Available online at www.sciencedirect.com

SCIENCE DIRECT®

J. Parallel Distrib. Comput. 65 (2005) 124 – 131

Journal of Parallel and Distributed Computing

www.elsevier.com/locate/jpdc

Optimal topology control for balanced energy consumption in wireless networks

Yingshu Li[a,*], Xiaoyan Cheng[b], Weili Wu[c]

[a]Department of Computer Science and Engineering, University of Minnesota, Minneapolis, MN 55455, USA
[b]Department of Computer Science, University of Missouri, Rolla, MO 65401, USA
[c]Department of Computer Science, University of Taxes at Dallas, Richardson, TX 75083, USA

Received 10 September 2004
Available online 9 December 2004

Abstract

Hosts in wireless networks are usually powered by batteries, thus the lifetime of a network depends on the battery life of each individual host. One major solution to improve energy-efficiency is to minimize the total energy consumption. However, battery energy is a local resource, to save energy at each host and balance the energy consumption among all the hosts in the network appear to be more practical. In this paper, we prove that minimum weight incremental arborescence (MWIA) is the optimal solution for minimizing the maximum transmission power among a set of wireless nodes. We propose an algorithm that utilizes MWIA to construct a connected topology, called MWIA-based Topology Control(MWIA-TC) algorithm. We further apply MWIA-TC to the accumulated energy consumption. The theoretical analysis and experimental results show that MWIA-TC outperforms a well-known algorithm, Minimum Incremental Power (MIP), in both energy saving and network lifetime extension.
Published by Elsevier Inc.

Keywords: Wireless networks; Topology control; Minimum spanning tree; Energy; Balance

1. Introduction

Hosts in wireless networks are usually powered by batteries. Sometimes it is difficult or impossible to replace or recharge the batteries after the network is deployed, for example in a battle field, once a solider consumes all the power while he is fighting, he cannot pause to change another battery. The energy consumption becomes a great concern in this case. We define the lifetime of a network as the longest time that the network is fully connected after the deployment without disconnecting any host. If a host runs out of energy and loses its communication ability, it has to be disconnected from the network and in this case the network lifetime is ended. But other hosts may still have much energy left and this is a waste of energy. To maximize the lifetime of a network, the energy at each host should be efficiently used.

The topology control problem studies how to adjust the transmission power at each node in the network in order to achieve a desired topological property while satisfying other requirements such as lifetime, throughput, etc. The topology of a network is dynamically maintained to obtain the global connectivity where there exits a path between each ordered pair of nodes. In our work, we focus on the network connectivity and try to find an energy-efficient way to maximize the lifetime of a network. The total energy consumption has been used as an important metric when evaluating routing algorithms. Although in some cases a low total energy consumption implies energy-efficiency, having a minimum total energy does not always produce a long-lived network. Fig. 1 illustrates such an example. If there is an arrow from node u to node v, v can successfully receive messages from u. Otherwise, u cannot reach v. Assume a broadcast tree is constructed as in Fig. 1. If the root node is on the right side

---

[*] Corresponding author.

E-mail addresses: yili@cs.umn.edu (Y. Li), chengm@umr.edu (X. Cheng), weiliwu@utdallas.edu (W. Wu).

0743-7315/$ - see front matter Published by Elsevier Inc.
doi:10.1016/j.jpdc.2004.09.014

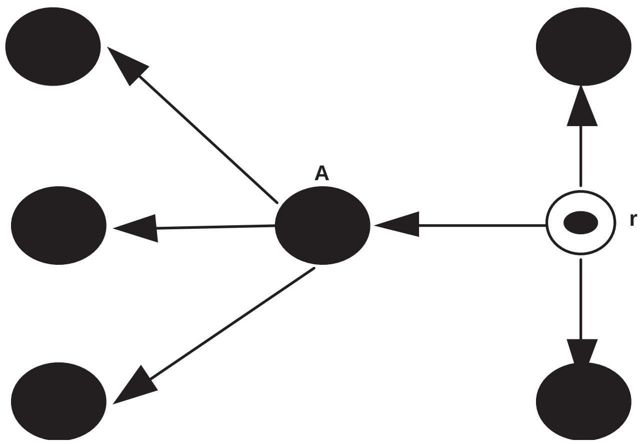


Fig. 1. Negative impact of using total energy consumption as energy-efficient metric.

of node A, then A works as the relay node. If we use *minimum total energy* as the metric of energy-efficiency, A will always be selected to transfer the information from the root to all the nodes on its left side. After some broadcast sessions, A will be depleted of energy and the lifetime of the network ends.

The above example shows that the total energy consumption should not be the only consideration for energy-efficiency. We also need to balance the energy consumption of each node. Each host in the network may transmit at different transmission power. The maximum transmission power is the power used by the host transmitting at the largest power among all the hosts in the network. The energy consumed by this host is the maximum energy consumption among all the hosts. To balance the energy consumption, we need to minimize the maximum transmission power while maintaining the global connectivity of the network which also means to minimize the maximum energy consumption of every single node.

In this paper, 'host' and 'node' refer to the same thing. In the context of wireless networks, we use 'host'. In the context of graph topology, we use 'node'. In this study, we assume that the node position is static or changes slowly in a 2D plane so that each host has enough time to determine the updated topology information. If the network has high mobility, the moving node and its communication host will have to increase their transmission power to minimize the disconnected time. So when the network is in a transition state, we should compromise the energy-efficiency for connectivity. Omni-directional antennas are used. If a node i's transmission range is r, all the nodes within the range r of node i can receive the signal. This property implies that a node's transmission power is only dependent on its farthest one-hop neighbor. The wireless network is modelled as a complete graph, where each node represents a wireless host and the edge between a pair of nodes is weighted by the cost (e.g., transmission power) needed to communicate between the two nodes. If a node runs out of power, the edges from this node to other nodes will not exist causing this node to be disconnected from the network. The energy consumed by a wireless host have two components: the receiving/processing energy and the transmission energy. We assume that the transmission energy is dominant, therefore, only the transmission energy contributes to the total energy consumption. The purpose of topology control is to find a subgraph of this complete graph such that the resultant topology satisfies some certain requirements.

The most basic requirement for topology control is to maintain the network connectivity, which means if every node transmits at its maximum power, the network is connected, i.e., there is at least one path between every ordered pair of nodes, then the resultant network topology from any topology control algorithm must also be connected. The Energy-Balanced Topology Control Problem is defined as follows:

Defnition 1.1 (*Energy-Balanced Topology Control Problem*). Given a set of hosts in an ad hoc network, adjust the transmission power of each host so that the resultant network topology is connected and the maximum energy consumption among all the hosts is minimized.

2. Related work

The topology control problem concerns about the construction of the graph topology of a wireless ad hoc network to achieve certain properties by varying the transmission power at each node. These properties may include energy-efficiency, network throughput, network lifetime and connectivity. A commonly used metric for energy-efficient topology control is the total energy consumption among all nodes. The minimum total energy topology control problem was proved to be NP-complete in [3]. The authors studied the problem of connecting a multi-hop packet radio network with the objective of minimizing the total energy consumption. An approximation algorithm whose performance ratio is 2 was provided.

In [18], Rodoplu and Meng proposed a distributed position-based protocol to maintain strong connectivity in mobile networks and this protocol was optimized for minimum energy consumption along the path between any pair of nodes that are connected in the original graph. Their algorithm was then improved by Li and Halpern [13], which is computationally simpler than the one in [18] and the resulting topology is a subnetwork of the one generated by the protocol in [18]. In [16], the authors considered generating a connected or bi-connected topology for a multihop wireless network by adjusting the transmission power at each node to minimize the total energy consumption. Their algorithms for mobile networks are based on simple heuristics and the connectivity is not guaranteed in all cases. A minimum energy heuristic that can be used to improve any spanning tree based topology is proposed by Cheng et al. [4]. The minimum total energy problem is also addressed by Wattenhofer et al. [19]. The authors proposed a cone-based distributed algorithm to guarantee the global connectivity by varying the transmission power at each node. The improvement is that directional information instead of exact location information for each node is the only information needed and a deployment region does not need to be specified, which is a great concern when nodes regularly change the deployment region. A detailed analysis of the algorithm is then provided in [14]. In [15], Lloyd et al. studied the topology control problem with more optimization objectives including both minimizing the maximum energy consumption and minimizing the total energy consumption. A centralized polynomial algorithm for minimizing maximum power for the graphs with monotone properties is proposed. Another approximation algorithm for minimizing the total power with the constraint of *two-node connected graph* is also presented and it provides a constant performance guarantee. Other topology control algorithms appeared in the literature in [12,11]. A distributed topology control algorithm for ad hoc networks with directional antennas is proposed by Huang et al. [12]. The number of neighbors of each node is reduced while the connectivity property of the network is still maintained by adjusting the antenna direction and the transmission power. In [11], Hu proposed a distributed algorithm based on Delaunay triangulation to control the transmission power and logical neighbors at each node in order to construct a reliable high-throughput topology. The resulting topology is degree-bounded and has a regular and uniform structure with greater throughput and reliability.

In wireless networks, to balance the energy consumption among all the nodes is a critical issue. If a relay node is heavily used for a period of time, then the relay task should be shifted to another node to ensure that no node will be depleted significantly faster than others. In this paper, rather than minimizing the total energy consumption, we focus on maintaining the network connectivity and minimizing the maximum energy consumption at each node. Our work will address the Energy-Balanced Topology Control Problem and provide an efficient solution for it. In [7], Cheng et al. propose the Minimum Incremental Power (MIP) algorithm and it is known as the most energy-efficient heuristic in terms of the total energy consumption among all the topologies. MIP is developed based on the Broadcast Incremental Power (BIP) algorithm [20]. The MIP algorithm is used in this paper as a comparison of our new solution to the *Energy-Balanced Topology Control Problem*, which instead of minimizing the total energy, minimizes the maximum energy consumption at each node. Our algorithm is developed based on the minimum weight incremental arborescence (MWIA) proposed in [5].

3. Energy-Balanced Topology Control Problem

We consider the Energy-Balanced Topology Control Problem under different scenarios. In all the scenarios, we use the link weight to represent the cost of transmitting over this link.

3.1. Symmetrical links

We first consider the basic undirected graph model. Based on the path loss model [17], transmitting power $P_t = C \cdot d_{uv}^{\alpha}$, where d_{uv} is the Euclidean distance between u and v. If all the nodes have the same power threshold, we can normalize the constant C to be 1 and assign each link (u, v) a unique weight: $W(u, v) = d_{uv}^{\alpha}$. All links are bidirectional and the link weights are symmetric in two directions.

Theorem 3.1. *Minimum spanning tree is the optimal solution for the Energy-Balanced Topology Control problem with symmetrical links.*

This is true based on the conclusion in [6] that the minimum spanning tree [8] has the minimum longest edge among all the spanning trees. Any topology H that satisfies connectivity requirement must contain a spanning tree as its subgraph and the maximum transmission power used by H cannot be smaller than that of its subgraph. So Minimum Spanning Tree is the optimal solution.

3.2. Asymmetrical links

Link weights may not always be symmetric. For example, if node u and v have different power detection thresholds, the actual transmission power needed for node u to reach its direct neighbor v can be different from that in the reverse direction. In this case, the network is modelled as a directed graph. Another example is to consider the accumulated energy consumption where we make the link weight reflect the preference of using the link. If a node has less energy left, the weights of the links starting from this node will be increased, so the Energy-Balanced Topology Control algorithm will avoid the use of this node as transmitting node. If the sender has run out of energy supply, the weights of the links starting from this node will be infinitely large, which means it is impossible to transmit through these links. We define

M	the maximum energy
E_i	the remaining energy of host i
P_{ij}	power needed to transmit from host i to host j
W_i	M/E_i
W_{ij}	$P_{ij} * W_i$

The maximum energy M of each node is assumed to be the same. There are two edges between every pair of nodes representing the paths from one to the other. The edge-weight W_{ij} depends on the weight W_i of the transmitting node i. It is possible that the two directed edges between a pair of nodes have different weights since they may have different remaining energy.

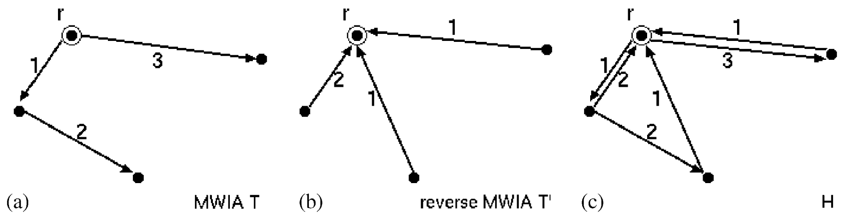


Fig. 2. (a) MWIA T rooted at r. (b) Reverse MWIA T' rooted at r. (c) Topology H generated by MWIA-TC.

For the above two scenarios, we use a generalized directed graph to represent the network, and Definition 1.1 can be restated using the following graph theoretical terms:

Definition 3.1. Given an edge-weighted complete graph G, find a subgraph H such that

1. for every ordered pair of nodes (u, v) in G, H contains a path from u to v, and
2. the largest edge-weight is the minimum.

The solution is based on the MWIA. We call it MWIA-based topology control (MWIA-TC) algorithm, which constructs a MWIA T and a reverse MWIA T' and the union of T and T' gives the optimal solution for the above problem. A MWIA rooted at r is obtained as follows: initially, only r is included in the tree. At each step, we add a node to the tree on a minimum weight basis, i.e., we find an edge with minimum weight from a vertex in the tree to a vertex not in the tree. If there are more than one such edges, the tie is broken randomly. We start from the source node and grow the tree one node at a time until all nodes are in the tree. A reverse MWIA is obtained by first exchanging the weight of edge (x, y) and the weight of edge (y, x), which results in a graph G', then we run the above MWIA algorithm to obtain the MWIA T'' on graph G' . By changing the direction of each edge in T'' to its reverse direction, we can get a sink-tree-like subgraph T' of the original graph G, we call it reverse MWIA of G.

The MWIA-TC algorithm is described as follows:

1. Choose any node r as a root.
2. Find a MWIA T rooted at r and a reverse MWIA T' rooted at r in G.
3. Output $T \cup T'$ as the solution.

Theorem 3.2. *The union $T \cup T'$ is an optimal solution to the topology control problem with asymmetrical links.*

Proof. T is an MWIA and T' is a reverse MWIA rooted at node r. An MWIA has the property that the largest edge-weight in it is the minimum among all the arborescences rooted at r. Suppose H is an optimal solution to the above topology control problem rooted at node u, then H must also contain an arborescence and a reverse arborescence rooted at node r, since for each node x in the graph G, H contains a path from r to x and a path from x to r. Therefore, the largest edge-weight in $T \cup T'$ is not larger than that of H. Thus, $T \cup T'$ is an optimal solution. □

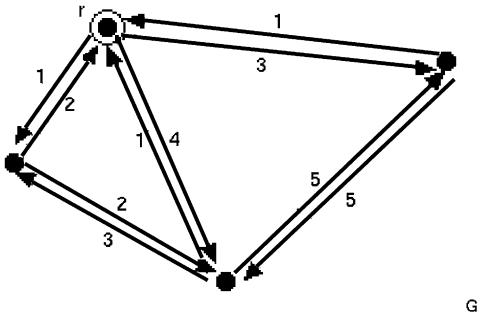


Fig. 3. Graph G.

A node is randomly chosen as the root. After the topology is decided at the root, this information will be broadcast to all the nodes. Fig. 2 illustrates the optimal topology control solution to the graph in Fig. 3.

For the networks with symmetrical links, we use Prim's algorithm to grow a minimum spanning tree. It is stated in [8] that complexity is based on the implementation. By using a heap, the complexity is $O(ElgV)$, where E is the number of the edges in the graph and V is the number of nodes in the graph. By using Fibonacci heaps, the complexity can be improved to $O(E + VlgV)$. For the networks with asymmetrical links, the way we grow an arborescence and a reverse arborescence is to add a least-weight edge one at a time. To find the least-weight edge at each step, the implementation decides the complexity and it is just like the Prim's algorithm. So the complexity is $O(E + VlgV)$.

4. Simulation results

A fixed value $\alpha = 2$ is used in all the simulations, which is a typical value for unobstructed environment.

In this simulation study, we only address the scenarios where links are asymmetrical. Link costs in two directions can be different if the transmission powers needed for both sides to reach each other are different, or the prices of using the same amount of energy are different.

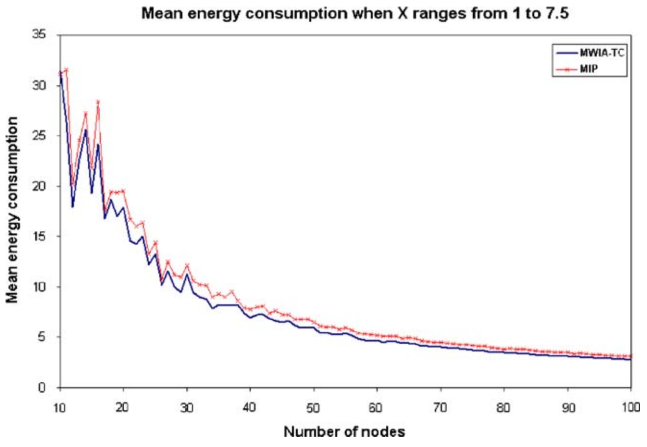


Fig. 4. Mean power consumption ($1 \leqslant X \leqslant 7.5$).

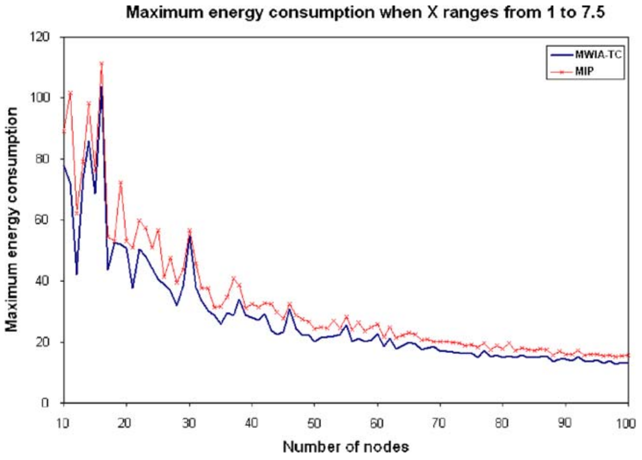


Fig. 5. Maximum power consumption ($1 \leqslant X \leqslant 7.5$).

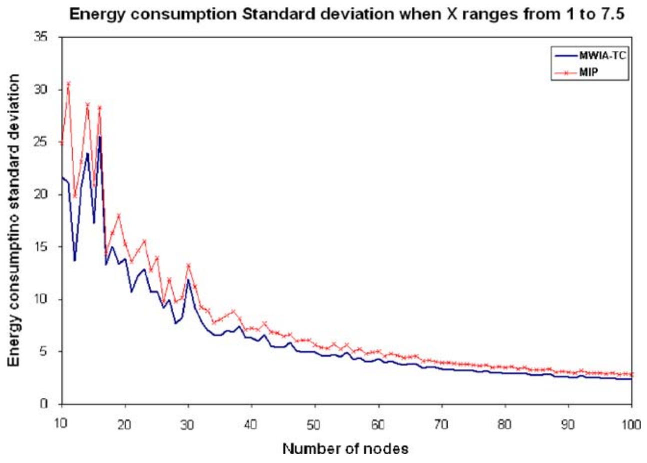


Fig. 6. Standard deviation of power consumption ($1 \leqslant X \leqslant 7.5$).

All the simulation results are compared with those of another algorithm MIP. MIP stands for MIP algorithm, which starts from a tree containing only the root node, and adds nodes to the tree one at a time on a minimum incremental power basis until all nodes are in the tree. For example, if node u's current transmission power is P_u, node v is added to the tree by edge (u, v) if $P_{uv} - P_u + P_{vu} = \min_{i \in T, j \notin T}\{P_{ij} - P_i + P_{ji}\}$ is satisfied. The limitation of MIP is that the topology generated by MIP can only be tree structures since if edge (u, v) is included, edge (v, u) must also be present in the solution, while the topology generated by MWIA-TC can be a directed graph.

4.1. Test I

The purpose of this simulation is to evaluate the effect of MWIA-TC on the energy consumption of a network where some nodes have different receiving power thresholds. We use link weight to represent the transmission power needed and the link weights can be different in two directions. The MIP algorithm is used for comparison. After determining the topology of a network, the mean, maximum and standard deviation of power consumptions among all the nodes are measured and compared with those in the MIP algorithm. We run the topology control algorithms for the networks of sizes from 10 to 100 nodes. All these networks are generated in a fixed $1000 * 1000$ region. For each network size, 100 network instances are investigated and the results averaged. We set link weight $W = C \cdot r^{\alpha}$, where r is the 2D distance between two nodes, α is fixed to 2, and C is a constant between $C_{\min}$ to $C_{\max}$. We control the ratio of $C_{\max}$ to $C_{\min}$ by introducing a control parameter $X = C_{\max}/C_{\min}$; we allow X to vary from 1 to 7.5 in the first test and compare the power consumption of the topologies generated by MWIA-TC and MIP. Figs. 4–6 illustrate the simulation results.

On an average, the mean power consumption of MWIA-TC is 10.1% lower, maximum power consumption is 14.9% lower and standard deviation is 15.6% smaller than that of MIP. MWIA-TC cannot only balance the energy distribution, but also reduce the total energy consumption. The reason for MWIA-TC to outperform MIP in total energy consumption for some network instances is that MIP can only generate a spanning tree, where each link is either not used at all, or used in two directions; while MWIA-TC can generate a directed graph. If the link weights show significant difference in two directions, MWIA-TC will only select the small-weighted uni-directional link and find a reverse path through other nodes. Fig. 7 gives an example network and it shows that MWIA-TC results in less total energy consumption than MIP does. Fig. 7(b) is the resulting topology by using MIP and Fig. 7(c) is the resulting topology by using MWIA-TC, where node C can bypass the large weight 8 and take a multihop path to reach B. MWIA-TC always outperforms MIP for minimizing the maximum transmission power and this is consistent with Theorem 3.2, since the MWIA- TC is the optimal solution. Another observation is that as the number of nodes increases, the total energy consumption decreases in general. This is true since

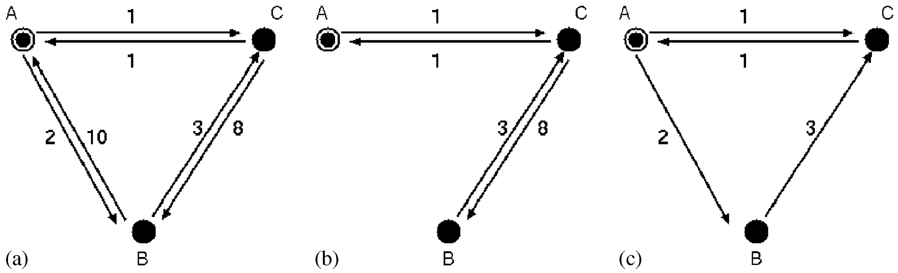


Fig. 7. An example showing MWIA-TC outperforms MIP in total energy consumption. For the network given in (a), (b) is the resulting topology from MIP and (c) is the resulting topology from MWIA-TC.

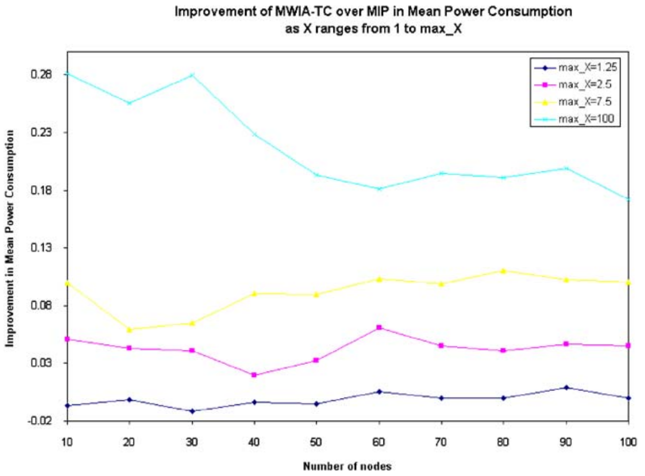


Fig. 8. $\frac{\text{MIP}-\text{MWIA-TC}}{\text{MIP}}$ in mean power consumption.

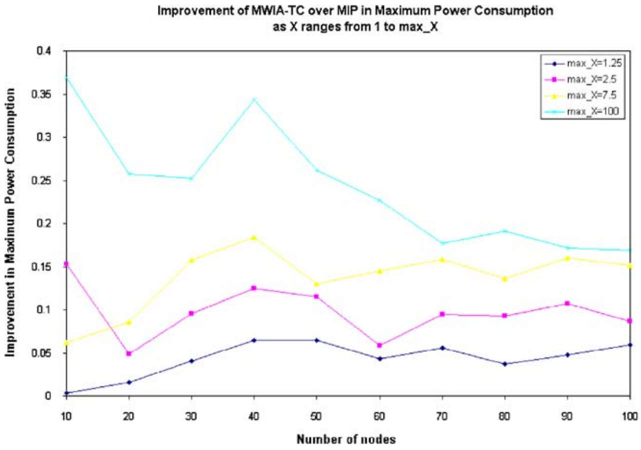


Fig. 9. $\frac{\text{MIP}-\text{MWIA-TC}}{\text{MIP}}$ in maximum power consumption.

the distance between each pair of nodes is getting closer and closer as the sizes of the networks are getting larger and larger. Therefore, the average transmission power levels are decreased.

In the second test, we further investigated the effect of the link weights on the performance of MWIA-TC algorithm. We set X to be a random number between 1 and an upper bound max $\_X$, and observed that when max $\_X$ increases, the improvement of MWIA-TC over MIP also increases. In the following simulation, when max $\_X$ is set to 1.25, MWIA-TC outperforms MIP by 4.3% in maximum power consumption and 4.9% in standard deviation, but MWIA-TC hardly outperforms MIP in mean power consumption. When we increase max $\_X$ to 100, MWIA-TC outperforms MIP by 21.8% in mean power consumption, 24.2% in maximum power consumption and 23.3% in standard deviation in an average. The results are shown in Figs. 8–10.

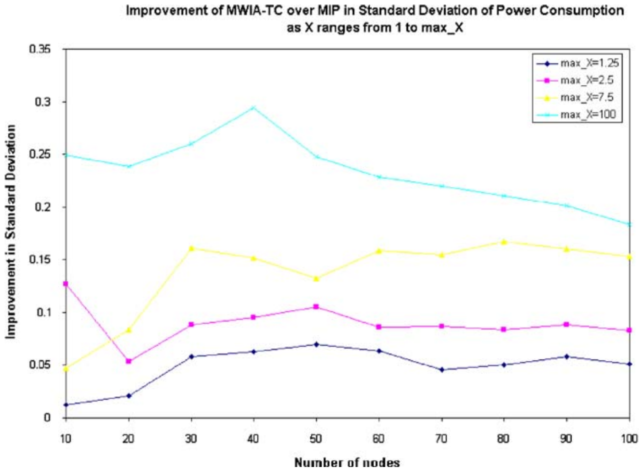


Fig. 10. $\frac{\text{MIP}-\text{MWIA-TC}}{\text{MIP}}$ in standard deviation of power consumption.

4.2. *Test II*

This simulation is designed to evaluate the effect of MWIA-TC on the network lifetime. When we consider the accumulated energy consumption, the topology control algorithm must take into account the current remaining energy of each node and update the topology periodically, rather than to use a fixed topology all the time. In this simulation, the 2D positions of nodes are randomly generated as described in Section 4.1 and the initial energy reserve of each node is assigned a random number between 1 and the maximum energy. The remaining lifetime of the network is

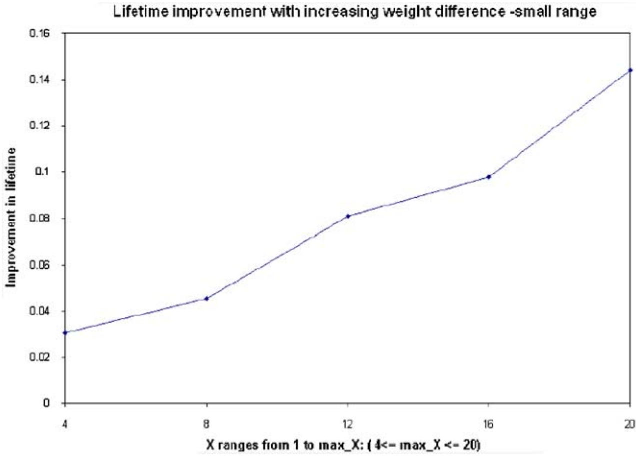


Fig. 11. Network lifetime improvement when the variance of energy reserves is small.

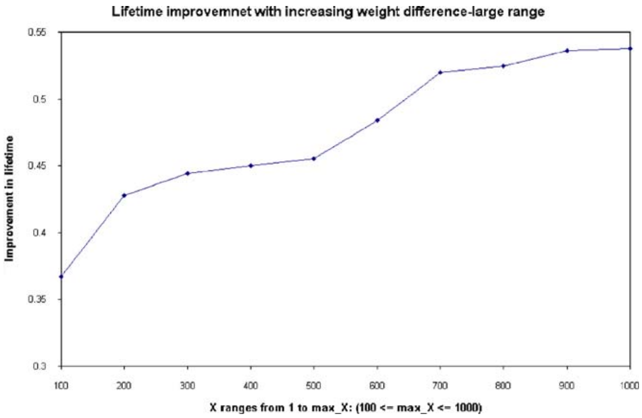


Fig. 12. Network lifetime improvement when the variance of energy reserves is large.

computed as following:

$$\text{Network lifetime} = \min_{i \in V} \frac{\text{remaining energy of node } i}{\text{transmission power of node } i}.$$

In MWIA-TC, we assign edge-weight to reflect the remaining energy of the transmitting node. The edge-weights are computed according to Section 3.2, while in MIP, the edge-weight is the actual transmission power needed to reach the receiver. We compare the remaining lifetime of the networks controlled by MWIA-TC and MIP and observed that the lifetime improvement by the use of MWIA-TC increases when we increase the variance of the initial energy reserve. Let $X = \frac{\text{maximum energy reserve}}{\text{minimum energy reserve}}$. The maximum and minimum value are taken from all the network nodes. The simulation results show that when X ranges from 4 to 20, the lifetime improvement from MIP to MWIA-TC is from 3% to 14.4%(Fig. 11). When X ranges from 100 to 1000, the lifetime improvement of MWIA-TC over MIP is from 36.7% to 53.8% (Fig. 12).

5. Conclusion and future research work

In this paper, we study the problem of minimizing the maximum energy consumption of individual nodes. This is solvable in polynomial time. MST is the optimal solution if the resulting topology use bidirectional links. The union of Minimum Weight Incremental Arborescence and Minimum Weight Incremental reverse Arborescence results in the optimal solution for the networks with uni-directional links. Both solutions optimize the network topology toward a balanced energy distribution. The simulation results show that the energy consumption of the resulting network topology by the use of MWIA-TC is more balanced than the topology generated by MIP.

It is our interest to further investigate the performance of the proposed topology control algorithm in terms of the network throughput, transmission delay, etc. The work can also be extended to develop a distributed algorithm in the mobile environment where node mobility is highly concerned. A centralized algorithm takes much time to gather information from each node and distribute the updated information to all the nodes. Thus in mobile environment, a localized search mechanism is necessary and the global information should be used less.

References

[1] J. Chang, L. Tassiulas, Routing for maximum system lifetime in wireless ad hoc networks, in: Proceedings of 37th Annual Allerton Conference on Communication, Control, and Computing, Monticello, IL, 1999.

[2] J. Chang, L. Tassiulas, Energy conserving routing in wireless ad hoc networks, in: IEEE INFOCOM 2000, Tel-Aviv, Israel, 2000, pp. 22–31.

[3] Wen-Tsuen Chen, Nen-Fu Huang, The strongly connecting problem on multihop packet radio networks, IEEE Trans. Comm. 37 (3) (1989) 293–295.

[4] M.X. Cheng, M. Cardei, J. Sun, L. Wang, Y. Xu, D.-Z. Du, Topology Control of Ad Hoc Wireless Networks for Energy Efficiency, Manuscript, 2003.

[5] M.X. Cheng, J. Sun, M. Min, Y. Li, D.-Z. Du, Energy-Efficient Broadcast and Multicast Routing in Ad Hoc Wireless Networks, Manuscript, 2003.

[6] M.X. Cheng, J. Sun, M. Min, D.-Z. Du, Energy-efficient broadcast and multicast routing in ad hoc wireless networks, in: Proceedings of IPCCC, Phoenix, AZ, 2003, pp. 87–94.

[7] X. Cheng, B. Narahari, R. Simha, M.X. Cheng, Dan Liu, Strong minimum energy topology in wireless sensor networks, IEEE Trans. Mobile Comput. 2 (2003) 248–256.

[8] T.S. Cormen, C.E. Leiserson, R.L. Rivest, Introduction to Algorithms, MIT Press and McGraw-Hill Book Company, Cambridge, MA and New York, 1976.

[11] L. Hu, Topology control for multi-hop packet radio networks, IEEE. Trans. Comm. 41 (10) (1993) 1474–1481.

[12] Z. Huang, C. Shen, C. Srisathapornphat, C. Jaikaeo, Topology control for ad hoc networks with directional antennas, in: Proceedings of the 11th International Conference on Computer Communications and Networks (ICCCN 02), Miami, FL, 2002, pp. 14–16.

[13] L. Li, J.Y. Halpern, Minimum energy mobile wireless networks revised, in: Proceedings of the IEEE Conference on Communications (ICC'01), Helsinki, Finland, 2001.

[14] L. Li, J.Y. Halpern, P. Bahl, Y. Wang, R. Wattenhofer, Analysis of cone-based distributed topology control algorithm for wireless multi-hop networks, in: Proceedings of the ACM Principles of Distributed Computing Conference (PODC'01), Newport, Rhode Island, 2001.

[15] E.L. Lloyd, R. Liu, M.V. Marathe, R. Ramanathan, S.S. Ravi, Algorithmic aspects of topology control problems for ad hoc networks, in: IEEE MOBIHOC, EPFL Lausanne, Switzerland, 2002.

[16] R. Ramanathan, R. Rosales-Hain, Topology control of multihop wireless networks using transmit power adjustment, in: Proceedings of IEEE INFOCOM 2000, Tel-Aviv, Israel, 2000, pp. 404–413.

[17] T.S. Rappaport, Wireless Communications: Principles and Practice, Prentice-Hall, Englewood Cliffs, NJ, 1996.

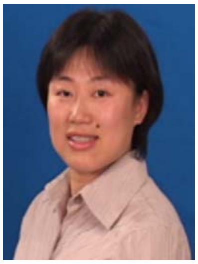
[18] V. Rodoplu, T.H. Meng, Minimum energy mobile wireless networks, IEEE J. Selected Areas Comm. 17 (8) (1999) 1333–1344.

[19] R. Wattenhofer, L. Li, P. Bahl, Y. Wang, Distributed topology control for power efficient operation in multihop wireless ad hoc networks, in: Proceedings of the IEEE INFOCOM 2001, Anchorage, Alaska, 2001, pp. 1388–1397.

[20] J.E. Wieselthier, G.D. Nguyen, A. Ephremides, On the construction of energy-efficient broadcast and multicast trees in wireless networks, in: Proceedings of the IEEE INFOCOM 2000, Tel-Aviv, Israel, 2000, pp. 585–594.

Yingshu Li is a Ph.D. candidate in the Department of Computer Science and Engineering at the University of Minnesota, Twin Cities. She received the B.S. degree in computer science from Beijing Institute of Technology, China, in 2001, and the M.S. degree in computer science from the University of Minnesota, Twin Cities, USA, in 2003. Her current research interests include mobile wireless network and mobile ad hoc network Database Systems. She is a student member of the IEEE.

Weili Wu received her M.S. and Ph.D. degrees in computer science both from University of Minnesota, in 1998 and 2002, respectively. She is currently an assistant professor and a lab director of the database research lab at the Department of Computer Science and Engineering, the University of Texas at Dallas. Her research interest is mainly in database systems, especially in spatial database with applications in geographic information systems and bioinformatics, distributed database in internet system, and wireless database systems with connection to wireless communication. She has published more than 30 research papers in various prestigious journals and conferences. She is an author of the textbook Mathematical Theory of Optimization and an editor of the research monograph Clustering and Information Retrieval. She is a member of the IEEE Computer Society.



Maggie Xiaoyan Cheng Received her Ph.D. Degree from the University of Minnesota, Twin Cities, in 2003. She is an assistant professor in the Department of Computer Science at the University of Missouri, Rolla. Her research interests include wireless networking and mobile computing, sensor and sensor networks, and combinatorial optimization. She is a member of the IEEE.