An Ecological Approach to Agent Population Management

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Abstract

The problem of maintaining a desired number of mobile agents on a network is not trivial, especially if what is required is a completely decentralized solution. Decentralized control makes a system more robust and less susceptible to partial failures. The problem of agent population management is exacerbated on wireless ad hoc networks where host mobility can result in significant changes in the network size and topology. System stability is also of critical importance. This paper analyzes the stability of a previously proposed ecology-inspired approach to agent population management, and proposes improvements. The stability of the new ecology based strategy is proved theoretically, and the conclusions are verified with a set of experiments.

Introduction

The problem of balancing supply and demand on multi-agent systems (*MAS*) is not new, and is becoming more prevelent as MAS and mobile ad hoc networks (*MANET*) become more popular. One specific type of supply-demand relationship is the demand for jobs of a certain kind and the supply of agents to complete those jobs. Satisfying this balance is critical to system performance and stability, since an insufficient number of agents forces jobs to accumulate over time, preventing the system from benefiting from the parallel nature of the networked MAS. On the other hand an excessive number of agents slow the system down with unnecessary processing and communications overhead. This problem is amplified if the agent system is running over a MANET, since such networks may be composed of lightweight devices that are restricted in terms of processing power, memory, available bandwidth and battery power.

Previously, attempts to solve this problem used auctioning, voting, cooperative negotiation (Conry *et al.* 2004) and distributed constraints satisfaction (Mailler & Lesser 2004). Because dynamics of MANETs make centralized approaches impossible, we present an analysis of an ecology based approach that does not require centralization. There are two major approaches to simulating an ecosystem (Flake 1998). One is a species-based view of the system, where large classes of individuals interact in the simulation (e.g., modeling the dynamics of species interaction rather than the interaction of individuals). The second approach is a bottom up construction of an ecological simulator, focusing on simulating individuals and their interactions. What is often missing in current research is the correlation between these two levels. Connecting these levels allows us to:

- Predict the system behavior on the global level;
- Deduce the set of local interactions leading to desired global behavior; and
- Analyze the stability of global behavior based on the stability of local interactions.

In this respect, this paper focuses on *species-based* analysis of *individual-based* software agent systems.

Related Work

Agent System Stability

Service replication. This approach to improving system robustness looks at replication of agents and/or services on the MAS network. It was investigated by several researchers (Gartner 1999; Marin *et al.* 2002). Most focus on the methodology of agent/service replication. This paper provides the extended analysis of the agent replication techniques based on an ecological model originally proposed by Peysakhov: (Peysakhov, M.; Cicirello, V.; Regli, W. 2004).

Probabilistic models. This research assumes some uncertainty in agent behavior or the agent's environment, and suggests techniques for estimating and improving the state of the agent-based system. One of the first researchers to analyze probabilistic survivability in an MAS was Kraus in (Kraus, Subrahmanian, & Tacs 2003). Kraus proposed a probabilistic model of MAS survivability founded on two assumptions:

1. The global state of the network is always known.
2. The probabilities of host or link failure are known.

Unfortunately, these assumptions rarely hold in real life (Leland & Porche 2004). An alternative approach enables agents to reason about the state of the network and security of their actions (Peysakhov *et al.* 2004).

Stability theory. The problem of system stability is by no means unique to agent systems. Agent based systems are a subset of a much larger class of discrete event systems. Ramadge and Wonham (Ramadge & Wonham 1989) summarized the control theoretic approach to controlling discrete event system models.

Ecological Model

The classic technique for analysis of natural predator-prey systems was proposed by Lotka (Lotka 1925) and Voltera, who presented a system with a single type of predator and a single type of prey. The system exhibited non-dampened oscillations, and would stay in neutral equilibrium (i.e., the cycle would persist, unless disturbed, but small disruptions could put it on a cycle arbitrarily close to the original).

Synthetic Ecology

An example of an individual-based approach to ecosystems is a simulated habitat populated with synthetic organisms (Olson & Sequeira 1995). These are often used to study the evolution and co-evolution of different species and to test their interactions and emergent behavior. Genetic Algorithms (Goldberg 1989) and Genetic Programming (Koza *et al.* 1999) engines can be used in conjunction with synthetic ecosystems to allow species to evolve over time. Some of the most well known examples of this are Evolve 1, 2 and 3 (Rizki, M., Conrad, M. 1985) and "Artorg world" (Assad & Packard 1992). Note that our paper focuses on solving the technical problem of agent population management, not simulating an ecosystem.

Problem Formulation

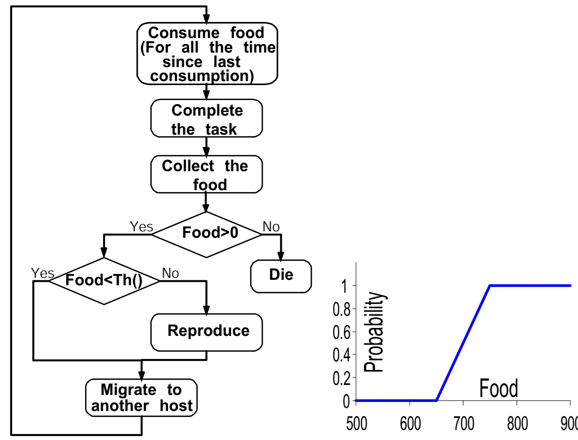
Motivation

A MANET is a challenging environment for software system designers due to its dynamism and unpredictable nature. Network links can go up and down and nodes can enter and leave the network depending on a variety of physical factors, such as movement of hosts, terrain, weather, interference, or available battery power. Agent based systems, with their runtime flexibility, can adapt to such an environment better than centralized systems (Sultanik *et al.* 2003).

If an MAS can be designed to be decentralized and distributed, it will be more robust than other, centralized, approaches when confronted with partial failures. This benefit comes at the cost of control—it is much more difficult to coordinate and control a decentralized MAS. As outlined by the DARPA ANTs project[1] without centralized control, designers need to count on emergent behaviors of the system, which arise from the combination of local interactions among individual agents. This paper concentrates on an ecology-inspired approach to the agent population management initially proposed in (Peysakhov, M.; Cicirello, V.; Regli, W. 2004).

System stability is a central problem for an MAS software engineer, just as it is in other complex systems. This is especially true for systems that must perform in noisy, dynamic environments. The distributed nature of an agent system increases the difficulty of enforcing system stability. Given the importance of stability theory in other fields, it is used here to analyze the stability of the following ecological approach and make improvements, which are presented in the improving for stability section.

[1] `http://www.rl.af.mil/div/IFT/IFTB/ants/ants.html`



(a) (b)

Figure 1: The agent's life cycle (a) and probability of reproduction vs food level (b).

Previously Suggested Approach

The model proposed by (Peysakhov, M.; Cicirello, V.; Regli, W. 2004) can be summarized as follows:

1. Jobs are associated with food producing areas.
2. Agents which successfully complete the job collect all of the associated food points.
3. Agents consume food regularly to stay alive.
4. Agents that exhaust their food supply die.
5. An abundance of food causes new agents to spawn.

An agent first checks the time since it last consumed food, and subtracts the appropriate amount of food from its food bank. If there is food on the local host, the agent completes the job and collects the associated food. Next, if the agent's internal food bank is empty, the agent terminates its thread of execution. If the internal food reserve of an agent is greater than the value returned by a fuzzy threshold function, the agent creates a replica of itself, splitting the food stored between itself and the new agent. In the last step, the agent migrates to another host, looking for more food, i.e., jobs to complete. A diagram depicting the agents' life cycle is shown in Figure 1(a). The reproduction is random, with a probability dependent on the current amount of food accumulated by the agent, as shown in Figure 1(b). An agent's probability of reproducing is 0 if it has less food than f_{min}, is 1 if it has more food than f_{max}, and increases linearly as the amount of food it has increases from f_{min} to f_{max}.

In some cases there is a sequence of migrations that leads to extinction. To recover from this state, tasks were allowed to spawn agents whenever an excess of food accumulated.

Formal Model

H denotes the set of food producers, with the production rate defined by a function $F_h(t)$ for each individual producer h. A defines the set of consumers and $f_a(t)$ is the predefined consumption function for each consumer a. Previously, these two functions were set to constant rates, $F_h(t) = g, \forall h \in H$, and $f_a(t) = b, \forall a \in A$. The third parameter c represents the probability that on a network of a given topology a random agent will find some amount of food. This parameter encapsulates properties of the graph, speed of agent migration and several other characteristics of the system and the only parameter outside of our control. The behavior of the system can be approximately described with a system of differential equations, where $\mathscr{A}(t)$ is the number of agents, and $\mathscr{F}(t)$ is the amount of food in the system as functions of time.

$$\frac{d\mathscr{F}(t)}{dt} = g - b\mathscr{A}(t), \frac{d\mathscr{A}(t)}{dt} = \mathscr{A}(t) \times (c\mathscr{F}(t) - b)$$

Dividing the second equation by the first one and integrating both sides results in the implicit equation for the system:

$$g \times \ln \mathscr{A}(t) - b\mathscr{A}(t) = \frac{c\mathscr{F}(t)^2}{2} - b\mathscr{F}(t) + K$$

All the solutions in the feasible region, i.e $\mathscr{A}(t) >= 0 \wedge \mathscr{F}(t) >= 0$ are periodic orbits with critical points at $(\frac{b}{c}, \frac{g}{b})$.

Figure 2(a) presents the trajectories in $(\mathscr{A}, \mathscr{F})$ coordinates for four different values of the integration constant. Note, that one stable solution has no agents $\mathscr{A}(t) = 0$ and linearly growing amounts of food $\mathscr{F}(t) = e \times t + K$.

Model Analysis. The only variable of interest in the system is the number of agents $\mathscr{A}(t)$, whose value at the critical point depends only on the ratio of the production rate g to the consumption rate b, and is independent of the parameter c that represents the network topology and communication delays for solutions with one or more agents.

Another important observation is that the system stays on a given closed trajectory for indefinite amounts of time, unless disturbed. An elliptically shaped trajectory in the neighborhood of $(\frac{b}{c}, \frac{e}{b})$, is implied by the solution:

$$\mathscr{A}(t) = K_1 \cos\sqrt{act} + K_2 \sin\sqrt{act}$$

of the following Jacobian matrix:

$$\begin{bmatrix} \dot{\mathscr{F}}(t) \\ \dot{\mathscr{A}}(t) \end{bmatrix} = \begin{bmatrix} 0 & -b \\ \frac{ec}{b} & 0 \end{bmatrix} \times \begin{bmatrix} \mathscr{F}(t) \\ \mathscr{A}(t) \end{bmatrix}$$

As the number of random samples along that trajectory goes to infinity, the average number of agents approaches $\frac{g}{b}$ for the trajectories that are close to the critical point.

$$\lim_{n \to \infty} \frac{\sum \mathscr{A}(t)}{n} = \frac{g}{b}$$

If perturbed, the system migrates off a new trajectory with the same critical point $(\frac{b}{c}, \frac{g}{b})$, unless the number of agents becomes zero. As the system transitions from one elliptic orbit to the next, the average number of agents stays at $\frac{g}{b}$.

It is necessary to mention that this model only approximates a real system. The key difference is that real system is discrete, whereas the differential equations used to describe it are continuous. Another difference is that the variable c,which encapsulates the properties of the network, is stochastic in nature. As shown in the Experimental Results section these discrepancies lead to some minor differences in predicted and observed system behavior.

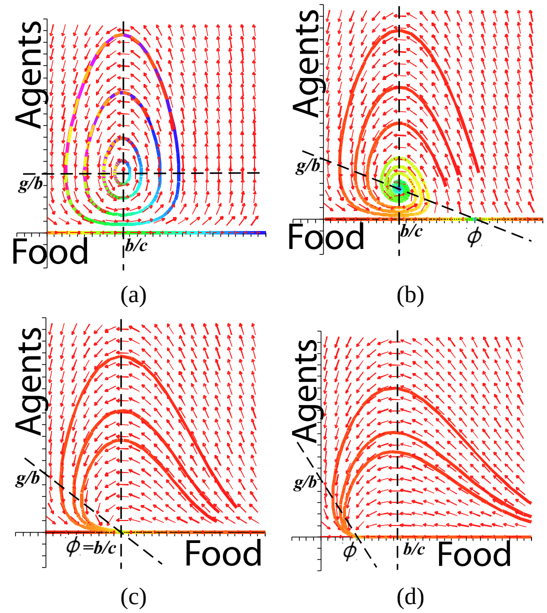


Figure 2: Phase plane analysis for: original ecology based system (a), self-stabilizing ecology based system (b), and self-stabilizing system with stable point at 0 agents (c), (d).

Correlation with the Experiments. The model described above correlates quite well with the set of experiments previously presented (Peysakhov, M.; Cicirello, V.; Regli, W. 2004). The experiments strongly suggest that the average number of agents on the network stays constant over long periods of time. Moreover, this number is largely independent of the network topology and communication delays, and is defined by the food production to consumption ratio.

Limitations. Although the ecology based approach provably ensures that the average number of agents on the system will stay close to the ratio $\frac{g}{b}$, it has limitations. As Figure 2(a) shows, the system is in a state of neutral equilibrium. Since the possibility of disruptive events are very likely on MANETs, the system experiences constant pressure from random disruptions, forcing the system to move from one limit cycle to another. Similar to Brownian motion", these disruptions result in the system moving to cycles farther away from the critical point.The average number of agents on the system is near the target value $\frac{g}{b}$, but the actual number of agents at a given moment can fluctuate wildly. Even this property may not hold as the system shifts to larger, less elliptical cycles.

Improving for Stability.

The need for a self-stabilizing solution is clear, given the aforementioned theoretical limitations of system stability in ecologically inspired agent population control models. In the previous model, food growth was an exponential function without a ceiling, similar to the growth rate of bacteria in the presence of unlimited resources. However, this is unsustainable, and it is more realistic to cap the amount of food that each task can accumulate at some value ϕ_h. The food growth on a single host is defined by the equation:

$$\frac{dF_h(t)}{dt} = g \times (1 - \frac{F_h(t)}{\phi_h})$$

Solving that differential equation yields the formula for computing the amount of food grown on the host.

$$F_h(t) = \phi_h + C_1 \times e^{-\frac{gt}{\phi_h}}$$

Summarizing over the set of hosts:

$$\frac{d\mathscr{F}(t)}{dt} = g \times (1 - \frac{\mathscr{F}(t)}{\Phi})$$

Where $\Phi = \sum_{h \in H} \phi$ is the maximum amount of food that can be produced by the system on H hosts. This model and the equations describing agent populations and food consumption can be combined into a system of differential equations.

$$\frac{d\mathscr{F}(t)}{dt} = g \times (1 - \frac{\mathscr{F}(t)}{\Phi}) - b\mathscr{A}(t)$$

$$\frac{d\mathscr{A}(t)}{dt} = \mathscr{A}(t) \times (c\mathscr{F}(t) - b)$$

The intersections of the isoclines produce two critical points $(\Phi, 0)$ and $(\frac{b}{c}, \frac{g}{b} - \frac{g}{c\Phi})$.

Phase-Plot Description. Figure 2 shows several trajectories for varying initial conditions and values of the parameters g, b, c and Φ. Some of these parameters, such as $\Phi = \infty$, will result in neutral stability and cyclic behavior of the system as shown in 2(a). Sub-figure 2(b) presents a stable solution at the point $(\frac{b}{c}, \frac{g}{b} - \frac{g}{c\Phi})$ and an unstable solution at $(\Phi, 0)$. This solution implies that system will eventually converge to the point $(\frac{b}{c}, \frac{g}{b} - \frac{g}{c\Phi})$ from any other feasible point with non-zero number of agents. Smaller values of Φ correspond to a faster convergence to the solution point, and a greater dependence on the network properties described by c, relative to large values of Φ. Figure 2(c) shows the phase plane with parameters set such that both critical points are equal, and 2(d) shows the system with a stable solution $(\Phi, 0)$ with zero agents. It shows that if the system cannot produce enough food to maintain a single agent, the agents die out and the amount of food stabilizes at the maximum.

Stability Analysis Point $(\Phi, 0)$ represents the equilibrium of the system without agents present. To analyze this solution for stability, we compute the Jacobian matrix and find Eigenvalues at the solution points. The solution is stable if and only if the real parts of all Eigenvalues are negative. By performing algebraic analysis one can see that the solution $(\Phi, 0)$ is stable when $\Phi \leq \frac{b}{c}$ (as shown in Figure 2(c)) and is unstable otherwise (Figure 2(b))Performing the same analysis at the second point, it is easy to show that the solution $(\frac{b}{c}, \frac{g}{b} - \frac{g}{c\Phi})$ is stable if $\Phi > \frac{b}{c}$ as shown in the Figure 2(b).

Experimental Results

A series of experiments using a discrete event simulator confirmed the above conclusions.The agents behaved as discussed in the previously suggested approach section and as

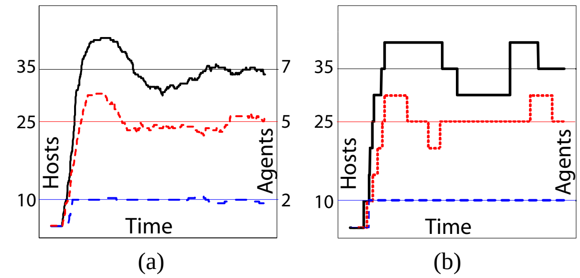


Figure 3: Transition process as given by average (a) and actual (b) number of agents for networks of 35, 25 and 10 hosts

depicted in Figure 1(a). They reproduced with the fuzzy threshold given in Figure 1(b). The experiments were limited to the set of homogeneous agents, but the theoretical part of this work does not require this limitation. Hosts used this same fuzzy threshold to spawn new agents.

All of the experiments were performed on a completely connected network of statically placed hosts. The hosts grew food at the rate 1 unit per iteration. Each experiment started with a single agent with an initial food bank of 500 units. The reproduction threshold was set to 700 ± 50 for hosts and agents. These values allow for less randomness in the system than the ones previously described (Peysakhov, M.; Cicirello, V.; Regli, W. 2004), resulting in more hosts reaching similar states simultaneously, thus increasing the chances of oscillatory behaviors. Hosts were not allowed to accumulate more than 900 food units.

System Behavior Over Time

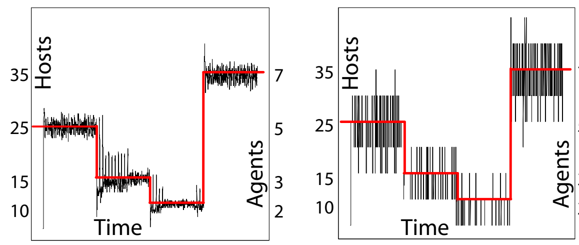
This section investigates the changes in the number of agents over time. The consumption rate was set to 5 food units per iteration for all agents. Each experiment consisted of 15 trials, which consisted of initializing a system and running 90,000 iterations. The number of agents was noted every 10 iterations and averaged across all trials. All experiments started with a single agent and gradually transitioned to the target number of agents. This process is shown in Figure 3. The average, 3(a), as well as actual, 3(b), number of agents increased rapidly, surpassed the target value, and then started to decrease, usually converging to the target value after a single cycle. The number of hosts and agents are shown on the left and right sides of the chart, respectively. The target relation is 5 hosts per agent. The horizontal lines show the target number of agents at any given moment in time.

Steady state description Given some final size performance band around the target value, the performance index describes the percentage of time the system spent inside the band. Given the target value of 1 agent per 5 hosts and 2 performance bands around it, Table 1 shows the performance indexes for fully connected networks of different sizes. The performance index of 94% for ± 1 band is usually acceptable for most practical applications.

Dynamic Environments The system was capable of responding to dynamic changes in the number of hosts. An experiment was set up similar to the one described above,

Perf. index	size			
	10	15	25	35
target	2	3	5	7
target ± 0	92.3%	69.8%	57.5%	49.2%
target ± 1	99.4%	99.5%	97.4%	94.4%

Table 1: The performance indexes for networks of different sizes for ± 0(i.e., right on target) and ± 1 performance bands.



(a) (b)

Figure 4: The average (a) and actual (b) number of agents for networks of changing size

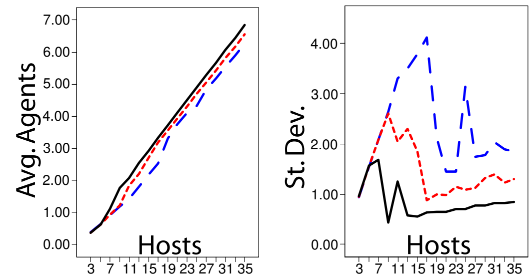
with one exception: the number of hosts was changed from 25 to 15 to 10 and then back to 35 without restarting the system. Such drastic changes in the number of hosts approximate the process of islanding and merging in wireless mobile networks of lightweight devices carried on foot by police or military units. When the hosts were shut down, all of the agents on these hosts and traveling to these hosts were also terminated. When brought back on-line, the hosts initially lacked food and agents. This change introduced a high level of disturbance into the system. With respect to the number of agents, Figure 4 shows the average across 15 runs and the actual number for a single run. The target number of agents at all times is presented by the bold step line.

The Effect of Demand on Equilibrium

As expected, the linear increase in task demand caused a linear increase in the number of agents. And, as the system model predicted, the actual equilibrium point was slightly lower than the target agents to servers ratio (e.g., with 35 hosts the average number of agents on the system was 6.8 rather than the target of 7). By increasing the maximum amount of food the host may accumulate, the equilibrium point could be brought closer to the target value, but at a price of decreased stability of the system. Figure 5 shows the linear growth of the average size of the agent population, the growth of the network, and the standard deviation.

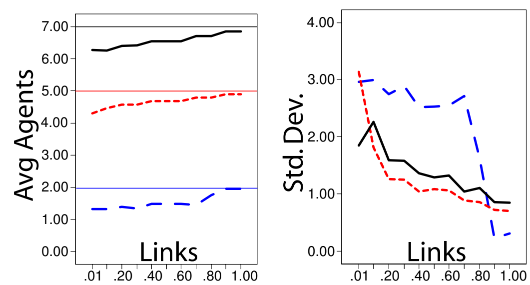
The Effect of Delays on Equilibrium

Out of all the factors *not* explicitly included in the model, the communication delays had the greatest significance. Introducing delays caused the average number of agents to diverge from the target, and the actual number of agents to oscillate within a wider range, reducing the system's stability. Table 2 shows how the performance index was affected by slower network speeds. All of the connections in the sim-



(a) (b)

Figure 5: The average number of agents (a) and the standard deviation (b), for networks with link delays of 0%, 50% and 100% of the maximum possible delay (top to bottom)



(a) (b)

Figure 6: The average num. of agents (a) standard deviation (b), for networks of 35 25 and 10 hosts (top to bottom)

ulator had a delay ranging from t_{min} to t_{max}. A link speed of p% means that the link delay is $\frac{t_{min} \cdot p + t_{max} \cdot (100-p)}{100}$.

This dependency between performance index and slower network speeds can also be shown with plots of the average number of agents and the standard deviation, with regards to link speed. Figure 6 shows such plots for networks of 35, 25 and 10 nodes. As the links became slower, the average population size declined by as much as 33% from the predicted equilibrium point. For larger networks, the decline was not as significant and ranged from 5% to 15%. Standard deviation was also higher, implying higher oscillations in the size of the agent population.

A Topology's Effect on Equilibrium

An idealized spectrum of network topologies, from linear to completely connected, corresponding to people moving in single-file formation, was used as the underlying topology for the experiments. In each subsequent experiment, the connectivity of the graph increased by one, i.e a connected linear graph is turned to 2-connected, 3-connected, ... , $(n-1)$-connected and fully connected graph, Figure 7(a).

As one can see from the resulting plots in Figure 7(b), 7(c) the average number of agents was largely independent from the network topology. Other than in linear or almost linear topologies, there was less than a 2% decrease in the average number of agents. This trend is insignificant and can be safely ignored for most practical purposes. Standard deviation is also higher for linear and almost linear graphs,

Net. Size	Perf. Band	Connection Speed 0.01	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
35	7 ±0	20.4%	18.3%	21.9%	23.1%	28.2%	29.0%	28.2%	37.7%	35.9%	47.7%	48.4%
35	7 ±1	55.1%	51.2%	62.2%	62.5%	74.9%	74.9%	74.4%	85.7%	83.7%	93.2%	94.0%
25	5 ±0	22.3%	23.3%	28.6%	30.2%	37.9%	36.8%	38.1%	46.7%	46.1%	56.5%	56.0%
25	5 ±1	54.2%	60.8%	73.8%	75.0%	85.0%	84.5%	83.15%	91.0%	92.6%	97.1%	98.1%
10	2 ±0	3.6%	2.4%	12.5%	7.0%	19.2%	23.2%	18.9%	20.7%	56.0%	94.3%	90.3%
10	2 ±1	11.0%	10.3%	25.9%	16.8%	39.6%	38.4%	38.1%	30.3%	77.1%	100%	100%

Table 2: Change in performance indexes for networks of different sizes with communication delays.

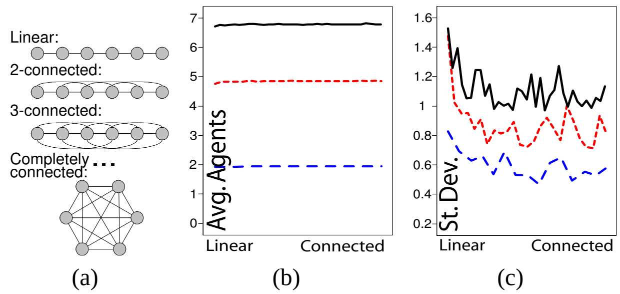


Figure 7: Graph topologies (a), average num. of agents (b), standard deviation (c), for networks of 35, 25 and 10 hosts

implying bigger oscillations of the number of agents.

Future Work and Conclusions

We are currently extending this work in several directions: 1. Create on-line methods for tuning parameters (such as consumption and production rates, and reproduction thresholds) using machine learning, swarm techniques or genetic algorithms; 2. Expand the model from a plant-herbivore system to a plant-herbivore-carnivore system. This would allow for more complicated food chains and more elaborate control over populations of different types of agents. For example, a system with information sources, information gatherers, and information evaluating agents will fit well into this model; 3. A closer analysis of the stochastic nature of the probability that an agent will find some amount of food. This investigation would allow for more descriptive model based on a system of stochastic differential equations.

This paper significantly improves the fidelity of an ecology-based model for managing agent populations on MANETs such as the Philadelphia Area Urban Wireless Network Testbed (PA-UWNT) (Cicirello *et al.* 2004), where ecology-based agents are being developed for a real-world-environment. The self stabilizing ecological agent population will be used used to disseminate information throughout the PA-UWNT network. The efficient use of the approach described above is possible because the demand for such tasks are highly dependent on the current size of the network. It has been determined through prototyping and testing that the proposed food growing strategy can lead to increased stability of the agent population and improve overall robustness of the system.

More importantly this paper showed the benefit of applying techniques from stability theory to the design of MAS.

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