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Impact of Social-Aware Forwarding on Traffic Distribution in Social Opportunistic Networks

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

***Abstract* — Social opportunistic networks (SONs) are delay-tolerant MANETs that exploit human mobility to enable message delivery in the networks. Humans tend to move in a way that is influenced by their social relations. Knowledge of social relationships therefore can be exploited to build social-aware routing protocols. These algorithms typically favour higher (social) ranking nodes as better relays for message transfers. The combination of this forwarding heuristic and the social network structure, which exhibits a non-uniform connectivity distribution with the existence of a few highly-connected nodes, leads the routing algorithm to direct most of the traffic through these hub nodes. Unbalanced traffic distribution therefore results in the network. This paper presents an analysis of traffic distribution in SONs when social-aware routing protocols are applied in the networks. Initially, we survey state-of-the-art social-aware routing protocols. We next investigate the topology characteristics of real-life SONs. Furthermore, we apply three forwarding strategies on these networks, categorising these strategies into social-aware forwarding and social-oblivious forwarding. The social-aware forwarding strategies consider node ranking when choosing traffic relays and the node ranking here is measured by degree and betweeness centralities. The social-oblivious forwarding, however, disregards node ranking on the forwarding decision and selects a relay node randomly. We show that the social-aware forwarding strategies result in very poor traffic distribution fairness, where a few (hub) nodes process a large fraction of the network traffic. Finally, we discuss the strategies for improving traffic distribution fairness in SONs.**

Keywords: social opportunistic networks, social-aware routing protocols, traffic distribution fairness, node centrality

I. INTRODUCTION

Mobile ad hoc networks (MANETs) are infrastructure-less networks where nodes can move freely in the network. A message traverses the network by being relayed from one node to another node until it reaches its destination (multi-hop communication). Opportunistic networks, on the other hand, represent a natural evolution of MANETS [1], maintaining the MANET's basic features of cost-efficiency and self-organization, as nodes still self-organize in order to build multi-hop message transfers without requiring any pre-existing infrastructure. However, they completely redesign the characteristics of networking protocols proposed in MANETs, making them able to support the absence of a stable path between pairs of nodes that wish to communicate.

Opportunistic networks are a class of delay-tolerant networks (DTNs), where contacts between mobile nodes occur unpredictably because the node's movement is effectively random, and where the duration of each node contact is also unpredictable. Examples of opportunistic networks include animal wildlife monitoring networks [2], vehicular networks [3], and social opportunistic networks (or mobile social networks) [4]. In recent years, social opportunistic networks (SONs) have been investigated as a promising approach for communications (e.g. the Haggle project [5]). SONs are opportunistic networks that exploit unpredictable contacts between mobile devices carried by individuals to enable message transfers. SONs are therefore human-centric because the node contacts reflect the way humans come into contact. Several studies [6,7] have shown that humans tend to move in a way that is influenced by their social relations. SONs are consequently tightly coupled with social (relations) networks, and knowledge of human relationships can be used to build social-aware routing protocols.

Social-aware routing algorithms use structural information of individuals in a social network. These algorithms exploit some properties of social network as the routing metrics, such as centrality and community (social clique). Centrality is a measure of the relative importance of an individual (node) within a social network and can be assessed by various centrality metrics, e.g. the Freeman's centrality metrics [8]. A higher centrality indicates that an individual appears to be more popular and thus has more contacts with other individuals in the network. On the other hand, people inherently form groups and this creates the concept of community. People within a given community are more likely to meet each other than randomly chosen people.

Unfortunately, despite its benefits, social-aware routing protocols present a drawback in traffic distribution among nodes in SONs. Since the algorithms favour higher (social) ranking nodes as traffic relays, a few most-popular nodes will process much more traffic than others, quickly depleting the constraint resources of these nodes, e.g. power and storage, and eventually degrading the network delivery performance. Hence, there is a need to further uncover the impact of social-aware routing algorithms on the traffic distribution fairness in SONs. The contributions of this paper are twofold. First, we perform a brief survey on state-of-the-art social-aware routing protocols and identify two main properties involved in the forwarding decisions. Second, we investigate the topology characteristics of SONs using real human mobility scenarios and confirm the non-uniform connectivity distribution in these networks with the existence of a few highly (socially)

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by Soelistijanto Bambang

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connected nodes (hub nodes). We furthermore show that this inherent characteristic results in unbalanced traffic distribution when social-aware routing algorithms are applied in SONs.

The remainder of the paper is organized as follows. Section II discusses social-aware routing algorithms. Section III describes the topology characteristics of real-life SONs. In Section IV, we discuss the simulation results of traffic distribution when social-aware routing strategies are applied on these human networks. Finally, we discuss the strategies for improving traffic distribution fairness in SONs in Section V, which is followed by conclusion and future work in Section VI.

II. SOCIAL-AWARE ROUTING PROTOCOLS

Routing in opportunistic networks is a challenging task, since node contact is unpredictable and network behaviour is random and unknown. Zhang *et al* [9] divided routing protocols in these networks into epidemic dissemination and prediction-based algorithms. In the epidemic routing, a node floods copies of a message to all its contacted nodes so that the copies are quickly distributed throughout the network. This oblivious forwarding indeed quickly depletes node resources which in turn degrades the network performance. In the prediction-based protocols, however, the algorithms use past observations of node behaviour to predict future contacts. Since node mobility in opportunistic networks is unpredictable and the network topology changes rapidly, these algorithms will create much control traffic over very limited bandwidth during node contact, such as in Prophet [10].

Instead, a novel approach of prediction-based protocols that uses structural information of individuals in a social network has been developed, namely *social-aware routing protocols*. The algorithms use some characteristics of a social network, which is less volatile than those of the physical network. In the networks that are formed by people, e.g. SONs, human relationships may vary slowly and therefore they can be used as forwarding metrics of routing algorithms. These measures are inferred from human contact graphs aggregated over time. With these graphs, the social-aware routing algorithms then analyse the structural properties of nodes to identify nodes which are important to the message delivery.

In general, we can identify two main properties involved when social-aware routing algorithms make forwarding decisions as follows:

a) **Transitivity**: When a node contact occurs, if either the forwarding node (a node that intends to transfer its message) or the contacted node has knowledge of the message destination, the former measures the relative closeness of the latter to the message destination. When the encountered node is closer to the destination, the forwarding node then selects it as a relay of the message. Transitivity therefore exploits a strong tie (connections) between two nodes to increase the message delivery probability. Tie strength can be evaluated based on metrics such as contact frequency, duration or recency.

b) **Global popularity**: When the message destination is unknown to both the forwarding node and its contacts, the routing algorithm routes the message to a structurally more popular node. Node popularity in a (social) network can be measured by a centrality metric, e.g. the Freeman's centrality measures [8], 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 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 Table 1, we list the routing metrics of several social-aware routing protocols in the literature, categorising these metrics based on the aforementioned properties. We furthermore note that most of the protocols were developed by assuming that nodes are homogenous and are distributed uniformly, randomly in the network. However, as we will show in Section III, this assumption does not hold in SONs, since these networks possess a strong non-uniform connectivity distribution with the existence of a few highly-connected nodes which are very popular in the network. Consequently, the forwarding heuristic of social-aware routing algorithms that favours popular nodes as traffic relays directs most of the traffic through these hub nodes in a SON, leading to the unbalanced traffic distribution in the network (we show this in Section IV).

TABLE 1. Properties of social-aware routing metrics

Protocol	Routing metric	
	Global Popularity	Transitivity
SimBet [11]	Betweeness centrality	Similarity, Tie strength
BubbleRap [12]	Degree centrality	Community
FairRoute [13]	Total interaction strength to all the neighbours	Total interaction strength to a specific node
CAR [14]	Connectivity change rate	Node collocation
Sociable Routing [15]	Sociability indicator	None
PeopleRank [16]	Social ranking	None

III. NETWORK TOPOLOGY OF SONS

In opportunistic networks, the network topology changes every time unit, so that data paths may not exist at any point in time but potentially do exist over time. Ferretti *et al.* **[17]** argued the different notion of a link between MANETs and opportunistic networks: while MANETs consider links as connections active at a given instant, opportunistic networks have a coarse grained time model. Hence, the concept of links in opportunistic networks should reflect the fact that temporal constraints are relaxed. In a MANET, the instantaneous network topology strongly depends on the geographical distribution of the node. In opportunistic networks, however, the network topology can be modelled as a graph where links characterize the interactions of nodes during a time interval (*time-window dependent*).

Human mobility characteristics discussed in [6,7] show that there exists a virtual, social network that drives humans to move, and that this graph is less volatile than the physical network. The overlay graph represents a macroscopic property of human mobility. We illustrate the structural topology of a SON in Fig. 1.

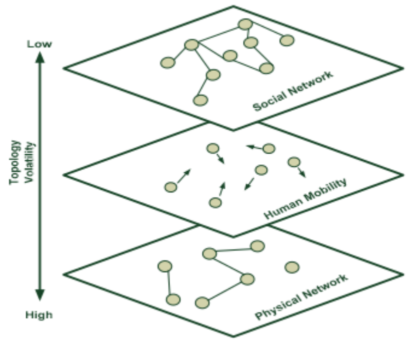

Fig. 1. Structural topology of a SON

By performing an *offline* analysis on the aggregated contact graphs of several real human mobility scenarios, the authors in [18,19] confirmed the topology characteristics of these real-life SONs as follows. First, the networks posses a strong heterogeneous connectivity structure, where a few hub nodes have a very large degree of connections. Second, the networks display a small-world phenomenon, where individuals are often linked by a short chain of acquaintances due to the existence of hub nodes. Lastly, the networks show a high degree of clustering where a node has strong relations (ties) with other nodes of one community, but has weak relations with other nodes of other communities.

We now focus on node connectivity distribution in SONs. Node connectivity (social-connection) of a node reflects the node popularity level in the network. In self-organizing networks, such as opportunistic networks, a node should be able to autonomously identify its popularity in the network. We therefore perform an *online* analysis of node popularity distribution in SONs using the ONE simulator [20]. Here, node popularity is quantified by the number of distinct nodes encountered in a given time interval. In the literature [12,19], this is equal to the node degree centrality (or node degree in the graph theory) in an aggregated contact graph. We use the C-Window technique of BubbleRap [12] for calculating node degree in a time interval (or time window). The technique 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. In this study, we use real human contact traces, namely the Reality [21] and Sassy [22] datasets.

From the simulation results, we depict the instantaneous node degree distribution in Reality and Sassy in Fig. 2 and 3, respectively. The time window used for calculating node degree is set to 24 hours for both scenarios. The figures show that there exist a few nodes with the degree much higher than the average degree in the network (e.g. the mean degrees are 2.12 and 0.74 for Reality and Sassy, respectively). Moreover, in Fig. 4 we depict the cumulative distribution function (CDF) of the degree distribution in Reality (due to space limitations, we omit the figure for Sassy). The figure shows that the node degree distribution in Reality is power-law distributed, where the probability of finding high degree node in the network is very low since the majority of nodes have low degree. The degree distribution in this real human network is therefore far from that of a random graph [24]. Ferreti *et al.* [17] also confirmed the feasibility of coupling between SONs and scale-free graphs, those with the main characteristic of a power-law degree distribution.

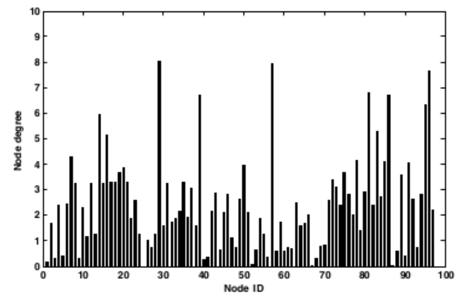

Fig. 2. Instantaneous node degree distribution in Reality

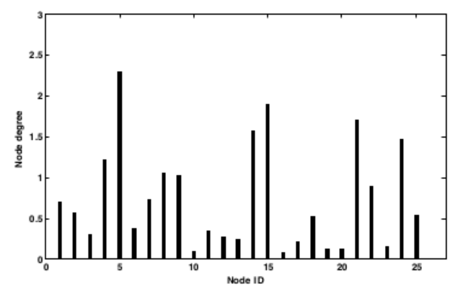

Fig. 3. Instantaneous node degree distribution in Sassy

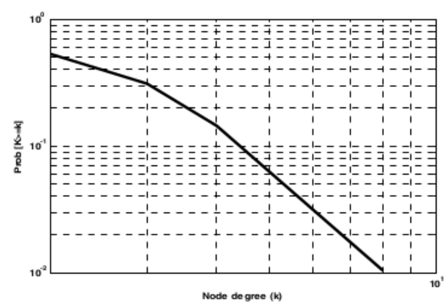

Fig. 4. CDF of node degree in Reality

IV. Traffic Distribution Analysis in SONs

In this section, we intend to investigate the impact of the social-aware forwarding heuristic of favouring higher (social) ranking nodes as traffic relays on traffic distribution in SONs. During a node contact, the algorithm selects the contacted node as a relay of the message if its ranking is higher than that of the forwarding node (a next best hop *hill-climbing* forwarding heuristic). We consider three forwarding strategies, categorising these strategies into social-aware forwarding and social-oblivious forwarding (in this study, we use the latter as a performance benchmark). Social-aware forwarding strategies take into account node (social) ranking when making forwarding decisions, and in this study the node ranking is measured by degree centrality and betweeness centrality. Social-oblivious forwarding strategies, however, disregard node social ranking in its forwarding decision, and in this study the node ranking is determined randomly, e.g. using a random number generator. We now briefly describe these forwarding strategies:

a) **Social-aware-forwarding (degree centrality):** Here, the selection of better relays is done based on node degree centrality. This metric is measured as the number of direct ties that involve a given node. Degree centrality for node i is calculated as:

$$C_D(i) = \sum_{k=1}^{N} a(i,k)$$

where $a(i,k)$ = 1 if a direct link exists between i and k and $i \neq k$. In our simulation, we define node degree centrality as the number of distinct nodes encountered in a given time window. We use the C-Window technique of BubbleRap [12] for calculating node degree centrality in a time interval.

b) **Social-aware-forwarding (betweeness centrality):** Betweeness centrality measures the extent to which a node lies on the paths linking other nodes. Betweeness centrality for node i is calculated as:

$$C_B(i) = \sum_{j=1}^{N} \sum_{k=1}^{j-1} \frac{g_{jk}(i)}{g_{jk}}$$

where g_{jk} is the total number of geodesic paths linking node j and k, and $g_{jk}(i)$ is the number of those geodesic paths that include node i. However, this centrality metric becomes difficult to evaluate in the networks with large delays such as SONs, since it requires complete knowledge of the network topology. We therefore follow [11] when calculating node betweeness centrality, i.e. using the ego network concept [27].

c) **Social-oblivious forwarding (random ranking):** In this strategy, the selection of better relay node is done randomly. When two nodes come into contact, they generate random numbers as their global rankings, and the forwarding node selects the peer as a relay if the latter's ranking is higher than the former. This strategy therefore disregards the structural information of a node in the social network when making forwarding decision.

We apply all three forwarding strategies to real-life SONs. We again use Reality [21] and Sassy [22] for the simulation's node mobility scenario. For all the strategies, we consider multiple-copy (replication) forwarding strategies. We use the ONE simulator [20] with the main parameters are described in Table-2. For performance evaluation, we use several evaluation metrics as follows:

- **Delivery ratio:** the ratio of the total number of messages successfully delivered divided by the total number of messages created.
- **Delivery delay:** the time between the creation of a message and the delivery of the message to its destination.
- **Message overhead ratio:** the ratio of the number of overhead messages (total message copies) to the number of messages successfully delivered.
- **GINI index**: This measure of statistical dispersion calculates the inequality among values of a frequency distribution [23]. In this paper, the GINI index measures the traffic distribution fairness level in the network, i.e. an index value of '0' means that the traffic is distributed evenly among all the network nodes and value '1' indicates that only a single node carries all the traffic.

TABLE 2. The ONE principal simulation parameters

Simulation Parameters		
Mobility scenario	Reality	Sassy
Number of nodes	97	25
Simulation time	196 days	74 days
Msg. generation interval	~ 12 msgs/h	~ 6 msgs/h
Node buffer size	20 MB	
Message TTL	7 days	
Message size	10 kB	

Fig. 5. Performance evaluation in Reality

In Fig. 5 and 6, we depict the delivery performance of all the aforementioned forwarding strategies in Reality and Sassy, respectively. For calculating node degree centrality, the time window is set to 24 hours for both scenarios. We now discuss the delivery performance of social-aware forwarding strategies (degree and betweeness centralities) and social-oblivious forwarding strategy (random ranking) in both scenarios. In delivery ratio performance, the figures show that the random ranking forwarding strategy outperforms both the social-aware forwarding strategies in Reality, but in Sassy the social-aware forwarding strategy (degree centrality) performs slightly better than two other strategies. In delivery delay performance, on the other hand, the random ranking forwarding shows the best performance among the two social-aware forwarding strategies in both scenarios. This social-oblivious forwarding strategy's best performance in delivery delay however considerably increases the message delivery cost (measured in overhead ratio) beyond those of the social-aware forwarding strategies in both mobility scenarios. Finally, in traffic distribution fairness performance (measured in GINI index), both Fig. 5 and 6 show that the social-aware forwarding strategies (degree and betweeness centrality) result in poorer performance than the social-oblivious strategy in both scenarios. In these social-aware forwarding strategies, most of the network traffic is directed through the most popular nodes, leading to the unbalanced traffic distribution in the network. Moreover, the social-aware forwarding strategy (betweeness centrality) has the poorest performance in traffic distribution fairness (i.e. highest GINI index). This result is inline with our analytical result in [24]. Subsequently, in the case of the social-oblivious forwarding strategy, we can see that even this strategy disregards node social ranking in the forwarding decision, the traffic distribution fairness is still quite poor in both scenarios, with the GINI index ≈ 0.45. This therefore confirms the natural unbalanced of traffic distribution in SONs due to the inherent characteristic of a heterogeneous connectivity distribution in these human-centric data networks.

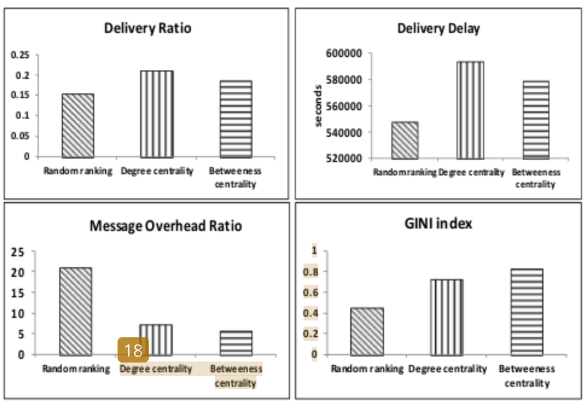

Fig. 6. Performance evaluation in Sassy

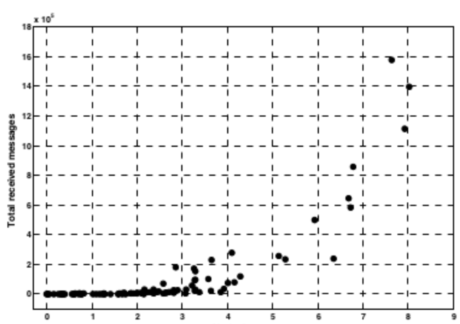

Fig. 7. Node popularity (measured in node degree) vs. total processed traffic in Reality

V. STRATEGIES FOR IMPROVING TRAFFIC DISTRIBUTION FAIRNESS IN SONS

We have discussed in Section IV that the forwarding heuristic that favours higher (social) ranking nodes results in poor performance in traffic distribution fairness (high GINI index) in SONs. For example, in Fig. 7 we depict the node degree (centrality) vs. total processed traffic when the social-aware forwarding strategy is applied in the Reality mobility scenario. The figure shows that a few nodes, i.e. the highest degree nodes, process a large fraction of the network traffic, while majority of the nodes only receive a small number of relay messages. This unbalanced traffic distribution quickly depletes constraint resources of these hub nodes, e.g. power and storage, and finally degrades the network delivery performance. In this section, we discuss the strategies for improving traffic distribution fairness in SONs, categorising these strategies into buffer congestion control and traffic-distribution-aware routing strategies. We now discuss both strategies in detail.

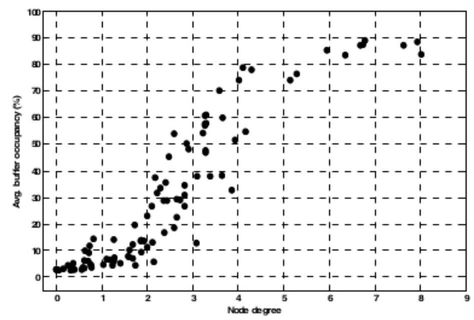

Fig. 8. Node popularity (measured in node degree) vs. avg. buffer occupancy in Reality

A. *Buffer congestion control strategy*

Unbalanced traffic distribution in the network consumes a lot of resources of hub nodes, e.g. storage (buffer) and power. In Fig. 8 we depict the node degree vs. average buffer occupancy when the social-aware forwarding strategy is applied in the Reality mobility scenario. The figure clearly shows that higher degree nodes typically have higher buffer occupancy (buffer queue length) and buffer congestion is consequently more likely to occur in these nodes, particularly in the highest degree nodes (hub nodes). The first strategy to improve traffic distribution in SONs is therefore by applying buffer congestion control that is able to reduce the number of messages received in the hub nodes.

We in [25] have thoroughly surveyed congestion control strategies in opportunistic networks. In addition, we noted that most of the algorithms have been developed under the assumption that all nodes have a uniform probability of meeting all other nodes in the network (i.e. a uniform, random geographical node distribution). Consequently, the buffer congestion probability is uniformly distributed in all the network nodes. In SONs, however, buffer congestion is most likely to occur in a few most-popular nodes. Properly detection of a node's popularity enables the node's congestion control algorithm to accurately estimate the node's buffer congestion probability. We therefore argue that buffer congestion control algorithms in SONs should be developed by considering the node popularity in the network. A buffer congestion control algorithm in a SON node is now in the form of a function of both the node buffer state and node popularity level as:

$$congestion\ control = f\ (buffer\ state, node\ popularity)$$

Node buffer state can be characterized with several metrics, such as buffer occupation ratio, buffer growth rate and message drop rate. Node popularity level, on the other hand, can be assessed with a centrality metric.

B. *Traffic distribution aware routing protocol*

Traffic distribution fairness in SONs can also be improved by adding or improving the routing metrics of social-aware routing algorithms. For example, the authors of SimBet [11] improve the SimBet's drawback of unbalanced traffic distribution in SONs by adding tie strength to the routing metrics. The authors of FairRoute [13], however, improve node popularity calculation to increase traffic distribution fairness in the network. They use aggregated interaction strength to all the neighbour nodes to measure node global popularity. We, on the other hand, argue that other centrality measures (than the Freeman's centrality metrics) in the sociology literature can be investigated to obtain better traffic distribution fairness. For example, we can mention the Bonacich centrality measure [26] to be used as the routing metric of social-aware routing algorithms. While in the Freeman centrality metrics node's popularity is measured based the node's itself position in the network, the Bonacich centrality metric however considers the neighbours' popularities when calculating node popularity in the network. With this centrality metric, non-hub nodes can increase their popularities when they have direct neighbours (friends) with higher popularity. Consequently, this increases the probability of the nodes to be selected as traffic relays and eventually improves traffic distribution fairness in the network.

VI. Conclusions and Future Work

In this paper we have investigated the traffic distribution fairness in SONs, by studying the forwarding heuristics of social-aware routing algorithms and the network topology characteristics of SONs.

In the future, we will investigate several centrality metrics in the sociology literature to find better centrality metrics (than the Freeman's centrality metrics) that are able to bring a better impact on traffic distribution fairness in SONs.

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