Emergent Ad Hoc Sensor Network Connectivity In Large-Scale Disaster Zones

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ABSTRACT

We introduce a disaster-zone-monitoring web-based application. While using this application, the user may simulate different large-scale disaster zones. He may use tools to define a disaster zone and its communication requirements. The web application uses the *Google Earth* infrastructure and is publicly available to use online during the conference from every computer connected to the Internet. The evolving deployment of nodes will be updated each second to reflect the current state of the entities residing within the monitored zone.

The user will be able to navigate through the disaster zone to inspect the dynamically changed environment, and to learn about node deployment and the current network connectivity and service availability. He could ask the system to find the number of agents required to be deployed and present this deployment. The user also will be able to define the budget limitations. Thus, the system will derive the number of agents, their deployment, and the resulting system utility. Given a system utility, the user can decide whether to adopt the deployment even though it does not guarantee full coverage, or to increase the budget to improve system utility.

1. PHASE TRANSITION EXPLOITATION

In a large-scale disaster such as an earthquake or a flood, one of the first things to collapse is the communication infrastructure. Communication is an essential means for rescue operations, and survivability of victims of such disasters decreases sharply with every minute that passes. Therefore, rapidly reviving the communication infrastructure in a large-scale disaster zone is crucial to saving many lives.

Nodes of an ad hoc sensor network should support both local and global requirements. The local requirement is to allow nearby users of mobile phones, computers, sensors, and PDAs to receive service, while the global requirement is to maintain network connectivity. Agencies responsible for establishing such networks wish to balance between the need to service as many users as possible and the maintenance of network connectivity. Formally, this balance could be defined by the agencies as a utility function of the system. These agencies wish to maximize the utility of the system under the limitation of a given budget. For the purpose of this work we narrow the budget considerations to be the number of network nodes. We define the system utility as the percentage of successfully delivering a message between two randomly chosen users. The utility is measured by averaging over M sets of randomly chosen users while M >> number of users.

Reflecting recent technology advances, we propose to use thousands of small, short-range, inaccurate, low-cost, mobile nodes to support the requirements. Following the fractal behavior of the network we show a phase transition in the utility of the system as a function of the number of nodes. That is, (i) for a few nodes, there is no applicable deployment while (ii) for many nodes any random deployment achieves the maximum utility, and (iii) the transition between zero utility and maximum utility is sharp.

Considering the phase transition phenomenon, we show how to determine the number of agents needed to maintain such ad hoc sensor networks and demonstrate an algorithm to drastically reduce the number of nodes required for the phase transition. We propose to apply intelligent behavior to every node. This behavior considers very limited partial information obtained by the node. To reduce resource consumption, a node does not use communication with other nodes for implicit cooperation but only for acquiring the location of its neighboring nodes.

2. PERCOLATION AND PHASE TRANSITION

Our model relies on the percolation theory [1], specifically on the site-percolation model. According to the percolation model a geometrical construction of sites and bonds between them is referred to as a lattice. A lattice may be considered a graph of vertices and edges, respectively. An edge may exist only between two sites considered as closest neighbors; that is, the distance between them is smaller than a predefined range. The percolation model may be characterized as two types, the bond and the site. In a bond percolation model a probability p represents the probability for an edge to be

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[1] This demonstration is a live demo software.

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open. In a site percolation model a probability p represents the probability for a vertex to be open. An open edge or vertex means that current, such as water or electricity, can pass along that edge or vertex. Site percolation is more general since every bond percolation may be reformatted to a site percolation while not all site percolation can be represented by bond percolation. In this paper we focus on the site percolation model.

We say that two occupied vertices belong to the same cluster if there is a path of edges leading from one vertex to the other. As we increase p we may see that the number of clusters is reduced while the average cluster size is increased. Percolation theory focuses on the behavior of an infinite lattice and studies the condition for existence of an infinite cluster. Such a cluster spans from one side of the lattice to the other, and current can pass from one side of the lattice to the other. Studies show that the probability for the existence of such a cluster is either zero or one, whereas for small p the probability is zero and for large p the probability is one. Given that, there is a critical probability p_c such that if $p > p_c$ almost surely, there is an infinite cluster for that lattice, while for $p < p_c$ almost surely, there is no infinite cluster. We refer to the probabilities below p_c as the subcritical phase, to the probabilities above p_c as the supercritical phase, and to p_c as the phase transition.

Large-scale random distribution of nodes has a very distinguished self-similarity property [3]. Benefiting from our physics metaphor, we may use scale-invariant statistical field theory to deduce that phase transition is not dependent on the scale of the system. The same theory proves that the important property is the particle density rather than the scale. That is, if we increase the size of the area and the number of agents by the same factor we will witness the same global utility. This means that if we keep the same agent density, it takes the same evolution time for the model to reach the same utility regardless of the scale of the problem.

Moreover, following scale invariance laws, if an agent senses other agents in a big enough area it may use the same conclusions about the whole system. In that case, an agent may find the probability to achieve consensus and act upon that knowledge. If it finds that a consensus could emerge, it would act to achieve it. If it finds that a consensus could not emerge, it could save its resources by not trying to cooperate in vain. In our study we validated these deductions when applying our model to the large-scale ad hoc network example.

3. LOCAL AND GLOBAL MOTIVATIONS

Using only partial information, each agent is motivated to increase the global utility while following its own utility function. To do that we built a utility function for an agent that is combined out of two elements, the local motivating the agent to defect and the global motivating the agent to cooperate. Based on our previous work [2] and [4], we represent the global considerations by a potential field that drives the agent toward other agents but rejects it from them if it is to close to them. The influence of an adjunct agent to the potential is represented in a grid around the agent, and the size of the grid depends on an *awareness range* defined for the agent. The potential contribution of each adjunct agent may reach up to an *interaction range* and its value is between -1 and 1 while negative potential values represent attraction and positive values represent rejection.

To represent the local motivations we used an exponentially decaying function. This function depends on the distance of the agent from its origin and aims to motivate the agent to remain in its original location. We used the same grid that was used to represent the potential field to incorporate the local considerations. The contribution of the local consideration to every cell in the grid may vary between 1, for maximum contribution, and 0, for minimum contribution.

To model the overall agent utility we prefer to use a model that does not require long-range interactions. In such a model we may take into account only local interaction and reduce the computational complexity. Since we want the local consideration to be dominant we represent the utility as a multiplication between the local and the global motivations. We use the grid to represent the range of possibilities to gain utility if the agent were in a certain location on the grid. We find the best places that result in the highest utility value and randomly choose one of them. The agent then moves in the direction of this cell.

4. AGENTS DEPLOYMENT

On December 26, 2004, a great earthquake located off the west coast of Northern Sumatra led to the worst tsunami in recorded history. In this storyboard we simulate a similar disaster zone across Indonesia. We define thousands of points of interest such as hospitals, command and control centers, and major disaster sites that require communication services. Using our settings of the disaster zone, points of interests and communication node capabilities we show that (i) While using the naive approach in which communication nodes are statically spread along the points of interest, we need 4300 communication nodes to establish a network with utility of 90%. (ii) While using our Phase Transition Exploitation (PTE) algorithm, we need only 2700 nodes to achieve the same utility value of 90%.

Next, we show how to deploy 3000 autonomous agents that follow the PTE behavior. We start with the naive deployment and a utility of 9% and evolve to gain a utility of over 99% after 238 evolution cycles (i.e., 238 seconds).

We present an online updated graph of the utility as a function of the evolution cycle and provide the evolved deployment to be presented with Google Earth. One could see how fast the PTE behavior results in good network performance, for instance, after only 10 evolution cycles the system crosses the utility of 90%.

5. REFERENCES

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