Intelligent Routing and Bandwidth Allocation in Wireless Networks

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***Abstract* – Sensor networks and satellite constellations face a number of challenges for reliable and robust communications. Increasingly heterogeneous nodes and a multitude of new emerging Earth science applications put additional restrictions on throughput and delay requirements. These problems are further aggravated by energy and bandwidth constraints on the network nodes. Quality of service and performance of such wireless networks, in the presence of such issues, are greatly affected by network routing and bandwidth allocation. We propose a new class of routing algorithms based on principles of biological swarms, which have the potential to address these problems in an autonomous and intelligent fashion. Such swarm-based algorithms adapt well to dynamic topologies, and, compared to the current state-of-the-art, have been shown to result in the highest throughput and lowest delays in internet-style networks.**

Swarm-based routing algorithms boast a number of attractive features, including autonomy, robustness and fault-tolerance. They rely on the interaction of autonomous agents who communicate with each other through the environment (a phenomenon known as *stigmergy*). Current swarm based routing algorithms focus on wired circuit or packet switched networks. We propose new swarm routing algorithms suitable for wireless sensor or satellite networks. Control for optimizing the transmitter power and data rate for network communication is also considered. Biologically inspired methodologies such as evolutionary computing and particle swarm optimization can be used for concurrent maximization of the data rate and minimization of transmitter power, subject to constraints on the bit error rate (BER) at the receiver.

I. Introduction

The rapid speed of technological innovation has resulted in increasingly sophisticated means for earth exploration and data collection from space. Without a pre-existing network infrastructure, nodes with wireless communication capabilities are tasked with information collection, processing, and communication. Lack of a fixed network and the nature of the nodes give rise to challenges for robust and reliable data routing, which must now compensate for: a) dynamic network topologies b) changing environments c) limited node energies d) limited bandwidth and e) background noise. These issues are, for example, typical for Mobile Ad-hoc Wireless Networks (MANETS), and require different routing approaches than those used in current conventional networks.

Swarm intelligence [1] forms the core of an enabling technology for a new class of routing and optimization algorithms boasting attractive features, such as autonomy, robustness and fault-tolerance – rendering it suitable for MANETS. Algorithms based on swarms have been developed in recent years for wired networks [2-12], but their properties are also attractive for ad-hoc networks. We investigate the specific challenges of wireless networks and propose adaptations of swarm-based algorithms to address them both for network routing, and network bandwidth allocation.

II. Routing in Wireless Data Networks

The usual performance metrics of a network are average *throughput* and *delay*. The interaction between routing and flow control affects how well these metrics are jointly optimized. The balance of delay and throughput is determined by the flow-control scheme [13] (see Fig. 1(a)). Good routing generally results in a more favorable delay-throughput curve (Fig. 1(b)). These curves serve as the standard metric for comparison of routing algorithm performance.

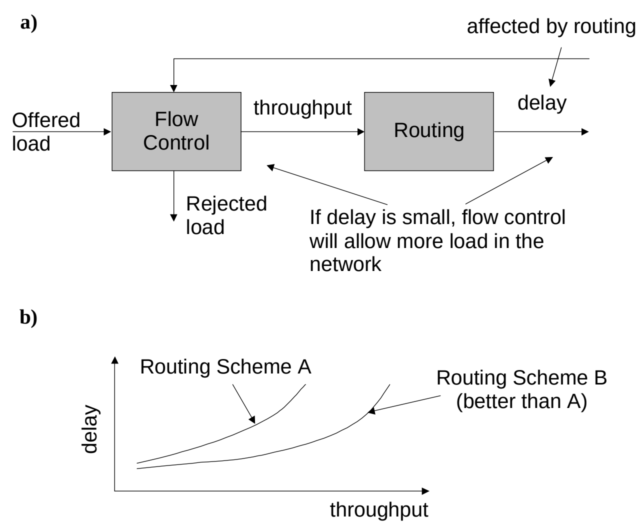

Fig. 1. a) Routing – flow control interaction, b) throughput delay curves.

Routing algorithms should handle different kinds of service requests, including *unicast* (one-to-one) and *multicast* (one-to-many) communication. Users may request *quality of service* (QoS) guarantees, which can involve a guaranteed allocation of bandwidth, a maximum delay, or a minimum hop-count. Such guarantees only make sense for *virtual-circuit* networks. This is because in applications that require logical connections there is demand for a minimum flow rate of data. This is unlike packet-switched types of service where best-effort routing is implemented. Although logical connections use static routing, the establishment of the connection is prone to the same problems that affect routing in the rest of the larger network.

In wireless networks, there are additional considerations to be taken into account. Node mobility and the wireless nature of communication – prone to noise and dependent on various environmental conditions – affect the connectivity of the network, causing its topology to change, often rather rapidly. This is aggravated by further constraints on energy reserves and available bandwidth – and signal degradation by noise and limited transceiver resources.

Therefore, instead of a traditional layered network control approach, a joint optimization scheme affecting both the link and the routing layer is necessary. This idea is discussed by Wiesellthier *et. al.* [14], where the Broadcast Incremental Power (BIP) algorithm for multicasting in ad-hoc networks is proposed. Although BIP is an improvement compared to previous techniques, it is still sub-optimal. Furthermore, it does not deal with unicast issues and assumes no mobility and no constraints on bandwidth or transceiver resources. Although in a later paper [15] the authors discuss an extension of BIP addressing bandwidth and transceiver limitations, there still remains ample room for improvement.

There are also numerous algorithms for ad-hoc networks that concentrate solely on the network layer. These can be categorized into *table driven* – where each node maintains routing information to every other node in the network and exchanges information when the state of the network changes – and *on-demand* routing algorithms where routing tables are created only when needed. The former category includes: dynamic destination-sequenced distance-vector routing; wireless routing protocol; global state routing; fisheye state routing; hierarchical state routing; zone-based hierarchical link state routing protocol; and clusterhead gateway switch routing. The later category includes on-demand routing protocols; cluster based routing; ad hoc on-demand distance vector routing; dynamic source routing; temporally ordered routing; associativity based routing and signal stability routing.

III. Swarm Intelligence

Swarm intelligence appears in biological swarms of certain social insect species. Flocking or group behavior gives rise to complex and often intelligent behavior through simple direct or indirect interaction of thousands of autonomous swarm members. The end result is emergence of very complex forms of social behavior and fulfillment of a number of very complex tasks [1].

This emergent intelligent behavior derives primarily from two principles: self-organization and stigmergy. From a very abstract perspective self-organization relies on four basic ingredients:

1. *Positive feedback* constitutes the basis for creation of intelligent structures (morphogenesis).
2. *Negative feedback* counterbalances positive feedback and helps stabilize the collective.
3. *Amplification of random fluctuations*. Randomness is crucial to discovery of new solutions (time-varying optimization) that in turn may result in network robustness.
4. *Interaction among multiple agents*. Usually agents utilize results of their own activities as well as others.

Stigmergy, or indirect communication through the environment, is the other primary principle behind swarm intelligence. This principle may be synthesized in many real engineering systems, in particular wireline and wireless communications.

One form of stigmergy alters the environment in such a manner so as to promote further similar action by the agents. This process is dubbed *task-related stigmergy*. An example is laying of sand grains by termites when constructing nests. In the initial stages of construction, termites lay sand grains at random locations. This stimulates further laying by other members of the swarm, until a single heap of sand grains randomly reaches a critical mass that is larger than its neighboring heaps. At that point, most termites are attracted to that specific heap, thereby selecting that site for construction of their nest.

Swarm intelligence boasts a number of advantages due to the use of mobile agents and stigmergy. These are:

1. *Scalability*: Population of the agents can be adapted according to the problem size. Scalability is also promoted by local and distributed agent interactions.
2. *Fault tolerance*: Swarm intelligent processes do not rely on a centralized control mechanism. Therefore the loss of a few agents does not result in catastrophic failure, but rather leads to graceful, scalable degradation.
3. *Adaptation*: Agents can change, die or reproduce, according to system changes.
4. *Autonomy*: Little or no human supervision is required.
5. *Parallelism*: Agent's operations are inherently parallel.

These properties make swarm intelligence very attractive for ad-hoc wireless networks. They also render swarm intelligence suitable for a variety of other applications, apart from routing, including robotics [16-19] and optimization [20,2].

A. *Swarm Routing*

The first routing algorithm based on swarm intelligence, known as Ant-based Control (ABC), was introduced by Schoonderwoerd et al [3], and was followed by AntNet, proposed first by Di Caro and Dorigo [7,8,10], and many others [9,11,12,21]. The basic difference between swarm-based algorithms and current routing schemes is the use of stochastic exploration for new route discovery in swarm based techniques. This stochastic property is achieved by using routing tables which assign probabilities to next-hops, and special agents that follow a next-hop based on these probabilities. Regular data packets, however, always follow the next-hop with the highest probability. A sample routing table is given in Table I, where each row corresponds to a destination and each column to neighbors of the node, with probabilities assigned to them.

TABLE I
SWARM-BASED ROUTING TABLE

		Next Hop	
		B	C
Destination	E	0.45	0.55
	F	0.75	0.25

Special exploration agents, dubbed "ants", who collect traveling time information as they traverse the network, determine the probabilities of the routing table. The ants go through the same queues as regular data packets, so that the travel-time information they collect is a valid estimate for data packet travel times as well.

There are two approaches to updating the routing tables. In ABC, the routing tables are updated as the ants move from node to destination. In contrast, AntNet uses two classes of agents: forward ants and backward ants. Once it reaches its destination each forward ant bequeaths the traveling time information to a backward ant, which updates the routing tables as it traces the path of the forward ant in reverse. The advantage of this approach is that routing tables are updated only when an ant is successful in reaching a destination, while in ABC ants that might never reach a destination can update routing tables.

The principles of these algorithms are similar to reinforcement learning. This is better explained in Fig. 2, where the trip-times are the raw reinforcement which is processed by the critic to produce an intermediate quantity *r'*, which, in turn, updates the routing tables.

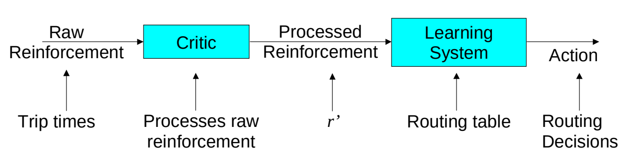

Fig. 2. Actor-Critic System

Swarm-based routing algorithms have so far been developed only for wired networks. They have not been thoroughly tested, nor does a proof for their convergence exist yet. However, preliminary simulations for AntNet [8] show that it outperforms all conventional algorithms, including OSPF, the internet standard.

B. *Preliminary Results*

To illustrate performance, AntNet, the most successful swarm routing procedure thus far demonstrated, was implemented on NS2, the standard research platform for network simulation. A simple 5-node wireline network (Fig. 3), was used as the demonstration testbed. For comparison purposes we also implemented the Distance Vector (DV) and Link-State (LS) algorithms [13]. The network considered had two sources of 500 kbps data rate at nodes 0 and 3, where the destination of source 0 is destination 4 and the destination of source 3 is destination 0. The capacity of all the links is 1 Mbps, and all links have a propagation delay of 10 ms, except for links 0-2, 2-3, 1-4 which have a delay of 40 ms. Link 0-1 failures occurs at time 7.5s of the simulation and the link recovers at 8.5s.

The test for AntNet was to see if (a) it could correctly identify the optimal path while the network is stationary (until time 7.5 s) and (b) when a link fails, whether it would adapt to find the next best path. It was shown that AntNet, indeed, is adept at dynamically adjusting to these changes, and for this small network, performs comparably if not better than DV and LS algorithms in terms of average delay and percentage of packets lost.

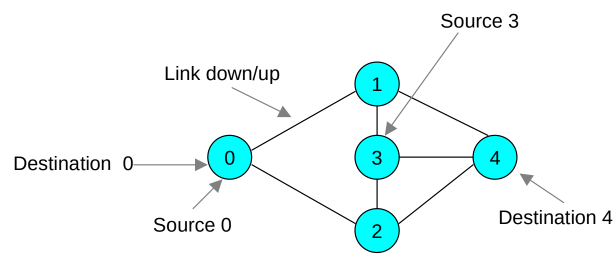

Fig. 3. Test Network

We expect that as the network grows in size, and more severe disruptions are inserted in its paths, AntNet will indeed perform considerably better than DV and LS. AntNet's distinguishing features such as scalability and robustness will demonstrate themselves much better under more realistic scenarios, rather then the proof of principle type network considered here as a first step.

C. *Swarm Routing for Wireless Networks*

Existing swarm-based algorithms have been developed for wired networks and have several features unsuitable for mobile ad hoc networks.

1. Energy

The *reinforcement signal* used for wired networks is the trip-time from the current node to the destination. This could be unsuitable for wireless networks, where energy is typically an important measure of network performance. It is thus necessary for a successful routing mechanism to be able to distribute traffic according to energy reserves of the current and downstream nodes. For this purpose, the routing tables shown in Table I should be modified, so that either (a) for each destination the probabilities correspond to complete paths instead of next-hops and are affected by the energy reserves of all the nodes of the path (Table II) or (b) the probabilities correspond to next-hops, while also reflecting the energy reserves of the remaining nodes to reach a destination. In both (a) and (b), data packets should still always choose the option with the highest probability.

TABLE II
MODIFIED SWARM-BASED ROUTING TABLE

Destination		Path: A→B→E	A→C→E
	E	0.45	0.55
	F	0.75	0.25

Another issue affecting energy consumption is the dispatch rate of the ants, which, if left uncontrolled, can become a source of significant energy drain. The rate of dispatch of ants from each node should be adjusted according to the traffic going through that node. The rate should increase if the node serves significant traffic and vice versa.

2. Broadcasting and Connectivity

Wireless networks possess the *broadcast advantage*, where one transmission by a node can reach all the nodes in its range, assuming use of omni-directional antennas and an isotropic environment. This property can be used both in unicast and multicast scenarios by adjusting the transmission power of the sending node, thus affecting the network *connectivity*. An interesting *unicast* approach would be to form the routing table of each node so that it includes all the nodes that can be reached when transmitting with maximum power. In addition, the probabilities should reflect the transmission power to the next-hop. For example, in Table III, the amount of time and energy required to reach node E is the same from all next-hops, but nodes B and C can be reached with the same transmitting power while node D requires more, thus its probability of being chosen as next-hop is smaller. This should only apply to ants, while data packets will still choose the next-hop with the highest probability.

TABLE III
MODIFIED SWARM-BASED ROUTING TABLE

Destination		Next-Hop: B	C	D
	E	0.4	0.4	0.2
	F	0.65	0.2	0.15

For the *multicast* scenario, adjustments need to be made to the update of the routing tables and the generation of the backward ants. The ants now have more than one node to visit. Thus, for the multicast tree to be optimal, a backward ant cannot be dispatched before all the destinations have been visited. Furthermore, the reinforcement signal should not be the remaining trip-time to a single destination, but, rather, should be the remaining time to reach all destinations.

The above modifications are currently being incorporated into a new swarm based routing algorithm for wireless networks.

IV. OPTIMAL TRANSMITTER POWER AND DATA RATE FOR NETWORK COMMUNICATIONS

In this section we consider another problem of interest to satellite and sensor networks, namely optimization of transmit power and data rate with a given bit-error rate threshold.

The relationship between the signal power at the receiver due to the transmitter (P_R), and the transmitter power (P_T) is given by

$$P_R = KFP_T r^{-\eta}\ , \qquad (1)$$

where K is a proportionality constant accounting for transmitter/receiver antenna gains and other factors, F is the channel fading factor, P_T is the transmitter power, r is the distance between the transmitter and the receiver, and η is the channel power loss exponent.

It can be shown that the actual Bit energy to noise ratio (BENR) at the receiver, E_{act}, is given by

$$E_{act} = \frac{P_R / D}{N_0 + (P_I / W)} = \left(\frac{W}{D}\right) \frac{K.F.P_T.r^{-\eta}}{WN_0} \qquad (2)$$

where the second equality follows from using Eq. (1), W is the bandwidth in Hertz, and D is the data rate in bits per second. Let Y_{des} be the minimum acceptable BENR at the receiver. When $E_{act} > Y_{des}$ the transmit power may be decreased (to conserve power) or the data rate may be increased (to increase throughput, and ultimately save power as well). Given that the transmitter acquires an estimate of excess BENR ($E_{act} – Y_{des}$) from the receiver, the data rate or power may be adjusted to achieve optimal power control. We define optimal power control to accomplish one of the following while minimizing $E_{act} – Y_{des}$ and maintaining $E_{act} > Y_{des}$ at the same time:

1. Maximize the data rate that may be transmitted while maximizing the battery life (the life of the network node).
2. Minimize the power required to transmit a block of data in a given time.

To accomplish either one of these goals requires optimization constrained upon the nonlinear charging and discharging curves of power storage devices (batteries). These curves generally change during the lifetime of the power storage device. This necessitates an optimization algorithm that operates over the lifetime of the network node. Furthermore, even though from Eq. (2) it is clear that transmit power and data rate trade linearly, assuming the additive white Gaussian noise channel, it is generally desirable to change the data rate rather than transmit power due to the physical constraints of the transmit power amplifier (these amplifiers are generally designed for a specific efficient region of operation or output power).

The tradeoff between power and data rate in the case of multipath or fading multipath (frequency selective and non-frequency selective) channels, often incurred in wireless communication networks is frequently nonlinear. Finding the optimum data rate and transmit power corresponds to the point in the data rate/power plane that minimizes $E_{act} - Y_{des}$ while maintaining $E_{act} > Y_{des}$. The optimization may also be extended to include the nonlinear charging and discharging cycles of batteries. Such an optimization could be done using exhaustive search. However, particle swarm optimization routines or other biologically inspired optimization methods (genetic algorithms) promise far more computationally efficient solutions. In addition, they offer the ability to optimize highly dynamic systems (real-time optimization) with input parameter variations that would be prohibitive to incorporate in an exhaustive search, rule-based, or look-up table optimization. In particular the investigation of distributed resource allocation in biological swarms is a key component in developing algorithms for such optimization and holds promise for extension to multiple sensor power/data rate optimization. Applications for such technologies include maximizing the life of a sensor network or cluster of sensors.

V. Conclusion

In this paper we have presented a brief description and simple performance analysis of swarm-based algorithms for network routing, and proposed significant modifications to them to render them suitable for ad-hoc wireless networks. We have also formulated the problem for computing the optimal transmitter power and data rate for satellite to ground communication. Several optimization tools are being considered for solving this problem in real-time.

References

1. E. Bonabeau, M. Dorigo, and G. Théraulaz, *Swarm intelligence: from natural to artificial systems*, Oxford University Press, 1999.
2. M. Dorigo, V. Maniezzo, and A. Colorni, "The ant system: optimization by a colony of cooperating agents," *IEEE Transactions on Systems, Man, and Cybernetics*, part B, vol. 26, no. 1, pp. 29-41, 1996.
3. R. Schoonderwoerd, O. Holland, J. Bruten and L. Rothkrantz. "Ant-based Load Balancing in Telecommunication Networks," *Adaptive Behavior*, vol. 5, pp. 169-207, 1996.
4. S. Guerin, "Optimisation multi-agents en environnement dynamique: application au routage dans les reseaux de telecommunications," *DEA Dissertation*, University of Rennes I, France, 1997
5. D. Subramanian, P. Druschel, and J. Chen. "Ants and reinforcement learning: a case study in routing in dynamic networks," *Proc. 1997 International Joint Conf. on Artificial Intelligence*, Palo Alto, CA, pp. 832-838, 1997.
6. M. Heusse, D. Snyers, S. Guérin, and P. Kuntz, "Adaptive agent-driven routing and load balancing in communication network," *Proc. ANTS'98, First International Workshop on Ant Colony Optimization*, Brussels, Belgium, October 15-16, 1998.
7. G. Di Caro and M. Dorigo, "AntNet: distributed stigmergetic control for communications networks," *Journal of Artificial Intelligence Research*, vol. 9, pp. 317-365, 1998.
8. G. Di Caro and M. Dorigo, "AntNet: a mobile agents approach to adaptive routing", *Tech. Rep. IRIDIA/97-12*, Université Libre de Bruxelles, Belgium, 1997
9. T. White, B. Pagurek, and F. Oppacher, "Connection management using adaptive agents," *Proc. International Conf. on Parallel & Distributed Processing Techniques & Applications*, pp. 802-809, 1998.
10. G. Di Caro and M. Dorigo, "Extending AntNet for best effort quality-of-service routing," *Proc. ANTS'98 - First International Workshop on Ant Colony Optimization*, Brussels, Belgium, October 15-16, 1998.
11. E. Bonabeau, F. Henaux, S. Guerin, D. Snyers, P. Kuntz, and G. Theraulaz, "Routing in telecommunications networks with "smart"ant-like agents," *Proc. Intelligent Agents for Telecommunications Applications*, 1998.
12. K. Oida and M. Sekido, "An agent-based routing system for QoS guarantees", *Proc. IEEE International Conf. on Systems, Man, and Cybernetics*, Oct. 12-15, pp. 833-838, 1999.
13. D. Bertsekas and R. Gallager. *Data Networks*, Prentice-Hall, 1992.
14. J.E. Wieselthier, G.D. Nguyen, and A. Ephremides, "On the construction of energy-efficient broadcast and multicast trees in wireless networks," *Proc. IEEE INFOCOM*, vol. 2, pp. 585-594, 2000.
15. J.E. Wieselthier, G.D. Nguyen, and A. Ephremides, "Resource-limited energy-efficient wireless multicast of session traffic," *Proc. 34th Annual Hawaii International Conf. on System Sciences*, pp. 3460–3469, 2001.
16. C.R. Kube and H. Zhang, "Stagnation recovery behaviors for collective robotics," *Proc. IEEE/RSJ/GI International Conf. on Intelligent Robots and Systems*, vol. 3, pp. 1883 –1890, 1994.
17. K. Kawabata, T. Suzuki, T. Hayama, and H. Kobayashi, "Distributed intelligent control structure for multi-legged walking robots," *Proc. 4th International Workshop on Advanced Motion Control*, vol. 1, pp. 231-236, 1996.
18. T. Fukuda, D. Funato, K. Sekiyama, and F. Arai, "Evaluation on flexibility of swarm intelligent system," *Proc. IEEE International Conf. on Robotics and Automation*, vol. 4, pp. 3210-3215. 1998.
19. K. Sugawara, M. Sano, M. Yoshihara, I. Abe, and K. Watanabe, "Foraging behavior of multi-robot system and emergence of swarm intelligence," *Proc. 1999 IEEE International Conf. on Systems, Man, and Cybernetics*, vol. 3, pp. 257-262, 1999.
20. A. Colorni, M. Dorigo, and V. Maniezzo, "An investigation of some properties of an ant algorithm," *Proc. Parallel Problem Solving from Nature Conference*, Brussels, Belgium, pp. 509-520, 1992.
21. S. Lipperts and B. Kreller, "Mobile agents in telecommunications networks – a simulative approach to load balancing," *Proc. 5th Intl. Conf. on Information Systems, Analysis and Synthesis*, 1999.
22. E.W. Dijkstra, "A note on two problems in connection with graphs," *Numeric Mathematics*, vol. 1, pp. 269-271,1959.
23. G. Navarro Varela and M.C. Sinclair, "Ant colony optimization for virtual-wavelength-path routing and wavelength allocation," *Proc. 1999 Congress on Evolutionary Computation*, pp. 1809-1816, July 1999.
24. S. Chakrabarti and A. Mishra, "QoS issues in ad hoc wireless networks," *IEEE Communication Magazine*, February 2001.
25. L. Raman, "OSI system and Network Managements," *IEEE Communications Magazine*, vol. 36, no. 3, March 1998.
26. R. K. Ahuja, T.L. Magnanti, and J.B. Orlin. *Network flows: theory, algorithms and applications*, Prentice Hall, 1993.
27. K. Bolding, M. Fulgham, and L. Snyder, "The Case for chaotic adaptive routing," *Technical Report UW-CSE-94-02-04*, University of Washington, Feb. 1994.
28. M.W. Subbarao "Dynamic power-conscious routing for MANETs: an initial approach," *Journal of Research of the National Institute of Standards and Technology*, vol. 104, no. 6, Nov-Dec 1999.