessary parameters only 10 parameters have a meaningful relationship with

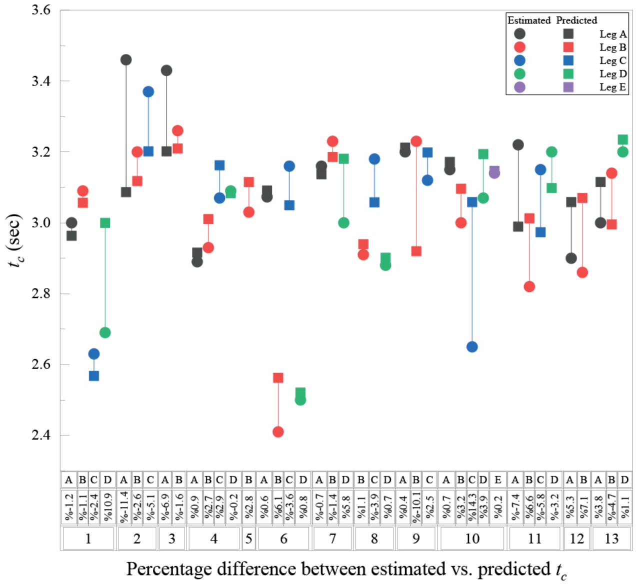

Fig. 3 Scatter plot of the roundabouts, legs, and percentage difference between estimated vs. predicted t_c

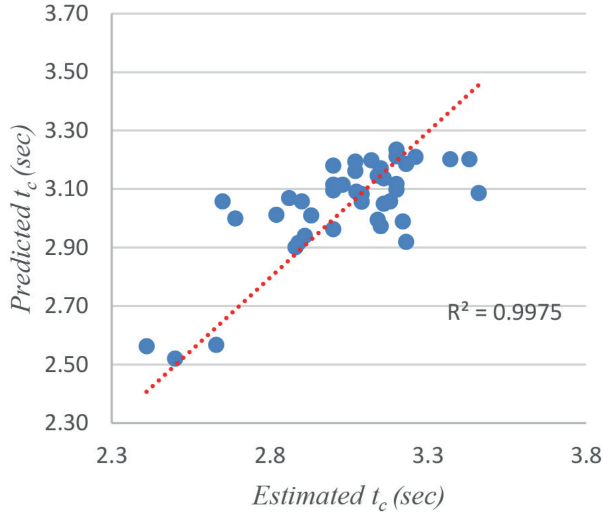

Fig. 4 Scatter plot of the Predicted t_c vs. Estimated t_c

critical gap. Collinearity analysis was implemented and 9 out of the 10 parameters were independent parameters. The nine parameters after collinearity analysis formed the basis of the further development of the models. Three models were developed. The first model was done using AI algorithm called MARS (Multivariate adaptive regression spline). The second regression model was based on the Pearson correlation. The third and last model was based on spearman correlation.

Our finding noted that W_{entry}, $W_{splitter}$, D_{island}, *Wcirculotry*, E_{angle}, and v_e have a low correlation with the critical gap in all three models. While $D_{iscribed}$ failed the collinearity analysis.

Based on the results of the first M1 MARS algorithm, $D_{distance}$ and v_c have the highest impact on t_c. While in Pearson correlation results $W_{approach}$, $D_{distance}$, and *vc* are the main parameters for the second model M2. Concurrently, Spearman correlation retained only two parameters the $W_{approach}$ and v_c while the other parameters have no significant relationship with t_c.

It was noticed that, in the three models v_c is part of all developed models. This indicate that v_c have a great impact on t_c. Since critical gap value decreases with the increase in v_c at the opposing mainstream supported by the finding of Troutbeck and Kako [13].

The findings are of a great importance revealing how geometric and operational parameters of the roundabouts have an impact on the t_c.

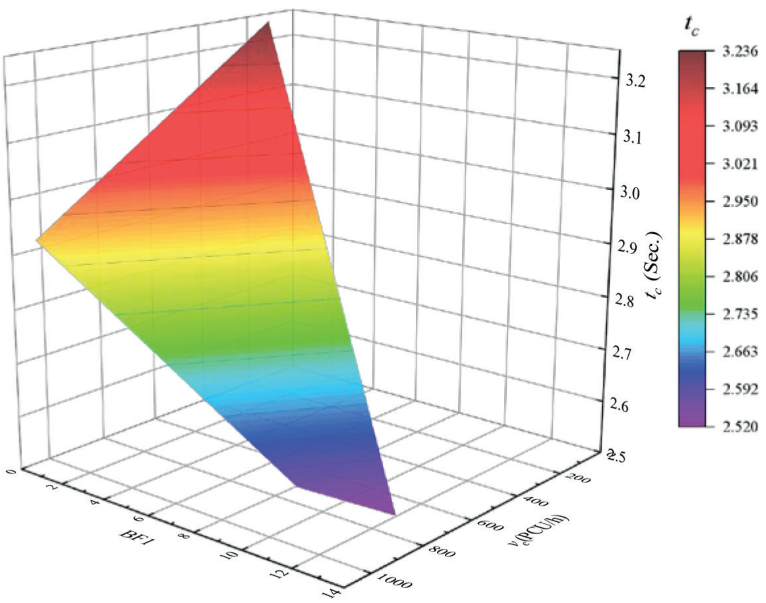

Fig. 5 The dependence of the critical gap as a function of circulating volume and distance between neighboring legs for the selected Mars model

After ranking of the three developed models based on the R^2 and RMSE. The best models describing the t_c is the model developed by MARS (M1). The model's coefficient of determination R^2 was 0.54 and RMSE of 0.0237. Accordingly, the critical gap can be predicted using Eqs. (4) and (5) explained in the previous section. In the end of the results section Fig. 4 shows the actual t_c and the predicted t_c of the MARS models (M1).

Limitation of the study that all the studied roundabouts are single-lane roundabouts of different geometries.

Future research can be achieved by linking different types of roundabouts such as two-lane roundabouts, turbo roundabouts etc. Similarly, the approach speed at the roundabout entry, circulating vehicles speed, and lane gradient can be examined too in the future study. Implementing different estimation method of critical gap such as Maximum likelihood method and determining the differences in the results. Comparison with the critical gap values of other maneuvers at conventional yield-intersections.

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