The Influence Mobility Model: A Novel Hierarchical Mobility Modeling Framework

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Abstract – **Practical mobile ad hoc systems include heterogeneous classes of mobile nodes, such as people and vehicles. The simultaneous presence and movement of these classes influence the mobility pattern of their members in a variety of random and deterministic manners. In addition, there is an inherent hierarchical and multi-resolution structure to the mobility patterns. In this paper, we present a novel hierarchical mobility framework which incorporates the fact that the movement of certain classes of mobile nodes (e.g., people) is affected by their surroundings and the movement of other forms of mobile nodes. The proposed model takes into account that mobile nodes' movement is neither completely random, nor a mere function of their routing decision and/or the trip's source and destination points. The proposed model is neither classified as microscopic nor macroscopic. Instead, it is categorized as a multi-scale mobility framework capable of modeling mobility scenarios of different scales, i.e. it is equally capable of modeling the movement of mobile nodes in a street intersection as it is to model the movement of nodes between a number of population centers in a state. The proposed mobility framework presented in this paper integrates and extends an *influence model* and hierarchical graph-based representations of the mobility area to achieve this goal. Our simulation results show that this framework accurately captures the influences among different groups of mobile nodes and the constraints imposed by their surroundings.**

Keywords: **Simulations, Mobility Modeling, Ad-hoc Network Simulation, Stochastic processes, Markov Chains, Influence Model, Graph theory.**

I. INTRODUCTION

Mobility models play a crucial role in the design, development, and implementation of traditional mobile systems and emerging ad hoc networks. Consequently, a variety of mobility models have been proposed and analyzed by many previous efforts (see for example [1]-[3]). These models have many strengths and advantages; however, they fail to capture some aspects of practical mobile scenarios. In particular, emerging ad hoc systems include heterogeneous classes of mobile nodes, such as people and vehicles that interact and influence each other's mobility in a hierarchical and multi-resolution manner.

In this paper, we propose a novel mobility model that we refer to as the *hierarchical influence mobility model* (HIMM). The proposed model is a novel mobility modeling framework that integrates and extends crucial aspects of an *influence model* [8] and a graph theoretic representation of the simulation area. The HIMM addresses the effect the movement of one group of mobile nodes has on the movement of other groups while the latter (graph-based representation) restricts movement due to the surroundings and resources available to the mobile nodes. The framework's flexibility allows us to apply it to mobility scenarios of different scales, i.e. it is possible to apply the same mobility model to successively more detailed views of the same simulation or apply it to entirely different mobility problems spanning geographical areas of widely varying magnitudes.

The rest of the paper is organized as follows. Section II is a list of shortcomings of previous mobility models that are addressed by the HIMM. Section III details the HIMM by explaining the graph-based representation of the simulation plane and the application of the binary influence model. Section IV describes how the proposed HIMM model is applied to two different scenarios. The first scenario is a pedestrian crossing across a busy one-way street on which traffic is controlled by a traffic signal. The second example models the movement of travelers using the interstate/ highway network, and air links within a large state. These two scenarios illustrate the ability of HIMM to capture the influences among heterogeneous nodes at different scales of mobility. Section V concludes the paper.

II. PREVIOUS WORK

In this section, we provide a brief overview of previously proposed mobility models and their shortcomings that our HIMM addresses.

1) *Task Based Movement*: A notion of tasks and starting and destination points. People do not move around at random. Their movement is usually task based. Kumar et al. make use of this feature in their model which they derived from the gravity model in [1]. Most of our movement is restricted to neighboring places, i.e. moving around in an office or around the house. It is rarely the case that once a person reaches a location he/she immediately moves on to another distant location. The longer the distance traveled to reach a location, the longer the stay. If a person moves from one room to another he/she may stay there for only a few seconds, minutes or a few hours, but if a person moves from one part of the city to another it is safe to assume that he/she will not stay at his/her destination for just a few minutes but stay for a few hours. Similarly if a person moves from San Francisco to New York we can again assume that he will not just stay for a few hours but probably for a few days. We believe that there exists a correlation between the distance traveled between two points and the time that a person spends in the vicinity of his destination.

2) *Path Selection*: People do not tend to walk around aimlessly and hope to reach their destination by chance. People select routes to their destination on the basis of (spatial) path congestion, cost, distance and travel time. We believe that this aspect of characterizing movement may be reducible to a routing problem for which there already exists a well established theory of routing algorithms.

3) *Mobile Node Classification*: It is possible to perform classification of mobile nodes into classes based on some features such as their location and speed. Nodes in the same class move together along similar paths, e.g. pedestrians and cyclists have a tendency to stay on the sidewalk and only rarely mix with fast driving cars on the road and vice versa.

4) *Class Transition*: A mobile node may switch classes, i.e. a person descending from a car and joining the stream of pedestrians and vice versa.

5) *Dependence*: The movement of mobile nodes is not independent of the movement of other nodes. The behavior of one class of mobile nodes has an effect on the behavior of nearby mobile nodes of other classes. The simplest example is that of a traffic signal, where the movement of pedestrians belonging to one group is dependent on the movement of road traffic.

6) *Scale Invariance*: The choice of a suitable mobility model should not be dependent on the scale of the scenario that is being modeled. Ideally, it should be possible to apply the framework to scenarios of all scales.

III. THE INFLUENCE MOBILITY MODEL

In this section we propose an HIMM that, according to Bettstetter's taxonomy in [2], can be categorized as a graph-based hybrid mobility model. Under such model, a graph theoretic element is employed to restrict the movement of mobile nodes due to obstacles in the environment. It defines which site can be reached from which other site. Our proposed mobility modeling framework is motivated by the *influence model* introduced in [8] to capture the dynamics of multiple (networked) Markov chains that influence each other. Several forms of the influence model exist and can be used to capture different aspects of mobility, randomness, and influences among nodes in ad hoc networks. In particular, the *binary influence model*, which is a special case of influence models, is a stochastic model that introduces a binary degree of randomness (as explained further below). Here, we propose a binary influence model that aims to incorporate the following characteristics of node mobility that previously proposed models do not capture.

A. Features of the Hierarchical Influence Mobility Model

Both, the graph-based representation of the simulation plane and the binary influence model are represented as graphs with the same set of vertices. However, the graphs differ in their respective sets of edges. The edges of the simulation plane graph represent accessibility between sites. The set of edges in the binary influence model's graph on the other hand represent the magnitude of the influence nodes in one site exert on nodes in another site. This is the reason our HIMM consists of two separate graphs.

B. Graph-based Representation of Simulation Plane

Let the simulation area be divided into n different sites s_i where $1 \le i \le n$, such that $\bigcup_{i=1}^{n} s_i$ consists of the entire simulation area that is reachable by any node. The mobility of a mobile node is determined by the site it is a part of. The sites are allowed to partially or fully overlap and are numbered 1 through n. The graph-based mobility model proposed in [9] restricts the movement of nodes between sites according to the graph $G(S,E)$ where S is the set of vertices representing the sites, and E is the set of edges representing the paths between the sites in S. This approach takes into account the restrictions put on people's movement due to physical obstacles. However, it does not take into account the fact that some sites may be accessible to some nodes at some time, but not to others. In particular, a node may not possess the necessary "resources" to pass through a site. For example, a node with the resources of a pedestrian should not be (at least normally) trying to pass through a site representing a highway. In order to simulate the movement of nodes between sites more accurately, we use a different representation for the simulation area. Our model of the simulation area is similar to the one used in a popular board game named 'Scotland Yard' that was first introduced in the 1980s ([11]). It consists of m transportation networks that are interconnected. Each transportation network i consists of n_i consecutively numbered sites, where $1 \le i \le m$. Obviously, the total number of sites n in the simulation area is $n = \sum_{i=1}^{m} n_i$.

The simulation area is represented by a matrix G, consisting of m^2 sub-matrices. An individual element g_{ij} of G is either 1 when there exists a path from site s_i to s_j, and 0 when there is no path. The m square matrices G_{ii}, where $1 \le i \le m$, of dimensions $n_i \times n_i$ correspond to the m transportation networks. The remaining $m^2 - m$ matrices G_{ij}, where $1 \le i, j \le m$ and $i \ne j$, of dimensions $n_i \times n_j$ describes the connections from sites in transportation network G_{ii} to transportation network G_{jj}. G is structured as shown in equation (1),

$$G = \begin{bmatrix} G_{11} & \cdots & G_{1m} \\ \vdots & \ddots & \vdots \\ G_{m1} & \cdots & G_{mm} \end{bmatrix} \tag{1}$$

Figure 1 shows a graphical representation of a simulation area consisting of three separate but inter-connected transportation networks. Each matrix G_{ii} represents a transportation network that can be traveled using its pre-requisite resources. A node is permitted to switch from site s_{from} in transportation network G_{ii} to another site s_{to} in transportation network G_{jj} only if;

1) There exists a corresponding path in G_{ij} between sites s_{from} and s_{to}.
2) The node possesses the resources required by transportation network j.

Nodes move across the simulation area from a randomly selected source site s_{source} to another randomly selected destination site $s_{destination}$ in what constitutes a trip. Once a node has decided on a new trip, it is assigned a set of resources. The resources take the form of tickets. Each transportation network requires one ticket for traveling through one of its sites. This way each node's set of resources is represented by a column vector $\overline{T}$ of length m, each of whose elements are initialized according to an arbitrary distribution. The cost of traveling one hop between two adjacent sites s_{from} and s_{to} both in transportation network G_{ii} is one ticket of type T_i. Traveling on an interconnection between sites s_{from} and s_{to} belonging to two different transportation networks G_{ii} and G_{jj} respectively costs the node one ticket of type T_j. Now the node has to select a route from s_{source} to $s_{destination}$ whose cost does not exceed the set of resources $\overline{T}$ available to it. When a node reaches its trip's $s_{destination}$ it remains there for a period of time that is proportional to the length of the trip that brought it there and then generates a new trip. The length of the trip may be defined in terms of the number of hops or the time it took the node to get from s_{source} to $s_{destination}$.

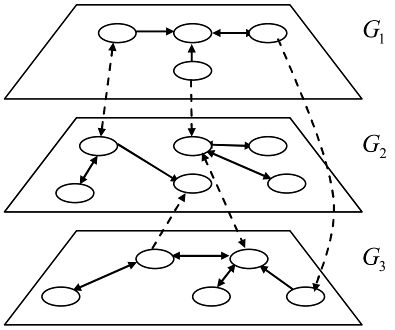

Figure 1. A graphical representation of the simulation area.

As we will show in this section, our proposed HIMM makes sites temporarily inaccessible to nodes. Although we do not address the issue of the routing protocol itself in this paper, we make the following observations regarding the times at which the routing protocol is invoked. The routing protocol may be invoked at the following times,

1) At the start of a trip when the node is searching for a path between s_{source} and $s_{destination}$.
2) When a node moving along a previously selected route encounters an inaccessible node and is forced to re-route its path within its remaining resources. If it is unable to find an alternate path it will be forced to wait until the blocked site becomes accessible again and continue on its previous path.

C. Binary Influence Model

The effect of the influence different nodes moving in a site exert on other nodes in other locations is introduced in the HIMM by the use of the binary influence model that was first presented by Asavathiratham in [8]. The binary influence model is a stochastic model based on Markov chains explained in [4], [5], [6], [7]. The influence one site exerts on another is captured in the network influence matrix D of dimensions $n \times n$. D is a stochastic matrix whose row elements sum to 1. $s[k]$ is the status vector of length n that indicates the accessibility of all n sites at time instance k. $s_i[k]$ equal to 0 indicates that site s_i is accessible at time instance k, while 1 means that the site is inaccessible or blocked. $r[k]$ is the probability vector of length n for the same time period. The evolution equations (2) and (3) for the binary influence model are defined below.

$$r[k+1] = D \times s[k] \tag{2}$$

$$s[k+1] = Bernoulli(r[k+1]) \tag{3}$$

The $Bernoulli()$ function is a traditional coin flipping function that returns 1 with the probability specified in the function argument. It introduces the element of randomness in the model.

Equations (2) and (3) are very similar to the evolution equations of a Markov chain. However, the graphical representation of a network influence matrix differs from that of a Markov chain. In a Markov chain the sum of the weights of all outgoing edges from a vertex is 1. In a network influence matrix on the other hand, the sum of the weights of all incoming edges of a vertex is 1. In our HIMM, the individual element d_{ij} of D, where $1 \le i, j \le n$, represents the fractional strength of the influence s_j exerts on s_i out of the total influence exerted on s_i, including its own. Thus, the diagonal elements d_{ii} of D is the tendency of s_i to remain in its current state and resist external influences.

D. 'Evil Rain' Model

A special case of the binary influence model yields what Asavathiratham calls the 'evil rain' model in [8]. In this model the graph consists of two autonomous classes with fixed status 1 and 0 and a dependent class D. The network influence matrix D_e is defined in equation (4) in terms of the network influence matrix D of the dependent class and two influence vectors e_1 and e_2 that define the magnitude of the direct influence of the autonomous sites on sites of the dependent class.

$$D_e = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ e_1 & e_2 & D \end{bmatrix} \tag{4}$$

Similarly the status vector $s_e[k]$ is a concatenation of 1, 0 and the status vector of the dependent class $s[k]$. Both D_e and $s_e[k]$ replace their counterparts D and $s[k]$ in the binary influence evolution equations. Both are shown in equations (4) and (5).

$$s_e[k] = \begin{bmatrix} 1 \\ 0 \\ s[k] \end{bmatrix} \tag{5}$$

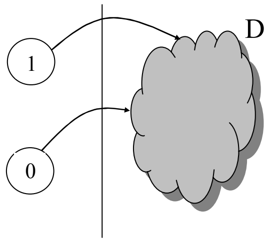

Figure 2. A graphical representation of the network influence matrix divided into autonomous and dependent classes.

Figure 2 shows a graphical representation of the 'evil rain' model which shows the separate autonomous and dependent sites. The 'evil rain' model is well suited for a scenario such as one involving a traffic signal without feedback.

IV. MOBILITY SCENARIOS

A. The Pedestrian Crossing

In our first example we apply the HIMM described in the preceding sections to a pedestrian crossing. The situation depicted in Figure 3 is a pedestrian crossing on a busy one-way street controlled by a traffic signal that switches periodically. There is a two lane one-way street running from east to west, a traffic signal, a pedestrian crossing, sidewalks on the north and south side of the road bounded by buildings or otherwise inaccessible to nodes.

Figure 4 is the same scenario as in Figure 3, but this time cut up into sites. Sites s_3 and s_4 overlap and are physically located on the zebra crossing. We assume that this area is populated by two kinds of nodes; pedestrians and cars. The pedestrians stay on the sidewalks but are allowed to cross the road to the other side when the traffic signal indicates it. Pedestrian nodes have any of sites s_5, s_7, s_8 or s_{10} as their s_{source} and $s_{destination}$. s_3 is part of the pedestrian transportation network while s_4 is part of the car transportation network. The road, consisting of sites s_{11}, s_4, s_{12}, s_{13} and s_{14}, is only traveled by cars arriving at s_{14} moving towards s_{11}. Since we assume the traffic in this scenario is controlled by an open loop control system, the 'evil rain' model ideally lends itself for this scenario. s_1 and s_2 are two autonomous sites that represent the traffic signal for the pedestrians and cars respectively. In this example it is obvious that the status $s_1[k]$ will always be the complement of $s_2[k]$. In order to simulate the traffic signal we switch the status of the traffic signals periodically after every 10 time periods.

Site s_1 exerts direct influence on s_3 only. The same is true for sites s_2 and s_4. On the pedestrian transportation network, inaccessibility of s_3 will exert some influence on s_6 and s_9 to make them inaccessible. This simulates the crowding effect on both sides of a road when the traffic signal is red. s_6 in turn exerts a weaker influence on s_5 and s_7 to make their status inaccessible due to crowding. The same is true for s_9, s_8 and s_{10} on the other side of the road. The congestion on both sides of the road eases when the pedestrian signal turns green.

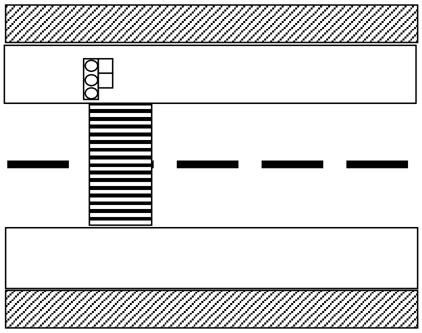

Figure 3. Real world example scenario.

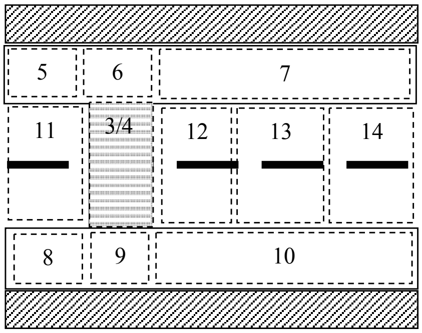

Figure 4. Real world scenario divided into sites.

On the car transportation network, a red traffic signal makes s_4 inaccessible to cars and causes congestion to build in s_{12}, s_{13} and s_{14} in the same order. The congestion eases when the traffic signal changes to green. A key objective of our simulator is to verify the ability of the HIMM to capture the aptitude of one group of nodes to influence the movement of another group of nodes. We performed 1000 simulation runs of the above scenario using the proposed HIMM. Each simulation run simulates the scenario for 100 time periods, with the traffic signals switching after every 10 time periods. For this specific example, we separately measure the number of congested or inaccessible sites in the pedestrian and car transportation networks and plot them versus time. Figure 5 is a plot of one simulation run. From our knowledge of the system we expect that whenever pedestrians have a red signal the number of congested pedestrian sites starts increasing while the number of congested car sites starts decreasing. When the traffic lights

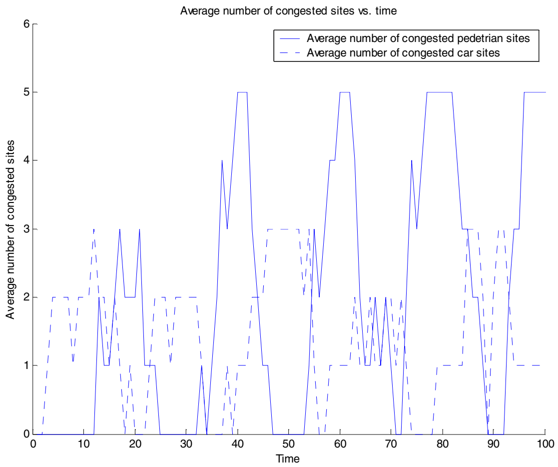

Figure 5. Graph of single simulation run with traffic signal switching every 10 time periods.

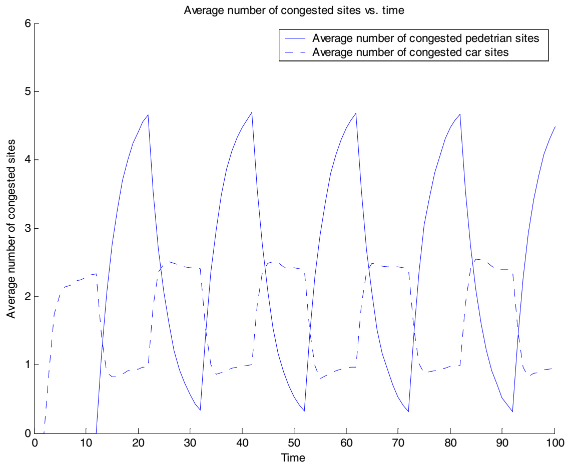

Figure 6. Graph of average of 1000 simulation runs with traffic signal switching every 10 time periods.

switch, the trend reverses. Figure 5 is a plot of these two quantities for a single simulation run. The trend we are expecting to observe is not very clearly visible in these results.

In order to make the trend in our results more clearly visible, we plot the average results of 1000 simulations in Figure 6. This time the trend is much more clearly visible.

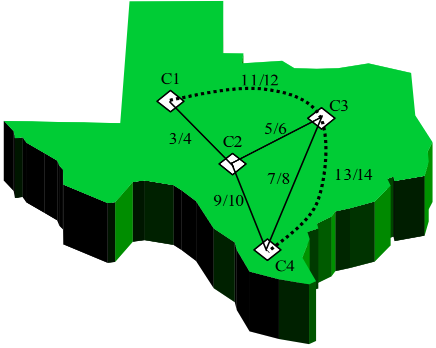

Figure 7. A geographical map of the area being modeled

B. Intra-state Travel

In our second example we apply the HIMM to the modeling of intra-state travel. For this example, we are assuming two means of transportation; 1) Cars on the Interstate/ Highway network, and 2) Air links. Figure 7 is a geographical map of the state of Texas with four population centers numbered $C1$ through $C4$. The road links are shown by solid lines and the air links by dotted lines. Each link is bidirectional. The map in Figure **7** is first converted to an equivalent graph-based representation. Since each edge in Figure **7** is bi-directional, it is mapped to two sites in the connectivity graph. The site numbers in the connectivity graph are also shown in the figure. Two population centers C_i and C_j are linked by sites s_{ij}/s_{ji}, where $i<j$, and s_{ij} leads from C_i to C_j and vice versa. Since we are using the 'evil rain' model for this example, the number of sites in the connectivity graph is twice the number of links in Figure **7**, i.e. 12, in addition to the two 1 and 0 sites that are randomly injecting and easing congestion. The cities are not represented as sites but nevertheless acting as sources and sinks of congestion. The degree to which this is true for every city is controlled by vectors e_1 and e_2. The values in the network influence matrix D should ideally be based on the travel behavior of people in the region being modeled. For our example, we have assumed values on the basis that all cities have an equal capability of introducing and easing congestion on any of its outgoing routes and incoming links respectively. Every link has been assigned a probability of 0.1 of staying in its current state, i.e. congested or available. We expect the number of congested sites in the interstate and airlink networks to continuously change over time without converging to some final value, because although congestion does occur it tends to ease after some time. More significantly, we expect congestion in an airlink to cause congestion in the interstate network and vice versa.

Due to the fact that there are multiple points of interaction between the two transportation networks, a simple plot of number of congested sites in each network may not be enough to clearly reveal a relationship between the two signals. Therefore, to clearly illustrate the effect of a congested site between two cities on the rest of the network, we plot the status of sites 3 to 14 against time in Figure 8. The plot at the top of the figure is the status of site 3 and the last that of site 14. Time progresses along the positive direction of the horizontal axis. Initially congestion is injected in site 3 at times 1, 2, 3 and 4, allowed to spread through the network and dissipate. We repeat the same process at times 20, 21, 22 and 23, and then again at times 40, 41, and 42. The values of elements of D are selected with the assumption that congestion in s_{ij} will cause congestion in other sites s_{ik} part of a detour for s_{ij}. We also take into account that the probability of congestion will be higher for sites closer to the source of the congestion and will reduce as we move away. Since congestion on s_{ij} implies that people are moving from C_i to C_j. We assume that there will therefore be a greater number of people moving back from C_j to C_i, and hence a greater probability of congestion on s_{ji}. In our example we inject congestion in the network in site 3. This leads us to expect congestion on sites 5 and 11 and to a lesser extent in sites 4 and 6. The plots in Figure 8 show that secondary congestion spreads to the appropriate sites for most of the time, besides some tertiary congestion that is caused indirectly by the secondary congestion.

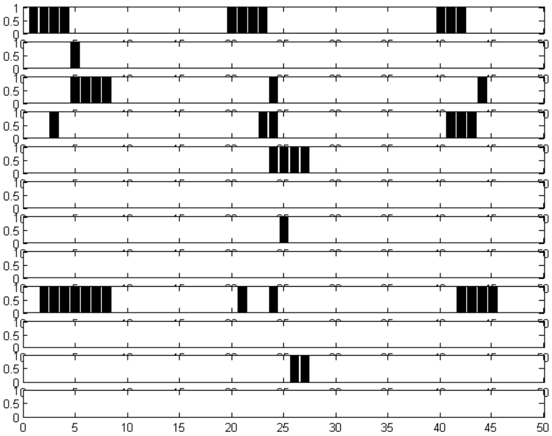

Figure 8. Plot of status of sites 3 to 14 against time

V. DISCUSSION AND CONCLUSIONS

The results from the simulation establish that the HIMM makes the mobility of nodes dependent on that of other nodes. We also see that it restricts the movement of nodes between vertices on a graph more realistically than previously proposed graph-based mobility models such as the one proposed by Tiang et al in [9].

Although the proposed HIMM was developed for use in ad hoc networks, we believe that due to the abstract nature of this framework it has much wider application. Real world scenarios, like the time varying city traffic in our pedestrian crossing example, are easier to simulate using our mobility framework than by any previously proposed mobility models because there are well established traffic rules that are followed. The first example has only one point of interaction between the two transportation networks. Our second example differs from the first in two respects; 1) It simulates mobility on a much greater geographical area 2) There are multiple points of interaction between the transportation networks.

We are currently considering key extensions of the proposed model. We plan to replace the binary influence model with a more general influence model, also proposed in [8]. This may yield a more accurate mobility model in which sites can have more statuses than the accessible/ inaccessible or $0/1$ status currently allowed by the binary influence model.

The simplicity and scale of the example scenario allowed us to replace a complex routing algorithm with a simple lookup table containing routes for different pairs of s_{source} and $s_{destination}$. The degree to which the routing algorithm is aware of the accessibility status of sites at the time of invocation may vary. If k is an integer representing the distance in terms of number of hops up to which the routing algorithm can see site status;

1) No awareness ($k = 0$): The routing algorithm may assume that all sites are accessible.
2) Full awareness ($k = \infty$): The routing algorithm may be aware of the accessibility status of all sites.
3) Partial awareness ($0 < k < \infty$): The routing algorithm may be aware of the accessibility status of all sites k or fewer hops away and assume all other sites' status to be accessible.

The evaluation of the different values of k on the mobility of nodes presents another interesting study.

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