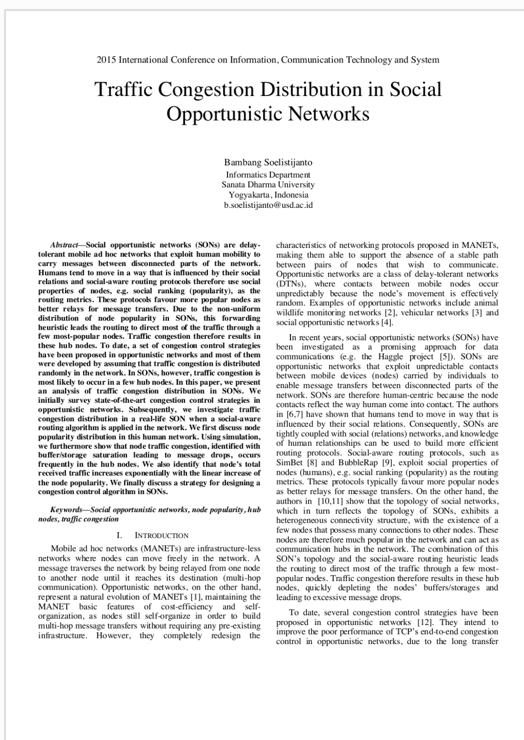
Digital Receipt

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:	Traffic Congestion Distribution in Social Opportunistic Netw...
File name:	fic_Congestion_Distribution_in_Social_Opportunistic_Network...
File size:	386.61K
Page count:	6
Word count:	4,724
Character count:	25,937
Submission date:	10-Jan-2023 02:05PM (UTC+0700)
Submission ID:	1990620587



2015 International Conference on Information, Communication Technology and System

Traffic Congestion Distribution in Social Opportunistic Networks

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

***Abstract*—Social opportunistic networks (SONs) are delay-tolerant mobile ad hoc networks that exploit human mobility to carry messages between disconnected parts of the network. Humans tend to move in a way that is influenced by their social relations and social-aware routing protocols therefore use social properties of nodes, e.g. social ranking (popularity), as the routing metrics. These protocols favour more popular nodes as better relays for message transfers. Due to the non-uniform distribution of node popularity in SONs, this forwarding heuristic leads the routing to direct most of the traffic through a few most-popular nodes. Traffic congestion therefore results in these hub nodes. To date, a set of congestion control strategies have been proposed in opportunistic networks and most of them were developed by assuming that traffic congestion is distributed randomly in the network. In SONs, however, traffic congestion is most likely to occur in a few hub nodes. In this paper, we present an analysis of traffic congestion distribution in SONs. We initially survey state-of-the-art congestion control strategies in opportunistic networks. Subsequently, we investigate traffic congestion distribution in a real-life SON when a social-aware routing algorithm is applied in the network. We first discuss node popularity distribution in this human network. Using simulation, we furthermore show that node traffic congestion, identified with buffer/storage saturation leading to message drops, occurs frequently in the hub nodes. We also identify that node's total received traffic increases exponentially with the linear increase of the node popularity. We finally discuss a strategy for designing a congestion control algorithm in SONs.**

Keywords*—Social opportunistic networks, node popularity, hub nodes, traffic congestion

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 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. Examples of opportunistic networks include animal wildlife monitoring networks [2], vehicular networks [3] and social opportunistic networks [4].

In recent years, social opportunistic networks (SONs) have been investigated as a promising approach for data communications (e.g. the Haggle project [5]). SONs are opportunistic networks that exploit unpredictable contacts between mobile devices (nodes) carried by individuals to enable message transfers between disconnected parts of the network. SONs are therefore human-centric because the node contacts reflect the way human come into contact. The authors in [6,7] have shown that humans tend to move in way that is influenced by their social relations. Consequently, SONs are tightly coupled with social (relations) networks, and knowledge of human relationships can be used to build more efficient routing protocols. Social-aware routing protocols, such as SimBet [8] and BubbleRap [9], exploit social properties of nodes (humans), e.g. social ranking (popularity) as the routing metrics. These protocols typically favour more popular nodes as better relays for message transfers. On the other hand, the authors in [10,11] show that the topology of social networks, which in turn reflects the topology of SONs, exhibits a heterogeneous connectivity structure, with the existence of a few nodes that possess many connections to other nodes. These nodes are therefore much popular in the network and can act as communication hubs in the network. The combination of this SON's topology and the social-aware routing heuristic leads the routing to direct most of the traffic through a few most-popular nodes. Traffic congestion therefore results in these hub nodes, quickly depleting the nodes' buffers/storages and leading to excessive message drops.

To date, several congestion control strategies have been proposed in opportunistic networks [12]. They intend to improve the poor performance of TCP's end-to-end congestion control in opportunistic networks, due to the long transfer

2015 International Conference on Information, Communication Technology and System

Traffic Congestion Distribution in Social Opportunistic Networks

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

***Abstract*—Social opportunistic networks (SONs) are delay-tolerant mobile ad hoc networks that exploit human mobility to carry messages between disconnected parts of the network. Humans tend to move in a way that is influenced by their social relations and social-aware routing protocols therefore use social properties of nodes, e.g. social ranking (popularity), as the routing metrics. These protocols favour more popular nodes as better relays for message transfers. Due to the non-uniform distribution of node popularity in SONs, this forwarding heuristic leads the routing to direct most of the traffic through a few most-popular nodes. Traffic congestion therefore results in these hub nodes. To date, a set of congestion control strategies have been proposed in opportunistic networks and most of them were developed by assuming that traffic congestion is distributed randomly in the network. In SONs, however, traffic congestion is most likely to occur in a few hub nodes. In this paper, we present an analysis of traffic congestion distribution in SONs. We initially survey state-of-the-art congestion control strategies in opportunistic networks. Subsequently, we investigate traffic congestion distribution in a real-life SON when a social-aware routing algorithm is applied in the network. We first discuss node popularity distribution in this human network. Using simulation, we furthermore show that node traffic congestion, identified with buffer/storage saturation leading to message drops, occurs frequently in the hub nodes. We also identify that node's total received traffic increases exponentially with the linear increase of the node popularity. We finally discuss a strategy for designing a congestion control algorithm in SONs.**

***Keywords*—Social opportunistic networks, node popularity, hub nodes, traffic congestion**

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 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. Examples of opportunistic networks include animal wildlife monitoring networks [2], vehicular networks [3] and social opportunistic networks [4].

In recent years, social opportunistic networks (SONs) have been investigated as a promising approach for data communications (e.g. the Haggle project [5]). SONs are opportunistic networks that exploit unpredictable contacts between mobile devices (nodes) carried by individuals to enable message transfers between disconnected parts of the network. SONs are therefore human-centric because the node contacts reflect the way human come into contact. The authors in [6,7] have shown that humans tend to move in way that is influenced by their social relations. Consequently, SONs are tightly coupled with social (relations) networks, and knowledge of human relationships can be used to build more efficient routing protocols. Social-aware routing protocols, such as SimBet [8] and BubbleRap [9], exploit social properties of nodes (humans), e.g. social ranking (popularity) as the routing metrics. These protocols typically favour more popular nodes as better relays for message transfers. On the other hand, the authors in [10,11] show that the topology of social networks, which in turn reflects the topology of SONs, exhibits a heterogeneous connectivity structure, with the existence of a few nodes that possess many connections to other nodes. These nodes are therefore much popular in the network and can act as communication hubs in the network. The combination of this SON's topology and the social-aware routing heuristic leads the routing to direct most of the traffic through a few most-popular nodes. Traffic congestion therefore results in these hub nodes, quickly depleting the nodes' buffers/storages and leading to excessive message drops.

To date, several congestion control strategies have been proposed in opportunistic networks [12]. They tend to improve the poor performance of TCP's end-to-end congestion control in opportunistic networks, due to the long transfer delays that occur in these networks. Moreover, most of the congestion control strategies were developed by assuming that traffic congestion is randomly distributed in the network. In SONs, however, traffic congestion is most likely to occur in a few hub nodes. As far as we know, the non-random traffic congestion distribution in SONs has not been investigated before. The contribution of this paper is therefore as follows. First, we perform a brief survey on state-of-the-art congestion control strategies in opportunistic networks and identify their potential issues when applied in SONs. Second, we investigate traffic congestion in SONs using real human contact traces and confirm the non-uniform congestion distribution in the human networks. Finally, we propose a new approach in designing congestion control algorithms in SONs that considers node's popularity in the algorithm's decision.

The remainder of the paper is organized as follows. Section II discusses congestion control strategies in opportunistic networks. Section III describes node popularity (social ranking) distribution in SONs. In Section IV, we discuss the simulation results of traffic congestion distribution when a social-aware routing algorithm is applied on a real-life SON. Finally, we discuss strategy in designing congestion control algorithms in SONs in Section V, which is followed by conclusion and future work in Section VI.

II. Congestion Control Strategies in Opportunistic Networks

TCP's end-to-end congestion control is ineffective against the impairment of opportunistic networks, namely long propagation delays or round-trip time: TCP has no explicit knowledge of congestion state in the network and instead relies on packet drop events which are signaled to the source through TCP's acknowledgment mechanism. Therefore, congestion control in opportunistic networks cannot rely on end-to-end acknowledgements and instead should be implemented on a per-hop basis, based on node's locally available information. Congestion control strategies in opportunistic networks are closely related to the number of message copies distributed throughout the network. Routing protocols may use a multiple-copy (replication) strategy to increase the delivery ratio and/or to reduce delivery latency. In this paper, we consider congestion control strategies in a multiple-copy case. A comprehensive survey of congestion control strategies in opportunistic networks can be found in [12]. We furthermore divide the strategies into two approaches as follows:

a) **Replication control**: While message replication can be used as a forwarding mechanism to increase message delivery probability, it can easily overwhelm node storage, e.g. Epidemic routing [13]. A dynamic replication control strategy is therefore required to adaptively adjust the message replication rate to the network congestion level. Since network (global) congestion information is not available in an opportunistic network node, the replication control strategy instead uses either the node's own knowledge or local knowledge to determine the network congestion level. For example, Retiring Replicant [14] uses the ratio of message drop rate to the rate of receiving message at a node as a local metric to control message replication in the network. RRFS [15], on the other hand, controls message replication by prioritising messages according to the number of message copies already distributed in the network. The algorithm uses a local estimate of total copies of the messages in a node's buffer and favours the messages with the lowest values of total copies to replicate first during node contact. Finally, CAFRep [16] uses node's buffer statistics, i.e. buffer free space, buffer queuing delay and buffer congestion rate, to determine global congestion level. To improve the congestion detection, the algorithm also considers local congestion information supplied by neighbouring nodes.

b) **Message drop strategy**: With the existence of message redundancy in the network due to the replication strategy, a node can now drop messages from its buffer when congestion occurs without causing loss of the messages from the network. We categorize message drop strategies based on the information required as follows:

- *Single-message statistics*: a simple drop strategy that only needs the attributes of a message in the node buffer, such as message forwarding or arrival statistics, or message TTL. For example, the authors in [17,18] investigated the performances of several simple drop strategies, namely FIFO (first in first out), MOFO (drop most forwarded first) and SHLI (drop shortest lifetime first), in term of delivery ratio and delay.

- *Network-wide message statistics*: a complex drop strategy that needs message attributes collected from the entire network. For example, when the node's buffer is full, AFNER [19] randomly drops a message with the forwarding number larger than the network's average forwarding number. GBSD [20], on the other hand, requires global information concerning the distribution of a message, such as the number of copies of a message and the number of nodes that have seen the message, to decide whether to drop the message when the buffer is full.

Congestion control strategies in opportunistic network nodes in general use either the nodes' own information or the nodes' locally available information to estimate network congestion level. However, when the network traffic changes dynamically over time, the strategies will slowly respond to the dynamic changes of congestion level in the network: due to the long transfer delays in opportunistic networks, node's local information may not properly identify the recent network congestion state. Furthermore, we note that most of the congestion strategies in opportunistic networks were developed by assuming that traffic congestion is distributed randomly in the network. As we will show in Section IV, this assumption however does not hold in SONs since traffic congestion is most likely to occur in a few most popular nodes. We identify that the total received traffic of a SON node increases with the increasing of its (social) popularity. Moreover, in Section III we note that node's social network properties, e.g. node popularity, are less volatile than node's physical network properties, e.g. node contact information, i.e. contact duration and frequency. Hence, we see a potential improvement in calculating node's buffer congestion probability based on the node's locally available information, i.e. by considering node popularity into the congestion control algorithm's decision (we will discuss it in Section V).

III. NODE POPULARITY DISTRIBUTION IN SONS

The knowledge of human mobility is important to identify the delivery performance of SONs. The mobility patterns of humans tend to be influenced by their social relationships. Human mobility characteristics discussed in [6,7] show that there exists a virtual social (relations) network that drives human to move, and that this graph is less volatile than SON's physical networks. The overlay graph represents a macroscopic property of human mobility. We illustrate the structural topology of a SON in Fig. 1.

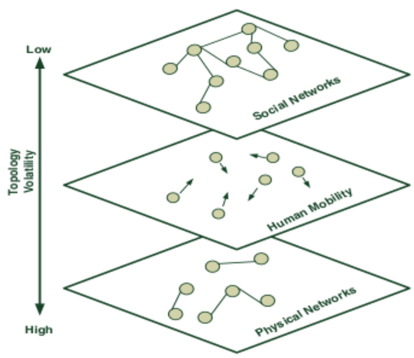


Fig. 1. The structural topology of a SON

The authors in [10,11] studied the topology of a SON by aggregating human contact data traces to form a contact graph. Each mobile device is a node of this graph and a link represents the social relationship between two nodes. Conti and Kumar [21] identified this human contact graph as an electronic social network. In the electronic social network, links (human relations) can be characterized based on node contact information, such as contact frequency, duration and recency. In order to discover the topology characteristics of SONs, the authors in [10,11] subsequently performed an off-line analysis on the contact graphs of several real-life SONs. They found that the derived graphs possess a strong non-random connectivity structure and exhibit a power-law node 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. The largest degree nodes are therefore (socially) very popular in the network and can act as communication hubs in the network.

We, on the other hand, perform an online analysis of node popularity in SONs. In self-organizing networks, such as opportunistic networks, a node should be able to autonomously identify its (social) popularity in the network. Node popularity in a social network can be measured by a centrality metric, e.g. the Freeman's centrality metrics [22], i.e. degree centrality, betweeness centrality and closeness centrality. Node degree centrality is the total number of links that a node has. The betweeness centrality of a node is the number of shortest-paths that pass through the node divided by the number of shortest-paths in the network. Node closeness centrality is the reciprocal of the mean the shortest-paths between a node and all other reachable nodes. In our analysis, node popularity is quantified by the number of distinct nodes encountered in a given time interval. In the literature [9,11], this is equal to the node degree (or degree centrality) in an aggregated contact graph. We furthermore use the C-Window technique of BubbleRap [9] to calculate node degree (popularity) in a time interval (or time window). This technique is a cumulative moving average that determines degree of a node in a time window by calculating the node degree value averaged over all previous time windows. For simulation, we use the ONE simulator [23], an event-driven simulator for opportunistic networks. For the simulation's node mobility scenario, we use a real human contact dataset, namely Reality [24]. In Reality, 100 smart phones were deployed among student and staff of MIT over period of 9 months.

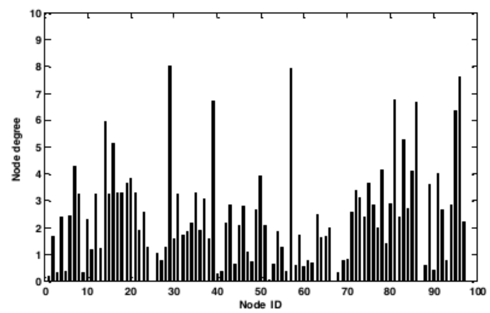


Fig. 2. Node degree distribution in Reality

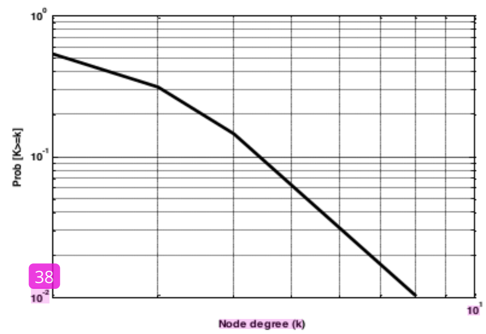


Fig. 3. CDF of node degree in Reality

From the simulation results, we depict the node degree distribution and its cumulative distribution function (CDF) in Reality in Fig. 2 and 3, respectively. The time window used for calculating node degree is set to 24 hours. Fig. 2 clearly shows that the human network in Reality exhibits a heterogeneous degree distribution where some nodes have degrees that are much higher than the average degree in the network (the mean degree is 2.12) and hence are much popular in the network. Moreover, Fig. 3 shows that the node degree 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. This is inline with the study in [25] that confirms the feasibility of coupling between SONs and scale-free graphs, those with the main characteristic of power-law degree distribution. When social-aware routing algorithms that implement a forwarding heuristic that biases towards more popular nodes are applied in SONs, as we will show in the next section, traffic congestion finally results in a few most popular nodes (hub nodes).

IV. TRAFFIC CONGESTION DISTRIBUTION IN SONS

In this section, we discuss the analysis of traffic congestion distribution when a social-aware routing protocol is applied in a real-life SON. Social-aware routing protocols, e.g. SimBet [8] and BubbleRap [9], use social properties of nodes as the routing metrics. In general, social-aware routing algorithms involve two main properties when making forwarding decisions as follows:

- *Transitivity*: during a node contact, if either the forwarding node (a node that intends to transfer its message) or its contact has knowledge of the message destination, the forwarding node selects the contacted node as a relay of the message when the latter is closer to the destination. A tie (connection) strength between two nodes can be evaluated based on the metrics, such as contact frequency and duration. SimBet includes tie strength and neighbour similarity to measure the closeness of a relay node to the destination. BubbleRap uses community knowledge to identify the probability of a relay node meeting with the destination.

- *Global ranking*: when the destination is unknown to both the forwarding node and its contact, the routing protocol routes the message to a structurally more popular node in order to achieve the message delivery in a short delay. Node popularity in a (social) network can be evaluated by a centrality metric, e.g. Freeman centrality measures, i.e. degree, closeness and betweeness centralities. SimBet uses betweeness centrality calculated in an ego network to measure node global popularity. BubbleRap, on the other hand, uses degree centrality to calculate node's popularity in the entire network.

We now investigate traffic congestion in a SON when a social-aware routing protocol is applied in the network. To be specific, we intend to study the impact of the social-aware routing heuristic that favours more (globally) popular nodes on traffic congestion distribution in SONs. In this study, we consider node degree (or node degree centrality) to measure node popularity in the entire network. As in Section III, node degree is calculated as the number of distinct nodes encountered in a given time window. We again use the C-Window technique of BubbleRap to calculate node degree in a time interval. We use the ONE simulator [23] with the main parameters are described in Table-1. The time window used for calculating node degree is set to 24 hours. In this evaluation, we consider a unicast message transmission, where the source and destination of each new message is chosen randomly during the simulation. For the simulation node mobility scenario, we use the Reality dataset [24], since it contains a reasonably large number of nodes and covers a long period of time. We consider several evaluation metrics to investigate traffic congestion as follows:

- **Total processed traffic**: the total number of relayed messages received by a node throughout the simulation time.

- **Buffer occupancy (buffer queue length)**: the fraction of node's buffer spaces occupied by the relayed messages.

- **Total message drops**: the total number of messages in the buffer dropped by a node when the buffer congestion occurs during the simulation.

TABLE 2. The ONE principal simulation parameters

Simulation Parameters	
Mobility scenario	Reality
Number of nodes	97
Simulation time	196 days
Msg. generation interval	~ 12 msgs/h
Node buffer size	20 MB
Message TTL	21 days
Message size	10 kB

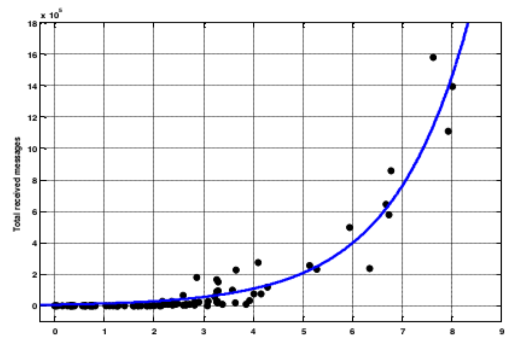


Fig. 4. Node degree vs. total processed traffic in Reality

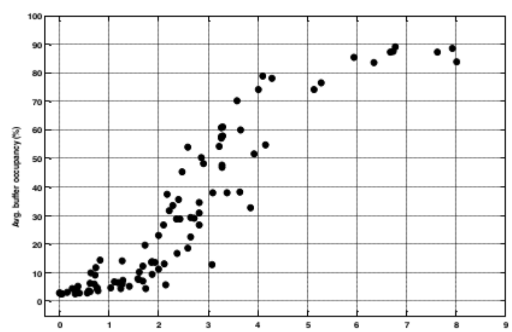
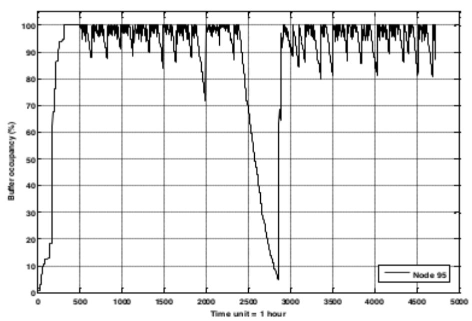
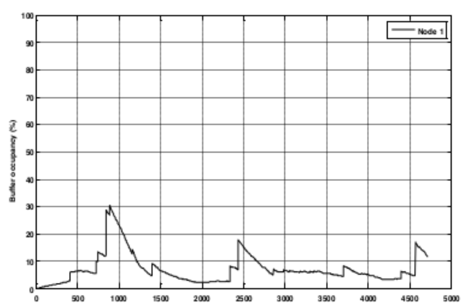


Fig. 5. Node degree vs. avg. buffer occupancy in Reality

From the simulation results, we depict the node degree vs. total processed traffic and the node degree vs. avg. buffer occupancy in Fig. 4 and 5, respectively, when a routing algorithm that favours higher degree (more popular) nodes is applied in Reality. Fig. 4 shows that a few nodes, i.e. the highest degree nodes (hub nodes), process a large fraction of network traffic, but majority of the network nodes only receives few relay messages. Furthermore, by applying the curve-fitting function of MATLAB on Fig. 4, the fitted curve that relates the node degree (k) with total processed traffic (l) is plotted (the blue line in Fig. 4), giving the scaling relation between them as $l \sim k^{3.487}$. This agrees with the investigation in [26] that in complex networks (i.e. scale-free networks), when a shortest-path forwarding strategy is applied, the network traffic is power-law distributed. This unbalanced of traffic distribution in the human network therefore results in traffic congestion in a few hub nodes. Fig. 5 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).



(a) The highest degree node



(b) A low degree node

Fig. 6. Buffer occupancy as a function of time for the nodes in Reality

Moreover, in Fig. 6(a) and 6(b) we depict the change over time of buffer occupancy of the highest degree node (node 95) and a low degree node (node 1), respectively, in Reality. Fig. 6(a) shows that in the highest degree node (hub node) the buffer queue length increases rapidly 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. Only in the inactive period of the Reality trace (i.e. holiday term) the hub node's buffer occupancy significantly decreases. In contrast, in the low degree node, as depicted in Fig. 6(b), the buffer occupancy is typically low and slightly fluctuates during the simulation. As a result, buffer congestion leading to message drops is less likely to occur in this low degree node. Indeed, Fig. 7 clearly shows that the majority of message drop events occur in high degree nodes, particularly hub nodes.

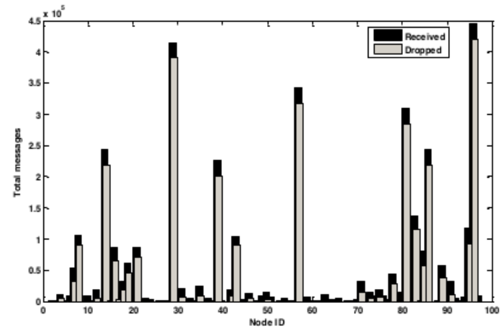


Fig. 7. Total received messages vs. dropped message for the nodes in Reality

V. STRATEGY IN DESIGNING CONGESTION CONTROL ALGORITHMS IN SONS

We have shown in Section IV that traffic congestion is not randomly distributed in SONs, but is most likely to occur in a few most popular nodes. However, we have noted in Section II that most of the existing congestion control strategies in opportunistic networks were developed by assuming that traffic congestion is distributed evenly in the network. The strategies rely on either node's own knowledge or node's locally available knowledge when calculating network congestion level. When the network traffic changes dynamically, the local knowledge may not properly identify global congestion state. As a result, the congestion control strategy in a SON node is not able to accurately calculate the node's buffer congestion probability. In Section IV, we have identified that the total number of received relay traffic of a node is closely related with the node degree (popularity). Moreover, in Section III we have noted that node's social properties, e.g. node popularity, are less volatile than node's physical properties in SONs. We therefore argue that calculating node's buffer congestion probability based on the node's local information can be improved by considering the node popularity into the computation. This relatively stable metric, node popularity, can help the congestion control algorithm in a SON node to identify the future node's buffer congestion probability more accurately.

In Fig. 8, we show a design architecture of a forwarding strategy in a SON node, which consist of two components: routing and congestion control modules. The routing module consists of a social-aware routing algorithm, which is responsible to select relay nodes that are able to deliver messages to the destinations in short delays. The congestion control module, on the other hand, consists of a congestion control algorithm that controls the node's buffer congestion. During a node contact, each module separately exchanges its information with its peer's module: the routing modules exchange routing metrics, such as node popularity and social community, and the congestion control module requires information of both nodes' buffer statistics, such as buffer queue length and total drop messages, as well as nodes' popularities (from the routing modules). The forwarding decision is eventually made by considering both the routing and congestion control calculations.

VI. Conclusions and Future Work

In this paper, we have investigated traffic congestion distribution in a real-life SON when a social-aware routing protocol is applied in the network. We identify that traffic congestion is not randomly distributed in the network, but is most likely to occur in a few most popular nodes (hub nodes). We also have proposed a new protocol design of congestion control in a SON node that considers node popularity in the algorithm's decision.

In the future, we will developed a new computation of SON node buffer congestion probability based on the node's local information, namely buffer statistics and social popularity, in the congestion control algorithm to minimize buffer congestion events and message drops, particularly in the most popular nodes (hub nodes).

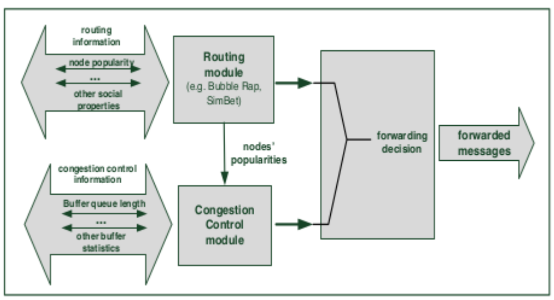


Fig. 8. The design architecture of social-aware forwarding strategy with congestion control in a SON node

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. ASPLOS 2002*, Oct. 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. 9th INFOCOM Workshops*, Rio de Janeiro, April 2009.

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

[6] T. Hossmann, T. Spyropolous, F. Legendre, "A Complex Network Analysis of Human Mobility", *Proc. IEEE Conf. on Computer Comm. Workshops 2011*, Shanghai, China, 2011.

[7] V. Borrel, F. Legendre, M. Amorim, S. Fdida, "SIMPS: Using Sociology for Personal Mobility", *IEEE/ACM Transactions on Networks*, vol. 17, no. 3, 2009.

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

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

[10] 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.

[11] E. Yoneki, P. Hui, J. Crowcroft, "Distinct Types of Hubs in Human Dynamic Networks", *Proc. SocialNets'08*, Glasgow, UK, April 2008.

[12] B. Soelistijanto and M.P. Howarth, "Transfer Reliability and Congestion Control Strategies in Opportunistic Networks: A Survey", *IEEE Comm. Surveys and Tutorials*, vol. 16, no. 1, pp. 538-555, 2014.

[13] A. Vahdat, D. Becker, "Epidemic Routing for Partially Connected Ad Hoc Networks", *Tech Report CS-200006*, Duke University, 2000.

[14] N. Thompson, S.C. Nelson, M. Bakht, T. Abdelzaher, R. Kravets, "Retiring Replicants: Congestion Control for Intermittently-Connected Networks", *Proc. IEEE INFOCOM'10*, San Diego, California, USA 2010.

[15] Y.K. Ip, W.C. Lau, O.C. Yue, "Forwarding and Replication Strategies for DTN with Resource Constraints", *Proc. IEEE 6th Vehicular Technology Conference*, Dublin, Ireland, May 2007.

[16] M. Radenkovic, A. Grundy, "Framework for Utility Driven Congestion Control in Delay Tolerant Opportunistic Networks", *Proc. 7th IWCMC*, Istanbul, Turkey, 2011.

[17] A. Lindgren, K.S. Phanse, "Evaluation of Queuing Policies and Forwarding Strategies for Routing in Intermittently Connected Networks", *Proc. First Intl. Conf. Comsware*, New Delhi, India, 2006.

[18] V. Erramili, M. Crovella, "Forwarding in Opportunistic Network with Resource Constraints", *Proc. Intl. Conf. MobiCom'08*, San Francisco, California, USA, Sep. 2008.

[19] L. Yun, C. Xinjian, L. Qilie, Y. Xiaohu, "A Novel Congestion Control Strategy in Delay Tolerant Networks", *Proc. 2nd ICFN'10*, Hainan, China, 2010.

[20] A. Krifa, C. Barakat, T. Spyropolous., "An Optimal Joint Scheduling and Drop Policy for Delay Tolerant Networks", Proc. *WoWMoM*, New Port Beach, California, USA, 2008.

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

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

[23] A. Keranen, J. Ott, T. Karkkainen, "The ONE Simulator for DTN Protocol Evaluation", *SIMUTools 2009*, Rome, Italy, 2009.

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

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

[26] K.I. Goh, B. Kahng, D. Kim, "Universal Behaviour of Load Distribution in Scale Free Networks", *Journal of Physical Review Letters*, vol. 87, no. 27, 2001.

Traffic Congestion Distribution in Social Opportunistic Networks

ORIGINALITY REPORT

14%	11%	10%	2%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	cnd.iit.cnr.it Internet Source	1%
2	www.ijetr.org Internet Source	1%
3	citeseerx.ist.psu.edu Internet Source	1%
4	Middleware for Network Eccentric and Mobile Applications, 2009. Publication	1%
5	mdpi-res.com Internet Source	1%
6	www.inderscience.com Internet Source	1%
7	www.research-collection.ethz.ch Internet Source	1%
8	josepmpujol.net Internet Source	1%
	coek.info	

9	Internet Source	<1 %
10	nrg.cs.uoi.gr Internet Source	<1 %
11	Submitted to Birla Institute of Technology and Science Pilani Student Paper	<1 %
12	ro.uow.edu.au Internet Source	<1 %
13	web-ext.u-aizu.ac.jp Internet Source	<1 %
14	Pan Hui, Jon Crowcroft, Eiko Yoneki. "Bubble rap", Proceedings of the 9th ACM international symposium on Mobile ad hoc networking and computing - MobiHoc '08, 2008 Publication	<1 %
15	Kaimin Wei, Song Guo, Xiangli Li, Deze Zeng, Ke Xu. "Congestion control in social-based sensor networks: A social network perspective", Peer-to-Peer Networking and Applications, 2015 Publication	<1 %
16	Aloizio Pereira da Silva, Scott Burleigh, Celso Massaki Hirata, Katia Obraczka. "Congestion control in disruption-tolerant networks",	<1 %

Proceedings of the 9th ACM MobiCom workshop on Challenged networks - CHANTS '14, 2014
Publication

17	Vastardis, Nikolaos, and Kun Yang. "Mobile Social Networks: Architectures, Social Properties and Key Research Challenges", IEEE Communications Surveys & Tutorials, 2012. Publication	<1 %
18	e-space.mmu.ac.uk Internet Source	<1 %
19	Carlo Augusto Grazia, Natale Patriciello, Martin Klapez, Maurizio Casoni. "Transmission Control Protocol and Active Queue Management together against congestion: cross-comparison through simulations", SIMULATION, 2018 Publication	<1 %
20	Deepak Kumar Sharma, Sanjay K. Dhurandher, Amit Gupta, Ashray Anand. "Centrality based congestion controlled routing protocol for social opportunistic networks", 2016 1st India International Conference on Information Processing (IICIP), 2016 Publication	<1 %

21	Lo, Shou-Chih, Chun-Chieh Tsai, and Yu-Han Lai. "Quota-control routing in delay-tolerant networks", Ad Hoc Networks, 2015. Publication	<1%
22	Submitted to University of Southampton Student Paper	<1%
23	ijarcsse.com Internet Source	<1%
24	journal.icter.org Internet Source	<1%
25	Xiangji Cai. "Quantum dephasing induced by non-Markovian random telegraph noise", Scientific Reports, 2020 Publication	<1%
26	dc.tsinghuajournals.com Internet Source	<1%
27	link.koreatech.ac.kr Internet Source	<1%
28	refubium.fu-berlin.de Internet Source	<1%
29	Xia, Feng, Hannan Bin Liaqat, Ahmedin Mohammed Ahmed, Li Liu, Jianhua Ma, Runhe Huang, and Amr Tolba. "User popularity-based packet scheduling for congestion control in ad-hoc social networks", Journal of Computer and System Sciences, 2016.	<1%

Publication

30	ddd.uab.cat Internet Source	<1 %
31	iiste.org Internet Source	<1 %
32	ira.lib.polyu.edu.hk Internet Source	<1 %
33	link.springer.com Internet Source	<1 %
34	mafiadoc.com Internet Source	<1 %
35	tel.archives-ouvertes.fr Internet Source	<1 %
36	www.mdpi.com Internet Source	<1 %
37	En Wang, Yongjian Yang, Jie Wu. "A Knapsack-based buffer management strategy for delay-tolerant networks", Journal of Parallel and Distributed Computing, 2015 Publication	<1 %
38	Gjoka, Minas, Maciej Kurant, Carter T. Butts, and Athina Markopoulou. "Practical Recommendations on Crawling Online Social Networks", IEEE Journal on Selected Areas in Communications, 2011. Publication	<1 %

39	Quan Yuan. "Predict and relay", Proceedings of the tenth ACM international symposium on Mobile ad hoc networking and computing - MobiHoc 09 MobiHoc 09, 2009 Publication	<1 %
40	Schurgot, Mary, Cristina Comaniciu, and Katia Jaffres-Runser. "Beyond traditional DTN routing: social networks for opportunistic communication", IEEE Communications Magazine, 2012. Publication	<1 %
41	Aloizio P. Silva, Katia Obraczka, Scott Burleigh, Celso M. Hirata. "Smart Congestion Control for Delay- and Disruption Tolerant Networks", 2016 13th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON), 2016 Publication	<1 %
42	International Journal of Operations & Production Management, Volume 33, Issue 1 (2013-01-05) Publication	<1 %

Exclude quotes	On	Exclude matches	< 5 words
Exclude bibliography	On		