Stenier-based Energy Efficient Multicast Routing for Wireless Sensor Networks

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Keywords: Wireless Sensor Networks, Multicast Routing, Steiner Tree, Sink Mobility.

Abstract: Wireless Sensor Networks (WSN) consist of a suite of sensor nodes capable of autonomous data collection and wireless communication deployed over an area of interest. They constitute a popular means of automated data collection with the sensors working together to form a wireless communication network and funnel collected data to nodes capable of transmitting data to a single or multiple collection points for interpretation. The routing instance from a single source to multiple destinations is formalized as a Multicast Routing Problem (MRP). Recent applications WSNs have focused on exploiting sink mobility technology (with multiple destinations) to extend network lifetime. As the nodes are often reliant on limited power sources, algorithms for efficient routing of data in these networks have been a source of increased research interest. However, few current algorithms consider the remaining energy levels of an individual network node during a single routing instance, creating a situation where the network may become disconnected faster than necessary. In this paper, we present an algorithm for multicast routing in wireless sensor networks implementing energy-reweighting techniques to simultaneously optimize the energy-cost of a routing and the network lifetime.

1 INTRODUCTION

Wireless sensor networks are a popular method of automated data collection consisting of a series of sensors distributed over a physical space. The sensor nodes, which are generally equipped with data processing and communication capabilities, autonomously collect data about their environment and cooperate to funnel the data to a single or multiple collection point nodes. Potential applications of such networks can be found in the military and medical fields, in environmental monitoring, in the monitoring of vehicles and machines, and anywhere else where spatially distributed collection of data about the environment is necessary. The individual sensor nodes employed by such networks are often battery powered, and therefore with a limited lifetime, making the conservation of energy within an individual node as well as over the entire network a relevant issue for the purpose of data transmission (Ren et al., 2011).

Routing in wireless sensor networks is very challenging and different to traditional networks due to characteristics specific to sensor nodes. These are tightly constrained in terms of transmission power, on-board energy, processing capacity and storage. In general, a routing protocol for WSNs needs to deal with scalability, energy efficiency, robustness, latency, low computation and memory usage. Many routing mechanisms have been proposed in WSNs to overcome these challenges; however finding and maintaining routes in such a way as to minimize energy expenditure is the most important issue in almost all applications of WSNs. To minimize energy consumption, routing techniques proposed in the literature employ well-known methodologies specific to WSNs, such as data aggregation, clustering, different node role assignment, and data-centric methods (Khan et al., 2012) (Kumar and Raj., 2012). All these routing methods are divided into flat-based routing, hierarchical-based routing, and location-based routing depending on the network structure. In flat-based routing which is considered in this work, all nodes are assigned equal roles and functionality (Yang and Mohammed, 2010).

The majority of energy aware wireless sensor network routing protocols seek to minimize the total energy consumption in each routing session to increase the network lifetime. Most energy-efficient protocols use algorithms for computing minimum cost paths with the link metric representing the energy required

Katerinchuk V. and Ozturk C..
Stenier-based Energy Efficient Multicast Routing for Wireless Sensor Networks.
DOI: 10.5220/0005217003460352
In *Proceedings of the International Conference on Operations Research and Enterprise Systems* (ICORES-2015), pages 346-352
ISBN: 978-989-758-075-8

to transmit a packet over the link (Chun and Tang, 2006). Research has primarily focused on wireless sensor network representations with a single or a small number of static sink nodes. Recently, however, there has been increased interest in exploiting mobile sink technologies for WSNs due to the positive impact these can have on energy conservation of individual nodes and network lifetime (Friedmann and Boukhatem, 2007).

Our focus is on energy efficient multicast routing in wireless sensor networks with multiple destinations, representing mobile sink nodes. In multicast communication data is delivered to a number of nodes which are geographically dispersed in a deployment field and there is no restriction on the boundary for data transmission. The most popular multicast routing approaches are based on trees which are constructed from source nodes to multicast group members. The computation of a minimum cost multicast tree in wireless networks is an NP-Hard problem (Čagalj et al., 2002). Researchers have proposed numerous heuristic algorithms for multicast communication in wireless sensors networks. However, while these algorithms are efficient for some scenarios they may perform poorly in others (Won and Stoleru, 2011).

Proposed energy-efficient algorithms have focused primarily on the networks' application natures and on optimizing limited capabilities of the sensor nodes. Most of these algorithms attempt to minimize the cost of the routing paths aiming to achieve minimum overall energy expenditure in all transmissions (Feng and Heinzelman, 2009), but in general this aim does not always significantly help to improve the network lifetime when there is insufficient focus on constructing routing trees balancing the minimum total energy and energy distribution.

(Simek et al., 2008) examine the inherent inefficiency of existing wireless protocols when adapted to wireless sensor networks. They proceed to identify two broad groups of Multicast Routing (MCR) protocols; blind flooding and geographical, and introduce a number of algorithms for these protocols. The papers A Node-Weighted Steiner Tree-Based Heuristic (Li et al., 2004) and Energy-Efficient Broadcast and Multicast Trees for Reliable Wireless Communication (Banerjee et al., 2003) present a Steiner tree based approach to MCR in wireless networks transposed directly from algorithms for wired networks. All these approaches, suffer from the same flaw of failing to consider the ongoing effect of energy depletion in the network over a number of Multicast requests, even where an individual request may be optimal. Indeed, algorithms focusing on finding a minimum cost MCR for this problem will often route over a subset of favourite edges when run over a number of consecutive Multicast requests. This results in a drastic decrease of the network's lifetime as depleted and overused nodes go offline.

(Cheng et al., 2006) proposed the MWIA algorithm which re-weighted the nodes in each iteration to reflect the energy depleted and guiding the broadcast tree around commonly used edges. The minimum spanning tree, choosen as a solution with the minimum cost but a larger number of used edges, compares unfavourably to a Steiner tree in terms of energy conservation. Furthermore, the adaptation of the broadcast tree algorithm toward MCR presented is deterministic, generating an issue of computational complexity for large networks.

In this work, we present a heuristic approach for a Steiner tree based algorithm considering the combined objectives of energy minimisation and extending the network lifetime by reliable multicast trees. We aim to propose a hybrid heuristic algorithm for routing a number of multicast requests through a wireless sensor network. The algorithm implements a new, weighted energy function with edges reweighted after the routing of each scheduled multicast request based on the depletion of the energy capacity of utilised nodes. The aim of the re-weighting is to guide the search around commonly used nodes where possible.

2 METHODOLOGY

The WSN is represented as a graph G=(V, E) where $V = m_1, m_2, .., m_i$ is a set of nodes and $E = l_1, l_2..l_j$ is a set of edges, where each edge l connects two nodes in V. We define an energy cost function Co over E such that each edge l_m in E has an associated cost of transmitting data over that edge $Co(l_m)$. An instance of a multicast-routing problem is defined as:

$$m = [s \rightarrow D] \quad (1)$$

where $s \in V$ is the source node of $m, D = v_1, v_2, ..v_k \subseteq V$ is the set of destination nodes. We assume full network knowledge by every sensor node. The MCR for multiple consecutive multicast routing requests is defined as

$$[P = G; Co; M], \quad (2)$$

where $M = m_1, m_2, ..m_s$ and G and Co are as defined above.

A popular way to model the Multicast Routing Problem is as a constrained Steiner Tree problem. The Steiner tree problem in energy-efficient MCR is summarised by finding in a graph G a minimum cost tree spanning the source and all destination nodes such that the number of edges is minimized. The Steiner tree is generally considered superior to the Minimum Spanning tree for the MCR as the process of also minimising the number of used edges reduces unnecessary data traversing the network (Novak et al., 2002).

Computing a Steiner Tree was shown to be NP-Complete in (Karp, 1972) however, there exist a number of heuristics for its computation. A popular heuristic approach is the KMB algorithm which comes within approximately 5% of the optimal. We use an adaptation of the KMB to generate Steiner tree based solutions for MCR requests over a dynamically re-weighted network. The KMB adaptation, for each transmission, works in the following manner:

Starting with the input graph G and a set of steiner points S (the source and destination nodes).
Constructs a complete undirected distance G1 graph from G and S. The only nodes in G1 should be modes listed in S.
Find the minimum spanning tree of G1.
Construct subgraph Gs of G by replacing each edge in G1 with its corresponding path in G.
Find the minimum spanning tree G2 of Gs.
Construct a Steiner tree T from G2 by deleting edges so that all leaves are Steiner points.

Definition 1. *A Wireless Sensor Network (WSN) is a number of sensor nodes distributed over a physical area where the nodes are computational units fitted with sensors and are capable of data collection and processing as well as transmitting data wirelessly and receiving wireless transmissions from other network nodes.*

Every node in the WSN must be within communication range of at least one other node in the network. Nodes collect data autonomously and cooperate to funnel data toward those sensor nodes capable of transmitting it to a data repository for analysis, otherwise known as *destination nodes* or *sink nodes*. Which of the sensor nodes in the network possess this capability is not fixed in our representation and can vary with time. All WSN sensor nodes are identical in every respect including the effective range at which they can transmit data. All wsn sensor nodes have a battery to provide power with a limited, identical amount of available energy before the battery runs dry and the node goes offline.

Definition 2. *An edge between two network nodes* $l = (v_x, v_y)$ *where* $v_x, v_y \in V$ *represents the fact that these nodes are within effective transmission range and can communicate.*

The cost of transmitting data is a unit cost by default as we assume in the current work the amount of power required to transmit over any edge in E is identical. This is because in the most common WSN scenario nodes cannot vary the strength of transmission and transmit at maximum power to any destinations in range. The amount of energy expended by a node receiving is negligible compared to the energy expended transmitting data. Therefore the cost of receiving in our representation is set to zero.

Definition 3. *A multicast request consists of data to be transmitted from one sensor node to one or more destination nodes.*

Definition 4. *A Successful request is a request where the data is delivered at all destination nodes. A successful requests depletes the energy of every node involved in transmitting it by a constant amount (That is, the source node, all intermediary nodes but no destination nodes).*

Definition 5. *A Bad request or Unsuccessful request is a request where data cannot be delivered to every destination node (because of network partitioning etc.). Such a request is marked as failed and not transmitted, therefore depleting no energy.*

A popular naive solution to the multicast problem is the routing of requests by generation of a Shortest Path tree in which the shortest paths from the source to each individual destination are calculated and these paths are superimposed to create the multicast tree. While possessing the advantage of ensuring the speediest delivery to each destination this method is wasteful of energy potentially creating unnecessary data duplication in the network by failing to consider the routing as a whole. A steiner tree based algorithm deals with this problem by aiming to reduce the number of edges used and minimising the total energy of the entire routing. However, current Steiner tree based algorithms fail to consider the effects of energy depletion, over consecutive runs with individual multicast requests, of nodes along popular (shorter) paths. This results in a shorter network lifetime and a speedier fragmentation of the network.

The energy-efficient MCR for WSNs as the consecutive routing of a set of multicast requests over a network is aimed to maximise the network lifetime by minimising the usage of energy for each request. The proposed algorithm takes into account the residual energy remaining in nodes after each multicast routing by re-weighting, each edge $l_k = (v_i, v_j)$ to reflect the energy levels of v_i and v_j, both of the nodes it connects. The purpose of this function is to increase the cost of an edge proportionally with the decreasing energy levels of the nodes it connects in order to encourage the algorithm to path around nodes with low residual energy in future runs, thus extending the network lifetime. The inputs are a randomly generated network and a randomly generated set of requests. It uses an adaptation of the popular KMB heuristic approach to calculate each individual routing. However, after each routing the cost of any edge connecting one or more nodes the energy level of which had diminished during the routing is calculated as:

$$C(l_k) = \frac{E_{max}}{E(v_i) + E(v_j)} \tag{3}$$

where $C(l_k)$ is the energy cost of the link l_k, E_{max} is the maximum energy of a node, $E(v_i)$ and $E(v_j)$ are the current energy levels of nodes v_i and v_j, respectively.

3 EXPERIMENTAL RESULTS

(Akyildiz et al., 2002) defined random deployment as one of the two primary deployment methods of wireless sensor networks. We have tested our algorithm on a set of randomly generated networks consisting of 100 nodes with 200 edges against a non-energy-weighted Steiner tree algorithm for multicast routing, based on the KMB algorithm by following the methodologies outlined in (Banerjee et al., 2003) and (Li et al., 2004).

Every node in the network has at least one and at most 99 neighbors (nodes connected by a link). No pair of nodes may share more than one link. Nodes have full knowledge of the network and the routing algorithm is run in a source node prior to transmission. Running the routing algorithm and receiving data from another node cost no energy. Energy cost is incurred only in transmitting data. Requests which cannot be transmitted to every destination are not sent and consume no energy. Both algorithms were given an identical sequence of randomly generated requests until the termination condition, the end of the network lifetime, had been reached. The computational times for all experiments and all algorithms were very close. A popular definition for the end of the lifetime of a network is the time when a node in the network has no more energy (Chang and Tassiulas, 2004), (Cheng et al., 2008), (Kang and Poovendran, 2005). Our initial experiments, therefore, terminated both algorithms when a single node died, with the results presented in the first row of the Table [1]. The columns in tables represent:

R_t The total number of requests processed before termination.

R_b The number of these requests which were not routed successfully.

E_t The total energy remaining in the network (out of 10,000).

E_m The mean energy remaining in a live node in the residual network.

T_c The termination condition which must be met for the algorithm to stop.

Table 1: Energy-Weighted and Non-Energy-Weighted algorithms results based on dead nodes termination condition.

	EW				NonEW			
T_c	R_t	R_b	E_m	E_t	R_t	R_b	E_m	E_t
1 node	420	0	54	4903	268	0	77	7003
10%	521	13	40	3663	471	57	58	5261
15%	656	111	35	3205	587	123	51	4609
20%	623	90	35	3154	720	243	48	4384

The results for a single node termination condition illustrate the improvement of the Energy-Weighted KMB based algorithm over the Non-Energy-Weighted one. The total number of requests processed successfully was 56% greater than in the Non-Energy-Weighted instance. There were no unsuccessful requests due to the termination condition used. Moreover, there was a 30% reduction in the mean energy within a live node in the residual network indicating a more efficient use of resources by the Energy-Weighted algorithm - with the energy being an average of 54 in the Energy-Weighted runs and 77 in the Non-Energy-Weighted case.
(Cheng et al., 2008) proposes that in a well designed network when the first node dies its neighbors will soon follow from having to take over the strain of the node, however we have seen that in random networks the mean energy of a node in the network at the time of the death of the first node tends to be still over 50%. Another common definition of the end of a network lifetime is when a certain percentage of the nodes become non-functional (Chen and Zhao, 2005), (Cheng et al., 2008). For the next set of tests we compared the algorithms using termination criteria of varying percentage of dead nodes, the results are demonstrated in the Table [1].

In running the algorithms with a 10% node death termination criteria we also calculated the shortest path to each destination node using Djkstra's algorithm and we noticed that the results for the Non-Energy-Weighted KMB and Shortest path algorithms are very similar, with the Shortest path approach being only slightly worse on average in every respect - 463 requests routed on average with an average mean energy of 58 and total energy of 5278 in the 10% nodes dead scenario. The shortest path based algorithm was also significantly worse in terms of unsuccessful requests with an average of 69 bad requests for the 10% nodes dead scenario. Therefore, we do not need to run the Shortest Path based algorithm and will instead keep only the non-energy-Weighted KMB for comparison in all other experiments. The Energy-Weigthed algorithm constitutes a significant improvement on the two previous algorithms, with around a 10% improvement on the number of processed requests with an average 81% reduction in the number of bad requests. Also indicative was a 32% reduction in the average energy of a live node in the residual network indicating that the Energy-Weighted algorithm was able to make far better use of network resources prior to the end of the network lifetime.

In the runs missed out from the results of the runs against a 15% network death termination criteria, the number of bad requests, as the percentage of dead nodes required to consider the network dead is increased, becomes an exponential curve. Past a certain point in the operational life of a WSN it becomes so disconnected that a successful request is routed very rarely. The network during the unsuccessful runs had already crossed this point with a 15% network death termination criteria. The Energy-Weighted algorithm processed over 1200 requests of which over half were unsuccessful, while the Non-Energy weighted algorithm failed to terminate within the requests set (as unsuccessful requests do not consume energy). It was ultimately felt that including these runs would skew the results. The comparative results of the Energy-Weighted algorithm are maintained, with a 15% improvement on the number of requests processed and a 12% reduction on the number of bad requests compared to the Non-Energy-Weighted algorithm. Consistently, there was a 31% reduction in mean energy of a live network node.

In the tests against a 20% network death condition the number of bad requests for both algorithms begins to increase exponentially indicating the increased partitioning of the network. Nevertheless, even under these circumstances, the Energy-Weighted algorithm constitutes a significant improvement over its counterpart with a consistent 16% improvement on the number of requests processed and a large 63% reduction in the number of bad requests. However, at higher percentages of nodes dead the difference in bad requests becomes significantly less as both networks become disconnected almost entirely and continuously process requests unsuccessfully. The improvement in the mean energy of a live node (a 27% reduction) is consistent with previous results.

We also carried out tests utilising a stopping criteria where a number of consecutive bad requests were taken as a sign of the end of a network lifetime. Table [2] presents the results for 10 and 30 consecutive bad requests for the Energy-Weighted and the Non-Energy-Weighted algorithms.

Table 2: Energy-Weighted and Non-Energy-Weighted algorithms results based on bad requests termination condition.

	EW				NonEW			
T_c	R_t	R_b	E_m	E_t	R_t	R_b	E_m	E_t
10	564	47	39	3492	545	102	54	4864
30	682	148	40	3131	767	288	54	4318

While the consecutive bad request termination criteria halted the algorithm at different points in the network life compared to the former stopping criteria, the results were, however, consistent. The results for the 10 consecutive bad requests were closer to those for a less disconnected network such as 10% or 15% network nodes criteria: The improvement by the Energy-Weighted function on the number of requests processed (compared to the Non-Energy-Weighted function) was a minor 3%, however the reduction in bad requests was 45.7%. The reduction in mean energy of a node was 28%. Tests against 30 consecutive bad requests placed the residual network closer to the point of being totally disconnected. However, with a 12% improvement on the number of processed requests, a 49% decrease in bad requests and a 26% decrease in mean energy per live node, the results for the Energy-Weighted algorithm are consistently superior.

We also ran a series of tests with a termination criteria based on the percentage of dead edges, which may more accurately represent the level of partitioning of the network, as the death of a highly connected node may have far more impact than that of an average node. The results are obtained by having stopping criteria of 10, 15, 20, 30 and 35 percent of edges dead, are given in Table [3].

Table 3: Energy-Weighted and Non-Energy-Weighted algorithms results based on dead edges termination condition.

	EW				NonEW			
T_c	R_t	R_b	E_t	E_m	R_t	R_b	E_t	E_m
10	413	11	5112	56	284	12	6912	76
15	496	24	4121	45	344	24	6317	70
20	527	32	3783	42	412	41	5700	63
30	577	55	3417	37	502	70	4878	54
35	623	86	3191	35	503	70	4867	54

The improvement in the number requests appears to decrease as the network nears full partitioning, ranging from 67% to 15%, however as the final value improved on the previous score raising the improvement to 24% this may indicate that the decrease is more general, or even a feature of the network, the average improvement being 35%. The decrease in bad requests fluctuated wildly and, in fact, in one instance, for the first time, the Energy-Weighted algorithm performed worse in terms of bad requests than its counterpart with a 23% increase in bad requests. However the overall performance of the algorithm in this instance was superior with a 24% improvement in the number of successful requests. The average improvement on the number of bad requests was 7.2%. The decrease of the mean energy of a node between the two algorithms fluctuated without pattern and averaged at 32.2% decrease of mean energy per live node in the Energy-Weighted algorithm compared to the Non-Energy-Weighted algorithm.

4 CONCLUSION

An algorithm for multicast routing in wireless sensor networks based on energy-reweighting is proposed to optimize the energy-cost of a routing and the network lifetime. We have found the proposed approach, based on re-weighting of edges to reflect the remaining energy level of the nodes, improves network lifetime, routing significantly more successful requests before the WSN becomes disconnected, while utilising the resources of the network far more effectively. This is represented by a steady decrease in the average remaining energy of a random, live node in the network after it is disconnected.

The results of the Energy-Weighted Steiner tree based approach for the multicast routing problem in Wireless Sensor Networks were consistently superior to a purely Steiner tree based algorithm and a Shortest path based algorithm. The percentage of improvement on the total number of requests processed varied greatly between runs, being between 3% and 56% on average, depending on the termination conditions. The percentage of improvement in this regard seemed to weakly decrease as the network became more disconnected with the average improvement over all experiments being 21%. The reduction in the number of unsuccessful requests (where applicable) also fluctuated between 7.2% and 81%. There was even a single instance where the Energy-Weighted algorithm performed worse than its counterpart in this regard, however simultaneously improving significantly on the number of successful requests. Nevertheless, there was a generally consistent improvement on the number of bad requests, with the Energy-Weighted algorithm averaging out at 43% less bad requests. The Energy-Weighted algorithm also maintained a consistent decrease in the mean energy level of a live residual network node after termination. The improvement here fluctuated very mildly averaging at a 29% decrease in energy and indicating a consistent, significantly more efficient use of network resources on the part of the Energy-weighted algorithm.

The paper considered identical transmission costs per node as this is the more common scenario in actual WSNs, as though the nodes may be at differenct actual distances from one another, each node in a common WSn transmits with the same invariable signal strength. Thus the cost of tranmission is the same to any node within range regardless of actual distance. However, if the transmission costs were different, perhaps under the assumption of different sensor types in the network, the model would require bi-directional edge costs, with the costs varying depending on the transmitting node. This may be an interesting future extension of the research.

ACKNOWLEDGEMENTS

The authors would like to thank Dr. Kathleen Steinhöfel for her support. This work is partially supported by the Scientific and Technical Research Council of Turkey and Erciyes University Scientific Research Projects, Project No: FBA-12-4029.

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