

Ant-based adaptive message forwarding scheme for challenged networks with sparse connectivity

Richard J. La
University of Maryland
hyongla@umd.edu

Priya Ranjan
Intelligent Automation, Inc.
pranjan@i-a-i.com

Abstract—We propose a new class of message routing schemes for mobile wireless networks with intermittent network connectivity. The proposed schemes are based on swarm intelligence (SI) and exploit the statistical properties of time-varying network connectivity for opportunistic message forwarding. We also consider a special form of our proposed schemes which can be viewed as a marriage between the SI and the backpressure algorithm and investigate its stability. We demonstrate that there is a fundamental trade-off between the adaptation rate and the stability region of the proposed scheme.

I. INTRODUCTION

Recently there have been growing interests in Disruption Tolerant Networks (DTNs), especially in military applications, e.g., [5], [6], [9], [10], [11]. One of salient features of DTNs is that one-hop connectivity of the network between nodes is assumed to be sparse and/or intermittent. As a result the network is disconnected or partitioned oftentimes. A consequence of this sparse connectivity is that an end-to-end route between a source and its intended destination (e.g., a gateway) is unlikely to be available when needed. This lack of end-to-end routes renders traditional multi-hop wireless network routing protocols (e.g., AODV [13] or DSR [7]) that assume the availability of an end-to-end route unsuitable. Instead, nodes must exchange messages (also called bundles) in an opportunistic manner when they encounter each other in order to deliver messages to their destinations.

In addition to intermittent/sparse connectivity, in general it is not guaranteed that every two nodes will ever meet each other. Therefore, even when infinite delay is allowed, some nodes may never be able to deliver messages directly to their destinations. As a result, nodes cannot count on a single (relay) node to deliver messages to intended destination(s), and multiple relay nodes may be required. For the same reason, in order to increase the fraction of messages successfully delivered to their

destinations, which is called message delivery ratio, some message forwarding schemes allow multiple copies of messages in the network (e.g., epidemic routing [16] and spray-and-wait [14]), at the expense of increased storage requirements at the nodes.

It is clear from above that nodes in a DTN will be expected to choose a sequence of relay nodes to be traversed by messages in a *distributed* fashion, using only local information governed by time-varying one-hop connectivity. This suggests that, for efficient and timely delivery of messages in a DTN, nodes should be able to determine the *quality* of other nodes they encounter as potential relay nodes and use the information in forwarding decisions.

The quality of a given node as a relay node will depend on

- (i) the set of other nodes the node meets and interacts with,
- (ii) distribution of inter-meeting times with other nodes (which determines the frequency of meetings) and distribution of meeting times (i.e., the amount of time the node spends in contact with other nodes when they meet), and
- (iii) the quality of the channel with other nodes when they meet, which determines how quickly the node can exchange messages with them if the meeting times are short.

It is obvious that these are mostly determined by the mobility of the nodes. Hence, the ability of the nodes to relay messages depends critically on their mobility (patterns), a fact exploited in [5].

This observation also suggests that a message forwarding scheme that permits the nodes to *learn* and *exploit* their knowledge on mobility of other nodes is likely to perform better. In this paper we propose a new class of single-copy message forwarding schemes that are inspired by what is known as *swarm intelligence* in the literature [1]. The proposed schemes, which we call ant-based message forwarding (ABMF) schemes, allow the nodes to capture the statistical properties of

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stochastic one-hop connectivity between nodes, utilizing an ant-based mechanism. These statistical properties are summarized by a variable called *pheromone*, which is maintained at each node. The pheromones at the nodes are then used to guide message forwarding decisions.

We then consider a special case of the ABMF scheme; this special case can be viewed as a marriage of an ant-based mechanism and the well known backpressure (BP) algorithm [15]. The rate at which the ABMF scheme can adapt to changes in network conditions, which we call its *adaptation rate*, depends on a discount rate set in the pheromone update rule. We investigate the stability of this special case of the ABMF scheme and demonstrate that there is a fundamental trade-off between the *adaptation rate* (i.e., selection of the discount rate) and the *stability region* of the ABMF scheme. To the best of our knowledge our result is the first that reveals this fundamental trade-off, which is likely to have much broader implications.

The rest of the paper is organized as follows: A brief overview of swarm intelligence is provided in Section II, followed by the description of the ABMF scheme in Section III. We study the stability of a special case of the ABMF scheme in Section IV. Simulation results are provided in Section V.

II. OVERVIEW OF SWARM INTELLIGENCE

Swarm Intelligence (SI) is based on the notion that *swarms* or large collections of simple interacting entities acting in some cooperative fashion can solve complex problems. Examples include large ant colonies and bee hives [1]. Swarms of these insects can, with seemingly low levels of intelligence, limited functionalities and information processing capabilities and/or minimal information exchange, can perform complex tasks (e.g., find the shortest paths to food sources, efficiently allocate resources or flexibly implement division of labor among workers in the colony). In all cases, the operation of the insect colony appears as an adaptive, decentralized, flexible and robust system.

The first step in exploiting this perceived intelligence comes from an understanding of the mechanisms that generate the collective behavior in social insects. To aid in this effort, an extensive body of work has been devoted to model this observed behavior in a large number of contexts. The resulting models have been found to reproduce features existing in the natural system they are supposed to describe, and to have good predictive powers in controlled experimental setups [1].

The foundations for SI start with the assumption that natural selection has retained only those biological systems and structures that are the most *efficient*, *flexible*, *resilient* and *robust*, since these qualities promote the survival of the species, hence have survival

value. Therefore, with some evolutionary justification, the mechanisms responsible for such outcomes can be considered as desirable.

III. ANT-BASED MESSAGE FORWARDING SCHEME

One of the most popular forms of SI-based mechanisms is ant systems [1]. Ant systems have several ways of solving different but related problems. The main mechanism for solving them is through the use of chemical substances known as *pheromones*, which have a scent that decays over time through the process of evaporation [1]. Use of these pheromones allows the ants to interact indirectly by utilizing and responding to the pheromones deposited by other ants and forms the basis of what amounts to a clever information storage, retrieval, and processing system that implements a form of positive or negative feedback.

In this section we describe a new class of single-copy message forwarding schemes that are inspired by ant systems, which we call ant-based message forwarding (ABMF) schemes. In an ABMF scheme, messages themselves act as simple agents (i.e., ants) which modify the pheromones maintained at the nodes as they traverse a sequence of nodes. The key idea is to use this ant-based mechanism to estimate the quality of each node as a relay node and use the information to guide message forwarding decisions when nodes meet and interact. This is achieved by employing a form of reinforcement learning which allows our scheme to adapt to (time-varying) mobility of the nodes and resulting network connectivities. More specifically, our scheme is designed to discover and exploit the statistical properties of network connectivity arising from node mobility, which are summarized by the pheromone.

A. Description of the ABMF scheme

Let $\mathcal{N} := \{1, 2, \dots, N\}$ denote the set of mobile nodes in the network. For simplicity of exposition we assume that there is only one commodity, i.e., all messages are destined for the same set of destination node(s).¹ However, our model and the ABMF scheme can be easily extended to multi-commodity scenarios. Let $\mathcal{D} \subset \mathcal{N}$ denote the set of destination nodes. Without loss of generality, let $\mathcal{D} = \{N - D + 1, \dots, N\}$, i.e., the last D nodes, $D \geq 1$, are the destination nodes. Define $\mathcal{N}^* := \mathcal{N} \setminus \mathcal{D} = \{1, 2, \dots, N - D\}$.

Each node maintains a variable called *pheromone*. We denote the pheromone of node $i \in \mathcal{N}^*$ at time $t \in \mathbb{R}_+ := [0, \infty)$ by $\phi_i(t)$ ($\in \mathbb{R}_+$). The pheromone $\phi_i(t)$ is used as a proxy to node i 's ability to deliver messages to destinations either directly or indirectly

¹In this setting a message needs to reach any one of the destinations to be successfully delivered.

through other relay nodes.

1. Pheromone update: The pheromone $\phi_i(t)$ is updated in two different ways: First, while a node does not deliver or relay messages to other nodes, its pheromone decreases with time. Second, when the node transmits a message to another node, its pheromone increases.

(i) Suppose that node i does not deliver or relay any messages to other nodes over an interval $I := (t_1, t_2] \subset \mathbb{R}_+$, $t_1 < t_2$. Then, for all $t \in (t_1, t_2)$,

$$\frac{d}{dt}\phi_i(t) = -\frac{\alpha}{Q_i^+(t)}\phi_i(t), \quad (1)$$

where $\alpha > 0$ is a discount rate, $Q_i(t)$ is the queue size of node i at time t , and $Q_i^+(t) := \max\{1, Q_i(t)\}$. In other words, assuming that no message is generated at node i over the interval I ,

$$\phi_i(t_2) = \phi_i(t_1^+) \exp\left(-\frac{\alpha}{Q_i^+(t_1^+)}(t_2 - t_1)\right).$$

(ii) Suppose that node i successfully transmits a message, say m , to another node j at time $t_0 \in \mathbb{R}_+$. Then, node i 's pheromone is increased according to

$$\phi_i(t_0^+) = \begin{cases} \phi_i(t_0^-) + \frac{\Delta r(d)}{Q_i^+(t_0^-)} & \text{if } s(m) \neq i \\ \phi_i(t_0^-) + \frac{\nu \Delta r(d)}{Q_i^+(t_0^-)} & \text{if } s(m) = i. \end{cases} \quad (2)$$

where $\Delta > 0$, $0 < \nu \leq 1$, d is the delay the message m experienced at node i , $s(m)$ is the source of message m , and $r : \mathbb{R}_+ \rightarrow \mathbb{R}_+$. If $\phi_i(t_0^+)$ in (2) is larger than $\phi_{\max} < \infty$, we set $\phi_i(t_0^+)$ to ϕ_{\max} .

One can view the update in (2) as a way of rewarding a node for delivering or relaying a message to another node, hence encouraging the ‘good’ behavior (which forms positive feedback as will be clear).

Note that we allow a discount factor $\nu \leq 1$ in the second case in (2). The reason for this is that if we want to use the pheromone as an estimate of the *extra* capacity of the node to relay other nodes’ messages, we need to discount the credit given to the node for delivering or relaying its own messages. Second, when we wish to reduce the end-to-end delivery delays experienced by messages, we can make the credit depend on the delay experienced by the message at node i through different choices of the function r .

2. Message forwarding decision rule: Under our proposed scheme, when two nodes meet, hence have an opportunity to exchange messages, they first compute

$$L_i(t) := \Gamma(\phi_i(t), Q_i(t), B_i) \quad (3)$$

where B_i is the buffer size at node i , $\Gamma : \mathbb{R}_+ \times \mathbb{Z}_+ \times \mathbb{Z}_+ \rightarrow \mathbb{R}$, and $\mathbb{Z}_+ := \{0, 1, 2, \dots\}$. The variable $L_i(t)$

is our estimate of the *effective* load currently carried by node i , and forwarding decisions made between the two nodes are based on their effective loads. Each time a message is forwarded from a node to another, both nodes update the value of $L_i(t)$ to reflect the change in the pheromone according to (2) and/or the queue sizes.

Exchange of messages between two nodes i_0 and i_1 in contact takes place as follows: Suppose that $L_{i_0}(t) < L_{i_1}(t)$. Let $\delta^* \in \mathbb{N} := \{1, 2, \dots\}$ and $\delta > 1/\phi_{\max} > 0$.

Message exchange procedure:

- while 1
 - $\kappa \leftarrow L_{i_1}(t) - L_{i_0}(t)$;
 - $v \leftarrow B_{i_0} - Q_{i_0}(t)$;
 - if $\kappa \leq \delta$ or $v \leq \delta^*$
 - break;
 - end
 - forward a message from node i_1 to i_0 ;
 - update $\phi_{i_1}(t)$;
 - update $Q_{i_k}(t)$ and $L_{i_k}(t)$, $k = 0, 1$;
- end

Note that our algorithm tries to equalize the effective load at the nodes given by $L_i(t)$, if possible, to within δ . The parameter δ^* set to a positive integer value keeps a node from taking on messages from other nodes when its buffer is almost full, so that it can have some space in the buffer for the messages it may generate in the future.

IV. STABILITY OF THE ABMF SCHEME

In this section we study the stability of the ABMF scheme when the function Γ in (3) is given by

$$\Gamma(\phi_i(t), Q_i(t), B_i) = \frac{Q_i(t)}{\phi_i(t)}. \quad (4)$$

If we interpret the pheromone $\phi_i(t)$ as the rate at which the node can deliver messages either directly to the destinations or through other relay nodes, we can view the normalized queue size $L_i(t)$ as (expected) draining time of the queue. It is clear that, in this case, our algorithm tries to equalize the normalized queue sizes of the nodes whenever nodes meet. In addition, if the pheromones of the nodes are static (i.e., $\alpha = \Delta = 0$ and $\phi_i(t) = \phi_i \in \mathbb{R}_+$ for all $t \in \mathbb{R}_+$), our algorithm reduces to the BP algorithm proposed by Tassiulas and Ephremides [15]. Therefore, in this special case the ABMF scheme can be viewed as a marriage of SI (in particular, ant mechanisms) and the BP algorithm.

It is well known that the BP algorithm is throughout optimal in the sense that when the average message arrival rates lie in the interior of stability region, the network is stable under the BP algorithm, i.e., the queues do not grow unbounded with time [3], [15]. Here, the stability region is the set of average message arrival

rates that can be stabilized by *some* message forwarding scheme.

The stability of the BP algorithm relies on creating ‘flows’ of messages which are guided by (weighted) queue size differentials between neighbors. However, the original BP algorithm and their variants assume that the weights used to reflect the preferences or priorities at the nodes do not vary with time (e.g., [12]). Thus, throughput optimality of the BP algorithm does not automatically carry over to the ABMF scheme. In fact, one may argue that it is unreasonable to expect the same throughput optimality of the BP algorithm because updating weights (through updates of pheromone values) at the nodes perturbs the flows of the messages *at the same time scale* queue dynamics occur.

One would, however, expect that, even though the updates of weights may cause the ABMF scheme to lose throughput optimality, if the discount rate α in (1) is close to zero, the reduction in the stability region, if there is any, should be small. In this section we prove that indeed this intuition is correct in some simple settings.

To this end we employ a discrete-time model where time is divided into contiguous timeslots $t \in \mathbb{Z}_+$. We assume that the duration of a timeslot, denoted by Δt , is large enough for transmission of one message. As a result, two nodes that are in contact (i.e., they can communicate directly with each other) during timeslot $t \in \mathbb{Z}_+$, can exchange at most one message from one node to the other during the timeslot. When two nodes i and j are in contact, we denote this by $i \leftrightarrow j$.

1. Setup: One-hop connectivities of the nodes are governed by a discrete-time stochastic process $\mathbb{C} = \{C(t); t \in \mathbb{Z}_+\}$. Here, $C(t) = [C_{ij}(t); i, j \in \mathcal{N}]$ is an $N \times N$ symmetric matrix, where the entries $C_{ij}(t)$ are given by

$$C_{ij}(t) = \begin{cases} 1 & \text{if } i \leftrightarrow j \text{ during timeslot } t \\ 0 & \text{otherwise.} \end{cases}$$

By convention, $C_{ii}(t) = 0$ for all $i \in \mathcal{N}$ and $t \in \mathbb{Z}_+$. We assume that the one-hop connectivities $C(t)$, $t \in \mathbb{Z}_+$, are given by independent and identically distributed (i.i.d.) random variables (rvs) with finite support $\mathcal{C} = \{c_1, c_2, \dots, c_K\}$. Let $p_k = \mathbb{P}[C(0) = c_k]$ for all $k \in \{1, 2, \dots, K\} =: \mathcal{K}$. Further, network connectivity is sparse and, for all $i \in \mathcal{N}$ and $t \in \mathbb{Z}_+$,

$$\mathbb{P} \left[\sum_{j \in \mathcal{N}} C_{ij}(t) \leq 1 \right] = 1. \quad (5)$$

This implies that a node is in contact with at most one other node at any given timeslot $t \in \mathbb{Z}_+$.

We denote the unidirectional link from node i to node j by either (i, j) or $(i \rightarrow j)$ and the set of all possible unidirectional links by $\mathcal{L} := \{(i, j) \mid i, j \in$

\mathcal{N} and $i \neq j\}$. We let $L := |\mathcal{L}| = N(N - 1)$ be the number of all possible unidirectional links. The originator and terminator of link $\ell = (i, j)$ are nodes i and j , respectively, and are denoted by $o(\ell)$ and $d(\ell)$, respectively.

The message arrival process at node $i \in \mathcal{N}$ is given by $\mathbb{A}_i = \{A_i(t); t \in \mathbb{N}\}$. We assume that $A_i(t)$, $t \in \mathbb{N}$, are i.i.d., and \mathbb{A}_i , $i \in \mathcal{N}$, are mutually independent. The average message arrival rates are denoted by $\lambda := \mathbb{E}[(A_1(1), A_2(1), \dots, A_N(1))]^T$ with $\lambda_i = 0$ for all $i \in \mathcal{D}$,² and the second moments $\mathbb{E}[A_i(1)^2]$, $i \in \mathcal{N}^*$, are assumed finite.

The queue sizes at the nodes (at the end of timeslots) evolve according to the following equation: For each $t \in \mathbb{Z}_+$,

$$Q_i(t+1) = Q_i(t) + A_i(t+1) + \mathbf{R} e(t+1),$$

where $\mathbf{R} = [R_{i\ell}; i \in \mathcal{N}, \ell \in \mathcal{L}]$ is an $N \times L$ matrix with

$$R_{i\ell} = \begin{cases} 1 & \text{if } i = d(\ell) \\ -1 & \text{if } i = o(\ell) \\ 0 & \text{otherwise,} \end{cases}$$

and $e(t)$ is an $L \times 1$ link activation vector with

$$e_\ell(t) = \begin{cases} 1 & \text{if } o(\ell) \text{ transmits a message to} \\ & d(\ell) \text{ during timeslot } t \\ 0 & \text{otherwise.} \end{cases}$$

Here, we implicitly assume that all transmissions are successful for simplicity of analysis. However, uncertainty in transmissions can be easily incorporated (e.g., [12]).

2. Link activation: The selected link activation vector $e(t)$ is determined by the one-hop connectivity $C(t)$ and the differentials in normalized queue sizes $Q_i(t)/\phi_i(t)$. In other words, if $C_{ij}(t) = 1$, the node with a larger normalized queue sizes transmits a message to the other node, assuming that the difference in the normalized queue sizes is larger than δ , as prescribed by the ABMF scheme.³

Given one-hop connectivity c_k , $k \in \mathcal{K}$, we denote the set of all possible link activation vectors by $E(k)$. The elements in $E(k)$ satisfy following two conditions: (i) If $C_{ij} = 0$ for some $i \neq j$, $e_{(i,j)} = 0$, and (ii) $\sum_{j \neq i} (e_{(i,j)} + e_{(j,i)}) \leq 1$ for all $i \in \mathcal{N}$, enforcing the constraint that a node cannot receive and transmit at the same time and can transmit to or receive from at most one other node.

From the description of the ABMF scheme and the sets $E(k)$, $k \in \mathcal{K}$, given one-hop network connectivity $C(t) = c_{k^*}$, link activation vector $e(t)$ belongs to

$$\arg \max_{e \in E(k^*)} \left(\sum_{(i,j) \in \mathcal{L}} e_{(i,j)} \cdot (L_i(t) - L_j(t)) \delta \right), \quad (6)$$

²All vectors are assumed column vectors throughout the paper.

³In this discrete-time model at most one message can be transmitted from one node to another during a timeslot.

where

$$\begin{aligned} & (L_i(t) - L_j(t))_\delta \\ & := (L_i(t) - L_j(t)) \cdot \mathbf{1}\{L_i(t) - L_j(t) > \delta\}. \end{aligned}$$

In addition, one can show from the assumption in (5) that the set in (6) contains only one link activation vector. Therefore, the link activation vector $e(t)$ is the unique maximizer in (6).

3. Pheromone update: For the purpose of studying the stability region of the ABMF scheme, we consider a slightly different form of pheromone update rule: First, we assume that the pheromones belong to an arbitrarily large, but finite set $\Phi = \{\phi^1, \phi^2, \phi^2, \dots, \phi^{M-1}, \phi^M\}$, where $0 < \phi^1 = \phi_{\min} < \phi^2 < \dots < \phi^{M-1} < \phi^M = \phi_{\max} < \infty$. This is a reasonable assumption since most, if not all, processors have finite precision.

The pheromones at the nodes are updated as follows.

$$\begin{aligned} & \sqrt{\phi_i(t+1)} \\ & = \left[\sqrt{\phi_i(t)} \left(1 + \frac{\beta}{Q_i^+(t)} - \Delta \frac{Z_i(t+1)}{Q_i^+(t)\sqrt{\phi_i(t)}} \right)^{-1} \right]_\Phi, \end{aligned} \quad (7)$$

where $\beta = \alpha \cdot \Delta t + o(\Delta t)$, and

$$\left[\sqrt{\phi} \right]_\Phi = \begin{cases} \inf\{\phi^* \in \Phi \mid \phi \leq \phi^*\} & \text{if } \phi \leq \phi_{\max} \\ \phi_{\max} & \text{if } \phi > \phi_{\max} \end{cases}$$

and

$$Z_i(t+1) = \sum_{\ell \in \mathcal{L}: o(\ell)=i} e_\ell(t+1).$$

Note that when $Q_i(t) \gg \beta$ and $Q_i(t)\sqrt{\phi_i(t)} \gg \Delta$,

$$\begin{aligned} & \sqrt{\phi_i(t+1)} \\ & \simeq \left[\sqrt{\phi_i(t)} \left(1 - \frac{\beta}{Q_i^+(t)} + \frac{\Delta \cdot Z_i(t+1)}{Q_i^+(t)\sqrt{\phi_i(t)}} \right) \right]_\Phi \\ & \simeq \left[\sqrt{\phi_i(t)} \left(1 - \frac{\alpha \cdot \Delta t}{Q_i^+(t)} + \frac{\Delta \cdot Z_i(t+1)}{Q_i^+(t)} \right) \right]_\Phi. \end{aligned}$$

Thus, as the queue size grows, the behavior of the scheme under consideration resembles that of the original scheme in the previous section with $\phi_i(t)$ replaced by $\sqrt{\phi_i(t)}$ and $\nu = r(d) = 1$. Clearly, when $\beta = 0$, there is no discounting of pheromones, i.e., they are nondecreasing.

A. Main result on stability

Let $\Xi := \{\Xi(t) = (Q(t), \Phi(t)); t \in \mathbb{Z}_+\}$, where $Q(t) = (Q_i(t); i \in \mathcal{N})$ and $\Phi(t) = (\phi_i(t); i \in \mathcal{N})$. Then, it is plain that Ξ is an irreducible discrete-time Markov chain with countable state space $\mathbb{Z}_+^N \times \Phi^N =: \mathcal{S}$. A common definition for stability of an irreducible

Markov chain is *positive recurrence* [4], and we adopt this definition for stability.

Let \mathcal{R}_{cl}^{BP} (resp. \mathcal{R}_{cl}^{AB}) denote the closure of the stability region of the BP algorithm (resp. the ABMF scheme). One can show [12], [15] that

$$\mathcal{R}_{cl}^{BP} = \left\{ \lambda \in \mathbb{R}_+^N \mid \text{there exist } \mathbf{f}_k \in \text{co}(E(k)) \text{ for all } k \in \mathcal{K} \text{ such that } \lambda = -\mathbf{R} \sum_{k=1}^K p_k \mathbf{f}_k \right\}, \quad (8)$$

where $\text{co}(E(k))$ denotes the convex hull of $E(k)$. The condition in (8) means that we can find feasible *link rates* that satisfy the conservation of flows at each node while creating end-to-end flows from sources to destinations to support the arrival rates.

Theorem 1: Suppose that nodes update their pheromone according to (7). Under the settings described in this section, there exists a decreasing function $\varphi: [0, \infty) \rightarrow [0, 1]$, such that

(i) $\lim_{\beta \downarrow 0} \varphi(\beta) = 1$, and

(ii) if $\mathbf{a} \in \text{int}(\mathcal{R}_{cl}^{BP})$, where $\text{int}(\mathcal{R}_{co}^{BP})$ denotes the interior of \mathcal{R}_{cl}^{BP} , then $\varphi(\beta) \cdot \mathbf{a} \in \text{int}(\mathcal{R}_{cl}^{AB})$, i.e., $\{\mathbf{a}^* \in \mathbb{R}_+^N \mid \mathbf{a}^* = \varphi(\beta) \cdot \mathbf{a} \text{ for some } \mathbf{a} \in \text{int}(\mathcal{R}_{co}^{BP})\} \subset \text{int}(\mathcal{R}_{cl}^{AB})$.

Theorem 1 implies that, if there is any reduction in the stability region of the ABMF scheme (in comparison to that of the BP algorithm) with an increasing discount constant β , the reduction will be gradual as β increases from zero. Therefore, if β is sufficiently close to zero, then the stability region of the ABMF scheme will be close, if not the same, to that of the BP algorithm given in (8). In addition, β determines how quickly the ABMF scheme can learn the environment and adapt to sudden changes in a network. Hence, if there is indeed a reduction in the stability region with increasing β , this points at a fundamental trade-off between the adaptation rate of the ABMF scheme and the stability region. Due to the space constraint, the proof of the theorem is provided in [8].

V. SIMULATION

In this section we simulate the ABMF scheme with the function in (4). We compare its performance against the BP algorithm and demonstrate that indeed learning and adapting to the environment (i.e., time varying one-hop connectivity of the network), which is achieved by the ant-based mechanism, improves the performance in terms of the average delay without compromising the stability of the system much. Although other forms of the function Γ in (3) is possible, we focus on the form in (4) due to the space constraint.

We simulate a discrete-time system described in the previous section, where time is divided into contiguous timeslots. There are five nodes in the network with a single gateway at the center. Each node moves according to Random Waypoint (RWP) mobility model with different mobility domain as shown in Fig. 1. The size of the rectangular region is 1×1 . The minimum speed of the nodes is set to 0.01 per unit time. The maximum speed of the nodes is shown in Table I.

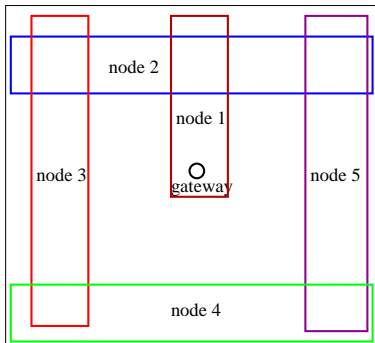


Fig. 1. Mobility domain of the nodes.

TABLE I
SIMULATION PARAMETERS.

node	1	2	3	4	5
max. speed	0.05	0.04	0.02	0.04	0.02

The minimum pheromone ϕ_{\min} is set to $\phi_{\min} = 0.01$. The credit for transmitting a message Δ in (2) is chosen to be 0.1. The discount for transmitting own messages, ν , is set to 0.5. The function $r(d)$ in (2), which discounts the credit for a transmission of a message as a function of delay, is given by $r(d) = \exp(-0.1 \times d)$. The buffer size is set to $B_i = 200$ at all nodes. The parameter δ^* , which is the threshold for denying messages from other nodes when own buffer is almost full, is set to 2. We select $\delta = 0.2$. Two nodes within a transmission range of 0.2 is assumed to be in contact.

New messages arrive at node i according to i.i.d. Bernoulli rvs with parameter λ_i . Define $\Lambda = (\lambda_i; i = 1, \dots, 5)$. The message arrival processes at the nodes are mutually independent. In order to study the effects of the traffic load on the average delivery delay and message loss rate and compare them under the ABMF and BP schemes, we select a vector $\mathbf{a} = (0.025 \ 0.03 \ 0.04 \ 0.023 \ 0.02)$ and set the average traffic arrival rate $\Lambda = \gamma \cdot \mathbf{a}$, i.e., γ serves as a scaling constant of the arrival rate.

1. Comparison of average delay and message loss rate: In the first simulation we set the discount factor $\beta = 0.05$. Since β is not large, Theorem 1 tells us that the stability region of the ABMF should be close to that

of the BP algorithm. Thus, one would expect that, given a fixed average message arrival rates at the nodes, the message loss rate of these two schemes should be close.

Simulation is run for 10^6 unit times. Figs. 2 and 3 plot the message loss rate (i.e., fraction of messages lost to buffer overflow and not delivered) and the average delivery delay, respectively, under both ABMF and BP algorithms as we vary γ in the message arrival rate from 0.3 to 1.6. As one would expect the message loss rate of the two schemes are close for most of the values of γ . Although it is not possible to precisely determine from the plot when the system loses the stability (i.e., the arrival rate vector lies outside the stability region), one can infer it by looking for a *knee* after which the message loss rate increases rapidly. From Fig. 2 this knee is just above 1.1 for the ABMF scheme while it is around 1.15 for the BP algorithm. Hence, this suggests that indeed the stability region of the ABMF scheme may be slightly smaller than that of the BP algorithm.

Fig. 3 tells us, however, that the average delivery delay is much smaller under the ABMF scheme than under the BP algorithm. In particular, note that the average delay grows much slower under the ABMF scheme as the network becomes highly loaded (for $\gamma > 1.1$). This tells us that the ABMF can capture, to some extent, the statistical properties of time-varying one-hop network connectivity and use them to reduce the delivery delay through the update of the pheromone $\phi_i(t)$ maintained at the nodes.

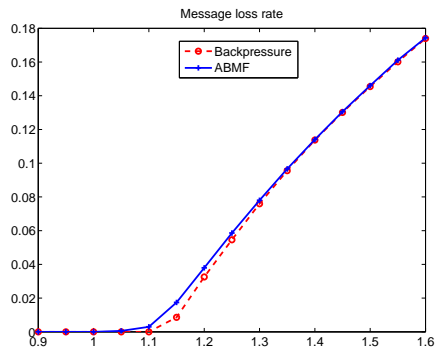


Fig. 2. Message loss rate under ABMF and BP algorithms.

2. Effects of pheromone discount factor β : Fig. 4 plots the message loss rate as a function of the discount factor β for two different value of γ - $\gamma = 1.4$ and $\gamma = 1.6$. The figure illustrates that the message loss rate tends to increase with β . This indicates that indeed the stability region of the ABMF scheme may decrease slowly with the discount factor β as proved in Theorem 1. However, it also shows that the increase in the message loss rate is very small, suggesting that the reduction in the size

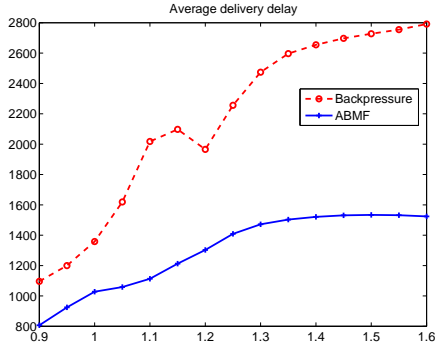


Fig. 3. Average delivery delay under ABMF and BP algorithms.

of the stability region may be minor with increasing β .

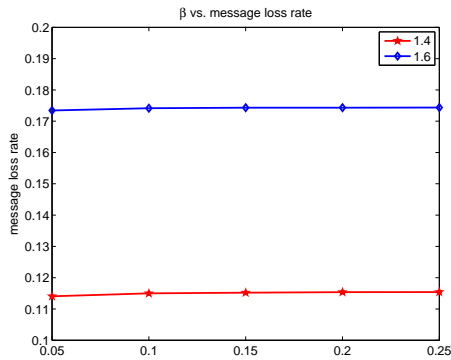


Fig. 4. Discount rate β vs. message drop rate.

VI. CONCLUSION

We proposed a new family of single-copy message forwarding schemes based on swarm intelligence, in particular ant-based mechanisms, for mobile ad-hoc networks with sparse/intermittent network connectivity. Then, we investigated the stability of a special case of our proposed schemes which is a marriage between the swarm intelligence and the well known backpressure algorithm. We demonstrated that there is a fundamental trade-off between the adaptation rate of the ant-based mechanism through the choice of discount factor and the stability region. Our simulation results indicate that indeed our proposed scheme can learn the statistical properties of time-varying network connectivity and exploit them to improve the performance without a significant compromise of the stability region.

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