Backpressure Delay Enhancement for Encounter-Based Mobile Networks While Sustaining Throughput Optimality

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***Abstract*—Backpressure routing, in which packets are preferentially transmitted over links with high queue differentials, offers the promise of throughput-optimal operation for a wide range of communication networks. However, when traffic load is low, backpressure methods suffer from long delays. This is of particular concern in intermittent encounter-based mobile networks which are already delay-limited due to the sparse and highly dynamic network connectivity. While state of the art mechanisms for such networks have proposed the use of redundant transmissions to improve delay, they do not work well when traffic load is high. In this paper we propose backpressure with adaptive redundancy (BWAR), a novel hybrid approach that provides the best of both worlds. This approach is robust, distributed, and does not require any prior knowledge of network load conditions. We also present variants of BWAR that remove redundant packets via a timeout mechanism, and that improve energy use. These algorithms are evaluated by mathematical analysis and by simulations of real traces of taxis in Beijing, China. The simulations confirm that BWAR outperforms traditional backpressure at low load, while outperforming encounter-routing schemes (Spray and Wait and Spray and Focus) at high load.**

***Index Terms*—Backpressure, DTN, ICMN, redundancy, duplicates, BWAR.**

I. Introduction

QUEUE-DIFFERENTIAL backpressure scheduling and routing was shown by Tassiulas and Ephremides to be throughput optimal in terms of being able to stabilize the network under any feasible traffic rate vector [55]. Additional research has extended the original result to show that backpressure techniques can be combined with utility optimization, resulting in simple, throughput-optimal, cross-layer network protocols [3], [8], [11], [13], [15], [21], [22], [24], [25], [30], [31], [37]–[44], [54], [57], [58]. Recently, some of these techniques have been translated to practically implemented routing and rate-control protocols for wireless networks [16], [27], [28], [46], [52], [53], [61].

The basic idea of backpressure mechanisms is to prioritize transmissions over links that have the highest queue differentials. Backpressure effectively makes packets flow through the network as though pulled by gravity towards their destinations. Under high traffic conditions, this works very well, and backpressure is able to fully utilize the available network resources in a highly dynamic fashion. Under low traffic conditions, however, there is inefficiency in terms of an increase in delay, as packets may loop or take a long time to make their way to their destinations.

In this paper, we focus primarily on intermittently connected mobile networks (ICMN), such as encounter-based mobile networks, also referred to as delay or disruption tolerant networks (DTN). In such networks, conventional path-discovery-based MANET routing techniques like AODV [45] and DSR [20] are not feasible because the network may not form a single connected partition at any time, and thus a full path may never exist between the source and the destination. Instead, it is necessary to use store-and-forward type protocols that can handle the intermittent connectivity. An important application of ICMN/DTN is disaster recovery networks which are used to deliver important messages in response to emergencies and can potentially save lives. A backpressure based routing scheme can be easily implemented in such a network, with the decision of what information to exchange being made between each pair of nodes based on their queue differentials whenever they encounter each other. However, the previously mentioned delay inefficiency of the backpressure mechanism at low traffic loads is further exacerbated in such networks, because they are already delay-limited due to sparse network connectivity.

In the literature on intermittently connected networks, there are several proposed schemes for store-and-forward based routing, such as [2], [5], [9], [48]–[50]. Some of these schemes, such as Spray and Wait, advocate the use of redundant transmissions, to make additional copies of the communicated information in the network. The replication of the content makes it faster for the destination to access a copy. However, as the additional replication always increases the network load, these protocols, which are not throughput-optimal to begin with, suffer additional congestion.

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In order to resolve the delay inefficiency of backpressure, we propose a novel hybrid approach, an *adaptive redundancy* technique for backpressure routing, that yields the benefits of replication to reduce delay under low load conditions, while at the same time preserving the performance and benefits of traditional backpressure routing under high traffic conditions. This technique, which we refer to as backpressure with adaptive redundancy (BWAR) [1], essentially creates copies of packets in a new duplicate buffer upon an encounter, when the transmitter's queue occupancy is low. These duplicate packets are transmitted only when the original queue is empty. This mechanism can dramatically improve the delay of backpressure during low load conditions for two reasons: (1) with multiple copies of the same packet at different nodes, the destination is more likely to encounter a message intended for it; (2) the algorithm builds up gradients towards the destinations faster and reduces packet looping.

The additional transmissions incurred by BWAR, due to duplication, utilize the available slots which would otherwise go idle, in an effort to reduce delay. This offers a more efficient way to utilize the available bandwidth during low load conditions. In order to minimize the storage resource utilization of duplicate packets, ideally, these duplicate packets should be removed from the network whenever a copy is delivered to the destination. Since this may be difficult to implement (except in some kinds of networks with a separate control plane), we propose and evaluate a practical timeout mechanism for automatic duplicate removal. We also introduce an energy-efficient variant of BWAR in which the number of copies of each packet is bounded.

Under high load conditions, when queues are rarely empty, duplicates are rarely created, and BWAR effectively reverts to traditional backpressure and inherits its throughput optimality property. By design, BWAR is highly robust and distributed and does not require prior knowledge of locations, mobility patterns, and load conditions.

The following are the key contributions of this work:

- We propose BWAR, a new adaptive redundancy technique for backpressure scheduling/routing in intermittently connected networks. We also present a timeout mechanism which provides for duplicate removal, and an energy-efficient variant of BWAR which limits the number of copies of each packet.
- We develop an analytical model of BWAR, and prove theoretically that it yields a smaller upper bound on the average queue size (and hence the average delay) than traditional backpressure, while retaining throughput optimality.
- Through simulations using an idealized cell-partitioned network with random walk mobility, and simulations using real traces of taxis in Beijing, we quantify the benefits of using BWAR. Specifically, we show that it outperforms both traditional backpressure and state of the art DTN/ICMN routing mechanisms (Spray & Wait [50] and Spray & Focus [49]).

The rest of the paper is organized as follows. In Section II, we introduce and describe BWAR. In Section III, we review the theory behind traditional backpressure scheduling and routing. We show in Section IV the queue dynamics for BWAR and how it can improve the delay theoretically. We show in Section V some enhancements of BWAR to provide a practical distributed timeout mechanism to remove delivered packets and to optimize power consumption. In Section VI, we present our model-based simulation results using random walk mobility. We present in Section VII simulation results over real traces of taxis in Beijing. In Section VIII, we describe related work on this subject to place our contributions in context. We conclude in Section IX and discuss future work.

II. Backpressure With Adaptive Redundancy

In this section, we first describe traditional backpressure scheduling and routing and then our new proposal for BWAR. In both cases, we assume that there are N nodes in the network, and time is discretized. We assume a multi-commodity flow system in which every node could be a potential destination (corresponding to a particular commodity).

A. Traditional Backpressure Scheduling and Routing

We assume that each node maintains N queues, one for each commodity, with the jth queue at each node containing packets that are destined for node j. Let $Q_i^c(t)$ indicate the number of packets of commodity c (i.e., destined to node c) queued at node i at time t. Naturally, $Q_i^i(t) = 0 \ \forall t$. Let $\mu_{ij}^c(t)$ be the scheduling and routing variable that indicates the number of packets of commodity c to be scheduled on link (i,j). Traditional backpressure scheduling/routing [8], [55] selects the $\mu_{ij}^c(t) \geq 0$ that solve the following problem (a form of maximum weight independent set selection),

$$\begin{aligned} &\max \sum_{i,j,c} \Delta_{ij}^c(t) \cdot \mu_{ij}^c(t) \\ &\text{subject to,} \\ &\sum_c \mu_{ij}^c(t) \leq \theta_{ij}(t), \quad \forall i, \forall j \\ &\mu_{ij}^c(t) \cdot \mu_{km}^d(t) = 0, \quad ((i,j),(k,m)) \in \Omega(t), \forall c, \forall d \\ &\mu_{ij}^c(t) \geq 0, \quad \forall i, \forall j, \forall c \end{aligned} \tag{1}$$

where $\Delta_{ij}^c(t) = Q_i^c(t) - Q_j^c(t)$ is the link weight, which denotes the queue differential for commodity c on link (i,j) at slot t. $\theta_{ij}(t)$ is the channel state in terms of number of packets that can be transmitted over link (i,j) during slot t. $\Omega(t)$ is the link interference set at slot t such that if link (i,j) interferes with link (i',j') at slot t then $((i,j),(i',j')) \in \Omega(t)$ and hence, those two links cannot both be scheduled at slot t. The maximization problem in (1) can be solved by first finding the maximum commodity $c_{ij}^*(t)$ for each link (i,j) at slot t that maximizes $\Delta_{ij}^c(t)$. Assign $\mu_{ij}^c(t) = 0$ for all $c \neq c_{ij}^*(t)$ and then solve,

$$\begin{aligned} &\max \sum_{i,j} \Delta_{ij}^{c_{ij}^*(t)}(t) \cdot \mu_{ij}^{c_{ij}^*(t)}(t) \\ &\text{subject to,} \\ &\mu_{ij}^{c_{ij}^*(t)}(t) \leq \theta_{ij}(t), \quad \forall i, \forall j \\ &\mu_{ij}^{c_{ij}^*(t)}(t) \cdot \mu_{km}^{c_{km}^*(t)}(t) = 0, \quad ((i,j),(k,m)) \in \Omega(t) \\ &\mu_{ij}^{c_{ij}^*(t)}(t) \geq 0, \quad \forall i, \forall j \end{aligned} \tag{2}$$

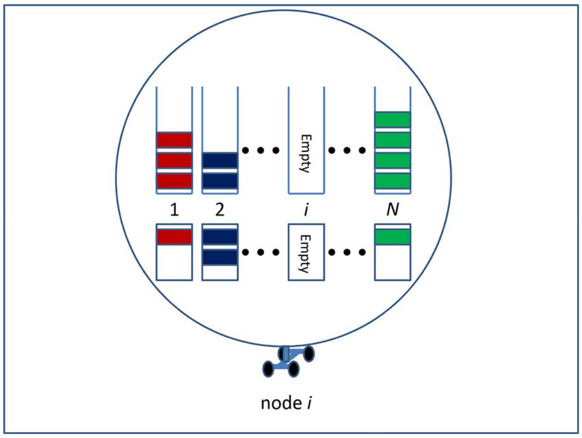

Fig. 1. A BWAR example at time t showing how node i maintains N queues and N duplicate buffers. Here, $Q_i^1(t) = 3$, $D_i^1(t) = 1$, $Q_i^2(t) = 2$, $D_i^2(t) = 2$, $Q_i^N(t) = 4$, and $D_i^N(t) = 1$. Queue i at node i is always empty. Similarly, Duplicate buffer i at node i is always empty.

B. BWAR Scheduling and Routing

Our proposed enhancement of backpressure with adaptive redundancy works as follows [1]. We have an additional set of N duplicate buffers of size $D_{\max}$ at each node. Besides the original queue occupancy $Q_i^c(t)$ which has the same meaning as in traditional backpressure, the duplicate buffer occupancy is denoted by $D_i^c(t)$ and indicates the number of duplicate packets at node i that are destined to node c at time t. Again, $\forall t Q_i^i(t) = D_i^i(t) = 0$ since destinations need not buffer any packets intended for themselves (see Fig. 1 where the top queues are regular queues and the bottom ones are the duplicate buffers). The duplicate queues are maintained and utilized as follows:

- Original packets, when transmitted, are removed from the main queue; however, if the queue occupancy is lower than a certain threshold q_{th}, then the transmitted packet is duplicated and kept in the duplicate buffer associated with its destination if it is not full (otherwise no duplicate is created). We found that setting both q_{th} and $D_{\max}$ to the value of the maximum link service rate is enough and gives superior delay results.
- Duplicate packets are not removed from the duplicate buffer when transmitted. They are only removed when they are notified to have been received by the destination, or a pre-defined timeout has occurred.
- When a certain link is scheduled for transmission, the original packets in the main queue are transmitted first. If no more original packets are left, only then are duplicates transmitted. Thus the duplicate queue has a strictly lower priority.
- Ideally, all copies of a delivered packet in the network should be deleted instantaneously when the first copy is delivered to the intended destination.

Similar to original backpressure scheduling/routing, the BWAR scheduling/routing also requires the solution of a similar maximum weight independent set problem:

$$\max \sum_{i,j,c} \Delta^c_{\mathrm{BWAR},ij}(t) \cdot \mu^c_{ij}(t)$$

$$\begin{aligned} &\text{subject to} \\ &\sum_c \mu^c_{ij}(t) \le \theta_{ij}(t), \quad \forall i, \forall j \\ &\mu^c_{ij}(t) \cdot \mu^d_{km}(t) = 0, \quad ((i,j),(k,m)) \in \Omega(t), \forall c, \forall d \\ &\mu^c_{ij}(t) \ge 0, \quad \forall i, \forall j, \forall c \end{aligned} \tag{3}$$

To take into account the occupancy of the duplicate buffer, we define an enhanced link weight for BWAR, $\Delta^c_{\mathrm{BWAR},ij}(t)$ as follows:

$$\begin{aligned} &\Delta^c_{\mathrm{BWAR},ij}(t) \\ &\quad = \left(Q_i^c(t) - Q_j^c(t)\right) + \frac{1}{2M}\left(\mathbf{1}_{j=c \text{ And } Q_i^c(t)+D_i^c(t)>0}\right) \\ &\qquad + \frac{1}{4M}\frac{1}{D_{\max}}\left(D_i^c(t) - D_j^c(t)\right) \end{aligned} \tag{4}$$

where M is chosen to be larger than the maximum number of transmissions in the network each time slot. Here the indicator function $\mathbf{1}_{j=c \text{ And } Q_i^c(t)+D_i^c(t)>0}$ denotes that node j is the final destination for the considered commodity c. This gives higher weight to commodities that encounter their destinations, a feature we refer to as Destination Advantage.[1] We show later how this effectively results in dramatic delay improvement. Similarly, the maximization problem in (3) can be solved first by finding the maximum commodity $c^*_{\mathrm{BWAR},ij}(t)$ for each link (i,j) at slot t that maximizes $\Delta^c_{\mathrm{BWAR},ij}(t)$ followed by the same approach discussed earlier in II.A. It is important to notice that any solution to (3) is also a solution to (1) (but not necessarily vice versa) assuming that $Q_i^c(t)$ and $\mu^c_{ij}(t)$ are integers. The additional terms added in (4), which are carefully designed not to add up to the next integer, give advantage first to links/commodities which encounter the destination and then to the higher duplicate buffer differential to increase the chance of serving duplicates. It can be shown that these additional terms do not affect stability by the constant additive analysis results shown in [34]. The small fractions in (4) ensure this priority in order to boost delay performance when there are ties in (1).

C. Backpressure Routing in ICMN

In general backpressure scheduling is NP-hard, owing to the maximum weighted independent set (MWIS) problem that needs to be solved at each time slot [32]. However, in this paper, we focus on intermittently connected networks, that consist of sparse encounters between pairs of nodes. Therefore, at any given time, the size of any connected component of the network is very small. In this case, the scheduling problem is dramatically simplified.

In the next section, Section III, we provide an overview analysis of traditional backpressure. After that in Section IV, we undertake an analysis of the performance of BWAR and compare it with the known results for traditional backpressure routing. Specifically, we prove that any feasible rate vector is also stabilized by BWAR, and the bound that we can give on the expected queue occupancy for BWAR is better than that for regular backpressure.

[1]In Section VI we evaluate the use of this destination advantage scheme versus regular backpressure.

III. Analysis Review of Basic Backpressure

We consider a timeslotted network with N nodes that communicate with each other. Packets arrive to each node, and each packet must be delivered to a specific destination, possibly via a multi-hop path. Each node maintains *several* queues, one per destination, to store packets. Each queue has the following dynamics:

$$Q(t+1) = \max[Q(t) - \mu(t), 0] + A(t) \tag{5}$$

where $Q(t)$ is the queue size at time t, $\mu(t)$ is the transmission rate out of the queue at time t, and $A(t)$ is the total packet arrivals to the queue at time t.

At each time slot, we observe the queue states and the channel states and make scheduling and routing decisions based on this information. Let $Q_n^c(t)$ be the queue backlog (number of packets) in node $n \in \{1, 2, \ldots, N\}$ that are destined for node $c \in \{1, \ldots, N\}$ at slot t. Let $A_n^c(t)$ be the exogenous packet arrivals that come to node n and are destined to node c at time t with rate λ_n^c. Exogenous arrivals are the packets that just entered the network. Endogenous arrivals, however, are arrivals from other nodes that were already inside the network. Packets may be forwarded to several nodes before reaching their destination. Let us define the capacity region Λ to be the set of all possible arrival rate vectors $(\lambda_n^c)_{n,c}$ that can be stably supported by some scheduling and routing strategy, in such a way that queues do not grow to infinity as time goes to infinity and successful packet delivery rate equals to packet arrival rate. Let $\theta_{ab}(t)$ be the channel state from node a to node b at time t in terms of how many packets can be transmitted. Let $\mu_{ab}(t)$ be the scheduled service rate from node a to node b at slot t. Let $\mu_{ab}^c(t)$ be the service rate for commodity c routed from node a to node b at time t, which must satisfy

$$\sum_c \mu_{ab}^c(t) \leq \mu_{ab}(t) \leq \theta_{ab}(t) \tag{6}$$

The queue dynamics for each time slot and for each queue is as follows:

$$Q_n^c(t+1) = \max[Q_n^c(t) - \sum_b \mu_{nb}^c(t), 0] + A_n^c(t) + \sum_a \tilde{\mu}_{an}^c(t) \tag{7}$$

where $\tilde{\mu}$ is the actual transfer rate due to insufficient packets in the queue. For example, on some slots we may be able to send 5 packets, but we only send 3, because only 3 were available in the queue. In (7), $A_n^c(t)$ are the exogenous arrivals and $\sum_a \tilde{\mu}_{an}^c(t)$ are the endogenous arrivals to node n.

Define the vector $\mathbf{Q}(t) = (Q_n^c(t))_{n,c}$ to be the vector of all queues in the network at time t. The Lyapunov function $L(\mathbf{Q}(t))$ can be defined as follows:

$$L(\mathbf{Q}(t)) = \sum_{n,c} Q_n^c(t)^2 \tag{8}$$

The Lyapunov drift $\Delta(\mathbf{Q}(t))$ is defined as follows:

$$\Delta(\mathbf{Q}(t)) = \mathbb{E}\{L(\mathbf{Q}(t+1)) - L(\mathbf{Q}(t)) | \mathbf{Q}(t)\} \tag{9}$$

It has been already proven by [8], [55] that

$$\Delta(\mathbf{Q}(t)) \leq \sum_{n,c} \mathbb{E}\left\{\beta_n^c(t)\right\} - 2\sum_{n,c} Q_n^c(t) \mathbb{E}\left\{\psi_n^c(t) | \mathbf{Q}(t)\right\} \tag{10}$$

such that

$$\beta_n^c(t) = \left(\sum_b \mu_{nb}^c(t)\right)^2 + \left(A_n^c(t) + \sum_a \mu_{an}^c(t)\right)^2 \tag{11}$$

and

$$, \psi_n^c(t) = \sum_b \mu_{nb}^c(t) - \sum_a \mu_{an}^c(t) - A_n^c(t) \tag{12}$$

Maximizing $\sum_{n,c} Q_n^c(t) \mathbb{E}\{\psi_n^c(t) | \mathbf{Q}(t)\}$ in (10) which is equivalent to the maximization problem defined in (1) yields the backpressure algorithm for scheduling and routing and it has been proven by [8], [55] that it supports the maximum capacity Λ. The average queue occupancy bound for backpressure scheduling and routing is

$$\bar{Q} \leq \frac{\bar{\beta}}{2\epsilon} \tag{13}$$

such that

$$\bar{Q} = \lim_{T\to\infty} \frac{1}{T} \sum_{\tau=0}^{T} \sum_{n,c} \mathbb{E}\left\{Q_n^c(\tau)\right\} \tag{14}$$

$$\bar{\beta} = \lim_{T\to\infty} \frac{1}{T} \sum_{\tau=0}^{T} \sum_{n,c} \mathbb{E}\left\{\beta_n^c(\tau)\right\} \tag{15}$$

$$\epsilon = \operatorname*{argmax}_{x \geq 0} (\lambda_n^c + x)_{n,c} \in \Lambda \tag{16}$$

where $\bar{Q}$ is the average of total queue backlog occupancy. $\bar{\beta}$ is the sum of the second moment of the scheduled transmission rate out of each queue plus the second moment of the sum of the arrivals and scheduled transmission rate into each queue and summed over all queues. ϵ is the maximum positive number such that adding ϵ to each arrival rate yields a value still inside the capacity region Λ.

IV. Analysis of BWAR

Here is a formal mathematical description of backpressure with adaptive redundancy (BWAR). As before, let $Q_n^c(t)$ be the queue backlog in node n for commodity c at time slot t. We define $D_n^c(t)$ to be number of redundant packets in node n of commodity c at time t. Redundant packets are stored separately in duplicate packet buffers. Redundant packets have lower priority in such a way that no redundant packet is served unless the queue of original packets is empty. For all time slots t, $A_n^c(t)$, $\theta_{ab}(t)$, $\mu_{ab}(t)$, $\mu_{ab}^c(t)$ and $\tilde{\mu}_{ab}^c(t)$ are defined exactly as before. Arrival rates λ_n^c are also defined as before. The queue dynamics in (7) are updated in BWAR to be

$$Q_n^c(t+1) = \max\left[Q_n^c(t) - \gamma_n^c(t) - \sum_b \mu_{nb}^c(t), 0\right] + A_n^c(t) + \sum_a \tilde{\mu}_{an}^c(t) \tag{17}$$

where $\gamma_n^c(t)$ is the number of original packets inside node n of commodity c at time slot t that are known to be delivered by some duplicates to the destination using our BWAR strategy. One ideal model is that we find out which packets are delivered immediately; another is that we find out after some delay. Our analysis allows for any such knowledge of delivered packets. We show later a practical timeout-based strategy for duplicate removals. Those $\gamma_n^c(t)$ packets need to be removed from the queue since they are already known to be delivered. We assume that the deletion happens during time slot t. Hence, at the beginning of time slot t none of those packets have been deleted yet but are known to be pending deletion. The queue dynamics in (17) consider only original packets and does not take into account the duplicate packets. We define the duplicate packet buffer dynamics that are isolated from the original queue dynamics as follows:

$$D_n^c(t+1) = D_n^c(t) - \tilde{\gamma}_n^c(t) + \delta_n^c(t) + \sum_a \omega_{an}^c(t) \quad (18)$$

where $\tilde{\gamma}_n^c(t)$ denotes the number of duplicates in node n of commodity c at time t that are known to be already delivered to the destination and hence they must be removed. $\delta_n^c(t)$ is the number of duplicates created at node n during slot t according to the adaptive redundancy criteria. $\omega_{ab}^c(t)$ is the actual duplicate transmissions from node a to node b of commodity c at time t. If $D_n^c(t) = D_{\max}$, then $\delta_n^c(t) = 0$ and $\omega_{an}^c(t) = 0$ for any a. Therefore, $D_n^c(t+1) \le D_{\max}\ \forall t$.

As before, $\mathbf{Q}(t) = (Q_n^c(t))_{n,c}$ is the vector of all queue backlogs at time t. Let $U_n^c(t)$ to be the undelivered queue backlog in node n of commodity c at time t. Hence,

$$U_n^c(t) = Q_n^c(t) - \gamma_n^c(t) \quad (19)$$

Let $\mathbf{U}(t) = (U_n^c(t))_{n,c}$ be the vector of all queue backlogs of undelivered packets at time t. Let $\mathbf{\Gamma}(t) = (\gamma_n^c(t))_{n,c}$ be the vector of all removed duplicates at time t. Define the Lyapunov function $L(\mathbf{X}) = \sum(X_i)^2$. Assume that $\bar{Q}$, $\bar{\beta}$ and ϵ are defined as before in (14), (15) and (16) respectively.

Let us also define

$$\bar{U} = \lim_{T\to\infty} \frac{1}{T} \sum_{\tau=0}^{T} \sum_{n,c} \mathbb{E}\left\{U_n^c(\tau)\right\} \quad (20)$$

$$\overline{\Gamma^2} = \lim_{T\to\infty} \frac{1}{T} \sum_{\tau=0}^{T} \sum_{n,c} \mathbb{E}\left\{(\gamma_n^c(\tau))^2\right\} \quad (21)$$

$$\overline{Q\cdot\Gamma} = \lim_{T\to\infty} \frac{1}{T} \sum_{\tau=0}^{T} \sum_{n,c} \mathbb{E}\left\{Q_n^c(\tau).\gamma_n^c(\tau)\right\} \quad (22)$$

$$\overline{U\cdot\Gamma} = \lim_{T\to\infty} \frac{1}{T} \sum_{\tau=0}^{T} \sum_{n,c} \mathbb{E}\left\{U_n^c(\tau).\gamma_n^c(\tau)\right\} \quad (23)$$

where $\bar{U}$ is the time average of total queue backlog occupancy for undelivered packets in the main queues. $\overline{\Gamma^2}$ is the second moment time average of the number of removed original packets that have already been delivered by duplicates, summed over all original queues. $\overline{Q\cdot\Gamma}$ is the joint second moment time average of the number of removed packets and the queue backlog summed over all queues. $\overline{U\cdot\Gamma}$ is the joint second moment time average of the number of removed packets and the queue backlog of undelivered packets summed over all queues.

For simplicity of exposition, we prove the result in the simple case when the arrival rates $A_n^c(t)$ and the channel states $\theta_{ab}(t)$ are i.i.d. across time slots. This can be extended to general ergodic (possibly non-i.i.d.) processes using a T-slot drift argument as in [32].

Theorem 1: If the channel states $\theta_{ab}(t)$ are i.i.d. and the arrival processes $A_n^c(t)$ are i.i.d. with rates λ_n^c that are inside the capacity region Λ such that $(\lambda_n^c + \epsilon)_{n,c} \in \Lambda$ for some $\epsilon > 0$, then BWAR stabilizes all queues with the following bound on the average of total queue occupancy of undelivered packets $\bar{U}$,

$$\bar{U} \le \frac{\bar{\beta} - \overline{\Gamma^2} - 2\overline{U\cdot\Gamma}}{2\epsilon} \quad (24)$$

Proof: Squaring both sides of (17),

$$Q_n^c(t+1)^2 \le (Q_n^c(t) - \gamma_n^c(t))^2 + \beta_n^c(t) \\ -2\left(Q_n^c(t) - \gamma_n^c(t)\right)\psi_n^c(t) \quad (25)$$

where $\beta_n^c(t)$ and $\psi_n^c(t)$ are defined as before in (11) and (12) respectively.

Summing over all n and c,

$$\sum_{n,c} Q_n^c(t+1)^2 \le \sum_{n,c} (Q_n^c(t) - \gamma_n^c(t))^2 + \sum_{n,c} \beta_n^c(t) \\ -2\sum_{n,c}\left(Q_n^c(t) - \gamma_n^c(t)\right)\psi_n^c(t) \quad (26)$$

Taking the conditional expectation $\mathbb{E}\{.|\mathbf{Q}(t) - \mathbf{\Gamma}(t)\}$,

$$\mathbb{E}\{L(\mathbf{Q}(t+1)) - L(\mathbf{Q}(t) - \mathbf{\Gamma}(t))|\mathbf{Q}(t) - \mathbf{\Gamma}(t)\} \\ \le \mathbb{E}\left\{\sum_{n,c}\beta_n^c(t) - 2\sum_{n,c}\left(Q_n^c(t) - \gamma_n^c(t)\right)\psi_n^c(t)\middle| \mathbf{Q}(t) - \mathbf{\Gamma}(t)\right\} \quad (27)$$

Since our BWAR policy maximizes (3) and hence (1) taking into account the undelivered packets $\mathbf{U}(t)$ only, it will also maximize (following the standard approach in [32])

$$\mathbb{E}\left\{\sum_{n,c}\left(Q_n^c(t) - \gamma_n^c(t)\right)\psi_n^c(t)\middle| \mathbf{Q}(t) - \mathbf{\Gamma}(t)\right\} \quad (28)$$

However, because $(\lambda_n^c + \epsilon)_{n,c}$ are inside the capacity region Λ, we know from [32] that there exists a stationary and randomized algorithm alg^*, which makes decisions independent of $\mathbf{Q}(t) - \mathbf{\Gamma}(t)$, yielding ${\psi^*}_n^c(t)$ that satisfy

$$\mathbb{E}\left\{{\psi^*}_n^c(t)\right\} \ge \epsilon \quad \forall n, c$$

Because BWAR maximizes (28), it follows that

$$\mathbb{E}\left\{\sum_{n,c}(Q_n^c(t) - \gamma_n^c(t))\psi_n^c(t)\middle| \mathbf{Q}(t) - \mathbf{\Gamma}(t)\right\} \\ \ge \mathbb{E}\left\{\sum_{n,c}(Q_n^c(t) - \gamma_n^c(t)){\psi^*}_n^c(t)\ |\mathbf{Q}(t) - \mathbf{\Gamma}(t)\right\} \\ \ge \sum_{n,c}\left(Q_n^c(t) - \gamma_n^c(t)\right)\epsilon \quad (29)$$

Using this in (27) yields

$$\mathbb{E}\{L(\mathbf{Q}(t+1)) - L(\mathbf{Q}(t) - \mathbf{\Gamma}(t))|\mathbf{Q}(t) - \mathbf{\Gamma}(t)\} \leq \sum_{n,c} \mathbb{E}\left\{\beta_n^c(t)|\mathbf{Q}(t) - \mathbf{\Gamma}(t)\right\} - 2\epsilon \sum_{n,c} \left(Q_n^c(t) - \gamma_n^c(t)\right) \quad (30)$$

Taking the iterative expectation (the expectation of the conditional expectation),

$$\mathbb{E}\{L(\mathbf{Q}(t+1))\} - \mathbb{E}\{L(\mathbf{Q}(t) - \mathbf{\Gamma}(t))\} \leq \sum_{n,c} \mathbb{E}\left\{\beta_n^c(t)\right\} - 2\epsilon \sum_{n,c} \mathbb{E}\left\{(Q_n^c(t) - \gamma_n^c(t))\right\} \quad (31)$$

Notice that

$$\mathbb{E}\left\{L(\mathbf{Q}(t) - \mathbf{\Gamma}(t))\right\} = \mathbb{E}\{L(\mathbf{Q}(t))\} + \mathbb{E}\{L(\mathbf{\Gamma}(t))\} - 2\mathbb{E}\{\mathbf{Q}(t) \cdot \mathbf{\Gamma}(t)\} \quad (32)$$

Hence by summing over time slots $\tau \in \{0, \ldots, T\}$ and by telescoping,

$$\mathbb{E}\{L(\mathbf{Q}(T+1))\} - \mathbb{E}\{L(\mathbf{Q}(0))\} - \sum_{\tau=0}^{T} \mathbb{E}\{L(\mathbf{\Gamma}(\tau))\} + 2\sum_{\tau=0}^{T} \mathbb{E}\{\mathbf{Q}(\tau) \cdot \mathbf{\Gamma}(\tau)\} \leq \sum_{\tau=0}^{T}\sum_{n,c} \mathbb{E}\left\{\beta_n^c(\tau)\right\} - 2\epsilon \sum_{\tau=0}^{T}\sum_{n,c} \mathbb{E}\left\{(Q_n^c(\tau) - \gamma_n^c(\tau))\right\} \quad (33)$$

Dividing by T and taking the lim as $T \to \infty$ implies

$$\bar{Q} - \bar{\Gamma} \leq \frac{\bar{\beta} + \overline{\Gamma^2} - 2\overline{Q \cdot \Gamma}}{2\epsilon} \quad (34)$$

Now for undelivered packets $\bar{U}$, we have by (19) and (34)

$$\bar{U} \leq \frac{\bar{\beta} - \overline{\Gamma^2} - 2\overline{U \cdot \Gamma}}{2\epsilon}$$

□

Remarks: Any removal of a delivered original packet that is computed in the second moment of Γ actually corresponds to an arrival and a transmission, both squared in $\bar{\beta}$. Therefore the second moment of the number of removed originals will be strictly less than $\bar{\beta}$ and the bound on $\bar{U}$ will remain positive. Also, note that the computation of $\overline{\Gamma^2}$ and $\overline{U \cdot \Gamma}$ is determined by the duplicate removal strategies. Depending on these terms, the queue bound in this above theorem could be much lower than the queue occupancy bound for regular backpressure in (13). Thus we have a formal guarantee that BWAR is no worse in terms of throughput than backpressure, and potentially much better in terms of delay, since by Little's theorem average delay is proportional to the average number of undelivered packets. We will validate this finding with model-based simulations in Section VI and real trace simulations in Section VII.

V. BWAR ENHANCEMENTS

In this section, we present three enhancements of BWAR. The first enhancement is that original packets are moved to duplicate buffers upon copy to reduce delay. The second enhancement is that duplicates are removed based on a distributed, easy-to-implement, time-out mechanism in an effort to obtain delay performance close to that of the ideal case. The third enhancement is to limit the number of duplicates for each packet in order to optimize energy consumption while at the same time maintaining the same delay and throughput performance.

We will refer to the BWAR presented in Section II as **BWAR with Ideal packet removal and original packets retained in the Main queue (BWAR-IM)**. To reiterate, when an original packet gets duplicated in BWAR-IM, the original packet is stored in the original queue at the receiver and the duplicate is stored in the duplicate buffer at the transmitter. Duplication will not occur if the duplicate buffer at the transmitter is full.

A. BWAR-ID

In the first enhancement of BWAR, we design **BWAR with Ideal packet removal and original packets moved to Duplicate buffer upon copy (BWAR-ID** which is very similar to BWAR-IM. The only difference is that whenever an original packet is duplicated, both the original packet and the duplicate are stored in duplicate buffers (original packet is stored in the duplicate buffer at the receiver and the duplicate packet is stored in the duplicate buffer at the transmitter). In BWAR-ID, whenever the duplicate buffer at the transmitter or receiver is full, no duplicates are created. The idea behind BWAR-ID is that when a packet is duplicated, the likelihood of this packet to be delivered to the destination can increase and hence lowering the priority of this message can result in a performance advantage for other packets to be served.

B. BWAR-TD

As a second enhancement of BWAR, we design **BWAR with Time-out based packet removal and original packets moved to Duplicate buffer upon copy (BWAR-TD)** which is a practical implementation of BWAR in which duplicates are deleted from the duplicate buffer after a predefined timeout value P has passed since the first time the original packet is admitted to the network. However, the original packet that is kept in the duplicate buffer is flagged and will not be deleted when a timeout occurs. A flagged packet is only deleted if it gets acknowledged directly by the destination if it has already been received or otherwise it is moved back to the main queue when it encounters the destination. It should be noted that BWAR-TD maintains throughput-optimality. The proof that BWAR-TD is throughput optimal can be derived by noting that the queue differential computed in BWAR-TD is bounded by a constant value difference from the actual undelivered packet differentials.

C. BWAR-ID-E and BWAR-TD-E

As a third enhancement of BWAR, we design **BWAR with Ideal packet removal and original packets moved to Duplicate buffer upon copy with Energy enhancement (BWAR-ID-E)** and **BWAR with Time-out based packet removal and original packets moved to Duplicate buffer upon copy with Energy enhancement (BWAR-TD-E)**. BWAR-ID-E is very similar to BWAR-ID except that the number of copies for each packet is bounded to be less than or equal to a constant L. Similarly, BWAR-TD-E is very similar to BWAR-TD except that the number of copies for each packet is bounded to be less than or equal to constant L.

To limit the number of copies for each packet by a constant L, we borrow the spraying idea presented in Spray and Wait (S&W) and Spray and Focus (S&F) [49], [50]. Each packet in the network has a field called *copycount* in its header to specify the number of copies allowed for this packet. When a packet is admitted to the network the value of its *copycount* is set to L. In BWAR-ID-E and BWAR-TD-E, only packets with *copycount*>1 are allowed to be duplicated. When a duplicate m' for packet m (that has a previous *copycount* value equal to L_m) is created, the *copycount* for m is set to $\lceil \frac{L_m}{2} \rceil$ and the *copycount* for m' is set to $L_m - \lceil \frac{L_m}{2} \rceil$. This method assures a fast way of distributing duplicates to different nodes (since *copycount* is split half and half when duplicates are created) and it also guarantees that the number of duplicates for any packet cannot exceed L.

VI. Model-Based Simulations

In this section, we present our simulation results over a cell-partitioned network with random walk mobility.

A. The Cell-Partitioned Model

We simulate BWAR in the context of encounter-based scheduling and routing for a simple model (a cell-partitioned network), which yields useful insights on its performance. In this idealized model adapted from [33], the network deployment area is separated into disjoint cells as follows. We have N nodes and C cells. For collision and interference simplicity, only one transmission (one packet) is allowed in each cell in each time slot. Because of this we set $q_{th} = D_{\max} = 1$. Another simplifying assumption is that the nodes in the network are organized into pairs, acting as destinations to each other. Each node has Bernoulli exogenous arrivals intended for its pair. Depending on the number of cells C in the network we can choose the right number of the nodes $N \approx 1.79 \cdot C$ in order to maximize throughput as shown in [33]. Our simulation results show that by optimizing the number of nodes based on the number of cells in an effort to maximize throughput, the delay is also improved. For duplicate removals we set the timeout value $P = C$.

Here we show how BWAR works in the cell-partitioned network with the simplifying assumption that only one transmission is allowed per cell per time slot. In each time slot t and for each cell l we choose two nodes a^* and b^* and commodity c^* such that:

- a^* and b^* are in cell l.
- $Q_{a^*}^{c^*}(t) - Q_{b^*}^{c^*}(t) \geq Q_a^c(t) - Q_b^c(t)$; for all c, for all a and b in cell l at time slot t. This captures the maximization of queue differentials of the main queues.
- If there exists a, b in cell l such that $Q_a^b(t) - Q_b^b(t) = Q_{a^*}^{c^*}(t) - Q_{b^*}^{c^*}(t)$ then $c^* = b^*$. This captures the destination advantage.
- If there exists a, b in cell l and c such that $Q_a^c(t) - Q_b^c(t) = Q_{a^*}^{c^*}(t) - Q_{b^*}^{c^*}(t)$ and $\{c^* \neq b^*$ or $[(c = b)$ and $(c^* = b^*)]\}$ then $(Q_a^c(t) + D_a^c(t)) - (Q_b^c(t) + D_b^c(t)) \leq (Q_{a^*}^{c^*}(t) + D_{a^*}^{c^*}(t)) - (Q_{b^*}^{c^*}(t) + D_{b^*}^{c^*}(t))$. This captures the maximization of duplicate buffer differentials if there are some ties in main queue differentials.

The algorithm simply assigns $\mu_{a^*b^*}^{c^*}(t)$ a value of 1, and assigns all other $\mu_{ab}^c(t)$ a value of 0 such that a, b in cell l.

When a transmission is made from node a to node b of commodity c at time slot t and that transmission will make $Q_a^c(t+1) + D_a^c(t+1) = 0$ then this transmitted packet is duplicated and stored in the duplicate buffer of node a making $D_a^c(t) = 1$ instead of 0. Duplicate packets are served only if there are no original packets to transmit. There is strict lower priority of duplicate packets compared to original packets.

B. Protocol Variants

In the simulations, we implement and compare the different BWAR routing protocol variants. These include Regular Backpressure (RB), Regular Backpressure with Destination Advantage (RB-DA), BWAR-IM, BWAR-ID, BWAR-TD, BWAR-ID-E, and BWAR-TD-E. In addition, we also include Spray and Wait (S&W), which is not a backpressure based mechanism.

Spray and Wait, presented by T. Spyropoulos *et al.* [49], is a state of the art routing scheme in intermittently connected mobile networks. S&W creates a predefined fixed number of copies (spraying) of a packet when it is admitted to the network. Those copies are distributed to distinct nodes and then each copy waits until it encounters the destination. We implemented S&W for comparison with BWAR[2]. Our results show that BWAR outperforms S&W especially in high load scenarios.

The evaluations are conducted using a custom simulator written in C++ (for repeatability, we make our code available online at http://anrg.usc.edu/downloads/).

C. Random Walk Mobility

We present here our simulation results for the case when nodes have random walk mobility, in which each node for each time slot either moves up, down, left, right, or stays at the same cell with equal probabilities of $1/5$.

Fig. 2 shows how BWAR variants have much better delay performance compared to traditional backpressure under random walk mobility. It also shows the great benefit of destination advantage when there are ties in queue differentials. As expected, delay enhancement decays as the load gets closer to the limits of the capacity region.

In Fig. 3, results show how BWAR has much better throughput performance compared to S&W, supporting almost twice as much as S&W. As the load gets higher, the delay performance of S&W gets much worse compared to BWAR.

Fig. 4 shows how S&W has superior energy consumption performance compared to traditional backpressure, RB-DA, BWAR-IM, BWAR-ID, and BWAR-TD. This inspired us to design energy efficient variants of BWAR, namely BWAR-ID-E and BWAR-TD-E, in which the number of copies for each packet is bounded by a predefined constant L. Fig. 5 shows how these energy-enhanced BWAR variants have efficient consumption performance that is very close to S&W.

Fig. 6 shows how this energy enhancement of BWAR maintains desirable delay performance. Results show that BWAR-

[2]We have implemented S&W with ideal packet removal to provide it the best possible advantage.

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

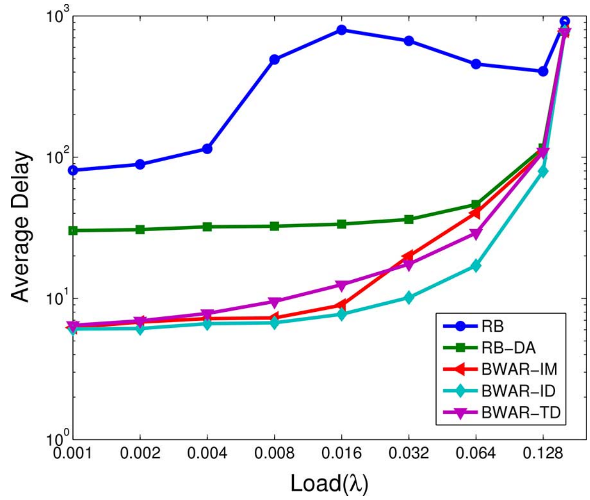

Fig. 2. Delay of backpressure variants under random walk mobility as we vary λ for $N = 44$.

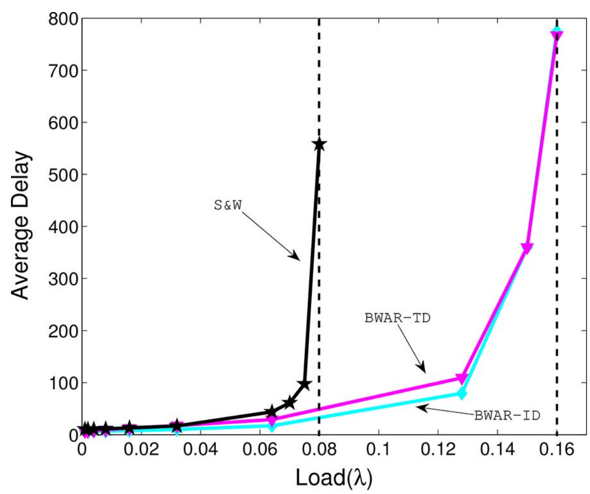

Fig. 3. Comparing S&W delay with BWAR-ID and BWAR-TD under random walk mobility as we vary λ for $N = 44$.

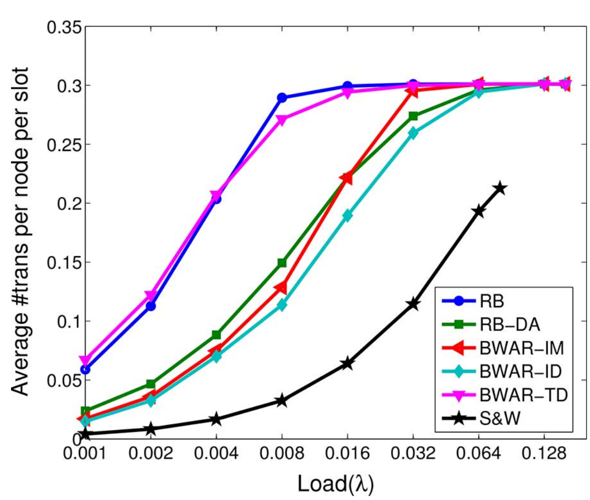

Fig. 4. Comparing energy consumption as we vary λ for $N = 44$ under the cell-partitioned model with random walk mobility.

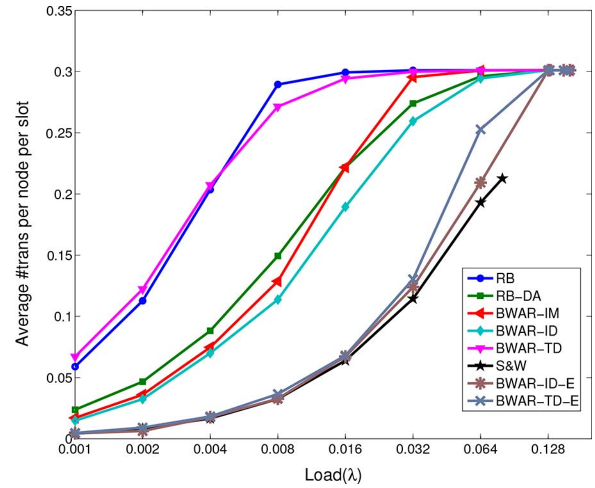

Fig. 5. Showing how energy-efficient BWAR-ID-E and BWAR-TD-E have close consumption performance to S&W under random walk mobility.

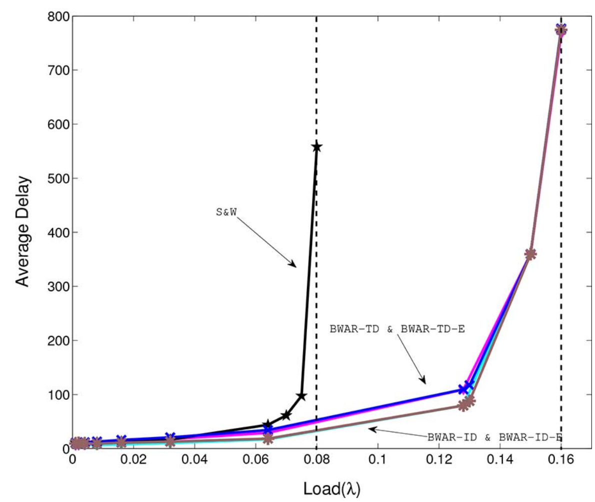

Fig. 6. Showing how energy-efficient BWAR-ID-E and BWAR-TD-E have close delay and throughput performance to BWAR-ID and BWAR-TD, respectively, under random walk mobility.

ID-E and BWAR-TD-E have almost the same delay results compared to BWAR-ID and BWAR-TD, respectively.

Fig. 7 gives some insight into how the maximum copy count affects the performance of BWAR-TD-E. There is improvement in delay with increasing L, but beyond $L = 10$ there is no significant change. This is the case for all tested values of λ. Fig. 8 shows the performance impact of the timeout value. For most values of λ, BWAR-TD-E performed the best around $P = 32$ for a network consisting of 44 nodes. However, at high load, the timeout parameter had no significant impact on delay.

With regards to the energy consumption of BWAR, it is important to note that if the packets used to share queue occupancy information between nodes are relatively small compared to the data packets, the power needed for this overhead will also be relatively small. Moreover, there is no need to send the length of empty queues thereby reducing the overhead power consumption under low load conditions. In light of this, the energy consumption results presented in this paper only take into

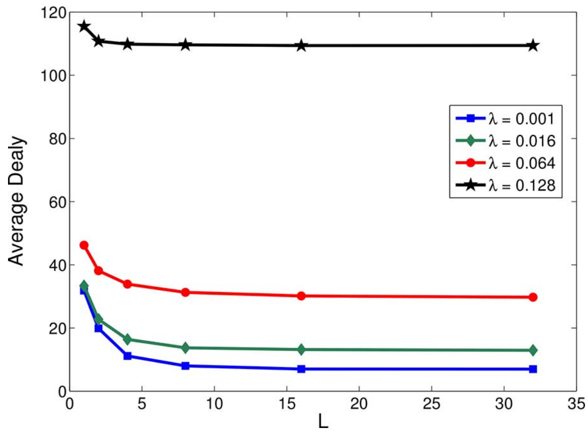

Fig. 7. Average delay of BWAR-TD-E as a function of L, the maximum copy count, for $N = 44$.

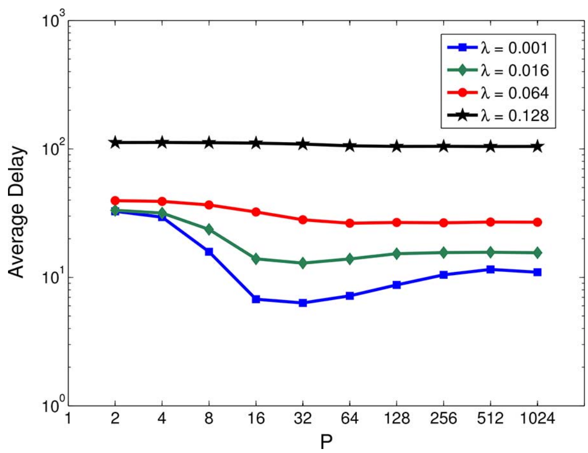

Fig. 8. Shows the effect the timeout value P has on the average delay of BWAR-TD-E for $N = 44$.

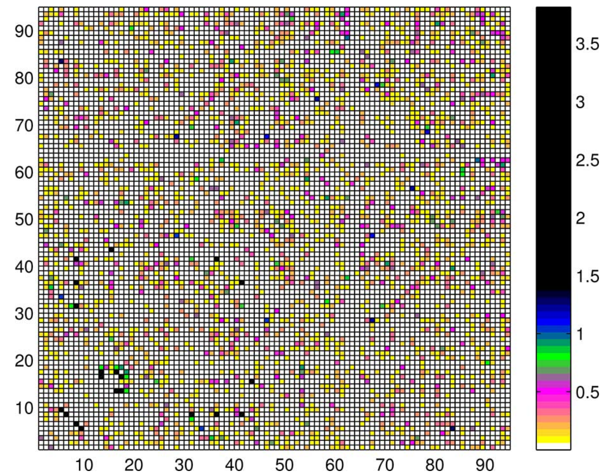

Fig. 9. Channel states showing average contact duration between each two taxis in terms of seconds per slot.

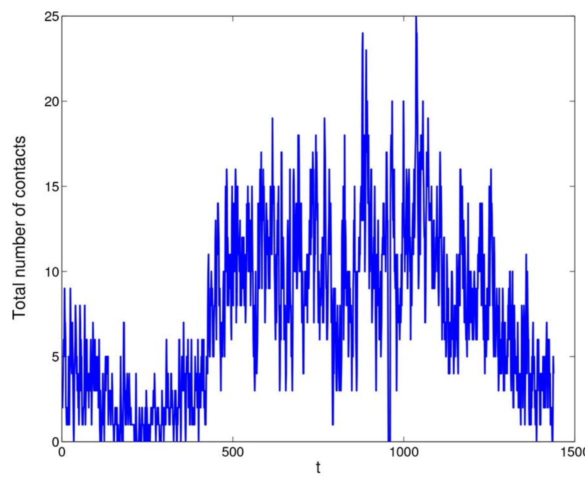

Fig. 10. Total number of contacts for each time slot t during the day.

account data transmissions, without any overhead transmissions included.

VII. Real Trace Simulations

In addition to our evaluation of BWAR under simplified model-based simulations, we went one step further to evaluate BWAR under more realistic mobility. We simulated BWAR based on real vehicular GPS traces obtained from a fleet of 95 taxis in Beijing over 24 hours [4]. Time is slotted so that the day has 1440 one-minute-length time slots. We assume taxis have a radio range of 100 meters. To obtain steady state throughput and delay results, we simulated for a large amount of time by repeating the traces to have a periodic channel states process, where the period is 24 hours. Our simulation time varies from 128 days to 1024 days depending on the load setting. We designed our simulation in such a way that it keeps running until it finds a steady state result by checking and comparing with previous observations. For high load case scenarios, it takes much more time to find the steady state result compared to low load case scenarios. Our simulation is also designed to identify the case when results keep increasing linearly with time, which means the network is unstable and the load is higher than what is supported by the capacity region.

We assume Bernoulli batch packet arrivals to each node that are destined to a random destination. Each batch consists of 60 packets. We assume packets have a fixed length of 375 000 bytes and the transmission rate, between two taxis that are in radio range of each other, is 3 Mbps. We assume taxis have enough transceivers so that they can transmit and receive to/from one or more taxis at the same time without collisions or interference. Fig. 9 shows the average contact duration between each pair of taxis in unit of seconds per slot. Fig. 10 shows total number of contacts for each time slot t during the day.

We compare BWAR with S&F [49], a state of the art DTN/ICN routing mechanism similar to S&W. S&F creates a predefined fixed number of copies (spraying) of a packet when its admitted to the network. Those copies are distributed to distinct nodes similarly to S&W. The difference is that each copy is routed to the destination based on utility timers reset each time the node encounters the destination. Packets are routed to nodes with a smaller timer value for its destination. The timer can be a good indicator of how close a node is to a destination. For this reason, we choose to compare BWAR with S&F, which could utilize those timers to route packets faster to their destinations under the real traces. However, our

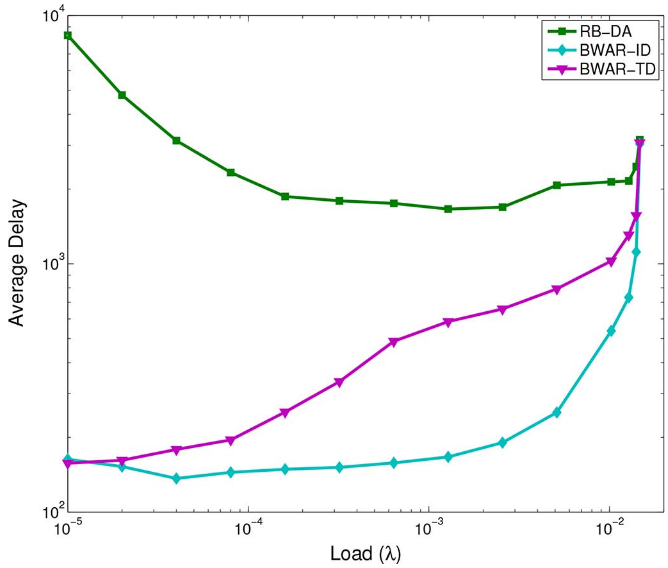

Fig. 11. Delay as we vary load λ under real mobility traces for RB-DA, BWAR-ID, and BWAR-TD.

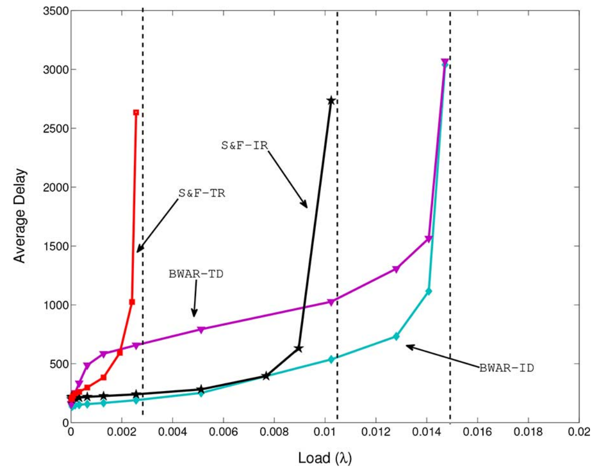

Fig. 12. Comparing S&F delay with BWAR-ID and BWAR-TD under real mobility traces as we vary load λ. Note that S&F-IR is the ideal removal version of S&F and S&F-TR is the timeout removal version of S&F.

results show no significant difference between the performance of S&F and S&W.

In our evaluations, we configure BWAR parameters as follows. The time-out for BWAR-TD is the period size, $P = 1440$. The duplicate buffer size is $D_{\max} = 60$, which is the maximum number of packets a taxi can send during a time slot. The queue threshold for duplication is $q_{th} = D_{\max} = 60$. For Spray and Focus, the number of copies for each packet is limited by constant $L = 64$.

Fig. 11, as expected, shows how BWAR-ID and BWAR-TD have great delay performance compared to regular backpressure with destination advantage (RB-DA) under the real mobility traces. Delay enhancement decays as the load gets closer to the capacity region. As you can see in the figure, BWAR-ID and BWAR-TD converge to regular backpressure because the queue occupancies rarely become low, so duplicates are rarely created.

In Fig. 12, the results show how BWAR has much higher throughput performance compared to S&F (under both ideal and timeout removal policies) with real mobility traces. It shows how as load gets higher, delay performance of S&F gets much worse compared to BWAR.

VIII. Related Work

The first theoretical work on backpressure scheduling is the classic result by Tassiulas and Ephremides in 1992, proving that this queue-differential based scheduling mechanism is throughput optimal (i.e., it can stabilize any feasible rate vector in a network) [55]. Since then, researchers have combined the basic backpressure mechanism with utility optimization to provide a comprehensive approach to stochastic network optimization [8], [23], [34].

Of most relevance to this work are papers on delay enhancements to backpressure. A number of papers [10], [14], [35], [36] address the utility-delay tradeoff in optimization-oriented backpressure, to obtain a tradeoff based on a V parameter such that the utility is improved by a factor of $O(1/V)$ while the delay is made to be polylogarithmic in V. Such a tradeoff has been shown to be practically achievable using LIFO queueing in [12], at the cost of a small probability of dropping packets. The first-ever implementation of dynamic backpressure routing aimed for wireless sensor networks (BCP) [27] uses such a LIFO mechanism. As our focus in this work is not on utility optimization, the techniques presented in these works are somewhat orthogonal to the redundancy approach we develop here. Another set of papers [29], [30], [62] considers the use of shortest path routing in conjunction with backpressure to improve the delay performance. These techniques are well suited for static networks in which such paths can be computed; however, since our focus is on encounter based networks with limited connectivity, such an approach is not applicable.

In [3], the authors present a mechanism whereby only one real queue is maintained for each neighbor, along with virtual counters/shadow queues for all destinations, and show that this yields delay improvements. In [15], a novel variant of the backpressure scheduling mechanism is proposed which uses head of line packet delay instead of queue lengths as the basis of the backpressure weight calculation for each link/commodity, also yielding enhanced delay performance. However, these works both assume the existence of static fixed routes. It would be interesting to explore in future work whether their techniques can be applied to intermittently connected encounter-based mobile networks, and if so, how these approaches can be further enhanced by the use of the adaptive redundancy that we propose in this work.

Ryu *et al.* present two works on backpressure routing aimed specifically at cluster-based intermittently connected networks [46], [47], [63]. In [47], the authors develop a two-phase routing scheme, combining backpressure routing with source routing for cluster-based networks, separating intra-cluster routing from inter-cluster routing. They show that this approach results in large queues at only a subset of the nodes, yielding smaller delays than conventional backpressure. In [46], the authors implement the above-mentioned algorithm in a real experimental network and show the delay improvements empirically. The key difference of these works from ours is that we do not make any assumption about the intermittently connected network being organized in a cluster-based hierarchy and we require no previous knowledge of a node's mobility.

Dvir and Vasilakos [6] also consider backpressure routing for intermittently connected networks, with link weights similar to that used in BCP [27]. They evaluate Weighted Fair Queueing in addition to LIFO and show through simulations that it offers energy improvements. Their work does not explicitly address additional delay improvements needed for these kinds of networks.

There is rich literature on routing in delay tolerant/intermittently connected encounter based mobile networks (see [51] for a comprehensive survey). Although there exist single-copy routing mechanisms for such networks [48], it has been well-recognized that replication is helpful in reducing delay. While basic epidemic routing [59] creates multiple message replicas for reliable, fast delivery, it incurs too high of a transmission cost. Smarter multi-copy routing mechanisms have therefore been developed such as Spray and Wait [49], and SARP [7]. These works introduce redundant packet transmissions to improve delay. However, all of these approaches are not adaptive to the traffic and therefore will hurt the throughput performance of the network. This has been noted before, by the authors of [46], who write that "replication-based algorithms such as epidemic routing for DTNs etc. result in lower throughput since multiple copies of a piece of data need to be forwarded and stored (and therefore not throughput optimal)." In fact, in [33], it has been theoretically proved that capacity of such schemes that use fixed redundancy is necessarily lower.

In this paper, we present the first backpressure algorithm that uses replication in an adaptive manner so as to maintain throughput optimality while reducing delay. We explicitly compare our BWAR scheme with Spray & Wait and Spray & Focus, and show through our evaluation that not only does it provide similar, or better, delay performance, it does so without hurting throughput optimality; specifically, we show that BWAR can handle much higher traffic load than Spray & Wait and Spray & Focus.

To summarize, this paper on BWAR is the first work that explicitly combines the best of both worlds: multi-copy routing and throughput-optimal backpressure scheduling for intermittently connected networks. This combination yields better delay performance than traditional backpressure, particularly at low loads, and better ability to handle high traffic than traditional DTN/ICN routing schemes.

IX. Conclusions and Future Work

In this paper we have presented BWAR, an enhanced backpressure algorithm that introduces adaptive redundancy to improve delay performance. We have proved analytically that BWAR is throughput optimal while providing a better delay bound, particularly at low load settings.

We have presented an enhanced variant of BWAR so that duplicates are removed based on a distributed, easy-to-implement, time-out mechanism in order to obtain close delay performance compared to the ideal duplicate removal of delivered packets. In addition, we have presented energy optimized variants of BWAR that have close energy performance to Spray & Wait and Spray & Focus while at the same time maintaining the great delay and throughput performance of BWAR.

Through simulation results we have shown that BWAR outperforms both traditional backpressure (at low loads) and conventional DTN-routing mechanisms (at high loads) in encounter-based mobile networks. Our simulations cover two different mobility scenarios. The first scenario is random walk mobility in which nodes can move up, down, left, right or stay at the same cell with equal probabilities during each time slot. The second scenario utilizes the GPS mobility traces of 95 taxis in Beijing, China.

There are a few open avenues for future work suggested by our study. First, it would be useful to undertake a more careful analysis of the delay improvements obtained, relating them more explicitly, for instance, to arrival process parameters and the underlying mobility model. Second, it would be good to investigate automated self-configuration of the timeout parameter for duplicate removal through a distributed mechanism, as this is currently statically configured in BWAR. Third, it would be great to perform real experiments with an actual implementation of BWAR so that it can be alive in practice and compared to other DTN-routing mechanisms. This would help to investigate other potential enhancements of BWAR. Finally, per a reviewer's suggestion, it may be of interest to consider "queue-aware" timer-based policies with S&W and BWAR, where the timeouts are chosen based on queue lengths rather than being statically defined.

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