EBC: A Topology Control Algorithm for Achieving High QoS in Sensor Networks

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Abstract. A novel approach for achieving high *Quality of Service* (QoS) in sensor networks via *topology control* is introduced and experimentally assessed in this paper. Our approach falls in the broader discipline of *graph structural mining*, and exploits a leading concept initially studied in the context of *Social Network Analysis* (SNA), namely *betweenness*. Particularly, in our research betweenness is applied in terms of a *graph structural mining measure* embedded in the core layer of our proposed topology control algorithm, called *Edge Betweenness Centrality* (EBC). EBC allows us to evaluate relationships between entities of the network (e.g., nodes, edges), and hence identify different roles among them (e.g., brokers, outliers). In turn, deriving knowledge is further exploited to define *raking operators* that look at structural properties of the graph modeling the target sensor network. Based on these amenities, our topology control algorithm is able of providing an "insight" of the graph structure of the network on top which control over information flow, message delivery, latency and energy dissipation among nodes can be easily deployed.

Key words: Data Mining, Sensor Networks, Topology Control, Graph Structural Mining

1 Introduction

Recent advances in low-power and short-range-radio technology arisen during last few years have enabled a rapid development of *Wireless Sensor Networks* (WSN). The range of applicability of WSN is very wide, and spans from environmental sensor networks monitoring (environmental) parameters, such as temperature and humidity, to industrial control robotics, from disaster prevention systems to emergency management systems, and so forth. Sensors are tiny,

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usually battery-operated devices with radio and computing capabilities, which are used to cooperatively monitor physical or environmental conditions.

As regards research issues of sensor networks, several efforts have been done by both the academic and industrial research community, mainly in the context of *routing algorithms* [11, 13], *network coverage aspects* [27, 15], *storage issues* [18, 25] and *topology control* [24, 16]. The common denominator of all these efforts is represented by the goal of *maximizing energy conservation* across the network, in order to gain efficacy and efficiency, as maximizing energy conservation corresponds to *maximizing network lifetime* For instance, as regards specific data management issues over sensor networks [4], maximizing energy conservation means that *multi-step* maintenance and query algorithms can be executed over the target sensor network, thus involving in more effective data management capabilities rather than the case of *single-step* algorithms. Another motivation of the need for energy conservation in sensor networks relies on inherent technological properties of sensors. In fact, sensors are unlikely to be recharged, especially since they may be deployed in unreachable terrains, or, in some cases, they may be disposed after the monitoring application running over the target network ends its execution.

In order to reduce energy consumption, *topology control algorithms* have been proposed in literature [23, 29, 12, 28, 16, 22, 30, 19, 24, 10, 17]. The final goal of these algorithms consists in reasoning-over and managing the topology of the graph modeling the target sensor network in order to reduce energy consumption as much as possible hence increase network lifetime accordingly. A different line of research appeared recently proposes driving sensor network topology control in terms of *Quality of Service* (QoS) requirements [17] over the target sensor network itself. Several QoS-based requirements have been designed and developed in this context, depending on the particular application scenario ranging from real-time video and content provisioning to time-critical control systems, and so forth (see [17] for a complete survey of typical case studies). Given a set of nodes performing a specific task which is critical for the target sensor network application (e.g., sink nodes in environmental sensor networks), the basic idea behind topology control algorithms is to select from the target network appropriate *logical neighbors* of the former nodes, namely a subset of *physical neighbors* of the former nodes that can be used to perform application-specific procedures (e.g., message transmission) without the need of involving the rest of physical neighbors during the execution of these procedures. QoS-based topology control algorithms select the suitable set of logical neighbors such that input QoS requirements can be satisfied.

Inspired by motivations above, in this paper we investigate the problem of QoS-based topology control over *homogenous WSN*. Given (*i*) a set of wireless nodes in a plane such that nodes have the same transmitting power and bandwidth capacity, and (*ii*) QoS requirements between node pairs, our problem consists in finding a network topology that can simultaneously meet the input QoS requirements and minimize the maximal power utilization ratio of nodes. In particular, in our research QoS requirements are modeled in terms of simple-yet-effective *node connectivity*, so that message transmission can be ensured (while node connectivity can be preserved in order to ensure correct message delivery), and network lifetime can be increased as much as possible accordingly. In this scenario, *avoidance of hotspots* also needs to be carefully considered. Therefore, *adaptive tasks* that depend on the current logical neighbor seem to play the role of most promising strategy to be investigated in order to avoid fast battery depletion.

Looking at deeper details, in our research we propose an innovative *weighted, bidirectional topology control algorithm*, called *Edge Betweenness Centrality* (EBC), and experimentally evaluate such algorithm against a state-of-the-art topology control algorithm, namely *Gabriel Graph* (GG) [8]. Fundamentals of our approach can be found in the conceptual basis drawn by several *centrality measures* that have been proposed in order to model and evaluate the *importance* of a node in a network [9, 3]. These measures have been initially applied in the context of *Social Network Analysis* (SNA), and later to other areas as well, such as *biological networks* [31].

Freeman [6, 7] defines the *betweenness* of a node as a possible centrality measure for detecting the importance of that node within the target network, thus achieving the fundamentalm concept of *betweenness centrality*. This concept founds on the property stating that vertices that occur on many shortest paths between other vertices have *higher* betweenness than those with lower occurrences. *Closeness centrality* [7] pinpoints vertices that tend to have short geodesic distances from other vertices with in the network. In network analysis, closeness is preferred over shortest-path length, as closeness gives higher values to more central vertices [7]. Finally, *Eigenvector centrality* [1] assigns relative scores to all nodes in the network based on the principle that connections to high-scoring nodes provide to the global score of the actual node a higher contribution rather than the one provided by connections to low-scoring nodes. For instance, Google's *PageRank* [21] is a variant of the Eigenvector centrality measure. Our research focuses on a meaningful variation of the betweenness centrality concept, namely *edge betweenness centrality* [9, 20], and its application to the leading context of sensor networks.

Summarizing, the contributions of this paper are the following:

- an innovative weighted, bidirectional topology control algorithm, EBC, and its application to the leading context of sensor networks;
- a comprehensive experimental evaluation of algorithm EBC, and its comparison with a state-of-the-art topology control algorithm, GG, on top of the well-known simulation environment *JSim* [26];
- critical analysis and discussion on performance of the two comparison topology-control algorithms, EBC and GG.

The rest of the paper is organized as follows. In Section 2 we discuss related work on topology control algorithms over networks. Section 3 describes in detail algorithm EBC. Section 4 focuses on the comparison algorithm GG. Section 5 is devoted to the experimental evaluation and analysis of the two comparison topology control algorithms, EBC and GG. Finally, Section 6 contains conclusions and future work of our research.

2 Related Work

There exists considerable related work addressing topology control issues over networks, even focalizing on QoS-based topology control. As regards studies on topology management for energy conservation in networks, it has been demonstrated that both powering off redundant nodes and lowering radio power while maintaining node connections can contribute to efficient power saving. In light of this assumption, Shen et al. [24] introduce algorithm *Local Shortest Path* (LSP). In the LSP approach, each node makes use of link weights in order to compute the shortest paths between itself and neighboring nodes. Then, all second nodes on these shortest paths are selected as logical neighbors. The final step of algorithm LSP involves in adjusting the power transmission of so-selected logical nodes to save energy.

Li et al. [19] instead propose algorithm *Local Minimum Spanning Tree* (LMST), which computes a "power-reduced" network topology by constructing a minimum spanning tree over the network in a fully-distributed manner. The aim of this approach relies in the evidence that the power-reduced network is less energy-consuming than the original network.

EasiTPQ [17] is another QoS-based topology control algorithm. EasiTPQ founds on the assumption that each node in the network has different functionalities during data transmission, e.g. some nodes bear more data relay tasks whereas some other nodes only transmit data generated by themselves. In order to achieve the desired QoS, EasiTPQ schedules as active nodes that are more involved in relaying data tasks rather than generating data flows.

Wattenhofer et al. [29] propose a simple-yet-effective distributed algorithm according to which each node makes *local decisions* about its transmission power, such that these local decisions then collectively guarantee *global connectivity* of the network. Specifically, based on directional information, a node grows it transmission power until it finds a neighbor node in every possible direction. The resulting network topology increases network lifetime by reducing transmission power, and, in turn, even traffic interference, thanks to the deriving availability of low-degree nodes. Huang et al. [12] further extend [29] to the case of using *directional antennas.*

Ramanathan and Rosales-Hain [23] describe a *centralized spanning tree* algorithm for building connected and bi-connected networks with the goal of minimizing the maximum transmission power for each node. Two optimal, centralized algorithms, namely CONNECT and BICONN-AUGMENT, are proposed for the case of static networks. Both are greedy algorithms, and resemble Kruskal's minimum cost spanning tree algorithm [14]. For the case of hoc wireless networks, two distributed heuristics hare proposed, namely LINT and LILT. However, these heuristics do not guarantee network connectivity.

Finally, Jia at al. [30] focus the attention on the problem of determining a network topology able to meet input QoS requirements in terms of end-to-end delay and bandwidth. The proposed scheme adopts an optimization criterion whose goal is to minimize the maximum per-node power consumption. In [30], authors demonstrate that, when network traffic is “splittable”, a sub-optimal solution can be achieved by means of linear programming techniques.

3 Edge Betweenness Centrality: A Novel Topology Control Algorithm for Sensor Networks

During past years, *vertex betweenness* has been studied in the vest of a measure of the centrality and influence of nodes in networks [6, 7]. Given a node v_i, vertex betweenness is defined as the number of shortest paths between pairs of nodes that run through v_i. Vertex betweenness is a measure of the influence of a node over the information flow among nodes of the network, especially in scenarios such that information flowing over the target network primarily follows shortest available paths.

In order to compute betweenness centrality, Brandes [2] proposes an efficient *backwards algorithm* which starts from leaf nodes of a tree of shortest paths and progressively accumulates the leaf-nodes’ betweenness values moving bask towards the root node of the tree.

Girvan-Newman algorithm [9] extends the definition of betweenness centrality from network vertices to network edges, via introducing the concept of *Edge Betweenness* (EB). Let $G = \langle V, E \rangle$ be a connected undirected graph, and v_i and v_j two nodes in G, respectively. Let $\sigma_{v_i v_j}$ denote the number of shortest paths between nodes v_i and v_j. Let $\sigma_{v_i v_j}(e)$ denote the number of shortest paths between v_i and v_j which go through $e \in E$. Betweenness centrality of an edge $e \in V$, denoted by $EB(e)$, is defined as follows:

$$EB(e) = \sum_{v_i \epsilon V} \sum_{v_j \epsilon V} \frac{\sigma_{v_i v_j}(e)}{\sigma_{v_i v_j}} \qquad (1)$$

In its original implementation [20], which focuses on unweighted, undirected networks, EB analysis makes use of algorithm *Breadth-First Search* (BFS). Girvan-Newman algorithm [9] works in the opposite way. Instead of trying to construct a measure that determines edges that are the “most central” for network communities, it focuses on edges that are the “least central” for network communities, i.e. edges that are “most between” for network communities. Communities are detected by progressively removing edges from the original graph, rather than by adding the strongest edges to an initially empty network. In our research, we do not use the centrality measure to find communities but instead to select the most important edges, energy-wise, to propagate messages.

Specifically, steps that are used to compute the edge betweenness centrality index are the following:

1. compute shortest paths through the network by means of Dijkstra's algorithm [5];
2. for each edge, compute the edge betweenness centrality index like in [20], but instead of un-weighted edges use the *average energy* of the two connecting nodes as edge weight.

Based on the edge betweenness centrality index, our algorithm EBC selects logical neighbors of actual node based on the following rules:

- for each node, logical neighbors must cover the 2-hop node neighborhood;
- 1-hop neighbors with the highest-scoring betweenness centrality index are selected.

Moreover, in order to avoid hotspots, our algorithm recalculates the edge betweenness centrality index based on the corresponding energy levels of each node, therefore selecting different edges to be part of the logical neighborhood of each node.

4 Gabriel Graph: A State-Of-The-Art Topology Control Method for Networks

Gabriel Graph has been introduced by Gabriel and Sokal in [8]. Formally, given a graph $G = \langle V, E \rangle$ and two vertices v_1 and v_2 in V, we say that v_1 and v_2 are *adjacent* if the closed disc of diameter v_1v_2 does not contain other vertices of V. In the context of sensor networks, we extend the basic adjacency concept above and we say that a sensor node s_i is *connected* with a sensor node s_j, who lies within the s_i's transmission range, if there not exist another node s_k which is contained by the closed disc of diameter s_is_j. This simple-yet-effective method is used by algorithm GG to find logical neighbors of a given sensor node.

In more detail, in our JSim-based experimental framework, logical neighbors of a given sensor node are found by algorithm GG according to the following steps:

1. each sensor node broadcasts its location – at the end, every node in the sensor network knows its neighbors and their locations;
2. each sensor node s_i determines its logical neighbor set L_i by computing the closed discs of diameters equal to the distance between the location of s_i and each other physical node belonging to the s_i's physical neighborhood set P_i – for each physical neighbor s_j in P_i, if the disc of diameter s_is_j does not contain other physical neighbors of P_i then s_j becomes a logical neighbor of s_i.

5 Experimental Evaluation and Analysis

In this Section, we present the experimental evaluation of algorithm EBC in comparison with algorithm GG, which can be reasonably considered a state-of-the-art result in topology control over networks.

5.1 Simulation Model

In our experimental framework, we have developed a simulation model based on JSim, a well-known Java-based simulation environment for numerical analysis [26]. In particular, in our simulation environment, the AODV routing protocol is deployed within the reference WSN [**REF**]. Also, we use IEEE 802.11 as the MAC protocol and the free space model as the radio propagation model. Wireless bandwidth is assumed to be 2 Mbps.

We performed a large number of experiments on top of various sensor network topologies, and by ranging several experimental parameters, but for the interest of space, here we present a subset of our experimental results. Table 1 summarizes the simulation parameters.

Parameter	**Values**
sensor node number	500, 750, 1000
terrain size	400 x 400
radio range	14m, 17m
initial energy charge	10 Joules
transmission energy	0.001 Joules
wireless bandwidth	2 Mbps

Table 1. Simulation parameters.

5.2 Experimental Results

As stated in previous sections, topology control algorithms over sensor networks try to minimize the energy consumption of nodes by transmitting data to a subset of a node's physical neighbors. Therefore, given the actual node, the first step deals with the issue of finding node's physical neighbors. Then, topology control algorithms are applied in order to select the subset of logical neighbors that can propagate messages throughout the network without any data loss, neither involving all the effective physical neighbors.

Our experimental analysis focuses on the comparison between algorithms EBC and GG in terms of logical neighbors found and energy consumption that is needed to propagate messages through logical neighbors. For each algorithm, we also analyze the impact of a change in network density on algorithm's performance.

Figure 1 shows the overall number of physical neighbors that exist in the network for 500, 750 and 1000 nodes, respectively. The increase in the number of physical neighbors is due to the increase in the sensor transmission radius from 14 to 17 meters. This means that each sensor node can communicate with nodes that exist in its wider vicinity. For a radius of 14m, the number of physical neighbors are 1298, 2640 and 4488, respectively. For a radius of 17m, we instead have: 1958, 3984, and 6797.

Figure 2 illustrates the average number of physical neighbors of each node in the network, for different size of the sensor network. In the first case, i.e. a network with 500 nodes, the average number of physical nodes per-sensor-node is 2.4 for a radius of 14m and 3.7 for a radius of 17m. The respective numbers for a network with 750 nodes are: 3.5 (14m radius) and 5.3 (17m radius). Finally, for a network with 1000 nodes, retrieved numbers are: 4.4 (14m radius) and 6.7 (17m radius). Notice that in all the cases retrieved numbers are the same for both algorithms EBC and GG since they are not applied to the initial step that finds the physical neighbors of each node.

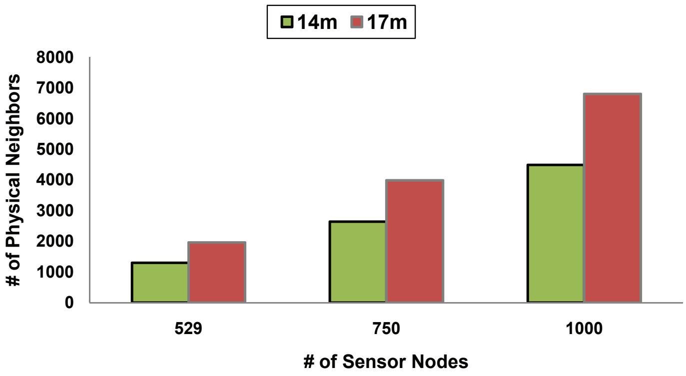

Fig. 1. Number of physical neighbors.

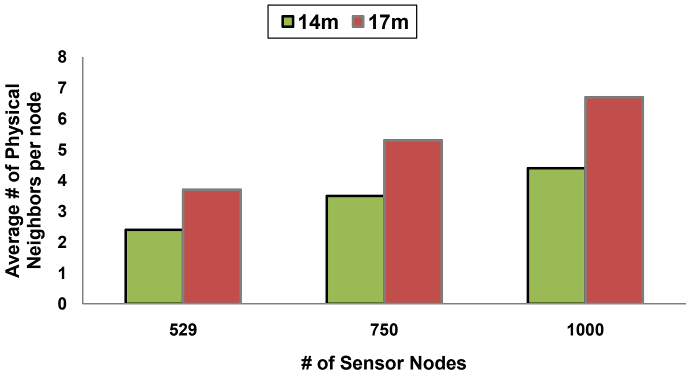

Fig. 2. Average number of physical neighbors per-sensor-node.

Moving the attention on the proper experimental comparison of the two investigated topology-control algorithms (i.e., EBC and GG), Figure 3 shows the overall number of logical neighbors found after each algorithm has been applied to each network setting with different size (500, 750 and 1000 nodes) when the radius is set to 14m. As shown in the Figure, starting from an initial number of physical neighbors found equal to 1086 (500 nodes), algorithm GG finds 1298 logical neighbors (750 nodes) while algorithm EBC finds a smaller subset of 752 logical neighbors (750 nodes). This difference increases as the number of sensor nodes in the network increases. For 1000 nodes, algorithm GG founds 3742 logical neighbors, whereas algorithm EBC 1513 logical neighbors only.

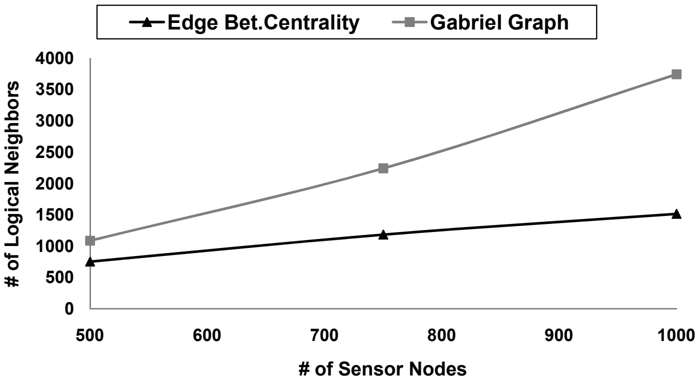

Fig. 3. Number of logical neighbors found (radius = 14m).

Figure 4 shows instead the performance of algorithms EBC and GG in terms of average logical neighbors found per-sensor-node, still with a radius equals to 14m. As clearly follows from Figure 4, algorithm EBC delivers *about the same* average number of logical neighbors per-sensor-node, i.e. about 1.5, irrespectively of the size of the sensor network. On the other hand, algorithm GG does not perform as well, since the average number of logical neighbors per-sensor-node ranges from 2 (500 nodes) up to 3.7 (1000 nodes).

Figure 5 shows the results for the same experiment when the radius is set to 17m. As shown in the Figure, when radius increases the difference between the two algorithms' performance is even more noticeable. In fact, the number of logical neighbors found by algorithm GG ranges from 1639 (500 nodes) to 5648 (1000 nodes). The respective numbers for algorithm EBC range instead from 1014 (500 nodes) to 2052 (1000 nodes). Therefore, it clearly follows that EBC outperforms GG even under this experimental analysis perspective.

Figure 6 confirms to us the superiority of algorithm EBC over algorithm GG in terms of the average number of logical neighbors found per-sensor-node, still with a radius equals to 17m. It should be notice again that algorithm EBC remains practically insensitive to the increase in the number of sensor nodes and provides an average number of 2 logical neighbors per-sensor-node throughout the simulation. On the other hand, algorithm GG performs poorly with an av-

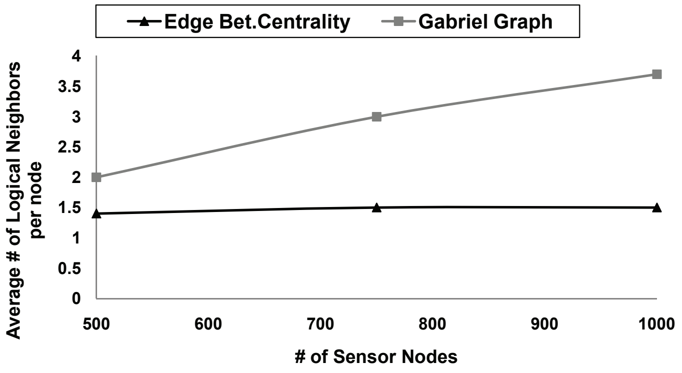

Fig. 4. Average number of logical neighbors per-sensor-node (radius = 14m).

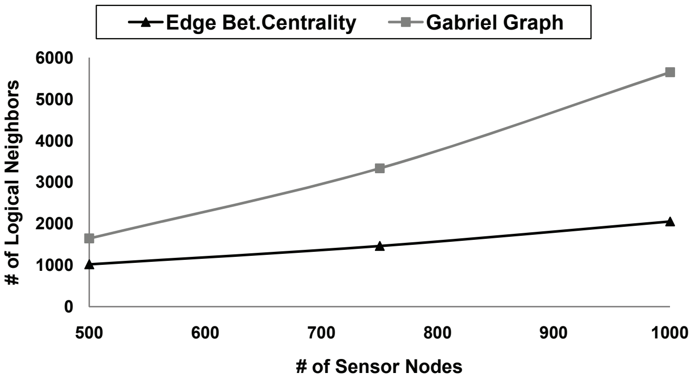

Fig. 5. Number of logical neighbors found (radius = 17m).

erage number of logical neighbors found per-sensor-node ranging from 3.1 (500 nodes) to 5.6 (1000 nodes).

Looking at energy consumption minimization, the main goal of topology control algorithms, Figure 7 shows the energy consumption per-node needed to propagate a message to logical neighbors, when the radius is set to 14m. Again, algorithm EBC requires an almost unchanged amount of energy to this goal, i.e. about 0.0015 Joules, whereas algorithm GG requires an amount of energy ranging from 0.0020 (500 nodes) to 0.0037 (1000 nodes) Joules to perform the same operation.

Finally, Figure 8 shows the results for the same experiment when the radius is set to 17m. Even in this experimental analysis, algorithm EBC outperforms algorithm GG with a transmission energy consumption per-node equals to of 0.002 Joules. Indeed, algorithm GG significantly increases the energy requirement by ranging from 0.0031 (500 nodes) to 0.0056 (1000 nodes) Joules.

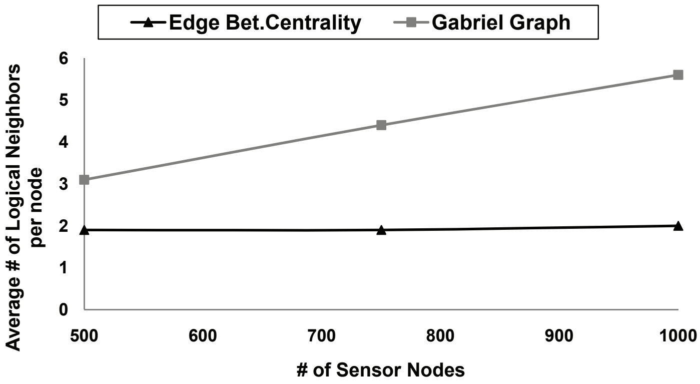

Fig. 6. Average number of logical neighbors per-sensor-node (radius = 17m).

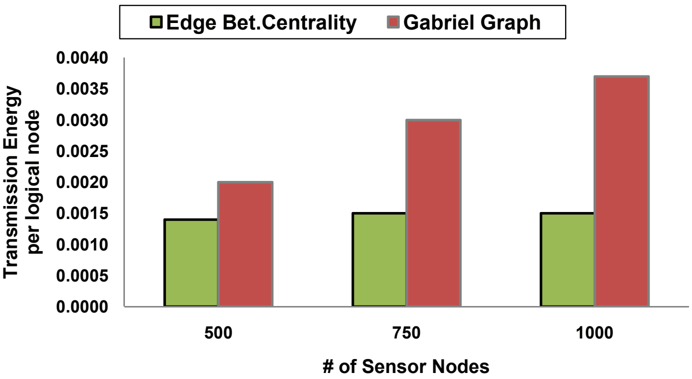

Fig. 7. Transmission energy consumption per-node (radius = 14m).

6 Conclusions and Future Work

Betweenness is a centrality measure for networks that has been initially studied in the context of SNA. This measure states that vertices that occur on many shortest paths between other vertices have higher betweenness than those with lower occurrences. Therefore, nodes with high betweenness are selected as nodes able to control the overall information flow within the network. Topology control algorithms aim at providing high QoS by maximizing network lifetime and ensuring message delivery. Inspired by these motivations, in this paper we have proposed a novel topology control algorithm for sensor networks, EBC, which exploits the edge betweenness centrality concept to ensure high QoS throughout the network. Also, we performed a comprehensive campaign of experiments where we compared the performance of algorithm EBC with the performance of algorithm GG, a state-of-the-art result in topology control over networks, under several perspectives of analysis. Experimental results have clearly demonstrated

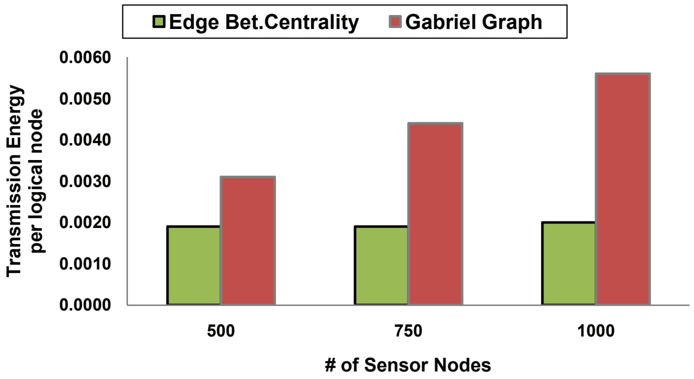

Fig. 8. Transmission energy consumption per-node (radius = 17m).

the superiority of algorithm EBC over algorithm GG, in terms of both logical neighbors found and amount of transmission energy consumption.

As future work, we plan to devise alternative centrality measures for networks, looking at the wide literature available on the topic, and experimentally compare these novel measures to edge betweenness centrality. Apart from number of logical neighbors found, transmission energy consumption and scalability, which have been investigated in this paper, in the future experimental analysis we will focus on other interesting experimental parameters that need more research efforts, such as message latency and message delivery.

References

1. P. Bonacich. Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology*, 2(1):113–120, 1972.
2. U. Brandes. A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology*, 25:163–177, 2001.
3. U. Brandes. On variants of shortest-path betweenness centrality and their generic computation. *Social Networks*, 30(2):136–145, May 2008.
4. A. Cuzzocrea. Intelligent techniques for warehousing and mining sensor network data. IGI Global, 2009.
5. E. W. Dijkstra. A note on two problems in connexion with graphs. *Numerische Mathematik*, 1(1):269–271, December 1959.
6. L. C. Freeman. A set of measures of centrality based on betweenness. *Sociometry*, 40(1):35–41, March 1977.
7. L. C. Freeman. Centrality in social networks: Conceptual clarification. *Social Networks*, 1(3):215–239, 1979.
8. R. K. Gabriel and R. R. Sokal. A new statistical approach to geographic variation analysis. *Systematic Zoology*, 18(3):259–278, September 1969.
9. M. Girvan and M. E. Newman. Community structure in social and biological networks. *Proc Natl Acad Sci U S A*, 99(12):7821–7826, June 2002.

10. G. Hackmann, O. Chipara, and C. Lu. Robust topology control for indoor wireless sensor networks. In *SenSys '08: Proceedings of the 6th ACM conference on Embedded network sensor systems*, pages 57–70, New York, NY, USA, 2008. ACM.
11. W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan. Energy-efficient communication protocol for wireless microsensor networks. In *HICSS '00: Proceedings of the 33rd Hawaii International Conference on System Sciences-Volume 8*, page 8020, Washington, DC, USA, 2000. IEEE Computer Society.
12. Z. Huang, C. chung Shen, C. Srisathapornphat, and C. Jaikaeo. Topology control for ad hoc networks with directional antennas. In *Proc. IEEE Int. Conference on Computer Communications and Networks*, pages 16–21, 2002.
13. C. Intanagonwiwat, R. Govindan, D. Estrin, J. Heidemann, and F. Silva. Directed diffusion for wireless sensor networking. *IEEE/ACM Trans. Netw.*, 11(1):2–16, 2003.
14. J. B. Kruskal. On the shortest spanning subtree of a graph and the traveling salesman problem. *Proceedings of the American Mathematical Society*, 7(1):48–50, February 1956.
15. B. Liu, P. Brass, O. Dousse, P. Nain, and D. Towsley. Mobility improves coverage of sensor networks. In *MobiHoc '05: Proceedings of the 6th ACM international symposium on Mobile ad hoc networking and computing*, pages 300–308, New York, NY, USA, 2005. ACM.
16. J. Liu and B. Li. Distributed topology control in wireless sensor networks with asymmetric links, 2003.
17. W. Liu, L. Cui, X. Niu, and W. Liu. Easitpq: Qos-based topology control in wireless sensor network. *J. Signal Process. Syst.*, 51(2):173–181, 2008.
18. G. Mathur, P. Desnoyers, D. Ganesan, and P. Shenoy. Ultra-low power data storage for sensor networks. In *IPSN '06: Proceedings of the 5th international conference on Information processing in sensor networks*, pages 374–381, New York, NY, USA, 2006. ACM.
19. J. C. H. N. Li and L.Sha. Design and analysis of an mst-based topology control algorithm. *IEEE Transactions on Wireless Communications*, 4(3):1195–1206, 2005.
20. M. E. J. Newman and M. Girvan. Finding and evaluating community structure in networks, August 2003.
21. L. Page, S. Brin, R. Motwani, and T. Winograd. The pagerank citation ranking: Bringing order to the web. Technical report, Stanford Digital Library Technologies Project, 1998.
22. J. Pan, Y. T. Hou, L. Cai, Y. Shi, and S. X. Shen. Topology control for wireless sensor networks. In *MobiCom '03: Proceedings of the 9th annual international conference on Mobile computing and networking*, pages 286–299, New York, NY, USA, 2003. ACM.
23. R. Ramanathan and R. Rosales-hain. Topology control of multihop wireless networks using transmit power adjustment. pages 404–413, 2000.
24. Y. Shen, Y. Cai, and X. Xu. A shortest-path-based topology control algorithm in wireless multihop networks. *SIGCOMM Comput. Commun. Rev.*, 37(5):29–38, 2007.
25. B. Sheng, Q. Li, and W. Mao. Data storage placement in sensor networks. In *MobiHoc '06: Proceedings of the 7th ACM international symposium on Mobile ad hoc networking and computing*, pages 344–355, New York, NY, USA, 2006. ACM.
26. A. Sobeih, J. C. Hou, L.-C. Kung, N. Li, H. Zhang, W.-P. Chen, H.-Y. Tyan, and H. Lim. J-Sim: A simulation and emulation environment for wireless sensor networks. *IEEE Wireless Communications magazine*, 13(4):104–119, 2006.

27. M. T. Thai, F. Wang, D. H. Du, and X. Jia. Coverage problems in wireless sensor networks designs and analysis. *Int. J. Sen. Netw.*, 3(3):191–200, 2008.
28. Y.-C. Tseng, Y. chee Tseng, Y.-N. Chang, and B. hour Tzeng. Energy-efficient topology control for wireless ad hoc sensor networks, 2002.
29. R. Wattenhofer, L. Li, P. Bahl, and Y. min Wang. Distributed topology control for power efficient operation in multihop wireless ad hoc networks. pages 1388–1397, 2001.
30. D. L. X. Jia and D.-Z. Du. Qos topology control in ad hoc wireless networks. *IEEE Infocom04*, 2004.
31. J. Yoon, A. Blumer, and K. Lee. An algorithm for modularity analysis of directed and weighted biological networks based on edge-betweenness centrality. *Bioinformatics*, 22(24):3106–3108, 2006.