

# Stigmergic Learning for Self-Organizing Mobile Ad-Hoc Networks (MANET's)

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## Abstract

*In recent years, mobile ad-hoc networks (MANET's) have been deployed in various scenarios, but their scalability is severely restricted by the human operators' ability to configure and manage the network in the face of rapid change of the network structure and demand patterns. In this paper, we present a self-organizing approach to MANET management based on stigmergic agents and demonstrate how to analyze its performance under different deployment assumptions. Our results emphasize the importance of attention to notions from dynamical systems theory in designing and deploying multi-agent systems.*

## 1. Introduction

The management of mobile ad-hoc networks (MANET's) [1] presents unique challenges that may overwhelm traditional network management approaches. Such networks are highly dynamic, severely constrained in their processing and communications resources, distributed and decentralized. Thus, centralized management approaches requiring accurate and detailed knowledge about the state of the overall system may fail, while decentralized and distributed strategies become competitive.

We have successfully applied fine-grained agent architecture modeled on algorithms used in biological systems [10] to a range of real-world problems, including manufacturing control [2], pattern recognition in sensor networks [4], collaboration and task assignment among multiple mobile platforms [12], path planning for unmanned vehicles [15], and information retrieval in massive data [16]. This paper explores the applicability of these mechanisms to another domain, mobile ad-hoc communication networks (MANET's). Like other domains in which swarming is effective, MANET's are distributed, decentralized, and dynamic. Self-organizing

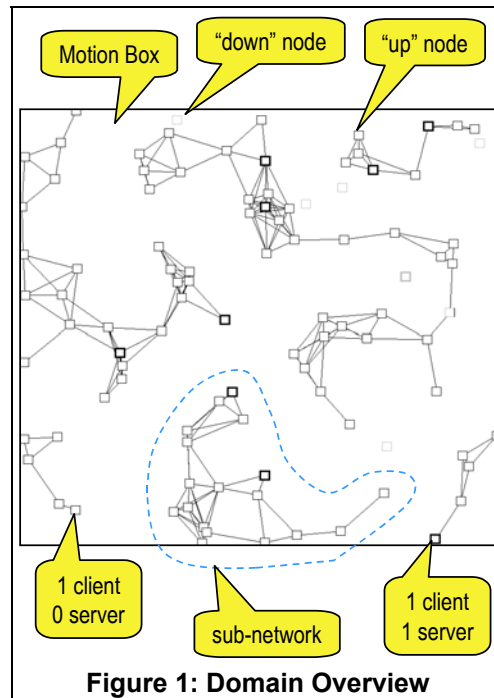


Figure 1: Domain Overview

systems of agents with emergent system-level functions offer an approach that is robust, flexible, adaptive and scalable. By applying our techniques to a new domain, we gain experience with their capabilities and restrictions, and further exercise the development methodology that we are developing for such systems [11, 14].

Section 2 presents a concrete management problem in the MANET domain. Section 3 offers a solution based on fine-grained agents dynamically interacting in the network environment.<sup>1</sup> Section 4 offers experimental evidence for the effectiveness of our solution. Section 5 concludes.

## 2. The MANET Server Management Problem

Figure 1 offers an overview of the MANET domain. Assume a

network of (randomly) moving nodes that may communicate within a limited range, and may fail temporarily. A canonical example of an application for a MANET is a fleet of vehicles (say, trucks or dismounted troops in a military operation, or rovers exploring a remote planet) equipped with line-of-sight radios.

We focus our attention on configurations in which nodes may host distinct client and server processes. Every node carries a client and some nodes carry a server process. Examples of services that might be restricted to some vehicles include

- long-range communications links back to a remote commander;
- wide-range sensors that can provide an integrating context for more local sensors carried on most vehicles;
- target recognition databases and data fusion capabilities that can provide interpretive support for platforms with more local access.

<sup>1</sup> A demonstration of this system (software simulation) will be available to be shown at the conference.

A server provides a stateless and instantaneous service to a client upon request if there exists a communications path between the client and the server and if the server node is currently active. Servers in our model have no capacity constraints, and may serve as many clients at the same time as requests arrive.

Because the nodes are mobile, weight and space are constrained, limiting the power available for communications and processing. Some of the likely services (long-range communications or sensing) impose especially high power demands on the servers, making it desirable to operate them only when they are needed to support the demands from the rest of the fleet. Vehicle movement must satisfy two

constraints: achieving mission objectives and maintaining communication connectivity. In the simple example we describe here, all vehicles share both objectives, but techniques that we have demonstrated elsewhere [12] permit vehicles to specialize for different tasks, so that some vehicles would dedicate themselves to serving as communication relays, reducing the constraints on the other vehicles imposed by the need to maintain connectivity.

The server management problem requires answering three questions: given the current topology of the network determined by node locations, communications ranges and node availability, decide

1. which server nodes should actually expend battery power to execute the server process;
2. to which server node a particular client should send its next service request; and
3. where to relocate server nodes to meet the current demand by the clients.

Thus, the network must be provided with mechanisms that self-diagnose the current network state (e.g., breaking of connections, availability of new connections, failure of nodes) and provide the information in a way that enables it to self-configure the ongoing processes appropriately. These functions could be satisfied if all servers executed constantly and if all clients had global knowledge of the overall system (Figure 2), but such a solution is impractical.

MANET's are an active area of current research, but until recently the focus of the MANET community has been on issues such as routing [8], access control [6], and security [18]. Recent research considers the service discovery problem in MANET's, using service brokers to maintain directories of available servers [5, 7, 9, 17]. This

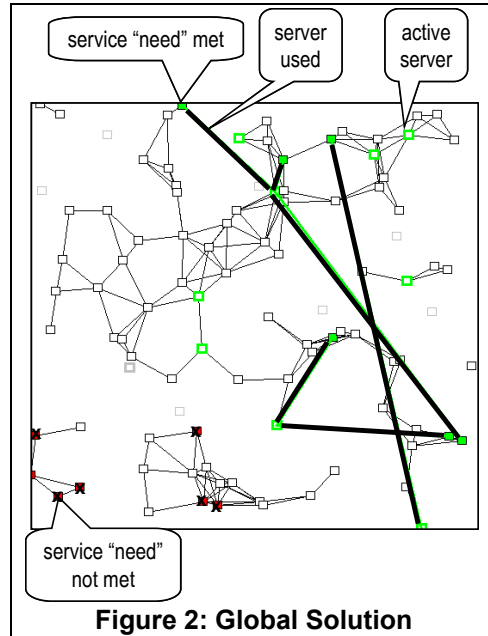


Figure 2: Global Solution

research addresses the second question of the server management problem but not the first and third, and does not contemplate highly dynamic situations that can frustrate directory-based schemes. Our approach offers an integrated solution to all three problems and does not require the construction or maintenance of any centralized directories.

### 3. Emergent MANET Management

A fine-grained, self-organizing agent system can solve the service location problem specified in Section 2. Our solution starts with the following initial conditions:

- Server processes shut down immediately if no requests arrive.

- A client does not know about the location of servers in the network, unless the client is co-located with a server on the same node.
- Server nodes move randomly (a zeroth order approximation to mission-motivated movement).

Thus, in terms of our design goals, we preserve maximum battery power, but most clients' service needs are not met since they don't know which server to address.

We now define a co-evolutionary learning process based on individual reinforcement. This learning process has three components.

1. The server population learns to maintain an appropriate number of active server processes,
2. and to adjust the position of these processes as they learn about the clients who are using them.
3. The client population learns to direct requests to active servers.

#### 3.1 Server Activation Learning

Any server node is aware of the incoming requests from one or more clients. If the server process is running, then these requests are served, otherwise they fail, but the node will immediately start up the server process to be available for any new requests in the next cycle. While the server process is running, it tracks the number of incoming requests. If there are no requests, it will begin a countdown. It will either abort the countdown if new requests arrive (and are served), or shut down if it reaches the end of the countdown.

Initially, the duration of the countdown is zero. Thus, server processes are shut down as soon as no new requests come in. We define the following simple rein-

forcement learning process to adjust the duration of the next countdown:

(+) If a request from a client arrives and the server process is down, we increase the length of the countdown period for subsequent countdowns, since apparently the server should have been up and we lost performance (failed to serve a request) while the server was down.

(-) If no request arrives while the countdown proceeds and the server process reaches the end of the countdown, then we decrease the length of the countdown period for subsequent countdowns, since apparently the server could have been down already and we wasted resources (battery power) while the server was up.

Driven by the demand pattern as it is perceived at the particular server node, the server process learns to maintain the optimal availability. In effect, the server learns the mean time between requests and adjusts its countdown length accordingly to stay up long enough. With this learning mechanism in place, the client population will now assume the role of the teacher as it generates a demand signal that leads some servers to stay down (extremely short countdown) while others stay consistently up (extremely long countdowns).

### 3.2 Client Preference Learning

Initially, only clients that are co-located with a server on the same node have any information about possible server addresses. These clients will become the source of knowledge of the client population as they share this information with their neighbors.

**Knowledge Representation.**—Clients manage their knowledge about and evaluation of specific servers in a dynamic set of scorecards, one for each server they know. A scorecard carries the address of the server, a score in favor (*pro*) and a score against (*con*) using this server. The current score of a server is computed as  $pro - con$ .

**Decision Process.**—When a client needs to select a server, it normalizes the current scores of all scorecards so that they add up to one and selects a server with a probability equal to the normalized score (roulette wheel selection). Thus, servers with a low current score compared to others have a lower probability of being chosen by the client. If the client currently does not have any scorecards, then it can only contact a server if it co-located with one, otherwise its service need will not be met in this decision cycle.

**Information Sharing.**—If a client selects a server on a node that is currently within reach, it sends a request to the server and share the outcome of this interaction with its direct neighbors. If the request is met, the client increases its own *pro* score of that server by one and sends the same suggestion to its direct neighbors. If the request is not met, the *con* scores are increased in the same way. These suggestions to the neighbors may lead to the crea-

tion of new score cards at those neighbors if they had not known about this server before. Thus knowledge about relevant servers spreads through the network driven by the actual use of these servers. Furthermore, the success or failure of the interaction with a server reinforces the preferences of the client population and thus (with a random component to break symmetries) dynamically focuses the attention on a few active servers while encouraging de-activation for others (see “Server Activation Learning”).

**Truth Maintenance.**—The constant change of the network topology, driven by the node movements and their failures, requires that the client population continuously update its knowledge about reachable servers and their evaluation. While the score-sharing mechanism ensures that the performance of a reachable server is continuously re-evaluated, the clients still need a mechanism to forget references to servers that do not exist anymore or that are out of reach now. Otherwise, in long-term operation of the system, the clients would drown in obsolete addresses.

A client “evaporates” its scores (*pro* and *con* individually) by multiplying them with a globally fixed factor between zero and one in each decision cycle. Thus, both scores approach zero over time if the client or its neighbors do not use the server anymore. If both scores have fallen below a fixed threshold, then the scorecard is removed from the client’s memory – the client forgets about this server.

A client also chooses to forget about a particular server, if the *con* score dominates the *pro* score by a globally fixed ratio ( $con / (con + pro) > threshold > 0.5$ ). Thus, servers that are trained by the client population to be down are eventually removed from the collective memory and are left untouched. They only return into the memory of clients if all other servers have also been forgotten and their co-located client is forced to use them.

### 3.3 Server Node Location Learning

In a co-evolutionary process, the server and client populations learn which clients should focus on which servers. We can stabilize this preference pattern and reduce the need for re-learning by decreasing the likelihood that the connection between a client and its chosen server is disrupted. Since the risk for a disruption of the path between a client and a server generally increases with the distance between their nodes, moving the server node towards its current clients will decrease this risk.

We assume that any client and server processes have means to estimate their respective node’s current spatial location and that the server node may actually control its movement within certain constraints if it chooses to.

As a client sends a request to a server, it includes its current location in the request message. The server node computes the vector between the client and the server

location and adds up all vectors from all requests within a decision cycle. Vectors of requests that failed are negated before they are added to the sum. The resulting combined vector determines the direction of the next move of the server node. If the requests failed because the server process was down, then the node moves away from the “center of gravity” of the clients that contacted this server. Otherwise, the node will move toward these clients. The length of the step for the server node is fixed to a global constant, characterizing the physical ability of the node to move.

### 3.4 Stigmergic Coordination

The coordinated behavior of many simple agents (server, client, node) in the highly dynamic and disruptive MANET environment emerges from peer-to-peer interactions in a shared environment driven by simple rules and dynamic local knowledge. The individual components of the system are not explicitly aware of the overall system functions of self-diagnosis and self-reconfiguration.

The coordination mechanism detailed in this demonstration is an example of stigmergy, in which individual agent activity is influenced by the state of the agent and its local environment. As agent activity manipulates the environment, subsequent agent activity dynamics may change (Figure 4). If this flow of information between the agents through the environment establishes a feedback loop that decreases the entropy of the options of the individual agents, then coordinated behavior emerges in the population. We engineer the agent behavior and the indirect information flow, so that the emergent coordinated

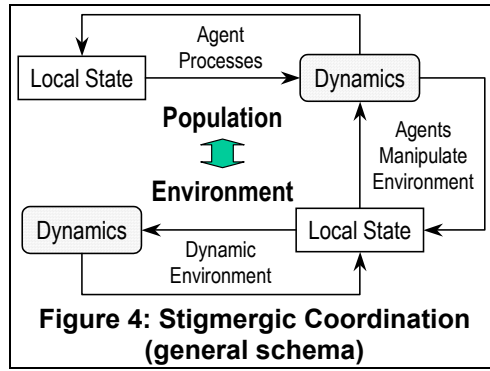


Figure 4: Stigmergic Coordination (general schema)

identify the emerging intention of the clients and to maintain the server processes on the correct nodes. Figure 3 identifies the main flow of information among the three populations driven by their respective dynamics and linked by the occurrence of successful or failed utilization events – requests from clients to servers.

A common feature of the server activation learning and client preference learning in our scheme is the combined reinforcement and decay of a critical decision parameter (the countdown on the server; pro and con scores on the server scorecards maintained by clients). Elsewhere [13] we describe this sort of process as “pheromone learning,” because it combines two of the hallmarks of insect pheromones: periodic deposits, and constant background evaporation. Pheromone learning can be viewed as reversing the traditional approach to truth maintenance. Rather than maintaining any knowledge until it is proven wrong, we begin to remove knowledge as soon as it is no longer reinforced. This approach is successfully demonstrated in natural agent systems, such as ant colonies, where information stored in pheromones begins to evaporate as soon as it is laid down.

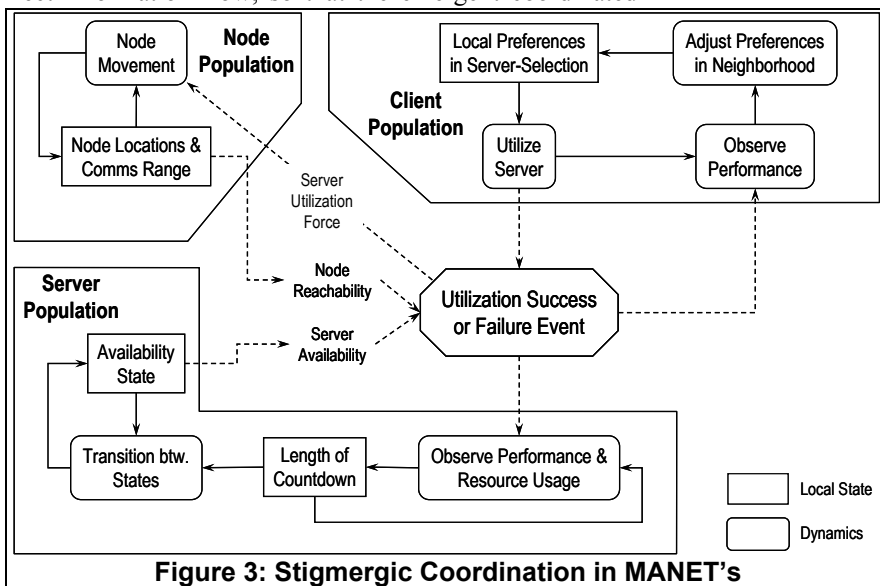


Figure 3: Stigmergic Coordination in MANET's

behavior meets the design goal.

Three populations of processes (agents) contribute to the emerging system functionality. Because each population operates in the shared network environment, the other populations influence its dynamics. For instance, the clients coordinate their server choice through the exchange of scores, but their ability to focus on only a few servers depends on the server population’s ability to

## 4. Performance Analysis

As engineers, we need not only to conceive innovative architectures to address challenging real-world problems, but also to analyze these architectures to determine their performance as a function of deployment conditions. Such analysis requires three elements: a baseline against which to compare the performance of the innovation, a set of metrics to make this comparison, and experiments to apply the metrics to the new system.

### 4.1 Baseline

Baselines for performance evaluation can be of two kinds. Sometimes

we have performance data for a conventional system and wish to show how our system compares with it (a relative evaluation). In other cases we have an upper bound on performance, a bound that may not be achievable in practice, but that shows how close to the theoretically best performance our solution (or any other) comes (an absolute evaluation).

In the case of MANET's, we can define a global solution that provides the highest possible request-success rate for the clients. We ignore the desire to preserve battery power and let all server nodes execute the server process at all times (maximum server availability). We use global knowledge (requiring very large bandwidth) to determine for a client that wants to send a request, which available server nodes are currently in range (path exists), and then we select the recipient of the request randomly from this set.

This solution formally avoids sending requests to servers that are out of reach, whose node is currently down, or whose server process is currently not executing. But its resource requirements are too large to meet the severe constraints of the application domain (ad-hoc mobile wireless network among battery-powered nodes). Also, from a more programmatic point of view, this solution does not demonstrate emergent cognition, since the complexity of the individual node (client) is as high as the system-level complexity. Nevertheless, this solution provides us with a performance and resource-usage baseline against which we measure our local approach in the demonstration.

## 4.2 Metrics

We focus our attention on two metrics of a system under a particular set of deployment constraints: resource gain and performance loss. Both are ratios comparing a key system-level feature with the baseline.

Resource gain describes the percentage of servers that our mechanism keeps on standby, that would be running and burning power in the baseline. The total number of servers is a constant in this scenario, and all of them are running in the baseline. So resource gain is directly proportional to the total number of servers on standby.

Performance loss measures the failure of service events in our mechanism compared with the baseline. Let

$N$  = total number of service requests

$N_b$  = total number of requests satisfied by the baseline;

$N_t$  = total number of requests satisfied by the test system.

Since the baseline is the best possible in any given circumstance,  $N_t \leq N_b \leq N$ . Performance loss is defined as  $(N_b - N_t)/(N - N_b)$ . Unlike resource gain, performance loss is compared against a changing baseline, since  $N_b$  varies

with system configuration, so we also track raw performance of our scheme.

## 4.3 Comparison with the Global Solution

With a baseline and metrics in hand, we can explore the performance of our system. The following discussion is meant to be exemplary, not exhaustive. We explore the variation in metrics as a function of three network characteristics: the degree of connectivity, the dynamics of individual servers, and the overall demand from the clients. <<Note to referees: the plots in the final edition of the paper will include error bars to reflect the precision of the points.>>

### 4.3.1. Configuration

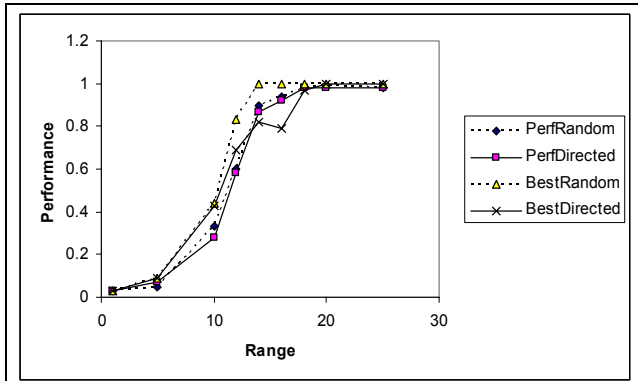
Our experiments envision a population of 100 nodes, of which 25 can serve as servers. They are initially distributed randomly in an arena sized 100 x 100, so the average area per node is 100, with radius  $\sim 5.6$ , leading to a mean internode separation on the order of 11. At each time step, several parameters determine the dynamics of the system.

- Range is a measure of the communications range of the nodes, in the same units that define the dimensions of the virtual world within which the nodes are distributed. The default setting is 15, which is greater than the mean internode separation of 11.
- DownProb ( $p_d$ ) is the probability that a node will go out of service due to failure. The default setting is 0.02.
- UpProb ( $p_u$ ) is the probability that a failed node will resume operation. The default setting is 0.90.
- UtilizationRate is the probability that a given node requests service. The default setting is 0.10.
- NodeMovementPolicy can be either directed (in which case servers and clients implement the algorithm outlined in Section 3.3) or random (in which case the direction of movement is chosen randomly, as a zeroth-order approximation to mission movement).
- ClientStepLength and ServerStepLength define the distance (in the same units as Range) that a node moves in adjusting its location under either movement policy. The defaults are 0.5 and 3.5, respectively.

### 4.3.2. Impact of Network Connectivity

A critical characteristic of a MANET is the range of the radios that provide the communication links. Figure 5 shows the raw performance of our scheme and of the baseline, using both random and directed node movement. We hold all parameters at their default settings and vary NodeRadius.

As one might expect, performance increases monotonically with radio range. In general, all four schemes are quite close. The baseline with random movement (BestRandom) dominates. Interestingly, the baseline with directed movement becomes worse than other schemes at



**Figure 5: Raw Performance as Function of Range**

high ranges. The directed movement of servers toward selected clients is not necessary, and distorts the distribution of servers, leading to less than optimal performance. This detail suggests an important insight for adaptive systems. A mechanism that is intended to provide adaptivity may actually prove harmful unless the system is configured to take advantage of the adjustment that it provides.

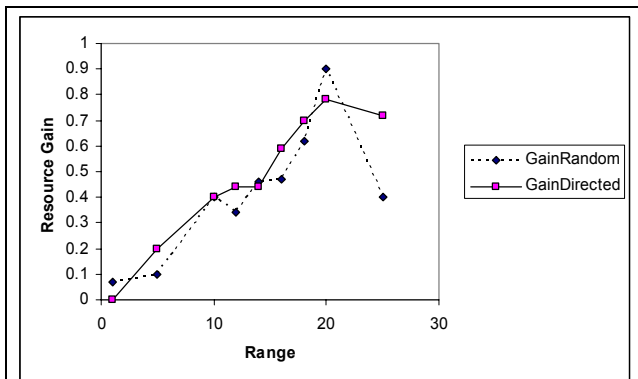
While the performance is comparable between our mechanism and the baseline, we show clear improvement with resource gain, as shown in Figure 6. (The standard deviation for resource gain at high ranges is on the order of 20%, so the apparent divergence at high ranges may be only statistical.)

Clearly, our mechanism improves resource utilization significantly without impacting performance, compared with a best-case solution that may not be implementable. The impact of directed movement does not appear to be significant at the level we are applying it, and we do not further consider it in this paper.

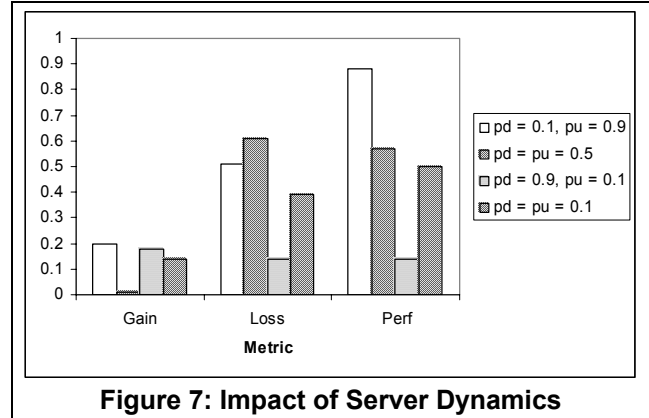
#### 4.3.3. Impact of Network Dynamics

Figure 7 shows how resource gain, performance loss, and raw performance vary as a function of server dynamics. Utilization is set at 0.5 and range at 15. For each metric, the figure shows four cases.

$p_d = 0.1, p_u = 0.9$ .—This configuration reflects highly



**Figure 6: Resource Gain as Function of Range**



**Figure 7: Impact of Server Dynamics**

reliable servers that seldom go down and are quickly repaired, a “best case” scenario from the operational point of view.

$p_d = 0.9, p_u = 0.1$ .—This configuration reflects highly unstable servers that take a long time to repair, a “worst case” scenario.

$p_d = p_u = 0.5$ .—This configuration reflects symmetric mean-time-to-failure and mean-time-to-repair characteristics with a moderate value.

$p_d = p_u = 0.1$ .—This configuration reflects symmetric mean-time-to-failure and mean-time-to-repair characteristics with a low value.

Consider first the performance loss (“Loss”) and raw performance (“Perf”) results. Performance does not vary greatly across the cases, except that it suffers badly in the worst case (as one might expect). Note that performance loss is also low for the worst case; relative to the baseline, our algorithm does better in the worst case than in the more stable cases, because of the adaptivity that it provides.

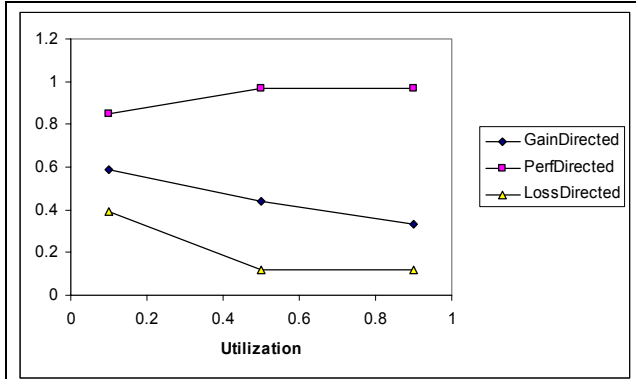
Now consider the resource gain results. Our worst case performance (the third bar) is almost as good as the best case performance (the third bar), again reflecting the benefits of adaptivity in coping with unstable systems. In the case of equal and moderate failure and recover probabilities, we do little better than the baseline. This configuration changes so frequently that our learning process does not have time to adapt to the changed environment.

#### 4.3.4. Impact of Demand

Figure 8 shows the impact of changing utilization. All other parameters are fixed at their default values.

Raw performance increases with utilization, and performance loss decreases. Adaptive schemes such as ours require a steady stream of information about the environment, which in our case is provided by the success or failure of service requests. When service requests are at a very low level, the system cannot adapt effectively, reflected in the performance changes.

In spite of this greater adaptivity, resource gain drops with increased utilization. The higher message traffic



**Figure 8: Impact of Varying Utilization**

stimulates servers to remain awake that would otherwise go to sleep, lowering the resource benefits. The system successfully adapts the number of active servers to changes in the overall message load.

## 5. Conclusion

Swarming fine-grained agents offer an effective approach to real-time control of mobile ad-hoc networks. Our experiments show that we can reduce the resource requirements for servers in a MANET without significantly diminishing the system’s performance, relative to an optimistic and probably unachievable baseline. Our experiments suggest two guidelines for when such approaches are applicable.

1. Because we rely on feedback from client attempts to access service as our source of information about the environment, the system requires a reasonable level of utilization. It is not appropriate for systems that are rarely utilized, but that must work appropriately when they are occasionally activated. However, the algorithms do adapt appropriately over a wide range of utilization levels.
2. Our methods work well when either failure probability or repair probability is low, since these characteristics lead to fairly stable server populations. When the probabilities of server failure and server repair are both high, the world changes too rapidly for our agents’ pheromone learning mechanisms, and system efficiency (as measured by resource gain) suffers.

The system described here is a highly simplified initial model of the MANET domain. We hope to explore several extensions of this domain.

- This model assumes that the movements of all vehicles are equally constrained by the same movement policy, either random (to simulate mission movement) or directed (to improve communications effectiveness). Using task allocation mechanisms similar to those we explored in [12], it would be interesting to examine fleets in which different platforms follow

different movement policies, enabling some platforms learn to specialize as communication relays, and leaving other platforms more latitude for their mission-oriented tasks.

- It will also be important to examine the effect of more realistic models of mission-related movement, instead of the surrogate of random motion used here. For example, we might explore space-filling behavior to model exploratory missions, or divergence and reforming of the fleet as it moves in a general geographical direction.
- The preliminary results reported here do not show any benefit to directed movement of servers with respect to their emerging client populations. This result is counter-intuitive, and we wish to do further analysis and experimentation to understand whether and under what circumstances servers can improve system performance by directed movement.
- The breakdown of our system at low utilization levels may be mitigated in part if we make use of the “heartbeat” signals that communication nodes routinely exchange to monitor their connectivity, and we wish to explore ways that these signals can contribute to the service provider problem.
- Service provision is only one of many functions that a MANET can provide. We believe our mechanisms hold far more general promise, and look forward to expanding them into a general scheme for MANET management.

Using self-organization and emergence to engineer system-level functionality may be advantageous in many application domains, but often it is not obvious how to design the underlying processes to achieve the desired function. We discuss this aspect of the problem elsewhere [3].

## 6. Acknowledgments

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