Optimal Routing for UWB-Based Sensor Networks

Yi Shi, *Student Member, IEEE*, Y. Thomas Hou, *Senior Member, IEEE*, Hanif D. Sherali, and Scott F. Midkiff, *Senior Member, IEEE*

***Abstract*—This paper considers ultra-wideband (UWB)-based sensor networks and studies the following problem: given a set of source sensor nodes in the network each generating a certain data rate, is it possible to relay all these rates successfully to the base station? We will show that such problem is intrinsic cross-layer, and subsequently we formulate an optimization problem, with joint consideration of link-layer scheduling, power control, and network-layer routing. For large-sized networks, we propose an efficient heuristic algorithm by partitioning the given network into a core centered around the base station and a boundary edge. For the network core, we formulate a nonlinear programming problem, which can be solved by branch-and-bound approach. For data generated at network edge, we propose an algorithm to connect it to the network core. We use simulation results to demonstrate the efficacy of the proposed solution procedure, as well as the importance of cross-layer considerations.**

***Index Terms*—Optimization, power control, routing, scheduling, sensor networks, ultra-wideband (UWB).**

I. Introduction

IN THIS PAPER, we study the data collection problem associated with UWB-based sensor networks. For such networks, although the bit rate for each UWB-based sensor node could be high, the total rate that can be collected by the single base station is limited due to the network resource bottleneck near the base station, as well as interference among the incoming data traffic. Therefore, a fundamental question is the following: *Given a set of source sensor nodes in the network with each node generating a certain data rate, is it possible to relay all these rates successfully to the base station?*

A naive approach to this problem is to calculate the maximum bit rate that the base station can receive, and then perform a simple comparison between this limit with the sum of bit rates produced by the set of source sensor nodes. Indeed, if this limit is exceeded, it is impossible to relay all these rates successfully to the base station. But even if the sum of bit rates generated by source sensor nodes is less than this limit, it may still be infeasible to relay all these rates successfully to the base station. Due to interference and the fact that a node cannot send and receive at the same time, the actual sum of bit rates that can be relayed to the base station can be substantially smaller than the bit rate limit that a base station can receive. Further, such limit is highly dependent upon the network topology, locations of source sensor nodes, bit rates produced by source sensor nodes, and other network parameters. As a result, testing for this feasibility is not trivial, and it is important to devise a solution procedure to address this problem.

In this paper, we study this admissibility (or feasibility) problem through a cross-layer optimization approach, with joint consideration of link-layer scheduling, power control, and network-layer routing. The link-layer scheduling problem deals with how to allocate resources for access among the nodes. Motivated by the work in [6], we consider how to allocate frequency subbands, although this approach can also be applied to a timeslot-based system. Note that a node cannot transmit and receive within the same subband. The power control problem considers how much power a node should use to transmit data in a particular subband. Finally, the routing problem at the network level considers which set of paths a flow should take from the source sensor node toward the base station.

For large-sized networks, due to storage and computational requirements, it is necessary to develop a scalable solution procedure. *Our contribution in this paper is the development of a fast heuristic algorithm that is effective for large-sized networks.* Our approach is to partition the network into two parts: a network core that is centered around the base station and a network edge that is outside the core. The size of the network core is determined by the computational capability for the following optimization problem: the objective is maximizing the total incoming rates to the network core from nodes outside the core, subject to the constraint that these incoming rates and the bit rates generated by source sensor nodes inside the core can be delivered to the base station, among other constraints. We formulate this problem as a nonlinear programming (NLP) problem by using the approximately linear property between rate and signal-to-interference-noise ratio (SINR), which is unique to UWB. Although an NLP problem is NP-hard [3], it can be solved by a branch-and-bound approach. During the iterations of this optimization problem, we examine whether it is possible to "reconnect" source sensor nodes that are *outside* the core with a feasible solution.

The remainder of this paper is organized as follows. In Section II, we give details of the network model for our problem and discuss the cross-layer nature of this problem. In Section III, we present an efficient heuristic algorithm for large-sized networks. In Section IV, we present simulation results to demonstrate the efficacy of our proposed solution

Manuscript received March 7, 2005; revised October 15, 2005. The work of Y. Shi, Y. T. Hou, and S. F. Midkiff was supported in part by the Office of Naval Research (ONR) under Grant N00014-03-1-0521 and Grant N00014-05-1-0179 and in part by the National Science Foundation (NSF) under Grant ANI-0312655 and Grant CNS-0347390. The work of H. D. Sherali was supported in part by the NSF under Grant DMI-0094462.

Y. Shi, Y. T. Hou, and S. F. Midkiff are with the Bradley Department of Electrical and Computer Engineering, Virginia Polytechnic Institute and State University, Blacksburg, VA 24061 USA (e-mail: yshi@vt.edu; thou@vt.edu; midkiff@vt.edu).

H. D. Sherali is with the Grado Department of Industrial and Systems Engineering, Virginia Polytechnic Institute and State University, Blacksburg, VA 24061 USA (e-mail: hanifs@vt.edu).

Digital Object Identifier 10.1109/JSAC.2005.863869

procedures and give insights on the impact of different optimization component. Section V reviews related work and Section VI concludes this paper.

II. Network Model

We consider a UWB-based sensor network. Within such a sensor network, we assume there is a base station (or sink node) to which all collected data from source sensor nodes must be relayed (see Fig. 4). For simplicity, we denote the base station as node 0 in the network.

Under this sensor network setting, we are interested in answering the following questions.

- Suppose we have a small group of nodes $\mathcal{N}$ that have detected certain events and each of these nodes is generating data. Can we determine if the bit rates from these source sensor nodes can be successfully sent to the base station?
- If the determination is a "yes," how should we relay data from each source sensor node to the base station?

Before we further explore this problem, we give the following definition for the feasibility of a rate vector $\mathbf{r}$, where each element r_i of the vector corresponds to the sensing rate produced by node $i \in \mathcal{N}$.

Definition 1: For a given rate vector $\mathbf{r}$ having $r_i > 0$ for $i \in \mathcal{N}$, we say that this rate vector is feasible if and only if there exists a solution such that all r_i, $i \in \mathcal{N}$, can be relayed to the base station.

To determine whether or not a given rate vector $\mathbf{r}$ is feasible, there are several issues from different layers that must be considered. At the network level, we need to find a multihop route (likely multipaths) from the source to the sink node. At the link level, we need to find a scheduling policy and power control for each node such that constraints associated with link bit rate, flow balance at each node, and that a node cannot send and receive within the same subband can all be met satisfactorily. Clearly, this is a cross-layer problem that couples scheduling, power control, and routing. The rest of this section will take a closer look at each problem.

A. Scheduling, Power Control, and Routing

At the link level, the scheduling problem deals with how to allocate link resources for access among the nodes. Motivated by Negi and Rajeswaran's work in [6], we consider how to allocate frequency subbands. For the total available UWB spectrum of $W = 7.5$ GHz, we divide it into M subbands. Since the minimum bandwidth of a UWB subband is 500 MHz per UWB requirement, we have $1 \le M \le 15$. For a given number of total subbands M, the scheduling problem considers how to allocate the total spectrum of W into M subbands and in which subbands a node should transmit or receive data. More formally, we consider a subband m with normalized bandwidth $\lambda^{(m)}$. We have $\sum_{m=1}^{M} \lambda^{(m)} = 1$ and $\lambda_{\min} \le \lambda^{(m)} \le \lambda_{\max}$ for $1 \le m \le M$, where $\lambda_{\min} = 1/15$ and $\lambda_{\max} = 1 - (M-1) \cdot \lambda_{\min}$.

The power control problem considers how much power a node should use in a particular subband to transmit data. Denote p_{ij}^m as the power that node i spends in subband m for sending data to node j. Since a node cannot send and receive data within the same subband, we have the following: if $p_{ik}^m > 0$ for any node k, then p_{ji}^m should be 0 for all nodes j.

The power density limit for each node i must satisfy

$$\frac{g_{\text{nom}} \cdot \sum_{j \in \mathcal{S}_i} p_{ij}^m}{W \cdot \lambda^{(m)}} \le \pi_{\max}$$

where $\pi_{\max}$ is the maximum allowed power density, g_{nom} is the gain at some fixed nominal distance, and $\mathcal{S}_i$ is the set of nodes that node i can send data to in one hop with the maximum allowed transmission power. A popular model for gain is

$$g_{ij} = \min(d_{ij}^{-n}, 1) \tag{1}$$

where d_{ij} is the distance between nodes i and j and n is the path loss index. Denote

$$p_{\max} = \frac{W \cdot \pi_{\max}}{g_{\text{nom}}}. \tag{2}$$

Then, the total power that a node i can use at subband m must satisfy the following power limit:

$$\sum_{j \in \mathcal{S}_i} p_{ij}^m \le p_{\max} \lambda^{(m)}. \tag{3}$$

Denote $\mathcal{I}_i$ as the set of nodes that can make interference at node i when they use the maximum allowed transmission power. The achievable rate from node i to node j within subband m is then

$$b_{ij}^m = W\lambda^{(m)} \log_2 \left(1 + \frac{g_{ij} \cdot p_{ij}^m}{\eta W \lambda^{(m)} + \sum_{k \in \mathcal{I}_j, l \in \mathcal{S}_k}^{(k,l) \neq (i,j)} g_{kj} p_{kl}^m} \right) \tag{4}$$

where η is the ambient Gaussian noise. Denoting b_{ij} as the total achievable rate from node i to node j among all M subbands, we have

$$b_{ij} = \sum_{m=1}^{M} b_{ij}^m. \tag{5}$$

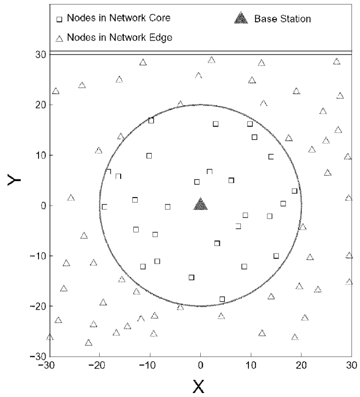
The routing problem at the network level considers the set of paths that a flow takes from the source node toward the base station. For optimality, we allow a flow from a source node to be split into subflows and take different paths to the base station. Denoting the flow rate from node i to node j as f_{ij}, we must have $f_{ij} \le b_{ij}$ and $\sum_{j \in \mathcal{S}_i} f_{ij} - \sum_{j \in \mathcal{R}_i} f_{ji} = r_i$, where $\mathcal{R}_i$ is the set of nodes that can send data directly to node i when they use the maximum allowed transmission power. The constraint $f_{ij} \le b_{ij}$ says that a flow's bit rate is upper bounded by the link capacity and the other constraint is for flow balance at node i.

III. A Solution Procedure for Large Networks

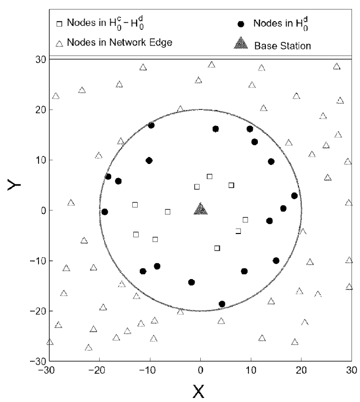
In [13], we presented an algorithm to the rate feasibility problem and a corresponding solution for a small-sized network. For large-sized networks, the algorithm in [13] has excessive storage and computational requirements that is beyond the capability of an ordinary desktop PC. Therefore, a new solution approach is needed.

A. Network Partitioning

We propose a heuristic algorithm that is effective for large networks. Our approach is based on the following observations for sensor networks. Since we only have a single base station as the sink node for all data generated in the network, the nodes that are close to the base station will be "bottleneck" nodes for



(a) Network core and network edge.



(b) Nodes in $\mathcal{H}_0^d$ within the network core.

Fig. 1. Illustration of network partitioning strategy.

the entire network. That is, the burden on a node near the base station is clearly much larger than that on a node far away from the base station. Therefore, we can partition the network into the following two parts, as shown in Fig. 1(a): a set of nodes $\mathcal{H}_0^c$ that lie within a circle centered around the base station and the remaining set of nodes that lie outside the circle. The size of $|\mathcal{H}_0^c|$ is determined by the maximum solvable size of rate feasibility problem (RFP), which focuses on finding a feasible solution for $|\mathcal{H}_0^c|$ and will be discussed in Section III-B. For convenience, we call the set of nodes in $\mathcal{H}_0^c$ as the network *core* and the set of nodes not in $\mathcal{H}_0^c$ as the network *edge*.

The partitioning of the network into the core and the edge has also effectively partitioned the source rate vector $\mathbf{r}$ into $\mathbf{r}^c$ and $\mathbf{r}-\mathbf{r}^c$, corresponding to the data rates generated within the network core $\mathcal{H}_0^c$ and outside the core, respectively. Now, our objective is to determine whether it is feasible to transport *both* $\mathbf{r}^c$ and $\mathbf{r}-\mathbf{r}^c$ to the base station. The feasibility test for $\mathbf{r}^c$ can be done when we solve RFP for the core network $\mathcal{H}_0^c$. The tricky part is how to test feasibility for $\mathbf{r}-\mathbf{r}^c$ at the *same* time.

Since not all nodes in $\mathcal{H}_0^c$ can receive data directly from nodes outside $\mathcal{H}_0^c$, we further identity a set of nodes in $\mathcal{H}_0^c$ as $\mathcal{H}_0^d$, where each node in $\mathcal{H}_0^d$ can receive data directly from nodes outside of $\mathcal{H}_0^c$. Intuitively, $\mathcal{H}_0^d$ includes the nodes at the edge within the set of $\mathcal{H}_0^c$ [see Fig. 1(b)].

Our algorithm is based on the following idea. For each node $i \in \mathcal{H}_0^d$, denote f_i^{in} as the rate of incoming flows to node i (for data generated outside of $\mathcal{H}_0^c$). We can set up an optimization problem RFP with the objective of maximizing $\sum_{i\in\mathcal{H}_0^d} f_i^{\text{in}}$, i.e., the total incoming rates to $\mathcal{H}_0^d$ from nodes outside the network core, subject to the constraint that these incoming rates and rates in vector $\mathbf{r}^c$ must be delivered to the base station, among other constraints. We can solve RFP by the branch-and-bound approach [7]. During the iterations of the branch-and-bound approach, for the current value of $\sum_{i\in\mathcal{H}_0^d} f_i^{\text{in}}$, if $\sum_{j\notin\mathcal{H}_0^c} r_j \le \sum_{i\in\mathcal{H}_0^d} f_i^{\text{in}}$, then we need to check whether it is possible to "reconnect" source sensor nodes $\mathbf{r}-\mathbf{r}^c$ to the nodes $i \in \mathcal{H}_0^d$ in the network core. If such a "connection" is possible, we declare the entire rate vector $\mathbf{r}$ as feasible and we have found a solution. Otherwise, we move on to the next iteration of maximizing $\sum_{i\in\mathcal{H}_0^d} f_i^{\text{in}}$.

B. Algorithmic Details

Since a node cannot send and receive within the same subband, we have that if $p_{jl}^m > 0$ for any $l \in \mathcal{S}_j$, then $p_{ij}^m = 0$ for all $i \in \mathcal{R}_j$. Instead of using integer (binary) variables, we can use the following approach to formulate the above requirement. We introduce the notion of a *self-interference parameter* g_{jj}, with the following property:

$$g_{jj} \cdot p_{jl}^m \gg \eta W \lambda^{(m)}.$$

We incorporate this into the bit rate calculation in (4), i.e.,

$$b_{ij}^m = W\lambda^{(m)} \cdot \log_2 \left(1 + \frac{g_{ij} p_{ij}^m}{\eta W \lambda^{(m)} + \sum_{k\in\mathcal{I}_j, l\in\mathcal{S}_k}^{(k,l)\neq(i,j)} g_{kj} p_{kl}^m + \sum_{l\in\mathcal{S}_j} g_{jj} p_{jl}^m} \right). \tag{6}$$

Thus, when $p_{jl}^m > 0$, i.e., node j is transmitting to any node l, then in (6), we have $b_{ij}^m \approx 0$ even if $p_{ij}^m > 0$. In other words, when node j is transmitting to any node l, the link capacity on node i to j is *effectively* shut down to 0.

To write (6) in a more compact form, we redefine $\mathcal{I}_j$ to include node j as long as j is not the base station node (i.e., node 0). Thus, (6) is now in the same form as (4). Denote

$$q_j^m = \sum_{k\in\mathcal{I}_j, l\in\mathcal{S}_k} g_{kj} p_{kl}^m. \tag{7}$$

Then, we have

$$\begin{aligned} b_{ij}^m &= W\lambda^{(m)} \log_2 \left(1 + \frac{g_{ij} p_{ij}^m}{\eta W\lambda^{(m)} + \sum_{k\in\mathcal{I}_j, l\in\mathcal{S}_k}^{(k,l)\neq(i,j)} g_{kj} p_{kl}^m} \right) \\ &= W\lambda^{(m)} \log_2 \left(1 + \frac{g_{ij} p_{ij}^m}{\eta W\lambda^{(m)} + q_j^m - g_{ij} p_{ij}^m} \right). \end{aligned}$$

To remove the nonpolynomial terms, we apply the low SINR property that is unique to UWB and the linearity approximation of the log function, i.e., $\ln(1+x) \approx x$ for $x > 0$ and $x \ll 1$. We have

$$b_{ij}^m \approx \frac{W\lambda^{(m)}}{\ln 2} \cdot \frac{g_{ij} p_{ij}^m}{\eta W\lambda^{(m)} + q_j^m - g_{ij} p_{ij}^m}$$

which is equivalent to

$$\eta W\lambda^{(m)} b_{ij}^m + q_j^m b_{ij}^m - g_{ij} p_{ij}^m b_{ij}^m - \frac{W}{\ln 2} g_{ij} \lambda^{(m)} p_{ij}^m = 0. \tag{8}$$

For node $i \in \mathcal{H}_0^c$, denote $\mathcal{R}_i^c$ as the set of nodes in $\mathcal{H}_0^c$ that can directly send data to node i, $\mathcal{I}_i^c$ as the set of nodes in $\mathcal{H}_0^c$ that can produce interference at node i, and $\mathcal{S}_i^c$ as the set of nodes in $\mathcal{H}_0^c$ to which node i can send data in one hop. We need special consideration for node $i \in \mathcal{H}_0^d$. The flow balance for node $i \in \mathcal{H}_0^d$ is as follows:.

$$\sum_{j \in \mathcal{S}_i^c} f_{ij} - \sum_{j \in \mathcal{R}_i^c} f_{ji} - f_i^{\text{in}} = r_i.$$

Denote

$$\left(q_j^m\right)^c = \sum_{k \in \mathcal{I}_j^c, l \in \mathcal{S}_k^c} g_{kj} p_{kl}^m.$$

It is clear that $\left(q_j^m\right)^c \le q_j^m$. Based on (8), we have

$$\begin{aligned}\eta W \lambda^{(m)} b_{ij}^m &+ \left(q_j^m\right)^c b_{ij}^m - g_{ij} p_{ij}^m b_{ij}^m - \frac{W}{\ln 2} g_{ij} \lambda^{(m)} p_{ij}^m \\ &\le \eta W \lambda^{(m)} b_{ij}^m + q_j^m b_{ij}^m - g_{ij} p_{ij}^m b_{ij}^m - \frac{W}{\ln 2} g_{ij} \lambda^{(m)} p_{ij}^m = 0.\end{aligned}$$

We now have the following problem formulation.

Rate Feasibility Problem (RFP):

$$\text{Maximize} \quad \sum_{i \in \mathcal{H}_0^d} f_i^{\text{in}}$$

subject to

$$\begin{aligned}
&\sum_{m=1}^{M} \lambda^{(m)} = 1 \\
&\sum_{j \in \mathcal{S}_i^c} p_{ij}^m - p_{\max} \lambda^{(m)} \le 0 \quad (i \in \mathcal{H}_0^c, 1 \le m \le M) \\
&\sum_{k \in \mathcal{I}_j^c, l \in \mathcal{S}_k^c} g_{kj} p_{kl}^m - \left(q_j^m\right)^c = 0 \quad \left(j \in \mathcal{H}_0^c \bigcup \{0\}, 1 \le m \le M\right) \\
&\eta W \lambda^{(m)} b_{ij}^m + \left(q_j^m\right)^c b_{ij}^m - g_{ij} p_{ij}^m b_{ij}^m - \frac{W}{\ln 2} g_{ij} \lambda^{(m)} p_{ij}^m = 0 \\
&\qquad (i \in \mathcal{H}_0^c - \mathcal{H}_0^d, j \in \mathcal{S}_i^c, 1 \le m \le M) \\
&\eta W \lambda^{(m)} b_{ij}^m + \left(q_j^m\right)^c b_{ij}^m - g_{ij} p_{ij}^m b_{ij}^m - \frac{W}{\ln 2} g_{ij} \lambda^{(m)} p_{ij}^m \le 0 \\
&\qquad (i \in \mathcal{H}_0^d, j \in \mathcal{S}_i^c, 1 \le m \le M) \\
&\sum_{m=1}^{M} b_{ij}^m - f_{ij} \ge 0 \quad (i \in \mathcal{H}_0^c, j \in \mathcal{S}_i^c) \\
&\sum_{j \in \mathcal{S}_i^c} f_{ij} - \sum_{j \in \mathcal{R}_i^c} f_{ji} = r_i \quad (i \in \mathcal{H}_0^c - \mathcal{H}_0^d) \\
&\sum_{j \in \mathcal{S}_i^c} f_{ij} - \sum_{j \in \mathcal{R}_i^c} f_{ji} - f_i^{\text{in}} = r_i \quad (i \in \mathcal{H}_0^d) \\
&\lambda_{\min} \le \lambda^{(m)} \le \lambda_{\max} \quad (1 \le m \le M) \\
&f_i^{\text{in}} \ge 0 \quad (i \in \mathcal{H}_0^d) \\
&p_{ij}^m, b_{ij}^m, \left(q_j^m\right)^c, f_{ij} \ge 0 \quad (i \in \mathcal{H}_0^c, j \in \mathcal{S}_i^c, 1 \le m \le M).
\end{aligned}$$

Problem RFP is in the form of NLP and can be solved by branch-and-bound framework [7]. During each iteration of branch-and-bound procedure, we use Reformulation-Linearization Technique (RLT) [11], [12] to obtain a relaxation solution and an upper bound of the objective. With the relaxation solution as a starting point, we can develop a *local search* algorithm to find a feasible solution to the original NLP problem. This feasible solution provides a lower bound of the objective.

Due to paper length constraint, we refer readers to [13] for the details of branch-and-bound procedure and RLT technique. We now provide some details of local search algorithm. We propose to use the same subband arrangement as that in the relaxation solution and obtain a power control arrangement from that in the relaxation solution. Recall that we introduced the notion of a self-interference parameter to avoid using binary variables in RFP. Then, it is possible that certain nodes may use the same subband for both transmission and receiving in the relaxation solution. Therefore, it is necessary to find a new power control arrangement to eliminate such behavior, which we propose as follows. We split the total spectrum bandwidth used at any node into two groups of equal spectrum bandwidth: one group for transmission and the other group for receiving. Again, we need special consideration for node $i \in \mathcal{H}_0^d$. Since the solution to the RFP problem does not show how scheduling is done for nodes $j \notin \mathcal{H}_0^c$, we aim that the total bandwidth of subbands used by node $i \in \mathcal{H}_0^d$ for transmission is no more than 1/2 of the entire spectrum W, which will give a balanced distribution of bandwidth between transmission and receiving.

After we obtain the subband and power control arrangement, we can compute b_{ij} from (4) and (5). Then, data routing in $\mathcal{H}_0^c$ can be solved by an LP. If we have $\sum_{j \notin \mathcal{H}_0^c} r_j \le \sum_{i \in \mathcal{H}_0^d} f_i^{\text{in}}$, we will need to check whether it is possible to "reconnect" source nodes in the network edge to those nodes $i \in \mathcal{H}_0^d$ corresponding to their f_i^{in}-values. The main idea of this reconnection check is as follows. We first find data routing solution for the farthest node s. Node s first chooses the nearest node in $\mathcal{H}_0^c$ as the destination t. Under the same subbands as that in the network core, we identify how many data can be transmitted from node s to node t via multihop routing. If all data of node s is transmitted, we are done for node s and we can move on to the data routing for the next farthest node. Once we are done with all source nodes in the network edge, we claim that it is possible to reconnect these nodes to nodes $i \in \mathcal{H}_0^d$. Otherwise, node s chooses the next nearest node in $\mathcal{H}_0^c$ as the destination. If all nodes in $\mathcal{H}_0^c$ have been used as destination for node s but there is still some remaining data from node s that has not been transmitted, we claim that it is impossible to reconnect source nodes in the network edge to nodes $i \in \mathcal{H}_0^d$. Fig. 2 shows such an algorithm.

IV. Simulation Results

In this section, we present numerical results for our solution procedure and compare it with other possible approaches. Given that the total UWB spectrum is $W = 7.5$ GHz and that each subband is at least 500 MHz, we have that the maximum number of subbands is $M = 15$. The gain model for a link (i, j) is $g_{ij} = \min(d_{ij}^{-2}, 1)$ and the nominal gain is chosen as $g_{\text{nom}} = 0.02$. The power density limit $\pi_{\max}$ is assumed to be 1% of the white noise η [10].

We consider a network of 100 nodes (see Fig. 4) over a 50×50 area and a larger network of 500 nodes (not shown) over a 100×100 area, where the distance is based on normalized length in (1). Both networks are generated at random.

0. **Routing Algorithm for Nodes Outside the Network Core**
1. Main function:
2. Identify a node that has not found a routing solution and is farthest from
3. the network core.
4. If no such a node exists, we are done. Otherwise, denote this node as s.
5. Node s chooses a node $t \in \mathcal{H}_0^d$ as destination in the order of
6. non-decreasing distance.
7. If all nodes in $\mathcal{H}_0^d$ have been considered in previous iterations, we
8. declare that we cannot find a solution.
9. $ret = \text{Rst}(s,\, t,\, \min\{r_s, f_t^{in}\})$; //Rst() returns how much data rate is
10. //transmitted to node t.
11. If $r_s > ret$, update $r_s = r_s - ret$ and go to Line 5.
12. Otherwise, we are done with node s and go to Line 2.
13. double Rst(s, t, req) { //This function attempts to send data rate req from
14. //node s to node t and returns the data rate that can be routed successfully.
15. For each next-hop node k, node s uses function Lsk(s, k) to find how
16. much data can be sent to node k.
17. Node s tries to find the nearest next-hop node k (to node t) that can
18. receive data rate req from s. In this case, let $r_{sk} = req$.
19. If no such a node exists, node s tries to find the next-hop k that can
20. receive the maximum data rate r_{sk} from s.
21. Node s uses a subset of available sub-bands to send r_{sk} data to node k.
22. If $k = t$, return r_{sk}. Otherwise, node s calls $ret = \text{Rst}(k,\, t,\, r_{sk})$.
23. If $ret < r_{sk}$, node s reduces its data rate $r_{sk} = ret$ by releasing
24. some used sub-bands. }
25. double Lsk(s, k) { //This function computes and returns the available link
26. //capacity from node s to node k.
27. For each sub-band, node s first checks whether it is available (cannot
28. send and receive within the same sub-band).
29. Moreover, node s checks if neighboring links can maintain the same
30. transmission rate by increasing their transmission power (subject to
31. maximum power limit).
32. For each available sub-band, node s then computes the maximum
33. available capacity and returns the sum of them. }

Fig. 2. An algorithm to check if data from nodes at network edge can be connected to nodes in network core.

Under both networks, the base station is located at the origin (lower left corner of the network). The details for each network will be elaborated shortly when we present the results.

We investigate the impact of scheduling and routing. We are interested in comparing a cross-layer approach to a decoupled-layering approach to our problem. We do not explicitly show the impact of power control, since power level at a node is the single most important factor in wireless communications and directly determines both scheduling and routing. For example, if $p_{ij}^m > 0$, then node i uses subband m to send data to node j. As a result, scheduling (which subband is used) and routing (which link is used) are immediately determined. Although $\lambda^{(m)}$ is not known, the lower bound of $\lambda^{(m)}$ is also given by $\sum_{j \in \mathcal{S}_i} p_{ij}^m / p_{\max}$ [from (3)].

A. Impact of Scheduling

We first consider the 100-node network shown in Fig. 4. There are eight source sensor nodes (marked as stars) in the network. The data rate are $r_1 = 5$, $r_2 = 2$, $r_3 = 2$, $r_4 = 4$, $r_5 = 5$, $r_6 = 3$, $r_7 = 3$, and $r_8 = 1$, with units defined in an appropriate manner. To show performance limits, we consider whether the network can transmit $K \cdot r_i$ from source sensor node i to the base station and investigate the maximum feasible K (feasibility factor) under different approaches. Fig. 3 (upper curve) shows the maximum achievable K for different M under our solution procedure. Clearly, K is a nondecreasing function of M, which states that the more subbands available, the larger traffic volume that the network can support. The physical explanation for this is that the more subbands available, the more opportunity for each node to avoid interference from other nodes within the same subband, and thus yields more capacity in the network. Also, note that there is a noticeable increase in K when M is small. But when $M \geq 4$, the increase in K is no longer significant. This suggests that for simplicity, we could just choose a small value (e.g., $M = 5$) for the number of subbands instead of the maximum $M = 15$.

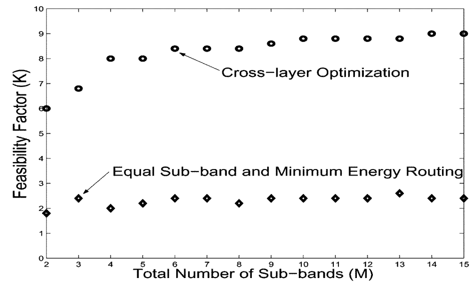
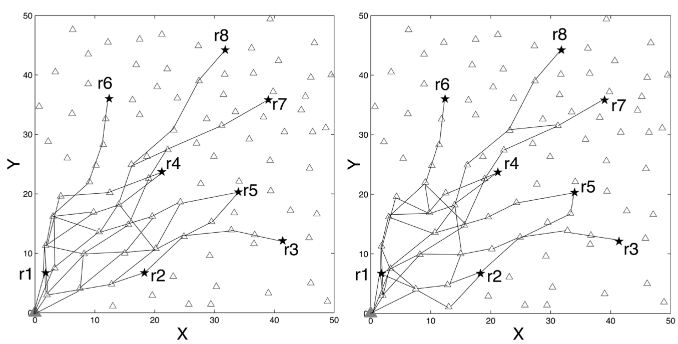


Fig. 3. The maximum achievable K as a function of M for the 100-node network.

TABLE I
PERFORMANCE OF FEASIBILITY FACTOR K UNDER DIFFERENT SPECTRUM ALLOCATIONS WITH $M = 5$ FOR THE 100-NODE NETWORK

Spectrum Allocation	K	Rate
Optimal: (0.4256, 0.2339, 0.1660 0.1066 0.0679)	8.0	200
Equal: (0.20, 0.20, 0.20, 0.20, 0.20)	4.2	105
Random 1: (0.36, 0.23, 0.20, 0.11, 0.10)	2.8	70
Random 2: (0.27, 0.24, 0.21, 0.17, 0.11)	4.2	105



(a) (b)

Fig. 4. Optimal routing obtained via the cross-layer optimization solution procedure for the 100-node network (a) $M = 5$ (b) $M = 10$.

To show the importance of joint optimization of link-level scheduling and power control and network-level routing, in Fig. 3, we also plot K as a function of M for a predefined routing strategy, namely, the minimum-energy routing with equal subband scheduling. Here, the energy cost is defined as g_{ij}^{-1} for link (i, j). Under this approach, we find a minimum-energy path for each source sensor node and determine which subband to use for each link and with how much power. When a node cannot find a feasible solution to send data to the next hop, it declares that the given rate vector is infeasible. In Fig. 3, we find that the minimum-energy routing with equal subband scheduling approach is significantly inferior than the proposed cross-layer optimization approach.

Table I shows the results for K under different spectrum allocations for $M = 5$. The routes are the same as those obtained under optimal routing from our cross-layer optimal solution [see Fig. 4(a)] and are fixed in this study. The first optimal spectrum

TABLE II
PERFORMANCE OF FEASIBILITY FACTOR K UNDER DIFFERENT SPECTRUM ALLOCATIONS WITH $M = 10$ FOR THE 100-NODE NETWORK

Spectrum Allocation	K	Rate
Optimal: (0.1551, 0.1365, 0.1283, 0.0962, 0.0952, 0.0916, 0.0901, 0.0702, 0.0689, 0.0679)	8.8	220
Equal: (0.10, 0.10, 0.10, 0.10, 0.10, 0.10, 0.10, 0.10, 0.10, 0.10)	3.6	90
Random 1: (0.14, 0.13, 0.12, 0.11, 0.09, 0.09, 0.09, 0.08, 0.08, 0.07)	4.0	100
Random 2: (0.17, 0.13, 0.11, 0.10, 0.10, 0.09, 0.08, 0.08, 0.07, 0.07)	3.8	95

TABLE III
LOCATION AND RATE FOR EACH SOURCE SENSOR NODE IN A 500-NODE NETWORK

Source Node Index	Location	Rate	Source Node Index	Location	Rate
1	(3.3, 82.0)	1	11	(4.2, 55.6)	1
2	(7.5, 4.1)	4	12	(15, 10)	2
3	(16.3, 35.8)	2	13	(19, 22.6)	2
4	(19.2, 58.7)	2	14	(20.9, 77.3)	4
5	(31.6, 94.4)	1	15	(36.2, 44.5)	1
6	(39.4, 20.5)	3	16	(39.8, 37.2)	3
7	(42.5, 96.2)	2	17	(45.8, 12.6)	1
8	(60.1, 17.1)	4	18	(63.4, 71.1)	1
9	(65.0, 66.6)	2	19	(71.4, 21.3)	3
10	(74.4, 74.8)	2	20	(90.5, 28.7)	3

allocation is obtained from the cross-layer optimal solution. The second is an equal spectrum allocation and the following two are random spectrum allocations. Clearly, the cross-layer optimal spectrum allocation provides the best performance among all these spectrum allocations. It is important to realize that in addition to the number of subbands M, the way how the spectrum is allocated for a given M also has a profound impact on the performance. In Table II, we perform the same study for $M = 10$ and obtain the same conclusion.

B. Impact of Routing

For the rest of this section, we consider a network of 500 nodes randomly deployed over a 100×100 area. Among these nodes, there are 20 source sensor nodes and the coordinates and bit rates for the source sensor nodes are listed in Table III. We study the impact of routing on our cross-layer optimization problem under a given optimal schedule (obtained through our solution procedure). Table IV shows the results in this study. In addition to our cross-layer optimal routing, we also consider the following two routing approaches, namely, minimum-energy routing and minimum-hop routing. The minimum-hop routing is similar to the minimum-energy routing, except the cost here is measured in the number of hops.

In Table IV, the spectrum allocation is chosen as the optimal spectrum allocation from our cross-layer optimal solution and is fixed. Specifically, for $M = 5$, we have $\mathbf{\Lambda} = (0.0758, 0.1144, 0.1234, 0.3045, 0.3819)$; for $M = 10$, we have $\mathbf{\Lambda} = (0.0692, 0.0719, 0.0758, 0.0781, 0.0853, 0.1047, 0.1084, 0.1144, 0.1234, 0.1688)$. Clearly, the cross-layer optimal routing outperforms both minimum-energy and minimum-hop routing approaches. Both minimum-energy routing and minimum-hop routing are minimum-cost routing (with different link cost). Minimum-cost routing only uses a

TABLE IV
PERFORMANCE OF FEASIBILITY FACTOR K UNDER DIFFERENT ROUTING STRATEGIES FOR THE 500-NODE NETWORK

Routing Strategy	$M = 5$		$M = 10$	
	K	Rate	K	Rate
Optimal Routing	4.6	202.4	4.6	202.4
Minimum-Energy Routing	1.0	44.0	1.2	52.8
Minimum-Hop Routing	0.6	26.4	1.0	44.0

single-path, i.e., multipath routing is not allowed, which may not provide good solution. Moreover, it is very likely that multiple sensors share a "good" path. Thus, the rates for these sensors are bounded by the capacity of this path. Further, minimum-hop routing has its own unique problem. Minimum-hop routing prefers small number of hops (with a long distance on each hop) toward the destination node. Clearly, a long-distance hop will reduce its corresponding link's capacity, due to the distance gain factor.

V. RELATED WORK

In [5], Negi and Rajeswaran first showed that, in contrast to previously published results, the throughput for UWB-based ad hoc networks increases with node density. This important result is mainly due to the large bandwidth and the ability of power and rate adaptation of UWB-based nodes, which alleviate interference. More importantly, this result demonstrates the significance of physical-layer properties on network-layer metrics such as network capacity. In [1], Baldi *et al.* considered the admission control problem based on a flexible cost function in UWB-based networks. Under their approach, a communication cost is attached to each path and the cost of a path is the sum of costs associated with the links it comprises. An admissibility test is then made based on the cost of a path. However, there is no explicit consideration of joint cross-layer optimization of scheduling, power control, and routing in this admissibility test. In [2], Cuomo *et al.* studied a multiple-access scheme for UWB. Power control and rate allocation problems were formulated for both elastic bandwidth data traffic and guaranteed service traffic. The impact of routing, however, was not addressed.

The most closely related research to our work are [6] and [9]. In [6], Negi and Rajeswaran studied how to maximize proportional rate allocation in a single-hop UWB network (each node can communicate to any other node in a single hop). The problem was formulated as a cross-layer optimization problem with similar scheduling and power control constraints as in this paper. In contrast, our focus in this paper is on an admissibility test for a rate vector in a sensor network, and we consider a multihop network environment where routing is also part of the cross-layer optimization problem. As a result, the problem in this paper is more difficult. In [9], Radunovic and Le Boudec studied how to maximize the total log-utility of flow rates in multihop ad hoc networks. The cross-layer optimization space consists of scheduling, power control, and routing. As the optimization problem is NP-hard, the authors then studied a simple ring network, as well as a small-sized network with predefined scheduling and routing policies. On the other hand, in this paper, we have developed a novel solution procedure to our cross-layer optimization problem, despite that it is highly complex.

VI. Conclusion

In this paper, we studied the important problem of routing data traffic in a UWB-based sensor network. We followed a cross-layer optimization approach with joint consideration of link-layer scheduling, power control, and network-layer routing. For large-sized networks, we designed an efficient heuristic algorithm by intelligently partitioning the network into core and edge components, where the problem associated with the core can be effectively addressed by a branch-and-bound approach. We also show how to connect the data in network edge to the network core. Our simulation results demonstrated the efficacy of our proposed solution procedure and substantiated the importance of cross-layer optimization for UWB-based sensor networks.

References

[1] P. Baldi, L. De Nardis, and M.-G. Di Benedetto, "Modeling and optimization of UWB communication networks through a flexible cost function," *IEEE J. Sel. Areas Commun.*, vol. 20, no. 9, pp. 1733–1744, Dec. 2002.

[2] F. Cuomo, C. Martello, A. Baiocchi, and F. Capriotti, "Radio resource sharing for ad hoc networking with UWB," *IEEE J. Sel. Areas Commun.*, vol. 20, no. 9, pp. 1722–1732, Dec. 2002.

[3] M. R. Garey, *Computers and Intractability: A Guide to the Theory of NP-Completeness*. New York: Freeman, 1979, pp. 245–248.

[4] A. Goldsmith and S. B. Wicker, "Design challenges for energy-constrained ad hoc wireless networks," *IEEE Wireless Commun.*, vol. 9, pp. 8–27, Aug. 2002.

[5] R. Negi and A. Rajeswaran, "Capacity of power constrained ad-hoc networks," in *Proc. IEEE INFOCOM*, Hong Kong, China, Mar. 7–11, 2004, pp. 443–453.

[6] ——, "Scheduling and power adaptation for networks in the ultra wide band regime," in *Proc. IEEE GLOBECOM*, Dallas, TX, Nov.–Dec. 29–3, 2004, pp. 139–145.

[7] G. L. Nemhauser and L. A. Wolsey, *Integer and Combinatorial Optimization*. New York: Wiley, 1999, pp. 354–367.

[8] D. Porcino, "Ultra-wideband radio technology: Potential and challenges ahead," *IEEE Commun. Mag.*, pp. 66–74, Jul. 2003.

[9] B. Radunovic and J.-Y. Le Boudec, "Optimal power control, scheduling, and routing in UWB networks," *IEEE J. Sel. Areas Commun.*, vol. 22, no. 7, pp. 1252–1270, Sep. 2004.

[10] A. Rajeswaran, G. Kim, and R. Negi, "A scheduling framwork for UWB & cellular networks," in *Proc. 1st Int. Conf. Broadband Networks (Broadnets)*, San Jose, CA, Oct. 25–29, 2004, pp. 386–395.

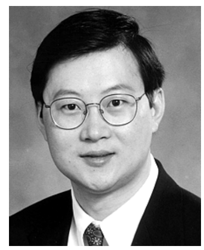
[11] H. D. Sherali and W. P. Adams, *A Reformulation-Linearization Technique for Solving Discrete and Continuous Nonconvex Problems*. Norwell, MA: Kluwer, 1999, ch. 8.

[12] H. D. Sherali, "Tight relaxations for nonconvex optimization problems using the reformulation-linearization/convexification technique (RLT)," in *Handbook of Global Optimization, Volume 2: Heuristic Approaches*, P. M. Pardalos and H. E. Romeijn, Eds. Norwell, MA: Kluwer, 2002, pp. 1–63.

[13] Y. Shi, Y. T. Hou, H. D. Sherali, and S. F. Midkiff, "Cross-layer optimization for routing data traffic in UWB-based sensor networks," in *Proc. ACM MobiCom*, Cologne, Germany, Aug. 28–Sep. 2, 2005, pp. 299–312.

Yi Shi (S'02) received the B.S. degree from the University of Science and Technology of China, Hefei, in 1998, the M.S. degree from the Institute of Software, Chinese Academy of Science, Beijing, China, in 2001, the M.S. degree from the Virginia Polytechnic Institute and State University (Virginia Tech), Blacksburg, in 2003, all in computer science. He is currently working towards the Ph.D. degree in electrical and computer engineering at Virginia Tech.

His current research focuses on algorithms and optimization for wireless sensor networks, ad hoc networks, and UWB networks.



Y. Thomas Hou (S'91–M'98–SM'04) received the B.E. degree from the City College of New York in 1991, the M.S. degree from Columbia University, New York, in 1993, and the Ph.D. degree from Polytechnic University, Brooklyn, NY, in 1998, all in electrical engineering.

From 1997 to 2002, he was a Principal Research Scientist and Project Leader at Fujitsu Laboratories of America, IP Networking Research Department, Sunnyvale, CA (Silicon Valley). Since Fall 2002, he has been an Assistant Professor at the Bradley Department of Electrical and Computer Engineering, Virginia Polytechnic Institute and State University (Virginia Tech), Blacksburg. His research interests are in the algorithmic design and optimization for network systems, with current focus on wireless ad hoc networks, sensor networks, and video over ad hoc networks.

Hanif D. Sherali is the W. Thomas Rice Endowed Chaired Professor of Engineering in the Industrial and Systems Engineering Department, Virginia Polytechnic Institute and State University (Virginia Tech), Blacksburg.

His area of research interest is in discrete and continuous optimization, with applications to location, transportation, and engineering design problems.

Dr. Sherali is a member of the U.S. National Academy of Engineering.

Scott F. Midkiff (S'82–M'85–SM'92) received the B.S.E. and Ph.D. from Duke University, Durham, NC, and the M.S. degree from Stanford University, Stanford, CA, all in electrical engineering.

He joined the Bradley Department of Electrical and Computer Engineering, Virginia Polytechnic Institute and State University (Virginia Tech), Blacksburg, in 1986, and is now a Professor. His research interests include system issues in wireless and ad hoc networks, network services for pervasive computing, and performance modeling of mobile ad hoc networks.