Conceptual Model of a Self-Organizing Traffic Management Hazard Response System

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ABSTRACT

The terrorist attacks of September 11, 2001 have sparked renewed interest in developing effective policies and strategies for evacuating densely populated areas. The current analytical tools for dealing with such evacuations are sorely lacking, in both theory and practice. The conceptual model presented in this paper marries the technical areas of cellular automata, evolutionary computation, and transportation science, along with some recent research on infrastructure security, to make significant progress in traffic management and hazard response systems.

The overall goal of this research is to develop a fundamental understanding of the evolutionary and emergent behavior of transportation systems that are operating under emergency evacuation conditions. This new knowledge can be utilized to develop more effective operational strategies and consequently more robust hazard response systems.

Furthermore, the specific research objective is to investigate the formulation and application of cellular automata models of metropolitan transportation systems, with a focus on systems operating under emergency evacuation conditions. The basic context is evacuation of a defined urban area, such as the urban core of Washington, DC under terrorist attacks. The conceptual model proposes the use of evolutionary algorithms to search the space of the evacuation control strategies and determine the most successful strategies for a given urban area.

INTRODUCTION

The terrorist attacks of September 11, 2001 have sparked renewed interest in developing effective policies and strategies for evacuating densely populated areas. The current analytical tools for dealing with such evacuations are sorely lacking, in both theory and practice. The conceptual model presented in this paper marries the technical areas of cellular automata, evolutionary computation, and transportation science, along with some recent research on infrastructure security, to make significant progress in traffic management and hazard response systems.

In order to effectively respond to crisis situations we need to gain a fundamental understanding of the evolutionary and emergent behavior of transportation systems that are operating under emergency evacuation conditions. This kind of behavior is substantially different from typical modes of transportation systems' operations. Hence, novel approaches are required to model, analyze, and optimize the performance of transportation systems operating under emergency evacuation conditions. Three hypotheses drive this research:

1. A typical transportation network can be understood as a complex system with many entities and actors, all pursuing their own somewhat limited objectives and acting with variable and limited information inputs. All of the actors in the system have actions they can take that are perceived to improve their own performance, or to advance their assigned operational objectives, and they often make decisions with little or no knowledge of the impacts of their decision on the performance of the overall system.
2. The emergent behavior of the system and its subsystems is of great interest for finding effective technology and policy approaches to improving performance.
3. Systems operating in crisis mode exhibit self-organizing behavior, so finding optimal operational strategies involves understanding and capitalizing on this attribute.

Agent-based models, with their use of individual agents following localized decision rules for interacting with other agents and the environment, appear to offer a powerful approach to capturing the many interactions in transportation systems. On the other hand, cellular automata (CAs) have been successfully used to model self-organization phenomena in various biological, chemical, and man-made systems. Hence, they offer an enormous potential for developing a new class of models of emergent behavior for traffic management and hazard response systems.

When such models are found, they can be subsequently used by transportation engineers to create effective operational strategies for robust hazard response systems. Evolutionary algorithms (EAs) can be used to identify optimal CA models in the vast solution spaces, i.e., they act as search and optimization mechanisms. They can also be employed to adapt and fine-tune solutions to specific types of transportation systems, geographical locations, etc.

One of the specific research objectives is to investigate the formulation and application of cellular automata models of metropolitan transportation systems, with a focus on systems operating under emergency evacuation conditions. The basic context is evacuation of a defined urban area, such as the urban core of Washington, DC under

terrorist attacks. Evolutionary algorithms are employed to search the space of the evacuation control strategies and determine the most successful strategies for a given urban area.

The results of this research should significantly contribute to the understanding of the dynamic operation of metropolitan transportation systems, how system behavior emerges, and how the self-interest or myopic actions of system participants affects system performance. The present paper develops the concepts employed in this modeling approach, provides some simple examples of the computational approaches that are used, and presents some initial formulations of hazard response traffic management systems that will be studied. Subsequent papers will present numerical and empirical results.

BACKGROUND

Cellular Automata

Cellular automata are one of the simplest mathematical representations of complex systems [1]. They appear to capture many essential features of complex self-organizing behavior observed in real world systems. CAs are prototypical models for complex systems and processes consisting of a large number of identical, simple, and locally interacting components. They can be used to study pattern formation and gain some insight into self-organization processes [2]. CA models have generated great interest over the last forty years because of their ability to exhibit very complex patterns of behavior using a set of relatively simple underlying rules. Recently, Wolfram [3] suggested that cellular automata and other simple programs may better model nature's most essential mechanisms than traditional mathematical equations.

CAs have been successfully applied in physics, biology, chemistry, economics, geology, and other disciplines. Some specific examples of modeled phenomena include fluid and chemical turbulence [4, 5], growth of crystals [6], social dynamics [7], patterns of electrical activity in neural networks [8], path planning for mobile robots [9], etc. Recently, Kicinger et al. [10, 11] applied cellular automata to topological optimum design problems in structural engineering. They proposed and studied generative representations of steel structural systems in tall buildings based on one-dimensional and two-dimensional CAs. The results have shown that cellular automata representations not only outperformed traditional models in optimizing engineering systems but also produced qualitatively novel solutions exhibiting remarkable shaping patterns.

Several initial applications of cellular automata to model human driving behavior [12] and simulate multi-lane [13] and city traffic [14] have been reported. CAs were also applied to study traffic planning and traffic flow in transportation systems [15, 16]. Recently, these ideas have been extended to simulations of large-scale transportation systems, e.g. the city of Geneva [17] and the entire country of Switzerland [18].

There are five generic characteristics of CAs [2]:

1. *Discrete lattice of cells*: the system usually consists of a 1-, 2-, or 3-dimensional lattice of cells.
2. *Homogeneity*: all cells are equivalent.
3. *Discrete states*: each of the cells can be in one of a finite number of possible discrete states.

4. *Local interactions*: each cell interacts only with cells contained in its local neighborhood.
5. *Discrete dynamics*: at each discrete time unit, each cell updates its current state according to a transition rule taking into account the states of cells in its neighborhood.

The simplest possible CAs, called elementary CAs, consist of a one-dimensional lattice of cells, in which each cell can be in one of two possible states. The value of each cell at a next time step is determined by a value of the cell itself and its two closest neighbors and is called the local neighborhood of size 3. In other words, an elementary CA is a one dimensional CA with binary states and with a local neighborhood of size 3 (or a neighborhood radius equal to 1). Results of a process of iteration of an elementary CA are presented in FIGURE 1a.

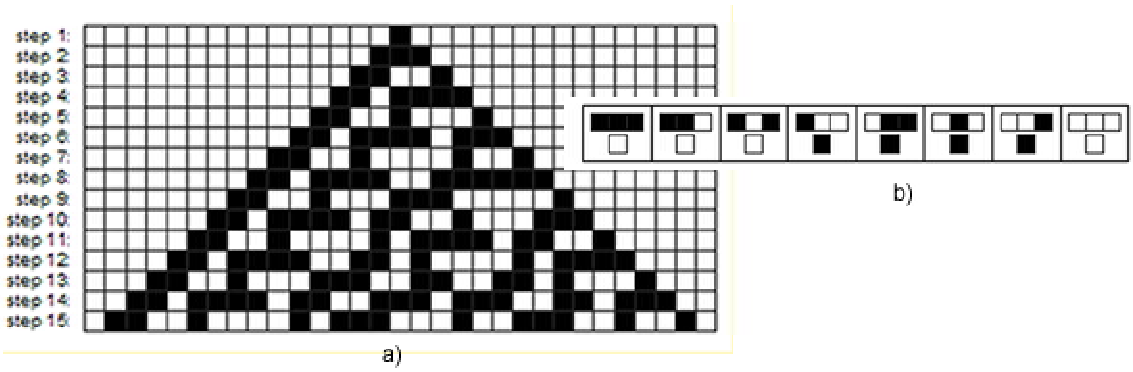

FIGURE 1 a) Process of iteration of an elementary CA and b) a transformation rule determining the values of cells at a next time step.

The top row of cells (step 1 in FIGURE 1a) is iterated 14 times (steps 2-15) using a CA transformation rule shown in FIGURE 1b. The CA transformation rule specifies all possible (8 in the case of an elementary CA) combinations of cell state values in a local neighborhood of size three (the top row) and the values achieved by the central cells at the next time step (bottom row).

Two-dimensional cellular automata (2D CAs) are generalizations of one-dimensional systems in which the lattice of cells is no longer one-dimensional but is extended to two dimensions. 2D CAs can be defined using a set of parameters known from 1D CAs but extended with several additional properties. These properties include an initial configuration of cells which is now two-dimensional as well as a CA transformation rule that now has to take into account a two-dimensional local neighborhood of a current cell. Thus, in order to fully define a 2D CA transformation rule one not only has to specify a radius of the local neighborhood but also its shape. Several popular shapes and radii of 2D local neighborhoods are presented in FIGURE 2.

FIGURE 3 shows several steps of a process of iteration of a totalistic (defined below) 2D CA started with a 2D lattice of cells with a single black cell (cell with value equal to 1) located in the middle of the 2D lattice shown at step 0. As before, 2D local neighborhoods are formed and a 2D transformation rule is applied to define the value of the central cell in these neighborhoods at the next time step. This process is repeated an arbitrary number of times (see FIGURE 3).

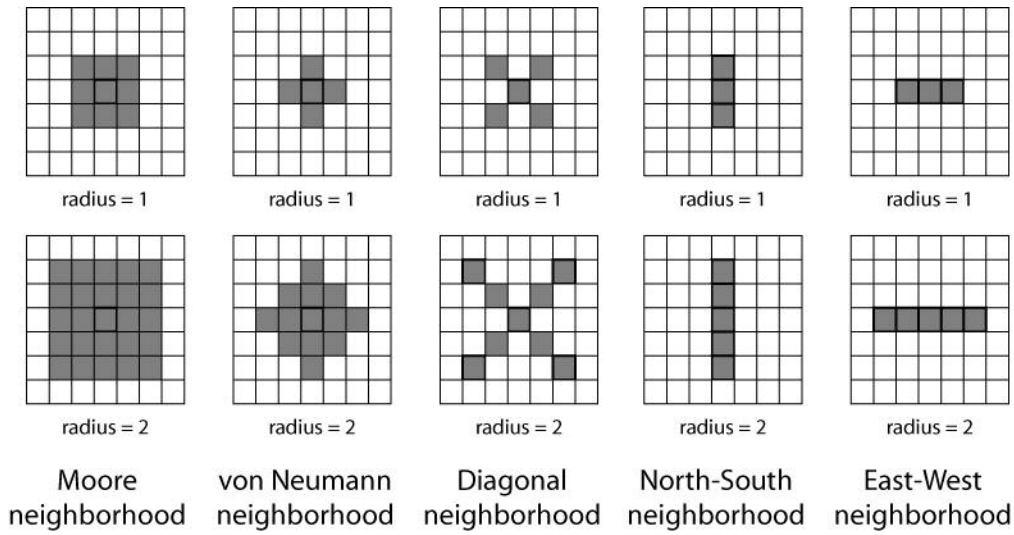

FIGURE 2 Commonly used shapes and radii of the local neighborhoods in 2D CAs.

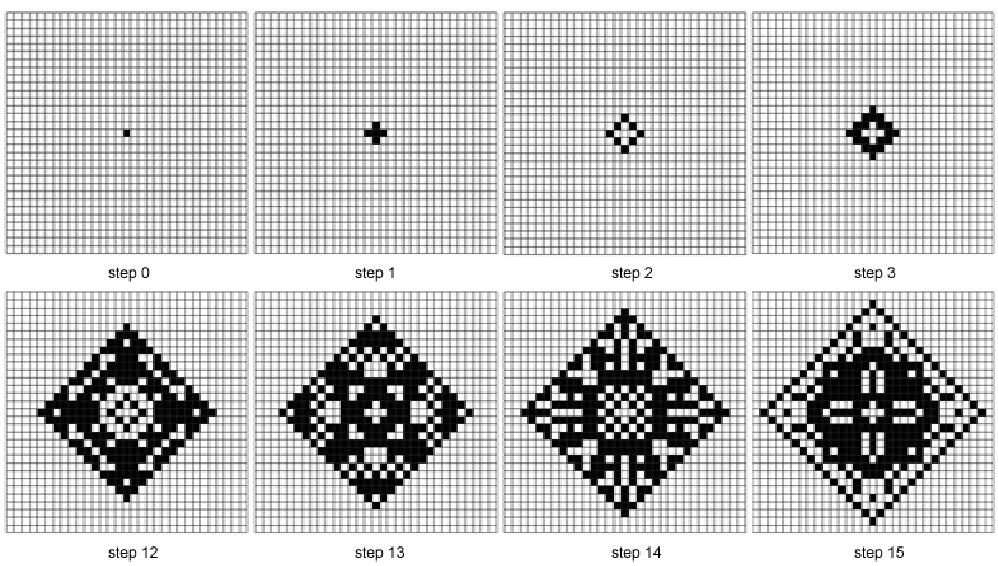

FIGURE 3 Several steps of iteration of a two-dimensional cellular automaton.

When the number of cell state values or the size of the local neighborhood increases then the number of possible CA rules grows rapidly according to the formula k^{k^s}, where *k* is the number of the cell state values and *s* is the size of the local neighborhood . This in turn causes a rapid growth of the search spaces in which well-performing CA rules are sought. For example, changing the number of cell state values to 3 in the case of a 1D CA with the same size of the local neighborhood yields $3^{3^3} = 7{,}625{,}597{,}484{,}987$ possible CA rules, compared to $2^{2^3} = 256$ CA rules for elementary CAs. These scaling up problems are even more severe for 2D CAs. There is, however, a way to significantly reduce this growth by introducing the concept of a totalistic CA. In a totalistic CA, a new value of each cell depends only on the *average* value of the neighboring cells and the cell itself, and not on their individual values [3].

For example, due to averaging, there are only 2187 possible totalistic CAs with 3 values and the neighborhood of size three compared to the more than 7.6 trillion rules found in the corresponding standard CAs.

FIGURE 4 shows a process of iteration of a totalistic CA with three state values (see FIGURE 4a) and a totalistic CA transformation rule (see FIGURE 4b). In this particular example, the rule specifies all 7 possible local neighborhoods of size 3 corresponding to 7 possible *average* cell state values, i.e. 0, 0.33, 0.66, 1, 1.33, 1.66, and 2. They are denoted graphically by various shades of gray (the top row). The values achieved by the central cells at a next time step, i.e. 0, 1, and 2 are shown in the bottom row.

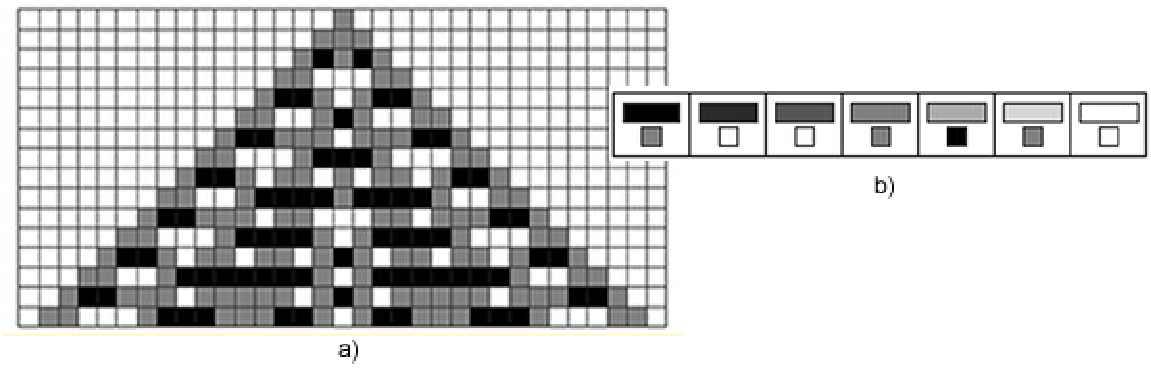

FIGURE 4 a) Process of iteration of a totalistic 1D CA and b) its transformation rule.

Agent-Based and Related Transportation Models

As noted earlier, this research is built around the notion that agent-based models and cellular automata provide a useful approach to analyzing transportation systems. The many actors in such systems make localized decisions based on limited information, to satisfy their own objectives. For example, in a traffic control network individual motorists attempt to progress to their destinations with the minimum expenditure of travel time, traffic control center staff attempt to adjust traffic signal settings to minimize system delays and queues, and police officers controlling traffic manually at key intersections react to traffic volume demands and queues on the intersection approaches. In most cases these individual actors are not in communication with each other, or at most have limited or sporadic information (generic traffic control directives to the police officer, intermittent radio traffic condition reports to drivers, etc.). All of these actors have actions that they can take to improve their own performance, and they often make decisions with little or no regard for the impacts of their decision on the performance of the overall system. Agent-based modeling seems to offer a powerful approach to capturing the many interactions in such systems.

Traditional simulation models seek to develop deterministic estimates of system behavior, or composite probability distributions over the possible range of system responses. Agent-based models offer a new paradigm, based on complexity theory. These are models in which the actions, interactions and adaptations of many autonomous, heterogeneous ‘agents’ produce emergent, system-wide behavior. These models help to examine emergent behavior and can also provide deeper understanding of how the

individual behaviors of agents self organize to produce the entire system's behavior [19, 20].

The units of analysis in agent-based models are not related to each other directly in closed form equations. Adaptive agent-based modeling attempts to directly replicate the interactions and/or decision processes of these individuals in an environment. Furthermore, agents are typically adaptive in that they remember events and can learn from experience. Therefore, an agent might not react the same way if presented with the same situation twice. Adaptation in a system causes fundamental changes in the way the system operates. Agent-based models allow the researcher to trace back the causes of individual decisions made by particular agents and diagnose that agent's decision process.

The environment in traditional simulation is usually given, and strict assumptions are placed on it. Since agent-based modeling is bottom-up, however, and agents adapt and learn, the environment in which they operate constantly changes. Therefore, the environment in an agent-based model is created by the actions of the agents; indeed, in some simulations the agents may be able to modify the assumptions originally placed on the model itself. Developing self-learning adaptive agent models is an active area of research in computer science [21].

A natural early target of agent modeling in transportation was traffic flow on highway segments and in traffic networks, and efforts along these lines began at the Federal Highway Administration (FHWA) in 1994 [22]. The earliest work successfully simulated a lane merge situation, using vehicles as agents interacting with very simple decision structures. Follow-up work at the University of Arizona is extending this type of analysis to pedestrian-vehicle interactions at intersections. Current work involves using commercial agent-based development environments to build urban traffic control system simulations.

For urban transportation planning applications, the TRANSIMS model that is currently under development includes some aspects of the agent-based approach, in that individual activity simulations and cellular automata representations of vehicular flow are used [23]. Work is currently underway at the MITRE Corporation to develop an agent-based model of the air traffic system, and the early results look very promising [24]. There is also a relatively small body of work on evacuation planning models. The leading extant model is the Oak Ridge Evacuation Modeling System (OREMS) [25], which was developed at Oak Ridge National Laboratory for FEMA and the U.S. Army to support the chemical weapon demilitarization program. OREMS was applied to evacuation scenarios for the eight former chemical weapons plants scattered around the country, in order to help develop emergency response plans for accidental releases of toxic substances to the environment. Other models reported in the literature include DYMOD [26] and TEDSS [27]. These models are all essentially static models that employ traditional traffic modeling relationships, for use in a planning context. They can be utilized in the proposed conceptual model as the simulation engines or comparative solutions generators for evolutionary algorithms.

SELF-ORGANIZING TRAFFIC MANAGEMENT HAZARD RESPONSE SYSTEMS

Cellular Automata Models of Traffic Control Systems

Two-dimensional cellular automata, introduced above, can be used to model emergent behavior of transportation systems operating under emergency conditions. Their significance in modeling evacuation control strategies can be motivated considering several facts. First, they can inherently model spatial relations of various elements of a transportation system. For example, FIGURE 5b shows a discrete representation of a configuration of a traffic control system in a given urban area which is schematically illustrated in FIGURE 5a. The spatial (in this case planar) relationships among elements of the traffic control system, e.g., north-south-east-west directions and relative distances (1 block away, 2 blocks away, etc.), can be expressed explicitly using these models.

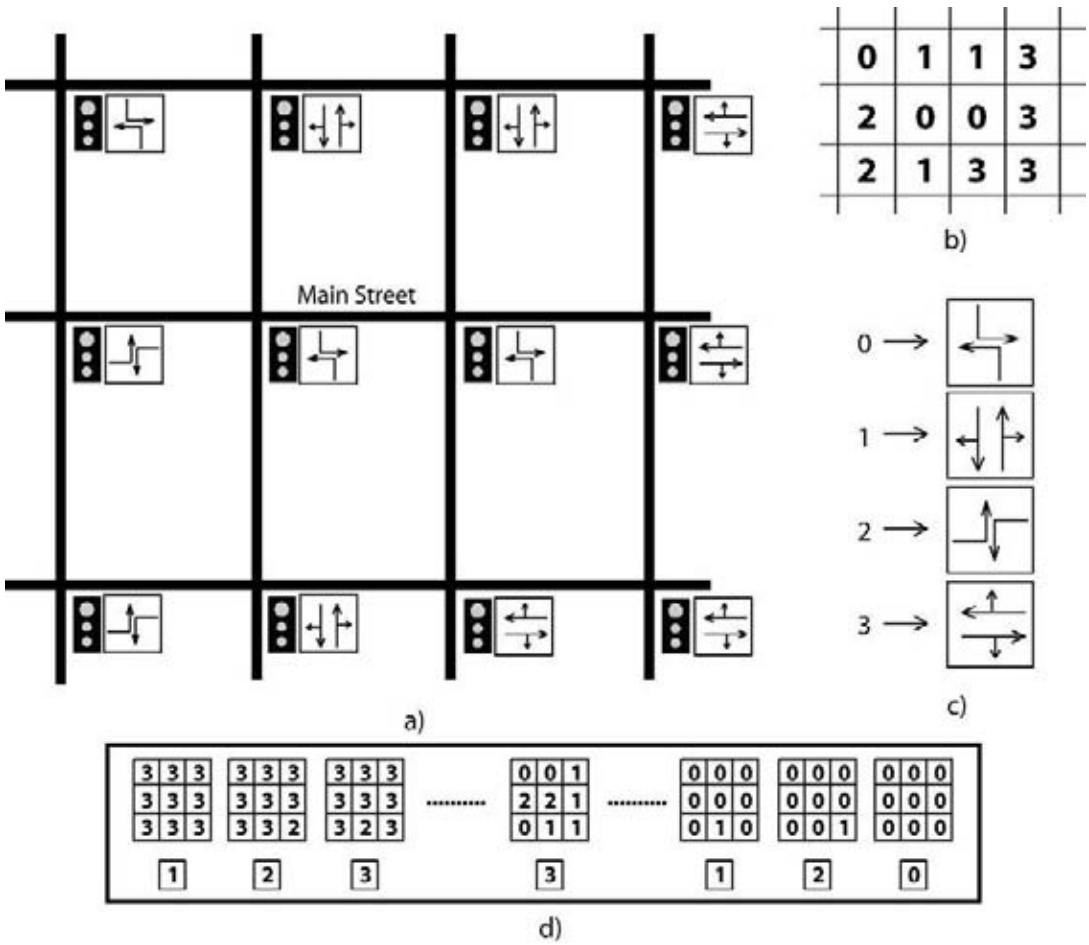

FIGURE 5 Simple model of an urban traffic control system based on cellular automata, a) schematic map of an urban area with locations of traffic signals, b) discrete model of a current configuration of a traffic control system, c) representation of states of traffic signals using symbolic (integer) values, d) a 2D CA rule which updates the current configuration of a traffic control system based on the local interactions among its elements.

Second, individual states (phases) of traffic signals can be readily represented by discrete values of a cellular automaton. For example, FIGURE 5c graphically illustrates the relationships between integer values of CA cells shown in part b and the states of a traffic signal. Here, traffic signals are represented by symbolic attributes, and their specific states, e.g., north- and southbound vehicles may go straight or turn right, assume integer values, e.g., in this case 1. This representation can be easily extended to include more complex traffic signal configurations.

Third, cellular automata can explicitly model local interactions among elements of an urban traffic control system, as shown in FIGURE 5d. Here, a 2D CA transformation rule with Moore neighborhood (see FIGURE 2) and the neighborhood radius of 1 is presented. It explicitly captures the local interactions among elements of the traffic control system as it is shown graphically in the upper part of FIGURE 5d) (3 x 3 grids). Based on these interactions, the value of the central cell of the local neighborhood (i.e., a state of a traffic signal at a specific location) is updated and assumes a new value determined by the bottom row of FIGURE 5d. These updates are performed concurrently for all cells in a given 2D lattice (i.e., all traffic signals in a given urban area) and determine the configuration of a traffic control system at a next time step. There are, of course, rules on traffic signal phase sequencing that must be followed (e.g., north- and southbound left turns, state 0, normally immediately precede or follow state 1), and these rules can easily be incorporated in the system by introducing constraints to CA transformation rules.

Fourth, one can easily model the range of local interactions among the elements of a traffic control system by varying the shape and/or the radius of the local neighborhood. FIGURE 2 shows several shapes and radii used in typical CA applications. They can be further extended and/or adjusted to specific configuration of a traffic control system in a given urban area. By this means, strategies such as arterial or centralized network control strategies can be introduced into the model. Furthermore, the optimal shapes and radii can be learned during the optimization processes conducted by evolutionary algorithms as discussed below.

Finally, CAs are known to produce various kinds of emergent and self-organizing behavior and, as discussed above, it is hypothesized that this property is highly relevant for transportation systems operating in crisis mode.

Evacuation Scenarios

Cellular automata models of the traffic control system described above can be employed to determine evacuation strategies following terrorist attacks in a given urban area. FIGURE 6a shows a schematic map of an urban area with several locations of terrorist attacks. The types of attacks considered in these simulations are presented in FIGURE 6b.

The input for each evacuation scenario simulation consists of a configuration of vehicles (pedestrians will be introduced in later versions) in the urban area under consideration, a specific CA model of a traffic control system to be evaluated, and a pre-determined terrorist threat situation, i.e., locations and types of terrorist attacks. In these preliminary studies, fixed locations and types of attacks will be assumed in all simulations. They will, however, be varied in future studies to determine sensitivity of

evacuation strategies against various terrorist threats. The locations and types of attacks determine the affected zone of the urban area.

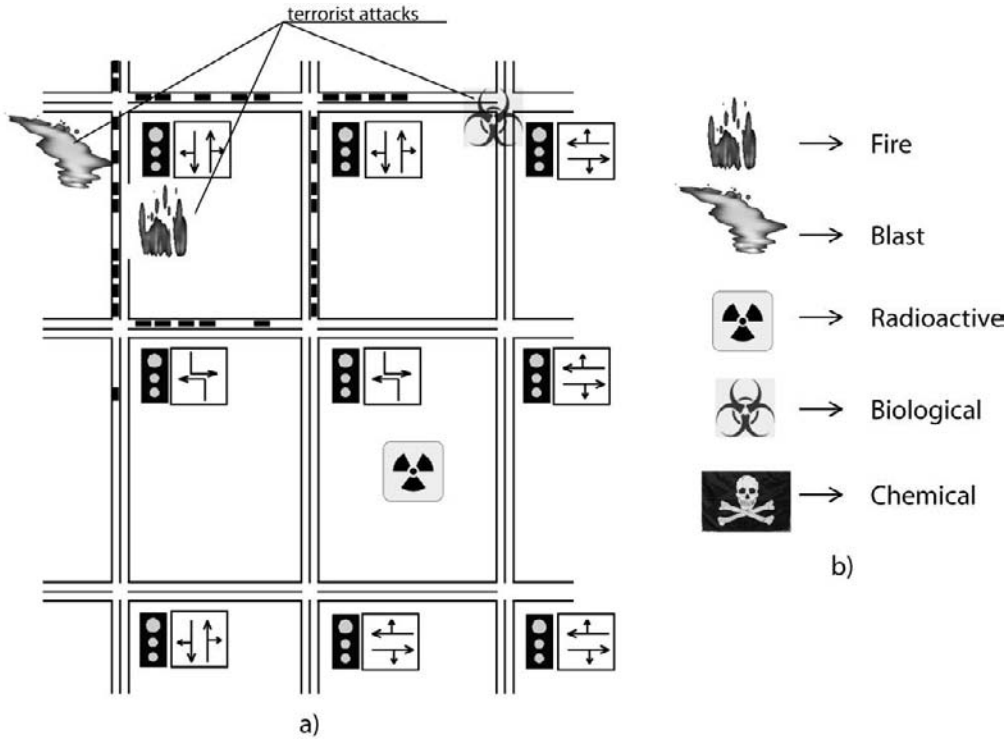

FIGURE 6 a) Example of an evacuation strategy simulation following terrorist attacks in a given urban area and utilizing cellular automata models of the traffic control system, b) types of terrorist attacks considered in the simulations.

The following assumptions on the configuration and movement of vehicles in the urban area have been employed for the initial models:

- Traffic signal state durations (phase lengths) will be fixed and constant. As described below, a traffic phase length will be an integral multiple of the model's fixed time step, and cycle times will be a product of the modeling results. The length of the time step will be a modeling variable.
- Vehicles will move only in marked lanes (i.e., not on the shoulders, sidewalks, or off-road areas), in the normal direction (i.e., not in opposing lanes, even if they are empty).
- The initial locations, destinations and travel paths of individual vehicles will be given and constant, which will determine the turning movement demand at individual intersections.

These assumptions will be relaxed or modified as more complex model formulations are attempted. In particular, it seems fruitful to model pedestrian activity and expanded vehicle movement paths as early experiments.

Given the configuration of vehicles and the affected zone of the urban area, the evaluation of a specific evacuation scenario can be performed in the following way. The urban area and street network under consideration, the affected zone, and the population, location, and desired system exit points of the vehicles to evacuate the area, and possibly

the background or through traffic, form the input to a traffic simulation system, e.g., OREMS. The initial configuration of a CA model determines the starting configuration of the traffic control system in the simulator. Subsequent iterations of the CA model update the status of the traffic control system in the simulator at pre-determined time intervals corresponding approximately to traffic phase subintervals (e.g., 30 seconds; selecting an appropriate time step is part of the research). The evacuation traffic simulator is then run for the duration of the time step, and traffic throughput statistics are gathered. The CA transition rule is then invoked to set the state of the traffic control system for the next time step. Note that if, at a given traffic signal, the decision rule is to maintain the same phase as in the preceding time step, we effectively simulate a phase length of 2t, where t is the time step. The sum of the simulated phase lengths will determine the simulated cycle length. One interesting outcome of the experiments will be to see if fixed or variable cycle lengths work better in an evacuation. This process repeats for a pre-specified simulation time, such as 10 minutes (another variable to be selected in the research). The effectiveness of this evacuation scenario is measured by the traffic throughput rates at the various intersections, the cumulative percentage of the affected population evacuated as a function of simulation time, and similar traffic performance variables. Specific values of these criteria are provided by the simulator at the end of the scenario evaluation run. Depending upon this outcome, another instance of a CA model is selected for testing, and the entire process is repeated.

Evacuation Scenario Optimization

Cellular automata models of evacuation scenarios described in the previous sections should provide valuable insights into emergent behavior of transportation systems operating in emergency conditions. They are, however, not sufficient for transportation engineers who are faced with the problem of designing *efficient* traffic management strategies in response to hazard situations.

This objective can be achieved by combining cellular automata models with optimization algorithms, e.g., evolutionary algorithms. These algorithms search the space of possible CA models and identify high-performance solutions. FIGURE 7 shows a simple example of how a CA model of a traffic control system can be encoded as a genome and manipulated by an evolutionary algorithm.

The genome shown in FIGURE 7c consists of two combined parts: encoding of an initial configuration of a traffic control system and encoding of a transformation rule (a 2D CA transformation rule) which updates the configuration of a traffic control system at pre-determined time intervals. The encoding of the initial configuration of a traffic control system is formed by linearizing the 2D configuration of traffic signal states shown in FIGURE 7a. On the other hand, the encoding of the transformation rule consists of outcome values of a 2D CA transformation rule (see FIGURE 7b).

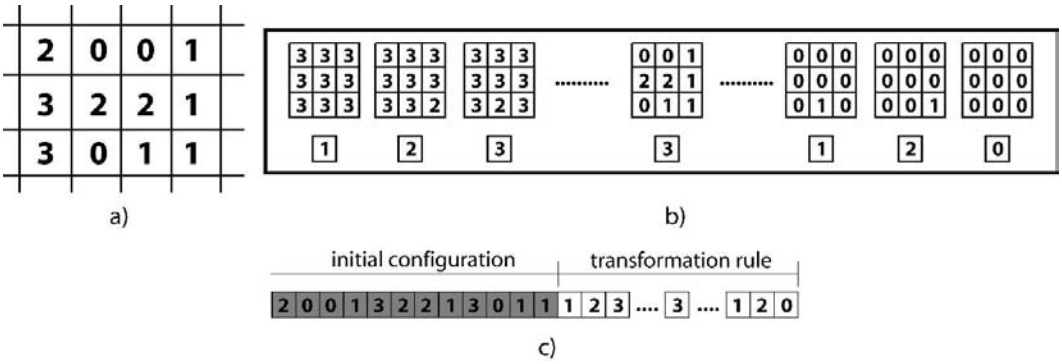

FIGURE 7 a) Initial configuration of a traffic signal control system, b) CA transformation rule updating the configuration of a traffic control system, c) genome representation of a CA model of traffic control system manipulated by evolutionary algorithm.

Thus, evolutionary algorithms search the space of representations of CA models and identify optimal initial configurations of traffic signal states as well as optimal update rules. These rules determine the optimal sequence of changes of traffic signal states for a given urban area in response to a terrorist threat situation. Similar approach can also be used to determine robust evacuation strategies. In this situation, the solutions generated by evolutionary algorithms should be evaluated using several, or more, terrorist threat scenarios (e.g., by varying the locations and types of attacks).

INITIAL CONCLUSIONS AND FURTHER RESEARCH

The proposed CA modeling structure is very promising, but much work remains to be done. First, we must make enough experimental runs of fairly simple "starter" models to identify the strong and weak points of this approach, and the points where greater realism is both needed and promises to yield analytical benefits. Next, the complexity of the simulations needs to be expanded in at least three directions: more complex traffic control systems; introduction of one-dimensional CA models of vehicle movements (replacing some elements of the vehicle system simulation); and incorporation of pedestrian traffic into the evacuation scenarios. It may ultimately be necessary to develop a vehicle flow simulator specifically for this application, if it proves to be too difficult to adapt existing simulators for this purpose. Another potential increase in complexity will be to investigate coevolutionary computation approaches, in which both terrorist attack scenarios and optimal traffic control responses are evolved in concert. Finally, the whole range of practical outputs and technology transfer resulting from this research remains to be planned and designed.

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