A STUDY OF MULTIAGENT SYSTEM OPERATION WITHIN DYNAMIC AD HOC NETWORKS

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ABSTRACT

Two enabling technologies for envisioned tactical network systems are mobile ad hoc network (MANET) routing and collaborative Multiagent Systems (MAS). Despite their respective technical value in enabling more distributed, autonomous networking, open research and engineering questions remain regarding robust interoperation, standardization, and design of these two technologies. Little work has been done to date to examine the interaction and performance of distributed agent designs within MANET environments. This paper examines the interactions and effects of running a team of Belief-Desire-Intention (BDI) agents within a wireless network using emerging MANET protocol frameworks. The focus of the interagent communication model applied in this study is a form of MANET multicast routing and is aimed at improving group-based agent collaboration. The developed simulation testing environment is specified and results from various experiments are discussed. We present recent results examining overall MAS task performance vs. related knowledge loss induced by the underlying MANET network disruptions. We conclude by outlining several open issues and areas of further work.

INTRODUCTION

The fundamental goal of our work was to perform research and develop solutions to enable more robust Multiagent Systems (MAS) designs for Mobile Ad hoc Network (MANET) environments. This report documents recent design, modeling, and experimental results in researching a combined MAS and MANET system. Our previous related earlier work has been documented in other publications [MCDA06]. We also provide a summary of project developments, test tools, lessons learned, and a future work direction perspective. It is our hope that the research tools, methods, and early lessons learned developed under this work will stimulate further cross disciplinary research in multiagent systems and dynamic, mobile wireless networks an area ripe for further exploration.

RATIONALE

DoD is planning to deploy MANET type network technology at the battlespace forward edge and within the "the first tactical mile". There is also early deployment of agent-based systems occurring with more extensive future deployment envisioned by the joint services. Previous design work done with MAS networking has often assumed benign network behavior and highly stable infrastructures not MANET environments [W02]. Technical challenges of our work involved tackling cross-disciplinary issues of dynamic network protocol and multiagent system design [CDCP05]. At present, there remains a limited understanding of appropriate architectural design tradeoffs in adapting network communication services and MAS models in these more challenging environments.

Before we discuss the particulars, it is important to frame our understanding of agent systems in some concrete way. To scope our work, we have adopted basic descriptions and properties defined by Woolridge and Jennings [WJ95]. Their discussions and definitions have helped refine our notion of rational agents and as an extension have better defined rational multiagent systems. Using their arguments and definitions, reference agents are not seen as disembodied systems, but rather are required to be situated within some environment. Agents also have the ability to sense their environment in some way and perform actions in order to modify the environment. In their definition, agents and agent systems are action-oriented. A simplified view

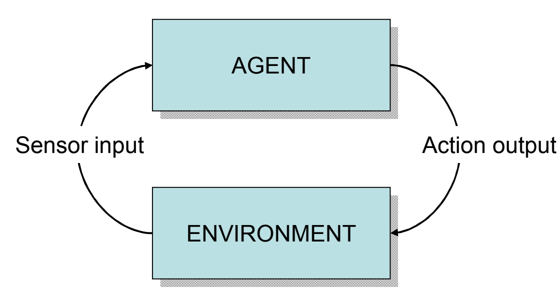

Figure 1: Agent Interactions

of agent and environment interaction is shown in Figure 1.

[W02] also discusses agents as exhibiting the following properties:

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- autonomy;
- proactiveness;
- reactivity; and
- social ability.

We were interested in examining these same fundamental properties and related performance issues in dynamic ad hoc wireless network environments.

The social feature of a rational agent is a key component of MAS. As in human societies, communications is a critical enabler in cooperating and collecting environmental awareness beyond local or individual self interests. This is especially true when considering group communications. A major challenge is that within MANET environments more efficient and reliable group communication constructs are still evolving. We believe we have improved this situation by applying emerging MANET multicasting techniques in this work. Although our hypothesis is that such network enhancements improve dynamic MAS collaboration capabilities, relevant MAS designs must continue to deal with more network disruption events regardless of overall protocol improvements. We shall also see that the very nature of agent environmental reaction involving motion contributes to particular types of network disruption that may affect specific MAS design components.

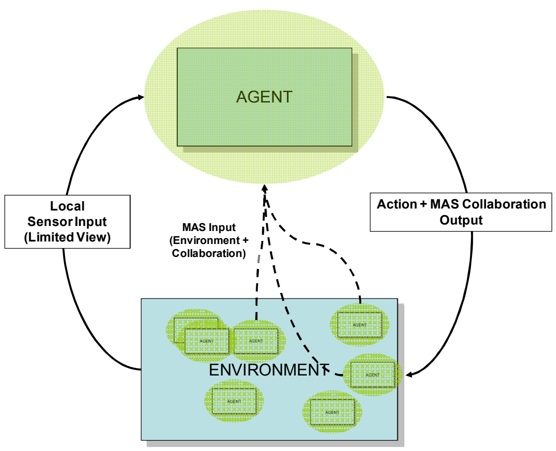


Figure 2: MAS Interactions

Figure 2 is a more detailed rational agent model relating to our MAS/MANET research model with richer environment interactions. In this revised version of Figure 1, sensor input is received by the agent from two logical sources: the agent local sensor system, and also from shared data input from other agents. The other agents are embedded within the MAS environment as well and are part of the individual agent environment view and interaction. Other related collaborative information is also part of the input and output of each agent process.

From a software engineering perspective, we focus on the Belief-Desire-Intention (BDI) model for our rational agents as discussed [W02]. We relate a number of our findings as lessons learned or pertinent issues for implementing BDI agent designs within dynamic ad hoc networks. Examples include the importance of intention persistence and also the need to carefully examine belief revision cycle processing in terms of network robustness and disruption assumptions. The belief revision cycle includes the time and means by which agents update their beliefs about their environment. In dynamic environments with disruption this cycle becomes a vulnerable design component. The problem is analogous to the "fog of war" syndrome.

MANET BACKGROUND

The goal of MANET routing is to provide enhanced IP routing for wireless networks, especially those that are possibly mobile or highly dynamic. There are numerous documented operational factors that significantly distinguish mobile, wireless networks from fixed wired networks such as the following [MC99]:

- Nominally lower capacity than wired networks.
- More frequent topological changes.
- Increased and unpredictable loss events.

When we began related work on agent system design in MANET around 2003, there was significant research progress in MANET unicast routing protocols but there remained a technology gap in effective MANET multicasting solutions. Throughout this effort we applied emerging work being done in multicast forwarding for MANET [M08]. The effective network collaborative needs of a MAS match well with the multicasting model and we believe this is an important step forward in MAS design support for MANET.

SIMULATION MODELS AND PARAMETERS

In recent MAS-MANET work, we have established a predator/prey agent scenario model to examine the interaction between agent and MANET performance. In our model, predator agent nodes have a group task to capture a set of prey target nodes. Multiple agent nodes are required to capture a target prey, introducing the concept of teamwork within the MAS design. This model was chosen in part because successful task completion required agent mobility that dynamically influences communication and network reliability.

Within our model, agent nodes had a maximum velocity and limited sensor and communication ranges. Within all simulations velocity and sensor limitations remained constant, while maximum communication range varied per scenario. Communication between agent nodes consisted of signaling for team allocation and coordination, sharing of individual agent intention, and dissemination of other shared environment knowledge. Dissemination of agent intention allowed agents to de-conflict ineffective or conflicting team assignments.

Target nodes were not equipped with communication capabilities and no coordinated system was implemented in opposition to the predator agent goal. Targets would however attempt to escape known agent nodes by moving away from the closest known predator agent within their environment awareness area. This movement introduced changes in the environment making communication between agents potentially more meaningful. For results presented here, agents were required to work in teams of four to successfully complete a capturing task. To perform dynamic role allocation we adapted an iterative distributed constraint optimization approach based upon the Hungarian algorithm [MDC04]. To minimize role oscillation we introduced a cost for switching roles. We also included a predictive inference method to allow for additional “look ahead” task capability. Predictive inference demonstrated longer short term task completion rates while shortening overall task completion times.

The ns2 simulation environment was used for these experiments with the addition of an NRL environment channel extension for simulating preys and external environment sensor data. We also applied the NRL AgentJ toolkit [ADMT06] to allow native java-based agent code to execute within the ns2 environment as application agents. In the experiment to be discussed, 8 agent and 8 target nodes were placed within a 900m x 900m size area. Within the hybrid grid scenarios, 9 static non-MAS relay nodes were placed to provide supportive network relay coverage. Agent nodes were given a maximum speed of 5.1 mps. To allow agent nodes to capture targets, targets were given a slower maximum speed of 1.1 mps. Target nodes would only move away from known agent nodes within a given sensor range and would otherwise remain stationary.

Simulations described here used the same sensor range settings. Agent sensor ranges used were omni-directional with a maximum distance of 20 meters. Omni-directional sensors with a max range of eight meters were used for the target nodes. To better control topology and connectivity, maximum communication range of agent nodes varied between 60 meters and 400 meters. For a given simulation run, communication range was homogenous and constant for all agents. The ranges can be viewed as relative ranges and were mainly used to control network neighborhood density probabilities. Using repeatable initial random node placement allowed for direct comparison of task completion time amongst different settings. In addition, agents and prey nodes are initiated without knowledge of other agent or target positions.

An NRL adaptation of the OLSR protocol, NRLOLSR, was used in conjunction with an NRL SMF implementation [PF] for routing multicast packets within the ns2 network simulation. Although multiple flooding cover set algorithms were used including the following: Classic, E-CDS, and S-MPR. The results in Test Sets A and B were based upon S-MPR based SMF forwarding. While the multicast results are limited in scope, due to the small network size limitations, we have examined the robustness of the different forwarding algorithms in a previous study [MDDA07].

SIMULATION EXPERIMENTS

We designed two sets of simulation scenarios: the first to examine MAS performance under congestion/contention conditions, and the second to examine network partitioning effects.

TEST SET A: PERFORMANCE WITH TRAFFIC LOADING

To perform a set of tests with minimal network partitioning, a scenario was designed with nine statically placed relay nodes. These relay nodes did not have role allocation agent functionality but participated in the MANET network solely as available forwarding nodes. They nodes ran the same SMF forwarding protocol (based upon S-MPR) and provided full grid area coverage. An example of the coverage and resultant starting network layout is given with and without statically placed relay nodes in Figures 3a and 3b.

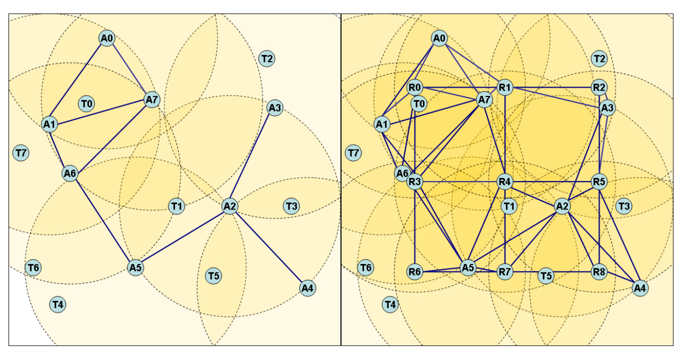


Figure 3a/b: Coverage Examples in Test A

For a given simulation, additional extraneous multicast traffic was sourced into the network at each agent node. This additional loading competed against MANET routing protocol and agent communication traffic for network resources. Nine different initial layouts were randomly selected for the agent and target nodes and these layouts remained constant for each set of simulation runs while traffic overhead was increased over a set of trials. Figure 4 shows the simulation time required by the MAS to capture all target nodes for each run layout as network load increases. It is interesting to note that higher amounts of network traffic generally increased simulation completion times but not consistently. The variance in task completion time also increases as the amount of traffic increases. All simulations finished well within the 2400 seconds maximum allotted time.

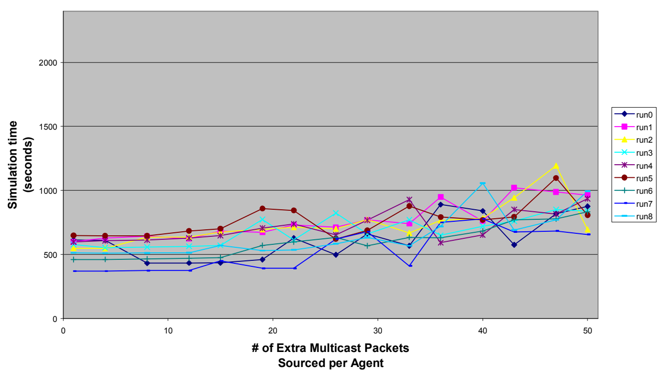


Figure 4: Task Completion vs. Loading

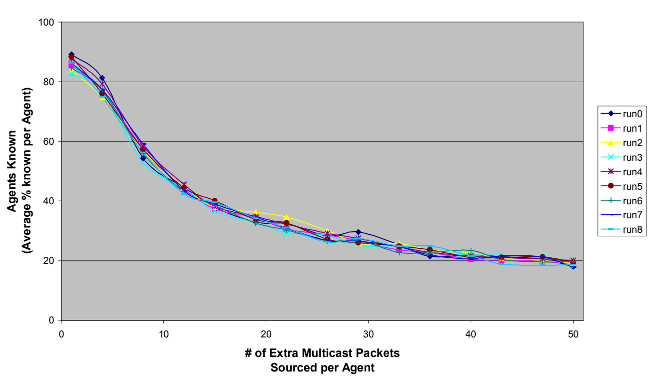


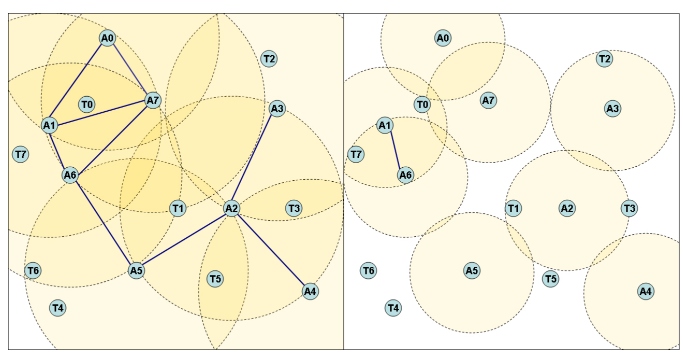
Figure 5: Agent Knowledge vs. Loading

Figure 5 shows the effect increased network loading has on agent knowledge with regards to other agents. The amount of knowledge about other collaborative agents drops off quite rapidly as the network becomes highly loaded but rate of decrease slows as the network becomes further saturated. Regardless of the initial starting layout the amount of peer knowledge loss relative to increasing network load remained quite stable.

Some interesting observations emerge when taking a look at average MAS performance. With only one packet per second per node overhead, agents know on average 86% of their peers and complete the capturing tasks in an average of 547 seconds. With traffic set to 15 packets per second per node overhead, agents know on average 38% of their peers yet task completion time only increased an average of 5.7% to 578 seconds. At first glance one would expect a greater impact on performance with this amount of information loss. At the highest level of congestion we tested, 50 packets per second per node, agents on average know 19% of their peers, and average simulation time increased to 843 seconds. These results at first seem non-intuitive with performance degradation less correlated with decreasing peer agent knowledge, but we feel this is explained by the agent persistence and the nature of the loss events as we will show later.

TEST SET B: PERFORMANCE WITH LIMITED RANGE

To explore how MAS performance might degrade due to information loss caused by network partitioning events we ran simulations with varying communication ranges. These tests used the parameters and procedures as the previous tests; however, no fixed relay nodes were used since we are interested in examining network partitioning and coalescing conditions. Communication ranges were varied from 60-400m at 25m intervals. Figures 6a and 6b shows the resultant network connectivity at 300m and 150m communication ranges.



Figures 6a/b: Connectivity Graphs vs. Range

Figure 7 shows the MAS task completion time for each decreasing network communication range. Compared to the traffic loading experiments, the trend analysis shows increased variance in completion times between initial layouts and runs with differing communication ranges. The effect of network partitioning induced knowledge loss on MAS task completion time becomes quite severe at the lower tested ranges, 200m and below.

As fragmentation becomes excessive below 150m, not all MAS simulations completed capture tasks within the allotted time. We found that by increasing the allowable simulation time by a factor of 10, many of these simulations still did not fully capture all target nodes. The network would fragment so severely that formation of teams, given our current agent design, would never occur. Because of this only simulation runs which completed within the 2400 seconds are plotted. The trend lines of each run stops at the last completed simulation.

Figure 8 shows the average known peer agents for each simulation run. Average peer knowledge levels were plotted for all runs, including simulations in which the

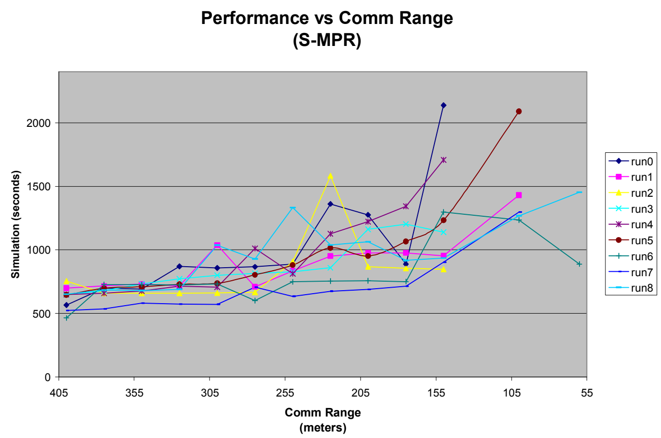


Figure 7: Task Completion vs. Comm Range

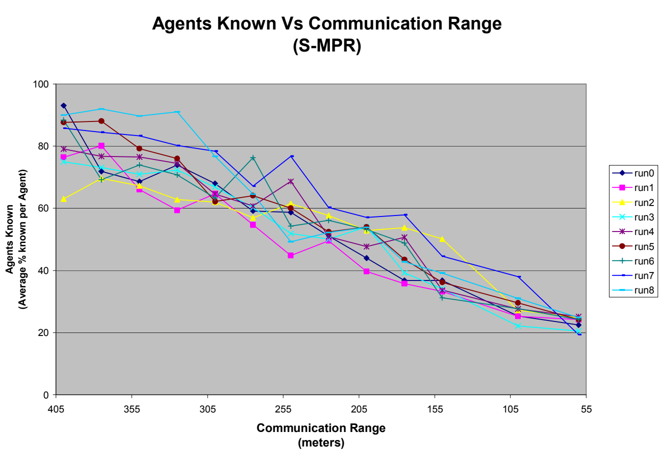


Figure 8: Agent Knowledge vs. Comm Range

MAS did not fully complete the task. The drop off in peer knowledge as communication range decreases follows a more linear trend when compared to the knowledge loss due to congestion/contention, as shown in figure 5. There is also much more variance than was exhibited by the congestion/contention model.

Taking a few average values across all 8 trials we find the following. At a 400m range, agents know on average 82% of their peers and take an average of 623 seconds to capture all targets. The time of 623 seconds differs from the fully connected congestion test with the least amount of overhead because the network did not remain fully connected throughout; the differing initial agent layouts also make direct comparison impossible. At a 225m range, agents know of an average of 53% of their peers but completion time is 1040 secs, or 67% longer than 400m. At 150m, agents knew 38% of their peers and task completion took 1239 seconds, almost twice as long as the initial average. This contrasts quite starkly with the 5.7% increase of simulation time measured at 38% known peers in the congestion/contention tests. As previously stated, not all simulations would converge to a solution, even given an infinite amount of time, using the smaller communication ranges, but an average of 23% of peers were known by agents with only 60m range.

LOSS CHARACTERISTIC ANALYSIS

We were curious why the general task completion trends differed so drastically when comparing traffic loading versus network partitioning induced information loss, so we examined further details of the loss properties. Figures 9 and 10 illustrate the patterns of loss, of two sample nodes with the same average knowledge values, resulting from Test Sets A and B.

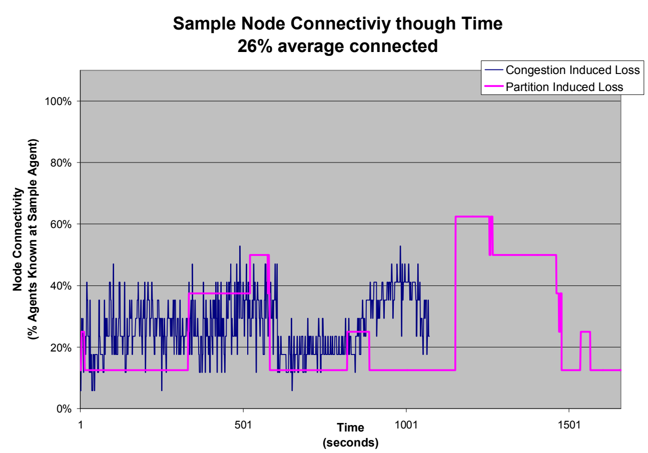


Figure 9: Loss Patterns at 28% Peer Knowledge

Traffic congestion induced random loss is clearly more temporally uniform while range limited loss is bursty in nature. This makes some intuitive sense since network partitioning causes periods in which a substantial amount of information loss would occur. With the congestion loss example, a percentage of source packets are received even during significant periods of loss. Since agents have some short term memory of the environment and role persistence this has less of an effect on cooperative behavior. We feel that this fundamental difference in network disruption types is a main factor in differing MAS-MANET performance characteristics and represents an important consideration in related MAS design. The nature of the environment and data persistence here directly affects the outcome of different types of temporal disruption emphasizing the need for more accurate modeling of such systems.

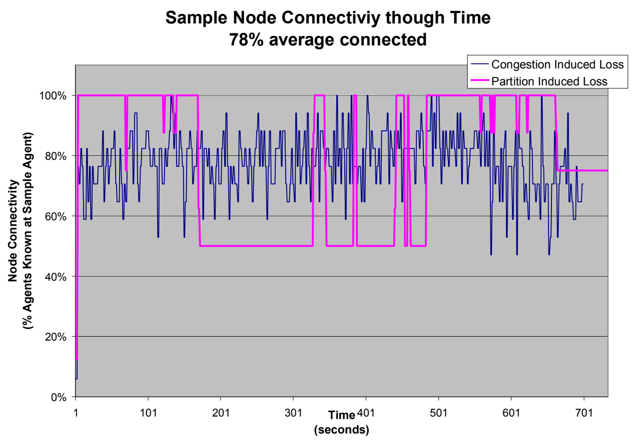


Figure 10: Loss Patterns at 78% Peer Knowledge

GENERAL EXPERIMENTAL OBSERVATIONS

During the course of simulating MAS strategies within MANET scenarios, we noticed significant variance across multiple trials. A cross dependency exists between cooperative agents and MANET communication approaches in our model. The network protocol approach had a significant effect on an agent systems belief revision cycle if that cycle relies on collaborative networking. The agents through their motion and communications also affect the network topology in turn affecting the amount/quality of information available throughout the agent system. For example, agent intentions to capture a specific target can cause a change in their location. This change in location affects the properties of the MANET network, in turn potentially causing a change in the agent's beliefs and intentions. This property helps explains why less agent information does not always result in longer simulation times or the converse that more information did not always result in shorter simulation times. For specific scenarios it can be difficult to determine if more or less network communication results in better system wide performance. However, some general trends do emerge.

GENERAL TREND ANALYSIS

Two differing methods of introducing network disruption: congestion and range limitation both caused longer task completion times with higher levels of information loss. The magnitude of the effect of this knowledge loss differed with the two methods. Figure 11 plots agent task completion, one point per simulation run, as a function of the amount of average percentage of the known environment. The known environment percentage for an agent is defined as the number of known agent and target locations, divided by the sum of all nodes. The percent of known environment plotted is the average known environment for all agents for one simulation. This value is the expected amount of information a random agent would have at a randomly selected time for a specific simulation run. A linear fit was added to the sets of simulation data to illustrate the difference in performance degradation with similar average loss knowledge. The differing patterns of loss information had a significant effect on system wide agent performance, with network partitioning losses being roughly twice as detrimental as congestion based losses. With higher levels of environment information loss (>60%) the network partitioning caused even more severe effects to performance when compared to congestion/contention, with some simulations entering states that never completed.

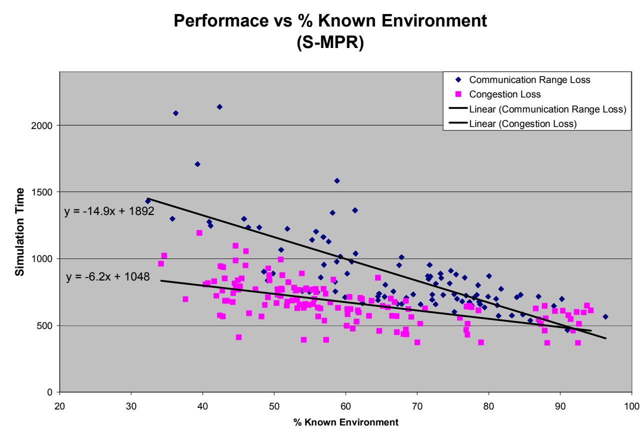


Figure 11: Performance vs. % Knowledge Metric

ADDITIONAL WORK

Due to the importance of maintaining network connectivity in multiagent systems, we have begun the development of MANET aware agents that include a network role along with other environmental roles. For our initial tests these "smart relay" agents used a modified attract/repel algorithm to attempt to self-organize a self-electing coverage strategy to minimize network fragmentation. We adopted the limited radio range simulation tests previously discussed but this time we added a set of intelligent mobile relay agents. Figure 12 shows the average simulation time as the range increases on the x axis and the number of relay agents is reduced on the y axis. The same parameters in the earlier network partitioning tests were used for these simulation runs with the exception of the additional relay agents.

The general trend demonstrates that additional smart relay agents decreased task completion time across all the communications ranges we tested. We did not thoroughly examine the effect of having a more sophisticated network role agent capability on a larger scale and more work is warranted. However, these initial results are encouraging and point the potential benefits from further work.

CONCLUSIONS

We developed and presented novel models that are enabling joint MAS and MANET research to be carried out. We demonstrated improved MAS interagent communications within MANET by applying emerging multicast forwarding capabilities. We also presented a set of experiments examining disruption effects in a MAS-MANET design environment.

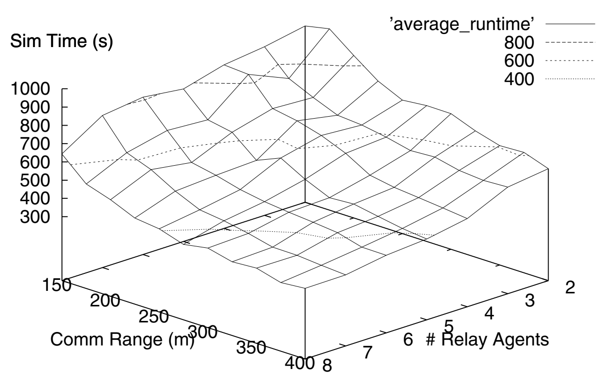


Figure 12: Smart Relay Agents and Task Effectiveness

We demonstrated that differing types of network disruption at the same average loss rates affected agent system performance in fundamentally different ways. Our MAS model dealt with the randomized loss of congestion/contention in a rather robust way due to short term memory and role allocation persistence. Losses caused by partitioning due to limited communication range were bursty and caused about twice the amount of agent performance degradation for the same average loss. We conclude that for examining MAS performance within a MANET environment random loss or congestion studies alone are not sufficient for modeling system wide performance. Introduction of bursty correlated information loss is critical to examine real world system effects such as network partitioning.

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