turnitin

Digital Receipt

This receipt acknowledges that Turnitin received your paper. Below you will find the receipt information regarding your submission.

The first page of your submissions is displayed below.

Submission author:	Bambang Soelistijanto
Assignment title:	Cek karya ilmiah
Submission title:	The Efficiency-Fairness Trade-Off of Social-Rank-based Forw...
File name:	ocial-Rank-based_Forwarding_in_Social_Opportunistic_Netw...
File size:	325.37K
Page count:	7
Word count:	5,263
Character count:	28,365
Submission date:	09-Jan-2023 01:27PM (UTC+0700)
Submission ID:	1990070758

The 2016 IEEE Asia Pacific Conference on Wireless and Mobile (APWiMob)

The Efficiency-Fairness Trade-Off of Social-Rank-based Forwarding in Social Opportunistic Networks

Bambang Soelistijanto
Informatics Department
Sanata Dharma University, Indonesia
b.soelistijanto@usd.ac.id

Abstract — **Social-rank-based forwarding algorithms favour the most popular nodes as the most likely relay nodes to deliver messages to the destinations. When these strategies are able to deliver messages with a high success rate and a low delay in social opportunistic networks (SONs), this however creates unbalanced load distribution, where the most popular nodes carry a much heavier burden compared to others. In this paper, we analyze the efficiency and fairness trade-off of social-rank-based forwarding strategies in SONs. Initially, we investigate the node popularity distribution in real-life SONs. We confirm that the node popularity is power-law distributed, with the existence of a few hub nodes that have many connections with other nodes and therefore are much popular in the entire network. Subsequently, we apply a social-rank-based forwarding algorithm on these human-centric networks. Moreover, we perform two distinct scenarios as follows. In the first scenario, we consider absolute delivery efficiency and examine the impact that hub nodes have on the network delivery performance. We show that these nodes enable the network to deliver messages with a high probability in a low delay; however, this consumes much resources on the central nodes. In the second scenario, in contrast, we consider the absolute fairness of resource allocation across the network nodes. We confirm that maintaining this fairness significantly degrades the network delivery performances.**

Keywords: social-rank-based forwarding, social opportunistic networks, node popularity, efficiency-fairness trade-off

I. Introduction

In recent years, opportunistic networks have gained popularity in research as a natural evolution from mobile ad hoc networks (MANETs) [1]. In opportunistic networks, nodes come into contact with each other at unpredictable intervals with an unpredictable duration of each contact. Technological advances are leading to a world replete with mobile devices, such as cellular phones, notebooks, and gadgets, thus paving the way for a multitude of opportunities for device contacts. Opportunistic computing exploits opportunistic communication between devices to share each other's content, resources and services. Examples of opportunistic networks include animal wildlife monitoring networks [2], vehicular networks [3], and social (human) opportunistic networks [4].

Social opportunistic networks (SONs) to date have been investigated as a promising approach for communications (e.g. the Haggle project [5]). SONs attempt to close the gap between human and network behaviour by taking a user-centric approach to networking. These networks exploit users' mobility as an opportunity to enable data forwarding. SONs are therefore human-centric because the node contacts reflect the way humans come into contact, and humans tend to move in a way that is influenced by their social relationships. SONs are consequently tightly coupled with social (relations) networks and knowledge of human relationships can be exploited to build more efficient and reliable communication protocols.

Social-aware forwarding algorithms [6,7] use node social structures, such as popularity (social rank) and community (social clique), as the forwarding metrics to efficiently select the most likely relay nodes to deliver messages to the destinations. Furthermore, social-rank-based forwarding [8,9] considers node popularity in the entire network and favours the most popular nodes as the best carriers to enable the data delivery in a low delay. Node popularity in a social network is commonly evaluated by a centrality metric, e.g. Freeman's centrality measures [10]. During node contacts, the algorithms transfer messages to nodes with a higher centrality than the forwarding node, so the centrality monotonically increases from source to destination (a next-best-hop *hill-climbing* heuristic). When these strategies are able to bring a high delivery success rate within a low latency in SONs, this however creates unbalanced load distribution among the network nodes, where a few most popular nodes carry a heavier burden compared to others, quickly depleting the constraint resources of these nodes, e.g. power and storage, and eventually degrading the network delivery performance. With the increasing workload today, it has become critical to make full use of the limited resources of mobile devices so that the resource efficiency can be improved and hence more and more mobile applications can be supported. Ensuring network resource distribution fairness is therefore a crucial goal if social-rank-based forwarding strategies are to be adopted in the future.

In this paper, we analyze the trade-off between delivery efficiency and network resource distribution fairness when social-rank-based forwarding algorithms are applied in SONs. Previous study in [11] has discussed this issue in general mobile opportunistic networking. This paper however focuses it in SONs, since these human-centric networks posses a unique characteristic, namely a non-random topology structure, exhibiting a power-law node degree distribution with the existence of a few high degree nodes [12,13]. These nodes have many connections with other nodes and therefore are much popular in the network and can act as communication hubs in the network. Consequently, a social-rank-based

The Efficiency-Fairness Trade-Off of Social-Rank-based Forwarding in Social Opportunistic Networks

by Soelistijanto Bambang

The Efficiency-Fairness Trade-Off of Social-Rank-based Forwarding in Social Opportunistic Networks

Bambang Soelistijanto
Informatics Department
Sanata Dharma University, Indonesia
b.soelistijanto@usd.ac.id

Abstract — **Social-rank-based forwarding algorithms favour the most popular nodes as the most likely relay nodes to deliver messages to the destinations. When these strategies are able to deliver messages with a high success rate and a low delay in social opportunistic networks (SONs), this however creates unbalanced load distribution, where the most popular nodes carry a much heavier burden compared to others. In this paper, we analyze the efficiency and fairness trade-off of social-rank-based forwarding strategies in SONs. Initially, we investigate the node popularity distribution in real-life SONs. We confirm that the node popularity is power-law distributed, with the existence of a few hub nodes that have many connections with other nodes and therefore are much popular in the entire network. Subsequently, we apply a social-rank-based forwarding algorithm on these human-centric networks. Moreover, we perform two distinct scenarios as follows. In the first scenario, we consider absolute delivery efficiency and examine the impact that hub nodes have on the network delivery performance. We show that these nodes enable the network to deliver messages with a high probability in a low delay; however, this consumes much resources on the central nodes. In the second scenario, in contrast, we consider the absolute fairness of resource allocation across the network nodes. We confirm that maintaining this fairness significantly degrades the network delivery performances.**

Keywords: *social-rank-based forwarding, social opportunistic networks, node popularity, efficiency-fairness trade-off*

I. Introduction

In recent years, opportunistic networks have gained popularity in research as a natural evolution from mobile ad hoc networks (MANETs) [1]. In opportunistic networks, nodes come into contact with each other at unpredictable intervals with an unpredictable duration of each contact. Technological advances are leading to a world replete with mobile devices, such as cellular phones, notebooks, and gadgets, thus paving the way for a multitude of opportunities for device contacts. Opportunistic contacting exploits opportunistic communication between devices to share each other's content, resources and services. Examples of opportunistic networks include animal wildlife monitoring networks [2], vehicular networks [3], and social (human) opportunistic networks [4].

Social opportunistic networks (SONs) to date have been investigated as a promising approach for communications (e.g. the Haggle project [5]). SONs attempt to close the gap between human and network behaviour by taking a user-centric approach to networking. These networks exploit users' mobility as an opportunity to enable data forwarding. SONs are therefore human-centric because the node contacts reflect the way humans come into contact, and humans tend to move in a way that is influenced by their social relationships. SONs are consequently tightly coupled with social (relations) networks and knowledge of human relationships can be exploited to build more efficient and reliable communication protocols.

Social-aware forwarding algorithms [6,7] use node social structures, such as popularity (social rank) and community (social clique), as these forwarding metrics to efficiently select the most likely relay nodes to deliver messages to the destinations. Furthermore, social-rank-based forwarding [8,9] considers node popularity in the entire network and favours the most popular nodes as the best carriers to enable the data delivery in a low delay. Node popularity in a social network is commonly evaluated by a centrality metric, e.g. Freeman's centrality measures [10]. During node contacts, the algorithms transfer messages to nodes with a higher centrality than the forwarding node, so the centrality monotonically increases from source to destination (a next-best-hop *hill-climbing* heuristic). When these strategies are able to bring a high delivery success rate within a low latency in SONs, this however creates unbalanced load distribution among the network nodes, where a few most popular nodes carry a heavier burden compared to others, quickly depleting the constraint resources of these nodes, e.g. power and storage and eventually degrading the network delivery performance. With the increasing workload today, it has become critical to make full use of the limited resources of mobile devices so that the resource efficiency can be improved and hence more and more mobile applications can be supported. Ensuring network resource distribution fairness is therefore a crucial goal if social-rank-based forwarding strategies are to be adopted in the future.

In this paper, we analyze the trade-off between delivery efficiency and network resource distribution fairness when social-rank-based forwarding algorithms are applied in SONs. Previous study in [11] has discussed this issue in general mobile opportunistic networking. This paper however focuses it in SONs, since these human-centric networks posses a unique characteristic, namely a non-random topology structure, exhibiting a power-law node degree distribution with the existence of a few high degree nodes [12,13]. These nodes have many connections with other nodes and therefore are much popular in the network and can act as communication hubs in the network. Consequently, a social-rank-based forwarding algorithm directs most of the traffic through these hub nodes, leading to unbalanced load distribution in the network, where a few hub nodes carry a much heavier burden compared to other nodes. In this analysis, we therefore perform two distinct scenarios as follows. In the first one, we consider absolute delivery efficiency. We examine the impact that the hub nodes have on the network delivery performance. In the second one, in contrast, we consider the absolute fairness of resource allocation across the network nodes. We investigate how this load balancing impacts on the overall delivery performance.

The remainder of this paper is organized as follows. Section II provides a brief overview of social-rank-based forwarding algorithms. Section III describes the node popularity distribution in SONs. In Section IV, we discuss the efficiency and fairness trade-off of social-rank-based forwarding strategies in SONs. Finally, Section V concludes the paper.

II. Social-Rank-Based Forwarding Algorithms

Routing strategies in opportunistic networks are designed to efficiently select the most likely relay nodes to deliver a message to the destination. A node has to decide whether or not to forward a message to the contacted node based on knowledge of the past behaviour of the peer. Such forwarding decisions are typically guided by, on one hand, the desire to reduce the number of copies of messages in the network and, on the other hand, the desire to decrease end-to-end transfer delay. Social-rank-based forwarding, a class of social-aware forwarding, represents one of the most promising methods for addressing this forwarding challenge. These strategies favour higher social ranked nodes as better carriers to deliver messages to the destinations with low delay. During node contact, the algorithms forward copies of messages to nodes with a higher ranking than the forwarding node until the destinations are encountered. We now provide a brief review of social-rank-based forwarding strategies. We distinguish between two types of these strategies based on the metrics used to rank nodes in the network, namely *centrality-based* and *contact-based* forwarding.

a) **Centrality-based forwarding:** Social network analysis (SNA) examines node popularity in a social network in term of centrality, such as Freeman's centrality measures [10], i.e. degree centrality, betweeness centrality and closeness centrality. Degree centrality is the total number of links that a node has. Betweeness centrality of a node however is the number of shortest paths that pass through the node divided by the total number of shortest paths in the network. Closeness centrality of a node is the reciprocal of the mean of the shortest paths between the node and all other reachable nodes. In the following, we mention two centrality-based forwarding algorithms in the literature:

- *DEGREE*: As part of the BubbleRap protocol [7], this algorithm uses degree centrality to measure node popularity in the entire network (global popularity). Node degree in intermittently-connected networks, such as opportunistic networks, is calculated as the number of distinct nodes encountered in a given time interval. *DEGREE* furthermore determines a node's degree in a time interval (or time window) by calculating the node degree value averaged over all previous windows.
- *PeopleRank* [8]: Inspired by the PageRank algorithm of Google, PeopleRank exploits node centrality to achieve efficient message transmission in SONs. The node centrality here is calculated by considering the popularity of the neighbouring nodes. Consequently, PeopleRank gives higher weight to nodes if they are socially connected to other important (popular) nodes in the network.

b) **Contact-based forwarding:** in this class, information learned during node contact, e.g. contact frequency, duration and recency, is used to quantify node importance (popularity) in the network. We now present three contact-based forwarding algorithms as follows:

- *Context Aware Adaptive Routing (CAR)* [14]: Here, node popularity is quantified by a connectivity change rate, which is the number of nodes that became neighbours or disappeared in a time interval and then normalized by the total number of nodes met in the same time interval. A high value of this metric indicates a node is very active in the network and hence is very popular in the entire network.
- *Sociable Routing* [9]: In this strategy, node popularity is evaluated using a sociability indicator. This metric considers both node own social behaviour, such as node's mobility pattern, and the neighbours' sociability levels. The social behaviour of a node is quantified by counting its encounters with all the other nodes in the network over a time period. Furthermore, the sociability degree of a node should intuitively benefit from having highly sociable neighbours.
- *Fair Route* [15]: This algorithm uses interaction strength (tie strength) to measure node popularity in the network. The tie strength is evaluated based on node contact frequency. Node global popularity is then calculated as the total tie strength of a node towards its all neighbour nodes.

III. Node Popularity Distribution in SONs

Knowledge of network topology structure is indeed required to analyze the delivery performance of a routing protocol in the network. In mobile communication networks, such as MANETs and opportunistic networks, the mobility pattern of mobile devices will directly affect the topology of the networks. Furthermore, SONs are human-centric networks and the node contacts in these networks consequently reflect the way humans come into contact. The authors in [12,13] investigated the topology characteristics of SONs using several real human contact datasets. They initially aggregated the data traces to form contact graphs and subsequently performed an *off-line* analysis on the derived graphs (in [16], the contact graphs are identified as electronic social networks). Finally, they confirmed that the graphs posses a strong non-random

978-1-5090-2767-5/16/$31.00 ©2016 IEEE

connectivity structure, which exhibits a power-law degree distribution where a few nodes have a very large degree of connections to other nodes, but most of the network nodes have few ones. These high degree nodes are therefore (socially) very popular in the network and can act as communication hubs in the network.

In this paper, instead, we perform an *online* analysis to investigate the node popularity distribution in SONs using the ONE simulator [17], a discrete event simulator for opportunistic networks. In self-organizing networks, such as opportunistic networks, a node should be able to autonomously identify its popularity in the network. In this study, node popularity is calculated as the number of distinct nodes encountered in a given time interval. This is equal to the node degree centrality (or node degree in the graph theory) in an aggregated contact graph. Moreover, we use the C-Window technique of BubbleRap [7] to calculate node degree in a time interval (or time window). This method is a cumulative moving average that determines the degree of a node in a time window by calculating the node degree value averaged over all previous windows. For the simulation's node mobility scenario, we use real-life mobility traces, namely the Reality [18] and Sassy [19] datasets. In Reality, 100 smart phones were deployed among the students and staff of MIT to capture the academic activities in the campus over one academic year. However, the Sassy dataset contains the contact information of 27 people of the University of St. Andrews during a period of 74 days.

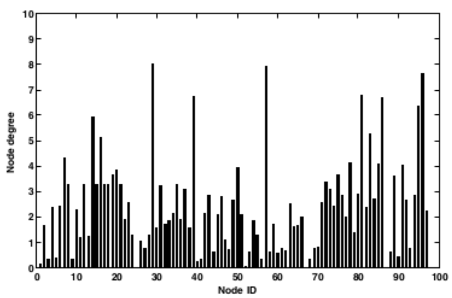


Fig. 1. Instantaneous node degree distribution in Reality

From the simulation results, we depict the instantaneous node degree distribution in Reality and Sassy in Fig. 1 and 2, respectively. The time window used for calculating node degree is set to 24 hours for both node mobility scenarios. From both figures, we see a few nodes that have degree much higher than the average degree in the network (e.g. the mean node degrees in Reality and Sassy, respectively, are 2.12 and 0.74). In addition, in Fig. 3 we depict the cumulative distribution function (CDF) of the node degree distribution in Reality (due to space limitations, we omit the figure for Sassy). The figure confirms that the node degree in Reality is power-law distributed, where the probability of finding a high degree node is very low, since the majority of nodes have low degree. The degree distribution in real human networks is therefore far from that of a random graph [20]. Moreover, Ferreti *et al.* [21] also confirmed the feasibility of coupling between SONs and scale-free networks, those with the main characteristic of a power-law degree distribution. When social-rank-based forwarding strategies favour higher degree nodes as better traffic relays, as we will show in the next section, unbalanced load distribution eventually results, where a few highest degree nodes carry a much heavier burden compared to others, quickly depleting the limited resources of these nodes, e.g. storage and power, and finally degrading the network delivery performance. Since most mobile devices have limited resources, this efficiency-fairness trade-off is therefore a crucial issue in mobile social networking.

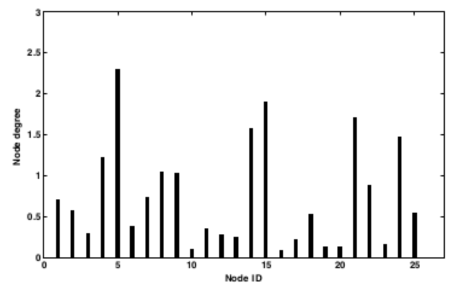


Fig. 2. Instantaneous node degree distribution in Sassy

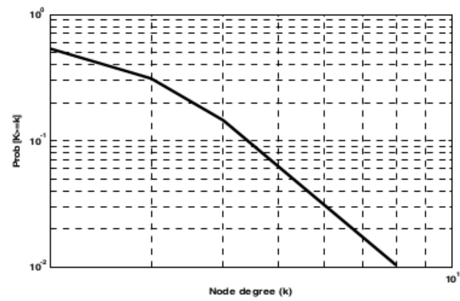


Fig. 3. CDF of node degree distribution in Reality

IV. EFFICIENCY-FAIRNESS TRADE-OFF

In this section, we quantitatively analyze the trade-off between efficiency and fairness of social-rank-based forwarding strategies in SONs. We first define these evaluation metrics and next investigate this trade-off using real human contact datasets.

We define *"efficiency"* as the delivery success rate of a forwarding strategy within a given time interval. Higher efficiency means more messages successfully delivered within a shorter delay. In addition to efficiency, fairness is a very important performance metric in mobile communication networks, since most mobile devices have limited resources, e.g. storage and power. We therefore define *"fairness"* as the relative equality in the distribution of resource utilization among nodes in the network. A forwarding strategy is "fair" when the resource capacity assignment of a given node is equivalent to that of all the network nodes. In this performance evaluation, we use the GINI index [22] to measure the resource distribution fairness level in the network (i.e. an index value of '0' means that the resource consumption is distributed evenly among all the network nodes, and value of '1' indicates perfect inequality where only the resource of a single node is fully exploited).

We investigate the trade-off between efficiency and fairness of social-rank-based forwarding strategies in SONs using the ONE simulator [17]. Our analysis is based on two human contact datasets collected in campus environments, i.e. Reality [18] and Sassy [19]. In this study, we use *DEGREE* as the forwarding strategy, where the time window for calculating node degree is set to 24 hours for both datasets. In addition, we perform two distinct scenarios as follows. In the first scenario, we consider absolute delivery efficiency: we compare the network delivery performance when hub nodes participate in the forwarding process with the one when the nodes refrain from the forwarding process. In the second scenario, however, we consider the absolute fairness of resource allocation across nodes in the network: we examine how this load balancing impacts on the overall delivery performance. We now discuss the two scenarios in detail as follows.

a) Absolute delivery efficiency

As discussed in [8,9], delivery efficiency deals with the participation of popular nodes in message delivery. In this scenario, we therefore investigate the impact of hub nodes on the network delivery performance. We compare the delivery performance of *DEGREE* in real-life SONs when the most popular nodes involve in the forwarding process with the one when these nodes boycott the delivery process. For the latter case, in the simulation we set the radio range of the highest degree nodes to be zero in both datasets (e.g. node 29, 39, 57, 86 and 95 in Reality, and node 5, 15 and 21 in Sassy), so that they cannot be active in both sending and receiving messages during node contacts.

From the simulation results, in Fig. 4 and 5 we depict the delivery success ratio of *DEGREE* as a function of different message time-to-lives (TTLs), in Reality and Sassy, respectively, for both the original case (when the hub nodes are included in the forwarding process) and the hub node removal case (when the hub nodes are excluded from the forwarding process). As expected, excluding the most popular nodes from the forwarding process deteriorates the success rate in both mobility scenarios. In the original case, the forwarding algorithm directs most of the network traffic traverses the shortest-paths through the hub nodes towards the destinations, resulting in message delivery with a low delay. Despite its benefit, however, this efficient delivery creates unbalanced load distribution in the network. For example, in Fig. 6 we illustrate the node popularity (measured in node degree) vs. node load (= total relay messages processed by a given node) in Reality for the original case. The figure shows that a few highest degree nodes process a large fraction of the network traffic, while majority of the network nodes only receive a small number of relay messages. Moreover, we depict in Fig. 7 the GINI index that measures the load distribution fairness level in Reality and Sassy for both cases. We see that the load distribution fairness in the original case is poorer (a higher GINI index) than that in the hub node removal case in both node mobility scenarios. Clearly, removing hub nodes in the forwarding process improves the load distribution fairness (i.e. a reduced GINI index), but this negatively impacts on the overall delivery time (i.e. a long transfer delay).

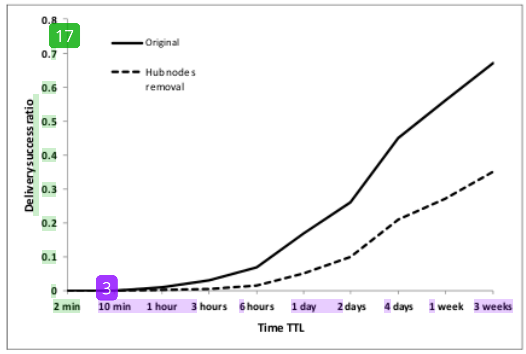


Fig. 4. Delivery performance of *DEGREE* with various message TTLs in Reality for the original and hub node removal cases

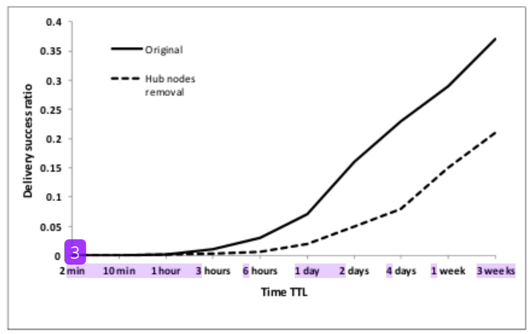


Fig. 5. Delivery performance of *DEGREE* with various message TTLs in Sassy for the original and hub node removal cases

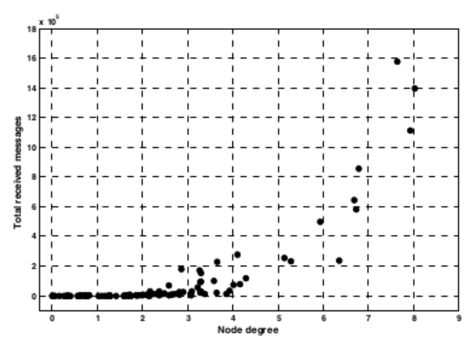


Fig. 6. Node popularity (measured in node degree) vs. node load (= total received relay messages) in Reality for the original case

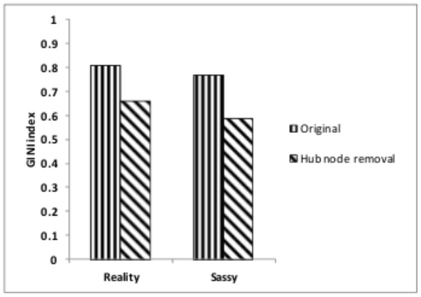
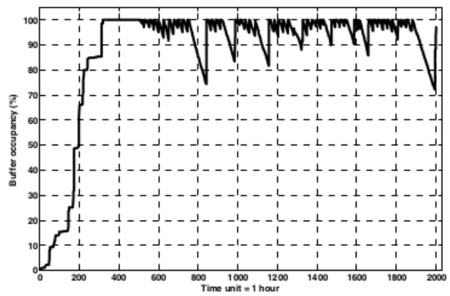
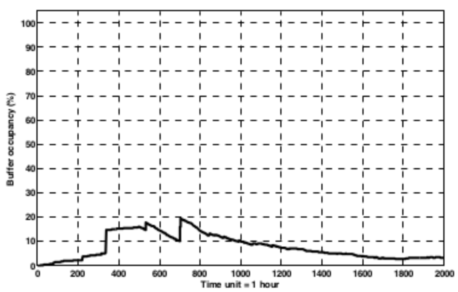


Fig. 7. Load distribution fairness level (measured in a GINI index) in Reality and Sassy for the original and hub node removal cases



(a) The highest degree node (hub node)



(b) A low degree node (non-hub node)

Fig. 8. Buffer occupancy growth of nodes in Reality for the original case

b) Absolute resource distribution fairness

From a networking perspective, it is desirable to have a uniform load distribution in the network in order to use network resources evenly and fairly. However, as we have shown previously, most of the communications in SONs rely on a few hub nodes (i.e. the most popular individuals), and this in turn quickly depletes the constraint resources of these nodes, e.g. buffer (storage) and power. For example, from the simulation results in Section IV.a we depict in Fig. 8(a) and 8(b) the change over time of buffer occupancy of an illustrative hub node and non-hub node, respectively, in Reality. Fig. 8(a) shows that the buffer queue length of the hub node increases quickly during initial period of the simulation and then fluctuates between 90% -100% during the simulation. In other words, the hub node's buffer is frequently saturated throughout the simulation. In contrast, in the low degree node, as shown in Fig. 8(b), the buffer occupancy is typically low and slightly fluctuates during the simulation. This therefore confirms the unbalanced resource utilization when a social-rank-based forwarding, e.g. *DEGREE*, is applied in a SON.

In this section, we aim to investigate the impact of absolute resource allocation fairness on the network delivery performance. Let us assume an absolute fair resource distribution in the network. This requires that the forwarding strategy should be able to ensure the fairness by balancing load across the network nodes. We subsequently modify the forwarding algorithm of *DEGREE* so that the network load can be uniformly distributed among the nodes (e.g. each node receives the same number of relay messages) as follows. When node j is in contact with node k, node j will forward a copy of its message to node k if:

$$degree(N_k) > degree(N_j) \text{ AND } load(N_k) \leq avg\_net\_load$$

Where $avg\_net\_load = \sum_{i=1}^{n} load(N_i)/n$, with N_i represents a node i, n is the total number of nodes in the network, and $load(N_i)$ is the number of messages that node i currently carries in its buffer (we assume that all messages have the same length). In this analysis, we first hypothesise that the forwarding algorithm has knowledge of instantaneous load of all nodes in the network, and hence global resource allocation fairness can finally be achieved (we name this forwarding strategy *Global_Fair*). In fact, however, global knowledge is not normally available to opportunistic network nodes due to a very long transfer delay. As a consequence, the forwarding algorithm of a node has to use locally available information when calculating the global load. In Algorithm 1, we show the modified *DEGREE* algorithm that uses local information from neighbouring nodes to estimate the average network load (we call this algorithm *Local_Fair*). When node j encounters node k, they initially exchange both their node load and average network load values. Afterwards, they update their average network load based on local information. When node j has a message, it will forward a copy of the message to node k if the degree of node k is higher than j's degree and the load carried by node k is lower than the average network load.

Algorithm 1. *Local_Fair* (N_j)

$avg\_net\_load \leftarrow 0$

while N_j is in contact with N_k **do**
  send $load(N_j)$
  send $avg\_net\_load(N_j)$
  receive $load(N_k)$
  receive $avg\_net\_load(N_k)$
  update avg_net_load

  while $\exists\, m \in buffer(N_j)$ **do**
    if $degree(N_k) \geq degree(N_j)$ AND $load(N_k) \leq avg\_net\_load$
    OR $N_k = destination\ (m)$
      then $forward\ (m, N_k)$
    end if
  end while
end while

From the simulation results, we depict in Fig. 9 and 10 the delivery success ratio of *DEGREE*, *Global_Fair* and *Local_Fair* as a function of different message time-to-lives (TTLs), in Reality and Sassy, respectively. It is clear that maintaining absolute resource allocation fairness, both globally and locally, significantly degrades the overall delivery success ratio in both node mobility scenarios. However, *Local_Fair* performs slightly better than *Global_Fair*, since the former considers locally average network load which is typically a little bit higher than the globally average network load.

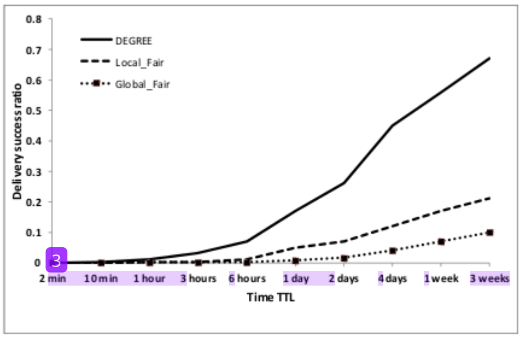


Fig. 9. Delivery performance of *DEGREE*, *Local_Fair* and *Global_Fair* with various message TTLs in Reality

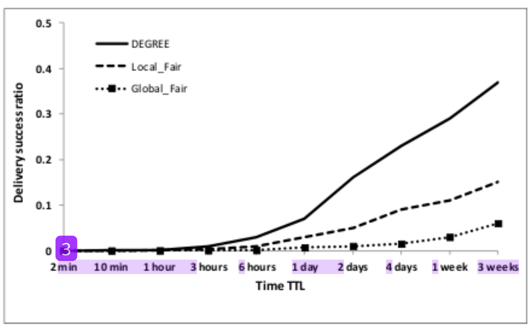


Fig. 10. Delivery performance of *DEGREE*, *Local_Fair* and *Global_Fair* with various message TTLs in Sassy

Finally, the above analysis confirms that when fairness is our goal, absolute fairness is not. The absolute fairness is likely to prevent popular nodes from participating in the forwarding process, resulting in significant network performance degradation. The goal of designing better forwarding algorithms in SONs is therefore to further satisfy popular nodes by moving from a situation where these nodes carry large burden in delivering messages to a "fair distribution" of this load among the popular nodes and their adjacent nodes (friends). In [23], we propose two strategies to increase load distribution fairness in SONs, namely improving social-based forwarding metrics and applying buffer congestion control on the forwarding algorithms. In the first approach, we argue that other centrality measures (than the Freeman's centrality metrics) in the sociology literature can be used to obtain better load distribution fairness, for example the Bonacich centrality measure [24]. While in the Freeman's centrality metric e.g. degree centrality) a node's popularity is measured based on the node's itself position in the network, Bonacich centrality however considers the neighbours' popularities when calculating the popularity of the node in the network. Consequently, unpopular nodes can increase their popularities when they have neighbours (friends) with higher popularities, leading to the increase of the probability of these low ranked nodes to be selected as traffic relays and eventually improving load distribution fairness in the network. In the second approach, on the other hand, buffer congestion control can prevent the forwarding algorithms from burdening popular nodes with relay messages. This can help the forwarding strategy to distribute the load more evenly among nodes in the network.

V. Conclusions and Future Work

In this paper, we have investigated the trade-off between efficiency and fairness of social-rank-based forwarding strategies in SONs. We performed two distinct scenarios in this study. In the first one, we considered absolute delivery efficiency and examined the impact of hub nodes on the network delivery performance. We showed that these nodes enable the network to deliver messages with a high probability in a low delay; however, this efficient delivery consumes much resource of the central nodes. In the second one, however, we considered the absolute fairness of resource allocation fairness across the network nodes. We confirmed that maintaining this fairness significantly deteriorates the network delivery performance.

For future work, we identify two important points. First, searching for other centrality metrics (than the Freeman's centrality metrics) that can bring better load distribution fairness in SONs, e.g. the Bonacich centrality measure [24]. Second, applying buffer congestion control on social-based forwarding algorithms to reduce large burden carried by popular nodes.

References

[1] M. Conti and S. Giordano, "Ad Hoc Networking: the Reality", *IEEE Communications Magazine*, vol. 45, no. 4, pp. 88-95, 2007.

[2] P. Juang, H. Oki, Y. Wang, "Energy-Efficient Computing for Wildlife Tracking: Design Tradeoffs and Early Experiences with Zebranet", *Proc. of the 10th Int'l Conf. on Architectural Support for Programming Languages and Operating Systems*, San Jose, CA, USA, pp. 96-107, 2002.

[3] P. R. Pereira, A. Casaca, J.P. Rodrigues, V.N.G.J. Soares, J. Triay, "From Delay-Tolerant Networks to Vehicular Delay-Tolerant Networks", *IEEE Comm. Surveys & Tutorials*, vol. 14, no. 4, pp. 1166-1182, 2012.

[4] A.K. Pietilainen and C. Diot, "Social Pocket Switched Networks", *Proc. of the 9th INFOCOM Workshops*, Rio de Janeiro, Brazil, pp. 1-2, 2009.

[5] Haggle Project, available at http://haggleproject.org, 2008.

[6] E.M. Daly and M. Haahr, "Social Network Analysis for Information Flow in Disconnected Delay-Tolerant MANETs", *IEEE Transactions on Mobile Computing*, vol. 8, no. 5, pp. 606-621, 2009.

[7] P. Hui, J. Crowcroft, E. Yoneki, "BUBBLE Rap: Social-based Forwarding in Delay Tolerant Networks", *IEEE Transactions on Mobile Computing*, vol. 10, no. 11, pp. 1576-1589, 2011.

[8] A. Mtibaa, M. May, C. Diot, M. Ammar, "PeopleRank: Social Opportunistic Forwarding", *Proc. of the 29th Conference on Information Communications (INFOCOM'10)*, San Diego, CA, pp. 111-115, 2010.

[9] F. Fabbri and R. Verdone, "A Sociability-based Routing Scheme for Delay Tolerant Networks, *EURASIP – Special Issue on Opportunistic and Delay Tolerant Networks*, vol. 2011, no. 1, 2011.

[10] L.C. Freeman, "Centrality in Social Networks: Conceptual Clarification", *Social Networks*, vol. 1, no. 3, pp. 215-239, 1979.

[11] A. Mtibaa and K.A. Harras, "Fairness-related Challenges in Mobile Opportunistic Networking", *Computer Networks*, vol. 57, no. 1, pp. 228-242, 2013.

[12] T. Hossmann, T. Spyropolous, F. Legendre, "Social Network Analysis of Human Mobility and Implications for DTN Performance Analysis and Mobile Modeling", *TIK-Report No. 323 Computer Engineering and Networks Laboratory*, ETH Zurich, Switzerland, 2010.

[13] E. Yoneki, P. Hui, J. Crowcroft, "Distinct Types of Hubs in Human Dynamic Networks", *Proc. of the 1st Workshop on Social Network Systems*, Glasgow, UK, pp. 7-12, 2008.

[14] M. Musolesi and C. Mascolo, "CAR: Context-Aware Adaptive Routing for Delay-Tolerant Mobile Networks", *IEEE Trans. on Mobile Computing*, vol. 8, no. 2, pp. 246-260, 2009.

[15] J.M. Pujol, A.L. Toledo, P. Rodriguez, "Fair Routing in Delay Tolerant Networks", *Proc. IEEE INFOCOM '09,* Rio de Janeiro, Brazil, pp. 837-845, 2009.

[16] M. Conti and M. Kumar, "Opportunities in Opportunistic Computing", *Computer*, vol. 43, no. 1, pp. 42-50, 2010.

[17] A. Keranen, J. Ott, T. Karkkainen, "Simulating Mobility and DTNs with the ONE", *Journal of Communications*, Academy Publisher, vol. 5, no. 2, pp. 92-105, 2010.

[18] N. Eagle and A. Pentland, "Reality Mining: Sensing Complex Social Systems", *Personal and Ubiquitous Computing*, vol. 10, no. 4, pp. 255-268, 2006.

[19] G. Bigwood, D. Rehunathan, M. Bateman, T. Henderson, S. Bhatti, Crawdad Dataset st_andrew/sassy, available at http://crawdad.org/st_andrew/ sassy, 2013.

[20] P. Erdos and A. Renyi, "On Random Graphs I", *Math. Debrecen*, vol. 6, pp. 290-297, 1959.

[21] S. Ferreti and V. Ghini, "Scale-Free Opportunistic Network: is it Possible?", *Technical Report. arXiv:1107.1937*, 2011.

[22] C. Gini, "On the Measure of Concentration with Special Reference to Income and Statistics", *Colorado College Publication General Series*, no. 208, pp. 73-79, 1936.

[23] B. Soelistijanto, "Impact of Social-Aware Forwarding on Traffic Distribution in Social Opportunistic Networks", *Proc. of the IEEE Region 10 Symposium*, Bali, Indonesia, pp.13-18, 2016.

[24] P. Bonacich and P. Lu, "Introduction to Mathematical Sociology", *Princeton University Press*, USA, 2012.

The Efficiency-Fairness Trade-Off of Social-Rank-based Forwarding in Social Opportunistic Networks

ORIGINALITY REPORT

19%	12%	18%	2%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Mtibaa, Abderrahmen, and Khaled Harras. "Exploiting Social Information in Opportunistic Mobile Communication", Opportunistic Mobile Social Networks, 2014. Publication	2%
2	web.archive.org Internet Source	2%
3	silo.pub Internet Source	1%
4	Huang, Yuanjiang, José-Fernán Martínez, Vicente Díaz, and Juana Sendra. "A Novel Topology Control Approach to Maintain the Node Degree in DynamicWireless Sensor Networks", Sensors, 2014. Publication	1%
5	jwcn-eurasipjournals.springeropen.com Internet Source	1%
6	Peiyan Yuan, Lilin Fan, Ping Liu, Shaojie Tang. "Recent progress in routing protocols of	1%

mobile opportunistic networks: A clear taxonomy, analysis and evaluation", Journal of Network and Computer Applications, 2016
Publication

---

7 Submitted to Indian School of Business — 1 %
Student Paper

---

8 personal.ee.surrey.ac.uk — 1 %
Internet Source

---

9 Mirco Musolesi. "CAR: Context-Aware Adaptive Routing for Delay Tolerant Mobile Networks", IEEE Transactions on Mobile Computing, 2008 — 1 %
Publication

---

10 Abderrahmen Mtibaa. "PeopleRank: Social Opportunistic Forwarding", 2010 Proceedings IEEE INFOCOM, 03/2010 — <1 %
Publication

---

11 nozdr.ru — <1 %
Internet Source

---

12 Bambang Soelistijanto, Michael P. Howarth. "Transfer Reliability and Congestion Control Strategies in Opportunistic Networks: A Survey", IEEE Communications Surveys & Tutorials, 2014 — <1 %
Publication

---

13 "Intrusion Detection, Prevention, and Response System (IDPRS) for Cyber-Physical — <1 %

	Systems (CPSs)", Securing Cyber-Physical Systems, 2015. Publication	
14	Submitted to Rutgers University, New Brunswick Student Paper	<1 %
15	arxiv.org Internet Source	<1 %
16	nrg.cs.uoi.gr Internet Source	<1 %
17	www.usukita.org Internet Source	<1 %
18	Routing in Opportunistic Networks, 2013. Publication	<1 %
19	Conti, M.. "Looking ahead in pervasive computing: Challenges and opportunities in the era of cyber-physical convergence", Pervasive and Mobile Computing, 201202 Publication	<1 %
20	dr.ntu.edu.sg Internet Source	<1 %
21	tel.archives-ouvertes.fr Internet Source	<1 %
22	Submitted to The University of Manchester Student Paper	<1 %

23	faraday1.ucd.ie Internet Source	<1 %
24	refubium.fu-berlin.de Internet Source	<1 %
25	Submitted to Deakin University Student Paper	<1 %
26	Lecture Notes in Computer Science, 2011. Publication	<1 %
27	Ding, Jianguo, Ilangko Balasingham, and Pascal Bouvry. "Management Challenges for Emerging Wireless Networks", Emerging Wireless Networks Concepts Techniques and Applications, 2011. Publication	<1 %
28	Submitted to Middle East Technical University Student Paper	<1 %
29	Narayanan, Sathya, Eric McDonald, and Geoffrey G. Xie. "A Framework for Simulation Analysis of Delay Tolerant Routing Protocols", 2012 IEEE Vehicular Technology Conference (VTC Fall), 2012. Publication	<1 %
30	Peiyan Yuan, Ping Liu, Shaojie Tang. "RIM: Relative-importance based data forwarding in people-centric networks", Journal of Network and Computer Applications, 2016	<1 %

Publication

31	Zhu, Hongzi, Mianxiong Dong, Shan Chang, Yanmin Zhu, Minglu Li, and Xuemin Sherman Shen. "ZOOM: Scaling the mobility for fast opportunistic forwarding in vehicular networks", 2013 Proceedings IEEE INFOCOM, 2013. Publication	<1%
32	citeseerx.ist.psu.edu Internet Source	<1%
33	www.jocm.us Internet Source	<1%
34	Abdul Nasser A. Abbood, H. S. Al-Raweshidy. "Reduction of bandwidth requirement in DRoF systems using optical duobinary modulation", 2017 9th Computer Science and Electronic Engineering (CEEC), 2017 Publication	<1%
35	Kaimin Wei, Xiao Liang, Ke Xu. "A Survey of Social-Aware Routing Protocols in Delay Tolerant Networks: Applications, Taxonomy and Design-Related Issues", IEEE Communications Surveys & Tutorials, 2014 Publication	<1%
36	ediss.uni-goettingen.de Internet Source	<1%

www.wanrg.cs.nott.ac.uk

37	Internet Source	<1 %
38	Albert-laszlo Barabasi. "The Architecture of Complexity", IEEE Control Systems Magazine, 8/2007 Publication	<1 %
39	Maria Benamar, Nabil Benamar, Driss El Ouadghiri. "The effect of cooperation of nodes on VDTN routing protocols", 2015 International Conference on Wireless Networks and Mobile Communications (WINCOM), 2015 Publication	<1 %
40	Radu Ioan Ciobanu, Ciprian Dobre. "Predicting encounters in opportunistic networks", Proceedings of the 1st ACM workshop on High performance mobile opportunistic systems - HP-MOSys '12, 2012 Publication	<1 %
41	dokumen.pub Internet Source	<1 %
42	mei.di.uminho.pt Internet Source	<1 %
43	oaktrust.library.tamu.edu Internet Source	<1 %
44	ro.uow.edu.au Internet Source	<1 %

45	surface.syr.edu Internet Source	<1 %
46	www.social-nets.eu Internet Source	<1 %
47	Computer Communications and Networks, 2016. Publication	<1 %
48	Huahong Ma, Guoqiang Zheng, Honghai Wu, Baofeng Ji, Jishun Li. "EBRP: An Energy-Efficient and Buffer-Aware Routing Protocol for Mobile Crowdsensing Network", International Journal of Distributed Sensor Networks, 2016 Publication	<1 %
49	Soelistijanto, Bambang, and Michael Howarth. "Traffic distribution and network capacity analysis in social opportunistic networks", 2012 IEEE 8th International Conference on Wireless and Mobile Computing Networking and Communications (WiMob), 2012. Publication	<1 %
50	Kaimin Wei, Song Guo, Deze Zeng, Ke Xu, Keqiu Li. "Exploiting Small World Properties for Message Forwarding in Delay Tolerant Networks", IEEE Transactions on Computers, 2015 Publication	<1 %

51	Liu, Qilie, Xiang Pang, Yong Wang, Yingjun Pan, and Leilei Li. "An Improved Path Management Policy for the Ferry in Opportunistic Networks", Journal of Networks, 2012. Publication	<1 %

Exclude quotes	On	Exclude matches	< 5 words
Exclude bibliography	On		