Cellular Automata Microsimulation of Bi-Directional Pedestrian Flows

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ABSTRACT

The Cellular Automata (CA) microsimulation of pedestrians is a particle hopping model in which a set of local rules prescribe the behavior of entities within local neighborhoods of cells. CA microsimulation has emerged as a tool for simulating traffic flow and modeling transportation networks. Pedestrian flow is inherently more complex than traffic flow, and simulation models that are used for emulating vehicular traffic are not directly applicable to modeling pedestrian movements. In previous work the authors demonstrated that unidirectional pedestrian flow patterns, consistent with well-established fundamental properties, could be generated with CA microsimulation. This paper expands upon the previous effort and presents a CA microsimulation model and emergent fundamental flows for a bi-directional pedestrian walkway. Simulation experiments indicate that the basic model is applicable to walkways of various lengths and widths and across different directional shares of pedestrian movements.

INTRODUCTION

Cellular Automata (CA) microsimulation has emerged as a tool for simulating traffic flow and modeling transportation networks. In a previous paper, the authors demonstrated the ability to generate fundamental pedestrian flows using a CA microsimulation of a pedestrian walkway with unidirectional flow (*1*). That model used six basic rules to direct basic forward movement and lane switching behaviors. It was shown that fundamental pedestrian flows, as described in the Highway Capacity Manual *(2),* could be generated by this unidirectional model. This paper presents the next phase of the research effort, constructing a microsimulation of a bi-directional pedestrian walkway.

CA simulation of a lane of vehicular traffic was put forward by Nagel and Schreckenburg (3). The Nagel and Schreckenburg (N-S) rule set was extended to a multi-lane model by Rickerts, et al. (4), and has been applied to a traffic network in the TRANSIMS project *(5).* A CA model of bi-directional vehicular traffic by Simon and Gutowitz *(6)* extends the case to vehicle travel in opposite directions on a two lane road where passing is allowed. The rule set has some common features with that used in this bi-directional pedestrian model.

Modeling pedestrian flow is very different from modeling vehicular flow. Like vehicular traffic, fundamental properties for pedestrian flows and methods for studying capacity are well established (see the Highway Capacity Manual *(2)*, for example). Transferring logic from a vehicular CA model to a pedestrian CA model is more than a scaling problem. Pedestrian movements are inherently different and more alterable than vehicular movements. Vehicular traffic moves along links where flow is governed by a set of regulations. Vehicles are separated by well-defined lane markings and controls are in place to regulate both travel speed and passing opportunities. On major roadways vehicles are separated by direction and head-on conflicts are minimized. Alternatively, pedestrian flows are not officially channelized; pedestrians are free to vary speed and allowed to occupy any part of a walkway. Bi-directional flow is the norm for most pedestrian walkways although larger concourses encourage multi-directional flows. Avoidance of head-on collisions must be considered. However, since safety and crash avoidance is less of a concern to pedestrians, there is a tendency for pedestrians to bump each other, bypass, or exchange places when density is high and sidestepping is not a better alternative. Pedestrians have individually-oriented maximum speeds with a mean and variance when taken in the aggregate. Pedestrians also do not have the same acceleration characteristics as cars; they are capable of changing speed more quickly when gaps arise and can accelerate to full speed from a standstill. They may change lanes more often and more casually. Unlike vehicular movements, it is not uncommon for pairs or groups of pedestrians to walk side-by-side or in clusters.

In terms of pedestrian modeling, recent efforts have taken diverse approaches. Lovas (7) created a mesoscopic simulation for evacuations and AlGadhi and Mahmassani (8) developed a macrosimulation of pedestrian traffic at a large gathering. Microsimulation of pedestrians was done earlier by Gipps (9) who used a hexagonal lattice to model spatial use through repulsive forces among individuals. Gipps' investigation did not examine flows at high densities and was not adaptable to simulating bi-directional flows. In the physics community work on traffic flow theory has evolved out of analogies with gases and fluids. Helbing and Molnar *(10)*, using a non-CA model, examined pedestrian movements as social fields, represented as attractive and repulsive forces, in which a pedestrian behaves as if acted upon by external forces. Their model displayed self-organization of collective pedestrian behavior in the formation of lanes by opposing direction flows and oscillatory changes in walking direction at a doorway. The pedestrians in their model separate into lanes by direction due to the interactions of the attraction-repulsion forces on the pedestrians. However, they only demonstrated a single instance of these abilities and did not publish results at many densities or calibrate them against established fundamental flows. In the CA model considered in this paper, the pedestrians choose lanes and move forward due to rules in which the automata evaluate movements in a forward-progression behavioral emulation of what individual pedestrians would do on a walkway. This CA approach is distinctly different from the social field model, computationally simpler and based on maximizing forward progress, but also has some noteworthy similarities that will be discussed.

CA modeling offers the possibility of emulating the essential, diverse movements of pedestrians as behavioral responses to varying local conditions. The CA microsimulation of pedestrians presented in this paper is a particle hopping model based on a set of local rules that prescribe the behavior of automata (pedestrians or entities) within their local neighborhoods. Such CA models are discrete systems that can be updated in parallel and are well suited to simulation on digital computers (*11*).

The modeling of vehicular or pedestrian traffic through a network lends itself to a two-dimensional system. A lattice is used to represent a segment of a network (such as a roadway link) and cells in the lattice represent locations that can be occupied by a single entity. During a single iteration of the microsimulation, cells within the lattice are assigned one of two properties, occupied by a single automaton or unoccupied. A set of local rules defines the movement of each automaton with respect to the status of neighboring cells. The emergent *behavior* of each entity and the system as a whole appears to exhibit artificial intelligence, self-organization, and complex dynamics. Since they behave like living systems, these models are often referred to as artificial life models *(12)*.

This paper describes the development and testing of the bi-directional pedestrian model. The paper presents the model formulation followed by the description of the microsimulation experiments and resulting data analyses. It concludes with suggestions for applying the model in practice and describes work underway to further expand the model.

BIDIRECTIONAL MODEL FORMULATION

The pedestrian walkway is modeled as a circular lattice (closed loop system) as described by Nagel and Rasmussen (*13*). The lattice has width W, length G, and class L = W*G. Cells within the lattice are given the notation L(i, j) where $1 \le i \le W$ and $1 \le j \le G$. Pedestrian densities are predetermined at the start of the simulation and remain constant throughout each run. At the start of each simulation, a density d, where $0.05 \le d < 1.0$, is generated and N = INT(d*W*G) pedestrians are created and assigned randomly to the lattice. A circular lattice enables the set of pedestrians to interact at constant density D = N/L and constant space allowance S = L/N while maintaining strict conservation of flow.

The CA microsimulation proceeds in time steps. In each time step T_i for i := 1 to a maximum number of time steps, lane assignment and speed updates change the positions of all pedestrians in four stages according to local rules applied to each pedestrian in parallel across the lattice. During the first stage, a set of lane changing rules determines the lane for each pedestrian on the lattice. In the second update all the pedestrians are moved to the chosen lanes. During the third stage, a set of rules is applied to find the allowable speed of each pedestrian based on the available gap ahead and the pedestrian's desired speed. Forward movements based on the allowed speeds are made in the fourth update. The rule set follows:

Parallel Update #1: Lane Assignments

(Rule 1): Check adjacent cells

IF the cell immediately to the left (right) is unavailable

THEN assign the cell to be occupied and GOTO Rule 3

ELSE GOTO Rule 2

(Rule 2): Determine if adjacent lanes are free

IF the cell two lanes over to the left (right) is occupied by a pedestrian

THEN with probability r assign the left (right) lane to be occupied

GOTO Rule 3

(Rule 3): Determine if pedestrian must remain in current lane

IF the lane immediately to the right is occupied

AND the cell immediately to the left is occupied

THEN assign pedestrian p_n to his current lane

ELSE GOTO Rule 4

(Rule 4): Assign to uniquely maximal gaps

Compute the gaps* for the current lane and for unoccupied adjacent lanes

IF a gap is uniquely maximal

THEN assign pedestrian p_n to the lane having maximum gap

ELSE GOTO Rule 5

(Rule 5): Tie-breaking of equal maximum gaps

Use the appropriate tie-breaking rule:

(***a - 3-way tie***): Randomly apply 80/10/10 split for current lane and two adjacent lanes.
(***b - 2-way tie between the adjacent lanes***): Randomly apply 50/50 split.
(***c - 2-way tie between current lane and single adjacent lane***): Randomly apply 50/50 split.

Parallel Update #2: Lane Movement

Move each pedestrian p_n, to the lane assigned in the lattice.

Parallel Update #3: Assigning Travel Speeds

(Rule 6): Update velocity

Let $v(p_n)$ = gap*
IF gap = 0 or 1 and gap = gap2 (cell occupied by an opposing pedestrian)
THEN with probability *p_exchg*, $v(p_n)$ = gap + 1
OR with probability (1- *p_exchg)*, $v(p_n) = 0$

Parallel Update #4: Forward Movement

Advance each pedestrian p_n, $v(p_n)$ cells forward in the lattice.

Subprocedure * Gap Computation

Look ahead a max of 8 cells (since 2 * largest v_max = 8)

IF occupied cell found with same direction

THEN set gap1 to number of cells between entities

ELSE gap1 = 8

IF occupied cell found with opposite direction

THEN set gap2 to INT (0.5 * number of cells between entities)

ELSE gap2 = 4

Assign gap = MIN (gap1, gap2, v_max)

Parallel Update #1 (Rules 1-5) is used to investigate lane switching. Pedestrians are assumed to change lanes when an adjacent cell is free and this cell has a gap that is greater than the gap in the current lane. Rule 1 determines if the adjacent cells to the immediate right and left are occupied. Rule 2 checks for possible lane changing conflicts if an adjacent cell is free but the cell two lanes over is occupied. A random number is used to specify if the lane should be designated as free or occupied. Rule 3 assigns the pedestrian to the current lane if both adjacent cells are occupied. If one or both adjacent lanes are free then lane assignment is based on the maximal gap. Rule 4 covers the case when one lane has a uniquely maximum gap and the pedestrian is assigned to that lane. The computation of gaps is covered more fully in the discussion of forward movement, Rule 6, below. If there is a tie in maximum gaps, Rule 5 states the probabilities for breaking ties and making lane assignments. In Rule 5 Case a, it is assumed that pedestrians usually remain in the current lane but sometimes drift out of it. For Rule 5 Case b, a 50/50 split is the most reasonable assumption for unidirectional flow. For Rule 5 Case c, a 50/50 split assumes pedestrians have as much interest in maintaining a cell-width of separation from an adjacent person (in the occupied adjacent lane) as they have in remaining in the current lane. These probabilities were selected since they worked best for the simulation, but other probabilities might be applied. In Rule 5c an 80/20 split as in Rule 5a is also reasonable.

Rule 2 has been changed slightly from an earlier version (*1*) to allow for more lane changing. Formerly, when two pedestrians were separated by one cell, that separator cell was considered out of bounds for both pedestrians in order to avoid collisions. However, this is considered overly restrictive and in this formulation the separator cell is available to one of them with an equal (50/50) probability. Lane changing is affected by this revised rule but does not affect flows noticeably. Lane changes may help as well as hinder overall flow and the net result is evidently less critical to the emergent group behavior. In simulations where no lane changing was allowed, the forward movement is in some cases enhanced, because the pedestrian spatial patterns that emerge stay in step with mode locking. However, though not rigorously studied or understood by researchers to date, lane-changing behavior is an important feature of pedestrian movement and is included in the model to avoid unrealistic marching in step and to add realism.

The second parallel update moves all the pedestrians into their new lanes. The purpose of parallel updates is to avoid the succession interdependencies encountered in sequential updates. In sequential updates, as each entity is moved, the following entities' moves over the whole system are affected, making the order of entity moves unrealistically important. The updating procedure used here avoids sequential updating succession problems by having all the entities choose their new positions without moving in the first update and then moving them all into their new positions in a separate second update.

The third parallel update of the pedestrian stream determines the new velocities of the pedestrians. Velocities are based on the available gap and which also depends on whether the next pedestrian downstream is moving in the same or opposite direction. Rule 6 states that if both pedestrians are moving in the same direction, then the new velocity for the follower is the minimum of the maximum velocity assigned for the pedestrian and the available gap. The case of opposing pedestrians guards against conflicts and having the two opposing pedestrians land in the same cell. If the gap between opposing pedestrians is greater than the total distance that both pedestrians could move at maximum speed, then the updated velocity is the minimum of vmax and moving halfway forward. To avoid permanent impasses and deadlocking of the system and to emulate what people actually do, under close conditions opposing pedestrians may exchange places. This is not in actuality always smoothly done, so the simulation builds in a probability of a temporary standoff between closely opposing entities. A random number is compared to probability ***p_exchg*** and used to determine if two opposing pedestrians can exchange places in the time step. The opposing entities each move the same number of spaces which is either 0 or gap + 1 cells.

The fourth parallel update moves all the pedestrians forward based on the gaps allowed in the third update.

SIMULATION EXPERIMENTS

The model is executed on a circular lattice L being G cells long and W cells wide for a total number of cells equal to G*W . Each cell is considered square, 18 inches (0.457 m) per side. This cell size is scaled according to minimal requirements for personal space as described in the Highway Capacity Manual *(2)* and to meet the speed-flow-density requirements that emerge. The lattice is connected as a loop where pedestrians circulate on a walking track at a given density. Conservation of pedestrians is strictly maintained. At the start of each run a predefined density of pedestrians (a percentage of the total number of cells available) is randomly assigned to the lattice. This number is strictly maintained throughout the simulation.

The duration of each simulation is 11,000 time steps with the first 1000 time steps used to initiate the simulation and the latter 10,000 used to generate performance statistics. One second was adopted as the length for each time step. Each set of experiments included 380 runs - 20 replications at 19 densities ranging from 0.05 to 0.95 in increments of 0.05.

Each experiment was conducted and the results compared with well-established level of service criteria as defined in the Highway Capacity Manual *(2)*. The three fundamental parameters of pedestrian flow are ***space***, ***flow rate***, and, ***walking speed***. ***Space*** is the inverse of density and relates area of walkway to number of pedestrians. Space is typically measured in square feet per pedestrian. ***Flow rate***, measured in pedestrians per minute per foot-of-width (or in pedestrians per minute per meter of width) is analogous to volume. ***Average speed*** is the rate of movement given in ft/min (m/min). The fundamental relationship is given as: Flow Rate = Ave. Speed/Space.

Flow rate is determined by counting the number of “laps” that each entity makes (i.e., the number passing a counting station at the end of the lattice L(N, j) over 10,000 seconds (2.78 hours). Speed is computed as the total number of steps taken by each entity divided by the number of time steps, which for the experiments is 10,000 seconds. Space is computed as the reciprocal of the predefined density. Values are then scaled against the cell size. For each run of the model, fundamental flow parameters for each density level are computed by averaging the results over the 20 replications.

To account for variation in walking speeds among the pedestrians, three walker classes were adopted: ***Class A,*** pedestrians those assigned with maximum rate of 3 cells per time step (about 4.5 ft per time step or 1.3 m per time step), ***Class B,*** pedestrians moving with a maximum rate of 2 cells/time step (about 3 ft per time step or 0.85 m per time step), and ***Class C,*** those moving with a maximum rate of 4 cells/time step (about 6 ft per time step or 1.8 m per

time step). A *90% distribution* (meaning 90%- Class A, 5%- Class B and 5%- Class C) was used for the microsimulation as it produced, in studies for the previous work *(1),* the best realization of peak volume (25 persons/min/foot-of-width or 8.25 persons/min/meter-of-width) in the fundamental diagram for pedestrian flows *(2)*. A distribution of walking speeds is important to reducing marching that can occur at some densities, as mentioned also in the section on lane changing rules.
Three sets of experiments were conducted:

a) One direction flow with varied lattice widths and lengths

b) Bi-directional flow assigned to directional lanes with no directional crossover on a 100 x 10 cell lattice with percent splits by direction (100/0, 90/10, 80/20, 70/30, 60/40, 50/50)

c) Bi-directional flow randomly assigned to 100 x 10 cell-lattice with percent splits by direction (100/0, 90/10, 80/20, 70/30, 60/40, 50/50) and 50% exchange probability.

The first set of experiments examines unidirectional flows over lattices of varied widths and lengths. This was done to inspect sensitivity issues with respect to lattice size. Two versions of bi-directional flows were then run. The first approach made use of a 10 lane wide lattice. Flow was divided by direction in increments of 10 percent and the number of lanes per direction was assigned proportionally to the directional splits. For example, for an 80/20 split, the direction assigned 80 percent of the traffic was allocated to 8 of the 10 lanes. This case of lane-separated, column-based walking behavior has been witnessed by the authors in a heavily used corridor in Grand Central Station in New York City and on busy sidewalks. In this mode walkers tend to stay to the right and do not mix into opposing lanes except very briefly. Lanes are unstable as demand changes, but at any given moment the lanes are generally coherent. In Helbing and Molnar's experiments with social force models *(10)*, lanes formed naturally without need for artificially separating them in the experiment. The authors to date have not studied emergent lanes, but it is not considered difficult to enhance that aspect in pedestrian walking using CA by slightly modifying the rules. In this experiment the emergent speed-density characteristics are examined for the artificially lane separated case.

The second bi-directional case represents walkways where opposing traffic mingle and directional lanes are not set up. In this case, walkers pick their way through the oncoming crowd as best they can. It is possible that some spontaneous lane formation does occur, though it be inhibited by the place exchange rules. Directional splits of the pedestrian volume were studied. In addition, to handle conflicting movements, as prescribed in Rule 6, different probabilities of exchange were studied. This random term is used to represent cases where opposing pedestrians converge on the same cell and, with some probability p_exchg, their forward movement is thwarted for a single time interval as the pedestrians try to negotiate passing one another.

MICROSIMULATION RESULTS

(a) Same direction flow with lattices of varied length and width

Subject to the modifications of the lane changing rule (Rule 2) new simulation runs were conducted. Sensitivity analyses were performed to determine if the shape of the curve changed with variations in the lattice width and length. A series of runs were conducted for width of 10 cells and lengths 40, 100, 200, and 400. In addition, runs were performed for lattices of length 100 and widths 2,4,6,8,10, and 12.

It was found that varying the length of the lattice did not provide significant changes in system performance. The maximum difference in average speed and average volume between 40 cells and 100 cells over all densities is 1.6 percent at a density of 0.25. There is less than 1 percent difference in average speeds and volumes among lattice lengths of 100, 200, and 400 cells at density of 0.25. As a result, to minimize the computational burden of examining the rule sets, a lattice length of 100 cells was adopted for the bi-directional study. Similar results were found from varying the lattice widths. At smaller widths, greater jamming is seen due to the limited space for pedestrians to maneuver around slower moving pedestrians. Little difference in performance is found in widths between 6 and 12 cells. A lattice width of 10 was adopted to ease the analysis of studying various directional splits.

For a 90% distribution of walker classes and a lattice of 100 x 10, fundamental flows were achieved. The results are shown in Figures 1 and 2. It is interesting that two-regime model can be fit with the following properties. For densities less than or equal to 0.45 May's bell curve was fitted with the following form:

$$V = \alpha e^{-\beta D^2} \qquad (1)$$

where α = -280 and β = 24.5. The maximum flow of 24.2 Ped/min/ft-of-width (8.0 Ped/min/m-of-width) was found to be close to the maximum capacity of 25 Ped/min/ft-of-width (8.25 Ped/min/ft-of-width) as shown in the HCM *(2)*.

For densities greater than 0.45 a linear model was fit. The equation of this model is:

$$V = -40D + 40 \qquad (2)$$

Virkler and Elayadath *(15)* examined several single- and multiple-regime regression models in a statistical study of unidirectional pedestrian flow, but did not examine the above combination. Because this two-regime pair emerges from a model does not mean it is correct, since the statistical sampling used in the CA simulations and field data is so different. The question of data sampling in field and simulation studies is interesting, but beyond the scope of this work.

(b) Bi-Directional Flow with No Directional Crossovers

This set of experiments examines the distinctions that arise as directionality is added to the pedestrian stream while lane directionality is maintained over a 100 x 10-cell lattice. Thus, for a 70/30 directional split, 7 lanes are dedicated to one direction and 3 lanes to the other direction. The lanes are grouped by direction and no crossover between groups is permitted, though lane changing is allowed within a directional group.

Figure 3 depicts speed vs. density curves for 6 directional splits. All of the curves are almost identical with little variation. These curves are also identical to the curves generated for the one directional model presented above. These results concur with field observations described in the Highway Capacity Manual *(2)* that bi-directional flows do not have different characteristics from single-directional flows. Videotapes made by the authors of high density pedestrian flows in a 30 foot or 9.9 meter (20 cell wide) corridor in Grand Central Terminal in New York City reveal that pedestrians tend to spontaneously form lanes for each direction of flow as persons follow a person moving in the same direction and multiple lanes emerge as demand requires it.

(c) Bi-Directional Flow with Crossovers

The usually rather short-lived case of pedestrians randomly interspersed on a lattice and moving in opposing directions that may occur at busy crosswalks, in crowded subway stations, and in emergency situations, (among others) is complex and historically has not been well documented, understood, or easily modeled on a microscopic level. The manner of modeling a short-lived case with a long simulation run allows statistics to be gathered that can be carefully applied to these cases and interfaced with larger models. Generally, given sufficient space, pedestrians will form their own lanes, but conditions may arise when that is not possible and this experiment allows for examination of such complex, generally transient, and difficult to model conditions.

Though this case is somewhat anomalous, it is important in some situations because (a) such a zone of interaction represents a bottleneck in separated bi-directional flow when it occurs, (b) can represent the emergency condition that is easy to treat simplistically as a lane-based case and yet is critical to a safe pedestrian design, and (c) is intractable to handle at the microscopic level with differential equations effectively. CA models function as discrete idealizations of the partial differential equations that describe fluid flows (*11*) and allow us to examine flows and interactions that are otherwise intractable. This is a treatment that reaches into some unknown and new modeling territory. The presentation aims to sufficiently depict the effects of (a) directional splits and (b) exchange probabilities (Rule 6 as discussed above) in a brief, but illustrative discussion. Short-term interspersed directional flows are not well documented with field observations and can be better understood with this CA model. The methodological ability of this CA model to capture even theoretically the complex behaviors of bi-directional interspersed pedestrians is in itself new knowledge.

It is well known that under high densities opposing walkers will bypass and even bump each other in order to maintain continuous movement. This microscopic activity is modeled by Rule 6 in which juxtaposed opposing pedestrians exchange their positions. This movement is particular to pedestrians and critical for modeling high-density bi-directional flows with crossovers.

Figure 4 presents a speed-density plot for a series of directional splits at exchange probability of 50%. It is shown that for the 100%-0% split (the case of one-directional flow), the curve's shape is logistic. As the opposing traffic increases the curves begin to show a distinct change in behavior. The speed-density curves do not overlap with the single directional curve. The split flow curves are in a relatively narrow band. The 50 percent exchange rate curve indicates lower speeds, and are not so well behaved due to the conflicts between opposing pedestrians.

Figure 5 is a chart of volume-density curves for the 90-10 directional split over the range of exchange probabilities. As the exchange probability falls, a reduction of flow is observed. At the 100% exchange case there is a significant (approximately 15 percent) reduction in capacity which concurs with what the HCM *(2)* describes for the 90-10 directional split case where lane formation does not occur. The 75 percent exchange case has a similar peak volume, appropriately diminished from the unidirectional and lane-separated bi-directional case. Lower exchange rates reveal peak volumes out of range of what the HCM *(2)* describes.

Processing Speed

The speed of the CA simulations varies with the density and type of run. A speed of 100,000 updates per second has been observed on a 150 Mhz Pentium processor on a 100 x 10 cell Lattice at density of 0.5 and directional split of 50-50. At lower densities processing can be 20 percent slower, since the possibilities for lane changing and forward movement are greater and at higher densities updates per second can run 20 percent faster.

CONCLUSIONS

The CA bi-directional pedestrian model reveals that complex and reasonable group behavior can emerge from a simple set of behaviorally based rules. The major difficulty is to ascertain the essential pedestrian behaviors with a minimum of applicable rules in order to capture the pedestrian dynamics. In this regard we have attempted to focus on the key criteria for pedestrian movement in the single- and bi-directional case. The range of emergent behaviors realized show that CA modeling of pedestrians is a powerful new tool to add to the urban planning, facility design, and traffic engineering toolbox. It also lends itself to a better understanding of pedestrian needs, interests, and abilities.

The model is not extremely sensitive to changes in length and width of the lattice, and a 100 x 10 lattice is representative of conditions that would arise in varied lengths and widths. However, the sensitivity that is present is useful for modeling actual performance, since especially narrow width is a factor that affects fundamental characteristics of flow. It is, however, encouraging that micro-modeling of pedestrian behavior reveals curves that have been observed in the field and that the rule set and scaling can be varied to situations and conditions by behavioral changes in the model that presumably would correspond to actual behaviors in the field. The single-directional speed-density case corresponds to a two-regime model with low densities following a May's Bell curve and high densities being linear. The bi-directional case where lanes are dedicated by directional split appears sufficiently validated in that those flows are not significantly different from single-direction flows.

Among those issues that would benefit from further examination, lane changing emerges as a performance measure that is important to the proper functioning of the model. The rule set used seems useful, though it may not represent sufficiently dynamics that could be encountered that are also important. In addition, field studies should verify the hypothetical lane change rate phenomenon of local minimum and maximum that was encountered. Previously published data were used to model the distribution of walker speeds. The use of a CA model as a design tool would require careful study of pedestrian populations with respect to characteristics of lane changing and forward movement (i.e., distribution of walkers with respect to maximum speed).

The CA model has some similarity with the social fields model of Helbing and Molnar *(10)* in which attractive and repulsive forces act upon the pedestrians externally. Their model displayed self-organization of collective pedestrian behavior in the formation of lanes by opposing direction. In our Case 2 experiments lanes were formed by design with the model to examine characteristics of bi-directional separated flows. However, the CA Case 3 model presented also exhibits self-organization that arises naturally from the collective behavior of the pedestrians as each lane change and forward move is made in each time step. The pedestrians arrange themselves in patterns and do not remain in an initial random state for long. The self-organization of the walkers has not been studied, though it has been observed in animations in the unidirectional JAVA-based animation (www.ulster.net/~vjblue). The CA bi-directional pedestrian flows would ideally form emergent lanes that can dissolve and reform as perturbations or irregularities are encountered, as has been observed in bi-directional flows at Grand Central Station in New York City. In fact, emergent lane formation probably occurs in the CA Case 3 model to some extent, though how much has not been evaluated. The tendency of walkers to get behind and stay behind same-direction persons can easily be added to the CA model to enhance lane formation, along the lines of attraction-repulsion used in the social forces model. Further exploration of spontaneous lane emergence as well as the characteristics of self-organization among the pedestrians will be undertaken.

The more complex and hypothetical case of bi-directional flows, where persons do not move into lanes but rather sidestep or exchange places with opposing pedestrians, clearly shows the modeling power of the CA method. This complex environment has been daunting to previous efforts of researchers. CA modeling is evidently an excellent method to capture micro-level pedestrian dynamics. The variety of emergent fundamental flows under various assumptions of exchange probability indicates that the CA model is capable of simulating the complexity of interactions of pedestrians and capturing their inherently non-linear activity. This is not a trivial finding because most modeling (i.e., using link performance functions, delays, etc.) presumes that the speed-flow-density characteristics are already known before the modeling is applied and the interactive effects are then presumed to be correct. Here the interactive effects are intrinsic and internal to the method. In short, the CA methodology captures innate real-world interactive dynamics, though appropriately simplified, and that opens up considerable possibilities for innovation.

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REFERENCES

1. Blue V. J. and Adler J. L. Emergent fundamental pedestrian flows from cellular automata microsimulation, Forthcoming in *Transportation Research Record.* 1998.
2. *Special Report 209: Highway Capacity Manual*. Transportation Research Board, National Research Council, Washington, D.C., 1985, Chapter 13.
3. Nagel, K. and Schreckenberg, M. A Cellular Automaton Model for Freeway Traffic. *J. Physique I*, Vol. 2, 1992.
4. Rickert, M., Nagel, K., Schreckenberg, M. and Latour, A. Two-Lane Traffic Simulations Using Cellular Automata. *Physica A*, Vol. 231, pg. 534, 1996
5. Nagel, K., Barrett, C. and Rickert, M. (1996*) Parallel Traffic Micro-simulation by Cellular Automata and Application for Large Scale Transportation Modeling*. Los Alamos Unclassified Report 96:0050 (submitted to Transportation Research C, Pergamon Press, England), Los Alamos National Laboratory, Los Alamos New Mexico.
6. Simon, P.M. and H.A. Gutowitz. Cellular Automaton Model for Bi-Directional Traffic. *Physical Review E*, Vol. 57., No. 2, February 1998, pp. 2441-2444.
7. Lovas, G. G. Modeling and Simulation of Pedestrian Traffic Flow. *Transportation Research.* **28B (6),** 1994, pp. 429-443.
8. AlGadhi, S.A.H. and Mahmassani, H. Simulation of Crowd Behavior And Movement: Fundamental Relations And Application. *Transportation Research Record 1320,* 1991, *pp.260-268.*
9. Gipps, P. G. *Simulation of Pedestrian Traffic in Buildings*. Schriftenreihe des Instituts fuer Verkehrswesen, 35, Institut fuer Verkehrswesen, Universitaet Karlsruhe, Germany, 1986.
10. Helbing D. and Molnar, P. Social Force Model for Pedestrian Dynamics. *Physical Review E*, Vol. 51, No. 5, May 1995, pp. 4282-4286.
11. Wolfram S.. *Cellular Automata and Complexity*. Addison-Wesley Publishing Company, 1994.
12. Levy S. *Artificial Life*. Vintage Books, New York, 1992.
13. Nagel, K. and S. Rasmussen. Traffic at the edge of chaos. *Artificial Life IV: Proceedings of the 4th International Workshop on the Synthesis and Simulation of Living Systems,* 1994, pp. 222-225.
14. Paczuski M. and Nagel K. Self-Organized Criticality and 1/f Noise in Traffic, published in *Traffic and Granular Flow*, eds. D.E. Wolf, M. Schreckenberg, and A. Bachem, Singapore: World Scientific, 1996.
15. Virkler, M. R. and Elayadath, S. Pedestrian Speed-Flow-Density Relationships. *Transportation Research Record 1438*, 1994, pp. 51-58.

Figure 1 – Flow vs. Density, One Directional Flow

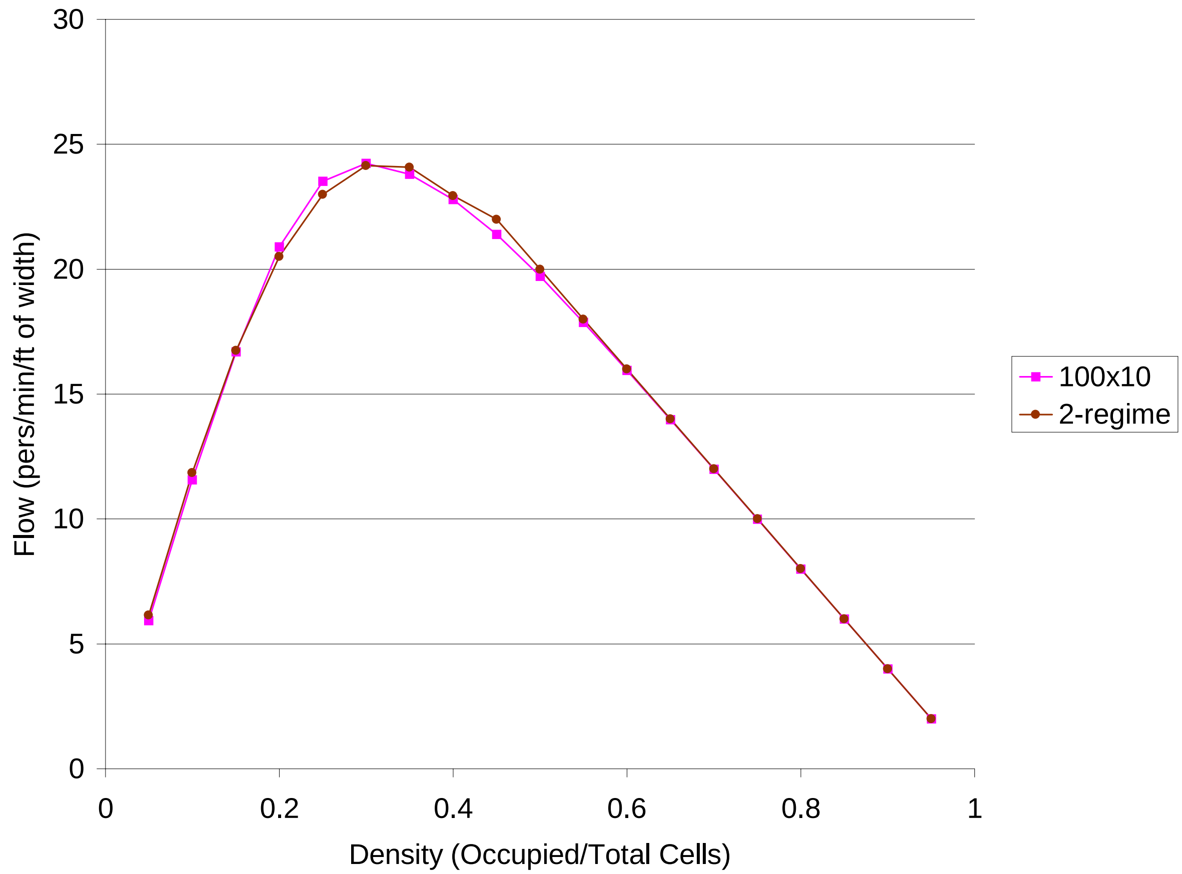

Figure 2. Speed vs. Density, One Unidirectional Flow

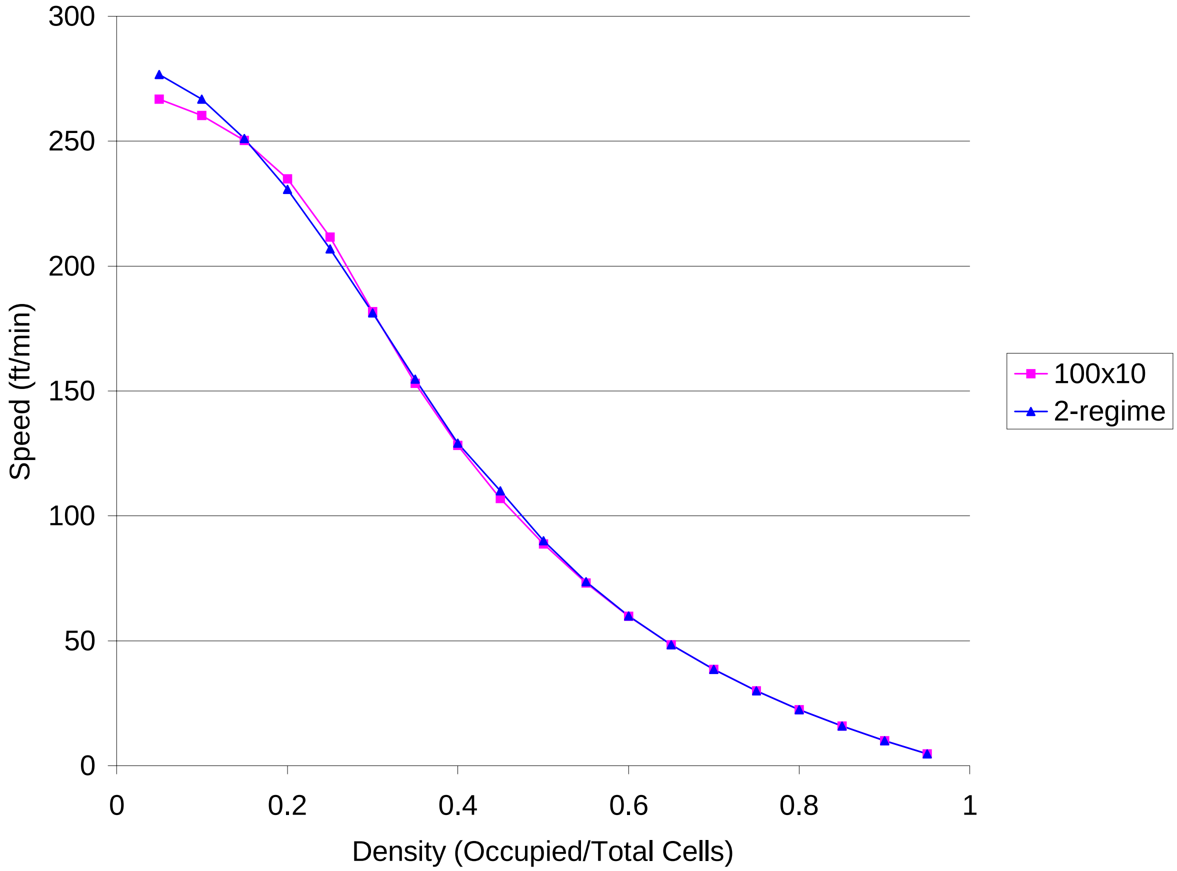

Figure 3. Bidirectional Flow, Restricted Lanes

Speed vs. Density for different splits

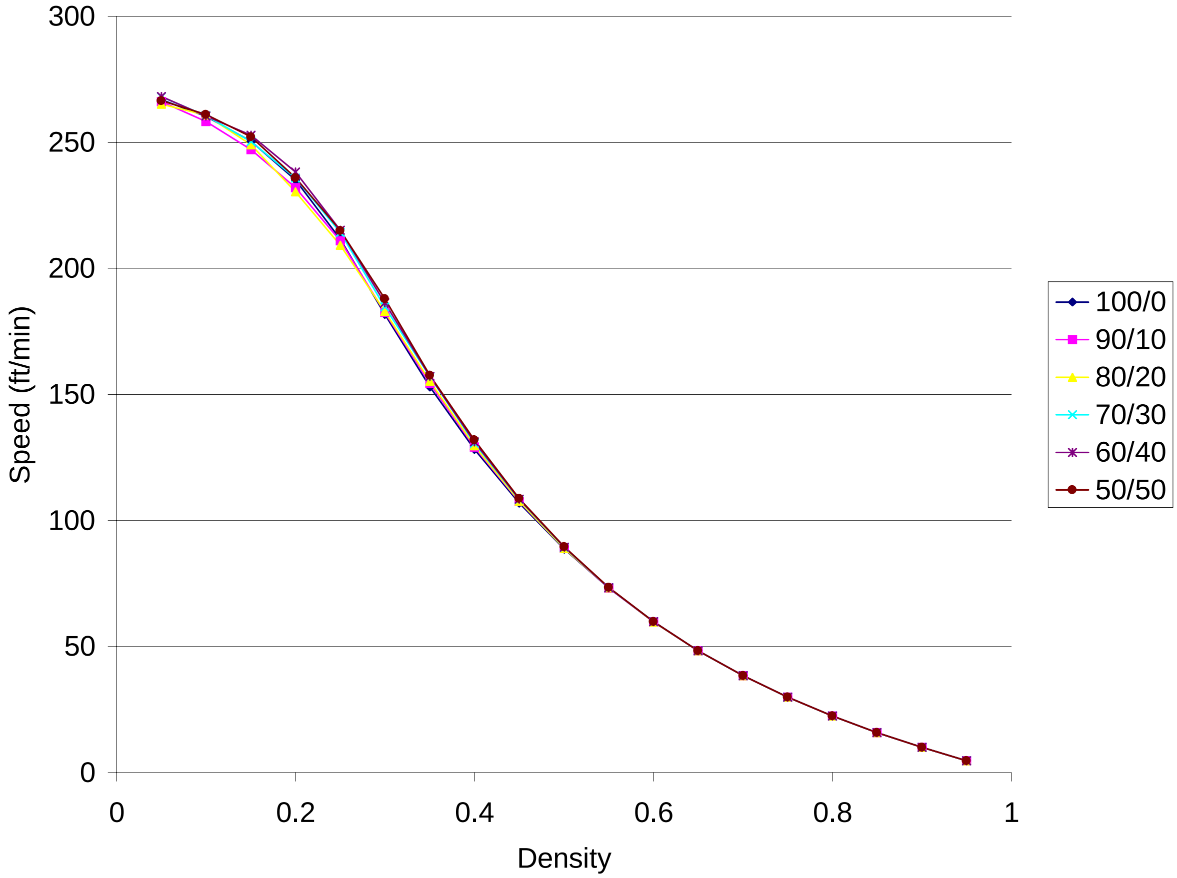

Figure 4. Bidirectional Flow : Speed vs. Density for different splits

Exchange Probability = 0.50

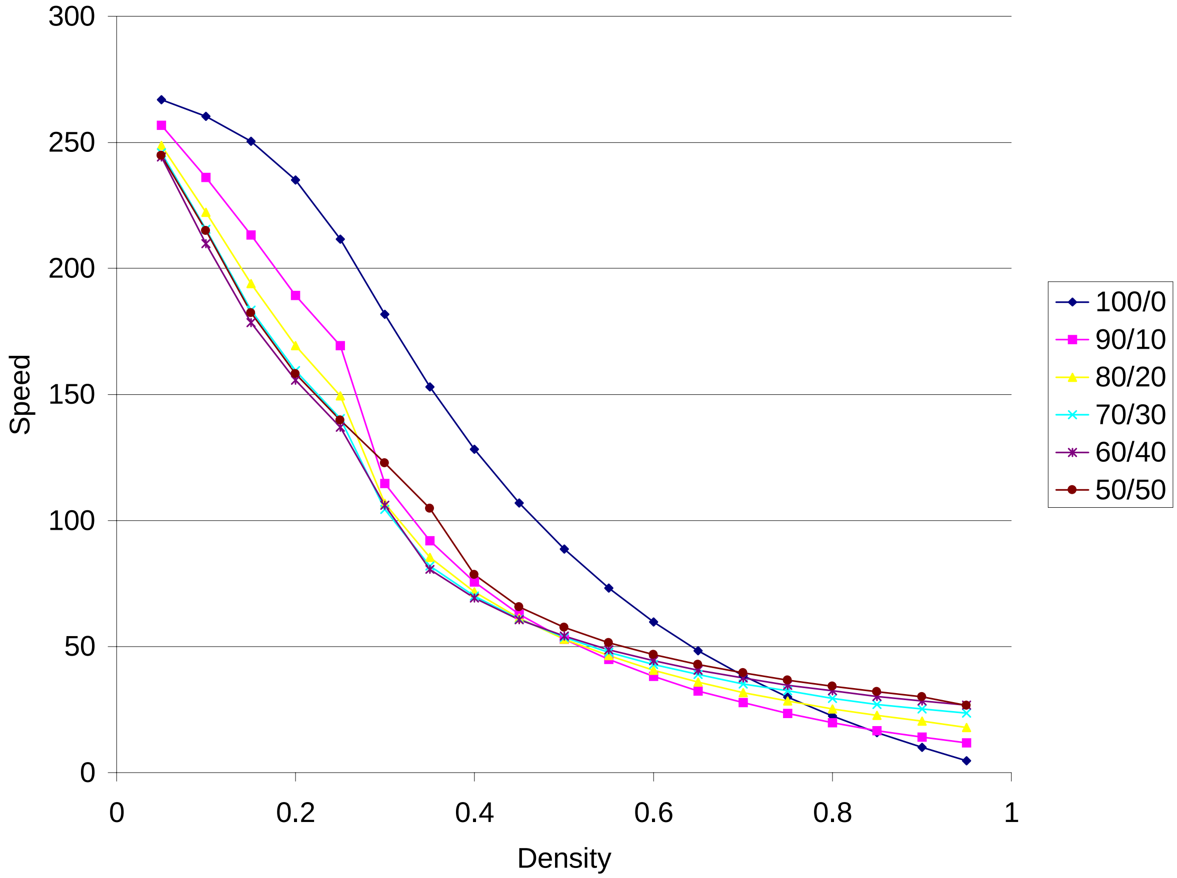

Figure 5. Flow vs. Density Curves for Bi-directional Walkway, Interspersed Flow, and 90:10 volume split