

# An Agent-Based Model of a Dynamic Mobile Ad-Hoc Network

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**Abstract**—Mobile Ad-hoc Networks are a very hot topic in computer network research. The most practical way to test and evaluate the details of implementing a mobile ad-hoc network is to simulate it. This paper describes an implementation of an agent-based model containing a mobile ad-hoc network combined with an empirically designed daily human mobility model. The agent-based model is both implemented and simulated using NetLogo. This model attempts to satisfy a number of standards that are important in a rigorous simulation of a mobile ad-hoc network. The results of the simulations will show emergent relationships between the amount of node mobility and several network routing statistics.

## I. INTRODUCTION

The advantages of mobile ad-hoc networks such as low infrastructure cost and rapid deployment make them a popular area of research. Unfortunately, it is difficult to obtain real empirical data for large scale mobile ad-hoc networks, so it becomes useful to simulate them. To accurately simulate the performance of a mobile ad-hoc network (MANET) its important to simulate it in a realistic scenario. One of the biggest challenges in designing a routing protocol for a MANET is efficiently dealing with a changing network topology. The performance of routing protocols such as DSR significantly changes depending on the mobility patterns of nodes in the MANET [9]. This means that moving nodes randomly is not particularly useful, instead it is important to provide an accurate mobility model. As Mobile devices are becoming increasingly ubiquitous, it becomes reasonable to assume that a majority of a developed population carries a mobile device. Modern smart phones also have the capacity to perform peer-to-peer communication with built in features such as Bluetooth and WiFi Direct. This means that the infrastructure required for a mobile ad-hoc network sits in the pockets of most people living in developed civilizations. This also means that node mobility in a MANET can be essentially equivalent to human mobility and node movement in a MANET particularly a smart phone mobile ad-hoc network can be accurately simulated by creating a model of human mobility.

This model attempts to achieve two goals. The first goal is to answer how human mobility affects the operation of a smart phone ad-hoc network. The second goal is to attempt to create a mobility model that could conceivably be adapted to become a simulation testbed for real mobile ad-hoc routing protocols such as AODV and DSR. To that effect, this model hopes to be very realistically simulate daily mobility of human agents.

Most mobility models used to test computer networks require using a network traffic trace or a synthetic model. Obtaining a network trace of a smart phone ad-hoc network is impractical since a MANET has to be already deployed and operating to obtain network trace data. This model attempts to simulate a mobile ad-hoc network using a mobility model based on empirical data, which hopes to be more realistic than the synthetic models presented in [10].

Before implementing the model, I expected to see human mobility have a large impact on the statistics of the mobile ad-hoc network. For example, it would make sense to see a much greater number of route failures in the network as more people are moving.

## II. BACKGROUND

### A. Mobile Ad-Hoc Networks

Mobile ad-hoc networks (MANETs) differ from traditional networks in that MANETs dont require a fixed, static infrastructure in order to be deployed or operated. There is also no central network administration such as a wireless access point or a cellular tower [7]. In a cellular network for example, all network traffic is managed and routed by the tower. Since there is no central infrastructure in a MANET, there will be many cases in which a destination node is not in direct communication range with the source node. This requires each node in a MANET to have the ability to act as a router. The topology of MANETs are also far more dynamic than a traditional network, devices can join and leave the network at any time and nodes in the network can move constantly. This can drastically change the topology of the network, putting some nodes out of range of each other and others in range.

Mobile ad-hoc networks require virtually no infrastructure to set up, allowing them to be deployed rapidly. This makes MANETs useful in disaster areas as well as underdeveloped areas where infrastructure does not already exist. The military battlefield is another ideal application for MANETs giving soldiers the ability to relay strategic information to each other. Networks composed of a number of sensors including temperature, pressure, pollution, etc. can also be connected via a MANET [6]. Ad hoc networks can also operate in tandem with existing cellular networks, helping to extend coverage and interconnectivity [7].

### B. Routing in a Mobile Ad-Hoc Network

A major element of research in mobile ad-hoc networks is the development of effective routing protocols. There are a number of popular routing protocols already developed which include Ad-Hoc On Demand Distance Vector Routing (AODV) and Dynamic Source Routing (DSR). I will provide a brief summary of some of the elements of AODV as they are relevant to the agent-based model developed in this paper.

Similar to DSR, AODV is an on-demand routing protocol. This means that routing tables are created as needed or whenever a source requires a route to a specific destination. Unlike DSR however, AODV does not use source routing, meaning that the source does not contain the complete route from source destination, but only the next hop in the route to the destination. When a source node in a MANET requires a route to a destination node, path discovery begins. In AODV this is done through flooding, which means that the source node broadcasts a route request (RREQ) to each of its neighbors, then each neighbor broadcasts the RREQ to their neighbors, and so on until a route to the destination is found. Each node also keeps track of who it received the RREQ from. The RREQ contains the source IP address, destination IP address, current hop count, and sequence numbers among other parameters. A node receiving a RREQ increments the hop count before broadcasting it to its neighbors.

Once a route to the destination node is found, the node containing the route to the destination, which may be the destination itself, unicasts a route reply packet (RREP) back to the previous node, which then forwards the RREP back to its previous node until it reaches the source. During this process each node in the route keeps a forward pointer to the node that sent it the RREP. Once the source node receives the RREP it has a route to the destination and can start transmitting data.

If a route fails at any point, route error (RERR) packets are unicast back from upstream of the failure through the route to the source node. If the source node receives a RERR it reinitiates the routing process to create a new route. A node can update its routing table if it receives a route with a greater sequence number indicating a fresher route or a route with fewer number of hops meaning its a shorter route. AODV contains many more details which can be found in [8], however, what's described here should be more than sufficient to understand the model presented in this paper.

### C. Simulating a Mobile Ad-Hoc Network

Simulating routing in a mobile ad-hoc network requires an appropriately rigorous framework to produce both accurate and useful results. There are three standards laid out in [9] that are useful guides to consider when simulating a MANET:

- *Standard 1: To rigorously evaluate generic MANET routing protocols, the average shortest-path hop count should be large.*

A scenario with an average shortest-path hop count of 1 or 2 is a scenario in which many packets are only sent between neighbors. In this

environment, the generic MANET routing protocols routing capability is not rigorously tested. Most protocols, even poor protocols, perform well in scenarios that have low average shortest-path hop counts.

- *Standard 2: To rigorously evaluate generic MANET routing protocols, the amount of network partitioning should be small.*

Since no routing protocol is able to route between a pair of nodes that is partitioned, most protocols, even good ones, perform poorly in scenarios that have a large amount of network partitioning. In other words, a large amount of network partitioning prevents rigorous evaluation of a generic MANET routing protocol.

- *Standard 3: To rigorously evaluate generic MANET routing protocols, the average neighbor count should be large.*

A low neighbor count potentially means few routes exist between a source and destination. To evaluate a generic MANET routing protocol rigorously, several available routes are required; otherwise the routing protocol does not have different routes to consider. [9]

It has also been demonstrated that the way in which nodes in a MANET move can drastically change performance of routing protocols such as DSR [10]. Because of this it is very important to develop an accurate mobility model for nodes in a MANET as opposed to simply random movement. In the case of a smart phone mobile ad-hoc network, the movement patterns of the nodes can be equated to the movement patterns of the humans carrying them. This means that it is required to accurately movement patterns of humans to create a useful MANET simulation.

### D. Daily Human Mobility Motifs

The majority of the agent based model that was implemented in this paper is based on the research done by [1], so I will summarize it here. Human mobility can be characterized by a sequence of visited locations and trips between them. These patterns of movement are referred to as motifs. To give an example of a motif, assume a person starts the day off at home, then goes to work at some time, stays at work for a while then goes to a grocery store and then returns home. This movement pattern corresponds to a motif containing three nodes (home, work, store) with one arrow going from home to work, one arrow going from work to the store and one arrow going from the store back home. A motif does not contain any notion of duration at each location or times at which a person travels from one location to another.

Based on phone data and survey data from Paris and Chicago, approximately 90% of peoples mobility patterns can be classified into seventeen different motifs. Each motif contains less than seven different locations. The mobility model presented in [1] assumes that the tasks people perform

which translates to their movement generally follows a circadian rhythm. The model also does not assume any correlation between different days, (i.e. each day is treated the same).

The model can be analytically analyzed by mapping each persons travel decision to a coin flip (non-identical independent Bernoulli trials). This means that if the day is divided into time intervals, the probability that a person changes locations during time interval  $n$  can be written as  $p_n$  which means that the probability of not changing locations equals  $1 - p_n$ . The crucial ingredient of this model lies in the observation that generally people exhibit periods of high activity followed by periods of lower activity. As such, if in time period  $n$ , the probability  $p_n$  is satisfied and a person decides to change locations, the person is likely to continue to be active in time period  $n+1$  so the probability of movement in time period  $n+1$  becomes  $10 * p_{n+1}$ . If there was no movement in time period  $n$ , then the probability of movement in time period  $n+1$  would simply be  $p_{n+1}$ . More details of this including the application of a finite Markov chain embedding technique can be found in [2].

It is generally accepted that humans travel time and subsequently their trip distance can be modeled by a power law distribution. It is shown empirically in [3] that human trip distance can be written as:

$$p(r) \propto r^{-(1+\beta)}$$

with  $\beta \approx 0.59$ .

### III. THE AGENT-BASED MODEL

#### A. The Conceptual Model

1) *Mobility Model*: As stated previously much of the mobility model used in this agent-based model is built off of the research done in [1]. This model looks at a single day, dividing it into 48, 30 in time intervals with each tick in the NetLogo representing one time interval. Each time interval contains a probability value obtained from [1] (shown below) representing the likelihood that each agent will move from one location to another. There are three types of locations within the model, homes, workplaces and other locations. If an agent does travel to an other location, in time interval  $n$ , they are 10 times more likely to travel to another other location in time interval  $n+1$ . If an agent does not travel to an other location again, then they return home or to work, wherever they happened to be before going out. Agents decide what location to travel to based on the power law distribution  $p(r) \propto r^{-(1+\beta)}$

0.0058 0.0037 0.0023 0.0015 0.0011 0.0008 0.0006 0.0005  
0.0005 0.0005 0.0007 0.0010 0.0016 0.0031 0.0066 0.0119  
0.0165 0.0201 0.0240 0.0250 0.0275 0.0284 0.0295 0.0313  
0.0353 0.0345 0.0313 0.0292 0.0277 0.0274 0.0290 0.0302  
0.0329 0.0355 0.0409 0.0443 0.0458 0.0445 0.0422 0.0384

Time Leaving Home to Go to Work*		
12:00 a.m. to 4:59 a.m. ....	5,209	3.8
5:00 a.m. to 5:29 a.m. ....	4,647	3.4
5:30 a.m. to 5:59 a.m. ....	6,420	4.6
6:00 a.m. to 6:29 a.m. ....	11,408	8.2
6:30 a.m. to 6:59 a.m. ....	13,620	9.8
7:00 a.m. to 7:29 a.m. ....	19,536	14.1
7:30 a.m. to 7:59 a.m. ....	17,686	12.8
8:00 a.m. to 8:29 a.m. ....	14,565	10.5
8:30 a.m. to 8:59 a.m. ....	7,425	5.4
9:00 a.m. to 9:59 a.m. ....	8,287	6.0
10:00 a.m. to 10:59 a.m. ....	3,705	2.7
11:00 a.m. to 11:59 a.m. ....	1,747	1.3
12:00 p.m. to 3:59 p.m. ....	9,270	6.7
4:00 p.m. to 11:59 p.m. ....	9,150	6.6

Fig. 1. Distribution of the times at which American workers leave for work from the 2009 census.

0.0340 0.0324 0.0281 0.0248 0.0224 0.0205 0.0148 0.0096

2) *Worker Model*: This model contains two types of agents, workers and non-workers. The most lacking element of the mobility model presented in [1] was their oversimplification of worker mobility. To compensate for this, United States Census data from 2009 published in [5] and shown below was used to construct the probability distribution modeling the times at which workers travel to work. The amount of time spent at work can be modeled as a normal distribution [4] with the mean being approximately 8 hours and 20 min:

$$N(\mu = 8.33, \sigma^2 = 1.42)$$

Based on these probability distributions, a work schedule is created for each worker at the beginning of each day. The schedule determines what time interval the worker goes to work and what time interval the worker comes home from work. Work locations for each worker are determined using the power law distribution, based on their distance from their house location.

3) *MANET Model*: Each agent in the model is assumed to be carrying a mobile device capable of connecting to the MANET. Initially the plan was to implement the AODV routing protocol and simulate it in the agent-based model. The performance capabilities of NetLogo prevented this from succeeding, so a simplified version of AODV was implemented. To imitate the flooding mechanism in AODV, a breadth-first search is used to find the shortest route between a source and destination. The model contains three adjustable parameters for the MANET network: num-new-routes, transmission-range, and route-capacity. Num-new-routes specifies how many new randomly generated routes should be created each tick. The agents interact with each other by moving in and out of each others transmission-range, and creating multi-hop routes. The transmission-range parameter indicates the maximum distance nodes can be from each other in order to be considered neighbors and have direct routes between them. The route-capacity parameter is meant to simulate network congestion, if a node in the network has more routes going through it than the route-capacity it gets overloaded and drops off of the network.

### B. Additional Implementation Details

- The geography of the model is not rigorously created. The simulation area is divided into 8x8 blocks laid out in a 12x7 grid and separated by roads (taken mostly from the traffic model in the NetLogo library).
- Each of the locations (house, workplace, store) is randomly (using NetLogos one-of operator) placed in one of the blocks allowing for a maximum of 84 locations.
- At the start of each day, all of the agents are evenly distributed among the houses.
- The agents travel along the roads (areas between blocks) to get from one location to another.
- When an agent reaches a road intersection, the agent chooses either to go North/South or East/West.
- An agent will go North/South if there is a greater vertical distance than horizontal distance between them and their destination, otherwise they will go East/West.
- Once an agent reaches their destination, they will stop on one of the four roads adjacent to the block the destination is located on.
- Routing for the MANET is started and completed before any of the agents have a chance to travel. This simplifies the routing process by assuming no errors can occur during routing.
- If there is no route possible between a source and destination, the destination unreachable counter is incremented.
- After all of the agents have a chance to move, each source attempts to transmit data to their destination. If the route is invalid due to node movement or death, a route error counter is incremented.
- The number of routes going through each node is kept track of so that the maximum number of routes going through any node can be calculated.

### C. Verification and Validation

1) *Face Validation:* Each persons movements were validated by looking at their movement patterns; does a person have a home location that they start and end at each day, do they go to a reasonable number of locations within a day (usually six or less). Workers movements were validated by ensuring that they went to work at some point during the day and came home at some point later in the day.

Route creation was validated first by setting up nodes in a grid and limiting the transmission range to extend only to the eight adjacent neighbors. It could then be ensured that connections were only made between neighbors and a route between a source and destination node had the least number of hops possible.

Routing statistics were validated by ensuring that any percentage value such as Percent Routing Error or Percent Destinations Unreachable, were never above 100%. The transmission range on was also changed to zero to make sure that the Percent Destination Unreachable was 100%, and also changed to be the size of the entire simulation area to ensure that the Percent Destination Unreachable was 0%. I also looked at the transmission links between nodes in a route,

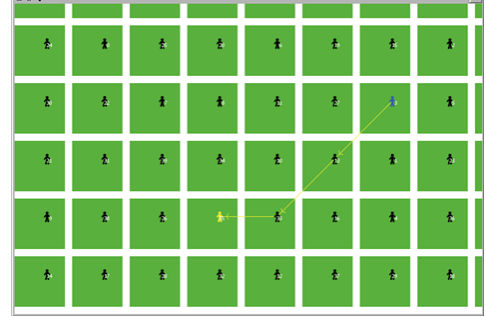


Fig. 2. NetLogo simulation showing a grid of nodes with a route between a source node (blue) and a destination node (yellow).



Fig. 3. Histogram generated by the agent-based model, showing the percent of people who visited a certain number of locations. More than 90% of the agents visit 6 or less locations per day.

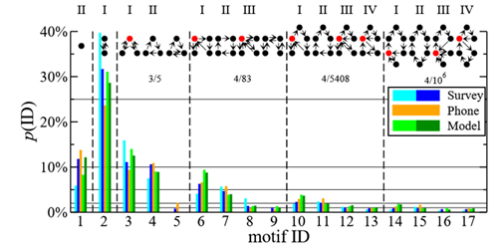


Fig. 4. This histogram from [1] shows the percent of people following each of the 17 mobility motifs. The dashed lines separate the number of locations in each motif. If the percentages of each motif between the dashed lines are added up, the percentage of people visiting each number of locations is quite similar to the results generated by the agent-based model.

to ensure that a link breaks if nodes move out of transmission range.

2) *Empirical Validation:* Each persons movements were validated empirically by running the simulation a large number of times and comparing the populations movement patterns to the common mobility patterns obtained from [1]. As can be seen in Fig. 3, the distribution of people visiting n number of locations is approximately equivalent to the mobility results from [1] shown in Fig4. The probability distribution of movement from [1] shown in Fig. 5, also has a similar shape to the agent movement results which includes noise shown in Fig. 6.

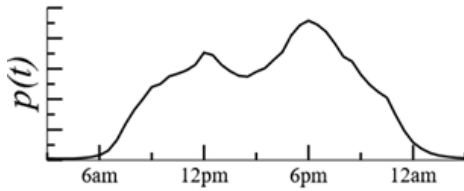


Fig. 5. The time-dependent probabilities of moving to an 'other' location taken from [1].

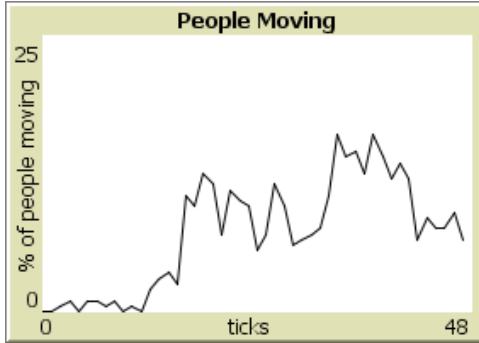


Fig. 6. The percentage of people moving during a single day.

#### IV. EXPERIMENTS AND RESULTS

##### A. Experimental Setup

To improve performance and reduce complexity of the model a drastically simplified routing protocol was implemented as opposed to a real one such as AODV which is described in [8]. The model also only has a time granularity of one half hour. This means that many conventional network statistics such as throughput, and routing delay are not applicable.

As suggested in [9] I examine the average hops per route, the percentage of unreachable destinations (network partitioning) and the average number of neighbors of each node. Additionally, I investigate the maximum number of routes going through one particular node since this will give a metric for network congestion. I also look at the percentage of routes that fail due to mobility or congestion.

To test the effects of how spread out agents are, the number of houses was swept. Since people generally spend most of their time at their houses, the number of houses in the simulation directly relates to how spread out agents are. The number of workers and non-worker is examined. Both of these experiments were completed using NetLogos BehaviorSpace tool which simulates one day. The percentage of people moving is tracked throughout the day along with the MANET performance statistics. To determine the relationship between node movement and network performance, each metric was plotted in NetLogo. The simulation was subsequently run over multiple days and the plot data was exported. The setup of each of the BehaviorSpace experiments is tabulated in Tables I-III.

TABLE I  
WORKERS SWEEP

Varying Parameter:	Number of Workers
num-stores	28
num-non-workers	0
route-capacity	22
num-houses	28
num-workplaces	28
num-workers	1:5:100
transmission-range	10
num-new-routes	25

TABLE II  
NON-WORKERS SWEEP

Varying Parameter:	Number of Non-Workers
num-stores	28
num-non-workers	1:5:100
route-capacity	22
num-houses	28
num-workplaces	28
num-workers	0
transmission-range	10
num-new-routes	25

TABLE III  
HOUSE SWEEP

Varying Parameter:	Number of Houses
num-stores	28
num-non-workers	50
route-capacity	22
num-houses	3:1:28
num-workplaces	28
num-workers	50
transmission-range	10
num-new-routes	25

The network statistics that were collected are described as follows:

- Route Failures: A route fails if a node in the route dies or moves out of transmission range with its neighbor.
- Hops Per Route: The average number of nodes between a source and destination, including the source and destination.
- Destinations Unreachable: If a route does not exist between the source and destination.
- Max Routes: The max number of routes going through a single node.

##### B. Results

An interesting emergent property of this model is the difference in relationships between the number of workers present in the simulation and percentage of route errors and the number of non-workers present in the simulation and percentage of route errors. As shown in Fig. 8 and Fig. 9, the greater the number of workers significantly increases the amount of route errors, while the number non-workers seems to have an insignificant effect on the percentage of route errors. I attribute this to the observation that increased movement is the source of most route errors (as can be seen in Fig. 7).

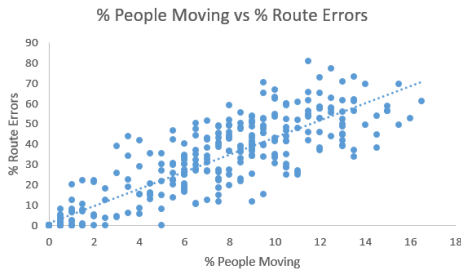


Fig. 7. This graph shows that increased movement results in increased route errors.

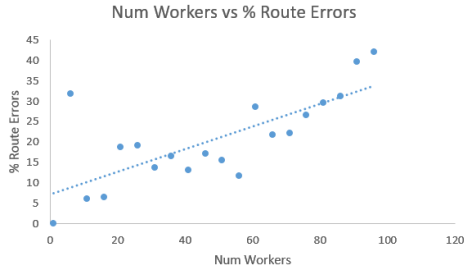


Fig. 8. This graph shows that as the number of workers increases the route errors increase as well, this is likely due to the increase in mobility.

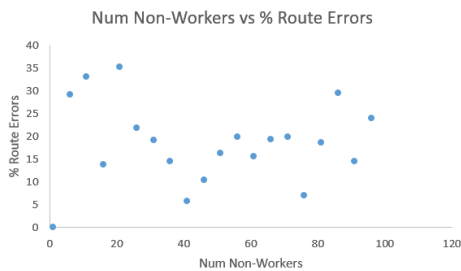


Fig. 9. Surprisingly the number of non-workers does not show nearly the same impact on route errors as the number of workers does.

Since workers generally travel between more location per day than non-workers (workers have to travel to and from work) having a greater number of workers increases the mobility of the nodes than compared to the number of non-workers, thereby increasing the percentage of route errors. This is also observed when looking at the destination unreachable percentages vs number of workers and non-workers. There is a steeper decline of the percentage of unreachable destinations when more workers are added into the system compared to non-workers. Again this is likely because workers add more mobility to the model and mobility directly correlates with decreased unreachable percentages.

As shown in Fig. 10, as the number houses increases, the percentage of route errors also increases on an approximately linear scale. This is likely because the more houses there are, the more spread out agents are likely to be. As agents are more spread out, more hops are required in between each source and destination which is shown in Fig. 11. When more

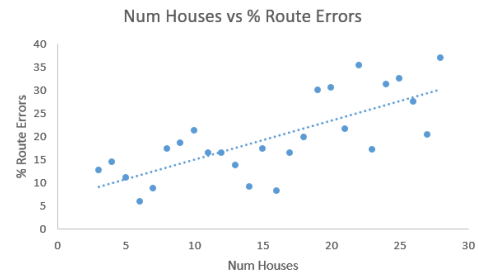


Fig. 10. This graph demonstrates the increase in houses causing an increase in route errors, likely due to increased population spread.

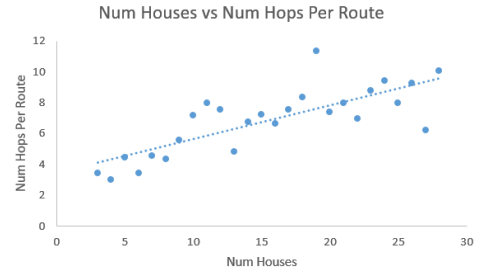


Fig. 11. More houses seem to spread the population out more, requiring more hops per route.

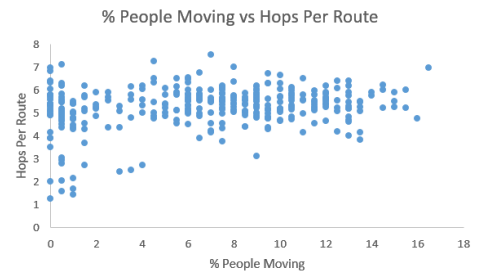


Fig. 12. There appears to be no correlation between mobility and the number of hops per route.

hops are present within a route, there are a greater number of failure points in the route. Surprisingly greater mobility does not result in greater hops per route as I originally expected. This might mean that mobility does not result in a greater population spread, since many people are traveling to common locations such as work places.

Standard 1 of [9] suggests that rigorously simulating a MANET requires that there should be a large number of hops in a given route, most certainly greater than just two. From the results in Fig. 13 and Fig. 14, we see that once the number of agents goes above twenty, we get an average of more than two hops per route. Having more agents certainly results in a greater number of hops per route, which supports the decision to run other sweeps with the max number of agents present.

It is suggested in standard 2 of [9] that most sources should be able to reach their destinations in order to rigorously test a MANET routing protocol. Interestingly, having more movement among the agents resulted in drastically improved



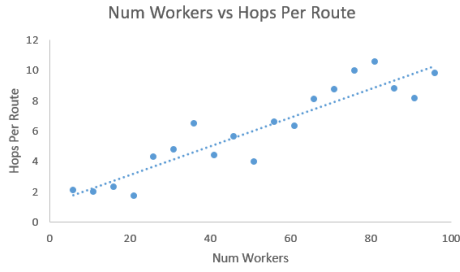


Fig. 13. More agents clearly result in a greater number of hops per route.

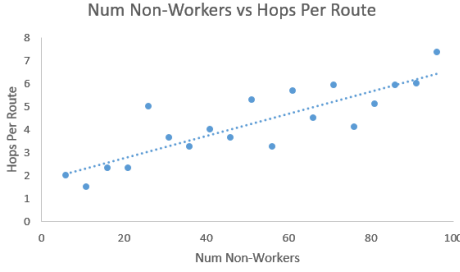


Fig. 14. More agents of both worker and non-worker clearly result in a greater number of hops per route.

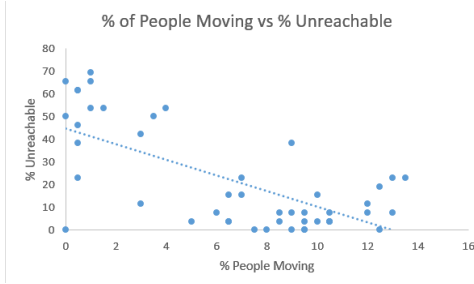


Fig. 15. Mobility seems to improve the span of the network.

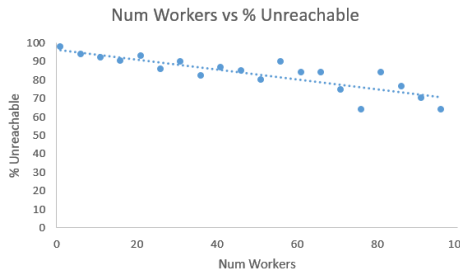


Fig. 16. Having more nodes in the network will result in less network partitioning.

unreachable rates, so it may be the case that MANETs could perform better in high mobility traffic areas. It is also clear as shown in Fig. 16. that more having a denser population will improve the unreachable rate. Which means that it is advisable to have a dense population of nodes when simulating a MANET.

Running the worker and non-worker sweeps, showed that

the model requires at least 36 agents in order to have an average of at least 3 neighbors for each node. Setting the number of agents to the max of 200, and placing 28 houses, the average number of neighbors fluctuates between approximately 12 and 16, which provides up to  $16^n$  with  $n$  = number of hops, possible shortest routes between a source and destination. This provides a MANET routing protocol with many different routes to consider as is suggested in standard 3 of [9].

## V. CONCLUSION AND FUTURE WORK

This paper demonstrates an implementation of a realistic daily mobility mode combined with a simplified mobile ad-hoc network, and simulated in NetLogo. This agent-based model was largely successful in revealing a number of emergent correlations between daily human mobility and mobile ad-hoc network performance. Most notably it was shown that increased node movement produced a greater number of route errors, however, the amount of network partitioning decreased, meaning more sources were able to find routes to their destinations. This model was also successful in providing a reasonably competent framework for simulating MANET routing protocols; the average number of hops between a source and destination was relatively high, as was the average neighbor count.

One of the drawbacks of this model was the small number of agents in the system. More nodes in the network produce less network partitioning and a greater number of hops per route which are both desirable when simulating a MANET. Other potential improvements to this model could include a more accurate geography, such as a simulation of a real city. Accompanying this could include a model of paths people generally take when traveling between different locations travel speeds. The time scale of the model could also be decreased to obtain routing statistics that require precise timing. In the future this model could be adapted to run on a network simulator such as ns3 so that it can be used to test real MANET routing protocols. The mobility portion of this model could also be decoupled from the MANET, and applied to other research areas such as vehicular networks or epidemiology.

A lot was learned from researching and implementing human mobility models and mobile ad-hoc networks. Despite humans being such complex creatures, its incredible that our daily movement can be simplified into simple circadian patterns. Mobile ad-hoc networks also have many promising uses, but there are still many implementation details to figure out in order to make MANETs efficient and optimal.

## REFERENCES

- [1] Schneider, C. M., V. Belik, T. Couronne, Z. Smoreda, and M. C. Gonzalez. Unravelling Daily Human Mobility Motifs. *Journal of The Royal Society Interface* 10, no. 84 (April 24, 2013): 2013024620130246
- [2] Schneider, C. M., V. Belik, T. Couronne, Z. Smoreda, and M. C. Gonzalez. *Daily Mobility Patterns - Electronic Supplementary Material* 2013
- [3] Brockmann, D., Hufnagel, L. and Geisel, T. 2006 The scaling laws of human travel *Nature* 439, 462-465. (DOI 10.1038/nature04292)
- [4] Bhat, C. R. 2001 Modeling the commute activity-travel pattern of workers: Formulation and empirical analysis. *Transp. Sci.*, 35 (1), 61-79

- [5] Brian McKenzie, B., and Rapino M., 2011 Commuting in the United States: 2009 US Census Bureau ACS-15
- [6] Bakshi A., Sharma A.K., and Mishra A. Significance of mobile ad-hoc networks (MANETS) International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-2, Issue-4, March 2013
- [7] Hoebeke J., Moerman I., Dhoedt B., and Demeester P. An overview of mobile ad hoc networks: applications and challenges. J-Commun Netw 2004;3(3):606.
- [8] Perkins, C., Belding-Royer, E., and S. Das, "Ad hoc On-Demand Distance Vector (AODV) Routing", RFC 3561, DOI 10.17487/RFC3561, July 2003, <http://www.rfc-editor.org/info/rfc3561>.
- [9] A. Munjal, T. Camp and W. C. Navidi, "Constructing rigorous MANET simulation scenarios with realistic mobility," Wireless Conference (EW), 2010 European, Lucca, 2010, pp. 817-824. doi: 10.1109/EW.2010.5483539
- [10] T. Camp, J. Boleng, and V. Davies. A survey of mobility models for ad hoc network research. Wireless Communications and Mobile Computing (WCMC), pages 483-502, 2002.