ENERGY MINIMIZATION-BASED CROSS-LAYER DESIGN IN WIRELESS NETWORKS

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ABSTRACT

In this paper, a cross-layer optimization framework is proposed for multi-hop time division multiple access (TDMA) networks. Particularly, given a set of quality-of-service (QoS) constraints on the network flows, we study a centralized controller that coordinates the routing process, link scheduling and power control to minimize the energy consumption in the network. The aforementioned design can be formulated as a mixed integer-linear program (MILP) in which finding optimal solution is well-known to have worst case exponential complexity. Realizing this inherent difficulty in computational complexity, our main contribution is to propose a novel approach to solve the cross-layer design problem which is based on a so-called *Difference of Convex functions Algorithm* (DCA). The proposed approach is able to provide either optimal or near-optimal solutions with finite convergence. The preliminary numerical results demonstrate the effectiveness of the proposed design.

INTRODUCTION

Wireless networks, for example mesh, ad hoc or sensor networks have recently emerged as essential means of communications to provide reliable data communication among many users. In such networks, wireless nodes usually self-configure to exchange information without the aid of any established infrastructure. However, due to the random deployment and mobility of wireless nodes, multi-hop transmission is necessary where nodes can forward other nodes' information. Due to interference between links, in this research, time division multiple access-based (TDMA) MAC is adopted to allocate communication resources to links/nodes. Note that the problem of optimal scheduling in TDMA-based networks is NP-complete (5) and is somehow similar to the vertex coloring problem in graph theory (13). Furthermore, in a multi-hop network, power allocation, link scheduling, routing, and rate control interact with each other. Thus, a cross-layer design across all layers (see, e.g., (3) for an overview) is shown to outperform the method of designing each layer by itself which is popular in wireline networks. Recently, cross-layer optimization with different design objectives and constraints has received much attention from the academia (2), (4), (15), (16).

In this work, we consider a cross-layer design problem to allocate communication resources, i.e., time and power to links in an interference-limited TDMA wireless network. Generally, nodes in a wireless network are battery-powered devices and energy is consumed when a node transmit or receive data to/from other nodes. Moreover, since nodes participate in the network operation by either generating or relaying information that needs to be communicated to a base station, we aim at minimizing the energy consumption for all nodes. The proposed design objective is helpful to estimate the energy expenditure for optimal network operation. We show that the proposed design can be formulated as a mixed integer-linear program (MILP) which is well-known to be computationally expensive. By employing the *exact penalty method* theory, we are able equivalently recast the proposed MILP as a *concave minimization* problem with only continuous variables without losing optimality. Next, we reformulate the concave minimization problem in the form of a DC (Difference of Convex functions) program that consists of minimizing a DC function on the whole space. We propose a technique which combines *DC Algorithm* (DCA) and the traditional *branch and bound* (BnB) to solve the resulting DC problem. Generally, DCA has linear convergence and achieves near-optimal solution. One of the powerful and distinct advantage of the DCA-BnB approach is its ability to solve very large-scale problems.

SYSTEMS DESCRIPTION

Consider a multi-hop network with node set $\mathcal{N}$. Uplink transmission is assumed where there is one common traffic destination (not included in $\mathcal{N}$) for all the nodes. Each node $n \in \mathcal{N}$ generates traffic at a rate r_n which is a integer number of unit rate. Let $\mathcal{L}$ denote the set of unidirectional links.

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TDMA-based MAC and Flow Conservation Model

In a multi-hop network, in general, all the links may not be scheduled to transmit concurrently since they contend and/or interfere with each other. In addition, due to primary interference, each node cannot transmit and receive simultaneously, and thus, a node's outgoing and incoming links cannot be active at the same time. Further, we assume unicast network in which a transmitter cannot transmit data to more than one receivers. In addition, any two simultaneous transmissions with a common receiver are not allowed due to collision in packet reception.

In the considered TDMA network, time is partitioned into fixed-length frames, and each frame is further divided into J time slots with unit duration. Since the resource allocation is the same in all frames, we concentrate our design on a single frame. A node may need to transmit in one or more slots for its own traffic and/or relay traffic from other nodes. If a node transmits in a slot, while its transmission power can be varied from [0, $P_{\max}$], its transmission rate is fixed at a unit rate. In the TDMA-based network, a channel is specified by two elements (j,l), $j \in \mathcal{J}$, $l \in \mathcal{L}$, where $\mathcal{J} = \{1, 2, ..., J\}$. For the channel, the resource allocation is denoted by (s^l_j, P^l_j), where $s^l_j = 1$ means link l is active at slot j while $s^l_j = 0$ otherwise, and $P^l_j > 0$ denotes the transmission power of link l at slot j if $s^l_j = 1$, $P^l_j = 0$ otherwise.

At each node, the difference of its outgoing traffic and its incoming traffic should be the traffic generated by itself, i.e.,

$$\sum_{l \in \mathcal{O}(n)} \sum_{j=1}^{J} s^l_j - \sum_{l \in \mathcal{I}(n)} \sum_{j=1}^{J} s^l_j = r_n, \quad n \in \mathcal{N} \tag{1}$$

where $\mathcal{O}(n)$ and $\mathcal{I}(n)$ are the set of outgoing links and incoming links at node n, respectively. The values of s_n for the non-source nodes are set to zero.

The energy consumption at node n can be written as

$$\mathcal{E}_n = \sum_{l \in \mathcal{O}(n)} \sum_{j=1}^{J} P^l_j + \sum_{l \in \mathcal{O}(n)} \sum_{j=1}^{J} \epsilon_l s^l_j + \sum_{l \in \mathcal{I}(n)} \sum_{j=1}^{J} \varepsilon_l s^l_j \tag{2}$$

where ϵ_l, ε_l denote the energy needed to transmit, receive a unit of traffic over link l, respectively. Note that ϵ_l, ε_l include the energy consumed by the signal processing blocks at the link ends.

Interference Model

Interference relations among the nodes and/or links in a wireless networks can be modeled in various ways, for example by using contention-based model (15) or the signal-to-interference-plus-noise-ratio (SINR)-based model (11), (1). The latter model is adopted in this research. Specifically, if the link $l \in \mathcal{L}$ is active at slot j (i.e., $s^l_j = 1$), the following inequality should hold so as to guarantee the transmission quality of the link

$$\mathrm{SINR}^l_j = \frac{P^l_j h_{ll}}{\sum_{k \neq l} P^k_j h_{kl} + \eta_l} \geq \gamma^{\mathrm{th}} \tag{3}$$

where SINR^l_j is the SINR for link l at slot j, h_{kl} is the path gain from the transmitter of link k to the receiver of link l, η_l is the noise power at receiver of link l, and γ^{th} is the required SINR threshold for accurate information transmission.

We assume that all wireless nodes are low-mobility devices and/or the topology of the network is static or changes slowly allowing enough time for computing the new scheduler. An example of such networks is a wireless sensor network for environmental monitoring with fixed sensor locations. In this case, the need for distributed implementation is not necessary.

PROBLEM FORMULATION

As discussed above, energy consumption is an important design criterion for a multi-hop wireless network. From the preceding discussions, the energy minimization-based cross-layer design, i.e., joint rate control, routing, link scheduling, and power allocation problem can be mathematically posed as

$$\min_{r_n, P^l_j,\, s^l_j} \quad \sum_{n \in \mathcal{N}} \mathcal{E}_n \tag{4a}$$

subject to:

$$\sum_{l \in \mathcal{O}(n)} \sum_{j=1}^{J} s^l_j - \sum_{l \in \mathcal{I}(n)} \sum_{j=1}^{J} s^l_j = r_n,\ n \in \mathcal{N} \tag{4b}$$

$$r_n \geq r^{\min}_n,\ n \in \mathcal{N} \tag{4c}$$

$$\sum_{l \in \mathcal{I}(\hat{n})} \sum_{j=1}^{J} s^l_j = \sum_{n \in \mathcal{N}} r_n \tag{4d}$$

$$\sum_{l \in \mathcal{O}(n)} s^l_j + \sum_{l \in \mathcal{I}(n)} s^l_j \leq 1,\ \forall n \in \{\mathcal{N} \cup \hat{n}\},\ \forall j \tag{4e}$$

$$h_{ll} P^l_j \geq \gamma^{\mathrm{th}} \sum_{k \neq l} P^k_j h_{kl} + \gamma^{\mathrm{th}} \eta_l + D(s^l_j - 1), \quad \forall l \in \mathcal{L},\ j = 1, \ldots, J \tag{4f}$$

$$0 \leq P^l_j \leq P_{max} s^l_j,\ \forall l \in \mathcal{L},\ j = 1, \ldots, J \tag{4g}$$

$$s^l_j \in \{0, 1\}, \quad \forall l \in \mathcal{L},\ j = 1, \ldots, J \tag{4h}$$

where $\hat{n}$ denotes the common sink node for all data generated in the network, D is a very large positive constant. The objective function is the energy consumption in the network. Constraints (4b) ensure that the data generated by source nodes are routed properly. Constraints (4c) guarantee that the rate for each node is no less than a minimum rate. The minimum rates are possibly different for nodes and are usually determined by the network QoS. Nodes which do not generate traffic have $r_n = r^{\min}_n = 0$. Constraint (4d) is the flow conservation at the traffic destination for all the sources. Constraints (4e) state that a node can not receive and transmit simultaneously in one particular time slot. Constraints (4f) make sure the SINR requirement is met: if a link l is active in time slot j, then the SINR at receiver of link l must be larger than the given threshold γ^{th} which also depends on the system implementation. Constraint (4f) is automatically satisfied if link l is not scheduled in time slot j. Constraint (4g) states that if a link l is scheduled for time slot j, i.e., $s_j^l = 1$, then the corresponding power value P_j^l must be less than P_{max}. Otherwise, P_j^l obviously equals to zero. We also impose binary integer constraints on s_j^l.

It can be seen that the cross-layer optimization problem (4a)–(4h) belongs to a class of well-known mixed-integer linear programs (MILPs). The combinatorial nature of the optimization (4a)–(4h) is not surprising and it has been shown in some previous works, albeit with different objective functions and formulations (11), (13), (1). Theoretically, MILPs are NP-hard which is clearly inviable for practical scenarios when the dimension is large. The following theorem is in order.

LEMMA 1: At optimality, the source rate constraints (4c) must be met with equalities for all sources.

PROOF: It is clear that at one node, the transmit power is an increasing function with respect to the node's transmission rate. Therefore, in order to minimize the transmit power, nodes should transmit at their minimum rate requirements or only relay data for other nodes. □

Since the proposed design aims at minimizing the total energy consumption, it may cause some particular nodes spending more energy than the other nodes, and thus, running out of energy quicker. Therefore, equal energy distribution among nodes is not optimal. In this context, the proposed design can be performed, for example during the stage of network planning. In such scenarios, the network designer needs to assign each wireless node a certain amount of energy (e.g., a number of AAA batteries) according to the network topology and QoS constraints of the nodes. Therefore, the proposed design helps to determine which nodes need to be equipped with more and/or less energy than the others. Moreover, it quantifies the minimum amount of energy needed in a TDMA frame to satisfy the QoS demands. Obviously, depending on a particular context, this energy value is closely related to the network lifetime depending how the network lifetime is defined.

As discussed, the routing algorithm resulted from the proposed design may cause some nodes spending more time than the others. Therefore, another design objective which may help to prevent such situation is as follows

$$\min_{r_n, P_j^l, s_j^l} \quad \max_{n \in \mathcal{N}} \mathcal{E}_n \tag{5a}$$

$$\text{subject to:} \quad \text{The constraints (4b)–(4h)}. \tag{5b}$$

The optimization problem (5a)–(5b) aims at minimizing the maximum energy consumed at nodes(s). As a result, more nodes are likely to be involved in the routing algorithm, i.e., relaying information for other nodes. Hereafter, for simplicity, we only consider the optimization problem (4a)–(4h).

The cross-layer optimization problem (4a)–(4h) has worst case exponential complexity when BnB methods are used to compute the solution. Moreover, when modeling practical networks and depending on the number of links, nodes and time slots, problem with large sizes may arise. As a result, it is extremely difficult to schedule links optimally. Most research in literature is based on heuristic at the cost of performance degradation, for example, see (11), (13). Here, we propose a method to solve the mixed 0-1 linear program (4a)–(4h) efficiently. To this purpose, we first apply the theory of exact penalization in DC programming (7) to reformulate the MILP as that of minimizing a DC function over a polyhedral convex set. The resulting problem is then handled by DCA which was introduced and extensively developed over the last decades (6), (8), (9), (10). The mentioned approach has been applied successfully in several large scale problems (see (6), (8), (9), (10) and reference therein). The details are provided in the following section.

AN EFFICIENT ALGORITHM FOR CROSS-LAYER DESIGN IN TDMA NETWORKS

DC Reformulation via Exact Penalty Method

Using an exact penalty result, we can reformulate the aforementioned MILP (4a)–(4h) in the form of a concave minimization program. The exact penalty technique aims at transforming the original MILP into a more tractable equivalent problem in the DC optimization framework. Let S be the feasible set of the problem MILP (4a)–(4h) which does not include the binary constraints. For notational simplicity, we group all the power variables and link scheduling variables in column vectors $P = [P_1^1 \dots P_1^J P_2^1 \dots P_L^J]^T$, $s = [s_1^1 \dots s_1^J s_2^1 \dots s_L^J]^T$ respectively where T denotes the transpose operator. We denote a new set $K := \{(P, s) \in S : s \in [0,1]^{LJ}\}$, and assume that K is a nonempty, bounded polyhedral convex set in $\mathbb{R}^{LJ} \times \mathbb{R}^{LJ}$. The cross-layer optimization problem (4a)–(4h) can be expressed in the general form

$$(P_{\text{opt}}, s_{\text{opt}}) = \arg\min \Big\{ e^T P + \eta^T s : (P, s) \in S, \; s \in \{0,1\}^{LJ} \Big\}. \tag{6}$$

where e is the column vector with all elements being 1, $\eta = [\eta_1^1, \dots, \eta_1^J, \eta_2^1, \dots, \eta_L^J]$, $\eta_l^j = \epsilon_l^j + \varepsilon_l^j$. Let us consider the function $p(P, s)$ defined by

$$p(P, s) = \sum_{l \in \mathcal{L},\, j \in \mathcal{J}} \min\{s_j^l, 1 - s_j^l\}. \tag{7}$$

It is clear that p is concave and finite on K, $p(P, s) \geq 0$ for all $(P, s) \in K$, and

$$\Big\{(P, s) \in S : s \in \{0,1\}^{LJ}\Big\} = \Big\{(P, s) \in K : p \leq 0\Big\}.$$

Hence problem (6) can be rewritten as

$$(P_{\text{opt}}, s_{\text{opt}}) = \arg\min \Big\{ e^T P + \eta^T s : (P, s) \in K, \; p(P, s) \leq 0 \Big\}. \tag{8}$$

The following theorem is in order.

THEOREM 2: (Theorem 1, (7)) Let K be a nonempty bounded polyhedral convex set, f be a finite concave function on K and p be a finite nonnegative concave function on K. Then there exists $\tilde{t}_0 \geq 0$ such that for $\tilde{t} > \tilde{t}_0$ the following problems have the same optimal value and the same solution set

$$(P_t) \qquad \alpha(t) = \min\Big\{f(x) + \tilde{t}p(x) : x \in K\Big\} \quad (9)$$

$$(P) \qquad \alpha = \min\Big\{f(x) : x \in K, p(x) \leq 0\Big\}. \quad (10)$$

Furthermore

- If the vertex set of K, denoted by $V(K)$, is contained in $x \in K : p(x) \leq 0$, then $\tilde{t}_0 = 0$.
- If $p(x) > 0$ for some x in $V(K)$, then $\tilde{t}_0 = \min\Big\{\frac{f(x)-\alpha(0)}{S_0} : x \in K, p(x) \leq 0\Big\}$, where $S_0 = \min\Big\{p(x) : x \in V(K), p(x) > 0\Big\} > 0$.

PROOF: The proof for the general case can be found in (7). □

From Theorem 2 we get, for a sufficiently large number $\tilde{t}\,(\tilde{t} > \tilde{t}_0)$, the equivalent concave minimization problem to (8)

$$\min : \Big\{e^T P + \eta^T s + \tilde{t}p(P, s) : (P, s) \in K\Big\} \quad (11)$$

which is a DC program

$$\min : \Big\{g(P, s) - h(P, s)\Big\} \quad (12)$$

where

$$g(P, s) = \mathcal{X}_K(P, s)$$
$$h(P, s) = -e^T P - \eta^T s - \tilde{t} \sum_{l \in \mathcal{L},\, j \in \mathcal{J}} \min\{s^l_j, 1 - s^l_j\}$$

and $\mathcal{X}_K(P, s)$ is 0 if $(P, s) \in K$, otherwise $+\infty$ (the indicator function of K).

We have successfully transform an optimization with integer variables into its equivalent form with continuous variables.

DCA for Solving (11)

In this section we investigate a DC programming approach for solving (11). In recent years, D.C. programming has been developed extensively, becoming an attractive topic of research in nonconvex programming. A DC program has the following form

$$\alpha := \min\Big\{f(x) := g(x) - h(x) : x \in \mathcal{R}^n\Big\} \quad (13)$$

with g, h being lower semi-continuous proper convex functions on $\mathcal{R}^n$, and its dual is defined as

$$\alpha := \min\Big\{h^*(y) - g^*(y) : y \in \mathcal{R}^n\Big\} \quad (14)$$

where $g^*(y) := \max\{x^T y - g(x) : x \in \mathcal{R}^n\}$ is the conjugate function of g.

Based on local optimality conditions and duality in DC programming, the DCA consists in the construction of two sequences $\{x^k\}$ and $\{y^k\}$, candidates to be optimal solutions of primal and dual programs respectively, in such a way that $\{g(x^k) - h(x^k)\}$ and $\{h^*(y^k) - g^*(y^k)\}$ are decreasing and their limits points satisfy the local optimality conditions. The idea of DCA is simple: each iteration of DCA approximates the concave part $-h$ by its affine majorization (that corresponds to taking $y^k \in \partial h(x^k)$) and minimizes the resulting convex function.

Generic DCA scheme:

Initialization Let $x^0 \in \mathcal{R}^n$ be a best guest, $0 \leftarrow k$.

Repeat

- Calculate $y^k \in \partial h(x^k)$
- Calculate $x^{k+1} \in \arg\min\{g(x) - h(x^k) - \langle x - x^k, y^k\rangle : x \in \mathcal{R}^n\} \quad (P_k)$
- $k + 1 \leftarrow k$

Until convergence of x^k.

Convergence properties of DCA and its theoretical basis can be found in (8), (9), (10), for instance it is important to mention that:

- DCA is a descent method (the sequences $\{g(x^k) - h(x^k)\}$ is decreasing) *without linesearch*.
- If the optimal value of problem (13) is finite and the infinite sequence $\{x^k\}$ is bounded then every limit point x^* of $\{x^k\}$ is a critical point of $g - h$.
- DCA has a *linear convergence* for general DC programs.
- DCA has a finite convergence for polyhedral DC programs ((13) is called polyhedral DC program if either g or h is polyhedral convex).

We now describe the DCA applied to the DC program (12). By the very first definition of h, a sub-gradient $(u, v) \in \partial h(P, s)$ can be chosen

$$(u, v) \in \partial h(P, s) \leftarrow u^l_j = -1; \quad (15)$$
$$v^l_j = \eta^l_j + \tilde{t} \text{ if } s^l_j \geq 0.5, \text{otherwise } v^l_j = \eta^l_j - \tilde{t}.$$

Algorithm 1 (DCA applied to (11))

Let $\epsilon > 0$ be small enough and (P^0, s^0). Set $k = 0$, $er = 1$.

while $er > \epsilon$ **do**

- Compute $(u^k, v^k) \in \partial h(P^k, s^k)$ via (16).
- Solve the linear program: $\min\{-{u^k}^T P - {v^k}^T s : (P, s) \in K\}$ to obtain (P^{k+1}, s^{k+1}).
- Set $er = \|(P^{k+1}, s^{k+1}) - (P^k, s^k)\|$, $k = k + 1$.

endwhile

Regarding the complexity of the proposed DCA, besides the computation of the sub-gradients which is trivial, the algorithm requires one linear program at each iteration and it has a finite convergence. The linear program has polynomial complexity. The convergence of Algorithm 1 can be summarized in the next theorem (9).

THEOREM 3:

i) Algorithm 1 generates a sequence $\{(P^k, s^k)\}$ contained in $V(K)$ such that the sequence $\{g(P^k, s^k) - h(P^k, s^k)\}$ is decreasing.

ii) If at iteration r we have $s^r \in \{0,1\}^{LJ}$, then $s^k \in \{0,1\}^{LJ}$ and $f(P^{k+1}, s^{k+1}) \leq f(P^k, s^k)$ for all $k \geq r$.

iii) The sequence $\{(P^k, s^k)\}$ converges to $\{(P^*, s^*)\} \in V(K)$ after a finite number of iterations. The point $\{(P^*, s^*)\}$ is a critical point of Problem (11). Moreover such an (P^*, s^*) is almost always a strict local minimum of (11).

PROOF: i) is a convergence property of general DC programs (9), (10) while ii) and iii) can be deduced from Proposition 2 in (6). □

Since DCA works on the continuous problem (11), its solution may not be integer, i.e. not feasible to (MILP). For obtaining an integer solution we combine DCA with the branch and bound method in which a lower bound is computed by solving the corresponding relaxed linear problem. At each iteration we restart DCA from the optimal solution of the relaxed problem. We stop the combined algorithm when the solution furnished by DCA is feasible to (MILP).

Algorithm 2: DCA with starting points obtained by BnB

Set $R_0 := [0,1]^{LJ}$, $k := 0$.

Solve the linear relaxation problem of MILP to obtain an optimal solution (P^0, s^0) and the optimal value $\beta(R_0)$.

If (P^0, s^0) is feasible of MILP **then** STOP

else: solve (11) by DCA from the starting point (P^0, s^0) to obtain $(\overline{P}, \overline{s})$.

If $(\overline{P}, \overline{s})$ is feasible of MILP, **then** STOP

else set $\Re = \{R_0\}$ and go to the iteration step.

While (stop = false) **do**

- Set $k := k + 1$ and select a rectangle R_k.
- Let $j*$ be the index to be separated. Divide R_k in to two rectangles R_{k_0} and R_{k_1} such that

$$R_{k_i} = \{s \in R_k : s_{j^*} = i, i = 0, 1\}.$$

- For each $i = 0, 1$ solve the corresponding relaxed linear problem to obtain an optimal solution (P^{k_i}, s^{k_i}) and the optimal value $\beta(R_{k_i})$.
- Launch DCA from (P^{k_i}, s^{k_i}) to obtain $(\overline{P^{k_i}}, \overline{s^{k_i}})$.

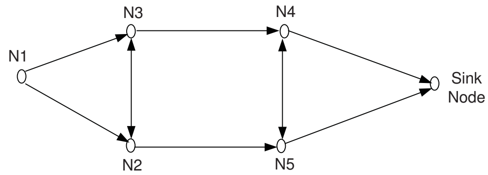

Figure 1: The network model used in Section V

- **If** $(\overline{P^{k_i}}, \overline{s^{k_i}})$ is feasible of MILP, **then** STOP **else**:

$$\Re \leftarrow \Re \cup \{R_{k_i}; i = 0, 1\} \setminus R_k$$

endwhile

We adopted an adaptive procedure for the choice of rectangle to be separated: choose the rectangle such as the optimal solution of the corresponding linear relaxed problem has one of the components s_j^l, for the links l connected to the sink node, is not integer; otherwise we choose the rectangle corresponding to the smallest lower bound.

COMPUTATIONAL EXPERIMENTS

In this section, we provide preliminary computational results of our approach. We have coded the **Algorithm 2** in C++ programming language and tested the instances using PC Pentium 4 3GHz, 1GB RAM. CPLEX 9.1 is used to solve the linear programs. The small-size network with 6 nodes and 10 links as in Figure 1 has been tested. It is worth mentioning that most of currently deployed wireless networks, for example sensor networks are of small scale which centralized synchronous TDMA is viable. Moreover, the implementation of centralized large scaled networks are extremely difficult, if not impossible. If that is the case, one likely approach is to partition the network into smaller clusters and our proposed design can be applied for each cluster. The node coordinates are showed in Table 1. The maximum transmit power is taken to be equal to $P_{max} = 5$. The noise variance $\eta = -20$ dB. The SNR threshold γ^{th} equals to 10 dB. Energy consumption for transmitting and receiving 1 unit data ϵ_l, ε_l is assumed to be 0.25. The link gains are computed using the path loss model as $h_{ij} = \frac{1}{10}[\frac{1}{d}]$ for $i \neq j$, and $h_{ii} = [\frac{1}{d}]$ where d is the Euclidean distance between nodes. The factor of $\frac{1}{10}$ can be viewed as the spreading gain in a CDMA system. We have tested this network with the different number of time slots $J = 10, 15, 20, 25, 30$.

In Table 2, we report the results of **Algorithm 2** (the number of iterations and the value of the objective function calculated by the algorithm). For evaluating the efficiency of **Algorithm 2** we indicate in this table the optimal value given by CPLEX 9.1 applied to (MILP). The following notations are used: J: the number of time slots; $VarC$: the number of continuous power variables P_j^l, $j = 1, \ldots, J$, $l = 1, \ldots, L$; $VarB$: the number of binary scheduling variables s_j^l, $j = 1, \ldots, J$, $l = 1, \ldots, L$; Con: the number of constraints in the optimization problem (4a)–(4h); $Value$: the computing ob-

Table 1: Node coordinates

Node	N1	N2	N3	N4	N5	Sink node
Coordinates	(-20,20)	(0,0)	(0,40)	(40,40)	(40,0)	(80,25)

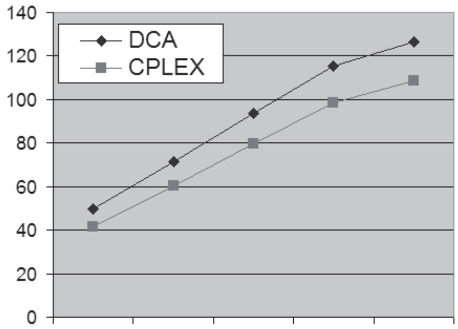

Figure 2: Comparative results of objective values between DCA and CPLEX

jective value by Algorithm 2; $iter$: the number of iterations of Algorithm 2. $OptVal$: the optimal value of (MILP) and $Gap = \frac{Value - OptVal}{Value}100\%$.

From Figure 2 and the column Gap in Table 2, it is clear that the solutions given by DCA are close enough to the optimal solutions. The ability to handle very large-scale problems makes the proposed method implementable for practical networks.

RELATED RESEARCH

There are numerous existing results in the areas of cross-layer design. Hereafter, we mention only the works which are mostly related to the research in this paper. In particular, we consider the system and interference model as in (1), (11). (11) presents a joint link scheduling and power control scheme for TDMA-based networks. Moreover, routing is assumed to be fixed and the network throughout, i.e., sum of links' throughput is maximized. A heuristic polynomial time algorithm to solve the proposed MILP is proposed. Our proposed formulation can be seen as an extension to the work in (11) where we also incorporate rate control, routing with quality-of-service (QoS) constraints on the end-to-end flows.

Routing algorithms have been designed to prolong the network lifetime (1), (12). In (1), a cross-layer design across physical, MAC and routing layers is proposed to maximize the network lifetime which is defined as the earliest time when the first node dies. Optimal TDMA scheduling to maximize the average transmission rate or to minimize the cross-link interference given fixed link transmission powers is considered in (14). Unsurprisingly, the resulting formulation is also a MILP but no efficient solution approaches are proposed. In (2), the authors investigate the problem of joint routing, link scheduling and power control in wireless multi-hop networks. The objective of the optimal policy is the minimization of the total average transmission power given that each link attains the minimum average data rate. The proposed approach via duality is applicable at low SINR regions since the capacity is assumed to be a linear function of SINR.

CONCLUSION

In this paper, we have studied the cross-layer design problem in an interference-limited TDMA wireless network. Particularly, the problem of joint rate control, routing, link scheduling and power control has been considered to minimize the energy consumption. The proposed design can be formulated as a mixed-integer linear program which has worst case exponential complexity to compute optimal solution. Our main contribution was to propose a computationally efficient approach based on DCA. The considered combinatorial optimization problem has been beforehand reformulated as a DC program with a natural choice of DC decomposition, and the resulting DCA then consists in solving a finite sequence of linear programs. DCA is original because it gives an integer solution while it works in a continuous domain. Preliminary numerical results were encouraging and demonstrated the effectiveness of the proposed method. Moreover, notice that most problem formulations arising in TDMA-based networks can be formulated as some sort of MILP problems, our proposed approach seems attractive and needs more investigation.

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Table 2: Computational results of Algorithm 2

J	VarC	VarB	Con	iter	Value	OptVal	Gap(%)
10	100	100	266	9	49.5	41.57855	16.0
15	150	150	396	72	71.5	60.56757	15.3
20	200	200	526	205	93.5	79.55660	14.9
25	250	250	656	770	115.5	98.54560	14.7
30	300	300	786	369	126.5	108.53460	14.2

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