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Adaptive epidemic dissemination as a finite-horizon optimal stopping problem

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Abstract Wireless ad hoc networks are characterized by their limited capabilities and their routine deployment in unfavorable environments. This creates the strong requirement to regulate energy expenditure. We present a scheme to regulate energy cost through optimized transmission scheduling in a noisy epidemic dissemination environment. Building on the intrinsically cross-layer nature of the adaptive epidemic dissemination process, we strive to deliver an optimized mechanism, where energy cost is regulated without compromising the network infection. Improvement of data freshness and applicability in routing are also investigated. Extensive simulations are used to support our proposal.

Keywords Ad hoc networks · Epidemic information dissemination · Optimal stopping · Scheduling

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1 Introduction

Ad hoc and wireless sensor networks are routinely used for applications that require the dissemination of information so that it becomes available to as many nodes as possible. This is feasible with periodic transmission of this information in the hope that it eventually reaches all nodes. Flooding is the obvious solution to the how question but takes its toll on the limited energy resources of small wireless nodes [1]. Epidemic dissemination [2],[3] introduced probabilistic rather than deterministic data dissemination, thus saving energy. Various methods have been introduced ([4], [5]) to further reduce energy cost, based on the on-the-fly intelligent adaptation of the forwarding probability or transmission characteristics. We utilize a cross-layer approach to expand the capabilities of combined parameter tuning and also reach a generic optimization scheme. The limited resources of wireless nodes in epidemic settings render information dissemination and energy conservation two contradicting demands. Our purpose is to intelligently schedule the broadcasting times and regulate selected cross-layer transmission characteristics, so as to achieve significant energy cost reduction, while guaranteeing network infection.

The energy cost problem in epidemic dissemination has been addressed before, but mostly based on heuristic approaches without addressing the optimality question. At the same time, research on cross-layer architecture has provided tools and motivation to tackle it.

We contribute to research in this area by exploiting the intrinsically cross-layer nature of adaptive epidemic dissemination and using optimal stopping to schedule transmissions and tune their characteristics.

Our choice for a cross-layer approach stems from the contradicting demands and the need for fast adaptation. Acquiring context information and tuning parameters from multiple layers allows for a parameter space large enough for an optimum scheduling to be approached. The lower layers parameters associated with the channel status typically exhibit stochastic behavior. Our approach is based on tuning the forwarding probability and the error-correction coding mode, as they strongly affect the infection dissemination. Performing combined tuning of these two allows for the exploitation of a larger parameter space and ensures successful information dissemination without resorting to flooding. Applying our findings in established dissemination settings offers additional motivation. Hence, we attempt to regulate energy cost in a routing scenario and also investigate the co-operation with an energy-intensive quality improvement scheme.

We build on previous research with and without optimal stopping logic [6], [7], with the following key innovations:

- The problem is addressed as an optimization problem within a cross-layer paradigm; optimal stopping is used to address it.
- It is shown that through maximum utility collection, greater energy cost saving is delivered, compared to a similar adaptive scheme.

- A biasing mechanism is introduced to control the tuning of the forwarding probability within values allowed by a finite state machine (FSM). This can be enhanced to an adaptive flavor (adaptive biasing, AB). Its adaptive trait is utilized to boost dissemination of fresher information.
- Significant energy cost reduction is exhibited compared to a non-adaptive epidemic, without a compromise in the infection ratio. Energy cost depends heavily on the minimum allowed value to which the forwarding probability converges.

The rest of this paper is organized as follows: Section 2 presents some important previous work, while Section 3 elaborates the system model and adds an essential theoretical aspect. Section 4 evaluates the proposed scheme through the presentation and discussion of simulation results. Conclusions and suggestions for future work are in Section 5.

2 Related Work

Epidemic information dissemination in ad hoc networks [2] and [3] was conceived to tackle the drawbacks of flooding [1]. Its adaptive form has also been studied, catering for some context-aware parameter tuning [4], [8], [9], [10]. More recent work provides essential insight to its dynamics [11] through solid mathematical treatment.

In [12] epidemics is used to address the tradeoff between bandwidth and information survivability. Energy cost is regulated by reducing the infection probability and this constitutes acknowledgment of a tradeoff needing further investigation. Similarly, in the active adaptive epidemic scheme of [13], nodes participate in a management mechanism that regulates transmissions. A rigorous comparison with other schemes including flooding shows that it achieves competitive reduction of transmissions. However, this takes its toll on the infection ratio. The researchers in [15] elaborate on probabilistic dissemination through monitoring of the duplicate messages, thus introducing a factor of context awareness. This effectively tunes down the forwarding probability. The infection ratio converges, as foreseen theoretically. In [16] the transmission power of the nodes is tuned. As a result, energy consumption is regulated and delivery probability is also affected as more or fewer nodes may be covered by the tuned transmission range of their broadcasting neighbors. Established algorithms are successfully enhanced with considerable energy cost reduction. It is obvious that most approaches affect a range of network layers, either for acquiring context or tuning operation parameters. In [18] the single packet transmission scheduling problem is addressed as an optimization one: the tuning is performed in such a manner that a perceived utility is maximized utilizing an optimal stopping approach. Assuming a discounted utility function, it is shown that an n-step look-ahead stopping condition optimizes the benefit.

Our work strives to deliver quantifiable energy cost reduction in epidemic settings especially in unfavorable ad hoc network deployments, such as sparse networks in noisy environments.

In [14] the reduction of the AODV routing protocol overhead is sought. The proposed mechanism achieves both energy cost reduction and increased data delivery compared to routing protocols established in the ad hoc networks domain. Indeed, the Advanced On-Demand Distance-Vector (AODV) routing protocol [19], whose route discovery phase is based on flooding, has seen broad adoption for some time now and some of its shortcomings have been brought to light [20]. The technique proposed in [21] does not suggest a modification of the route request message (RREQ) dissemination process; the enhancement relies on the handling of the resulting RREP messages and the way the routing table is constructed afterwards. Other attempts to regulate the energy cost in AODV tend to tune the transmission power, as for example suggested in [22]. This scheme reduces interference and improves throughput. A degree of context awareness is inherent in it, as knowledge of neighbor count and distance is assumed. Work in [25] proposes improvements to the protocol, where the forwarding probability is tuned according to the local nodes density. This can offer considerable reduction of energy cost due to transmission and reception. The link status is taken into account in [26] to avoid energy waste due to transmissions over broken links. In [23] the need to tune transmissions away from flooding is acknowledged and the cluster-based approach is studied. According to this, only elected clusterheads broadcast; broadcasts are within the cluster, and non-clusterheads do not broadcast. The clusterhead broadcast scheme in [24] is organized along similar lines, delivering better throughput and network infection and looking promising in terms of energy consumption in large networks.

We propose the application of our scheme in constraining unconditional flooding in the route discovery phase of AODV.

3 System model

Let us consider an ad hoc wireless network described by a partly connected graph $\mathcal{G}(\mathcal{V}, \mathcal{E})$. The nodes in the network are connected over fading channels. Some nodes possess a piece of information that is required to infect all nodes. To this end they regularly broadcast this information to their neighbors. In order to avoid the problems this entails, a different policy should be adopted.

3.1 Problem definition

We wish to tune transmissions down to a polite gossip, schedule them suitably, and adapt the transmission characteristics in such a way that the data spread is not compromised while the energy cost is severely reduced, which is critical in a network of energy-challenged nodes deployed in unfavorable environments.

3.2 Epidemic model

There is one broadcast per node within each interval of duration ϵ, termed an epoch. Originally, broadcasts are periodic and the period equals the duration of an epoch. The time domain is discretized into rounds. It is possible, although not necessary, that at every round some nodes generate fresh infecting information. Information from all nodes can infect irrespective of its age. At a random time instance, an infected node has a finite probability that it be cured. This cure probability summarizes all random mechanisms that can make the infecting information corrupt or unusable. Finally, it is assumed that once the age of the carried information exceeds a predefined expiry period, it is considered stale and unusable and the node is cured. A cured node may be infected again in the future. Nodes are infected when carrying the infecting information and susceptible when not. This environment subscribes to the SIS (susceptible-infected-susceptible) model [27]. The setup described above suits sensor data which needs to be disseminated and is of higher value when fresh, such as data from sensors monitoring a common scalar parameter. An alternative is when a single root node disseminates control messages in an attempt to schedule network behavior according to a centralized plan. In the latter case, there is a single node that starts the epidemic. A third possibility is the operation of routing protocols where information has to be learned by interested nodes. We make the following working assumptions:

– The time domain is discretized into *rounds* and further dissected into equal intervals of duration ϵ rounds, termed *epochs*. The terms *round* and *timeslot* are used interchangeably.
– Full temporal synchronization among nodes is assumed. Although not realistic for deployments in such unfavorable environments, it is however, judged adequate for showcasing our proof of concept without increasing the degrees of freedom of the problem. It also helps reduce simulation complexity.
– There can be collisions on the wireless channel when nodes are transmitting simultaneously in the same area. The related model is elaborated upon in subsection 3.3
– The infecting information consists of a single packet, which can be stored on a node. Hence, there is no packet drop due to lack of storage space. While storage space is limited in such constrained nodes, we neglect this limitation through the use of a single infecting packet. Storage of the full packet is deemed necessary in order for node infection to occur.
– Each node $i \in \mathcal{V}$ obtains channel state information (CSI) on the path between itself and each of its neighbors. Channel states change at every round. CSI acquisition is over a reliable channel but entails energy cost. Channel behavior is the same in both directions.
– Each infected node transmits with probability $\beta(t)$ at every round so that $\beta(t) = \beta_{min} + \kappa \Delta\beta$ with $\kappa = 0, 1, ...\kappa_0$, κ_0 an integer. The quantity $\Delta\beta$ is termed the β-step. Clearly $\beta(t)$ is discretized and upper and lower bound

by β_{min} and $\beta_{min} + \kappa_0 \Delta\beta$ respectively. It always holds that $0 \leq \beta(t) \leq 1$. Once the node transmits, it also ceases sending CSI information for the rest of the epoch.
- Each node becomes aware of its neighbors, i.e. other nodes within its range, through their data broadcasts. When a node i receives the infecting info from another node j, node j is added to the known nodes of i. Known nodes are "forgotten" after a predefined later time interval unless they make new contact till then. Of course this means that silent nodes (e.g. susceptible, but not only) are not "learned" by their neighbors. This leads to an underestimation of the neighbors count (eq. 5), especially during the initial period of low infection spread.
- Nodes are mobile, their movement following the random waypoint model.
- Transmission is best-effort. There is no direct acknowledgment of successful reception, neither are there any retransmission requests.
- Each infected node has the possibility to invoke at no cost one of a number of available encoding modes as it uses AMC (adaptive modulation and coding). This holds for both reception and transmission.

At every round, each node is characterized by its forwarding probability $\beta(t) \in B = \{\beta_1, \beta_2, \beta_i, ...\}$ and AMC mode $\mu(t) \in M = \{\mu_1, \mu_2, \mu_i, ...\}$. The pair ($\beta(t)$,$\mu(t)$) or ($\beta$,$\mu$) for simplicity constitutes the node state at timeslot t. Hence, possible states are from the set $B \times M$. Both sets B and M are finite.

We assume the set of possible actions $\mathcal{A} = \{$(change β, change μ), (change β, keep μ), (keep β, change μ), (keep β, keep μ)$\}$. These are operations $\alpha \in \mathcal{A}$ so that $B \times M \xrightarrow{\alpha} B \times M$. The set $B \times M$ is closed under such operations. A node changing its state implies tuning its transmission characteristics through such an action. To each possible action α taken by node i a utility value $U_{i,\alpha}(t)$ can be assigned, representing the immediate benefit of adopting this action. Consider the action α^* such that

$$\alpha^* = argmax_\alpha[U_{i,\alpha}(t)] \quad (1)$$

This is the most favorable of available actions. It is the per node candidate action for this timeslot is and offers utility $U_i(t) = U_{i,\alpha^*}(t)$. It represents the immediate benefit offered if this action α^* is adopted for the upcoming timeslot. Adopting the action entails changing the node state and transmitting with the new state.

The problem is whether to adopt α^*, change state, transmit from the new state and receive the immediate benefit $U_i(t)$ or wait while observing channel states till a better candidate utility is offered within in this epoch. This is expressed as a finite horizon optimal stopping problem:

Find the optimal moment within an epoch to change state and transmit with the new state; then remain silent till the end of the epoch.

It can be addressed as a finite horizon classical secretary problem [28]. The solution is to adopt the offered action if and only if during this epoch, the optimal stopping condition in eq. 2 [28] is satisfied.

$$t - T_j \geq 1/e \wedge U_i(t) \geq U_i(t') \forall t' \leq t \tag{2}$$

where T_j is the start of the j-th epoch, $T_j - T_{j-1} = \epsilon$, and e = 2.71828...

Then also the node state changes according to the specified action and the node broadcasts from this new state. The possible actions are presented in Table 1. In this context too, using multiple degrees of freedom in the optimization process delivers a greater parameter space; joint optimization of β and μ is uses the parameter space $B \times M$ with cardinality $\mid B \mid \times \mid M \mid$.

Finally, transmissions are suspended till the end of the present epoch and only resume at the next epoch start. In this manner, transmissions depart from a strictly periodic schedule, but there is still one transmission per epoch.

Table 1 Transmission characteristics tuning

	SNR increase	SNR decrease
β	decrease	increase
μ	increase	decrease

According to the solution to the well-known secretary problem [28] the proposed method offers the maximum cumulative utility. The algorithm described above is presented in Listing 1. The transmission characteristics tuning is done per node. Actions chosen from $\mathcal{A}$ are performed by each node independent of others.

The lower layers parameters associated with the channel status typically exhibit stochastic behavior. We depart from a plain short-sighted reactive transmission reconfiguration policy [7], as we want to avoid performing hasty changes and paying the cost of transmission in suboptimal conditions. Isolated changes in single layers do not allow for timely and efficient adaptation. This purpose can instead be served faster and more efficiently by combined, cooperative adaptations in every one of the lower layers that can affect the infection. In the cross-layer paradigm, tuning more than one parameters at the same time allows for favorable tuning without exhausting the range available for tuning a single parameter. Introducing extra degrees of freedom in the optimization process allows for the possibility to claim higher utility. We achieve the above through tuning of the forwarding probability and the error-correction coding mode, as they strongly affect the infection dissemination. By modulating the forwarding probability, some of the network nodes are temporarily silenced, hence effectively modifying the network topology. Moreover, tuning the encoding mode changes the packet size, hence affecting the data link layer. This renders a cross-layer scheme functioning in the data link and network layers. Performing combined tuning of these two allows for the exploitation of a larger parameter space and ensures successful information dissemination without resorting to flooding.

Listing 1 Optimal Stopping Algorithm

```
node state (β,μ)
infection state A(i)
hold_flag(i) node i does not retransmit in epoch
set of possible actions 𝒜

for each round t
  if A(i) == true
    for each α ∈ 𝒜
      calculate U_{i,a}(t)
    end for
    U_i(t) = U_{i,b}(t) : U_{i,b}(t) = max_α(U_{i,α}(t))
    if mod(t,ε) ≠ 0
      if ost_satisfied == true
        if hold_flag(i) == false
          (β,μ) := (β',μ'):(β,μ) -b-> (β',μ')
          broadcast with state (β',μ')
          hold flag(i) := true
        end if
      end if
    else if mod(t,epoch) == 0
        (β,μ) := (β',μ'):(β,μ) -b-> (β',μ')
        broadcast with state (β',μ')
    end if
  end if
end for
```

From the explanation above, it becomes clear that various layers are involved in this scheme. The interaction among them does not introduce new interfaces between non-adjacent layers. Rather than that, an abstraction plane is tasked with acquiring information from them (context acquisition) and dictating transmission parameter tuning (Figure 1). This mechanism is conceived as a cross-layer optimization plane according to the *MobileMan* cross-layer network stack paradigm [38]. It is running on each node independently.

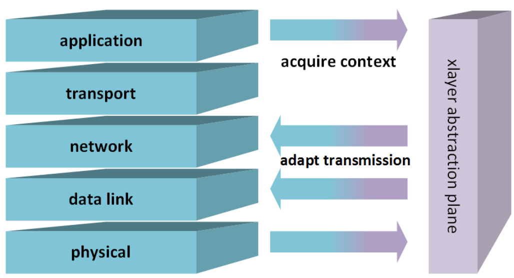

Fig. 1 Cross layer concept of the proposed mechanism

3.3 Noise and channel model

We assume the Rayleigh model [29] for the channel fading caused by multipath propagation on the link between any two nodes i and j within each others range. The underlying mechanism is stochastic but can be described using a finite sum of sinusoids [30], [31]. Such a model is described by a Markov finite state machine (FSM) [32] where ranges of signal-to-noise ratio correspond to channel states. Each timeslot t, each node i is aware of the SNR (and the state) on the links to all its neighbors j denoted by $\gamma_{i,j}(t)$.

To mitigate the impact of the channel fading on signal quality, error-detection encoding is assumed. This is implemented as part of an adaptive modulation and coding (AMC) scheme. The AMC scheme foresees a finite number of possible modes. For our simulations in section 4, we assume the AMC scheme from [33], which studies the PER in case of convolutional error control. Each mode of the AMC is taken to correspond to a single state of the channel, as derived from our noise model.

Furthermore, collisions are assumed and their mechanism is modeled in the following manner, similarly to [1]: Assuming three nodes i, j, k so that they are all neighbors of each other, their proximity is described by a binary symmetric adjacency matrix ADJ so that $ADJ(i,j) = ADJ(j,k) = ADJ(i,k) = 1$. Similarly, the status of channels between nodes is described by a symmetric matrix C so that $C(i,j) = 1$ if i and j are exchanging info. Our *collisions model* states that:

If node i is broadcasting then the communications between k and i and k and j are also disrupted. Therefore, if i is broadcasting then attempts by j or k to broadcast shall cause collisions damaging all ongoing and attempted infective broadcasts among i, j, k. Further attempts to transmit are defined by the optimal stopping scheme.

3.4 Forwarding probability biasing

The AMC mode μ may increase or decrease by one as long as it stays within an allowed value range. The forwarding probability β increases by $\Delta\beta$ but decreases by $\nu\Delta\beta$ (ν a predefined non-zero positive integer), thus following a biasing scheme whose impact is to be studied later in more detail. The allowed actions are elaborated in Table 2 together with the respective changes in β and μ. Note that actions (increment β, increment μ) and (decrement β, decrement μ) are not included: If the SNR has increased since the last round, dissemination is deemed effective even if transmission is done less frequently combined with a looser (higher coding rate) error-correction code. Assuming more frequent transmission with a looser code or vice-versa clearly introduces two mutually competing effects. A complementary explanation serves in case the SNR has decreased. The node state changes caused by the tuning of β and μ are also modeled as a Markov FSM (Figure 2).

Table 2 Possible Node State Transitions.

	increment μ	decrement μ	keep μ
increment β	-	$\beta(t+1) = \beta(\text{t}){+}\Delta\beta$ $\mu(t+1) = \mu(t)$-1	$\beta(t+1) = \beta(t) + \Delta\beta$ $\mu(t+1) = \mu(t)$
decrement β	$\beta(t+1) = \beta(t) - \nu\Delta\beta$ $\mu(t+1) = \mu(t) + 1$	-	$\beta(t+1) = \beta(\text{t})$-$\nu\Delta\beta$ $\mu(t+1) = \mu(t)$
keep β	$\beta(t+1) = \beta(t)$ $\mu(t+1) = \mu(t) + 1$	$\beta(t+1) = \beta(t)$ $\mu(t+1) = \mu(t) - 1$	$\beta(t+1) = \beta(t)$ $\mu(t+1) = \mu(t)$

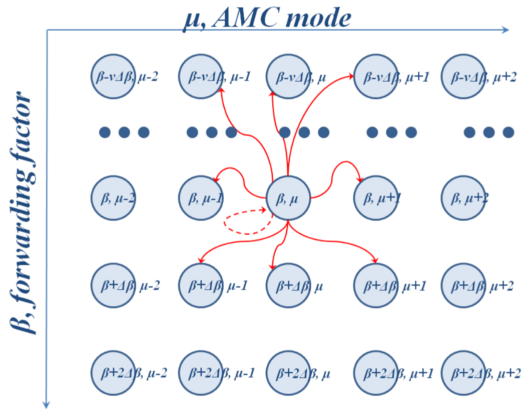

Fig. 2 FSM for the node states transitions

3.5 Utility function

The utility function chosen for our scheme is given in (3), where: $E_\alpha(t)$ is the expected energy cost for the next round (immediate energy cost) if the node assumes the suggested action α; it is normalized over the maximum possible energy cost for a single transmission, obtained for the maximum β and the minimum μ. $P_{sd,a}$ is the probability of successful delivery to neighbor nodes if action α is taken, and is given by (4) reproduced from [7].

$$U_a(t) = \frac{P_{sd,a}(t)}{E_a(t)} \tag{3}$$

$$P_{sd,\alpha} = (1 - \delta)\beta(1 - PER^n) \tag{4}$$

where δ is the statistical cure probability, n is the known neighbors count and PER is the packet error rate associated with transmitting with the new state assumed if the proposed action is adopted. The PER is calculated based on the SNR of all links to neighbors as in (5) according to [33].

$$PER = \alpha_n exp(-g_n \gamma) \tag{5}$$

where, α_n and g_n depend on the AMC mode. The value of γ can be assumed variously: we assume $\gamma = \langle\gamma_{i,j}\rangle$ for the SNR between node i and its neighbors j. However, assuming $\gamma = min_j(\gamma_{i,j})$ or $\gamma = max_j(\gamma_{i,j})$ would be more conservative or aggressive approach, respectively. The utility function can be low-pass filtered to give an average over a sliding temporal past window (6). Different window sizes define three different flavors of the scheme: aggressive, conservative and lazy flavor for window duration equal to 1 round, 3 rounds and equal to the node status lifetime.

$$\tilde{U}(t) = \frac{1}{w}\sum_{\tau=t-w}^{t} U(t) \tag{6}$$

We assume a reliable mechanism, which provides each node the CSI on the wireless channels with its neighbors. This takes place at every round. Having said the above, we need to elaborate the definition of the actions α. We define sets $\tilde{B}$ and $\tilde{M}$ as follows:

$$\tilde{B} = \{\beta - \nu\Delta\beta, \beta, \beta + \Delta\beta\} \tag{7}$$

$$\tilde{M} = \{\mu - 1, \mu, \mu + 1\} \tag{8}$$

$\tilde{B}$ and $\tilde{M}$ are the sets of allowed values for β and μ in the next round, given their present ones. Hence an action α is such that $\alpha\ B \times M \rightarrow \tilde{B} \times \tilde{M}$. Note that $\tilde{B}$ and $\tilde{M}$ change at every round as they depend on the present state of the node. The adopted action leads a node to a state reflecting the assumed transmission characteristics $(\tilde{\beta}, \tilde{\mu})$ such that

$$(\tilde{\beta}, \tilde{\mu}) = argmax_{\beta\in\tilde{B},\mu\in\tilde{M}}(\tilde{U}(\beta, \mu)) \tag{9}$$

The action choice algorithm is executed by each node at every round. Actions are chosen out of $\mid \mathcal{A} \mid$ possible ones. In this work, a number of $\mid \mathcal{A} \mid =$ 4 possible actions have been defined. Calculating the projected utilities at every round is of complexity $O(\mid \mathcal{A} \mid)$. Choosing an SNR value for the calculation of the projected PER of equation 5 is a constant time calculation if we use average over all n known neighbors and of the order of $O(n)$ if the minimum or maximum is used. Choosing the action offering the maximum utility is of complexity $O(n)$.

3.6 Quality enhancement

The regulation of the energy cost due to information dissemination can be exploited in conjunction with a scheme to improve information quality. Assume that fresh information is generated at every round and starts being disseminated. Then, different nodes are infected by data of different ages. We enhance the scheme described so far in an attempt to lower the average age of the carried information. When information received by a node is fresher, it re-infects the node, otherwise it is ignored as duplicate. That is, fresher data aggravates a nodes infection. Listing 2 summarizes this mechanism.

Listing 2 Epidemic Aggravation Mechanism

```
transmitting node i
receiving node j
infection state A(i)
age age(i)

for each round t
  if j receives info from node i
    if A(j) == false
      A(j) = true
    else if A(j) == true
      if age(j) ≤ age(i)
        do nothing
      else if age(j) > age(i)
        age(j) := age(i) % aggravate infection
      end if
    end if
  end if
end for
```

We can consider this situation as that of many distinct epidemics with different birth times. For each epidemic, nodes with staler (older) information are susceptible. The multi-epidemic situation has been studied [34] and it is shown that in order to encourage one epidemic, one needs to increase the probability that nodes be infected by it. This is reproduced in (10) here, adapted from [34] for an environment where partial cure does not occur and the infection probabilities are not constant as they depend on the varying forwarding probabilities and channel state.

$$P_{i,t+1}^{\tau} = \sum_{j \in V_i} q_{j,t}^{\tau} P_{j,t}^{\tau} + P_{i,t}^{\tau} \tag{10}$$

where $q_{i,t}^{\tau}$ is the probability at time t that node i infect another node with info generated at τ , $P_{j,t}^{\tau}$ is the probability at time t that node j be at a state of infection by info born at τ. V_i is the neighborhood of i. We suggest that the forwarding -and hence the infection- probability amplification be achieved through the use of an adaptive biasing scheme (AB), as described in eq. (3.5)

$$\beta^*(t+1) = \beta(t+1)(1 + \eta d(t)) \tag{11}$$

where β(t) is the forwarding probability value dictated by the scheme described in subsection 3.4, $\beta^*(t)$ is the forwarding probability biased to improve freshness, $d(t)$ is the duplicates ratio and η is a constant, termed the *biasing amplification factor*. Clearly η influences the extra energy cost. Essentially, we enhance our original scheme by encouraging infections with fresher info. The number of duplicates a node receives is considered a measure of the amount of nodes with staler info (ignoring uninfected nodes, though). Hence, the higher the duplicates ratio the more the forwarding probability is enhanced according to (11).

3.7 Enhancement of the dissemination stage of Directed Diffusion and AODV

The scheme previously described can be of benefit in settings where information dissemination plays a role. Such cases are the interest dissemination at the initial phase of directed diffusion and the *route request* (RREQ) message dissemination in the AODV routing protocol.

In directed diffusion an originator node disseminates periodically its interest in specific data [35]. Other nodes need to be informed of this interest as well as its originator so that data can be sent back to it when available. Interest dissemination can be a straightforward application of our proposed scheme. Important working assumptions are that there is a single requestor and the periodic interest posting occurs once per epoch. Finally, all nodes are always on, hence, all transmissions are MAC broadcasts.

In agreement with the previous sections, we postulate that our scheme is of greater benefit than pure flooding. The interest posted by the requestor is an epidemic which covers the network efficiently while the energy cost is kept at modest levels. Using a biased-β flavor of the scheme as in subsection 3.5, the freshness is also improved, which can be of benefit in case the interest changes with time.

In the AODV routing protocol, whenever a node needs to send data, it triggers a process to discover a route to the final receiver [19], [36]. The requesting node first floods the network with a request message (RREQ) which has to reach as many nodes as possible so that the intended receiver or a node with a route to it is reached. The RREQ is retransmitted only in case the requestor receives no response in the form of an RREP message or when a new fresher RREQ is received. The above essentially constitutes a dissemination landscape. An RREQ message contains attributes such as originator sequence number, link lifetime and TTL. These can be mapped to epidemic dissemination parameters such as information birth time, information expiry time and TTL (if used).

We propose that instead of flooding the network, our scheme be applied to the RREQ message dissemination phase of the AODV route discovery on behalf of a single requesting node. The desired benefit is efficient dissemination of the RREQ message while energy cost is kept checked. If we apply our scheme, the dissemination algorithm assumes the form of Listing 3.

Listing 3 Optimal Stopping Algorithm in an AODV setting

```
state (β,μ)
infection state A(i)
hold_flag(i) node does not retransmit in epoch
freshest(i) node has not transmitted fresher info
set of possible actions 𝒜

for each round t
  if A(i) == true
    for each α ∈ 𝒜
      calculate U_{i,a}(t)
    end for
```

```
      U_i(t) = U_{i,b}(t)  :  U_{i,b}(t) = max_α(U_{i,α}(t))
      if  mod(t,ε) ≠ 0
        if  ost_satisfied == true
          if  hold_flag(i) == false ∧ freshest(i) == true
            (β,μ) := (β',μ'):(β,μ) -b-> (β',μ')
            broadcast with state (β',μ')
            hold flag(i) := true
            freshest(i) := true
          end if
        end if
      else if mod(t,epoch) == 0
          (β,μ) := (β',μ'):(β,μ) -b-> (β',μ')
          broadcast with state (β',μ')
      end if
    end if
end for
```

Our working assumptions are:

- There is only one requestor
- All nodes are always on, rendering all transmissions MAC broadcasts
- The *freshest* flag is adopted to indicate the node has not transmitted data of this age or fresher.
- For the sake of simplicity, TTL is not considered at this stage.

To ease the reading of this paper, the quantities introduced and corresponding notation are presented in Table 3. Please note that a few are defined in section 4.

4 Simulation results and discussion

4.1 Definition of metrics and models

Simulation was used to evaluate the performance of the proposed scheme. The simulator [39] was developed on the Matlab platform and generates noise using the channel state Transit Matrix. The mobility patterns were created with Mobisim [40]. A random waypoint mobility model was used with the nodes moving within a square field. In order to make the benefits of the scheme clearer, a number of benchmark schemes were defined:

- **Benchmark 1, flooding**: Infected nodes broadcast unconditionally at the end of every epoch, hence $\beta = 1$. Neither β nor μ is tuned.
- **Benchmark 2, non-adaptive epidemic**: Probabilistic gossiping (PG). Infected nodes broadcast at the end of every epoch, with a constant $\beta < 1$. The AMC mode is tuned at that time instance according to [33]
- **Benchmark 3, non-OST-based adaptive epidemic**: Infected nodes broadcast at the end of every epoch. At that time instance, the utilities offered by the various allowed actions (Table 2) are assessed in a beauty contest and the action offering the highest is selected. The node changes state (β, μ) accordingly and broadcasts with its new state.

Table 3 Quantities introduced and their notation

quantity	notation
Forwarding probability	β
AMC mode	μ
Set of allowed values of forwarding probability	B
Set of allowed values of AMC mode	M
Set of possible values of forwarding probability at next round	$\tilde{B}$
Set of allowed values of AMC mode at next round	$\tilde{M}$
Nodes count	N
Epoch duration	ϵ
Statistical cure probability	δ
Utility function	U
Generalized utility function	$\tilde{U}$
Utility function value averaging window	w
Neighborhood of node i	V_i
Adjacency matrix	ADJ
Contention/collision matrix	C
Set of possible actions	$\mathcal{A}$
Possible action	α
Optimal allowed action	$\alpha*$
Beta step	$\Delta\beta$
Beta reset size	ν
SNR on link between nodes i and j	$\gamma_{i,j}$
Projected energy cost for next timeslot if action a is adopted	E_α
Projected probability of successful delivery if action a is adopted	$P_{sd,\alpha}$
Known neighbors count	n
Packet error rate	PER
Length of uncoded packet	L_0
Forwarding probability resulting from beta-biasing	$\beta*$
Duplicates ratio	$d(t)$
Corrupt packets ratio	$c(t)$
Biasing amplification factor	η
Time of birth of an infecting packet	τ
Lifetime of infecting information	τ_{expiry}

- **Benchmark 4, adaptive epidemic with active polling**: Infected nodes broadcast at the end of every epoch. During the epoch they poll their neighbors on whether they are infected. This polling process is assumed over a reliable feedback channel and is energy consuming. Then the infected node tunes its state, while assuming discrete allowed values as shown in eq. (12).

$$\beta(t+1) = \beta(t)(1-\tilde{n}) - mod(\beta(t)(1-\tilde{n}), \Delta\beta) \tag{12}$$

  where $\tilde{n}$ is the ratio of unique infected neighbors. The AMC mode is tuned at that time instance according to [33]. The modulo is subtracted to ensure β assumes an allowed value. Crossing outside the allowed range of β is disallowed.
- **Benchmark 5, passive adaptive epidemic**: Infected nodes broadcast at the end of every epoch. The node state is tuned as shown in equations (13) and (14).

$$\beta(t+1) = \beta(t)(1 - d(t)/Q) - mod(\beta(t)(1 - d(t)/Q), \Delta\beta) \tag{13}$$

$$\mu(t+1) = max(\mu(t), 1 - c(t)) \tag{14}$$

The ratios of duplicate and corrupt messages $d(t)$ and $c(t)$ respectively are calculated over the total message count received by an infected node over unit time. β and μ are always discretized. Q is a positive number. This scheme is similar, although not identical, to the counter-based scheme (CBS) [1] as the tuning of the forwarding probability is based on the received duplicates and also the channel state is taken into account. CBS allows transmission after a wait period if the duplicates received exceed a threshold. It is effectively an adaptive epidemic scheme, where the forwarding probability is tuned according to the probability that the threshold be crossed. This probability is proportional to the probability that the local infection ratio exceed a threshold. In our benchmark, this threshold depends on the parameter Q and forwarding is tuned by duplicates, but not in the binary manner of CBS. Another feature that makes this benchmark scheme more energy-aware is the concurrent tuning of the AMC mode. The parameters used in the simulations are presented in Table 4.

The parameters used in the simulations are presented in Table 3.

Table 4 Parameters used in the simulations

parameter	value
N, number of nodes	80 or 50
T, simulation duration	100
orig. forw. prob.	i.i.d. in 0.22-0.8
orig. AMC mode	i.i.d. in 1-6
number of betas	40
$\Delta\beta$, β step	0.05
I(0),originally infected nodes	4
re-infectors	1
network density	0.15
number of channel states	6
aggressiveness	conservative, unless otherwise stated
expiry period	32, unless otherwise stated
epoch duration	5
L_0 infecting packet payload	2048 bits, unless otherwise stated
random waypoint mobility field dimensions	500×500
maximum pause duration	10 rounds
maximum speed	10/round
minimum speed	5/round

The AMC used was assumed from [33]. Energy cost is normalized against the sum of costs to transmit and receive a single bit. This manner of representing energy cost is followed throughout this paper.

4.2 Energy cost reduction

In Figure 3 the tuning that β undergoes is presented (normalized against its original value). A comparison of the proposed scheme against the benchmarks of subsection 4.1 is presented. It is noticeable that the node state converges so that β is dramatically reduced. The AMC mode (μ) is conservatively tuned (± 1). Notice that some μ values correspond to higher coding rates, hence shorter packets that impose lower energy cost.

Energy cost reduction achieved with the introduction of OST is shown in Figure 4 through comparison against a non-OST scheme (benchmark 3). Meanwhile infection incurs no compromise, as presented in Figure 5. This is attributed to error-correction encoding and reduced collisions (Figure 6). A considerable amount of simultaneous broadcasts are attempted in the same vicinity resulting in contention and infection failure for all of them. Indeed, these redundant attempts are reduced when the suggested scheme is adopted.

In Figure 7 a comparison is presented among various flavors of the proposed scheme. The regular stepwise increase in energy cost is attributed to the tuning taking place once every epoch. This behavior is less obvious with the proposed OST-based scheme, as transmissions are not strictly periodic any more. It is evident that the use of the conservative flavor in the OST scheme offers considerable energy cost reduction. The near-linear energy increase after the infection is established is attributed to the fact that the forwarding probability has converged at that stage close to its minimum. In the non-adaptive case, it remains at its original value.

Furthermore, Figure 8 shows that the improvement of our scheme against the non-OST scheme (benchmark 3) is relatively consistent over infecting packet payload sizes.

Figure 9 shows a comparison of the proposed scheme against the adaptive schemes of benchmark 4 and 5 in terms of energy cost using the various parameter settings of Table 5. The energy cost is broken down to a part attributed to CSI acquisition and the remaining part, which is mainly attributed to the dissemination process ("w/o csi"). Excluding the CSI retrieval, the energy cost in case of shorter packets is lower than the cost for benchmark 4 and comparable with the passive benchmark 5. This indicates that the dissemination-related cost is successfully regulated and a large part of the residual cost is due to CSI acquisition. Further reduction of the cost would be possible through a sparser CSI, which would bring about a tradeoff between cost and precision, while noise impulses would tend to pass unnoticed.

Figure 10 gives a view of the usefulness of the forwarding probability biasing. It is shown that the adoption of an OST-based scheme offers considerable energy cost reduction across a broad scale of β-reset size values. It is understood that biasing is a parameter that allows for some tuning of our scheme.

As soon as the broadcast storm problem was formulated, some mechanisms to overcome it were suggested [1]. The Counter-Based Scheme approach already delivers energy cost reduction expressed as saved rebroadcasts of the order of up to 80%. Similarly, the Distance-Based scheme can also approach

Table 5 Parameter settings for comparison against benchmarks

parameter	setting 1	setting 2	setting 3
β reset size	7	18	24
minimum β	0.02	0	0
infecting info pkt (bits)	2048	128	128
CSI pkt = polling pkt (bits)	64	16	16

a remarkable 80%, whereas the Location-Based scheme can approach 90%. Cluster-Based schemes were introduced in the same work [1]. In that work, clustering is shown to reduce rebroadcasts by up to more than 90%. Cluster-based schemes have also been suggested later [24]. In the latter work, efficient infection is achieved with the energy cost reduced by more than 20% compared to other modern non-flooding mechanisms. In [16] the proposed scheme delivers efficient network infection through transmission power control and reduces energy cost by 75% compared to no-adaptive epidemics and approximately 35% compared to the CBS.

Our proposed scheme performs competitively and can deliver energy cost reduction of more than 80% compared to flooding, and more than 70% compared to non-adaptive epidemics. The benefit of the use of OST was also shown to be of in the area of 50%. It has to be noted that the energy cost is a monotonically increasing function of time.

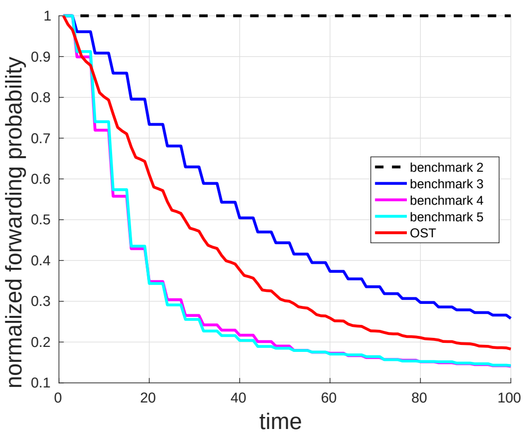

Fig. 3 Forwarding probability against time; normalized against its initial value. Comparison with benchmarks.

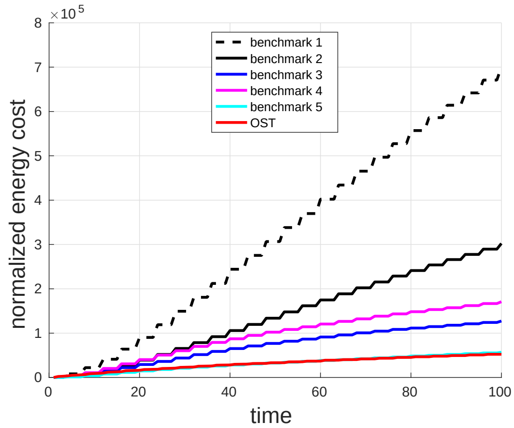

Fig. 4 Energy cost against time. Comparison with benchmarks.

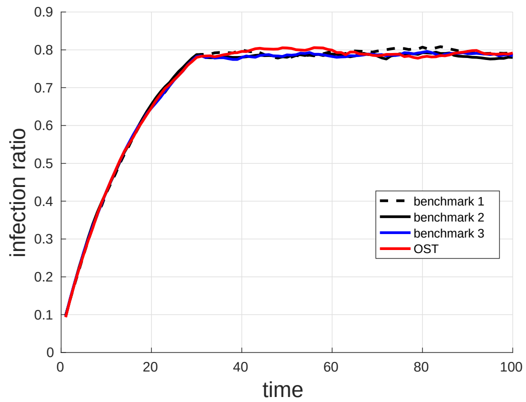

Fig. 5 Infection ratio against time: comparison of the proposed scheme against flooding (benchmark 1), non-adaptive epidemics (benchmark 2) and non-OST adaptive epidemics (benchmark 3)

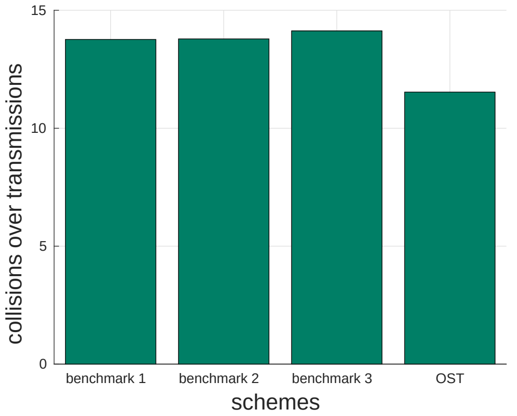

Fig. 6 Collisions count normalized over transmissions: comparison against flooding (benchmark 1), non-adaptive epidemics (benchmark 2) and non-OST adaptive epidemics (benchmark 3)

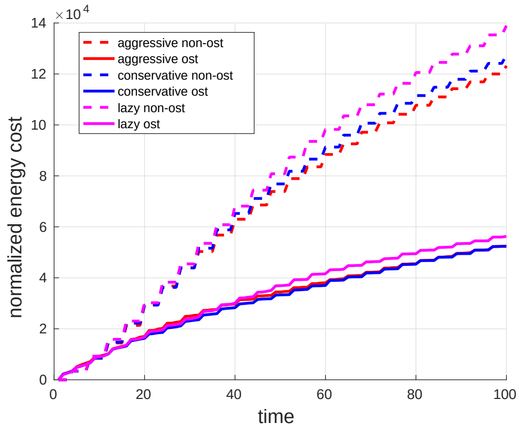

Fig. 7 Energy cost against infection ratio; aggressive, conservative and lazy flavors.

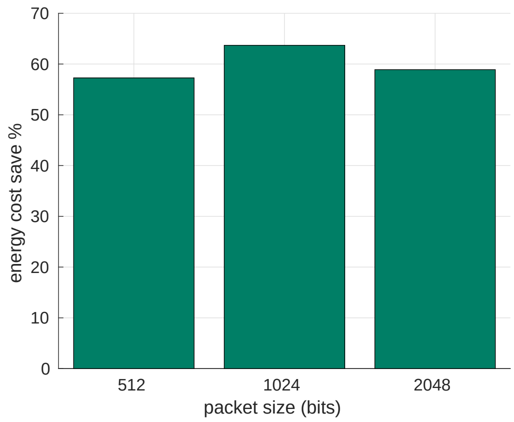

Fig. 8 Energy cost reduction delivered by the suggested scheme for various packet sizes against respective non-OST-based schemes (benchmark 3).

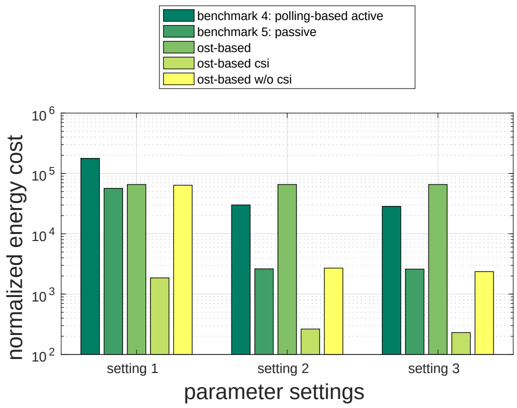

Fig. 9 Comparison against benchmarks for various packet and β-reset sizes. The cost of our scheme is broken down in CSI-related part and the remaining part (w/o csi).

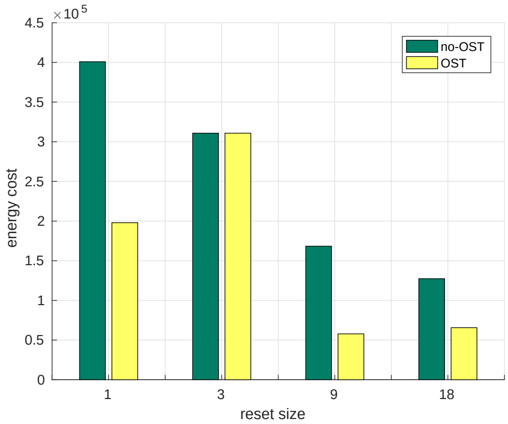

Fig. 10 Energy cost with and without (benchmark 3) the use of optimal stopping for various β–rest sizes; normalized against non-adaptive scheme size

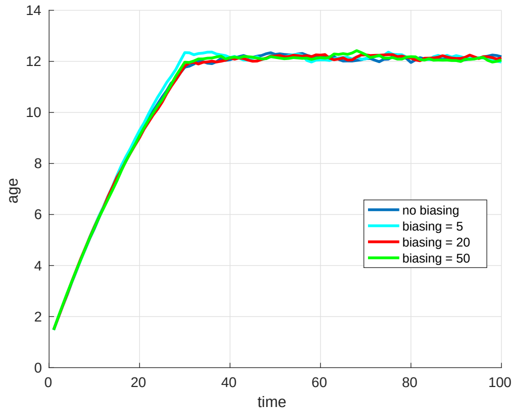

Fig. 11 Information age against time for various values of the amplification factor (biasing).

4.3 Information freshness improvement

The energy conserving traits of the proposed scheme can help regulate cost in energy intensive settings. In this mindset we assess the enhanced scheme with the adaptive biasing of eq. (11). For every $\tau \in \{1, 2, ...\}$ there is an epidemic that was born at time τ and can survive till no later than $\tau + \tau_{expiry}$. The parameter τ_{expiry} stands for the infecting information lifetime.

Each epidemic gradually gives way to fresher ones and is extinguished no later than the expiry threshold is reached. Info age improvement is, however, marginal, as shown for different values of the amplification factor (subsection 3.6) in Figure 11, and comes at increased energy cost (Figure 12). The use of the amplification factor essentially means encouraging some epidemics, hence increasing transmissions. This counterbalances the energy cost benefit delivered by our scheme. The answer to the tradeoff that surfaces here depends on the particular problem. A significant energy cost burden is tolerable only in case the freshness is of critical importance. Sensor measurements or routing protocol messaging can fall in this category, as we exhibit in section 4.4.

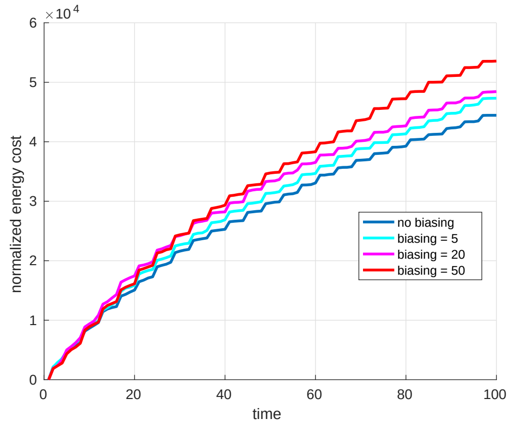

Fig. 12 Energy cost against time for various values of the amplification factor (biasing).

4.4 Application in AODV

In the route discovery phase of protocols like AODV or LOADng [42] it is required that the RREQ message covers as much of the network as possible in order to maximize the probability that the destination node or a node with a route to it be found (infected). An infected node, in this context, is a node informed of the route interest of the originally disseminating node. Additionally the age of the RREQ message should not be too old in order to avoid the dissemination of stale route requests. We assess the possibility that the proposed scheme replace flooding in such a setting.

Simulation results in Figures 13 - 15 compare the behavior of flooding, non-OST adaptive epidemics (analogous to the benchmark 3 introduced earlier) and the proposed OST-based epidemics in the RREQ dissemination phase of AODV. In such a setting the RREQ message propagates from a transmitting node gradually covering the network.

The existence of a finite expiration threshold introduces a trend that the epidemic decline even in a flooding scheme. Suppressing transmissions, as in our scheme, enhances further this trend. At the same time, it becomes less likely that the infection be replaced by fresher information stemming from more recent transmissions from the original node. The aforementioned factors contribute to the decline of the infection. However, if the message covers most of the network before it expires, the purpose will have been satisfied as the target node or one with a route to it will have been infected, i.e. informed of the requestor's transmitted interest.

The introduction of adaptive epidemics results in severe compromise in terms of infection (Figure 13). This holds for the proposed scheme, even modified with freshness enhancement (according to subsection 3.6) as well as with a non-OST based scheme, analogous to benchmark 3. Figure 13 shows the infection ratio for $\tau_{expiry} > 3 \times \epsilon$.

On the other hand the energy cost advantage is considerable (Figure 14). Adaptive schemes compete with each other but they constitute a decisive departure from the cost imposed by unconditional flooding. This performance compares favorably with both [22] and [14].

Similarly, a notable improvement in age is observed (Figure 15). In flooding, older information persists longer, whereas in adaptive schemes, the infection is based on fresher albeit less regularly broadcast information.

Finally, the impact of the expiry duration is shown in Figures 16 and 17. Quick expiry is intuitively understood to undermine the epidemic. A tradeoff is observed between persistent infection -even of potentially older age- and energy cost. Persistent infection, which possibly allows for potentially staler information, comes at a higher energy cost as there are more infected nodes to broadcast. Achieving an optimal situation requires further research. This should also expand on how an adequate amount or RREP messages are received while a young age is maintained.

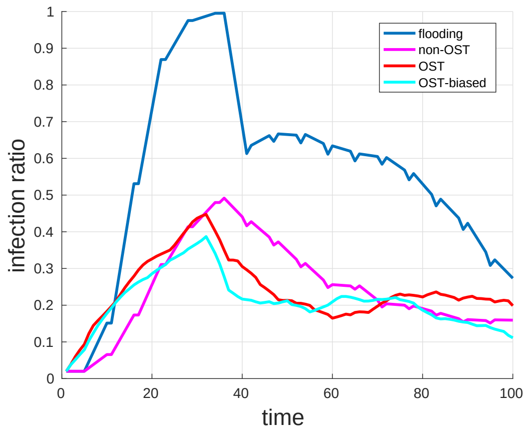

Fig. 13 Dissemination of RREQ in AODV: Infection ratio for flooding (benchmark 1), non-OST adaptive (benchmark 3) and OST schemes with and without β-biasing

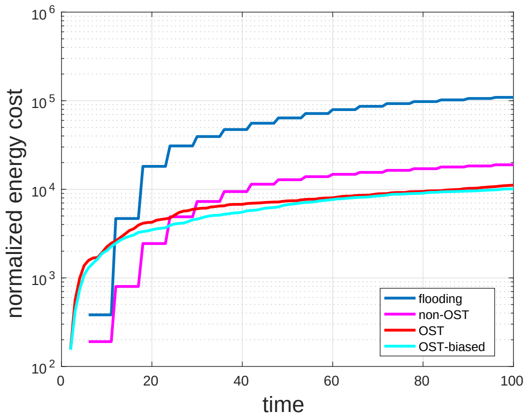

Fig. 14 Dissemination of RREQ in AODV: Energy cost for flooding, non-OST adaptive and OST schemes.

5 Conclusions

We have examined an optimized scheme of data transmission scheduling suitable for ad hoc networks where epidemic dissemination is triggered by regular broadcasts of infecting information. It successfully regulates the dissemination-imposed energy cost with no significant compromise in the spread of the epidemic.

Its enhancement through the use of adaptive biasing can favor information freshness. Moreover, this type of scheduling can be useful replacing flooding in the dissemination phases of directed diffusion and AODV. However, in such settings, tradeoff problems arise with no trivial optimum solution yet.

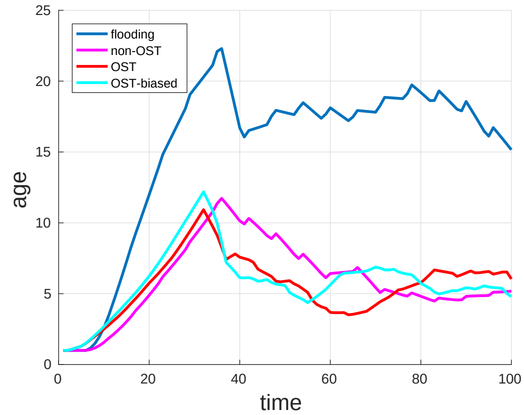

Fig. 15 AODV: Average age of the RREQ message for flooding, non-OST adaptive and OST schemes.

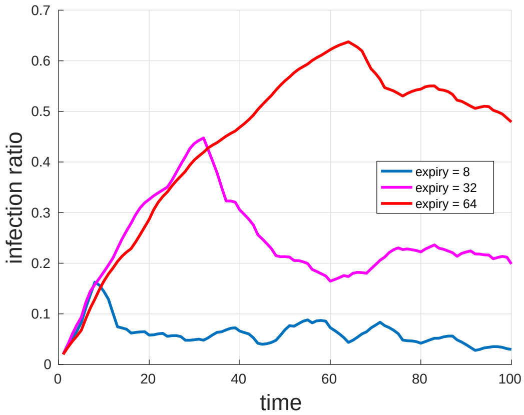

Fig. 16 Dissemination of RREQ in AODV: The impact of the ratio expiry over epoch on the infection rate.

The proposed scheme is a context-aware scheme of cross-layer nature, as it operates on the network and data link layers, and also proactive, thanks to the use of optimal stopping. To the best of our knowledge, it is the only scheme that exploits optimal stopping theory to reduce energy cost and hence prolong network life while retaining the infection in a noisy environment. It explicitly exploits the cross-layer nature of adaptive epidemics to optimally address the problem.

It delivers an exciting theoretical basis for complex dissemination models. It provides the possibility to use different utility functions thanks to its cross-layer nature and according to requirements of specific problems.

Next steps in this research topic could include information quality improvement beyond freshness, dynamic adaptation of the secretary problem

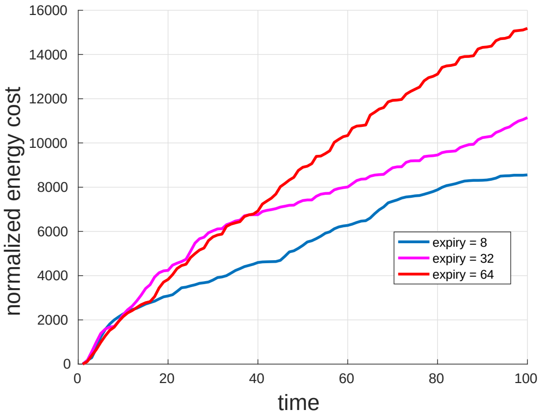

Fig. 17 Dissemination of RREQ in AODV: The impact of the ratio expiry over epoch on the energy cost

finite horizon and optimizing the application of the scheme in further routing protocol settings.

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