Modeling Bicycle Facility Operation

Cellular Automaton Approach

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Current concerns surrounding regional air pollution, climate change, rising gasoline prices, and urban congestion could presage a substantial increase in the bicycle mode share. However, state-of-the-art methods for the safe and efficient design of bicycle facilities are based on difficult-to-collect data and potentially dubious assumptions regarding cyclist behavior. Simulation models offer a way forward, but existing bicycling models in the academic literature have not been validated with actual data. These shortcomings are addressed by obtaining real-world bicycle data and implementing a multilane, inhomogeneous cellular automaton simulation model that can reproduce observations. The existing literature is reviewed to inform the data collection and model development. It is found that the model emulates field conditions while possibly underpredicting bike path capacity. Since the simulation model can "observe" individual cyclists, it is ideally suited to determine level of service based on difficult-to-observe cycling events such as passing. Future work on data collection and model development is suggested.

Bicycle traffic theory lags far behind its highway traffic counterpart and has received comparatively little attention in the literature (*1*). Traffic engineers typically concern themselves with the design of safe roadways that provide a sufficient level of service (LOS) to users. For highways, LOS is ranked from A to F (best to worst) according to its volume-to-capacity (v/c) ratio as defined in the 2000 *Highway Capacity Manual* (*2*). The capacity of a highway is the point at which a marginal increase in vehicle density results in decreasing traffic flow rates. This condition corresponds to LOS E. The relationships among highway traffic flow, density, and speed are well understood through observations, models, and simulations (*3*). However, Taylor and Davis (*4*) note that "significant research is required in almost all areas" of bicycle traffic including traffic flow, intersection control, capacity and LOS, modeling, and geometric design of cycling facilities.

In the near to medium term, with mode share dominated by motor vehicles, the focus of most construction and transportation funding is likely to remain on highways and related infrastructure. But poor regional air quality, climate change, rising gasoline prices, and urban congestion have renewed interest in the role of nonmotorized transportation—including bicycles. However, the quality and quantity of bicycle infrastructure must be increased before cycling can contribute significantly as a competitive form of transportation (*5*). Researching the optimal design and operation of bicycle facilities is timely because the facilities designed and operated today under limited budgets will influence the perception of bicycling as a viable form of transportation tomorrow. Limited funding should not be wasted on overbuilt bicycle facilities or on projects that provide such a poor LOS that users are unnecessarily inconvenienced or endangered.

This study contrasts vehicular flow on highways with bicycle traffic flow on shared-use paths through a review of the literature on bicycle flow theory as it relates to the determination of facility LOS and the design width of bike paths. The review finds that available data and data collection methods present two key problems for bicycle traffic research:

1. It is difficult to observe potentially important bicycle traffic parameters (such as the amount of passing and delayed passing) and
2. The absence of paths that receive a high volume of bike traffic limits the opportunities to observe the full range of possible traffic conditions.

A cellular automaton (CA) model is designed to simulate these difficult or impossible-to-observe aspects of bicycle facility operation. The modeled data are compared with bicycle traffic data collected from the University of California, Davis (UC Davis), campus, with results showing good agreement between the data. The CA model could be used to simulate future scenarios, such as different bicycle designs, cyclist capabilities (speed and acceleration), and cyclist experience. With some modification the model could also be used to study dynamic traffic behavior caused by topography, stop signs, and traffic signals or the influence of different path widths.

LITERATURE REVIEW

Many studies on bicycle operation and path design have been conducted over the past 40 years. Most of the early studies were conducted in Europe, where bicycling as a form of transportation (as opposed to recreation) makes up a larger mode share than in the United States (*6*). These early studies sought to determine the optimal bike path or lane width, the impact of bicycles on vehicular traffic flow, and the capacity of intersections or performed safety assessments (*4*). The focus of this study is the operation and design of dedicated bicycle (shared-use) facilities; therefore the review of the literature only includes studies that observed or modeled cyclists to determine an estimate of facility capacity or investigated LOS considerations for bicycle or shared-use facilities.

An early study of bicycle operation for the city of Davis, California, and the University of California (*7*) was conducted to determine the adequacy of then-current bicycle facilities and to plan for future bicycle facilities. The study determined that a cyclist requires a

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minimum 4-ft (1.2-m) travel lane because a bicycle cannot travel in a perfectly straight line and that a bicycle path should be at least twice this width to allow for passing. This finding was based largely on German design standards, which were widely utilized at the time the study was completed. Smith (*7*) also reviewed other early European studies and found that bicycle path capacities were variable but approximately equal to 235 (bikes · h)/ft [770 (bikes · h)/m]. These findings were the main pieces of information used to design many of the bike paths and lanes that exist in Davis today.

Building on Smith's (*7*) work, Miller and Ramey (*8*) sought to validate the applicability of the European design standards to the United States and develop a method to determine the LOS of bicycle facilities based on the approach used for highways and outlined in the 1965 *Highway Capacity Manual* (HCM) (*9*), assigning Grades A to F (best to worst) on the basis of volume-to-capacity (*v*/*c*) ratios. The HCM assumes that a user's perception of the quality of service provided by a highway facility depends on highway conditions including travel time, speed, safety, and freedom to maneuver, which are correlated with *v*/*c* ratios. To apply this method to bicycle traffic, Miller and Ramey determined the fundamental diagram of bicycle traffic, assigning LOS A to the area representing free-flow speeds and using *v*/*c* ratios from the HCM for the remaining service levels. The fundamental diagram was estimated by measuring bicycle flows on a selection of bicycle paths around Davis and on the American River path in Sacramento, speed was recorded with a radar gun, and density was calculated by using the well-known relationship between the three traffic parameters and the path width:

$$k = \frac{q}{c \cdot u \cdot w} \tag{1}$$

where

- q = flow (bicycles/h),
- u = average speed (mph or km/h),
- k = density (bikes/ft^2 or bikes/m^2),
- w = path width (ft or m), and
- c = constant equal to 5,280 when u is in miles per hour or 1,000 when u is in kilometers per hour.

Their results, summarized by Homburger (*10*), indicate a bicycle path capacity of 792 (bikes · h)/ft [2,600 (bikes · h)/m], much higher than capacities found in the earlier European studies reported by Smith (*7*). At no time did demand exceed capacity. Instead, a curve was fitted to the observed flow–density relationship to determine the maximum flow.

As an alternative to field observations, Navin (*11*) conducted a controlled experiment observing 11- to 14-year-old children riding on a 2.5-m wide oval track following a lead cyclist whose speed was varied. A capacity of 1,220 (bikes · h)/ft [4,000 (bikes · h)/m] was estimated from the experiment. The orderly flow of cyclists behind the lead rider may offer an explanation for the higher-capacity estimate.

Navin (*11*) validated his results with data from Botma and Papendrecht (*12*), who observed bicycles on a mixed-use (bicycles and mopeds) path under real-world conditions with a specially designed mat containing detectors capable of measuring moments of passage and lateral positions of bicycles. A quadratic function was fitted to the data, which indicated a capacity of 732 (bikes · h)/ft [2,400 (bikes · h)/m]. The authors noted that "this value is only an indication of the order of magnitude of bicycle path capacity" since it was not clear that the data followed a quadratic relationship, and capacity was not actually observed.

Finding that bicycle facility capacity was rarely, if ever, exceeded, Botma and Papendrecht (*12*) suggested that capacity could be estimated by observing cyclist headways at flows below capacity by using a method that was developed for highway traffic (*13*). This method defines capacity as the flow rate at which all vehicles are "nonfree," or constrained to follow the vehicle in front of them. The reciprocal of the mean headway of traffic is equal to the traffic flow rate; therefore, the reciprocal of the mean headway of constrained traffic is equal to capacity. It is assumed that the headway of constrained vehicles is the same whether or not the facility is actually at capacity, providing a convenient method to estimate capacity from observations of uncongested traffic. With this method Botma and Papendrecht (*12*) estimated that capacity varied between 1,170 and 1,400 (bikes · h)/ft [3,800 and 4,600 (bikes · h)/m], agreeing with Navin's (*11*) results. However, it has been noted that this method tends to overestimate capacity (*13*).

The lack of agreement between estimates of capacity is not surprising—capacity has never been observed on an actual bicycle facility and would likely be variable. Unlike highway vehicles, which tend to travel around the posted speed limit, the speed of cyclists is determined by trip purpose, experience, physical ability, topography, and climate. The mix of users and uses on a bicycle facility can result in a diverse range of speeds and other travel behavior affecting capacity. This diversity also presents challenges for defining LOS.

Navin (*11*) defined LOS to "reflect riding comfort and freedom to move laterally," proposing an LOS measure based on the free area surrounding a bicycle. The free area was divided into three zones representing shrinking distances to the reference cyclist. In LOS A, no zones overlap, whereas in LOS F, collisions are imminent; *v*/*c* ratios were calculated for each LOS.

These LOS approaches never caught on, and most paths were constructed on the basis of guidelines provided by AASHTO's *Guide for the Development of Bicycle Facilities*, the latest edition of which was published in 1999 (*14*). Earlier editions formed the basis of the 1985 HCM's bicycle recommendations (*15*). The AASHTO guide recommended a 10-ft-wide bike path increasing to 14 ft under expectations of high usage. These guidelines appear to be based on the earlier research cited by Smith (*7*) indicating that a cyclist requires a minimum of 4 ft (1.2 m) per lane, so that a two-lane bicycle path (two-direction path) should be at least 8 ft (2.4 m) wide. An extra 2 ft (0.6 m) is added to accommodate service vehicles and allow some extra room for passing.

Nearly two decades after the first LOS approach was proposed, Botma (*1*) and Allen et al. (*16*) proposed a new LOS approach based on the idea of hindrance. Botma (*1*) suggested that the quality of a bicycle path trip should be based on how constrained, or hindered, a cyclist's movements are, echoing Navin's (*11*) "free area" measure of LOS. Quantifying hindrance involves counting the number of passing and meeting (meeting a cyclist traveling in the opposite direction) events. Passing and meeting events may better reflect the quality of a bicycle facility since slow cyclists often impede faster cyclists, delaying the faster cyclist until an opportunity to pass arises. The passing cyclist also experiences increasing fatigue caused by the acceleration required to pass slower cyclists, adding to delay. Most bicycle paths are often in reality mixed-use paths that also serve pedestrians and other nonmotorized vehicles, which further impede cyclists, causing additional passing and meeting events.

Both studies (*1, 16*) provided similar methods for estimating the number of passing and meeting events based on assumptions about bicycle operation and the path: slow cyclists do not impede faster cyclists; two-lane path meeting events provide half the hindrance of passing events; and cyclist speed is normally distributed. These assumptions limit the generalizations that can be drawn from their work and produce questionable results. Slower cyclists certainly impede faster cyclists (as discussed earlier), cyclists do not necessarily travel in "lanes" and more than two may be desired, and the assumption about the relative hindrance of passing and meeting is based solely on the opinion of the researchers. Notwithstanding these reservations, at least one study (*17*) found that the proposed methods did a good job of predicting meeting and passing events.

As in previous cases, LOS was assigned a grade from A to F representing increasing numbers of passing and meeting events. The 2000 HCM (*2*) adopted this methodology as its recommendation for determining the LOS of a bicycle path. The formulas presented to determine passing and meeting events include the additional assumption that the mean speed of bicycle traffic is 11.2 mph (18 km/h) with a standard deviation of 1.9 mph (3 km/h). No guidance is provided on how to incorporate knowledge of different average speeds.

Hummer et al. (*18*) suggested a new method to determine LOS and bike path width. Motivated by the limitations of previous studies, they sought to produce an objective measure of bicycle facility LOS based on data that would be available at any location. They extended the methods of Botma (*1*) and Allen et al. (*16*) to account for passive passing events, delayed passing events, and variable path width. Passive passing events occur from the point of view of the cyclist being passed. Delayed passing events are those that a faster cyclist wishes to make but must wait for a suitable opportunity. An objective LOS measure is determined by surveying cyclists about their opinions of the quality of service provided by bike paths of different designs and under different traffic conditions.

The method presented by Hummer et al. (*18*) would require an engineer or planner to observe the number of active, passive, and delayed passing events to determine the LOS of an existing facility. However, these metrics are extremely difficult to measure in the field. Hummer et al. used a floating bicycle fitted with onboard video, speed, and audio recording devices to record these events; however, passive and delayed passing events were rare and not counted. Given these difficulties and to facilitate planning of new facilities, a method to estimate the required variables is required for practical implementation of this method by planners and engineers. Hummer et al. developed a model to estimate the required variables given the path width, the presence or absence of a center line, flow rate, and mode split (ratio of cyclists to pedestrians). Model results are validated by comparison with the field data and reasonably predict the number of passing and meeting events in most cases. Over all, these methods expand and improve on the earlier hindrance methods. However, hindrance events, particularly delayed and passive passing events, remain difficult to observe and model validation is limited to existing, relatively low-volume traffic conditions.

SIMULATION MODELS

Although simulation models cannot tell the analyst about a user's perception of bicycle facility quality, they can provide insight into how various parameters, including cyclist behavior, can affect facility operation. Potentially important variables such as passing and delayed passing can be difficult to observe in the field. In addition, field observations are limited to preexisting conditions. For example, congested bicycle facilities are rarely observed and studies are limited to bike paths that are no more than 20 ft (6 m) wide. Simulation models can help fill in knowledge gaps and explore alternative designs.

A particularly attractive modeling paradigm is the cellular automaton (CA), widely used across many disciplines to explore interactions between agents that possess a finite set of changeable characteristics. CA models are discrete since the interactions occur on a grid of finite size and number of locations (cells). These models have recently seen increasing academic attention particularly in physics, mathematics, and computer science. The application of a CA approach to vehicular traffic flow was first proposed by Nagel and Schreckenberg (*19*), who modeled a single lane under free-flow and congested conditions.

In a CA model for traffic flow in a single lane, each cell represents a discrete section of the roadway of a specified distance. In any given time step, that cell may be either occupied or unoccupied. An iteration of the model begins by updating all speeds (cells per unit time) in the network according to the following algorithm:

1. If the speed of a vehicle is less than some limit and the distance to the next vehicle is greater than the current speed plus 1, the speed is incremented;
2. If the space between the current vehicle and the next is less than the current vehicle's speed, it decelerates to the distance between vehicles minus 1; and
3. If a certain (usually) small probability threshold is exceeded, the current vehicle reduces its speed by 1.

The third property keeps the system from quickly entering a deterministic state (*19*). Finally, the positions of all vehicles are updated on the basis of their speeds, and the model is iterated until the desired number of time periods has been modeled. Traffic parameters (flow, speed, and density) can be calculated from the model outputs, which include the position and speed of each vehicle along the roadway for each time step.

METHODS

Simulation Modeling

Several parameters must be specified for CA model implementation. For traffic flow these include length of roadway, cell length (equal to vehicle length), speed limit (in miles per hour or cells per update time), and the time increment under study.

Because of the simplicity of the CA model, research on its implementation under various conditions has been extensive. Recent attempts include models purported to represent bicycle flow (*20, 21*). These models are not CAs in the strictest sense—they are multivalue CA models because each cell may be occupied by more than one vehicle. Neither model was empirically validated with actual bicycle data, which makes their relevance to bicycle planning applications questionable. In addition, the utility gained by switching to a multivalue CA model may be outweighed by added complexity. The approach taken here maintains simplicity and shows that a strict CA model with two lanes (multilane) and two types of cyclists (inhomogeneous) is able to provide rich behavioral data for comparison with field results. It is expected that this tool could be used to determine LOS measures for new bike path construction. The simulation model can provide a simpler way to observe hindrance events, and thus determine the LOS, for various facility designs with different uses and users. Pedestrians were not considered in this initial study; however, future work should be able to accommodate a mix of users.

The lane-changing algorithm used here is based on the work of Rickert et al. (*22*) and involves much of the same logic as the single-lane case with several exceptions. Before the acceleration step, both lanes are examined to evaluate lane-changing opportunities. The following four conditions are checked from the point of view of each vehicle and must be true for it to change lanes. The rules are checked simultaneously before the update:

1. In the vehicle's current lane, the distance to the next vehicle is less than or equal to the current vehicle's speed plus 1. This condition ensures that no slowdown will be necessary at the next update.
2. In the vehicle's adjacent lane, the distance to the next vehicle is greater than or equal to the current vehicle's speed plus 1. This condition ensures that a benefit is derived from changing lanes.
3. Looking backward, the closest vehicle is sufficiently far away.
4. A random number between 0 and 1 is less than the probability of a lane change.

The final condition prevents the formation of steady-state patterns during model initialization (*22*). For example, if lane changes occur with certainty and all vehicles begin the model run in the right lane in adjacent cells, they will change lanes immediately. This behavior will repeat in the next iteration with all vehicles changing from the left to the right lane. Probabilistic lane changing resolves this problem. In addition, all vehicles were randomly distributed across the two lanes with speed equal to zero for model initialization.

This lane-changing rule gives no preference to occupying either lane. This condition is known as symmetry but is not how cyclists behave. Instead, cyclists attempt to overtake slower vehicles and then shift back to a position in front of the vehicle just passed. To implement asymmetric lane changing in the model, the first lane-changing rule is omitted when it is determined whether to switch from the left to the right, causing vehicles on the left to move right at the first opportunity.

Model Calibration

The value of undertaking this modeling exercise lies in the calibration of the model results to the observed data. Several parameters were held constant across model runs because they reflect relatively constant physical values as observed in the literature, and others were varied across model runs. Above a certain value, the length of roadway considered and time periods studied should not affect model results as long as there is sufficient distance and time for steady-state formation. Preliminary testing revealed that 1 mi (1.6 km) and 600 time steps of 1 s were appropriate. Using 7 ft (2.1 m) as the cell length is justified in combination with the maximum speeds used for slow and fast vehicles. Average cycling speeds reported in the literature, as discussed earlier, all fall around 12 mph (approximately 2.5 cells/s). Similarly, faster bicycles seldom travel faster than 15 mph (approximately 3 cells/s), though higher downhill maxima may occur. Speeds of 2 cells/s (9.5 mph or 15.3 km/h) and 3 cells/s (15 mph or 24.1 km/h) were chosen for slow and fast cyclists, respectively. Different top speeds imply different lane-changing behavior: slower cyclists will find it necessary to pass less often, since their travel is less likely to be hindered, and vice versa. The probability of a random slowdown was fixed at 10%, based on field observation of relatively constant bicycle speed, the occasional cellular-phone-using bicyclist notwithstanding. Number of cyclists was increased from 50 to 1,500 in increments of 25 every 600 time steps for each run.

Varying model parameters included look-back distance, probability of lane change, and proportion of slow vehicles (see Table 1). Look-back distance was altered between low values since the consequences of obstructing another cyclist are low compared with obstruction of an automobile; probability of lane change varied between high values since passing was common; and the proportion of slow vehicles was varied between low and high values since speed distributions were not measured in the field.

Field Data Collection

The popularity of cycling in Davis due to a strong bicycle culture, extensive and well-maintained facilities, ideal climate, and lack of hills provides a unique opportunity to observe heavily used, near-capacity bicycle facilities. However, Davis cannot be considered representative of conditions elsewhere. The average Davis cyclist likely has a greater level of experience than would be expected in other locations, and Davis's college town demographics are not necessarily consistent with other cycling populations. However, the goal was not to produce a representative sample but to challenge the simulation model to capture the full range of traffic conditions for a particular facility.

TABLE 1 Data Collection Site Details: Three UC Davis Bike Paths

	Russell	Bio (Day 1)	Bio (Day 2)	ARC
Date	12/5/2007	11/30/2007	12/3/2007	11/30/2007
Time	8:45 a.m.	11:45 a.m.	8:40 a.m.	8:45 a.m.
Duration (min)	16	14	24	12
Path width (ft)	17.35[a]	12	12	20
Sampled traffic direction	East	North	South	East
Sampled area length (ft)	30	19.5	19.5	20
Center line	Yes	Yes	Yes	Yes
Surface	Asphalt	Asphalt	Asphalt	Concrete
Topography	Flat and straight	Flat and straight	Flat and straight	Flat and straight
Pedestrian mode share	2%	16%[b]	10%[b]	0%

[a]Uneven lane widths: 9.6 ft (east) and 7.75 ft (west).
[b]Includes observations of pedestrians on adjacent dirt path (not an official path).

Bicycle traffic data were collected in late 2007 at three locations on the UC Davis campus during peak traffic conditions (see Table 1). The sites were chosen to exhibit high flows and minimal cross traffic from pedestrians, motorists, or other bicycles. The sites were also free of sharp curves, hills, stop signs, and traffic signals. Bicycle traffic data were collected with a high-definition digital video camera (Sony HDR-SR1) mounted on a tripod along the side of each path, providing a perpendicular view of same. At each site, the camera was moved as far back from the path as possible to maximize the observation area, which was clearly marked with highly visible tape. Only bicycles were counted since the simulation model currently considers only bicycles. Pedestrians generally made up only a small portion of the traffic, as shown in Table 1. Those pedestrians who were present kept to the margins of the paths and in the case of the Bio site, walked on an adjacent dirt path.

Average bicycle flow rate [(bikes · h)/unit lane width] and density (bikes/unit sample area) were calculated separately for traffic flowing in each direction. Average directional flow rates were calculated by counting the number of bicycles entering the sample area during 30-s intervals and dividing by the lane width, assumed to be the distance from the center line to the edge. This assumption was based on observations that bicycles traveling in each direction generally observed the center line, keeping to its right side. The corresponding density was recorded in 1-s time steps by counting the number of bicycles within the sample area at a point in time and then dividing by the sample area. Similar to the flow calculation, the area for directional density was assumed to be the distance from the center line to the edge multiplied by the sample area length. The average density over 30 s was estimated by averaging 30 density observations. Speed data were not collected but could be estimated by using Equation 1.

RESULTS AND DISCUSSION

Field Observations

Field data collected at all three sites are described in Figure 1. The data are from the bike path direction that experienced the highest volume of traffic, since traffic was overwhelmingly unidirectional during the peak travel times that were observed. The three data collection sites were labeled ARC, Russell, and Bio. Traffic at Bio was observed over a period of 2 days. Figure 1*a* tracks the cumulative count of bicycles per unit time, indicating that the ARC site was the most heavily traveled of the three (approximately 30 bicycles/min), and Russell experienced the least amount of bicycle traffic (approximately 15 bicycles/min). Figure 1*b* shows the relationship between density and flow. A positive linear relationship is evident, indicating that all bike paths were operating below capacity and that average speed did not vary with increasing density. Figure 1*b* also indicates that the flow–density relationship across the three bike paths, and thus travel speed, was similar since there is little variation in slope.

Simulation Results

Seven simulation model runs were completed to test the sensitivity of various parameters and determine which values best describe the field observations. Parameters for each run as well as key results are shown in Table 2. Flow–density (the fundamental diagram of traffic flow) and speed–density plots were also created to analyze the results. Example plots of this type are shown in Figure 2.

Table 2 indicates that the simulation model was sensitive to the parameter variation. Increasing the proportion of slow bikes decreased the capacity (maximum flow rates) while increasing the critical density. These results agree with expectations: slower speeds reduce the flow rate but allow bikes to travel closer together before capacity is reached. Decreasing the probability of lane changing increased capacity but did not have a systematic effect on critical density. Clearly, reduced lane changing achieves a more orderly flow, allowing for a higher capacity. Plots of the fundamental diagram and speed–density relationships (Figure 2) also showed the expected relationships typical of vehicle traffic flow. Each dot represents one observation from the model; darker areas represent overlapping observations.

Because the results of Run 6 indicate that lane changing reduces capacity, more courteous lane-changing behavior was modeled in Run 7. A one-bike-length (equal to one cell) look-back distance was incorporated, allowing the cyclists to look back before changing

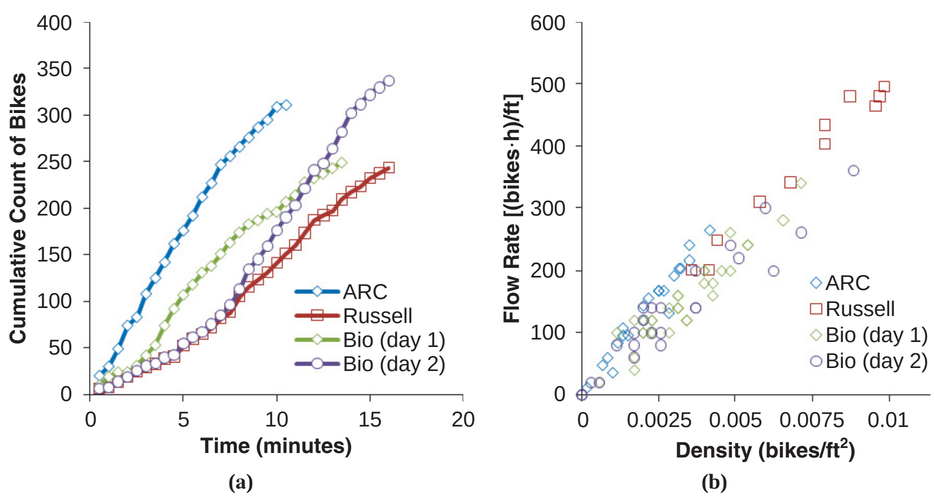

FIGURE 1 Field data collected from three bike paths at UC Davis (ARC, Russell, and Bio): (*a*) cumulative observation of number of bikes and (*b*) flow–density relationship, fundamental diagram of bicycle traffic (1 ft = 0.305 m, 1 ft^2 = 0.0929 m^2).

TABLE 2 Model Runs and Results

	Probability of Lane Change	Proportion of Slow Bikes	Look Back (cells)	Max. Flow [(bikes · h)/ft]	Critical Density (bikes/ft^2)
Run 1	0.9	0.25	0	389.4	0.0107
Run 2	0.9	0.5	0	379.1	0.0113
Run 3	0.9	0.75	0	374.5	0.0149
Run 4	1	0.5	0	371.0	0.0125
Run 5	0.7	0.5	0	397.9	0.0137
Run 6	0	0.5	0	452.9	0.0113
Run 7	0.9	0.5	1	461.7	0.0119

NOTE: 1 ft = 0.305 m, 1 ft^2 = 0.0929 m^2.

lanes so as not to cut another cyclist off. The result of the look back was that a higher capacity was achieved over all other runs while still allowing lane changes. Figure 3 compares the amount of lane changing that occurred in Runs 2 and 7, which are equivalent except for the incorporation of the look back. Overall, much less lane changing occurred in Run 7 than in Run 2. Also, passing in Run 7 generally occurred at lower densities compared with the case when cyclists did not look back.

Comparison with Field Data

Comparison of the simulation data with field observations resulted in a close match. The field data were reproduced most closely by model Run 7 (Figure 4), where cyclists had a high probability of changing lanes if they were being slowed down by other cyclists and could look back before changing lanes so as not to cut another cyclist off. Run 7 also corresponds to the scenario that subjectively seems to best describe actual cyclist behavior; fast cyclists do not wait behind slower ones if they have a reasonable opportunity to pass.

The simulation results and field data shown here provide evidence that simple CA models can be used to model cyclist behavior, providing bike facility capacity estimates under various speed distributions and simple behavioral rules (looking back before changing lanes). However, the field data were limited to existing traffic conditions in the study location. Traffic volumes on UC Davis bike paths are very high but never exceeded capacity, limiting the ability to fully validate the simulation results by observing the critical density and the downward-sloping portion of the fundamental diagram. The capacity estimate produced by the simulation model was at the low end of estimates noted in the literature (*8, 11, 12*).

CONCLUSIONS

A simple CA simulation model was shown to produce results corresponding to expected cyclist behavior and field data. The model performed well under a fairly limited set of conditions: college students with extensive cycling experience traveling on flat, well-maintained bicycle facilities free from pedestrian interference during ideal weather. Future work is required to validate the model over a wider range of users and conditions.

The model could be a valuable tool that would allow city and regional planners to experiment with various bicycle facility designs, expected traffic volumes, and user profiles. These experiments would help planners and engineers optimize bicycle facility design by exploring the trade-offs between alternatives, LOS, and other objectives without the collection of field data. Today planners and engineers

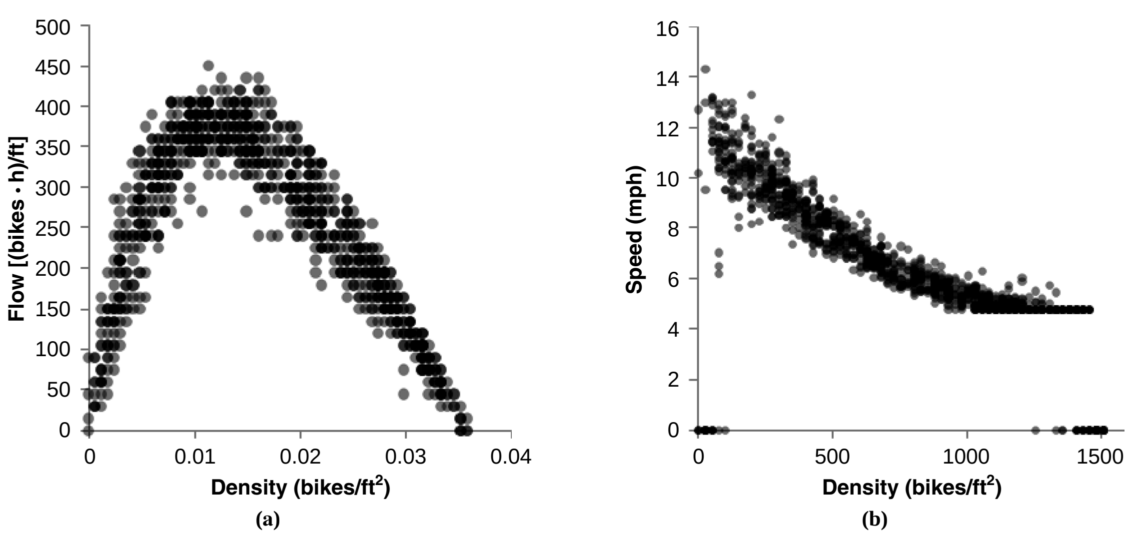

FIGURE 2 Example of bicycle traffic plots generated from simulation data (Run 2): (*a*) flow versus density and (*b*) speed versus density (1 ft = 0.305 m, 1 ft^2 = 0.0929 m^2, 1 mph = 1.61 km/h).

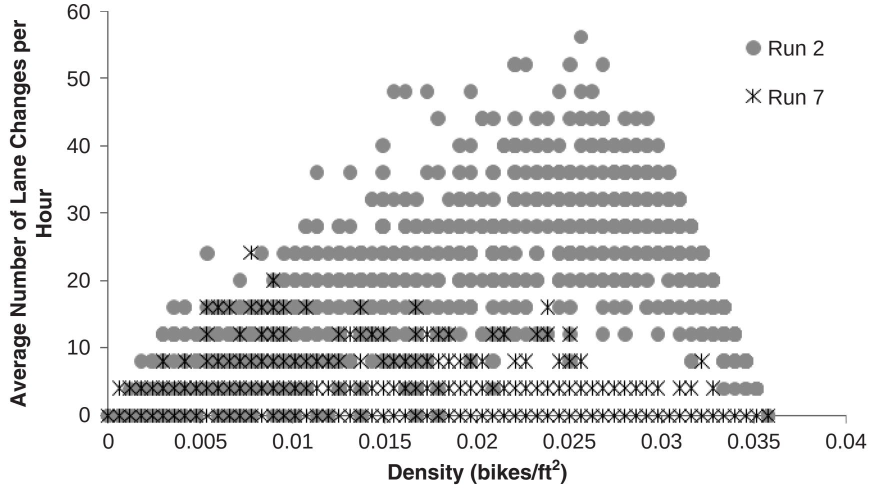

FIGURE 3 Comparison of simulation Runs 2 and 7 lane-changing behavior (1 ft = 0.305 m, 1 ft^2 = 0.0929 m^2).

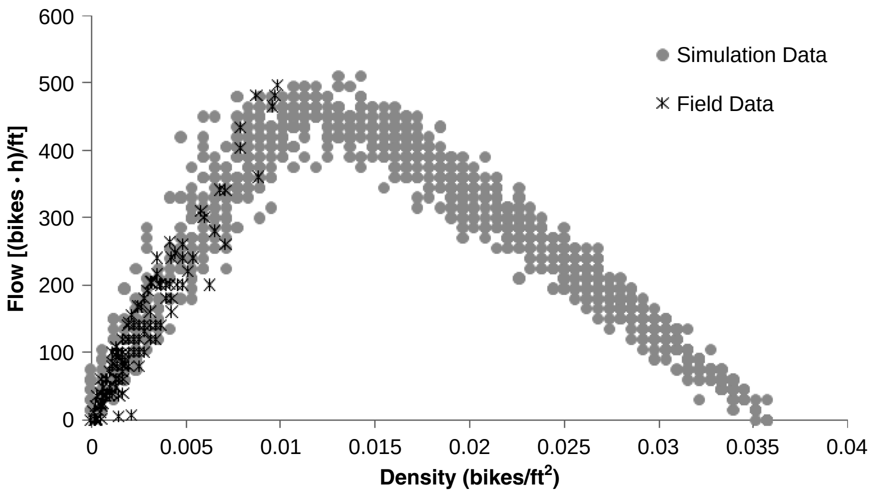

FIGURE 4 Comparison of fundamental traffic diagrams generated from Run 7 simulation data and field data (1 ft = 0.305 m, 1 ft^2 = 0.0929 m^2).

are limited to extrapolating from existing field data or applying rigid (nonoptimal) design guidelines. LOS could be determined by observing the number of lane changes and speed profiles of individual agents in the model, fewer lane changes and more constant speeds being associated with higher LOS. More optimal design will allow smarter investment of the limited funding available for bicycle facilities.

The model described here is basic, but with further development it could incorporate richer cyclist behavior and a greater range of facility designs. A potential improvement includes friction factors, which account for slower speeds in narrow lanes where passing requires more caution. The CA model can also be used to model traffic dynamics caused by topography, changes in lane widths, congestion, and traffic signals by adjusting the speed of cyclists over particular ranges of cells (sections of bicycle path). For example, the impact of a hill on traffic flow may be modeled by lowering the maximum speed limit for cyclists over a range of cells. Dynamic simulations can show how congestion propagates downstream though traffic and how long it takes for queues to clear. Results from dynamic simulations can help planners and engineers optimize signals and intersections for bicycles and study the effect of grades and curves on bicycle traffic.

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