Dynamic Adaptive Disaster Simulation: Developing a Predictive Model of Emergency Behavior Using Cell Phone and GIS Data

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Keywords: DDDAS, GIS, agent-based, emergency response, cell phone

Abstract
In this paper, we present our approach to developing a proof-of-concept Dynamic Adaptive Disaster Simulation (DADS), a system capable of predicting population movements in large-scale disasters by analyzing real-time cell phone data. It has been difficult for existing computer models to accomplish such tasks-they are often too inflexible to make realistic forecasts in complex scenarios. This has led to reactive, uninformed emergency response tactics with disastrous consequences. DADS resolves these issues by continuously updating simulations with real-time data. It accomplishes this by tracing movements of cell phone users on a GIS space, then using geospatial simulation algorithms to infer regional preferences. Inferences are incorporated into agent-based simulations which model future population movements through fluid dynamics principles. Due to privacy concerns, this research utilized synthetic data that were generated to mimic the cell phone location data associated with a recent disaster. Validation techniques such as Manhattan distance show that the simulation is both internally and predictively valid. DADS can adaptively generate accurate movement predictions in disaster situations, demonstrating a modeling paradigm that is highly applicable to population modeling and to other disciplines of computer simulation.

1. INTRODUCTION
This paper presents a novel approach to developing a Dynamic Adaptive Disaster Simulation (DADS)[1], a proof-of-concept system capable of predicting population movements in large-scale disasters by analyzing real-time cell phone data. Such disasters, including hurricanes, earthquakes, and terrorist attacks, can occur in densely populated areas without warning, causing significant human costs. Urban planners and authorities face the challenge of minimizing the toll of disasters on society by coordinating responses such as evacuations and provision of supplies. However, in order for such efforts to be effective, responders must be able to determine evacuees' locations in real-time and predict their future movements, allowing for timely and efficient distribution of necessary resources.

The vulnerabilities of existing emergency response systems were exposed by the 2005 Hurricane Katrina emergency. During this event, government officials lacked comprehensive knowledge of population movements and failed to provide aid to thousands [24].

Computer simulations are important tools for studying emergency response, enabling preparation for and understanding of disasters before they occur [1]. A common way to simulate population movements in disasters is with agent-based systems (ABS), which consist of large numbers of agents that represent individual people, vehicles, or other objects in an emergency scenario (e.g., [19]). Agents' individual interactions create emergent behavior. Other principal (non-ABS) modeling strategies utilize cellular automata [16] or simulate flowing continuums [12]. The WIreless Phone-based Emergency Response (WIPER) project [17, 20, 21, 23] is a state-of-the-art ABS used for the modeling and study of population movements in emergencies. WIPER examines cell phone calling activity to detect behavioral anomalies and simulates basic fleeing behaviors of pedestrians and vehicles.

Most current emergency behavior models are restricted to simulating a few predetermined or theoretical situations [7, 8, 11]. They also have difficulties with incorporating real-time data and are based on numerous speculations regarding how people act [14, 16]. As such, many existing models are "completely inadequate for providing realistic, real-time forecasts, essential for complex phenomena analysis" [5]. For example, though WIPER can incorporate real-time cell phone data, it only models a few fixed types of evacuations [23], and could not have generated the detailed movement predictions needed for a successful response to Hurricane Katrina. Additionally, WIPER agents utilize overly simplified fleeing movement patterns that cannot account for the complexities of a real-world disaster scenario.

[1] An abstracted version of this research was exhibited as a Best Student Paper presentation at the 2010 Computational Social Science Society (CSSS) Conference at Arizona State University. A version of this manuscript is under review for publication in the 2011 Agent-Directed Simulation (ADS '11) Symposium, part of the Spring Simulation Multiconference in Boston, MA.

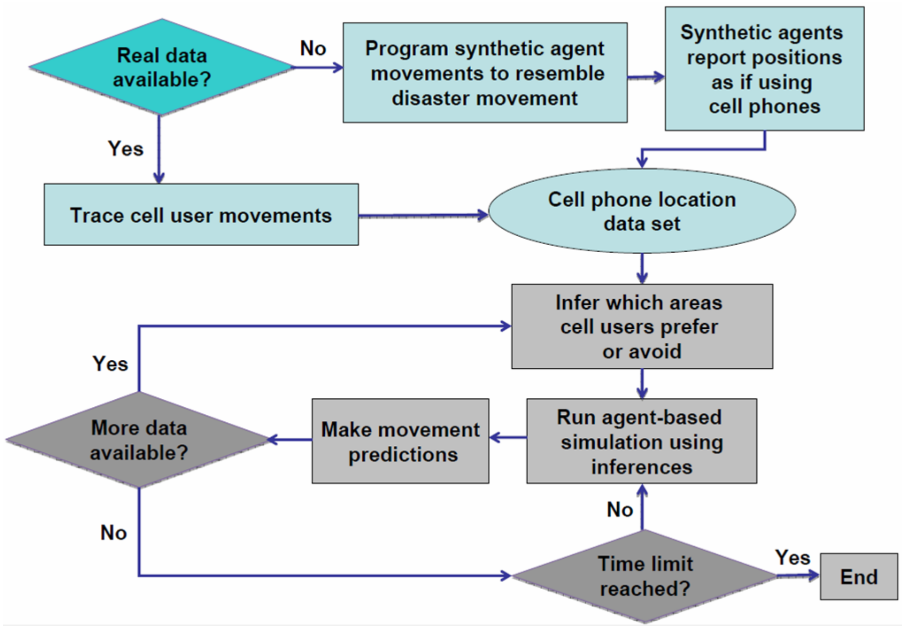


Figure 1. DADS system overview. The top two rows of blue boxes represent steps for obtaining or generating data. The gray boxes at the bottom are components of the simulation system.

Other modeling approaches have been used in related studies of crowd animation and geosimulation. In the former, dynamic potential fields allow computer-generated crowds to display realistic movements and continuously react to environmental changes [15, 26]. In the latter, simulated humans perceive their surroundings through "vision cones" [25], exhibiting appropriate movement and behavior as a result. To the extent of our knowledge, these methods have not been applied to large-scale simulations of emergency behavior.

Inspired by the above techniques, we have developed DADS to simulate emergency evacuations by modeling the area around the target disaster with a potential field. The potential field is conceptually portrayed as a terrain of varying elevations. Evacuees are represented on the terrain using a hybrid model which combines ABS and fluid modeling approaches. DADS can continuously modify the dynamic potential field according to the movements of cell phone users, based on an extended notion of vision cones. As a result, our model can adapt to a variety of emergency scenarios and generate accurate movement predictions. It can also conduct inferences about dynamic disaster situations through analysis of real-time cell phone data, using these to continuously refine its predictions. Therefore, DADS addresses the inadequacies of existing systems such as WIPER, demonstrating a modeling paradigm that has many potential applications in population modeling and in other areas of computer simulation. Due to privacy concerns, this research utilized synthetic data that were generated to mimic the cell phone location data associated with a recent disaster.

2. METHODS AND MATERIALS

The design and development of DADS synthesized a variety of different ideas and techniques from the field of computer science. This section discusses our principal computational methodologies and describes the hardware, software, and data sets used in our simulation.

2.1. Methods

The overall design of DADS is outlined in Figure 1. We must address two main challenges:

- Developing the key components of the simulation system (Section 2.1.1.)
- Generating data for the simulations (Section 2.1.2.)

2.1.1. DADS System Components

Agents. DADS includes two types of simulation agents — synthetic and predictive — for modeling the movements of a population during a disaster. Synthetic agents generate a set of real-time data in the same form as real-world cell phone data. They do so by mimicking population behaviors observed in past disasters while reporting their positions as if being tracked via cell phones. The reasons for using synthetic agents are discussed in Section 2.1.2. Once DADS starts to analyze real-time cell phone data, it deploys an ABS simulation consisting of predictive agents. DADS generates population movement forecasts by advancing the simulation faster than real-time events; each predictive agent is associated with a cell phone user and moves to represent predictions of the cell phone user's future movements. Both agent types move at realistic, random pedestrian speeds [4].

Simulation Space. We model the area where the disaster evacuation takes place (e.g., in a city) by using potential fields. Large crowds with common goals, such as city residents fleeing a large-scale disaster, can be modeled using agents that exhibit fluid-like movement from high to low potential on such fields [15, 26]. Intuitively, a potential field can be viewed as a field of various elevations, as fluids flow from high to low elevation. In the case of DADS, synthetic and predictive agents move according to two separate elevation fields.

The synthetic elevation field, used by synthetic agents, is calculated before such agents move and is not altered throughout a simulation run. We distinguish several types of regions on the synthetic elevation field with different elevation values: disaster sites (highest elevation), dangerous locations (high elevation; could represent features like chemical spills or low basins in Hurricane Katrina), safe locations (low elevation; could represent shelters, transportation centers, and areas of high ground during Katrina), and roads (low elevation).

Predictive agents use a predictive elevation field, which begins as a "flat" field of uniform elevations and has no *a priori* knowledge of the disaster. DADS dynamically changes the predictive elevation field according to inferences drawn from streaming real-time cell phone data. The elevation fields are represented as uniform grids, where each grid cell contains a numerical elevation value corresponding to a patch of ground within the area of interest.

Agent Movements. Synthetic and predictive agents act according to their respective elevation fields, moving as fluid particles flowing across terrain. We determine agent movement by adopting the following procedure from [29]:

1. Represent an elevation field as a matrix and convolve it with the following kernels:

$$\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix} \tag{1}$$

$$\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix} \tag{2}$$

   The central element of each kernel is its key element [29]. Convolving by (1) yields a matrix containing the south-north gradient (change in elevation) of each patch of ground; convolving by (2) yields a similar matrix containing east-west gradients [29].

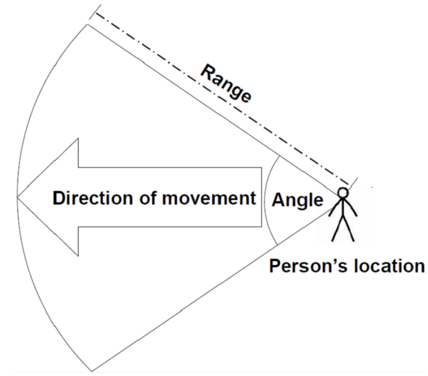


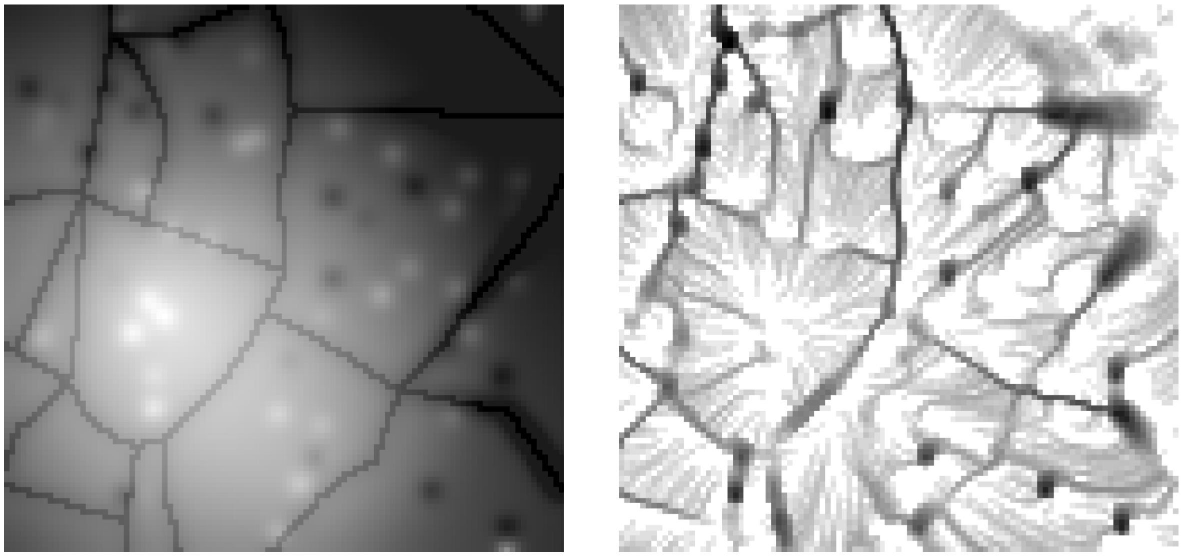
Figure 2. A vision cone. A sector of space centered at a person's location and facing the direction of the person's movement. The cone is symmetric about the direction of movement and is defined by the parameters of angle and range. People see and react to objects in their vision cones while fleeing [25].

2. Calculate the aspect (slope direction) a for each patch, using its east-west gradient x and its south-north gradient y, with the equation $a(x,y) = \arctan(y/x)$ [29]. We use a modified arctan function that gives values from 0^o to 360^o depending on the specific signs of x and y [28]. This yields a field of aspects.

This procedure is conducted on the synthetic elevation field before synthetic data is generated, and it is continuously performed on the predictive elevation field to reflect the progression of data availability. Both synthetic and predictive agents exhibit fluid-like movement by setting their headings to match the aspect of the patch of ground they are traveling over on their respective aspect fields.

Inferences and Dynamic Field Updates. DADS continuously modifies the predictive elevation field according to the movements of synthetic agents or real cell phone users. It performs these modifications by inferring which areas are preferred or avoided. Our technique for inference extends the idea of a "vision cone", used as a geosimulation tool in [25] (Figure 2). An agent only reacts to objects inside its vision cone [25], either preferring or avoiding them. We use the converse of this tactic to infer which areas are attractive or repulsive. Specifically, our inference technique is based on the following key observation: Suppose people only react to objects in their vision cones and are moving into their vision cones; then it is reasonable to assume that there are areas that people wish to move to within their vision cones. Thus, every time a cell phone user or synthetic agent moves forward, all areas in its vision cone decrease their predictive elevations by 1 to indicate that they become slightly more attractive. Results of this technique are shown in Figure 3.

When DADS is used for real-world predictions, synthetic agents and the synthetic elevation field are both unnecessary. In such a case, DADS tracks the movements of cell phone



(a) **Synthetic elevation field.** Represents a 10 km×10 km area in a city. Synthetic agents move on this map to produce synthetic data.

(b) **Predictive elevation field.** This map was generated by our inference technique acting on the cell data produced using Figure 3(a).

Figure 3. Elevations on both maps are colored in grayscale, with lighter colors representing higher elevations. Comparison of Figures 3(b) and 3(a) shows that DADS is able to nearly reconstruct the original synthetic elevation map through inference on cell phone data. Thus, it captures almost all of the factors influencing cell phone users' movement. This enables accurate predictions of future population movements.

users, using vision cones to modify a predictive elevation field. An ABS of predictive agents is then deployed, where predictive agents move across the predictive elevation field by exhibiting fluid-like movement. The ABS advances faster than real-time, so that the positions of predictive agents represent predicted locations of cell phone users at a given future time. Cell phone users are a sample of the population; their movements reflect population movements. If more data become available after the initial predictions, DADS incorporates the new data into its simulations, continuing the above procedure for as long as necessary.

When synthetic data is used, synthetic agents move across a predefined synthetic elevation field. They constantly report their positions to create a synthetic cell phone data set. DADS treats the synthetic data exactly as it would treat real data. However, we impose a time limit on the running of DADS with synthetic data, representing the end of the disaster. At this point, synthetic data is no longer generated, and simulations make final predictions.

2.1.2. Generation of Data

We developed and tested DADS using synthetic cell phone data because it allows a thorough evaluation of the system in more scenarios than real-world cell phone data could provide, and because it avoids privacy issues. Simulations ran on a two-dimensional Geographic Information System (GIS) representation of a large European city with several million residents; all specific place names were removed in order to maintain anonymity. GIS data consisted of layers of vector shapefiles describing the city's roads and cell towers.

Synthetic cell phone data was based on real cell phone data from a European cellular carrier. All carriers keep historical records of cell phone user actions in a Call Data Record (CDR) [21]. Furthermore, networks must always be able to locate all cell phones, so that incoming calls can be directed to the proper locations. This is done by identifying the cell tower which each phone is nearest to, and then locating the phones more precisely with advanced positioning techniques like triangulation [18]. This type of location technology can locate cell phone users' positions within a few meters [20]. Thus, by continuously paging all cell phones, networks can record the precise movements of all cell phone users [18].

Three large-scale crises recently occurred simultaneously in the city of interest. We used over 3200 synthetic agents to represent the evacuation from these disasters. This number of synthetic agents was chosen for computational efficiency and sufficiency in generating data for analysis. Synthetic agents were initially distributed uniformly throughout the city. During the disaster, they moved as people would, fleeing away from the three disaster sites and preferring to use major roads. We also chose several random safe and dangerous locations (see Section 2.1.1.), setting all synthetic elevations to appropriate values. We referred to each unique set of safe and dangerous locations as a scenario. Synthetic agents thus fled from the three main disaster sites in each scenario, preferring

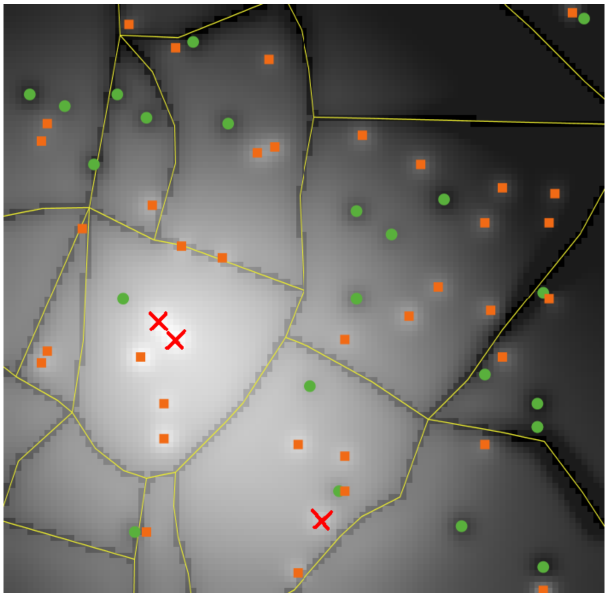


Figure 4. A disaster scenario modeled with a synthetic elevation field. Synthetic elevations are colored in grayscale, with lighter colors representing higher elevations. Red X's represent disaster sites, orange squares represent dangerous locations, green circles represent safe locations, and yellow lines represent major roads. This is the same synthetic elevation field as Figure 3(a).

roads while moving towards some regions and avoiding others. They constantly reported their positions while fleeing to produce a set of cell phone location data that takes the place of real cell phone data. Synthetic agents proceeded at randomly selected speeds; the distribution of their speeds is equivalent to the distribution of real pedestrian walking speeds [4]. Thus, synthetic data was based on real-world disasters and movement studies and was a reasonable substitute for real data. Figure 4 is a sample synthetic elevation field generated with this procedure.

2.2. Materials

All simulations and computations were performed on a PC with a 2.0 GHz Intel Pentium M processor and 1.99 GB of RAM. We implemented DADS in the Netlogo programming language and modeling environment [28], version 4.1.1, and also made use of the Netlogo GIS extension. Our final program occupied 1343 lines of original code.

3. RESULTS

We conducted a large number of experimental simulations to calibrate and validate DADS. Our first experiment determined suitable values for the parameters in the system. Our second evaluated the effectiveness of the system. We describe both experimental procedures and results in this section. The computational efficiency of the system is also addressed.

3.1. Parameter Calibration

Before validating DADS, we determined optimal values for the vision cone parameters of angle and range (see Figure 2). We accomplished this using 2-dimensional exhaustive sweeps on the parameters. Below, we discuss our prediction quality metric and sweeping approach.

Prediction quality was measured with the Manhattan distance metric, also used in the WIPER project [22]. To apply this measurement technique, we first construct an n-dimensional vector $\overline{p}$, n being the number of cell towers on the GIS space, such that the element in each dimension represents the number of cell phone users at one cell tower. Cell phone users at a cell tower are within the serving domain of the tower, i.e., the area 100 to 600 meters in radius that is closer to that cell tower than to any other tower [18]. (See [20] for further details.) We then construct another n-dimensional vector $\overline{q}$ for predictive agents, in which the value for each dimension is the number of predictive agents at each tower. We then compute the Manhattan distance between $\overline{p}$ and $\overline{q}$ with the following formula [22]:

$$d(\overline{p},\overline{q}) = \sum_{i=1}^{n} |p_i - q_i|, \tag{3}$$

where $\overline{p} = (p_1, p_2, ..., p_n)$, $\overline{q} = (q_1, q_2, ..., q_n)$.

Equation (3) yields a nonnegative integer value for the Manhattan distance between the simulation's prediction of cell phone users' locations at a point in time and the actual locations of cell phone users at that time. The smaller the distance, the more accurate the simulation. Note that this form of distance measurement can be generalized to any L_d distance metric (e.g., Euclidean or L_2 distance).

We adopted a multi-resolution approach for the parameter sweeping process. At the initial lowest resolution, we coarsely evaluated all combinations of angles from 30^o to 180^o and range values from 200 to 1000 meters in increments of 30^o and 200 meters, respectively. We then identified the best performing ranges for each parameter and continued to conduct finer and finer parameter sweeps on these ranges.

Here, we discuss the procedures used to identify the best parameter ranges at a given resolution. Each possible pair of values for the parameters of angle and range was used to conduct inference on the same three synthetic data scenarios. The disaster began at 8 a.m. in each scenario; simulations based on inferences began at 8:05, 8:35, and 9:05 a.m. At these times, predictive agents used the predictive elevation field to “move ahead” to the predicted positions of cell phone users 15 minutes after the simulation started (i.e., at 8:20, 8:50, or 9:20 a.m.), and at intervals of 30 minutes from then on. These positions represented predictions of future population movements. Simulations ran until the imposed time limit of 10:20 a.m. We tested each parameter pair in the following manner:

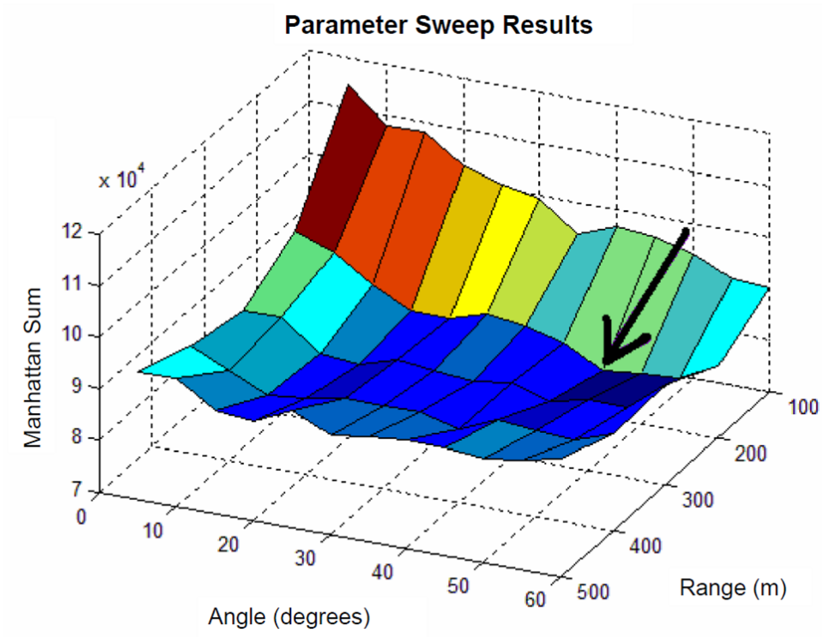


Figure 5. Results of final parameter sweep. Smaller Manhattan sums indicate more accurate predictive simulations. Adjacent data points are connected to one another to form a 3D surface plot. The lowest point on the surface corresponds to the parameter pair producing the overall closest simulation. This point, at an angle of 45^o and a range of 200 meters for cell phone users' vision cones, is indicated by the black arrow.

1. Calculate the Manhattan distance between each simulation and synthetic cell phone data for every set of predictions at each different point in time.

2. Sum individual Manhattan distances at each time point to give a "total Manhattan distance" corresponding to a pair of parameter values during the entire scenario.

3. Find total Manhattan distances for the pair in three different scenarios.

4. Sum the total Manhattan distances for the three scenarios to produce a "Manhattan sum" representing the overall predictive value of the parameter pair.

The best ranges of values for the vision cone parameters made the most telling inferences and produced the smallest Manhattan sums; thus, we conducted finer-resolution parameter sweeps on these ranges. Our finest 2-dimensional parameter sweep was conducted with angles from 5^o to 60^o and ranges from 100 to 500 meters. The results are shown in Figure 5. Optimal predictions are achieved with an angle of 45^o and a range of 200 meters.

3.2. Validation and Computational Efficiency

After calibrating DADS, we proceeded to validate the system. As discussed in [30], validation verifies that a model "is a reasonably accurate representation of the real world". In our case, we sought to determine whether predictive agents model the data (synthetic agents) with reasonable accuracy. We first tested DADS for internal and predictive validity, and then evaluated its ability to refine predictions with streaming real-time cell phone data.

Internal validation evaluates a model's stability [30]. Confirming the internal validity of a model can be done by running a simulation based on that model with different random inputs. If random inputs cause significant variations in performance, then the model is either invalid or unstable [30]. Recall that DADS was tested using synthetic data scenarios with fixed disaster sites and roads (based on a real disaster), but also with randomly placed safe and dangerous locations. To demonstrate internal validity, we ran DADS 500 times, using a different randomly generated scenario each time. We measured each run by the percentage of predictive agents that made correct predictions of the final positions of evacuees 75 minutes in advance. See Figure 6 for the results. The mean percentage of correct predictive agents was 77.30% with a standard deviation of 3.87%, testifying that the DADS modeling method is internally valid and would remain useful in varying or complex situations.

Next, we discuss the predictive validation of DADS, which is "used to compare the model's prediction with actual system behavior" [30]. An average of 77.30% of DADS predictive agents accurately predicted the movements of synthetic

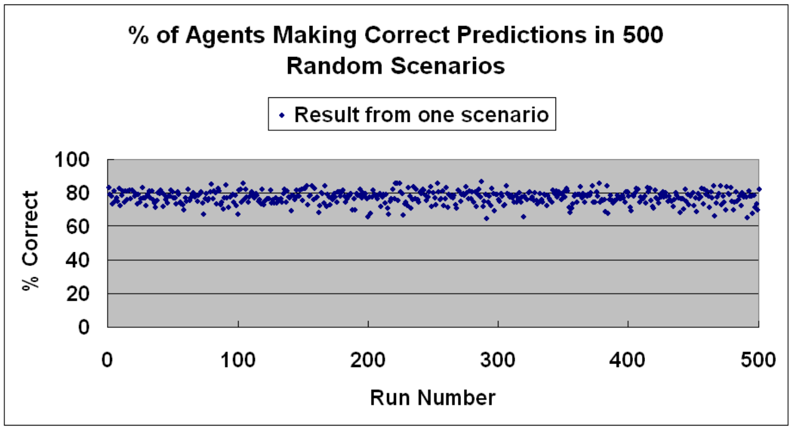


Figure 6. Percentages of predictive agents making correct predictions. Each point represents the percentage of predictive agents that correctly predicted the cell tower that an evacuee would be nearest to by 10:20 a.m. in a unique randomly generated scenario. Correctly predicting the cell tower provides reasonably accurate information on the actual position of evacuees [18], facilitating disaster response. The majority of agents predict accurately, and the percentage does not exhibit extreme variation.

agents that would occur 75 minutes later (see Figure 6). This demonstrates the high predictive effectiveness of DADS in forecasting population movements in a disaster before they occur.

The above quantitative measurements of predictive validity, however, have their limitations in this situation. Since

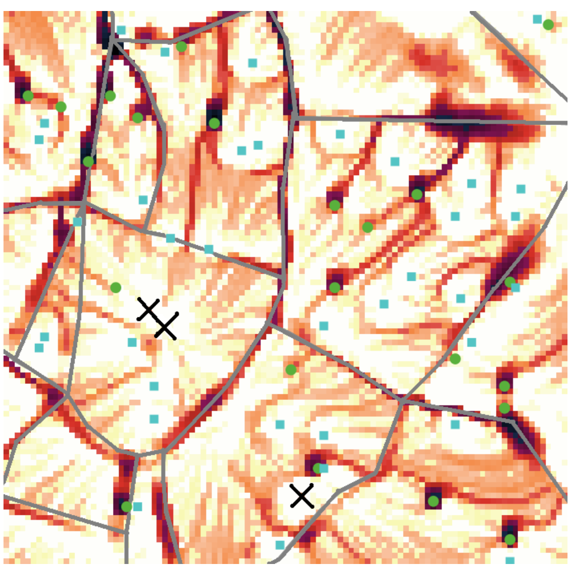


Figure 7. Inferred vs. programmed attractive and repulsive regions. Green circles are safe regions, black X's are disasters, gray lines are roads, and cyan squares are dangerous regions. DADS inferences are shown as a heat map — darker, "cooler" regions are inferred to be more attractive. This demonstrates that DADS correctly identifies all safe, dangerous, and disaster regions, labeling the first as attractive and the other two as repulsive. It also identifies heavily utilized roads and paths. This figure is from the scenario in Figure 4.

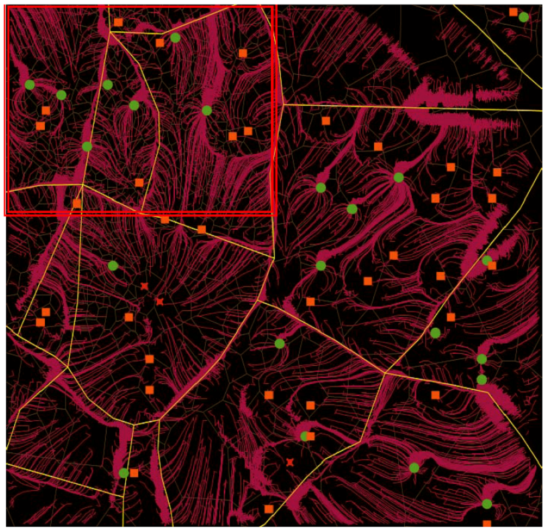
agents' predictions are counted as correct only if they are at the correct cell tower, predictions could be erroneously counted as incorrect if they happen to be in the domain of a different cell tower (e.g., a neighboring cell tower), regardless of how accurate they actually are. Therefore, to complement our quantitative measures of predictive validation, we present two qualitative validation techniques, as follows:

- Comparing the inferences of DADS with the conditions present within the synthetic disaster scenario (Figure 7) to see if correct inferences were made.
- Comparing the paths taken by synthetic agents with the paths of predictive agents that move based on the synthetic data (Figures 8(a) and 8(b)).

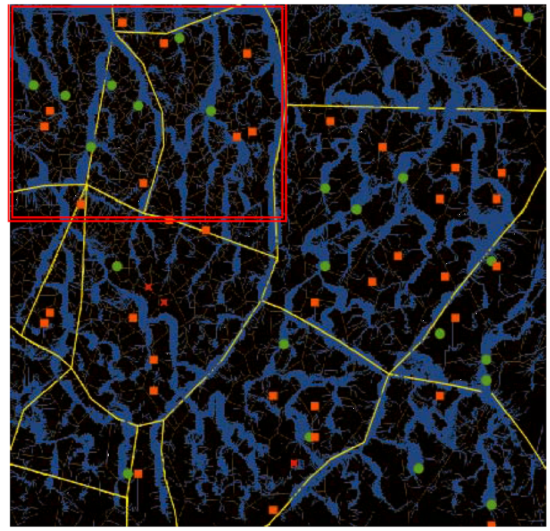
Our quantitative and qualitative validation techniques together demonstrate the internal and predictive validity of DADS with regard to synthetic data. The system accurately predicts population movements and regional attractiveness in a variety of scenarios.

Finally, we compared the predictions of simulations started at 8:05, 8:35, and 9:05 a.m. with one another. Manhattan distance was again used as the metric for evaluating simulation accuracy. More recent simulations are consistently more accurate, as shown in Figure 9. This exemplifies the DDDAS concept of correcting ongoing simulations with streaming data [5].

Using over 3200 synthetic agents and as many predictive agents on a 100×100 uniform grid of Netlogo patches, DADS took an average execution time of 5 minutes to process 140 minutes of streaming synthetic location data while running predictive simulations.



(a) **Paths of synthetic agents. Each magenta line is the traced path of a synthetic agent.**



(b) **Paths of predictive agents. Each blue line is the traced path of a predictive agent.**

Figure 8. Predictive agents in Figure 8(b) correctly prefer safe regions and avoid dangerous and disaster regions. Their movement is at times very similar to that of synthetic agents (Figure 8(a)), especially in the northwest region (boxed in red). However, paths can differ locally because predictive agents are overly sensitive to attractive and repulsive regions and "flow" less smoothly, congregating into streams around heavily utilized paths. Thus, DADS is more predictively valuable for large groups than for individuals.

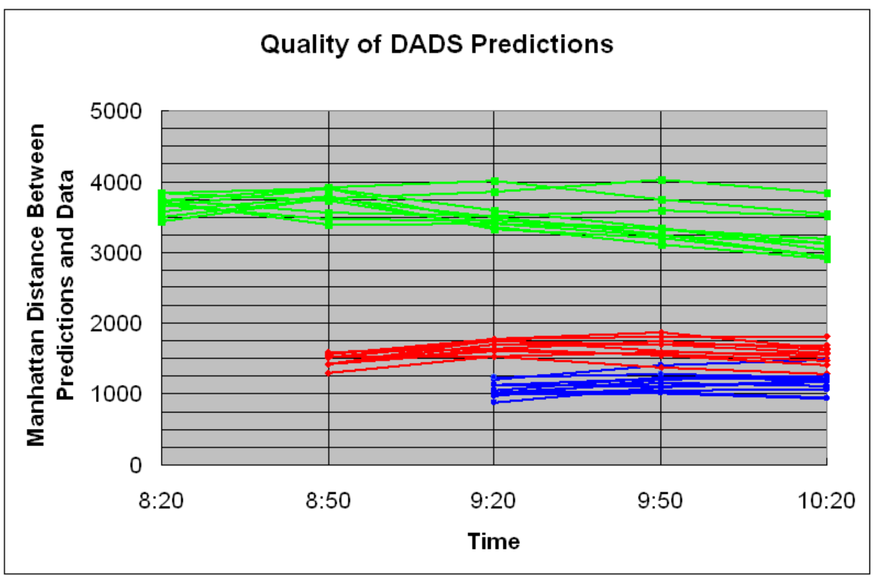


Figure 9. Evaluating use of streaming data. Green lines at the top of the figure represent simulations starting at 8:05 a.m, red lines in the middle represent simulations starting at 8:35 a.m., and blue lines at the bottom represent simulations starting at 9:05 a.m. Simulations from 10 different scenarios are displayed for all three. Smaller Manhattan distances indicate more accurate predictive simulations. When a simulation starts, it predicts all future movements of the population until 10:20 a.m. 30 minutes of streaming data and updates between the 8:05 and 8:35 simulations can dramatically improve predictions. 30 more minutes of streaming data further improve predictions from 8:35 to 9:05 a.m., but less significantly. This trend holds for all 10 scenarios in the graph.

4. DISCUSSION

In this paper, we presented the proof-of-concept Dynamic Adaptive Disaster Simulation (DADS), a simulation of population movements that is able to adapt to streaming dynamic cell phone data and predictively simulate a variety of crisis scenarios. Given a set of real-time cell phone location data during a crisis, DADS can identify attractive and repulsive areas on a map and predict future population movements accordingly. In the Hurricane Katrina example, a system like DADS could feasibly have identified areas such as the Cloverleaf and the Superdome, which evacuees would prefer [24], so that responders could allocate more aid to these areas. DADS could also have determined the most popular paths of travel, allowing for responders to better control traffic flow and predict where more assistance would be needed. This exemplifies its utility in a pre-disaster evacuation scenario, even if the disaster itself disables cell service. Additionally, as shown in Section 3., the simulation can be effectively applied to a variety of scenarios. This satisfies the DDDAS specification of leveraging streaming data during run-time to provide "realistic, real-time forecasts" that are specific to a given emergency situation [5]. Finally, DADS takes less than 5 minutes on average to process 2 hours of data, running fast enough to provide useful real-time predictions.

Like WIPER [20], DADS advances the use of cell phones as a data source and validation tool for simulations of population movements. Cell phones are becoming increasingly ubiquitous, with over 4.6 billion subscribers worldwide in 2009 [27]. However, the study and use of cell phone data is still "unexplored territory" [18]. DADS represents a step forward in the utilization of cell phone data to study human behavior. Since Call Data Records are kept by all cell carriers [21], DADS can also be used to analyze historical cell phone location data, so as to study and model past disasters and further engineer response to future disasters.

Our simulation integrates various approaches from crowd animation [15, 26] and geosimulation [25] into a new ABS system that is capable of addressing the problem of dynamic disaster response. Specifically, DADS incorporates the following techniques:

- Large-scale emergent intelligence, derived from cell phone users' local knowledge [6].
- Assigning numerical attractiveness values to regions based on cellular activity [2].
- Using vision cones for inference, as inspired by [25].
- Agent-based modeling for simulation of human emergency behavior [19, 20].
- Applying fluid modeling and dynamic potential fields to implement agent movement [15].

These methods are enhanced by incorporating streaming real-time cell phone data, giving DADS its dynamic and adaptive capabilities. Finally, though the WIPER system [20] also uses cell phone data to facilitate emergency response, DADS is able to predictively simulate scenarios of far greater complexity. Our work unifies approaches from different areas into a simulation system that can be effectively applied to respond to crisis situations.

DADS relies on several assumptions to achieve its simplicity and fast run-time. It is necessary to evaluate these assumptions because "a model is only as good as the assumptions on which it is based" [13]. For instance, DADS uses largely homogeneous agents and assumes that environmental factors alone determine population movements. Other agent-based evacuation models assign heterogeneous features to agents in order to reflect the heterogeneity of human populations [14] or emphasize the influence of human interactions and "crowd dynamics" on movement [3]. The study in [12] supports the use of homogeneous agents for large-scale, outdoor situations, and the work in [10] asserts that emphasizing the effects of environmental factors on population movements "would be appropriate for evacuation disaster modeling, as crowd behaviors in such situations are largely reactive and driven by danger avoidance". These studies somewhat justify our two assumptions, as DADS is intended to simulate citywide disaster evacuations. Nonetheless, it would be beneficial to study the effects of incorporating heterogeneity and crowd dynamics into an evacuation model.

There are additional assumptions in DADS indicating the need for further development. The most important one involves the use of synthetic data — although synthetic data was based on actual cell phone data during a recent disaster and assumed to be a reasonable substitute, it may not account for aspects of real data such as volume and "noise". Also, predictive agents had no restrictions on their movement and were assumed to have full knowledge of the surrounding environment. However, "visual occlusions" such as tall buildings can create uncertainty and influence decision making during a disaster [26]. Furthermore, features such as terrain may change the dynamics of an evacuation scenario [23]. We must account for these factors to increase the degree of realism in DADS predictive simulations.

5. CONCLUSIONS AND FUTURE WORK

Shortly after the 5th anniversary of Hurricane Katrina, we created DADS, a tool for simulation and prediction of emergency behavior. This system addresses some of the shortcomings that caused the ineffective response to the storm. Our work unifies diverse modeling concepts and techniques as well as considering cell phone and GIS data, resulting in a Dynamic Data-Driven Application System (DDDAS) [5] that can incorporate and adapt to streaming data and generate realistic forecasts of emergency behavior. Validation of DADS shows that it can feasibly make accurate predictions of population movements during a disaster like Hurricane Katrina, helping responders to make more informed decisions.

Though DADS has proven to be predictively accurate on synthetic data, we must test it on real cell phone location data in order to verify its efficacy in real-world settings. Lack of realistic validation is still an issue requiring further work; this observation concurs with [20]. However, due to the positive results of using synthetic cell phone data to create and test predictive simulations, it appears that our paradigm of "adaptive simulation" is quite promising.

We also intend to revisit some of the procedures used in developing DADS in order to improve upon several important aspects. First, we must closely examine the process of generating synthetic data if real data remains unavailable. This would ensure that results based on synthetic data are truly applicable to real cell phone data. Second, we plan to more thoroughly assess the great variety of techniques used in agent-based modeling of population behaviors in order to enhance the quality and efficiency of our simulation. Finally, we will adopt a more sophisticated method of parameterizing DADS, which could involve using advanced heuristics, genetic algorithms, AI methods, and statistical approaches.

Regarding the issues raised in Section 4., future work would also involve increasing the degree of realism in our simulation. Of course, a model is not expected to reproduce all factors present in a person's decision making, as this could dramatically increase the model's execution time and lead to a "naïvely realistic" model that emphasizes unimportant aspects of behavior [20]. Instead, a model should aim to capture enough key factors to generate a useful representation of a phenomenon. Thus, we must strike a balance between realism and run-time performance, creating a model that is both valid and efficient.

DADS represents only one of a host of useful simulations that can potentially arise from the DDDAS paradigm [5]. Examination of such simulations, such as that conducted in this work, can provide new insights into complex phenomena. For example, similar work could be conducted on a smaller scale, to study evacuations of buildings, or on a larger scale, to model global movement patterns. By combining existing methods with real-time data, simulations such as DADS can potentially provide profound understanding of population movements and increase the efficiency of human spatial interactions in ways previously unimaginable.

Acknowledgments

The research presented in this paper is based in part upon work supported by the National Science Foundation, CISE/CNS-DDDAS, Award #0540348.

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