Cooperative Multicast in Wireless Networks

by

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Submitted to the Program of Media Arts and Sciences,
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In partial fulfillment of the requirement for the degree of

MASTER OF SCIENCE IN MEDIA ARTS AND SCIENCES
at the
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2005

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Abstract

Wireless communication has fundamental impairments due to multi-path fading, attenuation, reflections, obstructions, and noise. More importantly, it has historically been designed to mimic a physical wire; in concept other communicators in the same region are viewed as crossed wires. Many systems overcome these limitations by either speaking more loudly, or subdividing the space to mimic the effect of a separate wire between each pair. This thesis will construct and test the value of a cooperative system where the routing and transmission are done together by using several of the radios in the space to help, rather than interfere. The novel element is wireless, cooperative multicast that could be the basis for a new broadcast distribution paradigm.

In the first part of the thesis, we investigate efficient ways to construct multicast trees by exploring cooperation among local radio nodes to increase throughput and conserve energy (or battery power), whereby we assume single transmitting node is engaged in a one-to-one or one-to-many transmission. In the second part of the thesis, we further investigate transmit diversity in the general context of cooperative routing, whereby multiple nodes are allowed for cooperative transmissions. Essentially, the techniques presented in the second part of the thesis can be further incorporated in the construction of multicast trees presented in the first part.

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Acknowledgements

I would like to thank my advisor Dr Andrew B. Lippman for his mentorship and tremendous support. I greatly appreciate his openness, challenge and understanding, which made my research at MIT enjoyable. I would like to thank Dr David P. Reed for his technical insights and encouragement, which have always been a great source of motivation for my work. I feel lucky to have the opportunity to know him and to interact with him. I would like to thank Dr Philip J. Fleming for his assistance, friendship and constructive comments on all aspects of my research. His candid advice is a great source of inspiration for my research.

My friends and colleagues at MIT made the last two years memorable: Xin, Wei, Jamie, Hector, Kwan, Aggelos, Xu, Xiaohua, Victor, Brian, John, Shie and all other people I have come to know in the US.

I would also like to thank my parents, my brothers, my sister and my wife, Jing Gao, whose support I enjoyed throughout the years.

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Chapter 1

Introduction

Wireless communication has fundamental impairments due to multi-path fading, attenuation, reflections, obstructions, and noise. More importantly, it has historically been designed to mimic a physical wire; in concept other communicators in the same region are viewed as crossed wires. Many systems overcome these limitations by either speaking more loudly, or subdividing the space to mimic the effect of a separate wire between each pair. This thesis will construct and test the value of a cooperative system where the routing and transmission are done together by using several of the radios in the space to help, rather than interfere.

In the first part of the thesis, we investigate efficient ways to construct multicast trees by exploring cooperation among local radio nodes to increase throughput and conserve energy (or battery power), whereby we assume single transmitting node is engaged in a one-to-one or one-to-many transmission. In the second part of the thesis, we further investigate transmit diversity in the general context of cooperative routing, whereby multiple nodes are allowed for cooperative transmissions. Essentially, the techniques presented in the second part of the thesis can be further incorporated in the construction of multicast trees presented in the first part. We determine this as one of our future directions.

The motivation of this work is two-fold. The first is the importance of energy efficiency: a portable radio system's utility for many applications is dependent on how long the battery can last. This is a basic design parameter for military, sensor and consumer networks. We often conserve energy by circuit design and operation (for example, see [4], where clock speed is varied to save power.) Others use multiple antennas (diversity) [10] to conserve radiated power. We will explore cooperation, where multiple nodes join in transmission to achieve similar savings as diversity.

The second motivation is scalability. In large and dense wireless networks, transmitting with excessive power on one link leads to interference with other receivers. This limits the throughput of the network -- more radios do not result in more communications. Multi-hop networks [1,2,5,7,9,12,13,15-20,25,28,30-33] reduce the power at each node, and thereby limit the spurious radiation in the space. This can help the network scale.

In the first part of this thesis, we extend the notions of cooperative distribution for the sake of energy efficiency to situations where the data is shared among many subscribers. The assumption has always been wireless point-to-point communications [13,25,28,33]. We show the utility and benefits of cooperation for broadcast and multicast applications in this thesis. More specifically, we present a random tree optimization approach that transforms the deterministic optimization problem of wireless multicast into a related stochastic one. We apply the cross-entropy method [8,27] to this problem. Preliminary results show that it achieves considerable power savings compared with state-of-the-art approaches.

Please note that we assume single transmitting node is engaged in a one-to-one or one-to-many transmission in the construction of multicast trees in the first part of this thesis. In the second part of this thesis, we explore transmit diversity in the context of cooperative routing where multiple nodes are allowed for cooperative transmissions. The Viral Communications group at MIT Media Lab pioneered the idea of multiple antenna radio systems, where the various antennas were on different nodes in a network, versus being fed from one source and physically distributed. Recently, others have also explored this idea. For example, Khandani et al in [13] showed that such cooperative transmission, where more than one node adds energy to a transmission saves overall energy. We improved on that to show further power savings with a simpler architecture. This is another essential component of this thesis. First, we prove the NP-hardness of the minimum energy cooperative path problem. We then present a cooperative shortest path algorithm to approximate the minimum energy cooperative path. The empirical results indicate that the presented approach tends to make the network more scalable and more efficient compared with existing approaches from both the energy conservation and fairness standpoints.

As mentioned before, the techniques presented in the second part of the thesis can be further incorporated in the schemes for the construction of cooperative multicast trees presented in the first part of the thesis. We determine this as one of our future directions.

Chapter 2

Cooperative Multicast in Wireless Networks

2.1 The Overview

Wireless communication is becoming increasingly important for both voice applications and data applications. Wireless networks are burgeoning at virtually every corner of the World. In particular, a wide range of mission-critical applications have been developed for all-wireless networks, such as battlefield operations for military missions, an emergency relief for terrorist-based biochemical attacks, monitoring of the live images of multiple condition-critical patients by the doctor using hand-held devices while away from the patients, etc. A description of such an all-wireless network was given by Cagalj et al in [1], and basically it consists of numerous devices (also referred as nodes throughout this thesis) that are equipped with processing, memory, wireless communication capabilities, and are linked via short-range ad-hoc radio connections.

Notably, the lifetime of a wireless network is limited due to the power capacity of the energy sources such as batteries. The lifetime of such a wireless network depends on the energy consumption of each node. To increase the longevity of such networks, power-efficient and power-aware protocols and techniques including link layer, MAC, routing and transport protocols must be employed to minimize the power consumption (we will use energy and power interchangeably throughout the thesis).

In this chapter, we focus on the construction of the energy-efficient broadcast tree. The broadcast tree is rooted at the source and should reach all of the desired destination nodes. Following [32], we consider a wireless ad-hoc network in which the node locations are fixed and the channel conditions are unchanged. The situation with the mobility of the nodes in the construction of broadcast tree can be addressed by adjusting the transmitter power to accommodate the new locations of the nodes, which is a topic for future studies. We also assume that the power level of a transmission can be chosen within a given range of values and the use of omni-directional antennas. Thus, all nodes within communication range of a transmitting node can receive its transmission.

Moreover, we assume that sufficient bandwidth resources and ample transceiver resources are available at each node. The energy consumption between the transmitting node and the receiving node is not linear because of the nonlinear attenuation properties of radio signals. Due to the non-linear path loss model of the transmission power, relaying information between nodes may lead to lower power attenuation than communication directly over large distances.

In this thesis, we explore performance improvement by applying the iterative maximum-branch minimization (IMBM) approach [15] to other existing schemes and the empirical results show that considerable power savings can be achieved in particular when the value of the power attenuation factor λ is small.

Our major contribution is the presentation of the random tree optimization (RTO) approach, which is based on the cros s-entropy method [8,27]. The basic idea behind the cross entropy method is to translate the deterministic optimization problem into a related stochastic optimization problem by randomly generating improved sample trees and then use rare event simulation techniques to find the solution. We will show that the RTO method obtains the best performance comparing to state-of-the-art heuristics for the MEB problem.

The rest of this chapter is organized as follows. We discuss related work in Section 2.2. We give the system model in Section 2.3. The power consumption rules are given in Seciton 2.4. We explore further power savings by combining some of the existing schemes in Section 2.5. We present the RTO algorithm in Section 2.6. The experimental results are presented in Section 2.7.

2.2 The Related Work

The multicasting problem in wireless networks has been addressed in several recent studies [1,7,15-20,23,24,30,32]. In particular, [1,7,15-19,30,32] addressed the construction of energy-efficient broadcast and multicast trees in wireless networks. Several interesting heuristics were proposed in [32], which can be roughly divided into two categories: link-based approaches and node-based approaches. As the names suggest, link based approaches, the BLU (Broadcast Least-Unicast-cost) algorithm and the MST (broadcast link-based Minimum-cost Spanning Tree) algorithm, use the link-based costs and further the shortest unicast paths and spanning trees. The node-based approach, i.e., the BIP (Broadcast Incremental Power) algorithm, constructs the broadcast tree incrementally in the sense that new nodes are added to the tree one at a time on a minimum incremental cost basis until all nodes are included in the tree. Compared with the link-based approaches, BIP better exploits the wireless multicast advantage in the construction of the broadcast tree and demonstrates better performance than BLU and MST [32]. However, due to the incremental nature of BIP, it lacks a global view of all the nodes and it can not fully utilize the wireless broadcast advantage to reduce the total required power of the broadcast tree further. In [30], Wan et al presents a quantitative and in-depth analysis on the approximation ratios of the heuristics presented in [32].

In [15], Li et al proved that the MEB problem is NP-hard for the general case. Most recently, Cagalj et al in [1] presented a systematic and elegant proof on the NP-completeness of the MEB problem both for the general case and for the geometric one. A heuristic called EWMA (Embedding Wireless Multicast Advantage) was also suggested in [1]. In EWMA, a distributed MST (Minimum-Spanning Tree) algorithm is executed in the first phase to obtain a feasible broadcast tree. In the second phase of EWMA, the so-called local EWMA is executed at each node in order to exclude some transmitting node from its neighbors to reduce the total required power of the tree by broadcasting or re-broadcasting messages based upon the calculation of the overlapping set for a sender.

An Iterative Maximum-Branch Minimization (IMBM) algorithm is proposed in [15] for the construction of energy-efficient broadcast trees. The algorithm assumes an initial tree and tries to minimize the required power for each transmitting node iteratively by minimizing its maximum branch using wireless broadcast advantage until the total required power for the broadcast tree can not be reduced further.

Das et al in [7] presented several different integer programming formulations of Minimum Power Broadcast (MPB) trees for wireless networks in order to achieve the optimal solution. The number of variables and constraints are at least in the order of $O(N^2)$, where N is the number of nodes in the network. The basic idea is to solve a linear relaxation of the problem first, if the solution is integer, then the algorithm terminates with an optimal solution. If the solution is not an integer it creates two sub-problems and branches down on a fractional variable until no active sub-problem exists any more. The downside of this approach is that problems with as few as 100 nodes can be practically intractable unless they demonstrate some simplified structures.

Other researchers also address the power efficiency issue in the areas of distributed topology control and wireless sensor networks. Rodoplu and Meng [26] proposed a novel distributed position-based network protocol to achieve the minimum-energy network topology. Wattenhofer et al [31] presented an ingenious distributed topology control algorithm for power efficiency in wireless ad-hoc networks based on directional information. In [12], Heinzelman et al proposed a cluster-based protocol to randomly rotate the local cluster base stations to evenly distribute the energy consumption in wireless sensor networks.

In Section 2.6, we propose the Random Tree Optimization (RTO) approach based on the cross-entropy method [8,27] to attack the MEB optimization problem from a different angle.

Our experimental results in Section VI indicate that the RTO method achieves the best results comparing to other methods.

2.3 The System Model

We consider an all-wireless network where numerous devices, i.e., nodes, that are equipped with micro-processor, memory, sufficient bandwidth and transceiver resources, limited power supply such as batteries are linked via short-range radio connections. We study the problem of source-initiated broadcast through which data are disseminated to each of the intended destination node in the network. As stated in Section I, we assume the use of omni-directional antennas and all nodes within communication range of a transmitting node can receive its transmission.

As pointed out in [22], the communication power includes several components such as the path loss, i.e., the power attenuation over the distance between the transmitter and receiver antennas, the start-up energy of the transceiver, the static power drawn by the transmitter and receiver electronics, power amplifier inefficiencies, coding energy and protocol overhead. Following [1,7,13,15-19,28,30,32], we only consider the path loss as the dominant factor of the communication power and most of the other components are static and hardware-dependent and can be easily incorporated in the protocol design.

2.4 The Power Consumption Rules

It is well known that the path loss of the signal power is non-linear. We assume that the required power for a range of d between the transmitting node and the receiving node is proportional to d^{λ}. Typically, λ takes a value between 2 and 4, depending on the characteristics of the communication medium. We assume that the communication medium is uniform, thus λ is a constant throughout the region. Given a source node S and destination nodes $D_1, D_2, ..., D_n$, we want to establish a broadcast tree, rooted at node S and reaching all of the destination nodes, with the least required energy.

Regarding the transmission energy, we have the following definitions:

Definition 2.1: The power required for a transmitting node, say T, to directly reach a set of destination nodes, say $D_1, D_2, ..., D_m$, is determined by the maximum required power to reach any of them individually. For the sake of brevity, throughout this thesis we will use d^{λ} to stand for the required power for a transmitting distance of d. Let $d_1, d_2, ..., d_m$ stand for the distances from the transmitting node T to the destinations $D_1, D_2, ..., D_m$, respectively. The required power is determined by:

$$p_{req} = \max(d_1^{\lambda}, d_2^{\lambda}, ..., d_m^{\lambda}) . \tag{2.1}$$

Definition 2.2: The power required for a broadcast tree is the sum of the energy required for each of the transmitting nodes in the tree. Let $S, T_1, T_2, ..., T_r$ stand for the transmitting nodes for the given broadcast tree and S is the source node and $T_1, T_2, ..., T_r$ are the relaying nodes.

Let $p_S, p_{T_1}, ..., p_{T_r}$ denote the required power for the transmitting nodes $S, T_1, T_2, ..., T_r$ respectively. The required power for the given broadcast tree is given by:

$$p_{tree} = p_S + \sum_{i=1}^{r} p_{T_i} \ . \tag{2.2}$$

The problem can be stated as how to construct a broadcast tree such that the total required energy is minimal.

According to Cayley [3], there are n^{n-2} distinct labeled free trees on n vertices. For if X is a particular vertex, the free trees are in one-to-one correspondence with oriented trees having root X [14]. Therefore, for the case with the root node S and N destination nodes, we have $(N+1)^{(N-1)}$ distinct labeled free trees.

In summary, the general MEB optimization problem is a difficult problem due to the fact that *(a)* the problem is combinatorial and NP-hard; *(b)* the cost function is non-linear, i.e., $d_{i,j}^{\lambda}$ for the required transmitting power from node i to node j and *(c)* the omni-directional nature of the wireless broadcast advantage (see Definition 3.1). To solve this problem, the naïve exhaustive search approach is nearly impossible to use even for a moderate number of nodes. For example, for 13 nodes, the number of the possible broadcast trees is more than 179 billion.

2.5 Combining Existing Approaches

As the IMBM approach [15] assumes an initial tree, an interesting direction is to apply this approach to the broadcast trees generated by other existing algorithms to further minimize the required tree power. In the following experiments, we evaluate the impact of the IMBM algorithm on other existing approaches if we apply IMBM to the trees generated by other approaches. We use the same simulation setup as in [32]. We consider many randomly-generated network examples (50 instances for each round of simulations), in which a specified number of nodes are randomly generated within a square region, say 5×5, the location of each node is randomly generated and the source node is randomly selected among the randomly-generated nodes. For the clarity and simplicity of the comparison, we use the same assumption as that in [32] that each node has enough power to cover all the other nodes and the power level of each node can be adjusted within a given range. We also consider the propagation loss exponents of $\lambda=2$, $\lambda=3$, and $\lambda=4$ in our experiments. For the performance comparison between the algorithms, we consider normalized tree power. For example, suppose we have three approaches to generate broadcast trees, say approaches A, B and C. Let p_A, p_B and p_C stand for the required tree power for the trees generated by approaches A, B and C, respectively for the same network topology. The normalized tree power for each of these approaches is given by the following:

$$p_A^{\cdot} = \frac{p_A}{\min(p_A, p_B, p_C)},$$

$$p_B^{\cdot} = \frac{p_B}{\min(p_A, p_B, p_C)},$$

$$p_C^{\cdot} = \frac{p_C}{\min(p_A, p_B, p_C)}. \quad (2.3)$$

As reported in [32], the performance of BLU approach is always much worse than BIP and MST. We therefore only examine the impact of IMBM on BIP and MST.

2.5.1 BIP+IMBM vs BIP

Table 2-1 shows the performance comparison between BIP+IMBM and BIP in a variety of circumstance, e.g., networks with different number of nodes $(N = 20,40,60)$ and different power attenuation factor values $(\lambda = 2,3,4)$. The average tree power decrement ratio after the application of IMBM to the trees generated by BIP ranges from 3.5% to 7.6% for each round of the experiments. We can also observe that the decrement ratio of the tree power after the application of IMBM slightly shrinks with the increasing of the λ value. The same trend holds with the increase of network density. This suggests that the incremental approaches like BIP works well for the networks with high node-density in fast power attenuation environments.

	$\lambda = 2$	$\lambda = 3$	$\lambda = 4$
N= 20	7.6%	5.6%	3.8%
N= 40	6.7%	5.3%	3.5%
N= 60	6.6%	4.6%	3.6%

Table 2-1: Average decrement ratio of the normalized tree power after applying IMBM to the broadcast trees generated by BIP (50 randomly-generated network instances for each group).

2.5.2 MST+IMBM vs MST

Table 2-2 depicts the performance comparison for MST+IMBM versus MST in the same settings as above. The average tree power decrement ratio after the application of IMBM to the broadcast trees generated by MST ranges from 3.5% to 8.6%, depending on the network densities and λ values for each round of the experiments. Similarly, we can observe that the decrement ratio of the tree power slightly shrinks with the increasing of the λ value, the increasing of the network density. Again, this suggests that both MST and BIP work well in a network with high node-density in fast power attenuation environments.

	$\lambda = 2$	$\lambda = 3$	$\lambda = 4$
N= 20	8.5%	6.4%	4.7%
N= 40	6.7%	5.0%	3.7%
N= 60	6.7%	5.0%	3.6%

Table 2-2: Average decrement ratio of the normalized tree power after applying IMBM to the broadcast trees generated by MST (50 randomly-generated network instances for each group).

In summary, the key findings are: (a) IMBM consistently improves the performance of the existing approaches like MST and BIP after the application of IMBM to the broadcast trees generated by these existing approaches. (b) IMBM's impact varies with different network densities and different λ values in both cases.

2.6 The RTO Algorithm

As we discussed in Section II, although the integer programming approach [7] can solve small-sized problems exactly, it will run into problems when the number of nodes in the network becomes large. For example, even when the number of nodes in the network greater than 10, the number of variables and constraints according to the Integer Programming (IP) formulations presented in [7] are both greater than 100, which is beyond the abilities of even the most powerful computers today. The Cross Entropy (CE) method, (see, e.g., Rubinstein et al [8,27]) is a useful meta-heuristic optimization method for finding near-optimal solutions in a variety of combinatorial optimization problems. The basic idea is to translate the deterministic optimization problem into a related stochastic optimization one and then use Rare Event Simulation (RES) techniques to find the solution.

We call the specification of the CE method to MEB problem the Random Tree Optimization (RTO) algorithm. We will see in the following that the algorithm operates iteratively by randomly generating improved sample trees until the optimization process converges based on our predefined performance function, i.e., the total required power of the tree.

First, we define the performance function $F(tree)$ as the total required power of a tree, which is given according Definition 2.2 (see Equation 2.2). There are two key components in the RTO process based on CE: (1) Generation of random sample trees; (2) Update of the parameters at each iteration. The update mechanism is supposed to encourage trees with high performance so that the randomization mechanism would lead to trees with even better performance.

We use a Markov chain that starts at the root node and stops after all of the destination nodes are reached to construct a sample tree. We define $Q = (q_{i,j})_{((N+1)\times(N+1))}$ as the one-step transition matrix, where $q_{i,j}$ denotes the probability that there is a transmission from node i to node j. We can observe that the sum of each column in the matrix has to be one as each destination has to be reached with certainty.

In order to find local neighbors first to avoid some "far-reached" transmissions to dominate the total required power of the tree, which could potentially degrade the performance of the RTO optimization process, the initial transition matrix Q_0 can be set as follows: (a) the column corresponding to transmissions to the root node in the matrix and the diagonal elements are set to *zero* as no node transmits to itself and no node transmits to the root node; (b) for other elements $q_{i,j}$, we have

$$q_{i,j} = \frac{1/(d_{i,j}+c)^{\lambda}}{\sum_{j(j\neq i)} \frac{1}{(d_{i,j}+c)^{\lambda}}}, \tag{2.4}$$

where c is a constant that is related to the diameter of the network. When c is zero, the transition probability $q_{i,j}$ is solely determined by the distance between node i and node j.

When c is much bigger than the diameter of the network, the transition probabilities in each column of the matrix are almost uniform. We will discuss this issue further in section VI.

In the following, we give a brief description of the random tree generation algorithm:

2.6.1 Random Tree Generation for RTO

The Random Tree Generation Algorithm:

1. Let $l = 1$.
2. Randomly choose a non-root node from the non-parented nodes (nodes who do not have parent node yet), say node n_i, then randomly choose a parent node for node n_i from its non-descendent nodes (nodes who are not under n_i's hierarchy) based on the transition probabilities given in the matrix Q.
3. If $l = N-1$ then stop; otherwise set $l = l+1$ and reiterate from step 2.

2.6.2 Speedup of the Random Tree Generation Algorithm

We use N-bit bitmap array for each node to indicate the ancestor-descendent relationship. During the tree generation process, when finding a parent node for a given node, we set this parent node and the parent node's ancestors as this given node's ancestors. It should be noted that when a given node's ancestors are updated, all of this node's descendents also need to inherit its updated ancestors. When checking the ancestor-descendent relationship to find a random parent node, it is faster to do so by directly examining the value of the bitmap array instead of a recursive search. The complexity of the resulted random tree generation algorithm is in the order of $O(N^3)$, where N is the number of nodes in the network.

2.6.3 Exploitation of Wireless Broadcast Advantage

During the process of the random selection of a parent node for a given node in random tree generation algorithm, we use a procedure called RandomFreeParent( ) to check that if there are some transmitting nodes in the current structure such that the given node is located in their coverage area. We call the nodes whose transmissions already covers a node the node's free parent as it does not need any additional power consumption by randomly choosing one of them to fully exploit the wireless broadcast advantage (WBA). If no free parent node can be found for this given node, we randomly choose one of its non-descendent nodes as its parent node based on the transition probability matrix.

2.6.4 The Criticality of Randomness

The randomness of the tree generation procedure is the key to the effectiveness and efficiency of the RTO algorithm. For example, we can have a seemingly random tree generation algorithm as follows:

1. Let $l = 1$ and include the root node only as the initial tree.
2. Randomly choose a node that is not yet included in the tree, say node n_i, then randomly choose a parent node for node n_i from those nodes that are already included in the tree based on the transition probabilities given in the matrix Q.

3. If $l = N - 1$ then stop; otherwise set $l = l + 1$ and reiterate from step 2.

Experimentally, we found that this seemingly random tree generation procedure leads to severely degraded performance of an RTO algorithm because this tree generation algorithm is not perfectly random as it gives biased priority to the root node.

We now turn our attention to the update algorithm. At each iteration of the RTO algorithm based on the CE method, we need to calculate the benchmark value of γ_t as follows:

$$\gamma_t = \min\{f : Q_{t-1}(F(T) \le f) \ge \rho\}, \tag{2.5}$$

where ρ normally takes a value of 0.01 so that the event of obtaining high performance is not too rare, $F(T)$ stand for the total required power of a randomly-generated sample tree, say T, based on the one-step transmission probability matrix in the $(t-1)^{th}$ round, e.g., Q_{t-1}, $P_{Q_{t-1}}(A)$ denote the probability of the event A conditioned on Q_{t-1}. Essentially, γ_t is the sample ρ-quantile of the performance of the randomly generated trees.

There are several choices to set the termination conditions. Normally, If for some $t \ge l$, say $l = 5$,

$$\gamma_t = \gamma_{t-1} = \ldots = \gamma_{t-l}, \tag{2.6}$$

then stop the optimization process.

The updated value of $q_{i,j}$ can be estimated as:

$$q_{i,j}^{e} = \frac{\sum_{k=1}^{M} H_{\{F(T_k)\le\gamma\}} H_{\{T_k \in T_{i,j}\}}}{\sum_{k=1}^{M} H_{\{F(T_k)\le\gamma\}}}, \qquad (2.7)$$

where M stands for the number of sample trees, $H_{\{\}}$ is an indicator function, $T_{i,j}$ denotes the set of trees in which there is a transmission from node i to node j. While there are solid theoretical justifications for Equation (2.7), we refer the readers to [8,27], and focus on the algorithms that were implemented in practice. In order to avoid overly quick convergence to 1s and 0s for the update of $q_{i,j}$, which could limit the randomness of the sample trees, normally we use a smoothed update procedure in which

$$q_{i,j}^{t} = \alpha \times q_{i,j}^{e} + (1-\alpha) \times q_{i,j}^{t-1}, \qquad (2.8)$$

where $q_{i,j}^{t-1}$ is the value of $q_{i,j}$ in the previous round and $q_{i,j}^{e}$ is the estimated value of $q_{i,j}$ based on the performance in the previous round according to Equation (2.7), and $q_{i,j}^{t}$ stands for the value of $q_{i,j}$ for the current round. Empirically, a value of α between $0.4 \le \alpha \le 0.9$ gives the best results [27].

In summary, we have a brief description of the RTO algorithm as follows:

2.6.5 RTO Algorithm based on Cross-Entropy (CE) method

1. Set $t = 1$ and set Q_0 according to the initialization of $q_{i,j}$ in Equation (2.4).

2. Randomly generate sample trees (normally we generate $20N^2$ sample trees).

3. Calculate γ_t according to Equation (2.5).

4. Update $q_{i,j}$ according to Equation (2.7) and Equation (2.8).

5. If for some $t \geq l$, say $l = 5$, such that $\gamma_t = \gamma_{t-1} = ... = \gamma_{t-l}$, then stop; otherwise, reiterate from step 2.

2.6.6 Speedup of the RTO process

As discussed before, the complexity of the random tree generation algorithm is in the order of $O(N^3)$ and normally we generate $20N^2$ sample trees for each round. Therefore, the overall computation complexity of the RTO algorithm is in the order of $O(N^5)$. For a large value of N, the RTO process could be slow. We use the following strategies to speed up the RTO algorithm: (a) Ignore small transition probabilities, say for $q_{i,j} < 0.01$, we force them to be zero and renormalize it for each column of the transition probability matrix. (b) Set a looser termination criterion. Normally, we set $l = 5$ for the termination condition according to Step 5 of the RTO algorithm. When N is large, we opted to set $l = 2$ instead, and we use a fast localized greedy routine to further optimize the tree generated by RTO.

In the following section we present extensive experiments that evaluate the performance of the RTO algorithm.

2.7 Performance Evaluation

Following similar assumptions and settings in Section 2.5, we examine the dynamics of the RTO algorithm and its performance compared with existing approaches in a variety of setups.

Table 2-3 shows the average power saving ratio of the broadcast trees generated by RTO compared with BIP for the same network topologies with different number of nodes and different power attenuation factor values. Clearly, the RTO algorithm outperforms BIP across the all setups. In comparison with Table 1, we observe that RTO performs better than combining BIP with IMBM. The advantage of RTO over BIP with IMBM is most noticeable for λ equals 2, where the average power saving is around 10%.

	$\lambda = 2$	$\lambda = 3$	$\lambda = 4$
N=20	15%	8%	6%
N=40	19%	9%	7%
N=60	16%	6%	6%

Table 2-3: Average power saving ratio of the normalized tree power of the broadcast trees generated by RTO compared with BIP (50 randomly-generated network instances for each group).

Table 2-4 demonstrates the average power saving ratio of the broadcast trees generated by RTO compared with MST for the same network topologies for three values of λ. In comparison with Table 2-2, we can clearly see that RTO performs better than MST+IMBM, in particular when λ equals 2, the average power saving is around 20%.

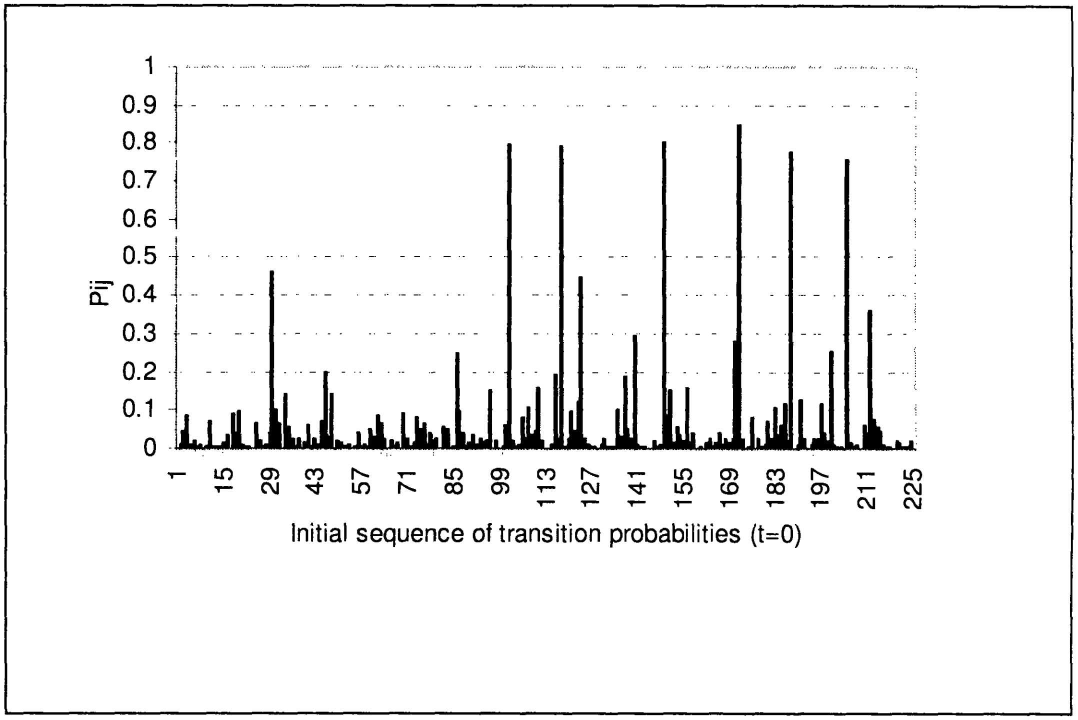
	$\lambda = 2$	$\lambda = 3$	$\lambda = 4$
N=20	28%	14%	8%
N=40	26%	15%	9%
N=60	27%	9%	9%

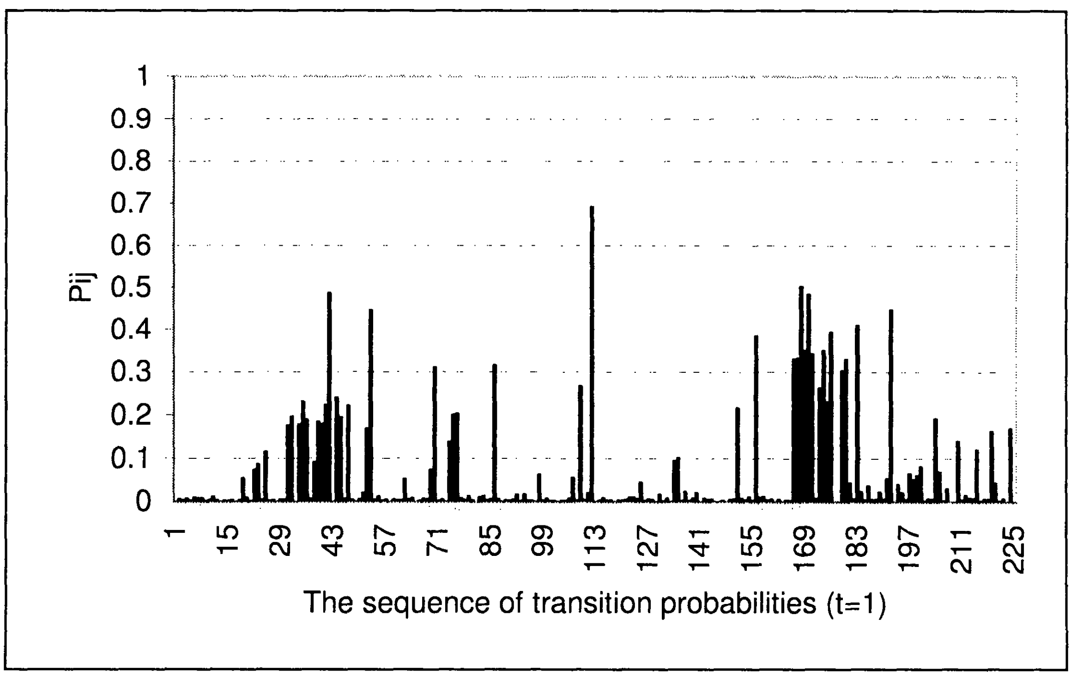
Table 2-4: Average power saving ratio of the normalized tree power of the broadcast trees generated by RTO compared with MST (50 randomly-generated network instances for each group).

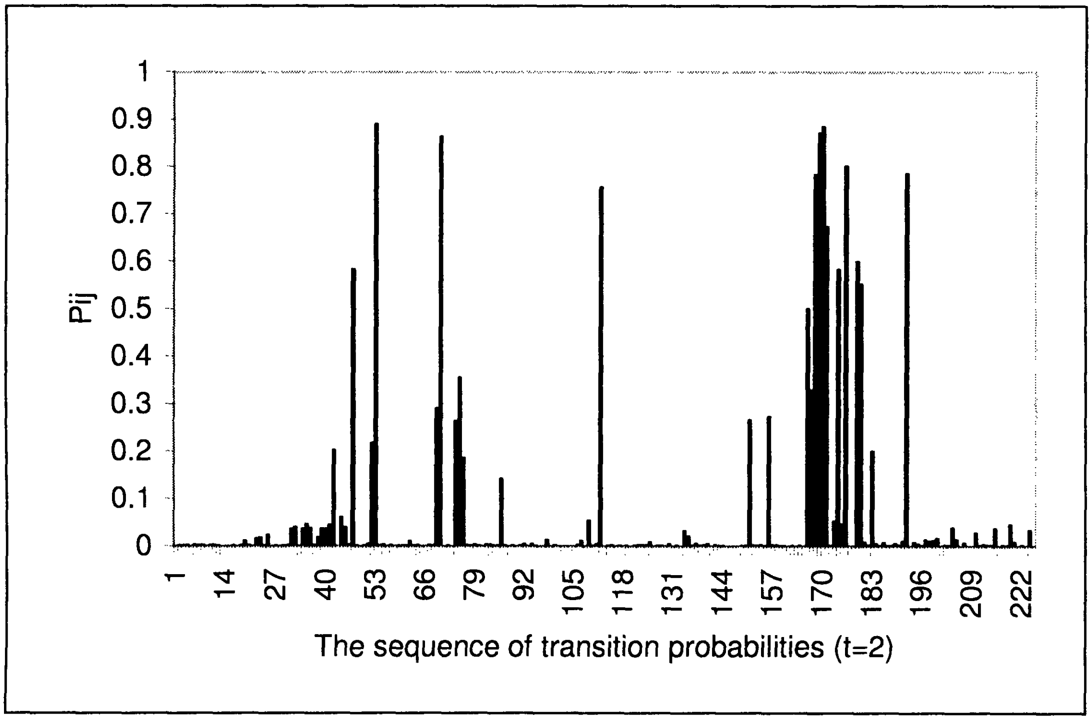
In order to provide some more insight into the inner working of the RTO algorithm, we show the evolution of the transition probability matrix for a single run of the RTO algorithm in Figure 2-1. We randomly generated $N=15$ nodes, and set λ to 2. The initial sequence of the $q_{i,j}$s is based on Equation (4), with c set to zero.

In the Figure 2-1, we plot a histogram of all the $q_{i,j}$s for different iterations. The y-axis denotes the one-step transition probability. The x-axis stands for the sequence of the elements in the probability matrix and we have a total of $15 \times 15 = 225$ ($N=15$) elements in the matrix.

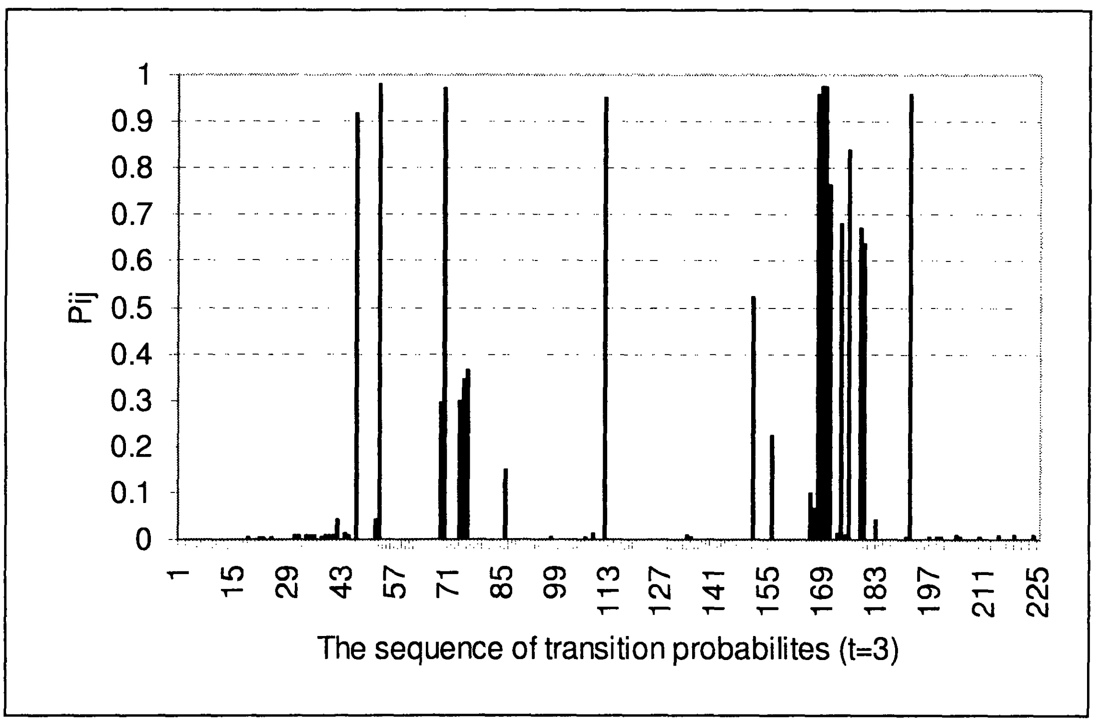
As typical to the CE method, the transition probabilities quickly converges with some transition probabilities converging to one and others to zero. Essentially, transitions that lead to good solutions are reinforced and transitions that lead to poor solutions become smaller.







Pij
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1
14
27
40
53
66
79
92
105
118
131
144
157
170
183
196
209
222
The sequence of transition probabilities (t=2)



Pij
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1
15
29
43
57
71
85
99
113
127
141
155
169
183
197
211
225
The sequence of transition probabilites (t=3)

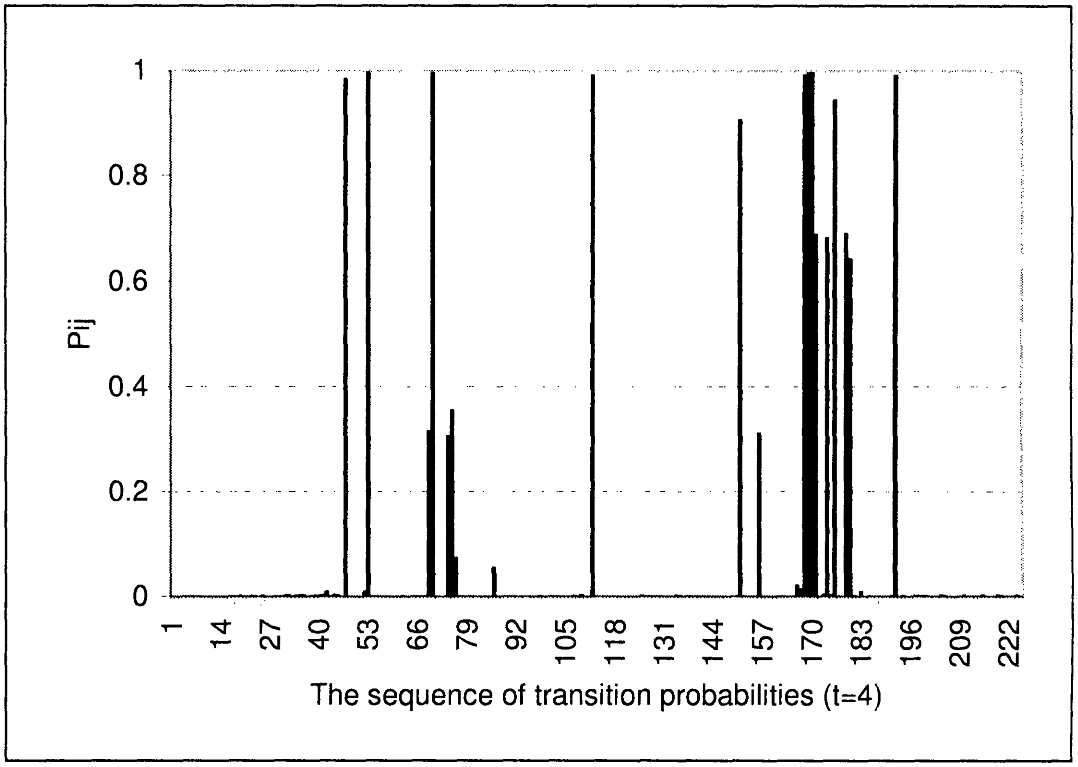


Figure 2-1: An illustration of an example run of the evolving of the transition probability matrix (N =15, λ =2) during the RTO process.

In order to demonstrate the robustness of the RTO algorithm to its parameters, we varied the smoothing parameter α.

In Table 2-5 and Table 2-6 we provide the normalized tree powers by RTO, BIP and MST for 30 randomly-generated network instances with different values of the transition probability update smoothing factor α.

The number of nodes in the network, i.e., N, is 15, and the value of λ is 2. For the results reported in Table 2-5, the value of α is **0.8**. For the results reported in Table 2-6, the value of α is **0.7**. In Table 2-5, the average normalized tree power for RTO, BIP and MST are 1.0, 1.20 and 1.325, respectively. The standard deviation for RTO, BIP and MST are 0.0, 0.12 and 0.15, respectively. In Table 2-6, the average normalized tree power for RTO, BIP and MST are 1.0006, 1.23 and 1.31, respectively.

It can be observed that RTO outperforms the other two algorithm in terms of both average performance and low standard deviation. In the following experiments, we use the value of 0.8 for α unless explicitly specified otherwise. By examining the values in Table 2-5 and Table 2-6, we observe that RTO significantly outperforms BIP and MST for N is 15 and λ is 2. In some cases, RTO saves as much as 60% to 90% power compared with BIP and MST.

	MEAN NORMALIZED TREE POWER	STANDARD DEVIATION
RTO	1.0	0.0
BIP	1.20	0.12
MST	1.325	0.15

Table 2-5: Normalized tree power by RTO, BIP and MST for 30 randomly generated networks. The number of nodes in the network, i.e., N, is 15, the value of λ is 2 and the value of α is **0.8**.

	MEAN NORMALIZED TREE POWER	STANDARD DEVIATION
RTO	1.0006	0.0029
BIP	1.23	0.19
MST	1.31	0.17

Table 2-6: Normalized tree power by RTO, BIP and MST for 30 randomly generated networks. The number of nodes in the network, i.e., N, is 15, the value of λ is 2 and the value of α is **0.7**.

We now consider the other parameter of the RTO method – the initialization procedure. In Figure 2-2 and Figure 2-3 we present the average normalized tree power by RTO, BIP and MST with different initialization methods of the transition probability matrix when the value of λ is 2.

For the results in Figure 2-2, we initialize the probability matrix according to Equation (4), when N is less than 40, we choose c as zero; when N is between 40 and 60, we choose c as half of the diameter of the network; when N is greater than 60 se choose c as the diameter of the network. For the results in Figure 2-3, the initial transition matrix is set with equal probability of $\frac{1}{N-1}$ for each $q_{i,j}$ (this is equivalent to choosing a large c).

The number of nodes in the network ranges from 10 to 100 in Figure 2-2 and the number of nodes ranges from 10 to 60 in Figure 2-3. Notably, for a small value of N, say N is less than 40, both initialization methods lead to good performance of RTO, while for a large value of N, the performance of the equal probability initialization method degrades, as shown in Figure 2-3. We attribute this to the fact that equal probability initialization method does not reflect the power requirement for each transition. Consequently, when the number of nodes is large, the algorithm fails to generate any "good" trees to start with and only generates trees whose power requirements are large.

From Figure 2-2, we can also observe that when the number of nodes in the network is less than 20, RTO performs slightly better compared with the case for a larger number of N. This could result from several factors: firstly, we choose to generate $20N^2$ sample trees for each round and this could certainly give some advantage for an N smaller than 20. If we choose to generate N^3 sample trees, we expect that the curve could be flat but the algorithm would be slower. Secondly, we use a loose termination criterion for a large N to speed up the RTO process and this could also cost some performance gains.

Figure 2-4 and Figure 2-5 show the results of the normalized tree power by RTO, BIP and MST for the same network topologies with different number of nodes when the value of λ is 3 and 4 respectively. Clearly, the power savings by RTO compared with BIP and MST degrades with a larger value of λ. This trend is consistent with the results of EWMA compared with BIP and MST reported in [1]. As λ becomes large, the advantage of using the RTO method degrades since incremental approaches like BIP and MST performs reasonably well for a fast power attenuation environment. For example, for a very large value of λ, the best trees would connect every node to its closest neighbor (since any transmission beyond the minimal possible is prohibitive). Since our performance measure is the ratio between performances, the advantage of the RTO becomes less significant for large values of λ.

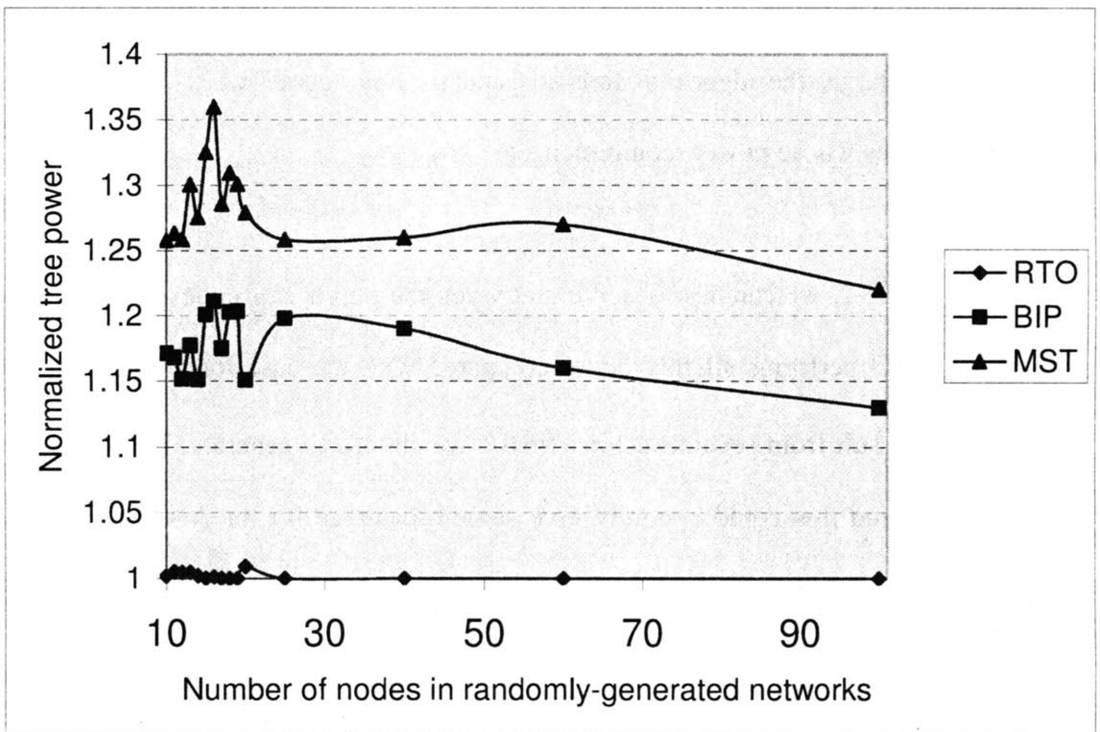


Figure 2-2: Average normalized tree power by RTO, BIP and MST (average over 60 randomly generated network instances for networks with a fixed number of nodes) with different number of nodes in the network and adaptive transition probability matrix initialization for RTO. The value of λ is 2.

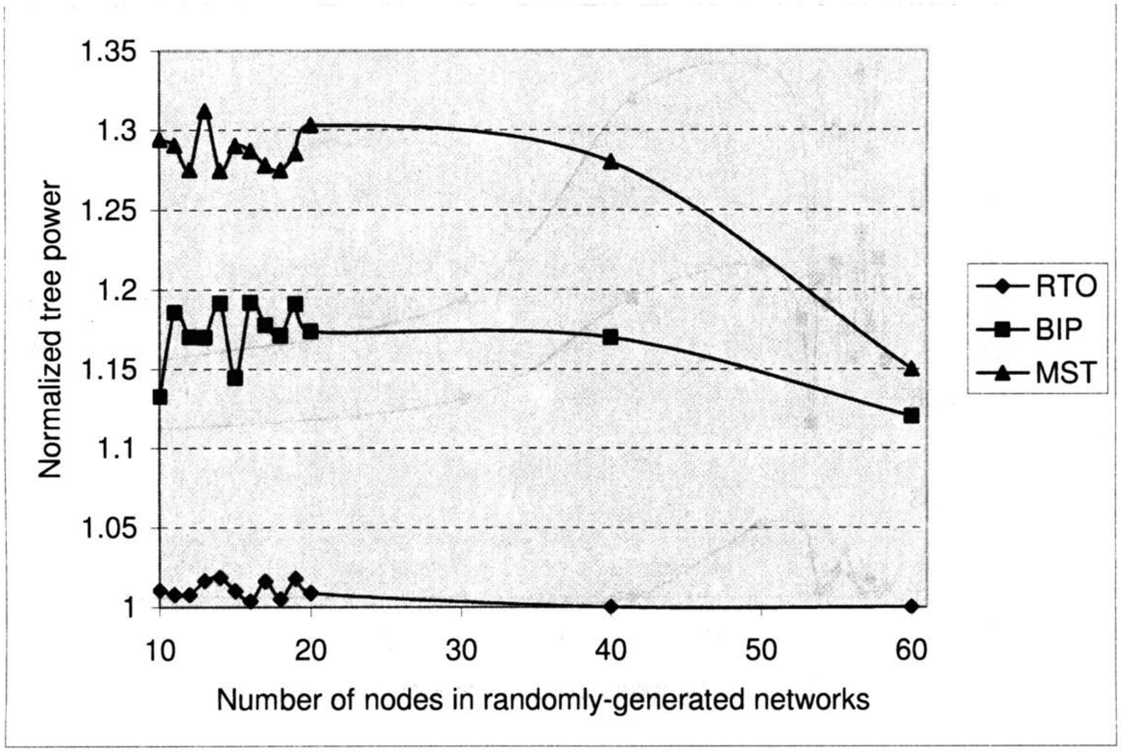


Figure 2-3: Average normalized tree power by RTO, BIP and MST (average over 60 randomly generated network instances for networks with a fixed number of nodes) with different number of nodes in the network and equal-probability initialization of the transition probability matrix for RTO. The value of λ is 2.

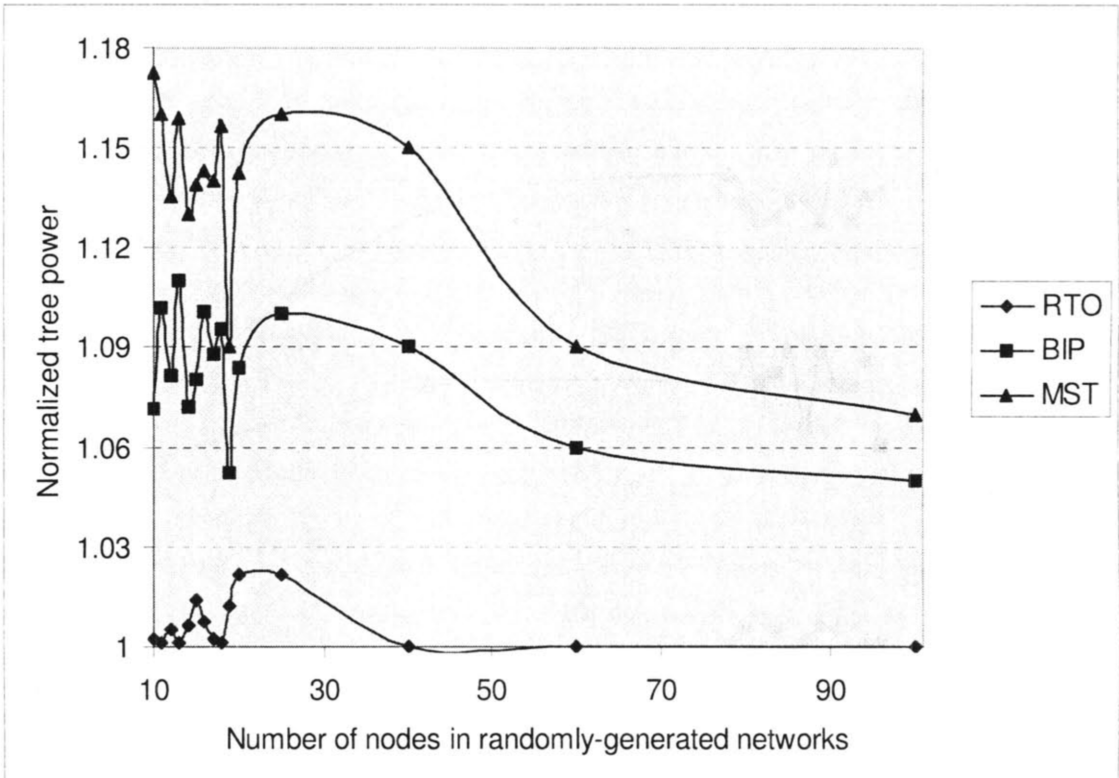


Figure 2-4: Average normalized tree power by RTO, BIP and MST (average over 60 randomly generated network instances for networks with a fixed number of nodes) with different number of nodes in the network. The initial transition matrix is set according to Equation (4). The value of λ is 3.

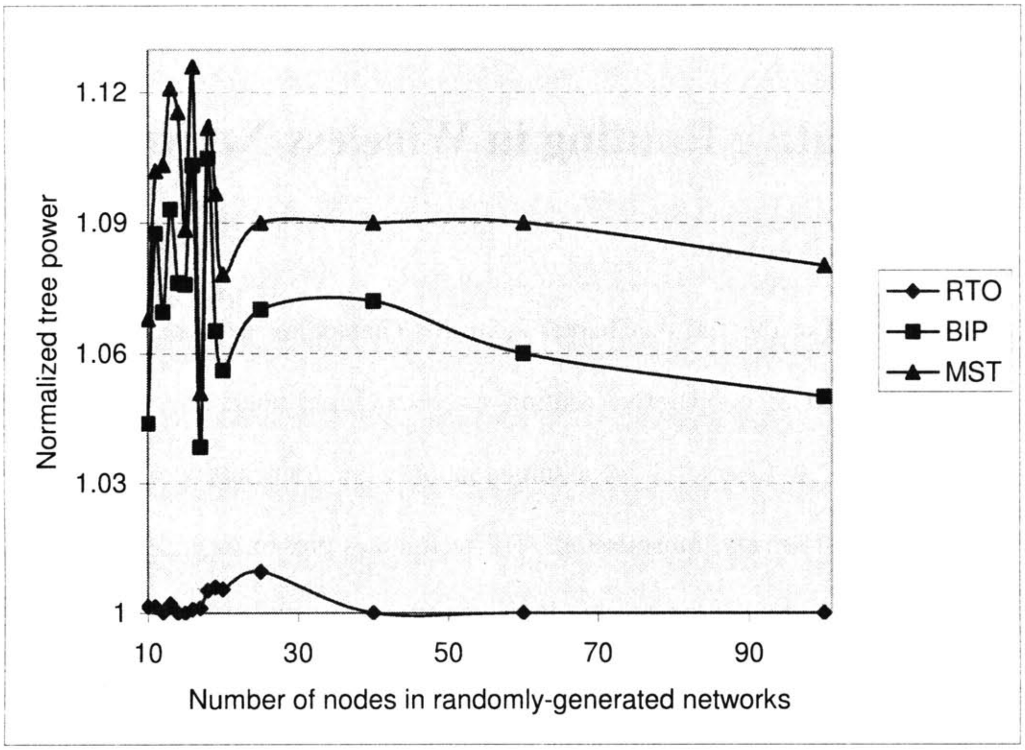


Figure 2-5: Average normalized tree power by RTO, BIP and MST (average over 60 randomly generated network instances for networks with a fixed number of nodes) with different number of nodes in the network. The value of λ is 4.

Notably, in this chapter we assume that only one transmitting node is engaged in a one-to-one or one-to-many transmission. In the next chapter, we will explore transmit diversity in the general context of cooperative routing, whereby multiple nodes are allowed for cooperative transmissions. The techniques presented in the next chapter can be further incorporated in the approaches for the construction of cooperative multicast trees proposed in this chapter.

Chapter 3

Cooperative Routing in Wireless Networks

3.1 The Overview

As mentioned at the end of Chapter 2, in this chapter we explore transmit diversity in the general context of cooperative routing where multiple nodes are allowed for cooperative transmissions. In Chapter 2, we assume that only one transmitting node is engaged in a one-to-one or one-to-many transmission. The techniques presented in this chapter can be further incorporated in the approaches for the construction of cooperative multicast trees presented in Chapter 2. Cooperative routing approach allows multiple nodes along the path for cooperative transmission (transmit diversity) to the next hop so long as the combined signal at the receiver satisfies the threshold value of *SNR* (signal-to-noise ratio). We say a transmission is successful only if the *SNR* of the received signal at the receiver is above a given threshold value, say SNR_{min}. The threshold value of SNR_{min} is chosen to achieve a desired *BER* (bit error rate) for the given modulation scheme and data rate [28]. Traditional routing scheme solely assumes the role of route selection based on some criteria such as the number of hops on the path, the cost of the path and/or some QoS parameters, while the cooperative routing approach combines route selection and the exploration of transmit diversity and the resulted cross-layer design method may be beneficial in wireless networks.

The motivation of this work is two-fold. The first is the importance of energy efficiency in wireless networks. The lifetime of a wireless network is limited due to the limited power capacity of the energy sources at each node such as batteries. The lifetime of such a wireless network totally depends on the energy consumption of each node. To increase the longevity of such networks, power-efficient and power-aware protocols and techniques including link layer, MAC, routing and transport protocols must be employed to minimize the power consumption (we will use energy and power interchangeably throughout the thesis). As will be seen later in this chapter, the cooperative shortest path algorithm can save about 30~50% power compared with non-cooperative shortest path algorithm, depending on the node density of the network. The empirical results indicate that as more nodes added in the network, more power savings compared with non-cooperative scheme can be achieved by the presented approach in that a dense network offers more opportunities for cooperative transmission.

The second motivation is for the scalability of the network. Wireless networks face scalability problems, in particular in large and dense networks, as transmitting with excessive power on one link often leads to severe interference to other links in the system. As discussed in [28], a wireless link is rather a "soft" concept in the sense that a "link" exists between two wireless nodes if the transmitting node transmits with sufficiently high power such that the SNR at the receiving node is above a given threshold, say $SNR_{\min}$. Moreover, wireless channel inherently has fundamental impairments due to multi-path fading, attenuation, reflection, obstruction, etc., besides interference and noise. As such, our objective is to optimize the distribution of information by exploring transmit diversity and to minimize the wireless channel impairment effects via cooperation among nodes in the network such that the network scales well. Further, optimizing the transmissions to achieve more fairness among nodes also makes the network more scalable in that fairness in resource allocation often leads to maximized transmission capacity. The concept of fairness here means the distribution of information in the network is optimized in such a way that each node is treated fairly based on the pre-defined utility function for each node (we will have more discussion on this in Section 3.6). As we will see later in the thesis that the cooperative routing approach substantially reduces the total consumed power along the path compared with the non-cooperative counterpart. Hence, the presented approach leads to less interference among transmitting nodes with considerably reduced transmitting power. Moreover, the experimental results also suggest that as more nodes added in the network, our approach achieves more fairness while the fairness curve for other existing schemes are mostly flat (see Fig. 3-6 for details).

The minimum energy cooperative path routing problem in wireless networks has been recently addressed in [13] and several heuristic algorithms were developed to approximate the minimum energy route based on non-cooperative shortest-path algorithm. One of the presented algorithms in [13] is called CAN (cooperative along non-cooperative shortest path). The basic idea is to run a non-cooperative shortest path algorithm to obtain the cooperative path. The computational complexity of CAN algorithm is in the order of $O(N^2)$, where N is the number of nodes in the network. Let L denote the number of nodes that are allowed for cooperative transmission along the path, and following [13] we always assume that the last L nodes along the path for cooperative transmission to the next hop. Another heuristic algorithm presented in [13] is called Progressive Cooperation (PC) algorithm. The PC algorithm operates progressively by iteratively calculating the non-cooperative shortest path from the Super node (initialized as the source node only) to the destination node based on updated link cost and combining the last L nodes along the current best path as one single Super node until the destination is included. Our presented cooperative shortest path algorithm (**CSP**) operates differently with the PC algorithm in that the CSP algorithm proceeds as a cooperative version of Dijkstra's algorithm with a new relaxation procedure to reflect the cooperative transmission cost and every time one un-included node with the least cooperative transmission cost along the current best path from the source node is added to the list who already find the cooperative shortest path from the source node instead of calculating the whole non-cooperative shortest path to include $(L-1)$ new nodes at one time. The resulted CSP algorithm has the complexity of $O(N^2)$, while the complexity of the PC algorithm is in the order of $O(N^3)$.

Our work builds upon that of Khandani et al [13]. In this thesis, we first prove that the minimum energy cooperative path (MECP) problem is NP-complete. We then propose a cooperative shortest path algorithm (CSP) that uses Dijkstra's algorithm as the basic building block and reflects the cooperative transmission properties in the relaxation procedure. Our approach consistently outperforms the heuristics in [13] in terms of energy consumption for the same settings with the same computational complexity of $O(N^2)$ as that of CAN algorithm (again, N is the number of nodes in the network). Another interesting finding is that the presented approach achieves more fairness as more nodes added in the network, which reflects the fact that the cooperative shortest path algorithm adapts itself more efficiently to the cooperative routing settings and better exploits the cooperative opportunities among nodes in the network.

Another closely related work by Catovic et al in [2] referred the concept of cooperative routing as power combining . They present approaches to explore transmit diversity via user cooperation in next generation wireless multi-hop networks. The network model used in [2] greatly differs from that assumed in [13]. We will discuss the detailed network model and assumptions in Section 2. In essence, Catovic et al assume that the m-finger RAKE receivers are used for wideband communications and each finger is in charge of the reception of the signal from a different transmitter. Khandani et al in [13] consider that conventional receivers are used and the channel parameters are estimated by the receiver and fed back to the transmitter. It is essentially a tradeoff between the use of complex receivers, e.g., the m-finger RAKE receivers, and the complexity to implement the feedback mechanism. The bottom line is that the feedback-based model in [13] can achieve more energy savings due to the coherent combining of the signals from multiple transmitters. Nevertheless, the basic framework of the algorithm presented in this thesis can be equally applicable to other cooperative routing environment, e.g., different fading/attenuation models, different receiver types, etc.

Other researchers also address the power efficiency issue in wireless networks. Wieselthier et al [32], Calgalj et al [1] and Liang [19] presented approaches for the construction of minimum energy broadcast trees in wireless networks. In particular, the seminal work by Wieselthier et al in [32] elucidates many fundamental aspects of energy-efficient routing in wireless networks. Rodoplu and Meng [26] proposed a novel distributed position-based network protocol to achieve the minimum-energy network topology. Wattenhofer et al [31] presented an ingenious distributed topology control algorithm for power efficiency in wireless ad-hoc networks based on directional information.

Min and Chandrakasan address the energy consumption issues of wireless communication in [22]. In [9], Feeney and Nilson reveal that nodes usually spend most of their energy in communication in wireless ad hoc networks. Srinivas and Modiano [28] presented algorithms for finding minimum energy disjoint paths in wireless ad hoc networks for the sake of energy efficiency and reliability. The work in [28] elucidates many of the network model concepts that are used in this work.

The major contribution of this thesis is the proof of the NP-completeness of the minimum energy cooperative path (MECP) problem, the development of a cooperative shortest path (CSP) algorithm for cooperative routing in wireless networks and the exploration of the impact of the presented approach on energy savings, fairness and network scalability compared with existing approaches.

The rest of this chapter is organized as follows. We give the description of the system model in Section 3.2 and the problem formulation in Section 3.3. We prove the NP-completeness of the minimum energy path problem in the context of cooperative routing in Section 3.4 and we present a cooperative shortest path algorithm for cooperative routing in Section 3.5. The experimental results, which are presented in Section 3.6, demonstrate the high performance of our algorithm compared with other cooperative routing algorithm and non-cooperative shortest path algorithms. Distribution and implementation issues are discussed in Section 3.7.

3.2 The System Model

3.2.1 The Network Model

We consider an all-wireless network consisting of N devices, i.e., nodes, that are equipped with micro-processor, memory, sufficient bandwidth and transceiver resources, limited power supply such as batteries are linked via short-range radio connections. We assume the use of omni-directional antennas and all nodes within communication range of a transmitting node can receive its transmission.

Following [13], we also assume that the power level of a transmission can be chosen at each node within a given range of values, say [0, P_{max}]. We assume that the channel parameters are estimated by the receiver and fed back to the transmitter. Each node can thus dynamically adjust its transmitted signal phase to possibly synchronize with other nodes, which can be realized by pre-compensation before transmitting based on the estimate of the phase and delay at each path as discussed by Tu and Pottie in [29]. This assumption is reasonable for slowly varying channels in that the channel coherence time is much longer than the block transmission duration.

3.2.2 The Power Consumption Model

It is well known that the signal power attenuation in wireless communication is non-linear. We consider a commonly used wireless propagation model [1,7,13,15-19,28,30,32] whereby the received signal power attenuates $d^{-\lambda}$, where d stands for the distance between the transmitting node antenna and the receiving node antenna and λ takes a value between 2 and 4, depending on the characteristics of the communication medium. We assume that the communication medium is uniform, thus λ is a constant throughout the region. Following [28], without loss of generality, we assume that the required power to support a wireless link at a given data rate between node i and node j is given by

$$P_{i,j} = d_{i,j}^{\lambda} \tag{3.1}$$

where $d_{i,j}$ denotes the distance between node i and node j. We say node i can reach node j if and only if the transmitting power at node i is greater than or equal to $d_{i,j}^{\lambda}$. Notably, each node can add or remove links by adjusting its transmitting power levels, hence the network topology totally depends on the transmitting range of each node.

Regarding the transmission energy, we have the following definitions:

Definition 3.1: The power required for a transmitting node, say t, to directly reach a set of destination nodes, say $r_1, r_2, ..., r_m$, is determined by the maximum required power to reach any of them individually and other nodes essentially get the transmission for free . This is referred to as WMA (wireless multi-cast advantage) by Wieselthier et al in [32]. As discussed before, for the sake of brevity, throughout this thesis we will use d^{λ} to stand for the required power for a transmitting distance of d. Let $d_{r_1,t}, d_{r_2,t}, ..., d_{r_m,t}$ stand for the distances from the transmitting node t to the destination nodes $r_1, r_2, ..., r_m$, respectively. The required power is determined by

$$P_{broadcast} = \max(d^{\lambda}_{r_1,t}, d^{\lambda}_{r_2,t}, \ldots, d^{\lambda}_{r_n,t}). \qquad (3.2)$$

Definition 3.2: Assume that nodes $t_1, t_2, \ldots, t_m$ cooperatively transmit information to a given destination node, say node r, where the received signal from each transmitting node is coherently combined. We say the cooperative transmission is successful if and only if the SNR of the coherently combined signal at the receiving node r is above a given threshold value. As discussed before, the threshold value of $SNR_{\min}$ is chosen to achieve a desired BER (bit error rate) for the given modulation scheme and data rate [28]. Let $d^{\lambda}_{t_1,r}, \ldots, d^{\lambda}_{t_m,r}$ denote the required power for point-to-point transmission to the given destination node r from transmitting nodes $t_1, t_2, \ldots, t_m$ respectively. The discovery by Khandani et al in [13] reveals that the total required power for this cooperative transmission is given by:

$$P_{coop} = \frac{1}{\sum_{i=1}^{m} \frac{1}{d^{\lambda}_{t_i,r}}} \qquad (3.3)$$

And the required power for each of the transmitting node in this cooperative transmission is given by:

$$P_{t_i} = \frac{d^{\lambda}_{t_i,r}}{\sum_{j=1}^{m} d^{\lambda}_{t_j,r}} \times \frac{1}{\sum_{j=1}^{m} \frac{1}{d^{\lambda}_{t_j,r}}}, \ (1 \le i \le m) \qquad (3.4)$$

One observation for Eq. (3.3) is that if $d^{\lambda}_{t_1,r} = \ldots = d^{\lambda}_{t_m,r}$, the total required power for this cooperative transmission is $\frac{1}{m} \times d^{\lambda}_{t_i,r}$ in the sense that cooperative transmission can use as little as only $\frac{1}{m}$ of the individual point-to-point transmission power if m nodes cooperatively transmit to a given destination node.

3.3 The MECP Problem

Given an energy cost graph $G = (V, E)$ with weighs $d_{i,j}^{\lambda}$, where V is the set of nodes and E is the set of links, $d_{i,j}^{\lambda}$ is the weight on the edge $<i, j>$ and $<i, j> \in E$, $i, j \in V$, source-destination pair $S, D \in V$, assuming that $|V| = N$ and the last L nodes along the path are allowed for cooperative transmission to the next hop, where $L \in \{1,...,N-1\}$, find a $S-D$ path, $Path = S->t_1, t_2,...,t_k->D$ and a corresponding transmission sequence arrangement, e.g., a link schedule, which could consist of point-to-point transmissions, multicast and cooperative transmissions, such that the total required energy along this path is the least. That is,

$$\min \sum_{x \in \{S, t_1, t_2, ..., t_k, D\}} P_x \tag{3.5}$$

where P_x stands for the required power for node x.

An example of cooperative transmission along the path from node S to node D is given in Figure 3-1, in which we allow the last two nodes along the path for cooperative transmission to the next hop, e.g., $L = 2$.

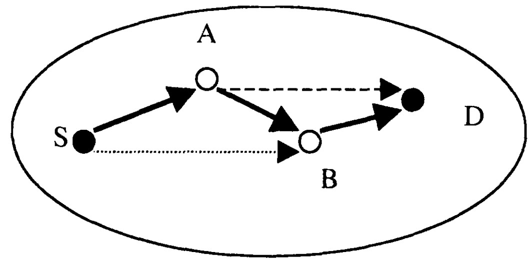


Figure 3-1: An illustration of cooperative transmission with $L = 2$.

The corresponding path can be stated as $S -> \underset{(S)}{A} -> \underset{(A)}{B} -> D$. The transmission procedure operates as follows: node S first transmits to node A, then node S and node A cooperatively transmit to node B, then node A and node B cooperatively transmit to node D. The total energy cost for this path is give by

$$P_{S-D} = d_{S,A}^{\lambda} + \frac{1}{\frac{1}{d_{S,B}^{\lambda}} + \frac{1}{d_{A,B}^{\lambda}}} + \frac{1}{\frac{1}{d_{A,D}^{\lambda}} + \frac{1}{d_{B,D}^{\lambda}}} \qquad (3.6)$$

We need to emphasize that the minimum energy cooperative path could be a combination of multicast (one to many), cooperative transmissions (many to one). and point-to-point transmissions (one to one). Please note that the case of many-to-many transmission is not a valid option as synchronizing transmissions for coherent receptions at multiple receivers is not feasible [13].

Regarding the point-to-point transmissions in the minimum energy cooperative path (MECP), we have the following theorem.

Theorem 3.1: if $L \geq 2$, i.e., at least the last two nodes along the path are allowed for cooperative transmissions to the next hop, and if there are point-to-point transmissions in the minimum energy cooperative path, which could be a combination of point-to-point transmissions, multicast transmissions and cooperative transmissions, then there must be only one point-to-point transmission and it must be the first-hop transmission.

Proof: we prove this theorem by contradiction. Assuming that there is a point-to-point transmission, say from node t_i to node t_{i+1} in the minimum energy cooperative path, which is not the first-hop transmission, there must be at least one predecessor node, say node t_{i-1}, for node t_i in the minimum energy cooperative path. As L is equal or greater than two, node t_{i-1} and node t_i are allowed for cooperative transmissions to node t_{i+1}. We also have

$$\frac{1}{\frac{1}{d^{\lambda}_{t_{i-1},t_{i+1}}} + \frac{1}{d^{\lambda}_{t_i,t_{i+1}}}} < \frac{1}{d^{\lambda}_{t_i,t_{i+1}}} \qquad (3.7)$$

as $\frac{1}{d^{\lambda}_{t_{i-1},t_{i+1}}}$ is always greater than zero due to the fact that node t_{i-1} and node t_{i+1} are different nodes at different locations in the physical space. Therefore, a cooperative transmission from node t_{i-1} and node t_i to node t_{i+1} always leads to less energy consumption than a point-to-point transmission from node t_i to node t_{i+1} does. This contradicts the assumption that the point-to-point transmission from node t_i to node t_{i+1}, which is not the first-hop transmission, is one of the transmissions along the minimum energy cooperative path that lead to the least total energy consumption. This concludes the proof.

In the development of the cooperative shortest path algorithm in Section 3.5, we do not consider the exploitation of wireless multicast advantage, e.g., WMA (see Definition 3.1), in the first place. The basic argument is that the possibility that using multi-cast to cover several nodes along the path to save energy compared with cooperatively transmissions along the path to cover the same set of nodes is slim except for the first hop as no cooperation occurs for the first hop transmission. Further, as discussed in [13], with the consideration of WMA the computational complexity to find the minimum energy route is in the order of $O(N2^N)$, which is exponential and intractable for a large number of N, where N is the number of nodes in the network. As will be seen later in the next section that the general minimum energy cooperative path (MECP) problem proved to be NP-complete.

Notably, all those heuristic algorithms presented in [13] did not consider WMA in the construction of the $S-D$ path. However, the first-hop opportunity to exploit WMA can be achieved by systematically selecting the source transmitting power levels and use our presented cooperative shortest path algorithm in Section 3.5 to obtain the remaining path from the already-covered nodes in the first-hop multi-cast to the destination node and evaluating the total required energy. We will have more discussion on this subject in the Section 3.5.2.

3.4 Complexity Issues

The problem of finding the minimum energy cooperative path (MECP) appears to be hard to solve [13]. This is due to the fact that an optimal path could be a combination of cooperative transmissions, multicast, and point-to-point transmissions. To find a good solution, acquiring insights into the complexity of the MECP problem is of great importance. In the following we show that the minimum energy cooperative path problem is NP-complete.

Notice that the theory of complexity is designed to be applied only to decision problems, i.e., the problems with either yes or no as an answer [1,11]. However, each optimization problem can be easily stated as a corresponding decision problem. A decision problem related to the MECP problem can be described as follows:

Minimum Energy Cooperative Path (MECP) problem in wireless networks

Instance: Given an energy cost graph $G = (V, E)$ with weighs $d_{i,j}^{\lambda}$, where V is the set of nodes and E is the set of links, $d_{i,j}^{\lambda}$ is the weight on the edge $<i, j>$ and $<i, j> \in E$, $i, j \in V$, source-destination pair $S, D \in V$, assuming that $|V| = N$ and the last L nodes along the path are allowed for cooperative transmission to the next hop, where $L \in \{1,..., N-1\}$, let P_x stand for the required power for node x, some constant $B \in \Re_+$.

Question: Is there a $S-D$ path, $Path = S->t_1, t_2,..., t_k->D$ and a corresponding transmission sequence arrangement, e.g., a link schedule, such that $\sum_{x \in \{S, t_1, t_2, ..., t_k, D\}} P_x \leq B$?

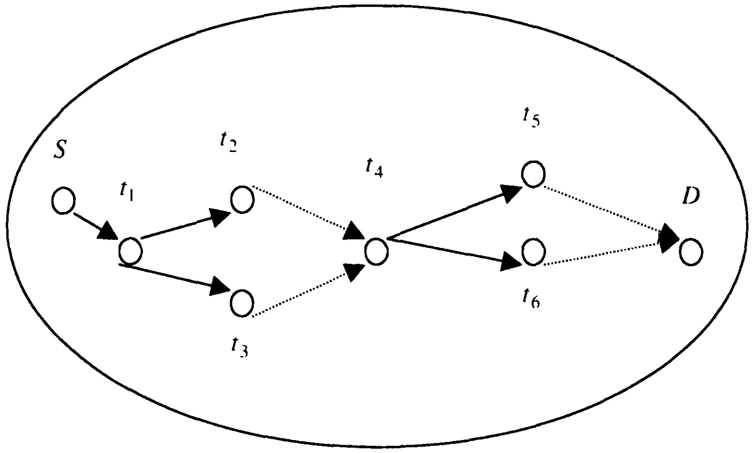


Figure 3-2: An example path that consists of point-to-point transmission, multicast and cooperative transmissions.

An example path that consists of point-to-point transmission, multicast and cooperative transmissions is given in Figure 3-2. The transmission procedure operates as follows: node S first transmits to node t_1, then node t_1 multicasts to node t_2 and node t_3, then node t_2 and node t_3 cooperatively transmit to node t_4, then node t_4 multicasts to node t_5 and node t_6, then node t_5 and node t_6 cooperatively transmit to node D. The corresponding path can be stated as $S->t_1->(t_2,t_3)->t_4->(t_5,t_6)->D$. The total energy cost for this path is give by

$$P_{S-D}=d_{S,t_1}^{\lambda}+\max(d_{t_1,t_2}^{\lambda},d_{t_1,t_3}^{\lambda})+\frac{1}{\frac{1}{d_{t_2,t_4}^{\lambda}}+\frac{1}{d_{t_3,t_4}^{\lambda}}}+\max(d_{t_4,t_5}^{\lambda},d_{t_4,t_6}^{\lambda})+\frac{1}{\frac{1}{d_{t_5,D}^{\lambda}}+\frac{1}{d_{t_6,D}^{\lambda}}} \quad (3.8)$$

In the following, we prove that the MECP problem is NP-complete. We prove NP-completeness of MECP problem by showing that a special case of it is NP-complete. In order to obtain a special case of MECP, we specify the following restrictions to be placed on the instances of MECP. First, we only allow cooperative transmission to the destination node D and up to $N-1$ nodes are allowed for this last-hop cooperative transmission. Further, we assume that the weight difference between link $<i, D>$ and link $<j, D>$, where $i, j \in V-\{S, D\}$, is negligible, e.g., $d_{i,D}^{\lambda} \approx d_{j,D}^{\lambda}$. This assumption is to simplify the calculation of the last-hop cooperative transmission cost and it is just for the convenience of analysis.

We call this special case of MECP as S-MECP. We prove NP-completeness of the S-MECP problem by reduction from the minimum energy broadcast (MEB) problem in wireless networks, which is known to be NP-complete [1,19].

Minimum Energy Broadcast (**MEB**) problem in wireless networks

Instance: Given an energy cost graph $G=(V,E)$ with weighs $d_{i,j}^{\lambda}$, where V is the set of nodes and E is the set of links, $d_{i,j}^{\lambda}$ is the weight on the edge $<i,j>$ and $<i,j> \in E$, $i, j \in V$, a source node $S \in V$, assuming that $|V|=N$, let P_x stand for the required power for node x, some constant $B \in \Re_+$.

Question: Is there a subgraph of G, say $G^{'} = (V^{'}, E^{'})$, where $|V^{'}| = |V| = N$ and $G^{'}$ is a tree rooted at node S, such that $\sum_{x \in V^{'}} P_x \le B$?

For the transformation from MEB to MECP, we first give the following description of minimum energy i-node multicast problem.

Given a source node S and a group of potential destination nodes, say N-1 potential destination nodes, we define that a minimum energy i-node multicast tree with source node S as a tree that is rooted at node S and reaching i-1 destination nodes among those N-1 potential nodes with the least required power among all possible i-node multicast trees, e.g., $\binom{N-1}{i-1}$ i-node multicast trees in total.

From the **theorem** in [1,19] that minimum energy broadcast problem in wireless networks is NP-complete, we have the following corollary.

Corollary 3.1: Minimum energy i-node ($1 \le i \le N$) multicast (MEiM) problem with one source node and $N-1$ potential destination nodes is NP-complete.

Proof: It is easy to see that minimum energy i-node multicast problem belongs to the NP class since a nondeterministic algorithm need only guess a set of nodes, e.g., i nodes, and check in polynomial time whether there is a path from the source node to any of the remaining i-1 destination nodes in a final solution, and whether the cost of the final solution is $\leq B$. Since the minimum energy broadcast (MEB) problem is a special case of the minimum energy i-node multicast (MEiM) problem when i is equal to N, and minimum energy i-node multicast problem belongs to the NP class, so the MEiM problem is NP-complete too.

Let $T(S,i)$ denote the required power of a minimum energy i-node multicast tree with source node S. Regarding the series of $T(S,1)$, $T(S,2)$, , $T(S,i)$, $T(S,i+1)$, , $T(S,N)$, we have the following lemma.

Lemma 3.1: The series of $T(S,i)$ is monotonically increasing , e.g., $T(S,i) \leq T(S,i+1)$, where $1 \leq i \leq N$.

Proof : We prove this lemma by contradiction. Assume that there is a minimum energy $(i+1)$-node multicast tree and a minimum energy i-node multicast tree for the same given settings and $T(S,i+1) < T(S,i)$ holds. For the minimum energy $(i+1)$-node multicast tree, there must be at least one leaf node among the i destination nodes, the removal of which will not cause the connectivity changes of other nodes and the total cost of the remaining i-node multicast tree, say $T^*(S,i)$, is equal or less than the original minimum energy $(i+1)$-node multicast tree, e.g., $T(S,i+1)$. Hence, $T^*(S,i) \leq T(S,i+1)$. From the assumption, we also have $T(S,i+1) < T(S,i)$. So, we have $T^*(S,i) < T(S,i)$. This contradicts the assertion that the original i-node multicast tree is the minimum energy i-node multicast tree; and the Lemma is shown.

As discussed before, for the special case of MECP, e.g., S-MECP, we only allow cooperative transmission to the destination node D and up to $N-1$ nodes are allowed for this last-hop cooperative transmission. Let $C(i,D)$ stand for the required power for the last-hop cooperative transmission from i already-covered nodes including the source node S to the final destination node D. Recall that among the restrictions we placed on the instance of MECP we assume that the link weight difference between link $<k, D>$ and link $<j, D>$, where $k, j \in V - \{S, D\}$, is negligible, e.g., $d_{k.D}^{\lambda} \approx d_{j.D}^{\lambda}$. Again, this assumption is to simplify the calculation of the last-hop cooperative transmission cost and it is just for the convenience of analysis.

Lemma 3.2: The series of $C(1,D)$, $C(2,D)$, $\ldots$, $C(i,D)$, $C(i+1,D)$, $\ldots$, $C(N-1,D)$ is strictly decreasing, e.g., $C(i,D) > C(i+1,D)$, where $1 \le i \le N-2$.

Proof: according to the definition and the restriction assumptions, we have $C(1,D) = d_{S.D}^{\lambda}$,

$$C(2,D) = \frac{1}{\frac{1}{d_{S.D}^{\lambda}} + \frac{1}{d_{x.D}^{\lambda}}}, \quad \ldots, C(i,D) = \frac{1}{\frac{1}{d_{S.D}^{\lambda}} + \frac{i-1}{d_{x.D}^{\lambda}}}, C(i+1,D) = \frac{1}{\frac{1}{d_{S.D}^{\lambda}} + \frac{i}{d_{x.D}^{\lambda}}}, \quad \ldots,$$

$$C(N-1,D) = \frac{1}{\frac{1}{d_{S.D}^{\lambda}} + \frac{N-2}{d_{x.D}^{\lambda}}}.$$

As $x \neq D$, we have $d_{x.D}^{\lambda} > 0$. Notably, all the link weights are non-negative. Without loss of generality, let us consider two consecutive elements $C(i,D)$ and $C(i+1,D)$. Based on the above analysis, we have

$C(i,D)-C(i+1,D)=\dfrac{d_{S,D}^{2\lambda}\times d_{x,D}^{\lambda}}{(d_{x,D}^{\lambda}+(i-1)d_{S,D}^{\lambda})(d_{x,D}^{\lambda}+i\times d_{S,D}^{\lambda})}$>0. So, the series of $C(i,D)s$ is strictly decreasing.

Lemma 1 and Lemma 2, coupled with Corollary 1, make up the basis for the proof of Theorem 2.

Theorem 2: The minimum energy cooperative path problem (MECP) is NP-complete.

Proof: we first show that S-MECP is NP-complete. As S-MECP is a special case of MECP, so the theorem follows. To see that S-MECP is NP-complete, the proof consists first in showing that S_MECP belongs to the NP class, and then in showing that MEiM polynomially reduces to S_MECP.

It is easy to see that S-MECP problem belongs to the NP class since a nondeterministic algorithm need only guess a set of nodes and check in polynomial time whether a given link schedule for the corresponding cooperative path from the source node S to the destination node D is feasible in a final solution, and whether the cost of the final solution is $\leq B$.

Now consider the following instance. Given an energy cost graph $G=(V,E)$ with weighs $d_{i,j}^{\lambda}$, where V is the set of nodes and E is the set of links, $d_{i,j}^{\lambda}$ is the weight on the edge

$<i,j>$ and $<i,j>\in E$, $i,j\in V$, source-destination pair $S,D\in V$, some constant $B\in\Re_+$. Let us consider the instances of MEiM in which the destination nodes belong to $V^{'}=V-\{S,D\}$. As shown in Lemma 1 and Lemma 2 that $T(S,i)$ series, which stands for the power of the minimum energy i-node multicast tree with source node S and destination nodes belong to $V^{'}$, is monotonically increasing and the $C(i,D)$ series, which denotes the cooperative transmission cost from the all the nodes in the minimum energy i-node multicast to the destination node D. The cost of the corresponding $S-D$ path, which satisfies the assumptions of S-MECP, is $P(S,i,D)=T(S,i)+C(i,D)$. Notably, the series of $P(S,i,D)s$ is not monotonically varying. By evaluating the instances of $P(S,0,D)$, $P(S,1,D)$, , $P(S,N-1,D)$, this solves the instance of S-MECP. Clearly, this instance of S-MECP can be constructed in a polynomial time of $O(N)$ from MEiM instances. This concludes the proof that S-MECP is NP-complete.

Since S-MECP is a special case of MECP problem, and MECP belongs to the NP class, which can be shown along the similar lines as for the S-MECP problem, MECP problem is NP-complete too.

3.5 Cooperative Shortest Path Algorithm

In this section, we present a cooperative shortest path (**CSP**) algorithm without WMA that uses Dijkstra's algorithm as the basic building block and reflects the cooperative transmission properties in the relaxation procedure. The CSP algorithm takes as input an energy cost graph $G=(V,E)$ with weighs $d_{i,j}^{\lambda}$, source-destination pair $S,D\in V$. We assume that the last L nodes along the path for cooperative transmission to the next hop. The CSP algorithm uses the basic structure of Dijkstra's algorithm and uses a modified relaxation procedure to reflect the cooperative transmission cost along the path. The presented approach (CSP algorithm) differs from those heuristics in [13] in the sense that we directly changed the relaxation procedure of the Dijkstra's algorithm to adopt the cooperative transmission cost instead of calculating the non-cooperative shortest path first. All those heuristics presented in [13] have the common thread to calculate the non-cooperative shortest path first, either statically (like CAN algorithm (cooperation along the non-cooperative shortest path) or dynamically (like PC algorithm (progressive cooperation heuristic), we refer interested readers to [13] for details. As will be shown later in Section 3.6, the CSP algorithm outperforms the existing algorithms in all circumstances from both energy efficiency and fairness standpoints.

The new relaxation procedure for CSP is described in Figure 3 and the rest of the CSP algorithm has the same structure as that of Dijkstra's algorithm. Notably, the algorithm maintains two labels for each node: $d[u]$ to represent the estimated total cost of the cooperative shortest path from the source node S to node u with respect to the cooperative transmission cost along the path and $\pi(u)$ to represent predecessors of node u along the cooperative shortest path. $\pi(u)$ only needs to keep as many as L-1 predecessors, e.g. , the last L-1 predecessors along the cooperative shortest path, which allows as many as L nodes including node u for cooperative transmission to another non-included node.

Relax (u,v)

if d[v] >d[u] + **Coop**(u,v) then
  d[v] = d[u] + **Coop**(u,v);
  set node u as node v's predecessor;
endif

Coop(u,v)

// calculate the cooperative transmission cost from node u
// and its predecessors to node v

Assume $Path_u^* = \{S, t_1, \ldots, t_k, u\}$

if (k+2) $\leq L$

$$\text{cost} = \frac{1}{\frac{1}{d_{S,v}^{\lambda}} + \sum_{i=1}^{k} \frac{1}{d_{t_i,v}^{\lambda}} + \frac{1}{d_{u,v}^{\lambda}}}$$

else if (k+1)==L

$$\text{cost} = \frac{1}{\sum_{i=1}^{k} \frac{1}{d_{t_i,v}^{\lambda}} + \frac{1}{d_{u,v}^{\lambda}}}$$

else if (k+1) > L

$$\text{cost} = \frac{1}{\sum_{i=k-L+2}^{k} \frac{1}{d_{t_i,v}^{\lambda}} + \frac{1}{d_{u,v}^{\lambda}}}$$

endif
endif
endif
return cost

Figure 3-3: New relaxation procedure for CSP algorithm.

As described in Figure 3-3, we define $coop(u,v)$ as the cooperative transmission cost from node u and its predecessors (at most $L-1$) to node v. Hence, the formulation of the problem depicted in Eq. (3.5) can be rewritten as

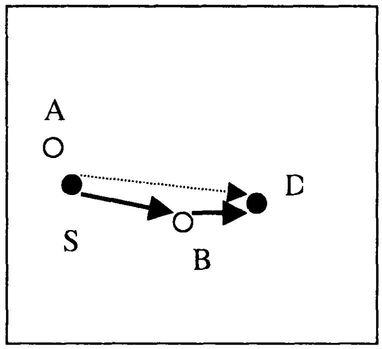
$$\text{minimize } (coop(S,t_1)+\sum_{i=1}^{k-1} coop(t_i,t_{i+1})+coop(t_k,D)) \tag{3.9}$$

where $Path = S->t_1->t_2->...->t_k->D$.

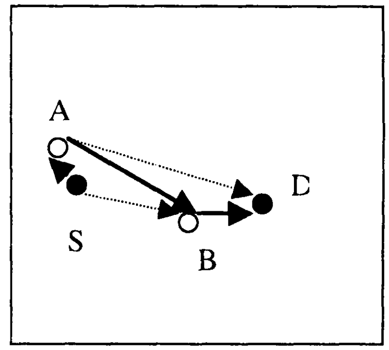
We omit the description of the rest of the CSP algorithm as it has the same structure as that of Dijkstra's algorithm, which can be found in virtually every algorithm book, e.g., the one by Cormen, Leiserson, Rivest and Stein [6].

The complexity of the presented cooperative shortest algorithm for cooperative routing is in the order of $O(N^2)$, where N is the number of nodes in the network. The CAN algorithm and the PC algorithm ([13]) have the computational complexities of $O(N^2)$ and $O(N^3)$ respectively but with sub-CSP performance, which will also be verified by the experimental results in the following Section.

To further illustrate the difference between CSP algorithm and the CAN and PC algorithms presented in [13], we give an example run in Figure 4, which is obtained from one of our simulation results.



(a) the path by CAN and PC



(b) the path by CSP

Figure 3-4: An example run of CSP, CAN and PC in a simple network setup.

We have four nodes located in a 10×10 plane. The two-dimension coordinates for node S, A, B, D are (1.72, 5.55), (1.64, 6.15), (4.23, 3,51), (5.53, 3.58) respectively. The $S-D$ paths found by CAN and PC are both $S->B->D$, while the $S-D$ path found by CSP is $S->A->B->D$. Assuming we allow the last two nodes along the path for cooperative transmission to the next hop and also we use the value of 2 for λ in this case, the cooperative transmission cost along the $S-D$ path found by CAN and PC is equal to $d_{S.B}^2 + \frac{1}{\frac{1}{d_{S.D}^2} + \frac{1}{d_{B.D}^2}} \approx 12$ and the cooperative transmission cost along the $S-D$ path found by CSP is equal to $d_{S.A}^2 + \frac{1}{\frac{1}{d_{S.B}^2} + \frac{1}{d_{A.B}^2}} + \frac{1}{\frac{1}{d_{A.D}^2} + \frac{1}{d_{B.D}^2}} \approx 7.85$.

3.5.1. CSP with Additive Constraints

As stated earlier and as will be shown later in the thesis that multi-hop cooperative transmission significantly reduces the total transmit energy along the path. However, delay may increase considerably when there are a large number of intermediate nodes along the path, each of which adds additional transmission delay, queuing delay and processing delay, etc. Hence, besides our first objective to minimize the total required energy of the path, we may need to add additional constraints to limit the number of hops.

Let H denote the number of hops constraint and basically given an energy cost graph $G=(V,E)$ with weighs $d_{i,j}^{\lambda}$, where V is the set of nodes and E is the set of links, source-destination pair $S,D \in V$ and assuming that the last L nodes along the path for cooperative transmission to the next hop, we want to find a $S-D$ path, such that the total required energy for cooperative transmission along the path is the least provided that the number of hops of the path is equal to or less than H.

```
Relax (u,v)
  if v==D then
     if path[S][u].hop<=H-1 then
         if d[v] >d[u] + Coop(u,v) then
              d[v] = d[u] + Coop(u,v);
              set node u as node v's predecessor;
              path[S][v].hop = path[S][u].hop + 1;
          endif
      endif
   else if path[S][u].hop<=H-2 then
          if d[v] >d[u] + Coop(u,v) then
              d[v] = d[u] + Coop(u,v);
              set node u as node v's predecessor;
              path[S][v].hop = path[S][u].hop + 1;
           endif
        endif
   endif

Coop(u,v)
// calculate and return the cooperative transmission cost
// from node u and its predecessors to node v, same as
// that in Figure 2.

path[S][v].hop
// indicates the number of hops of the current path from
// node S to node v
```

Figure 3-5: New relaxation procedure for the restricted CSP algorithm with the number of hops constraint.

The new relaxation procedure for CSP with the number of hops constraint (CSP-HC) is described in Figure 3-5 and the rest of the CSP-HC algorithm has the same structure as that of Dijkstra's algorithm. Notably, the algorithm maintains three labels for each node: $d[u]$ to represent the estimated total cost of the cooperative shortest path from the source node S to node u with respect to the cooperative transmission cost along the path, $h[u]$ to stand for the number of hops of the current path from the source node S to node u and $\pi(u)$ to represent predecessors of node u along the cooperative shortest path. $\pi(u)$ only needs to keep as many as L-1 predecessors, e.g. , the last L-1 predecessors along the cooperative shortest path, which allows as many as L nodes including node u for cooperative transmission to the next hop.

The rest of the CSP-HC algorithm has the same structure as that of Dijkstra's algorithm. Hence, the computation complexity in the worst case, is $O(N^2)$, which is the same as that of Dijkstra's algorithm.

3.5.2 Exploiting the first-hop WMA

As discussed earlier in Section 3.3 that the possibility that using multi-cast to cover several nodes along the path to save energy in the context of cooperative routing is slim except for the first hop due to the lack of cooperation in the first-hop transmission. It should be noted that incorporating WMA into minimum energy cooperative routing problem makes finding optimal solutions much more difficult even we limit this effort just to the first hop. Nevertheless, the first-hop opportunity to exploit WMA can be explored by systematically selecting the source node transmitting power levels and use our presented cooperative shortest path algorithm to obtain the remaining path from the already-covered nodes set by the first-hop multi-cast to the destination node. We then need to systematically evaluate the total required energy of the path. Namely, we want to find a path $Path = S -> t_1 -> t_2 -> ... -> t_k -> t_{k+1} -> ... -> t_m -> D$, where node $t_1, t_2, ..., t_k$ are all covered by the first hop transmission from node S. Assuming $d_{t_i}^{\lambda} = \max\{d_{t_1}^{\lambda}, d_{t_2}^{\lambda}, ..., d_{t_k}^{\lambda}\}$, where t_i is one of the nodes among $t_1, t_2, ..., t_k$. We can construct an equivalent path as $Path = S -> t_i -> t_1 -> t_2 ... -> t_{i-1} -> t_{i+1} ... -> t_m -> D$, where the energy cost along the edges $t_i -> t_1 -> t_2 -> ... -> t_{i-1} -> t_{i+1} -> ... -> t_k$ are all zeros. The above equivalent transformation allows us to use the formula Eq. (3.3) to calculate the cooperative transmission cost along the path. We need to emphasize that when finding the path from node t_k to the destination node D using the cooperative shortest path (CSP) algorithm, we must initialize the cost from t_k to any other node in the remaining graph, say node t_r ($t_r \in \{V - \{S, t_1, t_2, ... t_k\}\}$, as the cooperative transmission cost, say $coop(t_k, t_r)$. The total required energy for the path can then be calculated according to Eq. (3.2) and Eq. (3.3). Our objective is to find the minimum energy route in this setting, that is

$$\text{minimize } (P_S + \sum_{i=k}^{m} P_{t_i}), \tag{3.10}$$

where $P_S = \max\{d_{t_1}^{\lambda}, d_{t_2}^{\lambda}, ..., d_{t_k}^{\lambda}\}$.

Inspired by the Source Transmit Power Selection (STPS) algorithm in [28], the cooperative shortest path algorithm with the consideration of first hop WMA (CSP-FHW) is detailed below.

The CSP-FHW algorithm takes as input an energy cost graph $G = (V, E)$, a source-destination pair, $S, D \in V$. Moreover, assume that S has M outgoing edges, determined by its power level range ($P_S \in [0, P_{\max}]$), say $m_1, m_2, ..., m_M$ (the other endpoint vertices for these edges are $r_1, r_2, ..., r_M$, respectively), ordered such that $d_{S,r_i}^{\lambda} > d_{S,r_j}^{\lambda} \Leftrightarrow i > j$. Its output is a minimum-energy cooperative transmission path with the consideration of first hop WMA.

Initialize: Let P_{S-i} represent the current iteration source transmitting power, corresponding to the i closest nodes reached by S. Initialize $i = 1$. Let $E_{\min}$ stand for the overall energy cost of the $S - D$ path. Initialize $E_{\min}$ to ∞.

Step 1: Construct a new graph G_i, where G_i is a modified version of the energy cost graph that reflects all possible network topologies given the current iteration source transmitting power P_{S-i}. Accordingly, G_i can be obtained from G by removing edges $m_{i+1}, m_{i+2}, ..., m_M$, setting a path $S -> r_i -> r_1 -> r_2 -> ... -> r_{i-1}$ with the weights of the edges along the partial path $r_i -> r_1 -> r_2 -> ... -> r_{i-1}$ equal to zero, and updating the weight from node r_{i-1} to any node, say node r_x, where $r_x \in \{V - \{S, r_1, r_2, ... r_i\}\}$, as the cooperative transmission cost, say $coop(r_{i-1}, r_x)$.

Step 2: Run a cooperative shortest path (CSP) algorithm on G_i to find the remaining path from node r_{i-1} to node D, with the energy cost $P_{i-1,D}$.

Step 3: Evaluate the following condition: if $P_{S-i}+P_{i-1,D}<E_{\min}$, then set $E_{\min}=P_{S-i}+P_{i-1,D}$, and store the current best path information.

Step 4: Increment $i=i+1$ and correspondingly increase the source transmitting power , e.g., $P_{S-i+1}=d^{\lambda}_{S,r_{i-1}}$. Repeat steps 1-4 until $i>M$, at which point all relevant P_S will have been considered and the overall minimum energy path will be determined with the consideration of first hop WMA.

We conclude this subsection by addressing the issue of complexity. The worst case complexity of the CSP-FHW algorithm, as presented above, is $O(N^3)$. This is because the CSP-FHW algorithm iterates $N-1$ times in the worst case, and in each iteration we run the cooperative shortest path (CSP) algorithm whose complexity is $O(N^2)$.

3.6 Performance Evaluation

In this section, we evaluate the performance of the basic CSP algorithm compared with CAN algorithm and uncooperative shortest path (USP) algorithm (those three algorithms have the same computational complexity of $O(N^2)$) on three main aspects: (a) mean normalized path power, (b) fairness, (c) total consumed power of each node over a substantially large number of random source-destination pairs.

Following [13,28], we simulate networks of a varying number of nodes, N, placed randomly within a 10×10 plane, in a variety of circumstances, e.g., with the power attenuation factor, λ=2, 3, 4, and $L=2,3,4$. We use $P_{\max}=2\times 10^{\lambda}$ for each node and this allows every node being able to reach every other node in one hop so long as it transmits at a sufficiently high power level. As discussed before, each node is able to adjust its transmitting power in the range of $[0, P_{\max}]$ to add or remove links in the energy cost graph.

For the calculation of mean normalized path power, the results are averaged over 100 randomly-chosen source-destination pairs in randomly-generated networks in a variety of circumstances, e.g., varying N, λ and L. For the performance comparison between the algorithms, we consider normalized path power. For example, suppose we have three approaches to generate cooperative routing paths, say approaches CAN, CSP and USP, where USP stands for uncooperative shortest path algorithm. Let P_{CAN}, P_{CSP} and P_{USP} stand for the required path power for the paths generated by approaches CAN, CSP and USP, respectively, for the same source-destination pair in the same network topology. The normalized path power for each of these approaches is given by the following:

$$P'_{CAN}=\frac{P_{CAN}}{\min(P_{CAN},P_{CSP},P_{USP})},$$

$$P'_{CSP}=\frac{P_{CSP}}{\min(P_{CAN},P_{CSP},P_{USP})},$$

$$P'_{USP}=\frac{P_{USP}}{\min(P_{CAN},P_{CSP},P_{USP})} \tag{3.11}$$

Let the variable R_i stand for the ratio between the number of transmission sessions in which node i is either the source or the destination node and the total number of transmission sessions that node i participates. We call R_i as node i's utility function. Clearly, the bigger the value of R_i, the more benefits node i can get from the cooperation with other nodes. Let STD be the standard deviation of R_is among all the nodes in the network, we have

$$STD = \sqrt{\frac{\sum_{i=1}^{N} (R_i - \frac{\sum_{i=1}^{N} R_i}{N})^2}{N}}, \tag{3.12}$$

where N is the total number of nodes in the network.

The standard deviation of R_is describes how spread-out the values of R_is are. If the data all lies close to the mean, then the standard deviation will be small, while if the data is spread out over a large range of values, STD will be large. As we consider R_i as node i's utility function, clearly the smaller the value of STD, the more fairness among different nodes.

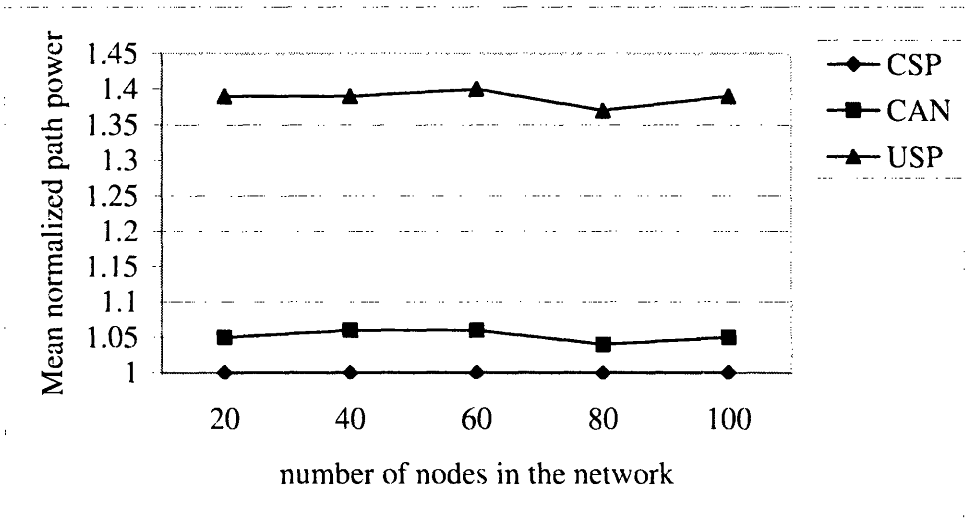
Let P_i denote the total consumed power of node i for the transmissions involved in a statistically large number of random source-destination pairs (we determined to conduct experiments with 100,000 random S-D pairs). Let STD_P be the standard deviation of P_is among all the nodes in the network

$$STD_P = \sqrt{\frac{\sum_{i=1}^{N}(P_i - \frac{\sum_{j=1}^{N} P_i}{N})^2}{N}}, \tag{3.13}$$

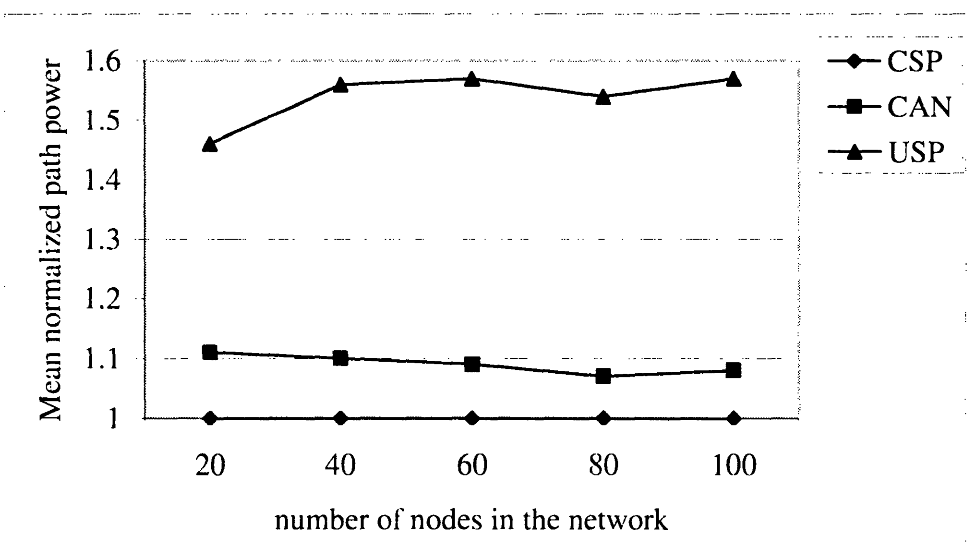
where N is the number of nodes in the network.

We begin with the evaluation of the mean normalized path power by CSP, CAN and USP. As shown in Figure 3-6, we first observe that CSP consistently outperforms CAN and USP in all circumstances. With more nodes added in the network, the gap between CSP and uncooperative shortest path (USP) approach slightly widens, ranging from 30~50% power savings. CSP outperforms CAN by a margin around 10% for the same settings. We also observe that as we allow more nodes along the path for cooperative transmission to the next hop, e.g., a larger value of L, both CAN and CSP achieve more power savings compared with the non-cooperative shortest path approach. This is due to the fact that a larger value of L offers more cooperative transmission opportunities, which leads to more power savings. Another observation is that the gap between CSP and CAN widens with a larger value of power attenuation factor, λ. We determined that the energy savings due to the use of the CSP algorithm, over the CAN algorithm is most notable in a deep power attenuation environment.

The standard deviation of the normalized path power over 100 randomly-chosen source-destination pairs in a variety of circumstances by CAN and USP is shown in Table 3-1, Table 3-2 and Table 3-3. Notably, the standard deviation of the normalized path power by CSP is always zero as CSP always offers the best performance and consistently has the normalized path power of 1 according to Eq. (3.11). The main point we observe from these results is that both CAN and USP perform pretty badly in some cases due to the noticeable standard deviation value and in some cases the path power values by CAN and USP are far from the mean values.



(a) $\lambda = 2, L = 2$



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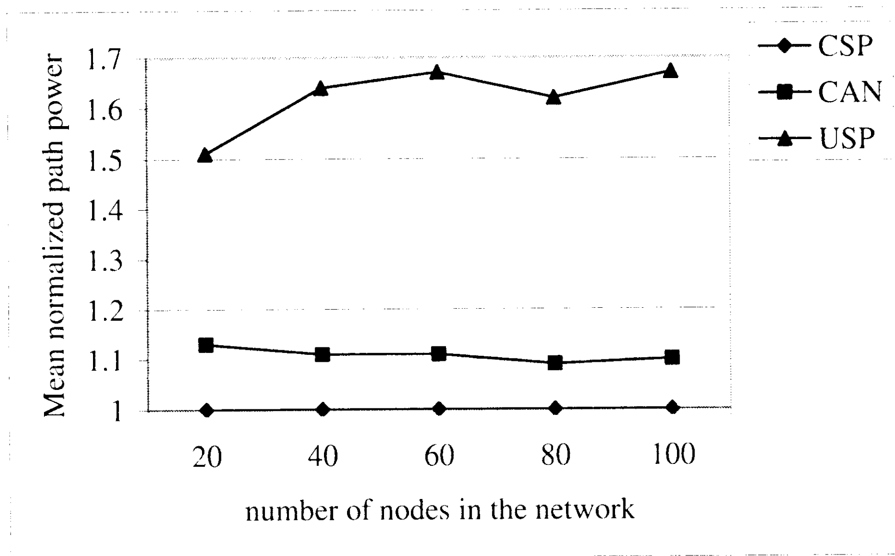
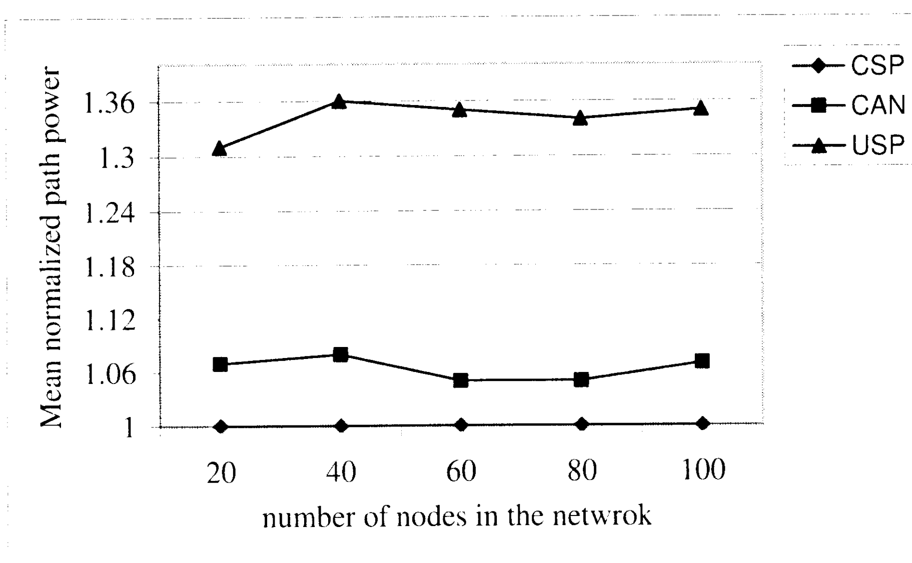
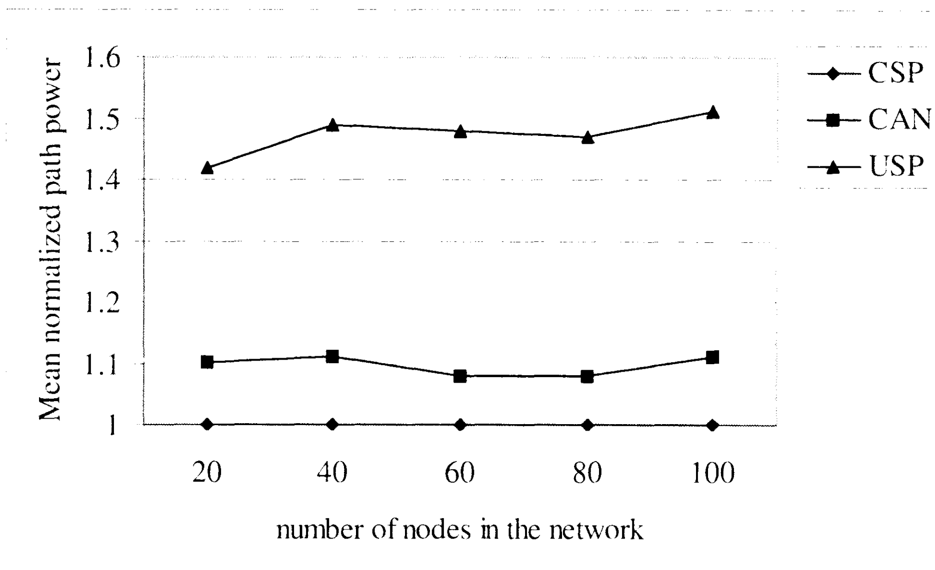


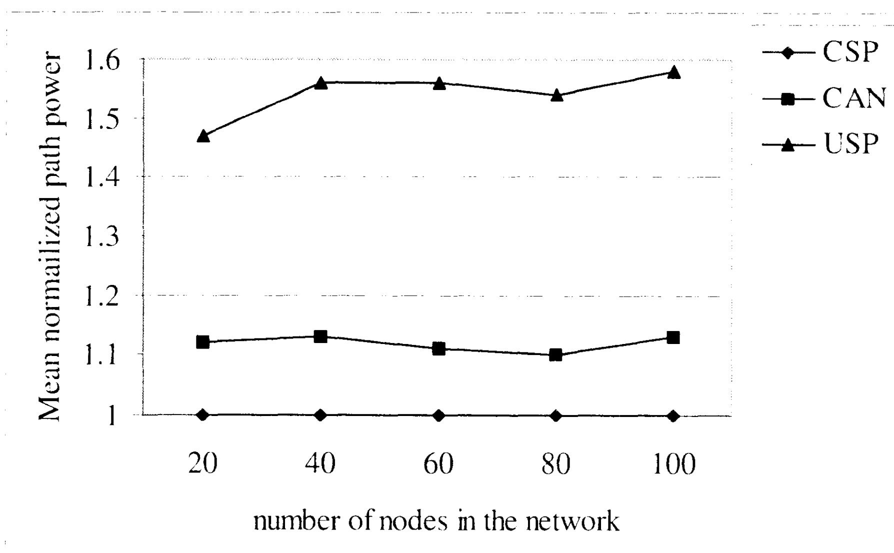
© $\lambda = 2, L = 4$



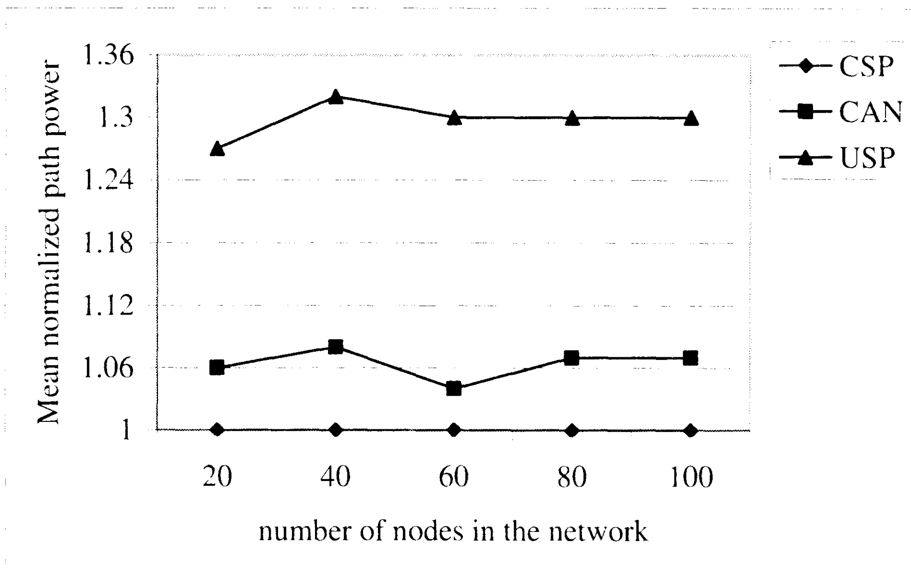
(d) $\lambda = 3, L = 2$



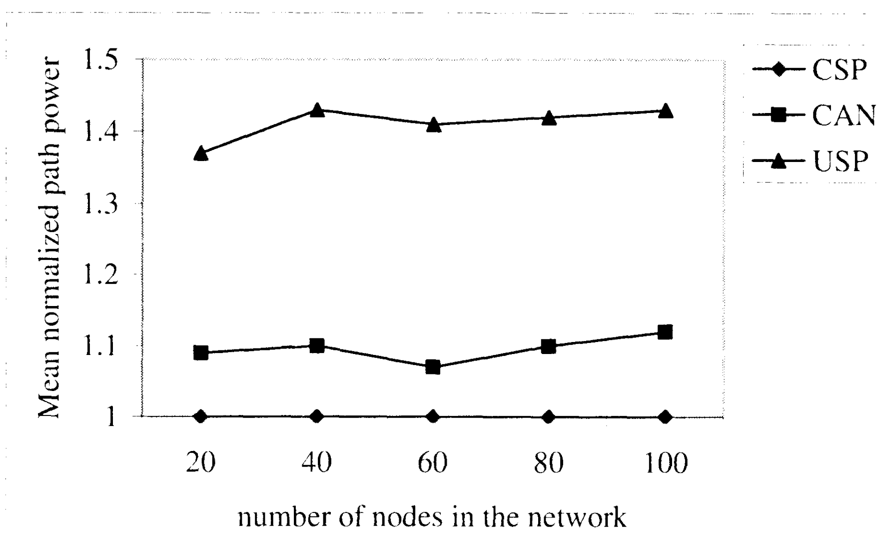
(e) $\lambda = 3, L = 3$



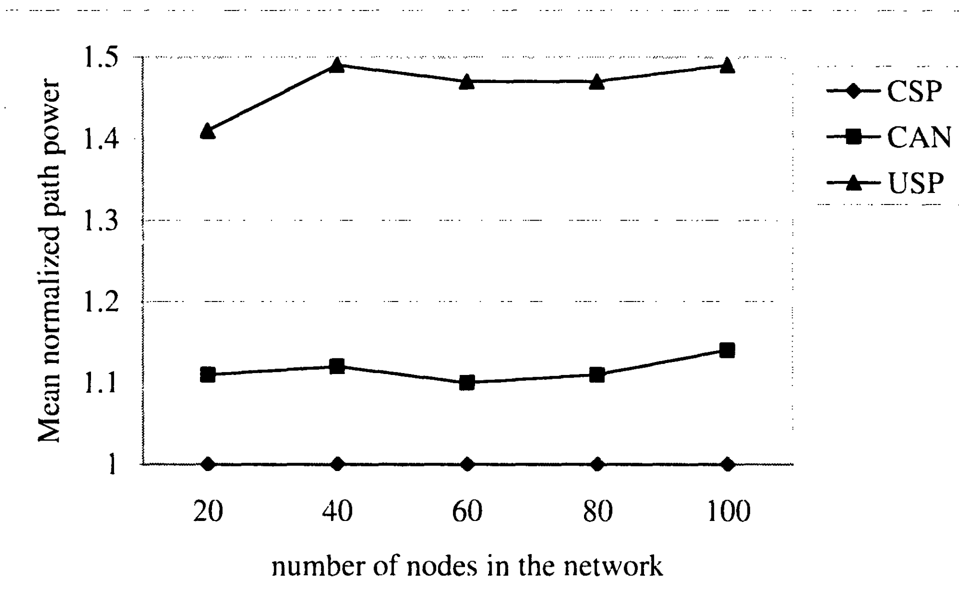
(f) $\lambda = 3, L = 4$



(g) $\lambda = 4, L = 2$



(h) $\lambda = 4, L = 3$



(i) $\lambda = 4, L = 4$

Figure 3-6: Mean normalized path power over 100 random source-destination pairs by CSP, CAN and USP in a variety of circumstances (N ranges from 20 to 100, $\lambda = 2,3,4$ and $L = 2,3,4$).

	$n=20$	$n=40$	$n=60$	$n=80$	$n=100$
CAN ($\lambda=2$)	0.16	0.11	0.09	0.06	0.09
USP ($\lambda=2$)	0.21	0.19	0.14	0.14	0.10
CAN ($\lambda=3$)	0.15	0.13	0.09	0.07	0.11
USP ($\lambda=3$)	0.20	0.18	0.14	0.15	0.12
CAN ($\lambda=4$)	0.12	0.12	0.08	0.09	0.12
USP ($\lambda=4$)	0.21	0.17	0.15	0.15	0.14

Table 3-1: Standard deviation of the normalized path power by CAN and USP with $L=2$ in a variety of circumstances. Notably, the standard deviation for the normalized path power by CSP is always zero.

	$n=20$	$n=40$	$n=60$	$n=80$	$n=100$
CAN ($\lambda=2$)	0.20	0.14	0.11	0.10	0.11
USP ($\lambda=2$)	0.30	0.29	0.21	0.21	0.17
CAN ($\lambda=3$)	0.18	0.16	0.11	0.09	0.16
USP ($\lambda=3$)	0.30	0.26	0.19	0.20	0.19
CAN ($\lambda=4$)	0.14	0.14	0.09	0.10	0.19
USP ($\lambda=4$)	0.29	0.25	0.20	0.21	0.22

Table 3-2: Standard deviation of the normalized path power by CAN and USP with $L=3$ in a variety of circumstances. Notably, the standard deviation for the normalized path power by CSP is always zero.

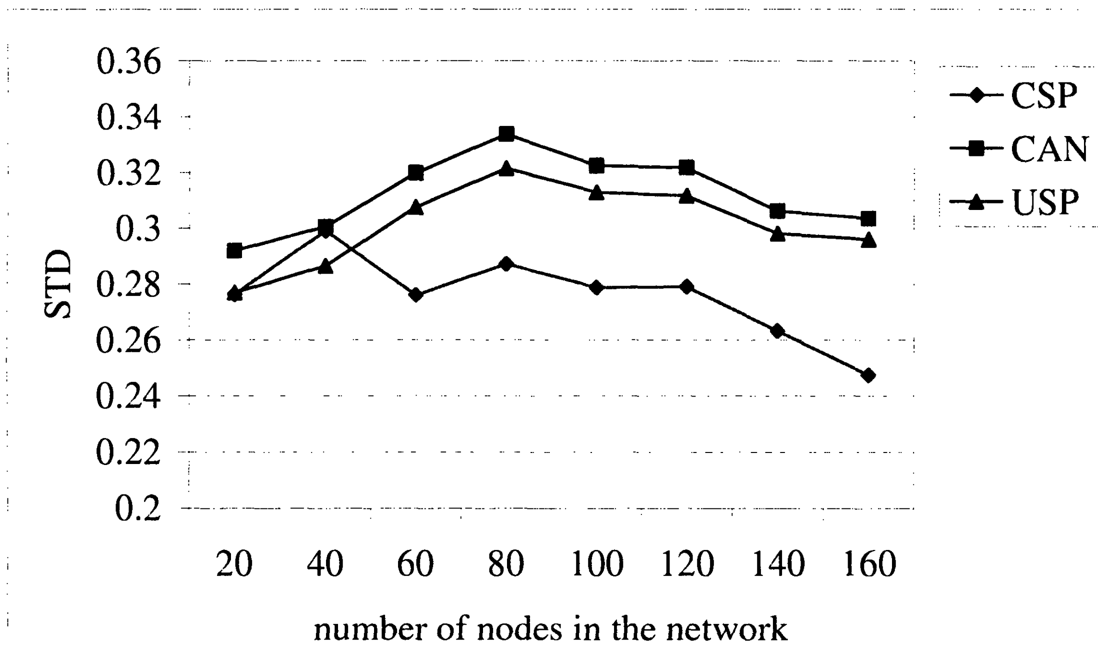
	$n=20$	$n=40$	$n=60$	$n=80$	$n=100$
CAN ($\lambda=2$)	0.21	0.15	0.14	0.11	0.13
USP ($\lambda=2$)	0.34	0.34	0.26	0.26	0.22
CAN ($\lambda=3$)	0.18	0.19	0.13	0.10	0.18
USP ($\lambda=3$)	0.33	0.31	0.24	0.24	0.23
CAN ($\lambda=4$)	0.16	0.15	0.12	0.11	0.20
USP ($\lambda=4$)	0.32	0.30	0.24	0.24	0.25

Table 3-3: Standard deviation of the normalized path power by CAN and USP with $L=4$ in a variety of circumstances. Notably, the standard deviation for the normalized path power by CSP is always zero.

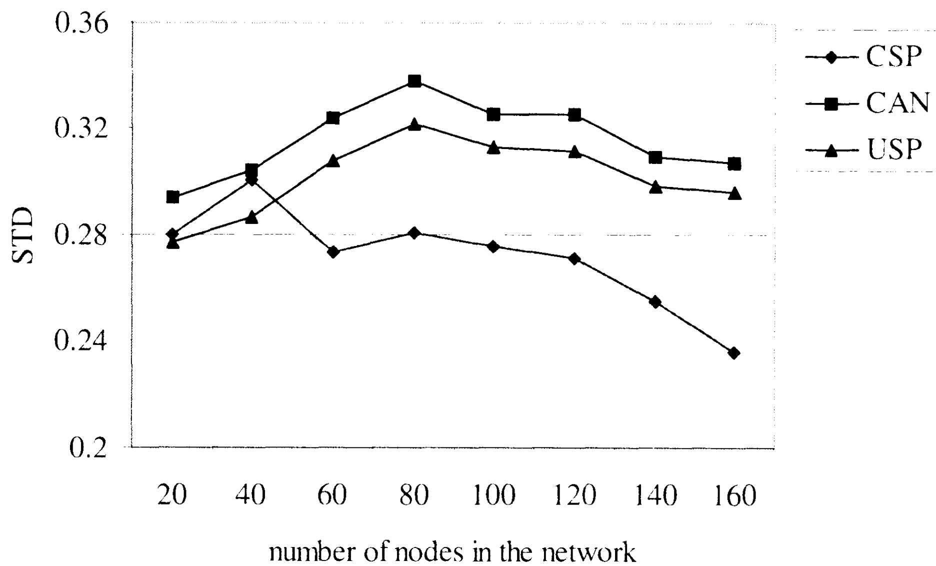
We next explore the performance of CSP, CAN and USP with respect to fairness defined in Eq. (3.12). Again, the variable R_i stand for the ratio between the number of transmission sessions in which node i is either the source or the destination node and the total number of transmission sessions that node i participates. *STD* stands for the standard deviation of R_i s. As shown in Figure 3-7, an interesting observation is that as more nodes added in the network, the CSP algorithm achieves more fairness among nodes in terms of the cooperative transmission participation. In particular, when the number of nodes in the network exceeds 60, CSP outperforms CAN and USP in all circumstances.

Another observation is that CAN performs slightly worse than USP with respect to fairness. This may be due to the fact that CAN uses the same path found by USP for cooperative transmission but it gives biased treatment for the source and destination. Notably, both source and destination nodes have less cooperative transmission participation opportunity than that of those in the middle. In particular for the destination node, it has no participation to the cooperative transmission at all.

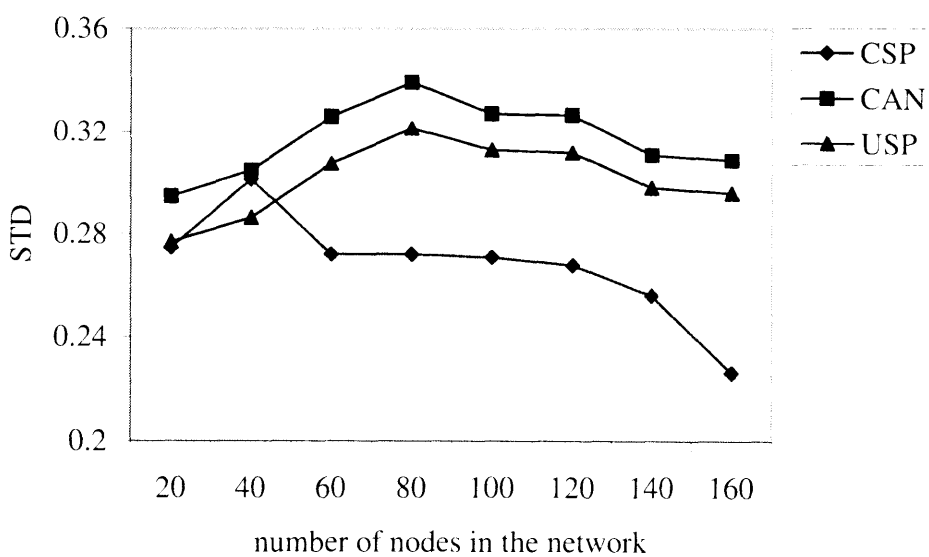
Another general intuitive perception with respect to fairness is that nodes in the middle of a network always have more chances to relay packets for other nodes than those at the edge of a network do. Hence, it may be impossible for the *STD* to approach zero.



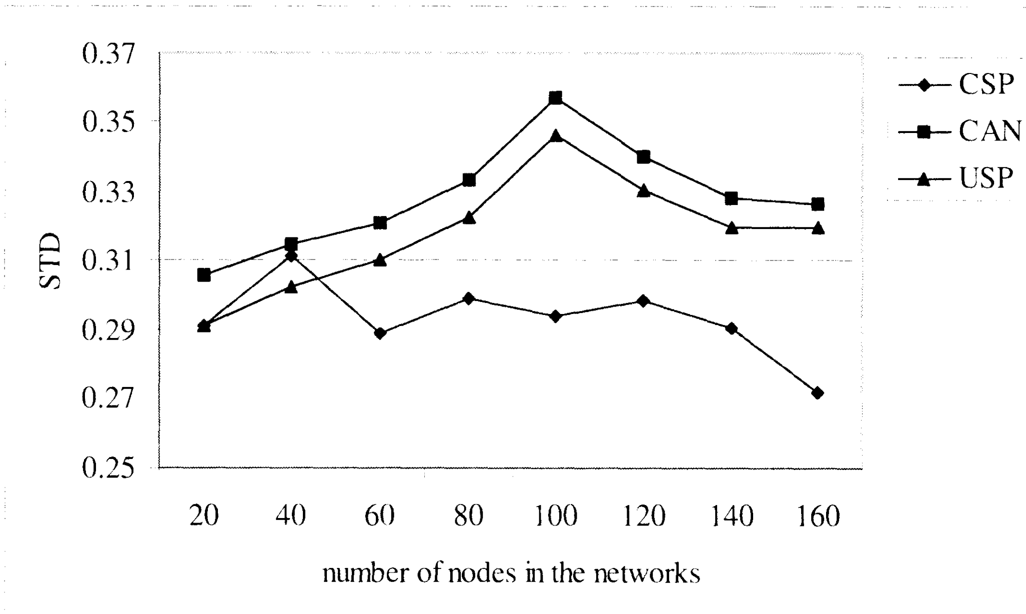
(a) $\lambda = 2, L = 2$



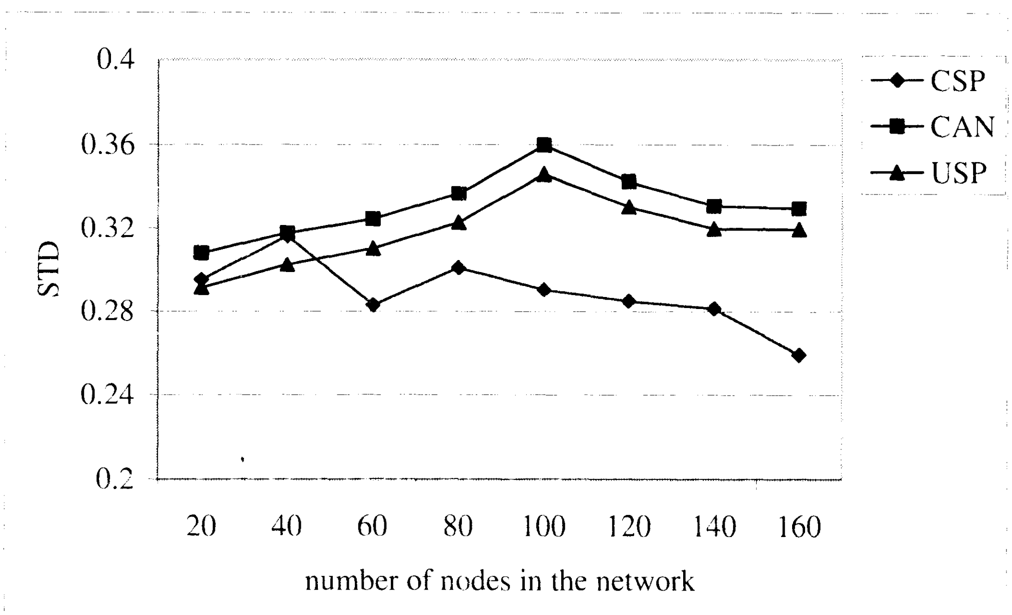
(b) $\lambda = 2, L = 3$



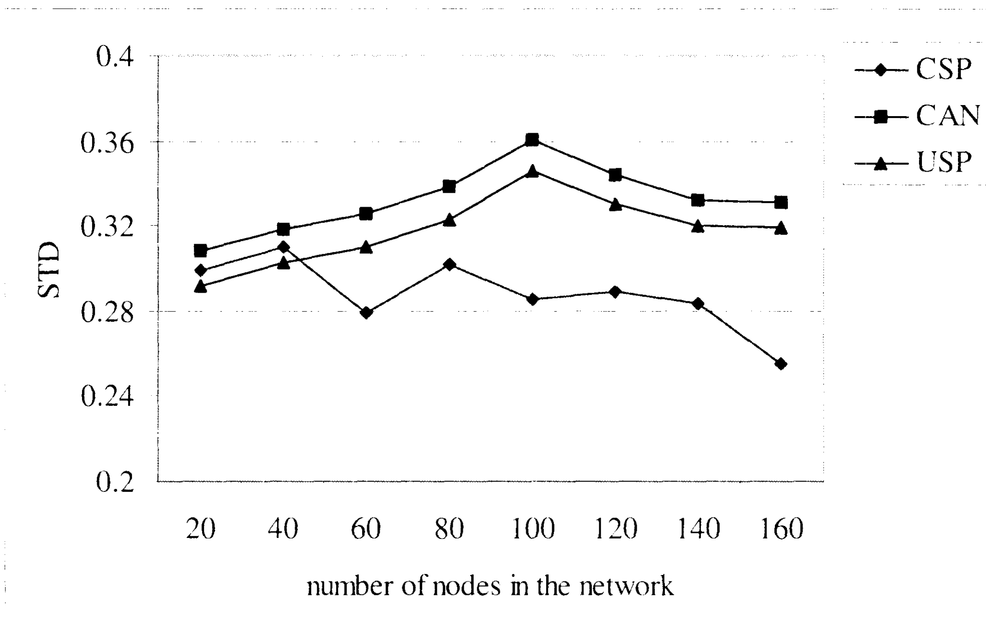
(c) $\lambda = 2, L = 4$



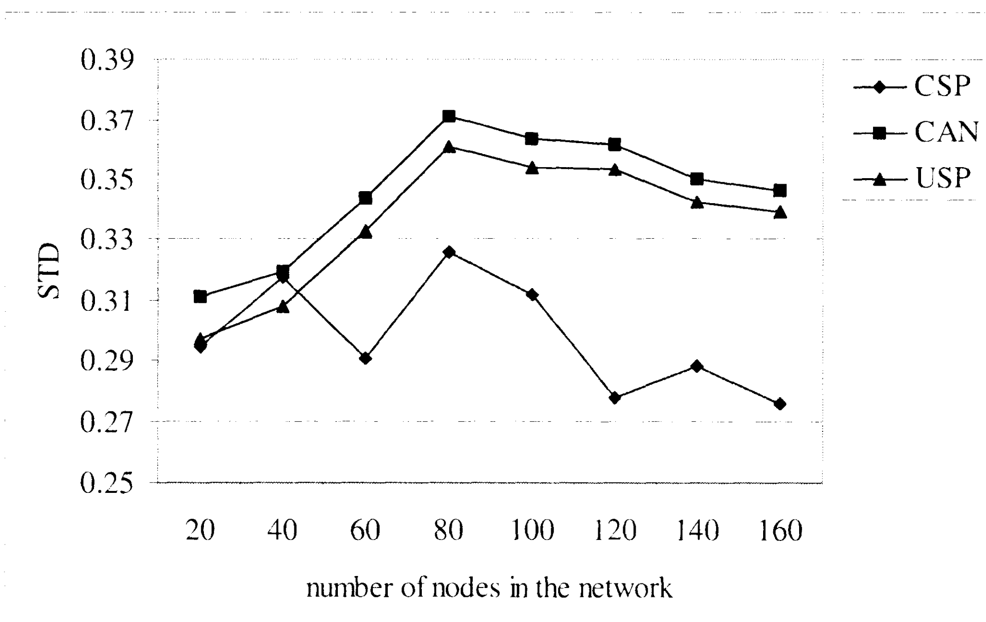
(d) $\lambda = 3, L = 2$



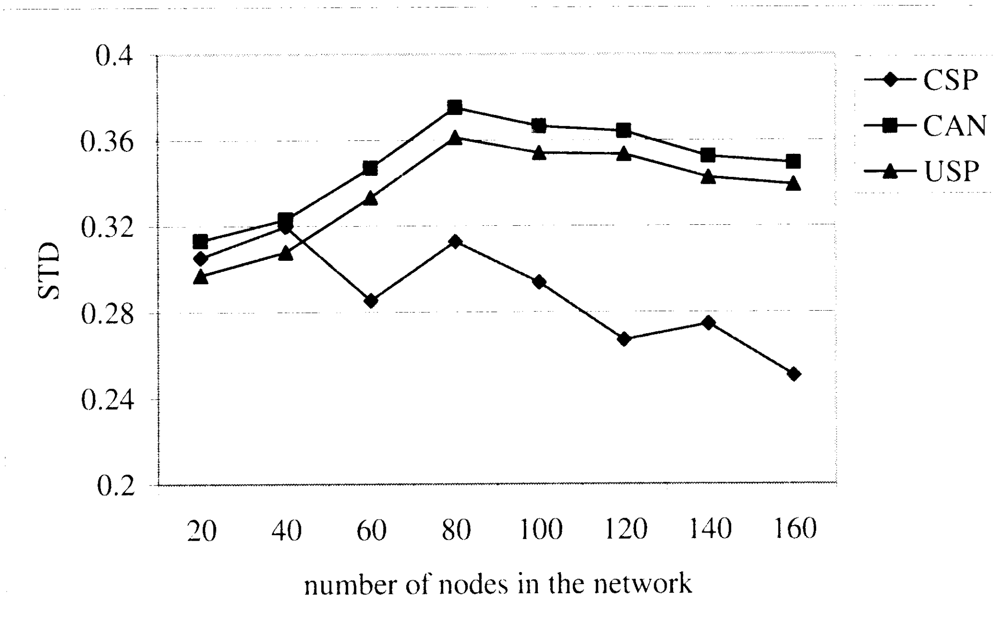
(e) $\lambda = 3, L = 3$



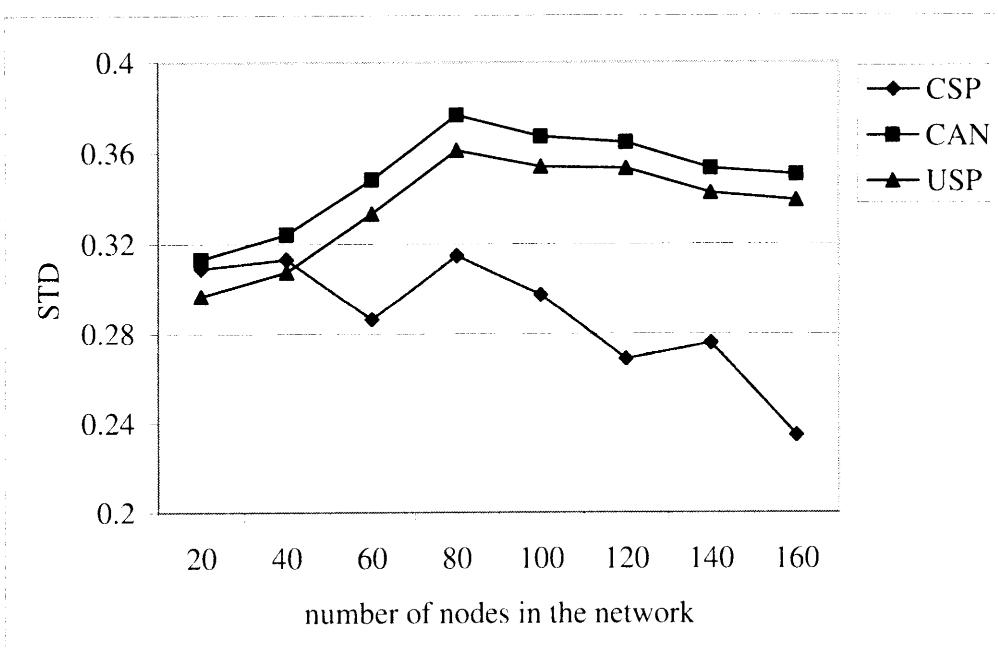
(f) $\lambda = 3, L = 4$



(g) $\lambda = 4, L = 2$



(h) $\lambda = 4, L = 3$

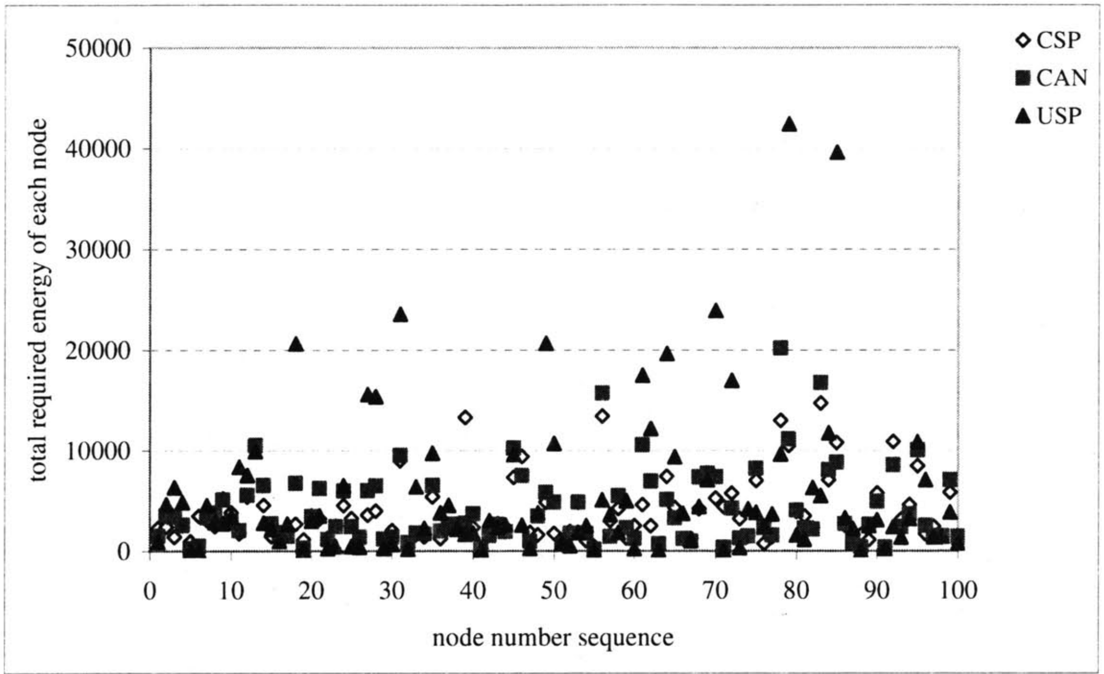


(i) $\lambda = 4, L = 4$

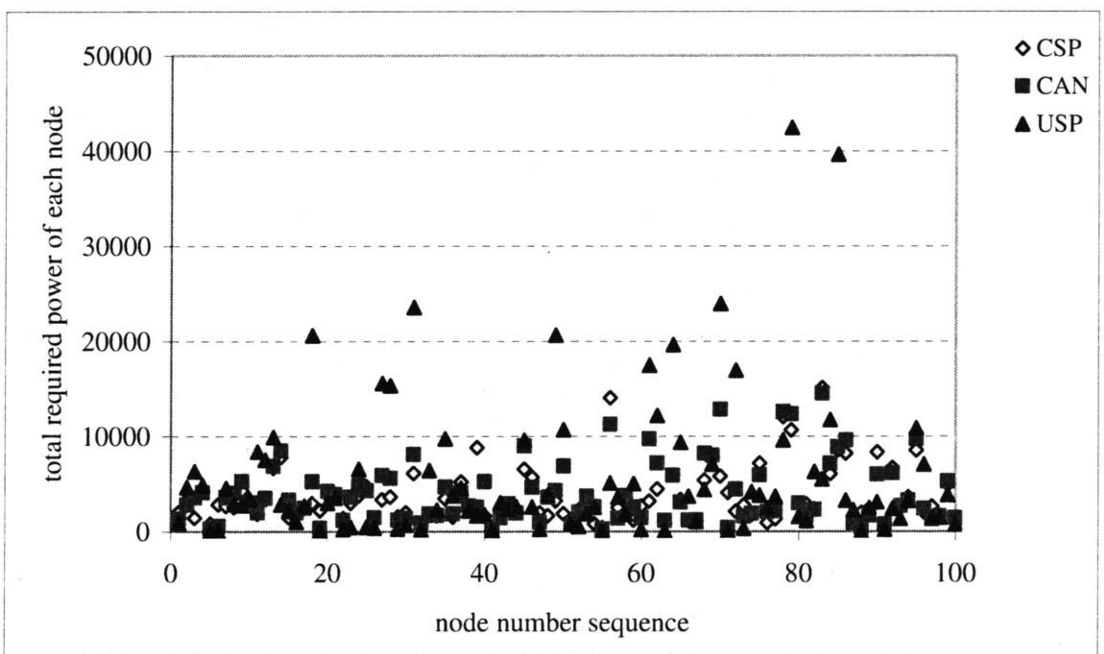
Figure 3-7: STD among each node's utility function values for 100,000 random S-D pairs by CSP, CAN and USP in a variety of circumstances.

Lastly, we explore the total required power for each node over 100,000 randomly-chosen source-destination pairs by CSP, CAN and USP in a variety of circumstances. Figure 3-8 shows the distribution of total required energy of each node by different algorithms, where $N=100$. The x-axis indicates the node sequence number and the y-axis represents the total required power for each node. We first observe that some nodes may consume less power under one approach while some other nodes may consume less power under other approaches. Mostly, the non-cooperative approach consumes much more power and in most cases the CSP scheme requires the least power among CSP, CAN and USP. In Fig. 3-8 (a), the ratios among total required power of all nodes by CSP, CAN and USP are 1.0:1.08:1.48, while in Fig. 3-8 (b), the ratios among total required power of all nodes by CSP, CAN and USP are 1.0:1.10:1.55 as a larger value of L offers more cooperative transmission opportunities.

Table 3-4 shows the standard deviation of the total required power for each node by CSP, CAN and USP for 100,000 random source-destination pairs in a variety of circumstances. Clearly, what we see in Table 3-4 is that the total required energy for each node is more evenly distributed for CSP approach.



(a) $\lambda = 3, L = 3$



(b) $\lambda = 3, L = 4$

Figure 3-8: Total required power of each node for 100,000 random source-destination pairs by CSP, CAN and USP, the number of nodes in the network is 100.

		N=20	N=40	N=60	N=80	N=100	N=120	N=140	N=160
$\lambda = 2$, $L = 2$	CSP	23258	8583	6138	3787	2751	2123	1836	1700
	CAN	24981	9145	6537	4158	2793	2301	2016	1785
	USP	45747	15641	10637	7283	5275	3777	3232	2865
$\lambda = 4$, $L = 2$	CSP	211606	28615	15514	8924	6670	3119	2120	1622
	CAN	205506	31718	17710	9408	6267	3985	2378	1860
	USP	415826	50937	29268	15394	11780	5924	3589	2862
$\lambda = 2$, $L = 4$	CSP	11699	4712	3501	2576	1950	1321	1166	1086
	CAN	14447	5390	4103	2891	2026	1573	1395	1263
	USP	45747	15641	10637	7283	5275	3777	3232	2865
$\lambda = 4$, $L = 4$	CSP	113403	19508	10507	7081	4477	2214	1555	1098
	CAN	115318	21468	10690	7250	4681	2902	1808	1410
	USP	415826	50937	29268	15394	11780	5924	3589	2862

Table 3-4: The standard deviation of the total required power for each node for 100,000 random S-D pairs by CSP, CAN, USP in a variety of circumstances.

3.7 Distribution and Implementation Issues

In this section, we give a brief discussion on distribution and implementation issues of the presented algorithm. In the situations where the global information about the network topology is not immediately available to all the nodes in the network and/or where the network topology may be changing frequently, a distributed implementation of the algorithm is much more desirable. Fortunately, the cooperative shortest path (CSP) algorithm presented in this thesis lends itself to such a distributed implementation as there are already efficient implementations of the traditional shortest path algorithms, e.g., the distributed Bellman-Ford algorithm. The additional difficulty is that each node needs to maintain as many as L-1 predecessors along the current best path from the source node to reflect the cooperative transmission cost in the new relaxation procedure (see Fig. 3-3). Another issue is to deal with the situation in which links or nodes fail or nodes move as the algorithm is running. A distributed asynchronous shortest path algorithm can deal with those difficulties more efficiently.

In the following, we give a brief description of the distributed version of the CSP algorithm. Let d_i be the cooperative shortest distance from node i to the destination node D. The update equation is given by

$$d_i = \min_{1 \le j \le N} \{coop(i, j) + d_j\} \tag{3.14}$$

where $coop(i, j)$ stands for the cooperative transmission cost from node i to node j (see detailed description in Fig. 3-3). Each node i regularly updates the values of d_i using the update Eq. (3.14) and each node maintains the values of $coop(i, j)$ to its neighbors as well as the values of d_j received from its neighbors. If no changes occur in the network, the algorithm will converge to cooperative shortest paths in no more than N steps, where N denotes the number of nodes in the network.

Even with the advent of commercial tuner receiver for phase coherence or the use of RAKE receivers for wideband communications, the coordination of transmissions from multiple transmitters to one receiver simultaneously to explore transmit diversity in a large wireless network is still a challenge. Collaborative media access control (MAC) protocols and adaptive scheduling algorithms have to be developed for the realization of cooperative routing in wireless networks. We determine this as one of our future research directions.

In summary, in this chapter we present algorithms to explore transmit diversity in the general context of cooperative routing where multiple nodes are allowed for cooperative transmissions. In Chapter 2, we present algorithms to construct multicast trees where we assume only one transmitting node is engaged in a one-to-one or one-to-many transmissions. The techniques presented in this chapter can be further incorporated in the approaches proposed in Chapter 2 for the construction of cooperative multicast trees.

Chapter 4

Prototype Implementation

4.1 Hardware Components

We use RFM TR1000 – 913 MHz radio as the basic radio component for each node. We use C8051 microcontroller for system and protocol operations and to interact with the radio chip for signal transmission and reception. We use the Pushpin platform, which was developed by Joshua Lifton at MIT Media Lab, and the Cygnal JTAG connector to program the microcontroller. We use the basic board design by Aggelos Bletsas to glue the radio chip, microcontroller, antenna, power sources together.

Additionally, we use CSS - 73B16 magnetic sound transducers for beeping and a simple amplifier circuit to pump in more current to the magnetic sound transducer using a transistor (F0229 2N 4401), the central pin of which is connected to one microcontroller pin that outputs 2.7 MHz on-off signals.

We also have ATVC 900 MHz downconverter, which converts 900 MHz signals from the radio nodes that we have built down to 67.15 MHz signals that can be received by TV channel IV, for the TV spectrum sharing demonstration.

4.2 Software Components

The software package consists of several key pieces: (1) the initialization of the microcontroller; (2) the definition of the packet format and packet types; (3) the detection/reception of a frame/packet; (4) the transmission of a frame/packet; (5) MAC (media access control) using RTS (ready to send) and CTS (clear to send) control packets; (6) the construction of the multicast tree;

In particular, we give more details on the construction of the multicast tree. The protocol works incrementally in the sense that if an intended subscriber can not hear the original signals from the source node, so long as it can overhear the transmissions from other neighbors, e.g., the control messages originated from its neighbors, it can ask the one with the best channel conditions, e.g., the radio signal strength indicator (RSSI), to relay the data. This way, the system grows without boundary. The power level of the transmitting node can be adjusted over time with the changes of the environments, e.g., node joins/leaves, channel condition changes, node mobility, etc.

An antenna that receives 900 MHz signals from the radio nodes that we build is connected to a downconverter that converts the 900 MHz signals to 67.15 MHz. The downconverter is then connected to a TV set that tunes in Channel IV – which operates at 67.15 MHz. We demonstrate that as more nodes added in the network to subscribe the multicast services, less interference can be perceived with the TV signals that operate at the same frequency.

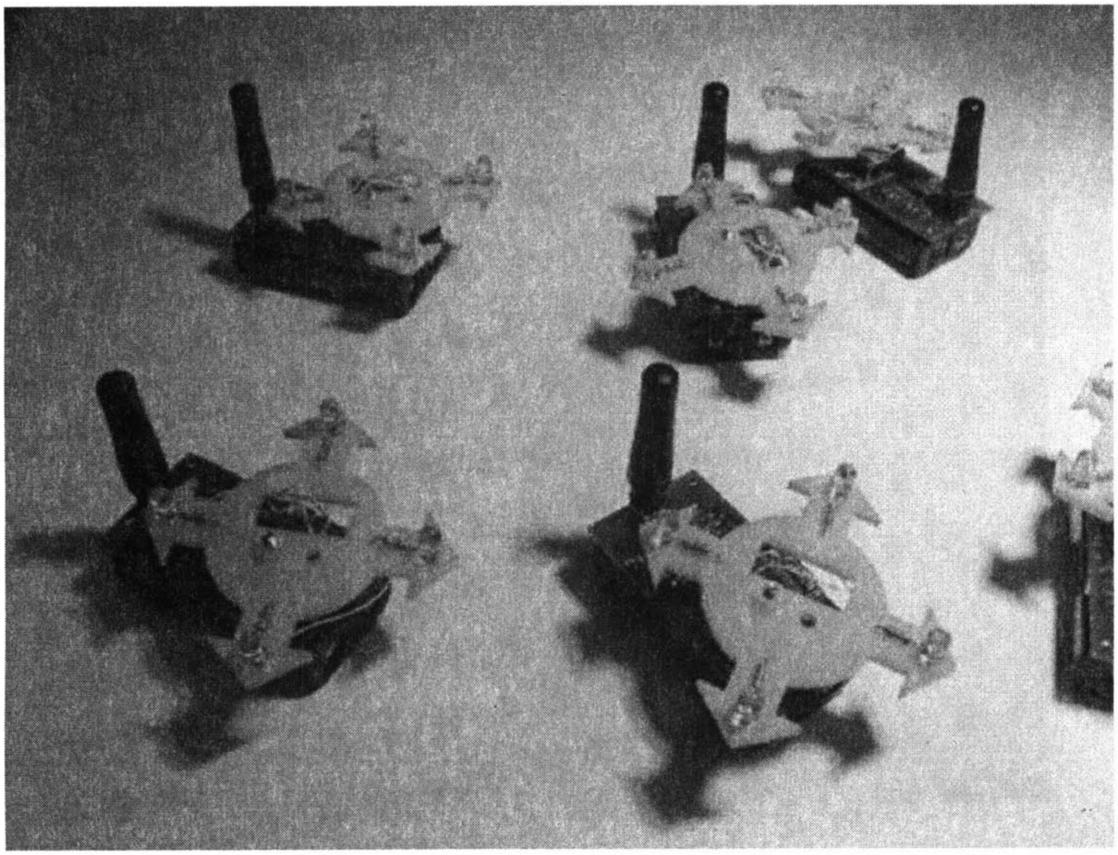


Fig. 4-1: Snapshot of the prototype implementation.

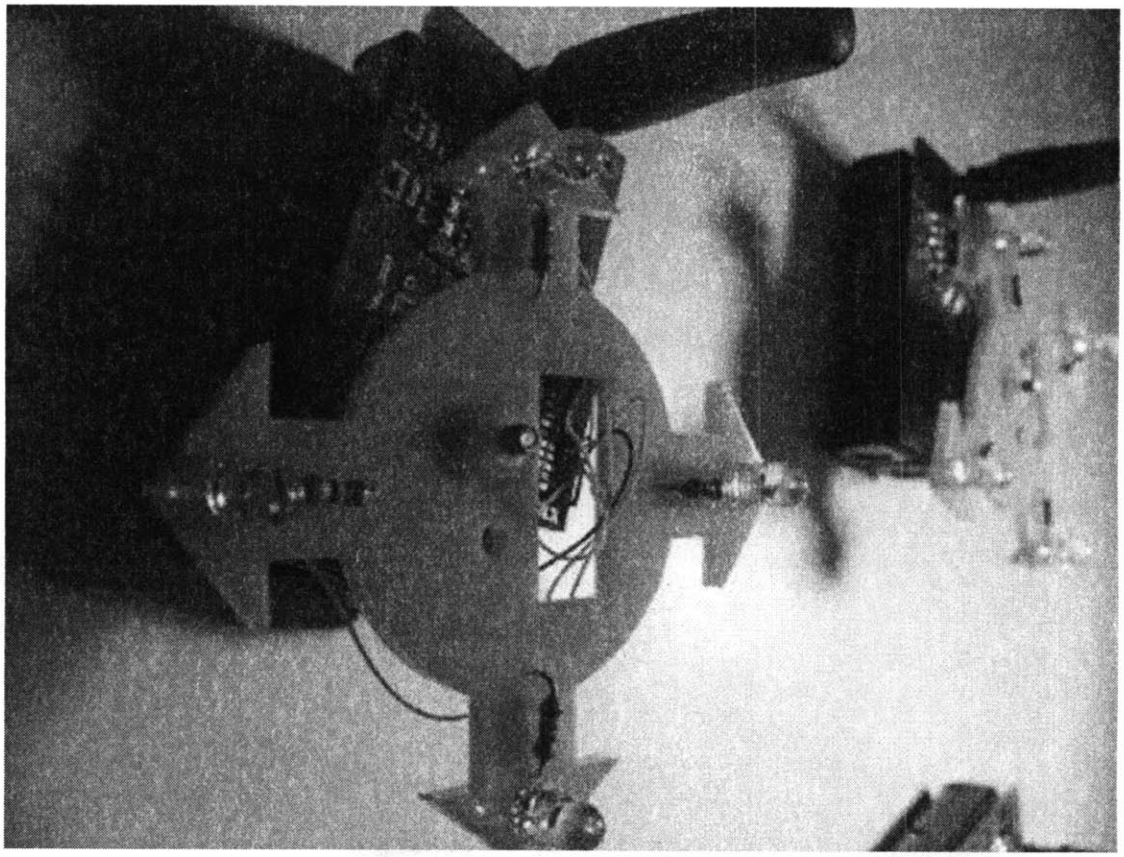


Fig. 4-2: Snapshot of the prototype implementation

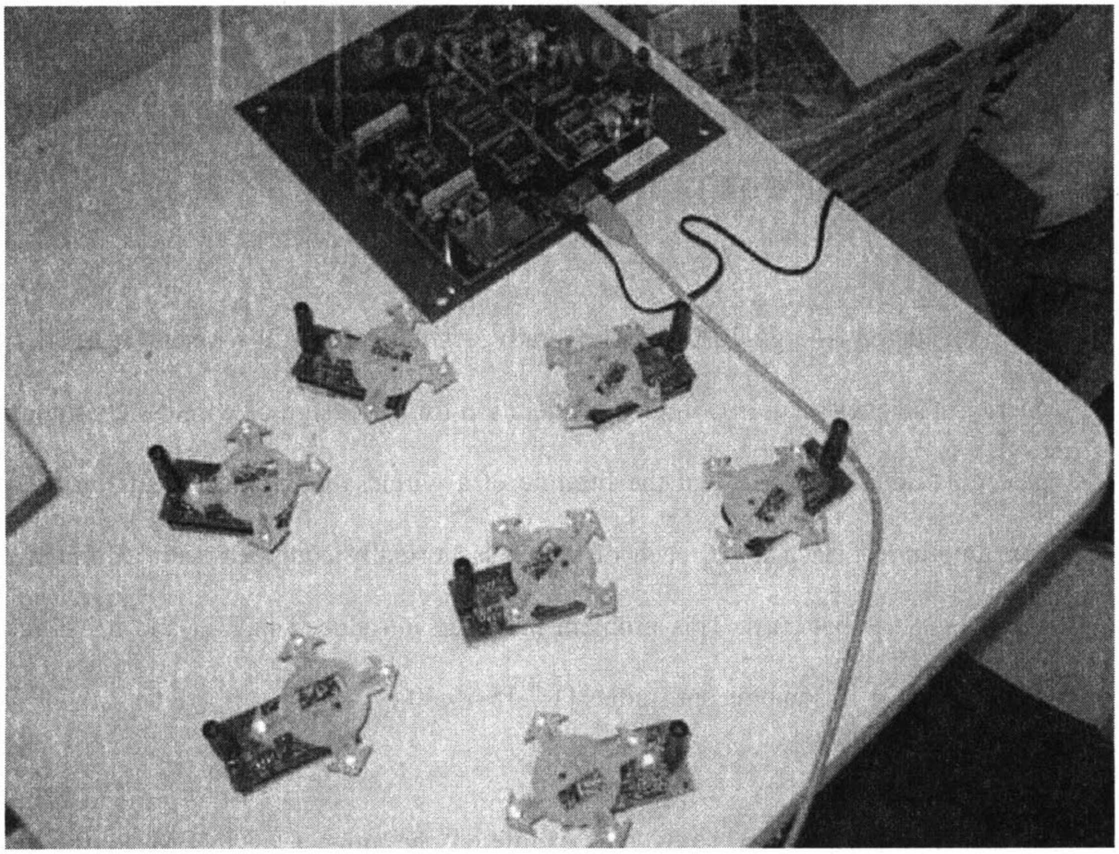


Fig. 4-3: Snapshot of the prototype implementation

Chapter 5

Conclusion and Future Directions

We considered energy-efficient cooperative multicast in all-wireless networks since energy-efficiency is an important consideration for the design of wireless communication protocols due to the fact that the lifetime of a wireless network depends on the power consumption of each node, each of which is normally equipped with a limited power supply such as batteries. This problem has been introduced in [32] and it has received much attention in some recent studies [1,7,15-19,30].

In the first part of our study, we examined the impact of IMBM to the existing approaches and we found that power savings can be achieved by applying IMBM to the broadcast trees generated by other existing approaches.

One of the major contributions of this work is the development of the RTO algorithm, which is based on the cross-entropy method ([8,27]). We proposed a random tree generation algorithm based on the transition probability matrix and explored efficient ways to initialize the probability matrix in different circumstances. We conducted extensive experiments to examine the performance of RTO compared with other existing approaches. Our empirical results indicate that it demonstrates the best performance of its kind.

We plan to consider other techniques for speeding-up the RTO algorithm. An interesting direction we plan to pursue is to implement the RTO algorithm in a distributed fashion, so that the nodes are divided into groups, on which sub-trees are generated separately and then merged to a single tree.

In the second part of this thesis, we explore transmit diversity in the general context of cooperative routing in all-wireless networks, whereby we assume that multiple nodes are allowed for cooperative transmissions. Notably, in Chapter 2, we assume that only one transmitting node is engaged in a one-to-one or one-to-many transmission for the construction of cooperative multicast trees. The techniques presented in Chapter 3 can be further incorporated in the approached presented in Chapter 2 on the construction of cooperative multicast trees. The cooperative routing scheme presented in Chapter 3 combines route selection, e.g., a network layer function, and the exploration of transmit diversity via cooperative transmission, e.g., a physical layer function. Such a cross-layer design approach may be beneficial for wireless networks to minimize the inherent impairments of wireless channels such as interference, multi-path fading, attenuation, etc.

We first proved in Chapter 3 that the minimum energy cooperative path (MECP) problem is NP-complete. We then present a cooperative shortest path (CSP) algorithm to approximate the MECP. The presented approach uses Dijkstra's algorithm as the basic building block and reflects the cooperative transmission properties in the relaxation procedure without WMA as there is little chance to exploit WMA in the context of cooperative transmission except the first hop due to the lack of cooperation in the first hop transmission. We give a brief discussion on how to exploit WMA in the first hop transmission by systematically select the transmitting power levels of the source node and apply the presented CSP algorithm to the rest of the graph and evaluate the total required power of the path.

The results show that our presented approach consistently outperforms other existing schemes. We also found that as more nodes added in the network, the gap between the presented approach and non-cooperative shortest path algorithm widens and the fairness among nodes with respect to the transmission cooperation participation is greatly improved. All these findings indicate that the presented approach tends to make the network more scalable and more efficient from both the energy conservation and fairness standpoints.

Notably, the algorithm presented in this thesis can be equally applicable to other cooperative routing environment, e.g., other fading or attenuation models, etc. We will also further explore efficient ways for the distributed implementation of the CSP algorithm as well as collaborative MAC protocols and adaptive scheduling algorithms as our future directions.

In essence, in the first part of the thesis, we investigate efficient ways to construct multicast trees by exploring cooperation among local radio nodes to increase throughput and conserve energy (or battery power), whereby we assume single transmitting node is engaged in a one-to-one or one-to-many transmission. In the second part of the thesis, we further investigate transmit diversity in the general context of cooperative routing, whereby multiple nodes are allowed for cooperative transmissions. The techniques presented in the second part of the thesis can be further incorporated in the construction of cooperative multicast trees presented in the first part of the thesis. We determine this as one of our future directions.

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