Adaptive Routing in Wireless Communication Networks using Swarm Intelligence

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1 Introduction

There has been growing general interest in infrastructureless or "ad hoc" wireless networks recently as evidenced by such activities as the MANET (Mobile Ad hoc NETworking) working group within the Internet Engineering Task Force (IETF). Other examples are plans unveiled for NASA's Earth orbit satellite constellation networks, and the Mars network, consisting of a "web" of satellites, rovers, and sensors within a ubiquitous information network[1]. The main issues inherent in such an ad hoc network are the following:

- Dynamic network topologies, presenting challenges in routing and link bandwidth allocation
- Providing consistent quality of service levels subject to a changing environment
- Conservation of power, which is essential to users of mobile wireless networks
- Global vs. local longevity, i.e., how routing may be desirable on more "long-lived" routes

Intelligent network routing, bandwidth allocation, and power control techniques are thus critical for such networks that have heterogeneous nodes with different data rate requirements and limited power and bandwidth. Such techniques coordinate the nodes to communicate with one another while exercising power control, using efficient protocols, and managing spectral occupancy to achieve the desired Quality of Service (QoS). They also let the network adapt to the removal and addition of different high and low rate communication sources, changing activity patterns, and incorporation of new services.

In this paper we focus on the network routing problem, and survey swarm intelligent approaches for its efficient solution, after a brief overview of power-aware routing schemes, which are important in the network examples outlined above. The aim of intelligent network routing is to detect dynamic traffic and topology events, thus identifying network bottlenecks, addressing them in an adaptive, intelligent manner, and therefore maintaining a desired Quality of Service.

2 Power-aware Routing

A *Mobile Ad Hoc network* (MANET) is a collection of wireless mobile nodes, which dynamically form a temporary network, without using any existing network infrastructure or centralized administration. They are sometimes called *infrastructureless networking* since the mobile nodes in the network dynamically establish routing paths between themselves. Current typical applications of a MANET include battlefield coordination and onsite disaster relief management.

Because of the environment in which MANETs are typically employed, individual nodes are usually powered by batteries. In recent years, considerable amount of research has gone into designing power conscious routing schemes, with a view to minimizing energy consumption at the nodes and thereby prolonging the life of the overall communication system.

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[1] See http://sensorweb.jpl.nasa.gov

In [1], Woo, Singh and Raghavendra propose a multi-tier power conservation approach, optimizing the MAC layer, network layer and transport layer protocols individually. The routing algorithm they propose and implement involves choosing the minimum residual energy path so as to minimize the total node cost per packet. The cost at each node is defined as the residual battery energy at each node. Their MAC layer power optimization algorithm is discussed in [2].

In [3], Xu, Heidemann, and Estrin propose a couple of algorithms which attempt to optimize the power consumption in an ad-hoc network by minimizing the *idle time power dissipation* of the transmitters, while introducing additional latency in the system. Since transceivers expend precious energy overhearing transmissions, the proposed algorithms involve using application layer information to induce them to a "sleep" mode when not involved in useful work. The Basic Energy-Conservation Algorithm, BECA, is essentially a duty cycle, which controls the amount of time a transceiver spends in the "active" mode (when transmitting/receiving data), "sleeping" mode (transceiver switched off) and in the "listening" mode. The Adaptive Fidelity Energy-Conservation Algorithm (AFECA) uses knowledge of *node deployment density* to improve on the performance of BECA. Intuitively, if a node has a large number of neighboring nodes, it can afford to spend more time in "sleep" mode without any detrimental effect on latency, since there will always be a few neighboring nodes which will be "awake" to handle any routing requests originally directed to the sleeping node.

In [4], Subbarao proposes using channel conditions (e.g., attenuation/fading, power loss, interference, noise, bandwidth, etc.) to model link costs such that the transmitter can transmit at an optimal power level, which will guarantee a satisfactory SNR at the receiver(s). Related work, but geared towards multicasting in wireless networks, can be found in [5].

In [6] Stojmenovic and Lin propose a new metric for power aware routing as a function of nodes lifetime and distance between the nodes. They suggest that placing new nodes in between the current nodes would make the transmission power a linear function of the distance between the nodes.

Havinga et al [7] propose energy efficient adaptive architecture design and protocols that provide QoS support for different traffic situations. The proposal here is to do energy optimization at each layer of the network. An extension of this work to ATM networks is provided in [8]. E^2MaC [9] is another protocol designed for multimedia traffic to do energy conservation at the MAC layer. The idea is to avoid unsuccessful actions, minimize the number of transitions, and synchronize the mobile and base stations.

Chang and Tassiulas [10] propose *Flow augmentation* and *Flow redirection algorithms* for energy conservation. In *Flow augmentation* the cost of each link is calculated as a function of the residual energy, initial energy, and energy per unit transmission. The cost of each shortest path chosen is augmented by an amount proportional to the traffic generation rates. In *Flow redirection* two paths are chosen and a part of the flow from the original path is redirected along the new path.

Michail and Ephremides [11] propose different metrics for the cost between links in a connection-oriented wireless network. These metrics are various functions of transmission power and residual energy. Each metric has a different emphasis, like minimum power path, or use of under-utilized nodes.

3 Overview of Swarm Based Routing

A large body of work exists on the general problem of network routing. Wireless networks present particular difficulties arising from the dynamic nature of their topology, due to node movement, radio interference, node failures, and new additions. A variety of routing protocols have been offered and the best-performing schemes generally depend on the specific characteristics of the operating environment (such as distribution of connectivity and topology change rates).

Although in its infancy, swarm intelligence [12-15] is being intensely studied for applications in communication network routing. France Telecom and British Telecommunications (BT) have applied swarm intelligence to their phone networks. MCI Worldcom is also seriously investigating swarm intelligence for telephone network management in the United States.

The potential advantages of swarm intelligence over conventional centralized telecommunications approaches are enormously compelling. The *New Scientist* [13] recently gave troubling details about problems with BT's network, and the company's investigation of swarm intelligence as a potential solution. BT's 24 million users are coordinated through a conventional web controller that, in 1995, was comprised of 30 programs with average memory requirements of 350 gigabytes. "Much of [the controller's]... time is spent just checking that all the elements of the network are working. It must also be constantly updated as new subscribers, new services, and new problems emerge. As it gets older it becomes harder to adapt, and a failure at the center could have potentially disastrous effects across the whole network". The distributed nature of swarm intelligence avoids the troubling bottlenecks that result from continuous use of such a centralized controller.

Presently, routing algorithms developed for sensor networks usually assume equal data volume and priority from every sensor in the network. This is often not the case however. For example, seismic and acoustic sensor networks typically have relatively low data rates while imaging and spectrometric ones need to collect high-resolution images, requiring high data rates. In a sensor network that has heterogeneous sensors with different data rate requirements and limited power and bandwidth, an intelligent sensor network routing algorithm is required not only to coordinate the existing sensors to communicate with one another by methods of power control, efficient protocols, and spectral management to achieve desired sensing goals, but also to sense and adapt to the removal and addition of different high and low rate sensors and changing activity.

Swarm based routing algorithms [16-42] derive from recent understandings of basic principles underlying the operation of biological swarms, such as ants or honeybees. These swarms, often containing thousands or tens of thousands of elements, routinely perform extraordinarily complex tasks of global optimization and resource allocation using only local information. The swarm can perform such complex tasks due to intelligence emergent from the collective of all its elements. This is while each such individual element has relatively little intelligence, incapable of understanding or modifying the swarm behavior on a global or often even a broad regional scale. As an example, while the direction-finding ("routing") efficiency of an individual ant appears to be poor due to its random behavior, in fact the routing efficiency of the ant colony super-organism is extremely high as judged by the survivability of the species through finding their way to various food sources. The underlying principles governing these swarms are such that operating within a highly dynamic, random, and often-hostile environment is the routine and the norm, rather than the exception. As such, they offer tremendous insight and guidance into the development of algorithms designed to intelligently control systems with similar underlying characteristics, such as those of a wireless communication network.

Swarm-intelligent routing methods will enhance the reliability and timeliness of data transfer within a heterogeneous multi-node wireless communication network. They will significantly contribute to achieving the goal of *robust pervasive communication coverage* of a network. They will furthermore reduce the overhead in network growth due to their inherently scalable features.

4 Algorithms and Performance

Biological "networks" or colonies of ants and bees consisting of thousands and in some cases tens of thousands of dynamic elements exist. In the case of ant colonies, each ant has relatively little intelligence, while the collective emergent behavior of the network exhibits a great deal of global intelligence capable of dynamic near-global optimization of certain tasks. Engineering models and algorithms based on these biological systems have the potential to leverage the tremendous gains made this century in understanding their individual and collective colony-based behavior.

Initial work in swarm intelligence has revealed a great deal of synergy between the routing requirements of communication networks and certain tasks that exist in biological swarms. For instance, a key characteristic of swarm intelligence is the ability of agents (ants) to find optimal (or near optimal) routing (in food gathering operations for example), where intelligent behavior arises through indirect communications between the agents, a phenomenon known as *stigmergy*. Work completed to date in developing swarm based routing algorithms exhibits the following potential benefits:

- Dynamic “online” optimization using local information
- No exchange of global information for routing determination
- Inherent scalable nature, resulting in graceful builds and degradations
- Characteristics leading to robustness (fault-tolerance) under most contingencies

Emergent routing uses only local information and has shown to be immediately applicable to optimization of communication traffic control. The so-called sign-based stigmergy is highly developed in ants, and is a key concept to the development and manipulation of local information. Here information is deposited in the environment (the nodes) via *pheromones* that makes no direct physical contribution to the task being undertaken (data transmission), but is used to influence the subsequent behavior that is task related (data throughput). Over time the behavior is classified as autocatalytic, that is, a behavior established for some time in the past becomes more likely in the future. As stated, these concepts are immediately applicable to adaptive scalable routing algorithms and bandwidth allocation, as well as other task/resource allocation tasks.

A very successful example of swarm-based routing algorithms is the *AntNet* adaptive agent-based routing algorithm [16-27], which has outperformed the best-known routing algorithms on several packet-switched communications networks. For telephone communication networks, there also exists a very successful application of swarm intelligence via *Ant-Based Control (ABC)* [28-30].

We present an overview of the mechanics of these two algorithms below, as representative examples of biologically inspired routing methodologies.

4.1 AntNet

In the *AntNet* algorithm, routing is determined through complex interactions of network exploration agents, called ants. These agents are divided into two classes, the *forward* ants and the *backward* ants. The idea behind this sub-division of agents is to allow the backward ants to utilize the useful information gathered by the forward ants on their trip from source to destination. Based on this principle, no node routing updates are performed by the forward ants, whose only purpose in life is to report network delay conditions to the backward ants. This information appears in the form of trip times between each network node. The backward ants *inherit* this raw data and use it to update the routing tables of the nodes.

A typical routing table is shown in Table 1. The entries of the routing table are probabilities, and as such, they sum to one for each row of the network. These probabilities serve a dual purpose. The exploration agents of the network, the ants, use them to randomly decide the next hop to a destination. However the actual network traffic uses them deterministically, choosing as the next hop the route with the highest probability.

		Next Hop	
		B	C
Destination	E	0.15	0.85
	F	0.75	0.25

Table 1: Sample routing table

The sequence of routing actions is simple and intuitive. Figure 1 provides a graphical explanation of the algorithm described below:

1. Each network node launches forward ants to all destinations at regular time intervals.
2. The ants find a path to the destination *randomly* based on the current routing tables.
3. The forward ants creates a *stack*, pushing in trip times for every node as that node is reached
4. When the destination is reached, the backward ants *inherit* the stack
5. The backward ants pop the stack entries and follows the path in reverse
6. The routing tables of each visited node are updated based on trip times

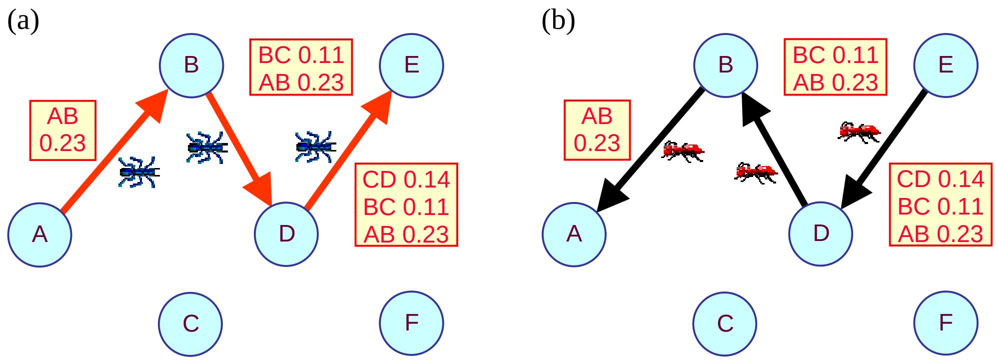

Figure 1: (a) Forward, and (b) backward ant movement in the AntNet algorithm.

The update of the routing tables of nodes is reminiscent of actor-critic systems [43-45], where the raw information contained in the trip time is processed by the critic and then used to train the actor in order to manage the system more efficiently (see Fig. 2).

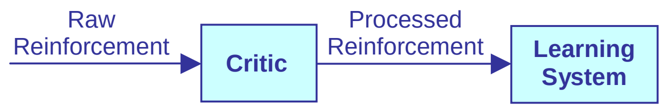

Figure 2: Actor-Critic System

The routing tables of nodes are updated as follows. First, one notes that in addition to the routing table, each node also possesses a table with records of the mean and variance of the trip time to every destination (see Table 2). This enables the algorithm to use the ratio of the variance to the mean (σ/μ) as a yardstick to measure the consistency level of trip times, and accordingly alter the effect of the trip time on the routing table.

Trip Times

Destination	Mean	Var
E	0.24	0.02
F	0.18	0.01

Table 2: Sample trip-time table

Next, we define a dynamic parameter *r'*, as an embodiment of route fitness information, which is changed according to changes in route trip times and statistics. It is defined as

$$r' = \begin{cases} \dfrac{T}{c\mu} \quad (c \geq 1), & \text{if } \dfrac{T}{c\mu} < 1 \\ 1, & \text{otherwise} \end{cases} \tag{1}$$

where T is the trip time, μ is the average value of T, and c is a scaling factor, usually set to 2.

Based on the computed value of *r'*, one determines if the trip time of an ant is good or bad. Corresponding strategies of either decreasing or increasing the value of *r'* by a certain amount are then followed, based on setting the threshold for the good/bad trip time to 0.5, and selecting a threshold δ for the (σ/μ) ratio (see Table 3).

The principle behind these updates is that small values of *r'* correspond to small values of T and

	$r' < 0.5$	$r' > 0.5$
$\dfrac{\sigma}{\mu} > \delta$	$+[1-\exp(-\alpha'\,\sigma/\mu)]$	$-[1-\exp(-\alpha'\,\sigma/\mu)]$
$\dfrac{\sigma}{\mu} < \delta$	$-\exp(-\alpha\,\sigma/\mu)$	$+\exp(-\alpha\,\sigma/\mu)$

Table 3: Processing for *r'*: Table values denote amounts by which *r'* is increased or decreased, based on the threshold for good/bad trip times (set to 0.5), and a threshold δ for the ratio σ/μ.

vice versa. By way of example, and examining the case where consistency is high and trip time is good, we would want the processed *r'* to be even smaller, to underscore the goodness of this trip time and its consistency. Therefore, an exponential quantity is subtracted. This quantity is an exponentially decaying function of the consistency ratio, therefore achieving its highest value when the variance is very small. The decay rate of the exponential can be controlled through parameters α and α'.

Further positive or negative reinforcement of good or bad routes takes place next, via *negative feedback*. Any positive reinforcement of probability should be negatively proportional to current probabilities, and any negative reinforcement should be proportional to current probabilities. The effect of this is to prevent saturation of the routing table probabilities to 0 or 1. The node that receives the positive reinforcement is the one that the backward ant comes from. This is exactly the same node that the forward ant chose as next-hop on its way to its destination. All the other neighbors of the current node need to be negatively reinforced, so as to preserve the equality to 1 of the sum of all the next-hop probabilities. The reinforcement equations are:

$$r_+ = (1 - r')(1 - P_{df}) \tag{2}$$

$$r_- = -(1 - r')P_{dn}, \qquad n \neq f, n \in N_k \tag{3}$$

where *d* is the destination node, *f* is the node from where the backward ant comes, N_k is the neighborhood of node *k* (current node), and P_{df} , P_{dn} are the previous probabilities (see Fig. 3).

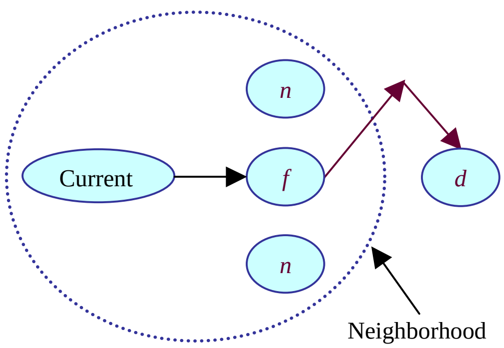

Figure 3: Current node neighbors and destination

Finally, routing table probabilities are updated using the following rules:

$$P_{df} = P_{df} + r_+ \tag{4}$$

$$P_{dn} = P_{dn} + r_- \tag{5}$$

The packets of the network then use these probabilities in a deterministic way, choosing as next hop the one with the highest probability.

4.2 Ant-based Control (ABC)

Ant-based Control (ABC) is another successful swarm based algorithm designed for telephone networks. This algorithm shares many of its key features with *AntNet*, but also has a few differences. The basic principle shared is the use of a multitude of agents interacting using stigmergy. The algorithm is adaptive and exhibits robustness under various network conditions. It also incorporates randomness in the motion of ants, which increases the chances of discovery of new routes. In this algorithm, the ants only traverse the network nodes probabilistically, while the telephone traffic follows the path of highest probability.

The routing table of every node is the same and satisfies the same constraints as in the *AntNet* algorithm. The update philosophy of the routing table is a little different though. There is only one class of ants, which is launched from the sources to various destinations at regular time intervals. The ants are eliminated once they reach their destination. Therefore, the probabilities of the routing tables are updated as the ant visits the nodes, based on the life of the ant at the time of the visit. The life of the ant is the sum of the delays of the nodes $T = \sum_i D_i$ where the delays D_i are given by $D_i = c\exp(-dS)$, c and d are design parameters, and S is the spare capacity of each node in the telephone network. Then a step size is defined for that node, according to $\delta r = a/T + b$, where a and b are both design parameters. This step size rule is intuitive, because it assigns a greater step size to those ants who are successful at reaching the node faster. The routing table is then updated according to:

$$r^i_{i-1,s}(t+1) = \frac{r^i_{i-1,s}(t) + \delta r}{1 + \delta r} \tag{6}$$

$$r^i_{n,s}(t+1) = \frac{r^i_{n,s}(t)}{1 + \delta r}, n \neq i - 1 \tag{7}$$

where s is the source node, i is the current node and i-1 the previous node. It should be noted that the ant uses and updates the routing table at the same time. For example, in Table 4, if the source is node F and the destination is node E, then the ant will update the row for F and use the row for E to find the next hop, emulating an ant which works both in the forward and reverse directions. It should be noted that the update rules are such that the condition $\sum_n r^i_{n,s} = 1$, where n are all the neighbors to i, is satisfied.

		Next Hop	
		C	D
Destination	E	0.60	0.40
	F	0.55	0.45

Table 4: Routing Table for ABC

5 Conclusions

The above-described algorithms are just two examples of successful application of swarm intelligence to telecommunication networks. Both algorithms show highly promising results [14]. However, there is tremendous potential for extending these algorithms and adapting other swarm intelligent principles to network communications and in particular to wireless networks. In summary, one of the most desirable features of swarm-based approaches is that it may allow enhanced efficiency when the representation of the problem under investigation is spatially distributed and changing over time. Many distributed time-varying network communications problems are thus well suited to swarm-based optimization. One future direction of such research is developing swarm-based methodologies for power-aware routing optimization. Here robustness, scalability, and routing efficiency, may trade against power efficiency in a wireless system.

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