A Bayesian Game Based Optimization Strategy Proposal for Routing in Energy Constrained DTNs

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Abstract. *In this paper, we propose an optimization strategy to be applied to a well-known DTN routing algorithm as PRoPHET and SimBetTS which, by default, don't regard to the issue of energy constraint. Our proposed strategy is based on modeling of the message forwarding as a Bayesian game that aims specifically to capture the dynamic nature of the multi-copy replication decisions, the energy constraint of the nodes and the belief about the energy of other nodes. In addition, we consider factors of evidence aging on accumulated observations used to update the belief that a node has about the energy of the other nodes. The main feature of this belief update system is not to utilize neighborhood watch or acknowledgment mechanism. Moreover, in this paper, we conduct simulation experiments to evaluate the performance of our optimization strategy proposal from a DTN scenario with heterogeneous nodes based on realistic human mobility traces. Simulations results show that our proposed optimization strategy is able to lead the network to remain operational for a longer period of time and, consequently, to achieve a higher final delivery ratio even when compared to a proposal using energy-aware routing.*

1. Introduction

Currently, the research community in communication networks has given special attention to the study of emerging wireless networks such as delay and disruption tolerant networks (DTNs). These networks do not require the presence of a communication infrastructure and often present limited connectivity and the interruptions are frequent. Most DTN routing algorithms employ the technique of store-carry-forward and can use multiple copies of the same message to increase the probability of at least one being delivered. The typical state-of-the art routing algorithms combine heuristics and social network structure to decide for forwarding message copies or 'replicas' among the candidate relays according to some utility function. However, a utility-based replication often leads the routing to direct most of the traffic through a small subset of good relays. This unfair load distribution can quickly deplete the constrained resources utilized by mobile devices, e.g., battery.

In DTN routing literature, the problem of optimal forwarding for message delivery in an energy constrained environment is investigated by some works as [Khouzani et al. 2012], [Yoon and Haas 2012], [Li et al. 2010] and [Rango and Amelio 2013] that utilize current energy-state information in making forwarding decisions.

However, most existing energy-aware routing are proposals applicable to routing algorithms that do not consider the candidate node selection, so potentially all nodes may receive the message copy. For this reason, we propose a solution to the problem of energy-efficient opportunistic forwarding for a DTN routing algorithm that uses some utility function based on a number of different parameters (e.g., encounter history, mobility, sociability, etc.) to discover the better relay nodes, but that was originally proposed without regard to the issue of energy constraint. For example, this is the case of the well-known and cited DTN routing algorithms PRoPHET and SimBetTS.

Our proposal is a new optimization strategy based on a game-theoretic model, the energy constrained forwarding game, which considers heterogeneous and energy constrained nodes able to learn the optimal multi-copy forwarding over time. The goal is to increase the operational period of the network from a better control of energy consumption by nodes, thereby improving the message delivery ratio. In the game, nodes are led to potential selfishness as they may refuse to take on the forwarding tokens of a message received to save energy. A forwarding token implies that the node that owns a message can spawn and forward an additional copy of the given message. In [Maia et al. 2014], we preliminary presented our proposed optimization strategy and simulation-based evaluation of the optimization strategy using synthetic simulation based on Community-based Mobility Model (CBM). However, in order to gain better understanding of our proposal, we extend the considerations about the assumptions, formalizations and definitions of the game-theoretic model.

Additionally, we improve the system to update the belief that a node has about the energy of the other nodes. Due to the dynamic governing the energy consumption, we propose factors of evidence aging on the accumulated observations which are used by the belief update system. Moreover, we present simulation-based evaluation using trace-driven simulation. The used trace captures some human-mobility environments from the Santa Mônica campus of the Federal University of Uberlândia, Brazil. In the end, we present the results of simulation comparing CBM model and mobility trace.

The remainder of this paper is organized as follows. The next section describes related work. In Section 3, we present the formal aspects of the energy constrained forwarding game and the behavior strategies for the nodes are discussed in Section 4. The simulation setup is presented in Section 5 and analysis of the results in Section 6. Section 7 concludes with a discussion of the paper.

2. Related Work

Since the decision makers in a wireless network are devices that need to deal with limited resources, this imposes a conflict of interest. As a result, in order to conserve their resources, the devices may decide not to participate in the process of forwarding the messages, i.e., they adopt a selfish behavior. The theoretical analysis of game-based incentive schemes to stimulate and reward cooperation for routing messages between DTN nodes has been a very active area of research (see, e.g., [Chen and Chan 2010] and [Ning et al. 2011]). In some cases, the analyses include detection of malicious and selfish behaviors of nodes and the implementation of punishment mechanisms [Altman 2009] and reputation spreading of nodes [Gao et al. 2012]. Different from existing incentive schemes which rely on neighbors' monitoring, scoring targets or rewards, our proposed optimization strategy is based on a dynamic non-cooperative game that uses the history of selected actions and the threats from others nodes in order to encourage the message forwarding. Therefore, we admit that the nodes may become aware of at least part of past behavior of the nodes' forwarding competency and change their strategies accordingly.

An adaptive learning framework that allows nodes to learn the optimal strategies over time can be seen in [El-Azouzi et al. 2013], where the authors apply the evolutionary game theory to non-cooperative forwarding control of relay nodes in DTNs. The paper presents a general framework for competitive forwarding in DTNs under two hops routing, without considering the candidate node selection. In opposition, our model presents forwarding in DTN under multi-hop and replications based on a utility function $U(\cdot)$.

The repeated traditional Bayesian game-theoretic model with an adaptive learning process reported in [Nurmi 2006] for an ad hoc network composed of selfish nodes is the closest one to our game model. However, we use an appropriate repeated *Bayesian signaling game* formulation for copies forwarding, in a heterogeneous and energy constrained DTN. Differently from ad hoc network, in DTN, due to long propagation delay, frequent disconnection, and opportunistic or predicable connections, the assumption that there is a contemporaneous end-to-end path may not be true. Therefore, the mechanisms to the update of the beliefs used by [Nurmi 2006] as watchdog mechanism and acknowledgement messages (ACKs) are not easy to be employed in DTNs. Such mechanisms are not utilized in our proposed belief update system presented in Section 3.

3. Model of the Energy Constrained Forwarding Game

In this section, we present assumptions based on which our forwarding game in energy constrained DTN was developed. Moreover, the interactions between the nodes in a communication opportunity are formalized and the game model is defined. The scenario consisting of quite heterogeneous and sparse node populations, where a limited budget of L message copies needs to be distributed to L relays. Then, the routing algorithm uses some optimization criterion to distinguish the "better" relays and avoid using the least useful ones. Table 1 lists the main variables and simulation parameters commonly used in this paper.

3.1 Message Generation and The Node's Willingness

In this paper, it is assumed the message to be transferred needs to be split into K smaller units called chunks as in [Altman 2009]. The chunks are forwarded independently of the others and can use different intermediate nodes. Only once a sequence of chunks corresponding to a message is received, the message is considered received by the destination node. This approach is used when the contacts between nodes have a finite duration, the file is large with respect to the buffering capabilities of nodes or when a subset of chunks are necessary to reconstruct the message due to redundant information inserted into the coding of the chunks generated. However, the assumption adopted in our proposal is that the number of successes and failures of delivery of a sequence of chunks is used by the destination node to estimate the willingness of intermediate nodes to participate in a multi-hop forwarding process.

Table 1. List of commonly used variables and simulation parameters

Variable/ Parameter	Description	Used Main Value
$U_i(d)$ [$U_j(d)$]	Reflects the fitness or utility that node i [j] will be able to make a delivery to destination node d	
θ	Energy class of a node	Ten classes: {0.1, 0.2, 0.3, …, 1}
$p(\theta)$	Prior probability	Beta(45,15)
K	Total chunks of each message	10
L	Total forwarding tokens for each chunk	16
	Total generated messages	600
s and f	Successes and failures of delivery of K chunks	
$\hat{\theta}_j$	Belief of node i about the energy class of node j	
$\psi(\theta)$	Probability to accept messages according to θ	$exp(-(1.0-\theta)/1.15)$
π	Behavior strategy	
α and β	Parameters of a beta distribution	
$l_i(c)$ [$l_j(c)$]	Forwarding tokens sent [accepted] by node i [j]	
ω	Discount weight	0.98
c_1	Parameter of the payoff function	1.4

3.2 Bayesian Signaling Game

Our proposed game considers that the general model is a Bayesian repeated game where each repetition is a stage. The stages of the game begin as simple Bayesian signaling games [Fudenberg and Tirole 1991] played by two nodes when they encounter and a node has chunk copies that can be relayed by other. Bayesian games (also known as games with incomplete information) are models of interactive decision situations in which decision makers (players) have only partial information about the data of the game and about the other players. Adopting a Bayesian statistical approach, we assume that the player who has partial knowledge about the game data has some beliefs or uncertainties about unknown parameters. Players choose their actions during the game according to their beliefs and private information.

One of the most common applications of incomplete information games is signaling games. In a typical signaling game there are two players, one called sender and the other called receiver. The sender observes its type θ from a set of types $\boldsymbol{\Theta}$ and sends a signal m_{sig} to the receiver selected from a set of signals $\boldsymbol{S}_{\theta}$. The receiver player observes the signal m_{sig}, but not the type θ of the sender, and decides to choose an action a from its action set $\boldsymbol{A}$.

3.3 Game Specification

Let node i be a node that has chunk copies to be forwarded to another node called j. Considering that the nodes will make decisions as in a signaling game, the player node j is the sender (of the signal) and player node i is the receiver. Regarding the type of player, the model assumes that each node in the DTN has a discrete representation for energy, which is uniquely known to him. This discretized energy is the energy class θ of a node and identifies the concept of type of the player in Bayesian games. The set Θ consists of all possible values of energy. In the admitted signaling game, node i can not observe the type of player j, however, i has a prior knowledge that j can be of type θ with probability $p(\theta)$. The probability $p(\theta)$ is called a prior probability or initial belief of i about the type of j. The prior probability distribution $p(\cdot)$ over Θ is common knowledge among the players, that is, it is assumed that the discretization is global. This means that all nodes in the network can have the same set of possible values for the energy classes.

In the game, node i 'looks for' the best candidates among the nodes of the network that it can trust to replicate the chunks it stores. A new stage of game begins when node i encounters a node j with no copy of a certain chunk m and mobility-aware or social-aware utility function $U_j(d)$, which reflects the probability of node j to deliver this chunk to node d. Thus, node i decides to forward a copy of chunk m to node j according to the criterion of relative utility $U_j(d) > U_i(d)$. Accordingly, this paper assumes that the value $U_j(d)$ for the chunk can be used by node i as a signal of node j's ability to replicate the copies. Then, the set of signals for node j is given by $S_{\theta_j} = \left[U_j^{min}(d), U_j^{max}(d)\right]$, where min and max values for U_j are given by the routing algorithm used. For example, in PRoPHET, U^{min} and U^{max} are 0 and 1, respectively. Node i can use the observable value of the utility function of node j to form a judgment about the real energy class of node j. At an encounter, the updated belief that node i has about the energy class of node j just by observing the value of the utility function is denoted by $\mu\left(\theta_j | U_j(d)\right)$.

The action space of node i derives from the possibilities of number of forwarding tokens for a chunk copy that the node has to grant to node j. Thus, for the chunk m stored in the buffer with $c > 1$ forwarding tokens, the action space of node i is the set $A_m^i = \{l_i(c) | 0 \leq l_i(c) \leq c - 1\}$, i.e., the possible amounts of $l_i(c) \in [0, c-1]$ tokens that node i can assign to the copy of chunk m to be sent to node j during the encounter. On the other hand, let $l_j(c)$ be the number of forwarding tokens effectively accepted by node j for the copy of chunk m with $l_i(c)$ forwarding tokens sent by node i. Thus, the action space of the node j is the set $A_m^j = \left\{l_j(c) | 0 \leq l_j(c) \leq l_i(c)\right\}$, i.e., it consists of all alternatives between zero (i.e., don't accept m) and $l_i(c)$. Therefore, the actions of node i clearly restrict the actions of node j within the game tree. As an example of this type of situation, Figure 1 shows a tree of a game with a node j that has two possible types and where node i may simply not send a copy of the chunk, i.e., $l_i(c) = 0$, or forward a copy of the chunk with the possibility of granting to node j from 1 to $l_i(c)$ forwarding tokens.

3.4 Belief Update

In this paper, a node cannot know exactly what energy is available to other nodes, because the scenario admits that there is no incentive for other nodes to reveal that information. Moreover, in our game, energy class is considered as a kind of reputation associated with forwarding competency mapped to match an energy class θ. Hence, it is not trustworthy a node to communicate directly to other nodes its own reputation, since reputation is the opinion of one entity towards another based on past experiences.

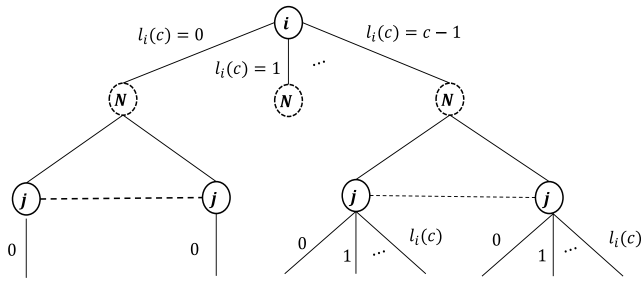

Figure 1. An example of game tree, which has a node j with two possible types, and where node i can decide to forward a chunk copy between 0 or $c-1$ forwarding tokens. In a Bayesian game, N represents the nature which chooses the type of node j, and this type is j's private information.

However, a node can make rough estimates about energy available to other nodes via prior knowledge of the network and own observations gathered during the encounters.

The model considers the chunks of a sequence which were forwarded by an intermediate node as the number of successes and it is denoted by s. Otherwise, the failures f will be given by $K - s$, where K is the number of chunks of a sequence. The chunks delivery of a sequence can occur in a fragmented way through more than one encounter. For this reason, each node that has been the destination of chunk sequences stores in a table the number of successes and failures regarding the nodes participating in the delivery of these sequences. Intuitively, this simply means that the greater the delivery successes assigned to a node, the more likely it is that the node has a greater forwarding competency. Thus, we assume the accumulation of observations of the successes and failures for a participating node can be used to estimate its energy class θ based on Bayesian inference [Neapolitan 2003]. To this end, we can assume that the parameter θ is a random variable and that its prior probability $p(\theta)$ is given by a beta distribution $Beta(\alpha, \beta)$, where α and β are non-negative shape parameters that are initialized to some values α_0 and β_0. When a new observation of s successes and f failures is collected at a new encounter, the prior distribution is updated by $\alpha \leftarrow \alpha + s$ and $\beta \leftarrow \beta + f$.

According to the definition of Bayesian inference, the basic value for a belief b of a reputation can be quantified by the expected value of the beta distribution given by $\alpha/(\alpha + \beta)$. However, this ratio cannot reflect the uncertainty of the distribution. Therefore, the model assumes that node i's opinion about node j is given by $b + \tilde{b} + u = 1$, where b, $\tilde{b}$ and u denote belief, disbelief and uncertainty, respectively. From the Dempster-Shafer theory, the normalized variance of the beta distribution is used to define u as

$$u = \frac{12 \cdot \alpha \cdot \beta}{(\alpha + \beta)^2 \cdot (\alpha + \beta + 1)}. \tag{1}$$

This uncertainty satisfies two important attributes expected for the concept of uncertainty. First, when there is more evidence, u will be consequently lower. Second, when there is greater evidence for s successes or f failures, u will be smaller than when compared to the situation in which both evidences are equal. The total certainty is $(1 - u)$, which is used as the proportion of supporting evidence in the observed results given by belief. Thus, according to the Bayesian inference, we have that the belief is given by

$$b = \frac{\alpha}{(\alpha + \beta)} \cdot (1 - u). \tag{2}$$

In this paper, in addition to adding uncertainty to the opinion of the node on the estimation of the energy class of other nodes, we include two factors of evidence aging which didn't mention in our previous paper [Maia et al. 2014]. Intuitively, it is expected that the energy value fades along the time because the nodes are continually expending energy on message transmissions. This fading should be considered even that the nodes do not receive messages for updating the prior distribution or that, by the nature of DTNs, the observations are made between long intervals. Thus, the model considers a discount and addition weight, i.e., $\mathcal{D}$ and $\mathcal{A}$, to indicate the freshness, respectively, of success and failure evidences as aging factors for a window of time ΔT, such that

$$\alpha = \alpha \cdot \mathcal{D} + s \quad \text{and} \quad \beta = \beta \cdot (1 + \mathcal{A}) + f, \tag{3}$$

where $\mathcal{D} = \omega^{\frac{\Delta t}{\Delta T}}$, $\mathcal{A} = 1 - \mathcal{D}$ and Δt is the time interval since the last observation, since ω is a discount weight defined empirically and ΔT is the average time interval from an empirically defined number of time intervals between updates of evidence. Therefore, the factors of evidence aging considers that over time the success evidences tend to decrease and the failure evidences, to increase.

4. Strategies of the Proposed Game

In a signaling game, it is possible to classify the equilibria in pure strategy in two extreme cases. The equilibrium is called a separating equilibrium if each type of sender player behaves differently, sending different signals. If the types behave in the same way in the equilibrium, i.e., the same simple signal is sent by all types with probability equal to 1, the equilibrium is called pooling equilibrium. In this section, the behavior of nodes i and j are described considering that the model assumes that the nodes decide on strategies in a pooling equilibrium.

Behavior of node $\boldsymbol{j}$ – The model assumes that at each stage in the first period of game node j observes its type θ_j and sends the signal $U_j(d)$. Then node i observes $U_j(d)$ and acts deciding on the value of $l_i(c)$ forwarding tokens for a chunk copy to be forwarded to node j. In a second period of the game, node j decides how many of the $l_i(c)$ forwarding tokens that have been granted it must accept. For each period, node j has its behavior strategies given by the set $\boldsymbol{\pi}_j = \{\pi_j^1(\cdot), \pi_j^2(\cdot)\}$, where $\pi_j^1(\cdot)$ is the strategy for the first period and $\pi_j^2(\cdot)$ is the strategy for the second period.

So, let $\pi_j^1(U_j(d)|\theta_j)$ be the probability with which node j of type θ_j sends the signal $U_j(d)$. The model assumes that, in the first period of each stage, the signal $U_j(d)$ can be sent by any type θ_j of node j, i.e. $\pi_j^1(U_j(d)|\theta_j) = 1$ (pooling equilibrium). Therefore, node i understands that the received signal may have come from a node of any energy class because we assume that the utility function is no energy-aware.

It is assumed that the behavior strategy of node j in response to the action of i, i.e., $\pi_j^2(\cdot)$, is due to a probabilistic event. The event is given by the probability of node j

to accept the forwarding tokens granted by node i to it for the chunk copy sent. The probability of accepting the forwarding tokens is due to the energy class θ_j at the moment of the encounter. Energy management is fundamentally concerned with energy spending on future transmissions of copies that are associated with forwarding tokens of the copy received. So, let $\psi(\theta_j)$ be the function that assigns a probability to the current energy class θ_j. It is assumed that the function $\psi(\cdot)$ maintains orderly energy classes, i.e., if θ_{j1} represents less energy than θ_{j2} then $\psi(\theta_{j1}) < \psi(\theta_{j2})$.

Of course, this means that the nodes with more energy will probably have a greater willingness to accept the forwarding tokens associated to copies to be sent. Thus, given the action of node i to grant $l_i(c)$ tokens for each chunk copy, node j will take on average $\psi(\theta_j) \cdot \sum_n l_i(c_n)$ forwarding tokens for all the n copies of forwarded chunks at the time of the encounter. This corresponds to the behavior strategy for node j in the second period of the stage.

Behavior of node $\boldsymbol{i}$ – The model assumes that the actions of node i must balance the dispersion of copies of chunks it carries and the use of energy. For this purpose, node i forms beliefs that guide its decisions about how many forwarding tokens, for each chunk copy, it must grant to node j. These beliefs or theories are about the types of other players and their behavior strategies. Let $\boldsymbol{\phi_j}$ be the theory of node i about the parameters of interest to a node j, i.e.,

$$\boldsymbol{\phi}_j = \{\hat{\pi}_j, \hat{\theta}_j\}, \tag{4}$$

where $\hat{\pi}$ is the belief of node i about the behavior strategies of node j and $\hat{\theta}_j$ is the belief of node i about the enegy class of node j, i.e., the type of node j.

Once the pooling equilibrium is admitted in which all possible types of node j can send the same type of signal $U_j(d)$, a perfect Bayesian equilibrium with this behavior strategy of node j is only consistent with a belief of node i such that, according to Bayes' rule, $\mu\left(\theta_j | U_j(d)\right) = p(\theta_j)$. This means that the node cannot form any other expectation about node j besides the prior distribution that exists between the node types, so the signal is inefficient in revealing the type. For this, we assume that each node update the prior knowledge about other nodes based on the use of Bayesian inference about accumulated observations of successes and failures in the delivery of a sequence of chunks as is shown in Section 3. Hence, according to Bayes' rule, the belief $\hat{\theta}_j$ about the type of node j should be calculated as $\hat{\theta}_j = [\alpha/(\alpha+\beta)] \cdot (1-u)$.

The model then assumes that node i assigns a probability $\psi(\hat{\theta}_j)$ for each node j, where $\psi(\cdot)$ is a function that assigns a probability to an energy class. This probability is the node i's belief about the node j's capacity to receive and retain a chunk copy with a certain number of forwarding tokens associated to this chunk. In other words, $\psi(\hat{\theta}_j)$ is the node i's belief regarding the behavior strategy of node j in the second period of the game stage. It is assumed that this probability offers a degree of confidence about the value $U_j(d)$ in the sense that corrects it to a new value given by

$$U_j'(d) = U_j(d) \cdot \psi(\hat{\theta}_j). \tag{5}$$

Note that, given a lower probability assigned to node j, the delivery predictability of node for that destination will be corrected downward. It must be remembered that the calculation of the utility function given by the routing algorithm originally proposed does not take into account any energy constraint.

Regarding its own utility function, it is assumed that node i performs a balance on its utility function based on its current energy class θ_i, such that low energy levels for node i compromise its own delivery predictability. Hence, the new value for $U_i(d)$ is given by

$$U_i'(d) = U_i(d) \cdot \psi(\theta_i). \tag{6}$$

After reevaluating the value of its own utility function and the value of the utility function of node j, node i must decide how many forwarding tokens for the chunk copy to be sent it should grant to node j. The model assumes that the actions of node i must balance the dispersion of copies of chunks it carries and the use of energy. For this purpose, we assume that a node i of energy class θ_i and $U_i'(d)$ decides how many tokens $l_i(c)$ for a chunk copy it should grant to a node j maximizing the payoff composed of two components (gain and cost) given by

$$\mathcal{U}_{\theta_i, U_i'(d)}\left(l_i(c), U_j'(d), \hat{\theta}_j\right) = \tag{7}$$

$$\left(U_j'(d)/\left(U_i'(d) + U_j'(d)\right)\right) \cdot l_i(c) - \left(1 - \psi\left(\hat{\theta}_j\right)\right) \cdot exp\left(c_1 \cdot l_i(c)\right),$$

where c_1 is a parameter whose value is set empirically so that the payoff function meets the requirement of being of Neumann - Morgenstern type and reflects the node i's sensitivity to make the decision for an action $l_i(c)$.

The gain component of the payoff equation considers that node i has more to gain by granting a greater number of forwarding tokens when the ratio of the corrected values of utility given by $U_j'(d)/\left(U_i'(d) + U_j'(d)\right)$ is greater. Evidently, for any fixed $U_j'(d)$, when the node i's energy is more low, $U_i'(d)$ will be consequently lower, then such ratio will present greater values and node i will gain if it grants more forwarding tokens. However, with more energy it could experiment to grant fewer tokens and wait for the next encounter opportunities in the hopes that there will be nodes more favorable to the forwarding. On the other hand, for an action $l_i(c)$, it is assumed that if the probability estimation of node j to reject the granted tokens, given by $1 - \psi\left(\hat{\theta}_j\right)$, is greater, also then the cost component is greater. Furthermore, the model guarantees the experiment conditions of the adaptive learning framework [Groes et al. 1999]. According to this theory, node i selects action $\hat{l}_i(c)$ that maximizes (7) with a probability of $1 - \epsilon_k$, where ϵ_k is a sequence of small errors that decreases in relation to the number of contacts. The equilibrium and optimality proofs of the game-theoretic model with the learning process can be seen in [Nurmi 2006].

5. Modeling and Simulations

We conduct simulation experiments to evaluate our optimization strategy applied in PRoPHETv2 [Grasic et al. 2011] and SimBetTS [Daly and Haahr 2009]. We have chosen these algorithms because they are quite popular within the DTN research community. PRoPHETv2 is the old PRoPHET updated with a new transitive update equation and direct encounter update equation; and SimBetTS is based on social analysis of past interactions of a node. For the experiments of this paper, we developed the DTN simulator presented in [Maia et al. 2013] from the OMNeT++ Simulation Environment, which provides the basic machinery and tools to write network simulations. The main simulation parameters can be seen in Table I.

5.1 Simulation Setup

Differently of our previous paper, we have run simulations based on traces to evaluate how our proposed strategy can optimize message delivery in a DTN with heterogeneous and energy constrained nodes; the used routing algorithm relies on mobility-aware or social-aware utility function. The used trace data represent a human social network of the Campus Santa Mônica of Federal University of Uberlândia, Brazil (area of 280,119 m^2). Forty nodes are uniformly and sparsely distributed as the users of four department buildings of the Campus. A node can move inside its own community for subareas as office rooms of the university department building. Once in a while, the node can leave its community. When the nodes leave their communities, they are directed to points of interest (POIs). In this paper, four locations of Campus are defined as POIs: one university restaurant, one library e two cafeterias. In these POIs, the encounters occur especially with nodes from other communities. Once out of its community, the node can choose to continue to visit other POIs or return to its community of origin.

Four groups of nodes are used in our simulations: fixed nodes, community nodes, local nodes and roaming nodes. Community nodes are users which do not usually go to POIs and spend the day working in their own offices and occasionally visit other offices in their department building. Local nodes are users which can occasionally go out for library or cafeterias. Roaming nodes are users which daily lunch at the university restaurant, take morning and afternoon coffee break at the Campus' cafeterias and also can go to library. Mobile nodes move with maximum speed of 3.0 m/s on paths defined in the form of Campus' map and choose the shortest path based on movement model of Simulation of Urban Mobility (SUMO) [Krajzewicz et al. 2012]. Values used for movement speeds and wait times represent values commonly observed for real users of Campus. A small transmission range of 5 m was adopted so that can be expected the network will be highly partitioned and not clustered. In addition, the simulator considers that when two nodes move within their transmission range they can exchange information successfully.

In the experiments, after a warm-up period of 5 hours, ten messages are sent every minute for 60 minutes. The pair source and destination nodes are chosen randomly and belong to different communities. With this, the most requested nodes to forward chunks between communities are the roaming nodes and these chunk exchanges occur at POIs or on the paths of Campus. Nodes of a particular department building do not roam around other department buildings. Therefore, the deliveries usually do not occur directly from the source node to the destination node, i.e., the chunks are largely delivered in more than one hop. Hence, the generated network traffic in our scenario requires network routing in order to be delivered, which favors the emergence of some relay nodes most requested than others.

In this paper, a node in the network has the prior probability distribution $Beta(45,15)$ of the energy level of all other nodes. The charge for a battery is defined as being able to perform 2400 transmissions. The proposed evaluation is performed assuming that the energy reserves of the nodes are not replenished. Thus, when a node runs out of energy, it dies and does not forward any chunks nor does it generate new traffic to the network. Although such assumption is not always true for real users of a Campus since they can recharge their batteries, under this assumption, energy-efficient forwarding algorithms can be better evaluated in terms of the balance of energy consumption of nodes and period of time that the network will remain operational. The traces from Campus environment were used because they insert an adequate repeatability and predictability that could leverage a routing algorithm based on mobility-aware or social-aware utility function.

Under the same energy constrained scenario, we compare the performance of PRoPHETv2 and SimBetTS with regard to three different settings: default mode, energy-aware mode and our optimization strategy. The former mode takes routing decisions based on original utility function. The second introduces energy awareness in the routing decision. In this mode, there is a resultant utility function that is the sum of the original utility function defined by routing algorithm and an energy-aware utility function as used in [Chilipirea et al. 2013]. In both modes, the amount of copies is split between two nodes in proportion to their utility function. In this paper, the results are average from five simulation runs, and the error bars in the graphs represent the 95% confidence intervals.

6. Simulation Results Analysis

Initially, we only consider the performance comparisons of the routing algorithms in relation to the network as a whole. For this, the performance metrics observed are average values of the delivery ratio, the delivery delay, the total transmission and the offline nodes ratio at the end of simulated time of 50h, as are shown in Figure 2.

As can be seen from Figure 2a, the use of our proposed strategy reduces the amount of offline nodes by more than 30% when compared to default and energy-aware mode. As are mainly roaming nodes those nodes more saved by our strategy, then the network remains operational for a longer period of time so the shutdown is delayed. This allows more encounters can happen, thus increasing the likelihood of new successful forwarding. Therefore, the gain in deliveries observed in Figure 2b for our proposed strategy, i.e., 20% for SimBetTS and 13% for PRoPHETv2 when compared to default mode, is primarily due to the lower ratio of offline nodes. This, in turn, is result of the optimization of routing algorithms that achieves as minimal energy consumption as possible, while maintaining adaptability to challenges of the DTN scenario considered. Due to its energy-efficient forwarding, our proposed strategy allows the whole network to achieve similar amount of total transmission as in default and energy-aware mode (see Figure 2c), however, without the same ratios of offloads battery observed for these two modes of operation of the routing algorithms.

It is interesting to note that the improvement in average delivery ratio obtained by our strategy results in increased average delivery delay, as is shown in Figure 2d. This result is in agreement with the most of the research on routing algorithms for DTN, which focuses on reducing the total energy consumed for forwarding at the expense of increased delivery delay. Moreover, we observe that energy-efficient forwarding due to our proposed strategy is achieved by slightly better balance of transmissions between the node classes. In both routing algorithms, the proposed strategy increases slightly the participation of community and fixed nodes on total transmission. How can be seen in Figure 3, our proposed strategy reduces the participation in the total transmission especially for roaming nodes in SimBetTS. In this routing algorithm, it is a common observation the best nodes carry out most the final hop by which the message arrives to destination. Therefore, we observe that when our proposed strategy is used, a portion of those final hops is transferred to the community and fixed node classes.

Finally, Table 2 provides a comparison between the simulation results in CBM model and mobility trace, considering the use of optimization strategy proposal and the maximum simulated time for the respective scenarios. In general, our proposed optimization strategy applied to SimBetTS takes better advantage of the higher number of contacts between the nodes and the greater degree of predictability and repeatability of node mobility in trace-driven simulation. This results in higher average delivery ratio and lower average delivery delay when compared to PRoPHETv2's results.

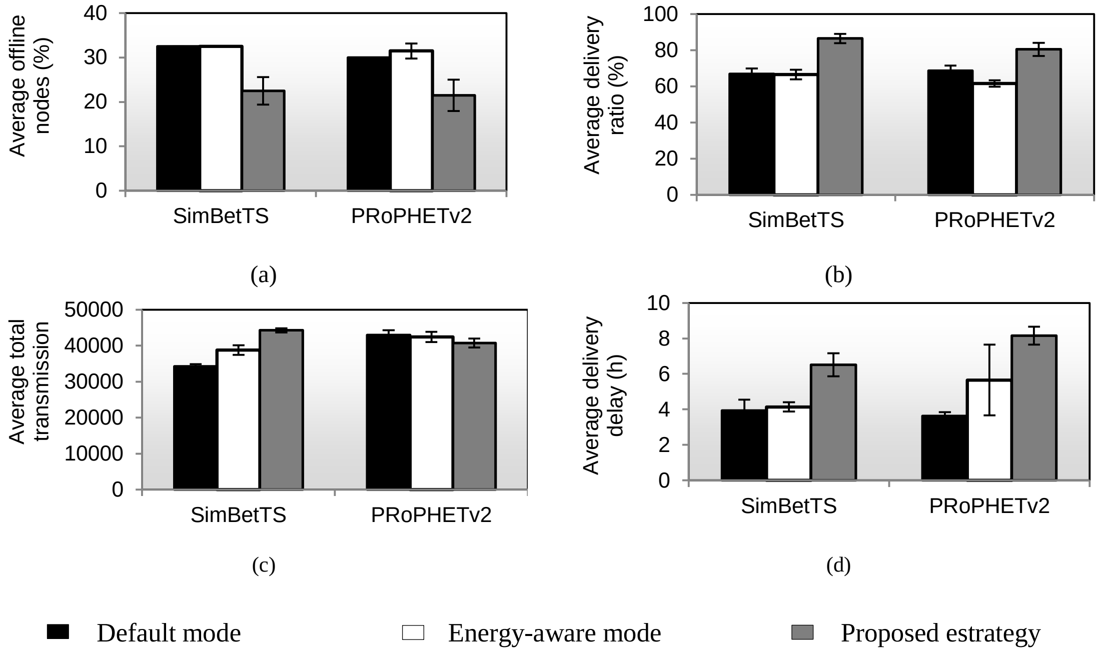

Figure 2. The performance comparisons of the routing algorithms in relation to the network as a whole: a) average offline nodes; b) average delivery ratio; c) average total transmission; and d) average delivery delay.

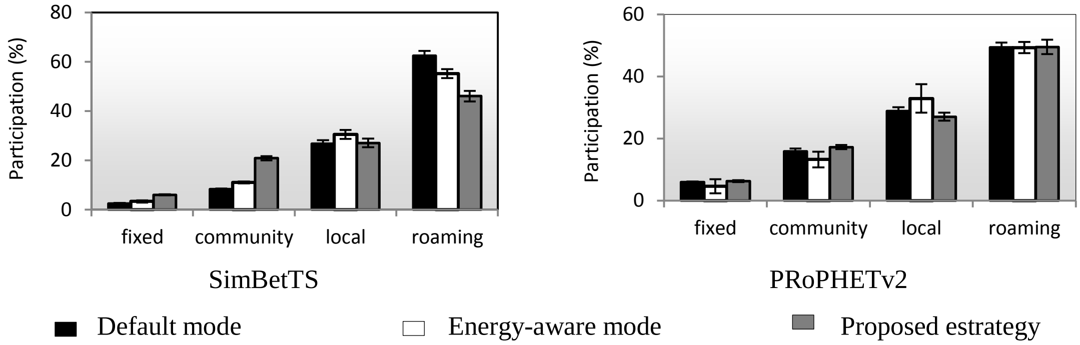

Figure 3. Average participation of the node classes in the total transmission.

Table 2. Result summary of PRoPHETv2 and SimBetTS for CBM and trace at maximum simulated time

Metrics	PRoPHETv2		SimBetTS	
	CBM	Trace	CBM	Trace
Delivery ratio (%)	82	81	83	87
Delivery delay (h)	4	8	3	7
Total contacts	6221	8201	6649	8096
Total transmission	40458	40735	45193	44275

Furthermore, the use of our proposed optimization strategy allows SimBetTS to reduce the total transmission in mobility trace scenario when compared to CBM model.

7. Conclusions

In this paper, we present a new Bayesian game model which optimizes routing in a DTN comprising heterogeneous node populations and subjected to energy constraint. In the proposed game model, a node can learn how to decide on the number of forwarding tokens associated with a chunk to be sent to another node taking into account the estimates created concerning energy and behavior strategies of the other node. The proposed game model can be implemented in DTN scenarios where the routing algorithm uses some utility function to select the best nodes to relay. In addition, we use a system to update beliefs that does not include acknowledgement confirmation or neighborhood watch mechanisms, which are difficult or impractical to be implemented in DTNs. The results of our proposed optimization strategy show a better balance of energy in the network, and keeping it operational for a longer period of time. Social-aware routing as SimBetTS and mobility model based on trace favor our proposed optimization strategy to achieve better performance. For future work, we plan to evaluate other strategies for belief update to lead to even better estimates of the energy classes of network nodes.

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