Social-aware Clustering for Wireless Ad hoc Networks

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***Abstract*—Clustering is a widely used solution to provide routing scalability in wireless ad hoc networks. The design of clustering schemes is a complex problem due to the dynamic nature of this type of networks. This work proposes a Social-aware Clustering Scheme (SoCS) based on link history to improve the performance of clustering management operations. Each node maintains a history of past links with neighbour nodes with the prospect of improving the performance of future cluster formations. SoCS was evaluated with the Social Network Theory (SNT) mobility model, analysing clustering, routing and traffic performance. Obtained results demonstrate an overall significant improvement, proving that social-awareness is a quality attribute in a clustering scheme.**

***Index Terms*—wireless ad hoc networks, clustering, social**

I. INTRODUCTION

Wireless ad hoc networks are autonomous systems, capable of self deployment and maintenance, not requiring network infrastructures for their operation. In such environments, the network topology is highly dynamic, due to the unpredictable behaviour of nodes. Numerous clustering schemes were developed, following different approaches and objectives in order to improve the network scalability. In recent studies, a substantial number of routing protocols, based on social relationships, have been proposed [1][2][3]. These protocols exploit social relations amongst nodes to help making forwarding decisions. The recent abundance of social relationships between individuals, makes social awareness a promising research topic to tackle the dynamic problem of wireless ad hoc networks.

This work proposes a clustering solution (SoCS) capable of exploiting social ties, while maintaining its normal functioning when social relationships do not exist. SoCS manages the network topology optimizing the grouping of nodes based on the history of their past connections. There are some routing protocols for Delay Tolerant Networks (DTNs) that also explore the history of connections in order to predict the reliability of nodes for message forwarding [4][5]. However, to the best of our knowledge, this is the first social clustering scheme exploring the connection history to improve the performance of clustering.

The next Section discusses the related work on social grouping solutions. Section III describes the SoCS clustering scheme. Section IV evaluates SoCS by comparison with a non social clustering scheme. Finally, Section V concludes this work.

II. RELATED WORK

In the past decade, clustering has been the most successful approach to impose an hierarchical structured network aiming to provide routing scalability. Many cluster based routing protocols have been proposed, combining in one solution a sectored network with route discovery. More recently a wide range of routing protocols based on social metrics have been exploiting social relationships to improve forwarding decisions. In these solutions, clustering is based on identified social groups. However, creating clusters that are only related to social groups is insufficient, as some relationships may be unknown or the size of social groups may be very discrepant, originating unbalanced clusters.

Due to the complexity of human relationships, their exact characteristics are still unknown. Therefore, it is not possible to directly use social ties in routing or clustering schemes. Social ties must be analysed according to metrics to identity their features. Some of the most relevant metrics used in the literature are as follows.

a) Degree centrality: [6] determines the number of neighbour connections. Usually it is used to identify the most popular node in a network.

b) Closeness centrality: [6] is the mean of geographic distance between a node and all the nodes in the network. Assuming that all nodes are reachable, closeness centrality is used to measure how long is necessary to spread information from a given node to all other nodes.

c) Betweenness centrality: [6] is defined as the amount of shortest paths from all nodes to all nodes that pass through a given node. It can be used to determine the amount of load of a given node.

d) Clustering coefficient: [7] measures the tendency of nodes to cluster together in a network. There are some variations to calculate this metric. The most popular is determined as the number of connections between neighbour nodes divided by the total of possible connections of the node.

e) Similarity: [8] measures common features between nodes, such as interests and locations. It is used to identify common groups of nodes.

f) Selfishness: [3] measures the willingness or cooperation of a node with other nodes. Selfishness is considered a negative effect for message transmission [9], particularly in ad hoc networks. However, it can also be used to reduce traffic in a network with low resources.

People with similar interests, location or professions are more likely to have social ties. They are also more likely to interact more often than strangers, thus the probability of being located in the same geographic area is higher. The assumption that nodes with higher similarity tend to be in-range more frequently motivated some routing protocols [2] [10] to adopt similarity to make forwarding decisions.

Centrality suggests the relative location of nodes in a network. High centrality or popular nodes are more likely to encounter other nodes than unpopular nodes. Centrality-based routing protocols rely on these nodes to forward messages. PeopleRank [11] is an opportunistic forwarding algorithm that relies on popular nodes to deliver messages. Using this paradigm often causes popular nodes to become bottlenecks, leading to traffic congestion and fast energy depletion. This contradiction between conserving resources and efficient message transmission is addressed in the Socially-Based Routing for Delay Tolerant Networks (SBR-DTN) [12]. This approach replicates the same message in the network to increase the probability of reaching its destination, instead of concentrating traffic in shortest paths.

Selfishness affects willingness of node cooperation in forwarding messages. Most routing protocols are designed on the false assumption that nodes are willing to forward messages for others. Mostly due to energy saving, some selfish nodes are only willing to forward messages to nodes with whom they have social ties, which is harmful for message transmission. There are however, some routing protocols aware of this phenomenon and even take advantage of it to preserve network resources [13].

III. Social-aware Clustering Scheme (SoCS)

Nowadays, with the effortless extraction of social relationships, social awareness can be regarded as an opportunity to improve the performance of clustering management. The main purpose of SoCS is to build a low overhead network topology in order to increase the scalability of the network. Relying on social awareness, nodes are able to maintain a history of connections to neighbour nodes in order to improve maintenance operations, such as aggregation to clusters. SoCS is a distributed clustering scheme which implements some features of the Distributed and Location-aware Clustering (DiLoC) clustering scheme [14]. DiLoC is designed for indoor environments exploiting potentially existent WLAN infrastructures to provide location references in order to increase the stability of clusters.

A. Node States

In SoCS, nodes can be in one of three distinct states, namely *Unclustered*, *Clustered* and *Clustered-GW*.

The *Unclustered* state typically represents a temporary role, as the node is waiting to be assigned to a cluster. In this state, when the node discovers neighbors, it waits a predefined period of time in order to calculate the best candidate cluster to join. The *Unclustered* state occurs on two different ocasions:

1) Node isolation - in this case the node does not have any in-range neighbour nodes, therefore cannot create or be assigned to a cluster
2) Cluster transition - the management of clusters occasionally requires nodes to change clusters, due to cluster balancing. In this phase, nodes can be unassigned from a cluster.

Nodes on *Clustered* state usually represent the majority of nodes on the network, whereas all in-range nodes must belong to its cluster. Thus, the communication with foreign nodes (i.e. nodes assigned to a different cluster) is performed through gateway nodes.

Finally, the *Clustered-GW* state is assigned to nodes that have in-range foreign nodes, i.e. they must have direct connectivity with at least one different cluster. Thus, they are responsible of forwarding inter-cluster maintenance messages and typically are located on the edge of clusters.

The possible node state transitions are defined as follows.

Clustered to Clustered: This transition occurs when a node becomes aware of an in-range cluster or an unclustered node. In the first situation, the node joins the cluster automatically. However, if the node only detects unclustered nodes, a new cluster is created to adopt the unclustered nodes.

Unclustered to Clustered-GW: This transition is similar to the previous, but more than one cluster is discovered. In this case, the node determines which cluster is the most suitable, either relying on its link history list or according to a best clustering metric. If a link history between the unclustered node and its in-range clustered nodes exists, this will be the used methodology (further described in Section III-B). However, if no previous connections existed, the node calculates which cluster is the best, taking several parameters into account: number of in-range nodes for each cluster and the size of clusters. The greater the number of in-range nodes, the stronger connection to the cluster. However, if the size of the cluster is high, possibly close to the maximum allowed, this cluster would be a bad choice. To measure this trade-off, the best clustering metric 1 is used, where BC_i is the metric value for cluster i.

$$BC_i = \alpha_i + \frac{\gamma_i}{C} \tag{1}$$

α_i is the number of the available positions in cluster i until it reaches the maximum allowed. γ_i represents the number of in-range nodes belonging to the cluster. C is an arbitrary constant, allowing to reduce the impact of γ_i. Using this metric, the cluster with the higher BC value is chosen by the node.

Clustered to Clustered-GW: This transition occurs when a node becomes aware of clusters, excluding its own.

Clustered-GW to Clustered: Whenever a clustered gateway node loses connection with all its foreign clusters, it automatically transits to a normal clustered state.

Clustered/Clustered-GW to Unclustered: A node becomes unclustered when willingly disconnects from the network or loses connection with all its neighbour nodes due to mobility.

B. Link History

Nodes keep information about their previous connections with neighbour nodes (i.e. at 1-hop distance). This information can be used in future connections to improve both the cluster joining process and durability time of connections.

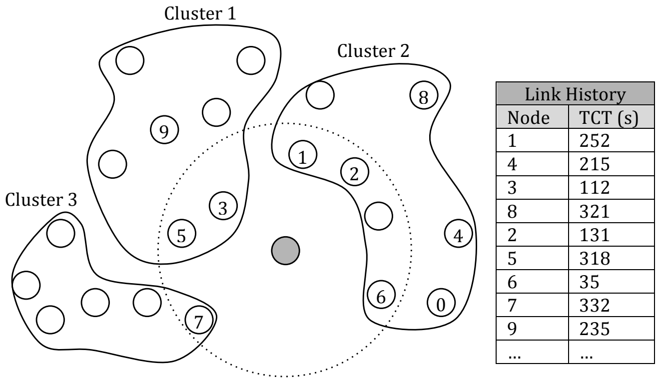

Fig. 1: Example cluster decision based on link history

Each node keeps a list of previous neighbour nodes with which a past connection occurred. The list contains the total of connectivity time with each neighbour, which is the sum of the amount of time in all connections. Figure 1 shows an example of a node making a decision to join a cluster. Three clusters are in-range of the node, since it has at least one in-range node inside each cluster. Based on the link history list, it can be determined that *Cluster 1* has a total of 665 seconds (sum of nodes 5, 3 and 9), *Cluster 2* has a total of 954 seconds (sum of nodes 1, 2, 8, 4 and 6) and *Cluster 3* has a total of 332 seconds (node 7). Thus, the decision will favour in joining *Cluster 2*. To be noted that, despite nodes 9, 8 and 4 not currently being in-range with the joining node, the latter is still able to see them, since the full table of clustered nodes is broadcasted upon the presence of an unclustered node. Otherwise, in this example, the decision would favour in joining *Cluster 1*. The utilisation of link history potentially increases the durability of connections, and decreases the complexity of future cluster assignments, particularly with the existence of repeated connection patterns, often observed in social grouping.

IV. Evaluation and Results

The evaluation of SoCS was performed in a simulated environment using the OPNET Modeler [15]. The main purpose of this evaluation is to access the overhead and scalability of clustering regarding the gain obtained with social awareness. This study features the performance of clustering, routing and generated traffic.

A. Environment and Parameters

The evaluation parameters are presented in Table I. The objective of this evaluation was to obtain the gain of clustering scalability using social awareness presented in SoCS. The evaluation methodology was defined as follows.

TABLE I: Simulation Parameters

Simulator	OPNET Modeler 17.5.A PL6
Field Size (m^2)	500×500
Mobility Model	RWP; SNT
Transmission range (m)	150
WLAN IEEE Standard	802.11b (11 Mbps)
Simulation time (s)	900
Network size (number of nodes)	40; 80; 120; 160; 200
Routing Protocol	C-OLSR
Traffic Pattern	
Packet size ($bytes$)	U(512, 1024)
Rate ($packets/sec$)	U(0, 1)
Number of intra-group packets	5
Number of inter-group packets	5
RWP Parameters	
Node speed (m/s)	U(0, 2)
Maximum pause time (s)	50
SNT Parameters	
Node speed (m/s)	U(0, 2)
Number of groups (Caveman model)	10

1) Scheme Comparison: SoCS was compared with DiLoC due to the similarity of clustering characteristics, such as distributed cluster topology, type of messages, and maintenance operations.

2) Routing Protocol: In these simulations, the C-OLSR [16] routing protocol was used. C-OLSR is an extension of the well known proactive OLSR routing protocol, capable of creating an hierarchical network topology, thus supporting any clustering scheme.

3) Mobility Models: Social relationships are strongly related with social mobility. Thus, in order to achieve a real evaluation of a social clustering scheme it becomes necessary to use either real movement traces or synthesised traces, generated by social mobility models. In this evaluation, the Random Waypoint (RWP) and the Social Network Theory (SNT) [17] mobility models are used. The SNT model studies social relationships based on social network theory. By assuming that social ties between individuals are symmetric, the relationships of a group of individuals can be measured according to an interaction matrix, which can also be interpreted as the likelihood of geographic location of individuals. Mobility traces are generated based on this matrix, following a model of social attractivity between individuals within a group. After their generation, a trace matrix is fed to each node of the SoCS scheme before execution, in order to build the link history lists. Each index of the matrix is translated to a link history time of nodes. To be noted that during execution time, SoCS updates the link history in each node, according to neighbourhood nodes.

4) Generated Traffic: The used traffic pattern is characterized as follows:

- At each time interval U(0, 1) 10 nodes are randomly selected to generate packets.
- The first 5 nodes generate one packet each, of size U(512, 1024) bytes, to a random destination node, in the entire network.
- The remainder 5 nodes generate one packet each, size U(512, 1024) bytes, to a random destination inside its corresponding cluster.

This pattern intends to mimic a real scenario message exchange, with messages travelling within a cluster and across different clusters.

B. Discussion of Results

This section presents the obtained results from the simulation. The evaluation features the analysis of clustering, routing and traffic performance. Each used metric is described further, along with the discussion of the obtained results.

1) Clustering Performance: The clustering metrics evaluate the performance of SoCS in comparison with DiLoC, using the RWP and the SNT mobility models.

a) Number of Clustered Nodes: This metric provides the average number of nodes that are associated with the cluster structure.

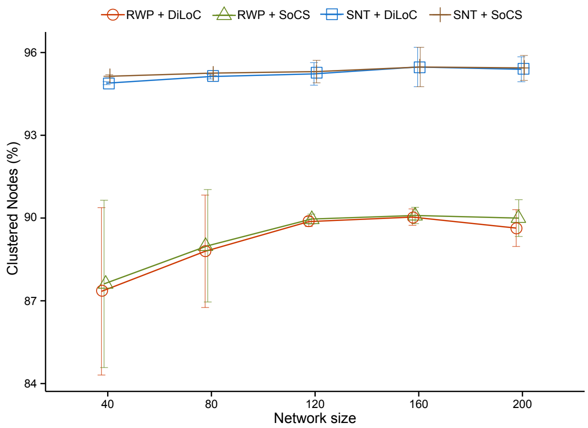

Fig. 2: Amount of Clustered Nodes (in percentage)

Nodes that are isolated cannot be affiliated to a cluster. Thus, scenarios with few nodes are likely to have more unclustered nodes, due to poor connectivity. Figure 2 represents the percentage of average amount of clustered nodes. With the SNT mobility model, the clustering scheme presents around 95% of clustered nodes for all network sizes. With the RWP, the amount of clustered nodes is quite irregular in the low density networks. Nodes in low density scenarios typically have lower connectivity, hence the lower amount of clustered nodes, particularly with random mobility. Moreover, the difference between SoCS and DiLoC is not significant, meaning that the link history of nodes is not relevant in this metric, as DiLoC is still capable of clustering as much nodes as SoCS.

b) Cluster Stability: The stability of clusters can be measured according to the amount of time that nodes are affiliated to a cluster, without suffering re-affiliation operations. A cluster stability metric is utilised, which defines a stability time (ST), from which nodes are considered to be stable (2).

$$ST = C \times \frac{\rho \times \psi}{\upsilon \times \delta} \tag{2}$$

ρ is the transmission range of nodes, ψ is the pause time, υ the average of node speed (mean value of minimum and maximum speed), δ the density of nodes (number of nodes per Km^2) and finally, C represents an arbitrary constant, equal in all simulation executions enabling the increase or decrease of the stability time. A value of 1 was chosen in this simulation. The stability metric provides a measurement on the amount of nodes that were stable during execution, for a period greater than the ST value.

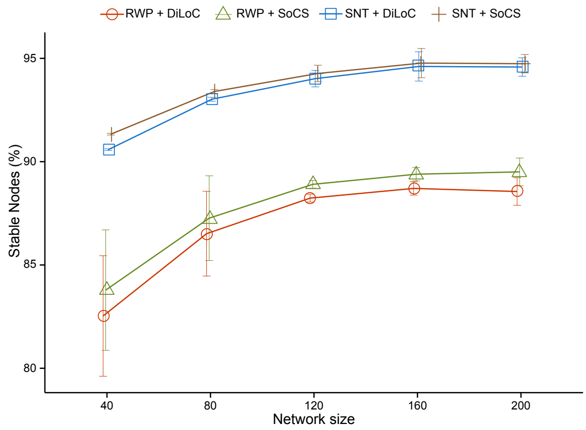

Fig. 3: Amount of Stable Nodes (in percentage)

Figure 3 shows the average amount of nodes that are stable (within a period greater than ST) in percentage. The stability of clustered nodes increases for larger networks, meaning that, in denser networks, there is a lower percentage of nodes that require re-affiliation operations. As expected, SNT provides more stability than RWP, since nodes remain in the same areas for longer. Also in this metric, the increase of stability with SoCS is not significant when compared to DiLoC. Particularly with the SNT model, DiLoC is capable of maintaining nodes stable, regardless of social link history.

c) Clustering Overhead: This metric represents the total amount of traffic sent, required to maintain clusters.

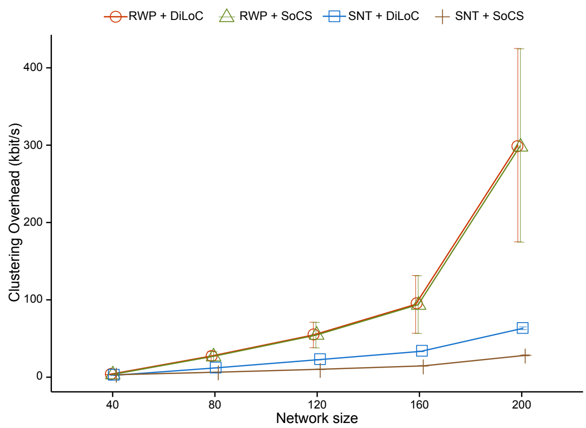

Fig. 4: Clustering Overhead per second (kbit/s)

Figure 4 shows the average clustering overhead per second. As expected, the RWP model requires a larger overhead. As nodes move randomly the number of re-affiliations is high, forcing the number of required maintenance messages to increase. The standard error also increases significantly in RWP due to the random pause time of nodes. With the SNT model, however, nodes move with coordination, often in the same area, thus requiring less clustering messages. The SNT model presents a slightly decrease of overhead with SoCS, when compared to DiLoC. The amount of clustered nodes in DiLoC is similar to SoCS, however the former uses more network resources as it presents a larger overhead. The link history kept by SoCS provides the social grouping of nodes, hence it is capable of creating more accurate clusters, resulting in overhead reduction.

2) Routing Performance: A stable cluster structure usually provides routing better performance. This section analyses the routing performance to establish the quality of the cluster topology.

a) Neighbourhood Changes or MPR Calculations: A neighbourhood change occurs when a 1-hop or 2-hop node neighbour is added or deleted.

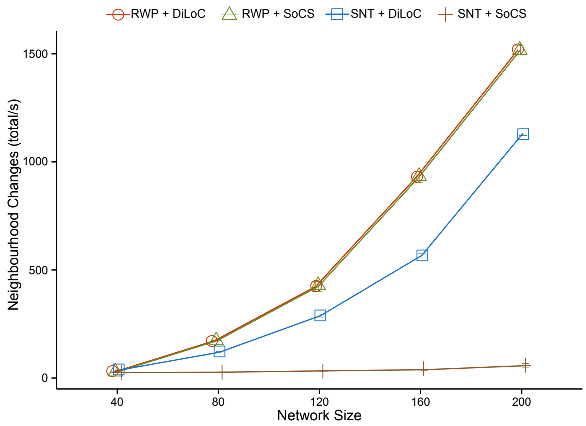

Fig. 5: Amount of Neighbourhood Changes (per second)

Each neighbourhood change leads to a recalculation of the multipoint relay (MPR) and route table recalculation. Thus, the number of neighbourhood changes is equal to the number of MPR calculations. Figure 5 depicts the average amount of neighbourhood changes per second. With the RWP model, the amount of neighbourhood changes significantly increases with network size, due to constant connection losses. With SNT, the DiLoC model has a larger amount of neighbourhood changes than SoCS. Since SoCS creates and maintains clusters according to social links, the probability of having a node affiliated with a ”foreign” cluster, not belonging to a specific social group, is very reduced. DiLoC, lacking this information, is more prone to more neighbourhood changes, specifically in this metric, as it detects 2-hop node changes.

b) Topology Changes: In C-OLSR, upon recalculation of MPRs, topology control (TC) messages are sent and forwarded. Each received TC message leads to a topology change. The topology changes metric can be used to access the scalability of C-OLSR. Figure 6 shows the average amount of topology changes per second, in the entire network. The RWP model shows significant higher topology changes when compared to the SNT model. Similarly to the neighbourhood changes metric, the gain related to the social link history in SoCS is very clear. To be noted that the topology changes of SoCS with SNT are very low, reaching a maximum average of 31.1 in the 200 node network size.

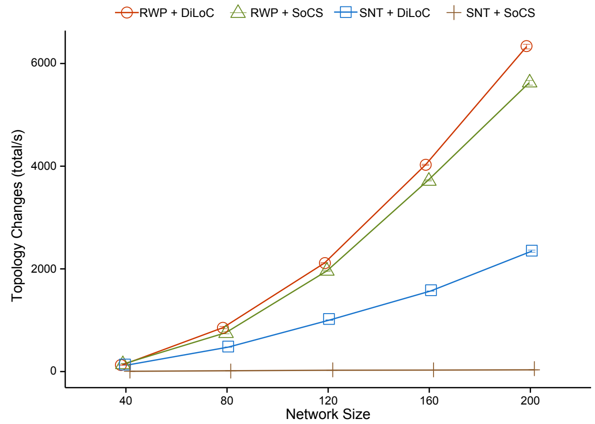

Fig. 6: Amount of Topology Changes (per second)

3) Traffic Performance: The analysis of traffic outlines the overall network performance. Here, it is discussed the amount of received traffic and the delay.

a) Received Traffic: Figure 7 shows the average percentage of successfully received traffic per second.

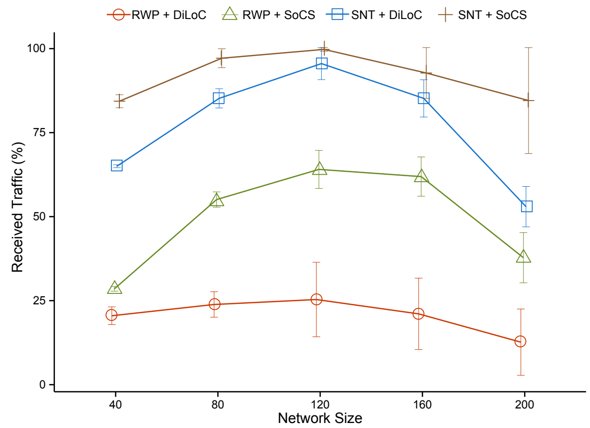

Fig. 7: Percentage of Received Traffic (per second)

For networks larger than 120 nodes, the increase of packet loss is often associated with radio interferences inherent to wireless ad hoc networks. In smaller networks, the received traffic is also lower due to poor connectivity related with a low node density. To be noted that in spite of most nodes in the network being clustered, it does not mean that all clusters are connected. A cluster may become isolated, not being able to perform inter-cluster communication. Thus, since some part of the generated traffic is destined to random nodes in the network, it may not reach the destination. The amount of received traffic is consistent with the obtained results in the routing performance, in both SoCS and DiLoC.

b) End-to-end Delay: The End-to-end delay measures the delay of generated packets, in seconds, in the entire network. Figure 8 shows the average end-to-end delay for the evaluated scenarios. The confidence intervals of delay are considerable, particularly in larger/denser networks, which is related with the radio interference inherent to wireless ad hoc networks. As expected the RWP model is prone to more delay, compared to the SNT model.

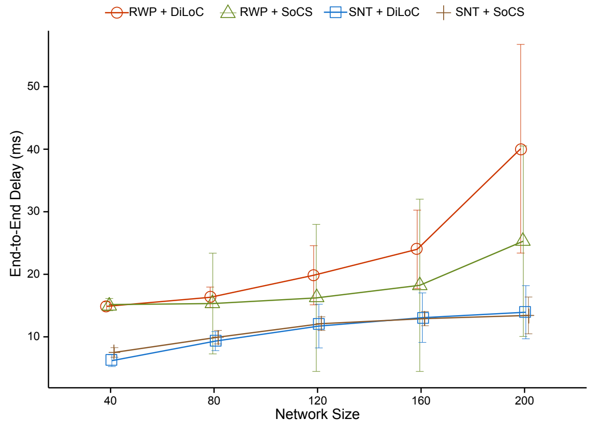

Fig. 8: End-to-End Delay (in milliseconds)

Regarding the SNT model, even though the amount of received traffic if higher with SoCS, the delay is not significantly lower than DiLoC, mainly because only the successfully delivered packets are considered for delay measurement.

V. Conclusion

This work proposes a Social-aware Clustering Scheme (SoCS) exploiting the link history between nodes. A list of connections with neighbours is preserved by each node, attempting to create reliable clusters, consistent with social groups. SoCS was evaluated using the C-OLSR routing protocol and compared with the DiLoC clustering scheme. To reflect the gain of social group mobility, the Random Waypoint (RWP) and the Social Theory Network (SNT) mobility models were used. Results demonstrate that SoCS provides a significant increase of network scalability, improving the routing performance and transmitted traffic. This proves that node connection history is a key feature to further improve the connection stability of wireless ad hoc networks. Social mobility particularly enhances the potential of SoCS, due to the organised dynamic of social grouping. Generally, it is shown that SoCS outperforms DiLoC in clustering, routing and traffic performance.

Acknowledgments

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References

[1] P. Hui, J. Crowcroft, and E. Yoneki, “BUBBLE Rap: Social-Based Forwarding in Delay-Tolerant Networks,” *IEEE Transactions on Mobile Computing*, vol. 10, no. 11, pp. 1576–1589, Nov. 2011. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5677535

[2] A. Mei, G. Morabito, P. Santi, and J. Stefa, “Social-aware stateless forwarding in pocket switched networks,” in *2011 Proceedings IEEE INFOCOM*. IEEE, Apr. 2011, pp. 251–255. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5935076

[3] Q. Li, S. Zhu, and G. Cao, “Routing in Socially Selfish Delay Tolerant Networks,” in *2010 Proceedings IEEE INFOCOM*. IEEE, Mar. 2010, pp. 1–9. [Online]. Available: http://ieeexplore.ieee.org/articleDetails.jsp?arnumber=5462138

[4] A. Lindgren, A. Doria, and O. Schelén, “Probabilistic routing in intermittently connected networks,” *SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 7, no. 3, pp. 19–20, Jul. 2003. [Online]. Available: http://doi.acm.org/10.1145/961268.961272

[5] V. Rolla and M. Curado, “Time message system for delay tolerant networks,” in *Future Internet Communications (BCFIC), 2012 2nd Baltic Congress on*, April 2012, pp. 239–245.

[6] L. C. Freeman, “Centrality in social networks conceptual clarification,” *Social Networks*, vol. 1, no. 3, pp. 215–239, Jan. 1978. [Online]. Available: http://www.sciencedirect.com/science/article/pii/0378873378900217

[7] F. D. Cunha, G. G. Maia, A. C. Viana, R. A. Mini, L. A. Villas, and A. A. Loureiro, “Socially inspired data dissemination for vehicular ad hoc networks,” in *Proceedings of the 17th ACM international conference on Modeling, analysis and simulation of wireless and mobile systems - MSWiM ’14*. New York, New York, USA: ACM Press, Sep. 2014, pp. 81–85. [Online]. Available: http://dl.acm.org/citation.cfm?id=2641798.2641834

[8] E. M. Daly and M. Haahr, “Social network analysis for routing in disconnected delay-tolerant MANETs,” in *Proceedings of the 8th ACM international symposium on Mobile ad hoc networking and computing - MobiHoc ’07*. New York, New York, USA: ACM Press, Sep. 2007, p. 32. [Online]. Available: http://dl.acm.org/citation.cfm?id=1288107.1288113

[9] Y. Zhu, B. Xu, X. Shi, and Y. Wang, “A Survey of Social-Based Routing in Delay Tolerant Networks: Positive and Negative Social Effects,” *IEEE Communications Surveys & Tutorials*, vol. 15, no. 1, pp. 387–401, Jan. 2013. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6177189

[10] J. Wu and Y. Wang, “Social feature-based multi-path routing in delay tolerant networks,” in *2012 Proceedings IEEE INFOCOM*. IEEE, Mar. 2012, pp. 1368–1376. [Online]. Available: http://ieeexplore.ieee.org/articleDetails.jsp?arnumber=6195500

[11] A. Mtibaa, M. May, C. Diot, and M. Ammar, “PeopleRank: Social Opportunistic Forwarding,” in *2010 Proceedings IEEE INFOCOM*. IEEE, Mar. 2010, pp. 1–5. [Online]. Available: http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=5462261

[12] T. Abdelkader, K. Naik, A. Nayak, and N. Goel, “A Socially-Based Routing Protocol for Delay Tolerant Networks,” in *2010 IEEE Global Telecommunications Conference GLOBECOM 2010*. IEEE, Dec. 2010, pp. 1–5. [Online]. Available: http://ieeexplore.ieee.org/articleDetails.jsp?arnumber=5683230

[13] Y. Zhang and J. Zhao, “Social network analysis on data diffusion in delay tolerant networks,” in *Proceedings of the tenth ACM international symposium on Mobile ad hoc networking and computing - MobiHoc ’09*. New York, New York, USA: ACM Press, May 2009, p. 345. [Online]. Available: http://dl.acm.org/citation.cfm?id=1530748.1530806

[14] L. Conceição and M. Curado, “Onto scalable wireless ad hoc networks: Adaptive and location-aware clustering,” *Ad Hoc Networks*, vol. 11, no. 8, pp. 2484–2499, 2013. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1570870513001352

[15] OPNET TECHNOLOGIES INC. (Bethesda USA), “Opnet: Making networks and applications perform.” http://www.opnet.com/, 1986.

[16] F. J. Ros and P. M. Ruiz, “Cluster-based olsr extensions to reduce control overhead in mobile ad hoc networks,” in *Proceedings of the 2007 International Conference on Wireless Communications and Mobile Computing*, ser. IWCMC ’07. New York, NY, USA: ACM, 2007, pp. 202–207. [Online]. Available: http://doi.acm.org/10.1145/1280940.1280985

[17] M. Musolesi and C. Mascolo, “Designing mobility models based on social network theory,” *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 11, no. 3, p. 59, Jul. 2007. [Online]. Available: http://dl.acm.org/citation.cfm?id=1317425.1317433