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Models of Roundabout Lane Capacity

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1 Abstract

Accurate roundabout capacity models are essential for optimal roundabout designs, but there exists significant differences in the predicted capacities of various state-of-the-art models and in their included explanatory variables. An empirical study into roundabout lane entry capacity was thus performed in the U.K. using data from 35 roundabout entry lanes, where various model forms and explanatory variable sets were tested. Two regression models and an artificial neural network were developed. A negative exponential relationship with circulating flow predicted lane capacity better at high and low circulating flows, and better reflected the overall trends in the aggregated capacity data compared to a linear model. The regression models performed relatively well, and provided better information on the impacts of the variables than the neural network. The models consistently suggest that entry-exit separation and flows exiting on the same arm have stronger significant effects

14 on capacity than variables such as entry angle and entry radius. These findings
15 could thus contribute to an improved understanding of the variables which affect
16 entry lane capacity and therefore the development of better roundabout capacity
17 models.

18 **Introduction**

19 Roundabouts are a major form of at-grade junction, and operate based on
20 offside priority where entering vehicles give way to those circulating one-way around
21 a central island. Their traffic performance in terms of queues and delays typically
22 depends on entry capacity, which is the maximum sustainable throughput of vehicles
23 across the give-way line of an entry with fully-saturated demand. Offside priority
24 means that this primarily depends on the circulating flow, but many other traffic,
25 geometric and environmental factors have also been found to affect entry capacity.
26 Existing capacity models for roundabouts are based on at least one or more of three
27 major methodologies: empirical approaches based on statistical evidence from
28 observed roundabout capacity measurements, gap acceptance based on theoretical
29 models of driver behavior and vehicle interactions, and microscopic simulation of the
30 movements and interactions of individual vehicles on a simulated network (Yap et al.
31 2013).

32 In the design of roundabouts, the geometric layout is the most crucial aspect
33 for achieving the required operational performance as the designer has little control
34 over traffic and environmental variables. Hence, understanding the impact of
35 changes in geometry on capacity is vital. Of the major empirical models, the linear-
36 in- Q_c LR942 model (Kimber 1980) of ARCADY (TRL Software 2012) is sensitive to
37 the most geometric variables, given its basis in data from track experiments and a
38 very large sample of public roundabouts of various geometries to determine the entry
39 capacity of whole approaches. Other empirical models such as the French Girabase
40 (Guichet 1997) and U.S. HCM 2010 (Transportation Research Board 2010) relied
41 more on theoretical models; for example, their negative exponential relationship
42 between Q_e and Q_c parallels that of the Siegloch gap acceptance model (Akçelik
43 2011; Louah 1992). In comparison, other models such as SIDRA (Akcelik &
44 Associates Pty Ltd 2011) and the Swiss Bovy-Tan (Simon 1991) model, being more
45 heavily based on gap acceptance theory and/or microscopic simulation, took more
46 account of traffic variables and driver behavior.

47 However, as discussed in Yap et al. (2013), despite the relative similarity of
48 how roundabouts operate worldwide, there can be large differences in prediction
49 between the major capacity models. Given that the models significantly rely on
50 empirical data from their origin countries, part of these errors may be attributed to
51 differences in driver and vehicle behavior in different populations. However, the
52 differences in explanatory variables used and the size of the model predictive errors
53 also suggest that the models may not have adequately accounted for all the factors
54 and processes affecting roundabout capacity, at least to a level which enables
55 transferability without relatively arbitrary calibration measures.

56 The research in this paper thus attempts to develop a better understanding of
57 whether existing models are adequate given possible differences in geographical
58 context, roundabout design, driver and/or vehicle behavior, and whether further
59 model development is needed to adequately describe the effects of factors and
60 variables on roundabout capacity for improved predictive ability and model
61 transferability.

62 **Data Collection**

63 In line with the objectives, it was necessary to collect up-to-date capacity and
64 input data from the field for the assessment of existing models, and to investigate the
65 relationships between at-capacity entry flows and geometric or traffic variables.
66 Determining these relationships was particularly important given the disparities in the
67 forms of capacity models and significant variables in existing literature. An empirical
68 methodology with directly-measured capacity flow data was used, in preference to a
69 gap acceptance approach involving intermediary driving or traffic behavior models
70 based on headway measurements which could introduce additional uncertainty into
71 the relationships between geometry and capacity.

72 Sample selection for an empirical investigation should ideally maximize the
73 range of each variable to be investigated, with random and/or stratified sampling to
74 improve the sample's representativeness. However, the need for direct
75 measurement of at-capacity entry flows meant that the sites were limited to those
76 which had sustained queues at the give-way line during peak periods – the queues
77 indicated an excess of demand over capacity (i.e. the maximum flow for the given
78 conditions) and the resulting entry flows therefore reflected the capacity. Desktop-
79 based reconnaissance using live traffic information (Google 2012; Hampshire County
80 Council 2005) and local knowledge was used to identify congested roundabout
81 entries. Geometric measurements were based on high-resolution aerial or satellite
82 photographs (Google Inc. 2013) scaled to superimposed Ordnance Survey digital
83 mapping (Ordnance Survey 2012) in CAD software (Autodesk Inc. 2012). The final
84 sample comprised of data from 35 lanes in 19 entries to 10 roundabouts in
85 Hampshire and Berkshire (Table 1), representing a wide range of geometry and
86 roundabout sizes (Table 2).

87 The at-capacity entry flow (Q_e) and the corresponding circulating flow (Q_c) and
88 exiting flow (Q_x leaving on the same arm as the subject entry) were enumerated from
89 digital videos recorded from the roundabout entries during peak periods. This
90 involved recording the number of vehicles crossing the respective positions
91 illustrated in Figure 1, during one-minute periods with continuous queuing at the
92 entry yield line and uninterrupted circulating flows. The passenger car unit (pcu)
93 factor for heavy vehicles was taken to be 2 pcu based on existing studies (Kimber
94 1980; Rodegerdts et al. 2007, table 44), given the relative insensitivity of Q_e to the
95 rounding of pcu values (Glen et al. 1978; Semmens 1988). 1753 one-minute flow
96 data points were obtained, although 193 did not include exiting flows due to
97 recording limitations.

98 The explanatory variables (listed in Table 2 and shown in Figure 1) were
99 selected on the basis of previous roundabout studies (Guichet 1997; Kimber 1980;
100 Tan 1991; Troutbeck 1989), and included several two-way interactions between
101 them where appropriate. As this study focused on lane capacity rather than whole-
102 approach capacity, lane width was used in lieu of flare geometry variables,
103 particularly as several sites also had approach half-width V greater than lane entry
104 width E. The lane width 10 m upstream of the give-way line (W_L) was generally found
105 during the subsequent analyses to produce better model fit compared to E, as the
106 latter was sensitive to the final flare geometry at the entry and could thus be less
107 representative of the conditions at entry during the gap acceptance process.

108 It was generally observed that entering vehicles gave way to all circulating
109 vehicles regardless of entry lane position (although this may not be the case for
110 other roundabout entries where the first downstream exits are much further and inner
111 circulating vehicles do not change lanes until they exit). Hence, only the upstream

circulation width (W_C) was investigated due to its possible influence on circulating vehicle headways (Troutbeck 1989). Similarly, as queued delay could affect critical gaps and thus capacity (Ashworth and Bottom 1977; Polus et al. 2003; Polus et al. 2005), the duration of the queues (as a proxy to average queued delays) was also investigated, as was the adverse effects of wet weather (Tenekeci et al. 2010).

Additional short lanes in flared entries can affect measured lane entry flows, since a vehicle which changes lanes leaves behind a gap in the queue which may not be closed by the next vehicle before it reaches the give-way line. This could be significant if the queue has a fast move-up rate with many lane changes, and prevents measurement of the entry capacity of the lanes at the give-way line as restricted by offside priority (as opposed to that restricted by the supply from upstream approach or link). Hence, data points were measured from periods which uninterrupted continuous queues were present, defined by the presence of at least one vehicle at or near the give-way line at all times. This was to some extent subjective, as it was based on observation of the acceleration/deceleration of vehicles and their relative positions and headways. Investigation of the effects of flaring on lane capacity will necessarily require more data from more entries of different flare lengths and lane choice patterns, but this was beyond the scope of this study.

Evaluation of existing models

Observed data

The first step of the process to assess the existing models and identify possible relationships between the inputs and capacity comprised exploratory data analyses of the data obtained from the survey. At-capacity entry flows are plotted against the corresponding circulating flows in Figure 2 along with local regression (loess) lines, which are least-squares polynomial lines fitted to localized subsets of the data and weighted using nearest-neighbors algorithms (Cleveland 1994, chapter 3.7). There appears to be a clear non-linear trend in the aggregated data; however, the typically limited range of observed circulating flows (which depended on the prevailing origin-destination patterns at the roundabout during the peak hour periods) meant that a non-linear relationship is less evident within individual sites.

A few sites had significantly steeper slopes compared to others with a similar circulating range, while there were also differences in entry flow ‘intercept’ among those with similar slopes. Within individual sites, there was little evidence of heteroscedasticity across the circulating flow range, although this may have been due to the limited number of data points at low and/or high circulating flows as seen in the example in Figure 3.

Existing model predictions

To evaluate their predictive ability for a new set of roundabouts, the predicted and actual entry flows were compared for several existing major capacity models in their default form, albeit with appropriate assumptions to estimate lane capacity where necessary e.g. by treating each lane as a single-lane approach. The models tested were the LR942 model of ARCADY, the HCM 2010 model, the German Brilon-Wu model (Wu 2001), the Swiss Bovy-Tan model and the SIDRA model.

The results are shown in Figure 4. Some of the predictive errors could possibly be attributed to differences in behavior between different driver or vehicle populations (for example, the HCM2010 model was calibrated to data from U.S. drivers who may generally have had less experience with roundabouts compared to say, U.K. drivers). Nevertheless, the U.K.-based LR942 model – which was extensively validated in the 1990’s (Barnard et al., unpublished report, 1995) – did

not show much better performance for predicting lane capacity, although this could partly be due to its focus on whole-approach capacity particularly for multilane flared entries. However, most of the models show a systematic trend of greater under-prediction of lane capacity at higher entry flows (corresponding to lower circulating flows), suggesting that there could be other reasons for their limited accuracies when applied to this new dataset.

These capacity prediction errors could be reduced by using relevant site-specific measurements such as critical gaps or recommended calibration methods such as intercept corrections or 'environment factors'. However, such procedures would not reflect how these models could be applied to new roundabouts in the absence of local information, and it is not clear how further changes in geometry affect parameters which have been calibrated (Yap et al. 2013). Thus, the results here point to the need for improved models to more accurately predict lane entry capacity, and to have a better understanding of factors affecting capacity given the differences in inputs of existing models.

Development of improved models

Regression approach

Using the available data, new empirical models were developed using statistical methods such as multiple linear or nonlinear regression; further information on these methods can be found in many statistical textbooks such as Kutner et al. (2005) and Cohen et al. (2003). Previous empirical studies (Brilon and Stuwe 1993; Glen et al. 1978; Kimber 1980; Kimber and Semmens 1977; Louah 1992; Polus and Shmueli 1997; Rodegerdts et al. 2007; Semmens 1988) variously used linear or negative exponential relationships between Q_e and Q_c . To investigate the best regression form for the analyses here, smaller 30-second measurement time intervals were used in several roundabouts, with observations in both morning and afternoon peak periods to widen the range of circulating flows (data points from different periods did not show any statistically-significant differences in linear slopes and intercepts, and so were combined together; likewise, there were no statistical differences between 30-second and one-minute regression lines). As shown by the example in Figure 3, these did not conclusively show that nonlinear relationships were better than linear for individual roundabouts, despite the wider range of circulating flows. However, the slopes of the linear model for large and grade-separated roundabouts had previously been found to depend on prevailing circulating flows (Semmens 1988), while Figure 2 suggests that a nonlinear relationship could be more appropriate in the absence of advance knowledge of the applicable circulating flow range for a proposed roundabout.

Both linear-in- Q_c and exponential-in- Q_c forms were therefore investigated in the regression analyses, using one-minute data points for all sites. The 'slopes' and/or 'intercepts' appeared to be site-specific, so the tested models were linear with input-dependent intercept and gradient ($Q_e = A + BQ_c$), or negative exponential with constant or input-dependent asymptote, 'slope' and/or 'intercept' ($Q_e = Ae^{BQ_c} + C$); A, B and/or C was $m + \sum p_i X_i$ where X_i were included explanatory variables, m and p_i were parameters to be determined through least-squares regression. Quadratic or piecewise linear spline functions in Q_c were also investigated but they suggested counterintuitive behavior within the range of observed data, such as increasing capacity at very high circulating flows.

Based on the residual scatterplots and previous studies (Marstrand 1988; Troutbeck 1989), a nonlinear relationship between Q_e and D was tested using D^2 or two-way D interaction terms. There was little consistent evidence to suggest the form

212 of the relationship between Q_e and the other explanatory variables so simple linear
213 additive effects were assumed, complemented by checks on the regression
214 assumptions through residual scatterplots.

215 The regression models assumed additive, homoscedastic and normally-
216 distributed errors (ϵ), as part of the observed entry flow variability is likely to be from
217 driver and vehicle characteristics which were not explicitly included in the model;
218 there was no evidence from the scatterplots to show that these were proportionate to
219 Q_e nor that the assumptions were inappropriate. For the nonlinear exponential model,
220 least-squares error minimization using numerical methods was used to estimate the
221 parameters; statistical inferences assumed large-sample theory as the similarity of
222 confidence intervals from bootstrap sampling and asymptotic nonlinear regression
223 did not suggest this to be inappropriate (as explained in Kutner et al. 2005, p.529).

224 Backwards elimination with all (and various subsets of) the variables in Table
225 2 showed that many variable coefficients were significant at the 5% level due to the
226 large sample size, despite having relatively little contribution to explained variability.
227 There was also limited information within existing studies regarding the relative
228 importance of the explanatory variables, apart from circulating flow and diameter.
229 Hence, hierarchical forward variable selection was used to develop more
230 parsimonious final models, with the main effect and interaction terms entered
231 manually based on the improvements in adjusted R^2 observed during the stepwise
232 regression process.

233 All the regression (and the neural networks discussed in the following section)
234 analyses were performed in SPSS (IBM Corporation 2012a). Over 210 regression
235 models were investigated, and although these were not exhaustive given the number
236 of possible combinations of variables and their interactions, the final models below
237 (and Table 3) represent the best combinations based on the process outlined earlier:

238 *Model 1:* Multiple linear regression ($R^2=0.825$, adjusted $R^2=0.824$, root-mean-
239 square-error RMSE=126.5):

$$240 Q_e = 1113 + 15.9 D - 5.99 d_{sep} - 0.243 D \cdot d_{sep} + 0.0103 Q_x - 7801 (1/r) + 0.00435 Q_x \cdot d_{sep} \\ 241 + [-0.952 - 0.00313 D + 0.0153 d_{sep} - 0.000108 Q_x + 7.51 (1/r)] Q_c$$

242 *Model 2:* Nonlinear exponential regression model with additive error and variable
243 asymptote ($R^2=0.839$, adj. $R^2=0.838$, RMSE=121.3):

$$244 Q_e = -771 + 8.01 D + 7.00 d_{sep} - 0.103 D \cdot d_{sep} + 0.0572 Q_x + 2088 (1/r) + 40.7 W_C \\ 245 + 1580 \text{EXP}(-0.00103 Q_c)$$

246 Despite having only five and six traffic and geometric variables respectively,
247 the linear and exponential models above compared favorably to models of equivalent
248 form but including all other variables and interaction terms (those had adjusted R^2
249 values of 0.835 and 0.842). For the exponential model, an alternative model form
250 which had the exiting flow Q_x as part of a conflicting flow (i.e. $Q_c+k \cdot Q_x$ or $Q_c+k \cdot d_{sep} \cdot Q_x$
251 in place of Q_c) did not show an improvement in model fit. Other additive-error
252 exponential models using input-dependent ‘slopes’ and ‘intercepts’ did not improve
253 on the model fit, while the implied complex interactions among the variables in these
254 models were difficult to justify. Exponential models with multiplicative error terms and
255 multiplicative variable effects [$Q_e=m_0 \cdot (\prod X_i^{p_i}) \cdot e^{m Q_c} \cdot \epsilon$] which could be linearly regressed
256 via logarithmic transformation also produced poorer fits to the data. Model forms
257 based on the LR942, Girabase, Brilon-Wu and SR45 (Troutbeck 1989) capacity
258 models were also tested by recalibrating their parameters for the new dataset, but
259 these also produced poorer model fit.

260 ***Neural network modelling***

261 An important alternative to statistical regression models for data analysis and
262 pattern recognition in large datasets is the artificial neural network (NN). This is a
263 mathematical model represented by a layer of input nodes, a layer of output nodes
264 (where the numbers of nodes in each layer depend on the number or type of input
265 and output variables respectively), and typically at least one layer of hidden units
266 with sigmoidal activation functions which transform the combined weighted inputs
267 from preceding layers into an output value. The connections between the nodes in
268 successive layers depend on weights and biases whose values are optimized
269 through learning algorithms from a set of training data. Appropriately-structured and
270 trained NN's can approximate complex nonlinear relationships with interactions
271 between input variables (see Kutner et al. 2005 chapter 13.6 and Sarle 1994 for
272 further information), and has been used in various transportation studies (Karlaftis
273 and Vlahogianni 2011; Özysal et al. 2009). Given the uncertainties around the form
274 of the capacity relationships shown by the differences in existing models and in the
275 exploratory scatterplots, NN modelling was thus used in this study to assess the
276 ability of the regression models above to represent the relationships between the
277 input and capacity, given the constraints of assumed functional relationships. It also
278 enabled the determination of the extent to which the observed variation in the
279 capacity could be explained by the inclusion of the selected explanatory variables, in
280 the absence of any *a priori* relationship forms and interactions.

281 The dataset of explanatory variables and capacity flows was used to develop
282 and train a simple feed-forward multilayer perceptron with a single hidden layer using
283 hyperbolic tangent activation functions. The number of hidden nodes was
284 determined through progressive removal or inclusion of hidden units based on the
285 changes in training errors, while weights and biases were optimized through error
286 back-propagation using numerical methods to minimize the sum-of-squares error. To
287 account for the stochastic nature of the NN optimization process (IBM Corporation
288 2012b, p.5), ten NN's were developed for each set of explanatory variables. It was
289 found that NN's with all the variables included had an average R^2 of 0.877. However,
290 as shown in Table 4, NN's with a subset of 4 or 5 variables including either exiting
291 flow or entry-exit separation was sufficient to account for most of the model fit.

292 **Discussion**

293 As shown in Figures 5, 6 and 7, the inherent flexibility of the neural network
294 models enabled them to produce the best fits to the observed data, but given that
295 scatterplots of predicted capacity from the all-variable NN's appeared to indicate
296 some over-fitting, the linear and exponential regression models would be preferred
297 for engineering application due to their comparable predictive ability and easier
298 interpretation of variable effects. Although the exponential Model 2 provided
299 marginally better overall fit, linear Model 1 was a slightly better fit for sites with
300 steeper slopes despite slightly under-predicting at low and high circulating flows
301 (Figures 5 and 6). Hence, although the nonlinear relationship between entry capacity
302 and circulating flow across the whole dataset could be represented by either an
303 exponential-in- Q_c model or a linear-in- Q_c model with interactions, the latter may be
304 less accurate at very low or very high circulating flows.

305 Figure 7 shows that the RMSE of the existing capacity models in default form
306 exceeded those of the new empirical models, by a minimum of 60 pcu/h or 50%
307 when compared against the regression models. While the performance of the
308 existing models could be acceptable in their origin countries, ongoing research and
309 development (e.g. Brilon 2014, Rodegerdts 2014) suggests that there is scope for

improvement, not least to better account for site-to-site variation. And although the lower errors are not unexpected given that the new models have been specifically calibrated to this particular dataset, the size of the errors further illustrates the limited accuracy of existing models when applied to new roundabouts without calibration, and also the potential improvement in accuracy possible with the inclusion of additional explanatory variables in an appropriate form.

The regression and neural network analyses show that the circulating flow and diameter were the most important explanatory variables for lane entry capacity. At the other end, queue duration and wet weather had insignificant impacts, although the latter may have been due to the lack of data from heavy rain conditions. Between these, separation and exiting flow appear to contribute significantly more to the fit of the models compared to other variables such as entry radius, entry angle and lane width (Table 5).

Assuming all other variables were unchanged with realistic values for interacting explanatory variables, the effect of larger diameter was to increase the lane entry capacity in both regression models, although this increase was less at higher circulating flows in Model 1. Greater circulating width significantly increased capacity in Model 2 but not in Model 1, illustrating the sensitivity of the parameter effects to the form of the assumed relationships. In contrast to SIDRA and LR942, both models suggested that greater entry curvature increased capacity (except at lower Q_c in Model 1), although the effects of both entry curvature and circulating width were quite weak compared to other variables. Variables thought to have greater impact such as entry angle and entry width (Akcelik & Associates Pty Ltd 2011; Kimber 1980) also appeared to have comparatively weak or insignificant effects, although it is likely that entry width would be more important for the overall capacity of flared entries compared to a single line of queuing vehicles.

The regression and neural network analyses consistently suggest that separation and exiting flow had significant and relatively important effects on lane entry capacity, beyond those of inscribed circle diameter. Although a few previous studies found that exiting flows or separation do not usually or significantly affect entry capacity (Kimber 1980; Kimber and Semmens 1977; Troutbeck 1990), others found a separation-dependent negative impact of exiting flow (Hagring 2001; Louah 1992; Mereszczak et al. 2006; Tan 1991), while Semmens (1988) found that larger separation reduced the Q_e intercept for very large roundabouts greater than 130 m in diameter. The Girabase model (Guichet 1997) in contrast predicts an increase in capacity with larger exiting flows, apart from large roundabouts with small separation. However, both the linear and exponential regression models above suggest a more complex relationship than those previously seen, where for example, larger exiting flows appear to increase capacity at low circulating flows regardless of roundabout size or separation (Figure 8); this suggests a need for further research into the effects of exiting flows and separation on lane capacity.

Resource limitations and thus the limited sample size available for model calibration and validation mean that there are a number of caveats to the findings above. For example, queues and delays are more important measures of performance for intersections, but could not be included within the scope of this study as they are modelled separately and field measurements were not available. Although the chosen sample attempted to maximize the range of each of the variables, it was ultimately limited by the availability of entry lanes with measurable capacity flows, which in turn could also limit the generalizability of the findings to all roundabouts especially with other driver and vehicle populations. The statistical

significance of regression parameters may have been affected by collinearity between several of the variables arising from the constraints on the geometric layout imposed by design guidelines, vehicle swept paths and geometric compatibility. Although a large number of different regression model forms were investigated, there remains a possibility that another model form could more accurately describe the effects of the variables on capacity, although the neural network modelling suggested that this improvement would likely be limited. Furthermore, the “noise” in the flow measurements from the short time intervals did not allow the determination through exploratory data analyses of more definitive functional forms of the relationship between many variables and Q_e , while there was also limited theoretical background available for this purpose – further research to address this could then explain the discrepancies between the two regression models in terms of the impacts of the variables on capacity. Also, the empirical models here have focused on lane capacities by excluding the effects of flaring which could significantly reduce the usable capacity; in flared roundabout entries, additional modelling such as the Entry Lane Simulation of ARCADY / Junctions 8 (TRL Software 2012) will be required to account for the reduction in lane entry flows caused by entry starvation due to lane choice patterns and lane queues.

In light of several of these caveats, the new models were tested by retaining a proportion of the dataset (comprising data from a given site) for validation rather than for calibration. The results for two sites are shown in Figure 9; notwithstanding the reduced dataset used to calibrate their parameters, the regression models provided a reasonably good fit to the actual observed capacities. In contrast, the NN had poor transferability due to over-fitting, and therefore was likely to be less appropriate for predictive purposes. However, for the final regression models to be more suitable for wider use, further validation with other datasets would be needed to assess their transferability to other sites without recalibration; otherwise, a practical calibration facility would have to be developed given that driving behavior (which may not be wholly determined by roundabout geometry) or other unquantifiable factors could have significant impacts on capacity.

Conclusions

An exploratory empirical study on lane entry capacity has been performed using at-capacity flow and geometric data from 35 roundabout entry lanes in Hampshire and Berkshire. There is limited evidence of non-linear relationships between lane entry capacity and circulating flows for individual sites, due primarily to the limited range of observable circulating flows. However, the aggregated data on a wider scale shows a distinct non-linear relationship between entry flow and circulating flow.

Existing capacity models showed relatively limited predictive accuracy for this dataset, with many under-predicting lane entry flows particularly at lower circulating flows. Hence, a linear-in- Q_c model and a nonlinear exponential-in- Q_c model were developed through least-squares regression, where the former accounted for over 82% of the variability in the data and the latter showed similar performance. The linear model provided better fit for several sites, but the nonlinear model had better accuracy at the high and low ends of the circulating flow range. The performances of both regression models were close to the more flexible neural network models which were developed as benchmarks for predictive performance.

It was found that the inclusion of only a few explanatory variables was sufficient to explain most of the variability. Among these, the entry-exit separation distance and exiting flows were found to produce significant contributions to the

410 model fits, more than variables such as entry width and entry angle. However, their
411 interactions with other variables imply a more complex relationship than those which
412 have been found by previous studies.

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Tables

Table 1: Roundabout sites in sample

Roundabout reference name	Coordinates	Entry arm(s) direction
bassett	50° 56' 27" N, 1° 24' 25"W	S and SW
baswinc	51° 15' 18" N, 1° 6' 13" W	SW and SE
binfield	51° 17' 8" N, 1° 3' 41" W	NE and SW
coralreef	51° 23' 27" N, 0° 44' 4" W	NW
hilllane	50° 56' 3" N, 1° 25' 9"W	W
imperial	51° 25' 6" N, 0° 58' 33" W	SE
owrnmr	51° 23' 5" N, 0° 47' 35"W	S and W
peacock	51° 24' 34" N, 0° 47' 15" W	NE and SE
thornycroft	51° 15' 56" N, 1° 6' 29" W	S, N, W, E
welshln	51° 21' 32" N, 0° 58' 15" W	S and E

Table 2: Explanatory variables investigated in this study

Variable	Units	Minimum	Mean	Maximum
At-capacity entry flow, Q_e	pcu/h	0	667	1920
Circulating flow, Q_c	pcu/h	0	1266	2880
Exiting flow, Q_x	pcu/h	0	958	2460
Inscribed circle diameter, D	m	31	68	100
Lane width 10 m upstream, W_L	m	2.0	3.2	4.2
Entry curvature, $1/r$	m^{-1}	0 ($1/\infty$)	1/74	1/20
Entry angle, ϕ	$^\circ$	6.6	26.3	54.2
Circulation width, W_C	m	6.7	8.4	11.6
Entry-exit separation, d_{sep}	m	13.8	39.7	95.7
Distance to previous entry, d_{upe}	m	20.7	55.5	117.5

Table 3: Parameter estimates and their standard errors from regression models; all parameters are significant at the 5% level except for that marked *

Parameter	Linear model 1		Exponential model 2	
	Estimate	Std. Error	Estimate	Std. Error
Intercept parameter	1113.2	51.1	-771.0	64.7
Q_c	-0.952	0.038	-0.00103	0.000045
D	15.91	1.01	8.011	0.449
d_{sep}	-5.988	1.458	6.997	0.963
Q_x	0.010*	0.024	0.057	0.007
$1/r$	-7801.1	790.9	2088.0	325.2
$D \times d_{sep}$	-0.243	0.013	-0.103	0.011
$Q_c \times D$	-0.003	0.001	-	-
$Q_c \times d_{sep}$	0.015	0.001	-	-
$Q_c \times Q_x$	0.000108	1.63E-05	-	-
$d_{sep} \times Q_x$	0.004	0.001	-	-
$Q_c \times 1/r$	7.51	0.67	-	-
W_C	-	-	40.67	5.54
Multiplicative parameter	-	-	1580.1	26.1

Table 4: Comparison of neural networks with best-performing variable sets

No. of variables	Variables										Mean R ²	Mean RMSE
	Q _c	D	W _C	d _{upe}	1/r	W _L	d _{sep}	ϕ	Q _x	Wet/dry		
1	✓										0.736	152.0
2	✓	✓									0.809	129.4
3	✓	✓					✓				0.848	115.3
4(a)	✓	✓	✓						✓		0.865	111.3
5(a)	✓	✓	✓	✓					✓		0.867	110.2
4(b)	✓	✓	✓				✓				0.857	112.1
5(b)	✓	✓	✓				✓		✓		0.862	112.1
All	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	0.877	106.2

Table 5: Ranking of the explanatory variables (including interactions) by contribution to model fit, where # denotes insignificant or weak contributions to model R^2 of less than 1%

	Variables						
	Q_c	D	d_{sep}	Q_x	1/r	W_c	$\phi, d_{upe}, W_L, \text{wet/dry, queue duration}$
Linear Model 1	1	2	3	4	5	#	#
Exponential Model 2	1	2	4	3	5	6	#
Neural Networks	1	2	4	5	6	3	#

Figure Captions

Figure 1: Measured variables for each entry lane.

Figure 2: At-capacity lane entry flows from surveyed entries, with local regression (loess) lines.

Figure 3: Class mean lane entry capacity flows from the middle lane of the east entry of Thornycroft roundabout, based on 30-second measurement time intervals.

Figure 4: Observed and predicted lane capacities (pcu/h) from international models.

Figure 5: Comparison of actual against predicted capacities for the new empirical models, with loess fit lines.

Figure 6: Predicted lane entry capacities of models, by site.

Figure 7: Comparison of RMSE values between empirical models and international models.

Figure 8: Impact on entry capacity by separation distance (d_{sep}), exiting flow (Q_x), diameter (D) and circulating flow (Q_c) in the regression models assuming other variables unchanged.

Figure 9: Comparison of capacities predicted by recalibrated models against the actual data from two sites reserved for validation.