Chapter 1

On the Trade-offs of Cross-Layer Protocols for Cognitive Radio Networks

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Cross-layer solutions have been extensively proposed for various types of wireless networks. Although the literature is rich in showing the benefits for this approach, the inherent drawbacks associated with an increased overhead are seldom analyzed. In this book chapter, we attempt to better understand the tradeoffs involved with cross-layering for the new emerging generation of wireless networks that adds intelligence, flexibility and control to the network nodes. To this extent we propose a joint distributed power control, routing and MAC protocol for cognitive radio networks and we obtain performance tradeoffs via analysis and simulation.

1.1. Introduction

Wireless networks are evolving towards networks of small, smart devices which opportunistically share the wireless spectrum with minimal infrastructure and coordination. The new generation of smart terminals can provide intelligent adaptive services by adjusting to the environment thanks to the Software Defined Radio (SDR) technology. This intelligence is incorporated into a cognitive cycle,[1] which allows the wireless devices to gather information about its environment (”learn”) and make decisions (”act”) regarding their transmission parameters and possible access strategies. The development of this new technology is further motivated by the new paradigm of the FCC's spectrum management policy[2] that adopted new rules to promote active spectrum sharing techniques in both licensed and unlicensed bands.

Distributed spectrum sharing techniques. The performance of radio networks is limited by interference, which reduces the nominal throughput of users in the network. Consequently, efficient interference management techniques, such as power control,[3] channel assignment,[4,5] or end-to-end interference aware routing[6] are key elements in providing QoS of such networks. A classic problem in cognitive networks is the distributed channel allocation scenario where the users measure the available spectrum and dynamically decide which frequency they should use for transmission,[4] based on their current measurements. Such channel measurements are usually related to their desired quality of service metrics. For instance, when users require the highest possible throughput, they look for the best achievable Signal to Interference Ratio (SIR), knowing their adaptive modulation and/or coding capabilities. Consequently, the users can cooperate to distributively assign the channels to the nodes and to mitigate interference in the network. Current distributed channel allocation schemes are based on graph coloring algorithms[4] and game theory.[7] In these algorithms, cooperation can be enforced at both the physical and medium access layers, where every node selects the channel that maximizes the SIR on its communication link, providing local performance improvements.

Based on the current allocation of the channels and powers, multi-hop routes can then be established. If costs related to QoS or energy expenditures are employed by the routing protocol, then the performance can be further improved at the network layer. However, as all these techniques (power control, channel allocation and route allocation) are influenced by, and in turn influence the distribution and the level of interference in the system, they are inherently cross-coupled, and a joint optimization might lead to additional gains. This joint optimization is addressed via cross-layer design.

A cross-layer approach. Cross-layer design is a recent protocol definition technique that jointly optimizes the behavior of two layers of the protocol stack that have no common interface. According to Srivastava and Motani,[8] cross-layer design can be defined by "*the violation of a reference layered communication architecture with respect to the particular* *layered architecture.*" Cross-layer design may build on the inherent flexibility of the software defined radio architecture in the higher level decision protocols. Adjusting to the current environment by selecting transmission frequencies and waveforms needs communication and coordination between the physical layer and the upper layers. For example, if a set of nodes decides to adjust to a high or low multi-path channel, they have to cooperate at the network level to concurrently change their transmission settings. For our particular case, to mitigate interference and reduce the energy spent for every data bit sent via cross-layer cooperation, additional information must be shared between the routing layer, the medium access control layer and the physical layer, violating the reference OSI layered protocol model. An illustration of the cross-layer architecture is given in section 1.2.2 and in Figure 1.1.

Designing cross-layer protocols has to be attempted carefully, as stated by Kawadia and Kumar,[9] as unintended cross-layer interactions can have undesirable consequences on the overall system performance. There is indeed a price to pay for designing a cross-layer implementation for our spectrum sharing problem in cognitive networks. Our proposed cross-layer implementation requires an iterative optimization of the transmission parameters and the source-destination routes, which results in an increased energy consumption. This increase is due to the additional overhead triggered by the supplementary route updates created at each new routing iteration. There is also an overhead at the physical/medium access layers due to the packet exchange for channel and power updates required for enforcing cooperation at each new iteration.

The aim of this chapter is to show how and when the cross-layer implementation benefits more or less the overall network performance. When does the energy saved by the concurrent network and physical layer parameters' optimization outweigh the energy loss due to the cross-layer design overhead? How long does it take to get a final and stable minimum energy route configuration? For what kind of networks is a cross-layer approach beneficial?

Next section 1.2 presents the cross-layer framework considered for the joint routing and spectrum sharing algorithm. A detailed implementation of this framework is provided in Section 1.3, presenting the solutions chosen for the routing protocol, channel allocation and power control algorithms. Analysis for the overhead triggered by this cross-layered implementation is presented in Section 1.4. Section 1.5 presents the performance results of the proposed solution with respect to the overall energy consumption, the data delivery ratio and the delay. These metrics are assessed for several network densities, providing a good insight on the trade-offs that arise in cognitive networks with cross-layering.

1.2. A Cross-layer Framework for Cognitive Radio Networks

1.2.1. *System Model and Assumptions*

We consider an example of a cognitive radio network consisting of a set of N nodes uniformly distributed in a square region of dimension $D \times D$. It is assumed that the nodes are fixed. In this network, a node generates continuous data traffic (worst case scenario) that is transmitted towards a randomly chosen destination node. The traffic can be relayed through intermediate nodes which also act as routers, forwarding packets to the destinations. To accomplish the transmissions, a node must determine the route of an outgoing packet according to a preset routing metric. The route with the minimal cost from the source to the destination is selected to forward the packets. If a node is selected to relay packets for multiple flows, the transmissions for different traffic flows at that node are time multiplexed.

There are various ways to define the routing metric. A simple hop count metric can be considered, as well as other performance-oriented metrics, such as congestion load or energy consumption, which are based on information originating from lower layer protocols. In this work, we define a link Quality of Service (QoS) measure for an arbitrary link (i, j) as the energy consumed for the correct transmission of a data bit[10],[11] E_b^{ij} :

$$E_b^{ij} = \frac{M\ p_i}{m\ R\ P_c(\gamma_{ij})}, \tag{1.1}$$

where M is the packet length, m is the number of information bits in a packet, R denotes the transmission rate and $P_c(\gamma_{ij})$ is the probability of the correct reception of a packet, which depends on γ_{ij}, the achieved link Signal-to-Interference Ratio (SIR).

In this work, the Energy per bit over a link, E_b^{ij}, is considered as the routing metric to define the link cost. Accordingly, we define the Energy per bit over a route, E_b^r, as the energy consumption for a data bit to travel along a route r (from its source to its destination).

$$E_b^r = \sum_{(i,j)\in r} E_b^{ij}. \tag{1.2}$$

The cognitive radio nodes in the network are assumed to be capable of measuring the spectrum availability and making a decision on the transmission channel. We assume that there are K frequency channels available for transmission, with $K < N$. Multiple users are allowed to transmit at the same time over a shared channel. By distributively selecting a transmitting frequency, the radios effectively construct a channel reuse distribution map with reduced co-channel interference.

The transmission link quality can be characterized by a target SIR, which is specific for the given application. The SIR measured at the receiver j associated with transmitter i can be expressed as:

$$\gamma_{ij} = \frac{p_i G_{ij}}{\sum_{k=1,k\neq i}^{N} p_k G_{kj} I(k,j) + \sigma^2}, \tag{1.3}$$

where p_i is the transmission power at transmitter i, G_{ij} is the link gain between transmitter i and receiver j. σ^2 denotes the received noise and it is assumed to be the same for all receiver nodes. $I(i,j)$ is the interference function characterizing the interference created by node i to node j and is defined as

$$I(i,j) = \begin{cases} 1 \text{ if transmitters } i \text{ and } j \text{ are transmitting} \\ \quad \text{over the same channel} \\ 0 \text{ otherwise} \end{cases} \tag{1.4}$$

For the nodes sharing the same frequency channel, their transmission powers affect their link quality and the interference temperature on that particular channel. It is assumed that the radio nodes are able to adjust the transmission power to improve the link quality and to enable the group of users who are transmitting over the same channel to meet a certain target SIR.

Analyzing Eq. (1.3), we note that in order to maintain a certain SIR, the nodes can adjust at both the medium access control layer and the physical layer. At the medium access control level, the nodes can minimize the interference by appropriately selecting the transmission channel frequency, which leads to minimized values of the interference function in Eq. (1.3). At the physical layer, for a feasible system, the nodes can adjust their transmission power level via distributed power control to reduce interference and ensure that all the nodes sharing the same channel meet the target SIR requirement at their intended receiver.

In the cognitive network considered, multi-hop routing is implemented at the network layer. Once the routes are set by the protocol, adjusting the power level and the channel values modifies the performance of the links of the network. In this case, the next hop receiver of a node may not be the optimal hop anymore. The other way around, when the channels and the power values are defined, better routes may be chosen by the network protocol, optimizing the end-to-end performance of the communication. These interactions between individual layers are explored in the cross layer solution described in the next section.

1.2.2. *Cross Layer Framework*

This subsection defines a cross layer framework designed to reduce the energy consumption of end-to-end data transmissions for the aforementioned cognitive radio network. The structure of this framework and the cross-layer interactions are illustrated in Fig. 1.1. A two-way information exchange between the layers is necessary in our case.

In the downward direction, information from the upper layers determines the configuration of the lower layer protocols. In particular, at the network layer, the routing protocol assigns the next hop identification to the medium access layer. Let R^* denote the route from a source node to its destination node. As a node may belong to several source-destination paths, there may be different next hop nodes for every relayed flow. As there is only one radio per node, a single next hop node has to be chosen by the protocol. The node that belongs to the link with the highest routing cost, i.e the highest energy per bit metric (cf. Eq. (1.1)) is selected. In this case, we consider the link with the worst quality, and improve its performance through channel allocation and power control at the lower layers.

The medium access layer communicates the channel values to the physical layer. To reduce the co-channel interference and improve the quality of the links, the channel allocation mechanism at the medium access control layer creates a channel reuse map, denoted by C^*, based on the current transmitter-receiver pair configuration. Nodes are arranged into K groups with each group sharing the same transmission channel. For each group of nodes, the distributed power control algorithm adjusts the nodes' transmission power to a power assignment P^* at which all the nodes in the group meet the target link quality in terms of SIR at their intended receivers.

In the upward direction, lower layer information can effect the performances of the upper layer algorithms. Reconfigured transmission power assignment P^* leads to a reconstruction of the channel reuse map at the medium access control layer due to the changes of the interference temperature in the network. When channel reuse profile and transmission power

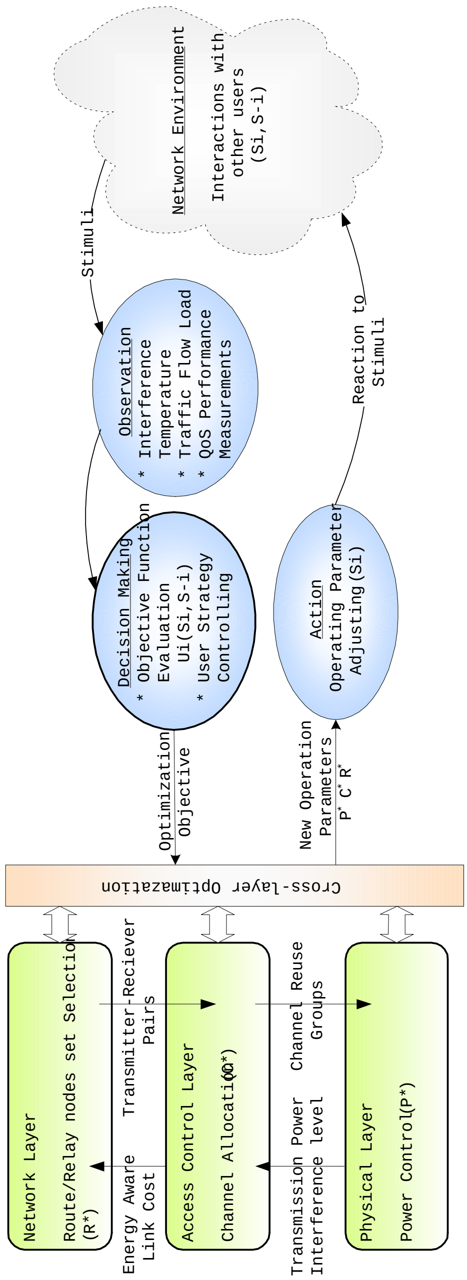


Fig. 1.1. Cross Layer Framework for Cognitive Radio Networks

distribution are updated, the quality of the links and therefore the link costs defined at network layer change accordingly, which may trigger routing updates with new link costs.

Considering these interactions, an iterative algorithm is presented for this cross layer framework to reduce the energy consumption of the end-to-end data transmission over the network. The macro-algorithm is given in Algorithm 1.1.

Algorithm 1.1.

(a) *Initial state.* Nodes operate at an initial transmission power and randomly select a transmitting channel. Routing link costs are computed and routes are built up by the routing protocol.
Iteration number $N_I = 0$.
(b) *Iteration begin.* Nodes determine their intended receiver with current route selection.
$N_I = N_I + 1$.
(c) Nodes select their transmitting frequency and adjust their transmission power level via Channel Allocation and Power Control algorithm.
(d) Routing link costs are computed
(e) IF at least one route r can be found that reduces the total data transmission energy consumption E_{data}
THEN Update the routes, GOTO (b)
ELSE Algorithm terminated.

E_{data} is defined as the sum of the energy per route over the network:

$$E_{data} = \sum_{r \in R^*} E_b^r. \quad (1.5)$$

It indicates the total energy requirement for every node in the network to successfully deliver one data bit to its destination. This cross layering iterative algorithm converges towards a local minimum E_{data}. The convergence time of this algorithm is a function of the number of iterations N_I.

1.3. Implementation Aspects of the Cross-layer Framework

Specific routing protocols, channel allocation mechanisms and power control algorithms can be chosen for our above defined cross-layer framework for various application scenarios. The protocol and algorithms employed in this work are described in this section.

1.3.1. *Routing protocol*

The choice of a routing protocol influences the way the routes are built in the network. In this implementation, an On-demand routing protocol, Ad hoc On-demand Distance Vector routing (AODV),[12] has been chosen. The traditional hop count routing metric of the AODV protocol is replaced by the energy per bit metric, E_b^{ij} of Eq. (1.1).

The main steps of the routing mechanism of AODV are described in the following. When a node S needs a route to some destination D, it broadcasts a *Route Request* to its one hop neighbor nodes. Each intermediate node forwarding the Route Request packet records the reverse route back to node S. Once node D or a node having a route to D hears the Route Request, it generates a *Route Reply* packet including the information about the last known sequence number of D and the energy requirement to reach D (according to our energy aware metric and given SIR measurements for each link on the path). This Route Reply packet is then sent back along the reverse route to node S. The source node S is now aware of the energy requirement of each hop from S to D along the path that conveyed this Route Reply.

Different replying nodes send back their Route Reply packets individually. Among these available routes, S selects the one that has the most recent sequence number or the lowest energy requirement given the same sequence numbers.

1.3.2. *Channel Allocation and Power Control*

In our previous work,[13] we have proposed a game theoretic formulation of the channel assignment and power control problem. We have shown that an iterative algorithm for channel scheduling and power allocation can be implemented, which converges to a pure strategy Nash-equilibrium solution, i.e., a deterministic choice of channels and transmission powers for all the nodes.

In this game theoretic formulation, the radio nodes are modeled as a collection of agents that distributively act to maximize their utilities in a cooperative fashion. The radios' decisions are based on their perceived utility associated with each possible action which is related to the transmission power and to the channel selection. The players of the game are rational and aim to maximizing their own utility. The utility function is defined by Eq. (1.6) where s_i stands for the strategy chosen by node i and s_{-i} the set of strategies chosen by all the other nodes in the game. The strategy of node s_i is set by the channel it has selected.

$$U_i(s_i, s_{-i}) =$$
$$- \sum_{j \neq i, j=1}^{N} p_j(s_j) G_{ji} f(s_j, s_i) - \sum_{j \neq i, j=1}^{N} p_i(s_i) G_{ij} f(s_i, s_j) \tag{1.6}$$
$$\forall i = 1, 2, ..., N$$

In equation 1.6, we denote $P = [p_1, p_2, ..., p_N]$ as the set of discrete transmission powers for the N nodes and $S = [s_1, s_2, ..., s_N]$ the nodes' strategy profile. $f(s_i, s_j)$ is an interference function defined as:

$$f(s_i, s_j) = \begin{cases} 1 & \text{if } s_j = s_i\text{, transmitter } j \text{ and } i \text{ choose} \\ & \text{the same strategy (same channel)} \\ 0 & \text{otherwise} \end{cases}$$

This utility function characterizes the preference of a user for a particular channel, given the fact that he knows that power control is employed by all the users sharing each given channel. It accounts for both the interference perceived by the current user, as well as for the interference that a particular user is creating to neighboring users sharing the same channel. Cooperation is imposed on the nodes to achieve a fair allocation of resources.

For the users sharing the same frequency channel, their transmission powers affects their link quality and the interference temperature on that particular channel. The goal of power control is to adjust the transmission powers of all users to improve the link quality and to enable the group of users who are transmitting over the same channel to meet a certain target SIR γ^*. For a feasible system with N users, a non-negative power vector P^* can be obtained by solving the system of equations (1.7):

$$P^* = (I - H)^{-1} \eta, \tag{1.7}$$

where $H = (h_{ij})_{i,j \in [1,..,N]}$ is the normalized link gain matrix such that $h_{ij} = \gamma^* \frac{G_{ij}}{G_{ii}}$ for $i \neq j$ and $h_{ij} = 0$ for $i = j$, $\eta = (\eta_i)_{i=1..N}$ is the normalized noise vector such that $\eta_i = \gamma^* \frac{\sigma}{G_{ii}}$, and σ^2 is the received noise power density.

For the K available frequency channels, each channel is shared by a group of users that transmits at the same frequency. Each group determines their transmission powers via power control. It is clear that by selecting different transmitting channels, a user will belong to different groups and will choose its operating power level with respect to the interference environment of that particular group. The population and the members of these user groups will change with respect to the channel strategy profile S.

Let $s_i = 1, 2, ..., K$ denote the choice of transmitting channel for user i, $i \in N$, then the power vector for the kth user group can be determined by:

$$P_k^* = (I - H_k)^{-1}\eta_k, \quad \text{for} \quad k = 1, 2, ..., K \tag{1.8}$$

where $H_k = (h_{ij})_{i,j\in[1,..,N]}$ for $s_i = k, s_j = k$ and $i \neq j$, and η_k the normalized noise vector for $s_i = k$. The number of the elements of P_k^* is equal to the number of the users who transmit on the same channel.

For a feasible system, P_k^* should be a non-negative vector, $P_k^*(i) > 0$, $i \in N_k$, with the assumption that the transmission power can be adjusted without limitations. However, in practice, the maximum output power of a transmitter is upper-bounded. Taking this limitation into account, the transmission power vector P_k^* can still be determined by Eq. (1.8) but with the constraint that:

$$0 \leq P_k^*(i) \leq P_{MAX}, i \in N_k, \quad \text{for} \quad k = 1, 2, ..., K \tag{1.9}$$

where P_{MAX} denotes the maximum transmitter output power depending on the physical device, and/or regulation restrictions. Consequently, the constrained transmission power $\bar{P}_k^*(i) = \mathbf{min}\{P_k^*(i), P_{MAX}\}, i \in N_k$ is selected.

1.4. Overhead Analysis for the Cross-Layer Framework

On analyzing the cross-layer algorithm 1.1 presented in Section 1.3, it can be seen that there is no extra control overhead for the route discovery and construction of the AODV routing protocol, since the modification of the routing metric does not impact direct changes on these protocol specific mechanisms. However, there is an overhead for the cross-layer architecture originating from the following two points:

(1) The route updates triggered by the reconfigurations of transmission channels and power levels at each iteration result in a control overhead for route maintenance. Let O_R be the number of additional packets triggered by the iterative cross-layer implementation at the routing level.
(2) The adaptive channel and power allocation relies on a signaling packet exchange to broadcast the interference distribution information across

the network. Let O_{SP} be the number of signaling packets needed by the channel and power assignment algorithms.

The value of the routing overhead O_R can not be easily assessed analytically as it depends on the routing protocol implementation. Therefore, we performed a simulation-based estimation of O_R. The worst-case signaling packet overhead O_{SP} can be estimated analytically by a simple analysis of the distributed channel and power allocation scheme, which is presented in the following.

For the channel selection and power control mechanism, the evaluation of the utility function of Eq. (1.6) includes two aspects during each iteration:

i) a measure of the interference created by others on the desired user;
ii) a measure of the interference created by the user on its neighbors' transmissions.

The first part can be estimated at the receiving node, while the second part can only be estimated by the neighboring nodes and has to be communicated to the user via a packet exchanging.

It is required that both the transmitter and its one hop neighbors listen to a common control channel and that each maintain a Channel Status Table (CST) for all the frequencies, similar to a NAV table in 802.11. The CST table of a given node i stores the list of neighbor nodes requesting the same channel, along with their transmission powers. It also includes the estimated link gain between the node i and its intended receiver nodes and the estimated link gains from the neighbor transmitters to node i, which are used for estimation of the interference level. To update this table, a 3-way handshaking procedure is required.[5] The handshaking process and the information carried by the packets between the nodes are illustrated in Fig.1.2 where each handshaking session carries out a 3 packets exchange. In the first **START** packet, every node of the network advertises its chosen power for its current channel plus the interference level sensed at its location. In the second packet, **START_CH**, a neighbor node sends its chosen channel to the transmitting node which is acknowledged by the **ACK_START_CH** packet. All the nodes that heard the **START_CH** and **ACK_START_CH** packets update their CST table accordingly.

For a network of N nodes with a constant traffic pattern, let N^i_{neb} denote the number of neighbors of a particular node i, SP^i_{ini} the number of signaling packets in the initial iteration and SP^i_{ite} the number of signaling packets for node i to make a channel selection in the following iterations.

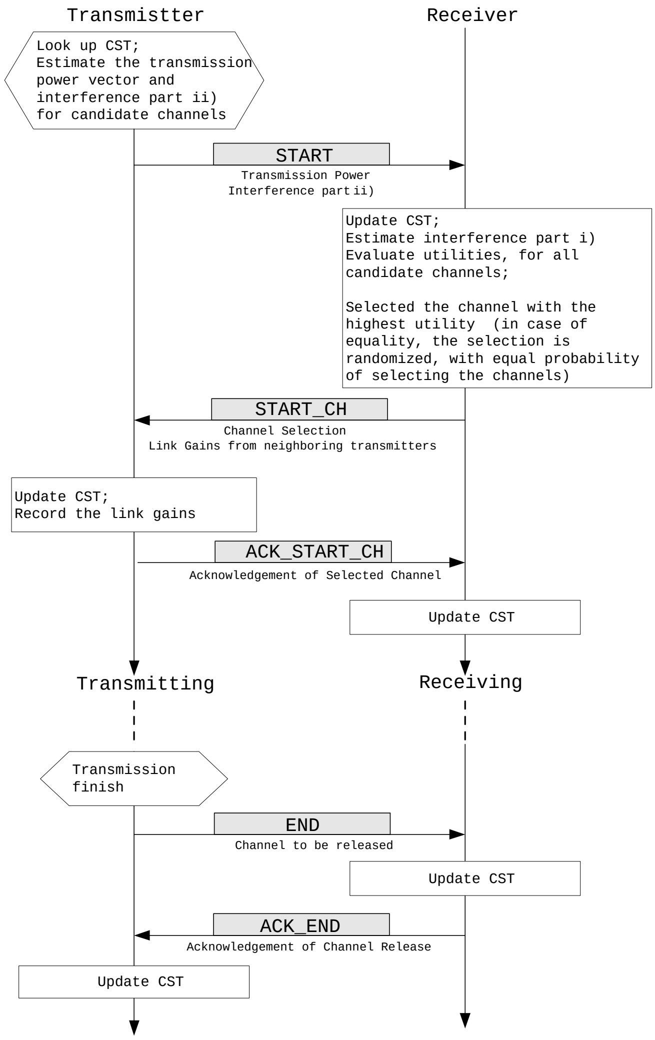


Fig. 1.2. Handshaking Process for the Signaling Packet Exchange

The transmitter/receiver should hear at least one packet from each neighboring receiver/transmitter. In other words, all the nodes should send out a **START** packet (in a 3-way handshaking) to their neighbors during a certain period in the initial information collection stage. This **START** packet broadcasting should be completed before the transmitting of any **START_CH** packet in the network. After this initial **START** broadcasting period, each node carries out at least one 3-way handshaking process (i.e. completes the **START_CH** and **ACK_START_CH** following the initial **START**). Following this procedure, all the nodes can get the required information about their neighbors, and are thus able to complete their Channel Status Table. Consequently,

$$SP_{ini}^{i} = 1 + 2N_{neb}^{i} \tag{1.10}$$

All the following iterations see a node i carrying out a 3-way handshaking procedure with its neighbors to update the information in its CST table. Therefore,

$$SP_{ite}^{i} = 3N_{neb}^{i} \tag{1.11}$$

.

We consider N_{ite} iterations of the cross layer framework (including the initial iteration with the initial **START** packet exchange). The total number of signaling packets O_{SP} is then calculated as:

$$O_{SP} = \sum_{i=1}^{N} (SP_{ini}^{i} + SP_{ite}^{i}(N_{ite} - 1)) = \sum_{i=1}^{N} (1 + N_{neb}^{i}(3N_{ite} - 1)) \tag{1.12}$$

The number of neighboring nodes, N_{neb}^{i} depends on the network density and on the receiving threshold. In the worst case (all the nodes are within the sensing range of a node, nodes are neighbors of each other), $N_{neb}^{i} = N$. In this case, $O_{SP} = (3N_{ite} - 1)N^2 + N$, we thus have a complexity in the order of $O(N^2)$.

In Fig. 1.3, the analytical estimation of the signaling overhead O_{SP} for several network sizes is presented. In this figure, the network is composed of 25 nodes spread across a field of dimension $D \times D$. The plot indicates the number of signaling packets exchanged in the network as the radio nodes collect the required information from their neighboring nodes. In this figure, the node density varies from an average of about 17 neighbors (D=100) to an average of less than 1 neighbor node (D=1000).

The total control overhead of this iterative cross-layer algorithm consists of the signaling packet load O_{SP} and the routing maintenance overhead O_R. The next section 1.5 presents an analysis of these values via simulations, for various network densities. We will discuss the impact of these overhead figures on the performance of the cross-layer scheme.

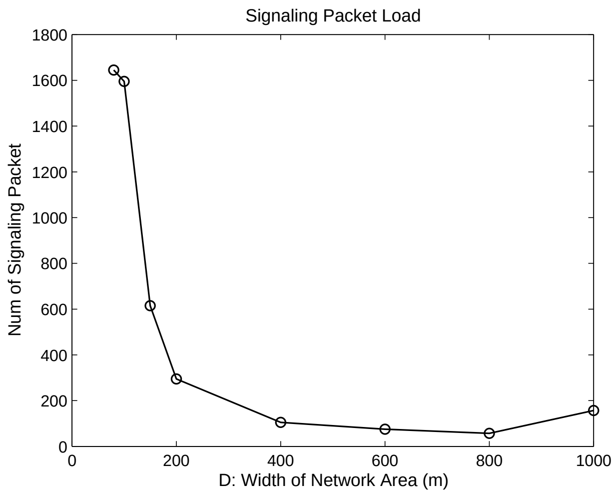
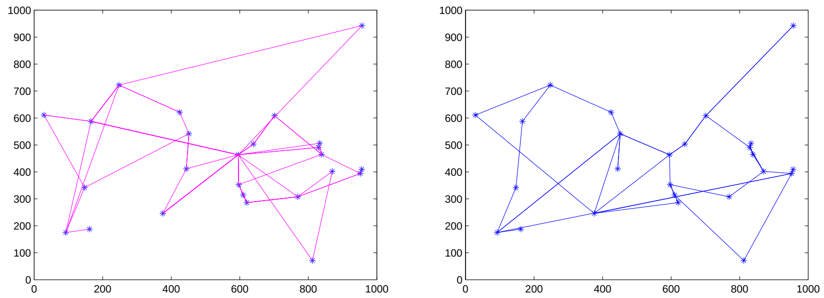


Fig. 1.3. Number of Signaling Packets vs. Network Area Width

1.5. Performance Evaluation and Trade offs in Cross-layering

Numerical results are presented in this section to illustrate the performance of the proposed implementation of our cross-layer framework. These results are compared to a non cross-layer scenario where no iterative cross-layering optimization is performed. The non cross-layer algorithm stops once an operating profile (including the channel reuse map, transmission power assignment and the corresponding route selection) is determined. This non cross-layer solution contrasts with the cross-layer algorithm that further searches for a solution (power, channel and routes) that minimizes the energy consumption of the network by iteratively performing routing and channel/power allocation.

For simulation purposes, we consider a cognitive radio network with N fixed nodes, where $N = 25$, and the width of network area, D, spans from 80 to 1000 meters, which yields various network densities. The message packet length M is 64 bytes and for simplicity it is assumed that all the bits are information bits, which means $m = M$. The transmission rate R is 11 Mbps. The number of available channels for the radios to share is $K = 4$. The SIR requirement γ^* is 7 and the noise power σ^2 is set to be 10^{-13}. For the numerical results, a path loss coefficient of $\alpha = 2$ is



(a) (b)

Fig. 1.4. Routing example. (a) Initial route assignment over the network. (b) Route assignment over the network after cross-layering iterations.

selected. The maximum transmission power at a node P_{MAX} is 10^{-3}W and the initial power of the nodes is set to be P_{MAX} for the power control. To obtain average performance measures, 50 simulation runs are carried out.

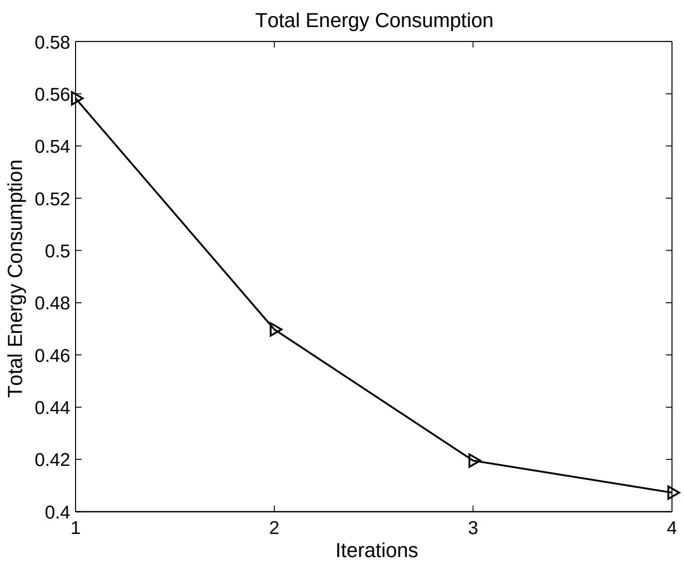


Fig. 1.5. Iterative reduction of the total Energy Consumption for a particular network with $D = 1000$

An example network topology with a network width $D = 1000$ is illustrated in Fig. 1.4. Fig. 1.4(a) gives a snapshot of the initial route assignment over the network. The updated route assignment over the network after cross-layering iterations is demonstrated in Fig. 1.4(b). The iterative reduction of E_{data} is shown in Fig. 1.5. E_{data} is defined by Eq. (1.5) as the total energy requirement for every node in the network to successfully deliver one data bit to its destination. It can be seen that the cross layering iterative algorithm converges to a local minimum in 4 iterations, with about 27% reduction in the energy consumption.

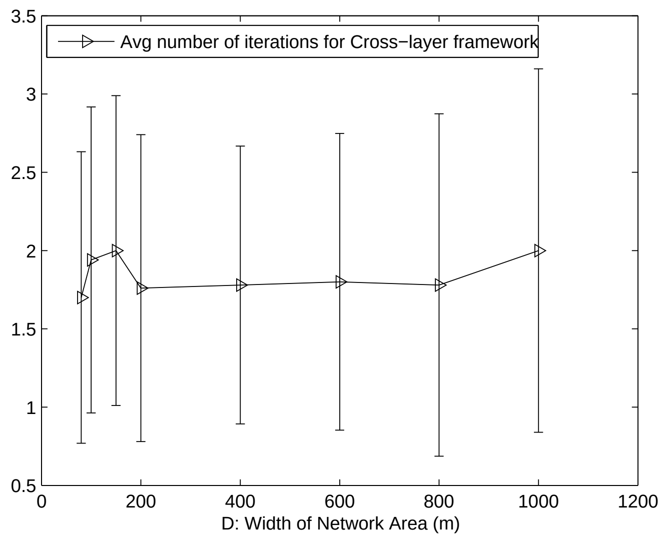


Fig. 1.6. Average and Standard deviation for the Number of Iterations, as a function of the network width D.

In Fig. 1.6, we show the average number of iterations carried out by the cross-layer algorithm, with the network width ranging from 80 to 1000 meters. The error bar of each point represents the standard derivation of the number of iterations. It can be seen that, in most of the cases, the algorithm converges in about 2 ± 1 iterations which corresponds to a fast convergence speed.

To compare the performance of the cross-layer algorithm with that of the non cross-layer algorithm, serval performance measures are considered. First, E_{data}, the total energy requirement for every node in the network to successfully deliver one data bit to its destination is plotted in Fig. 1.7 for several network sizes. The energy consumption in terms of E_{data} is reduced by employing a cross-layer algorithm in average, but it is for denser networks that cross-layering is the most beneficial. When the nodes are distributed in an area of less than $400m^2$, more energy is saved with the cross-layer scheme that better mitigates interference for higher density networks. For both cross-layer and non cross-layer schemes, there is an increase in the energy consumption for dense networks which is impacted by the signaling protocol for power and channel allocation. For lower densities (i.e. larger D values), the gains of cross-layering in terms of energy does not compensate for the cost in energy as interference is not as limiting as for dense networks.

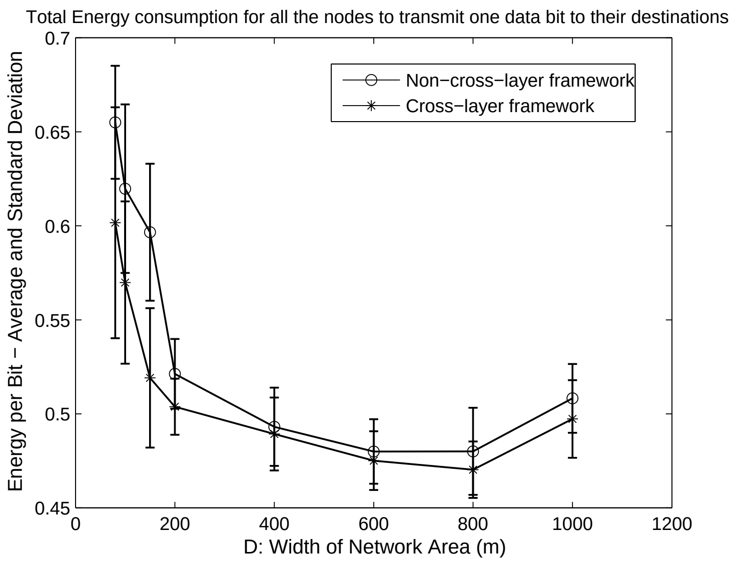


Fig. 1.7. Average and Standard deviation for the Total Data Energy Consumption as a function of the network width D.

The performance gain achieved by cross-layering can also be seen in Fig 1.8 with respect to the end-to-end data packet delivery ratio defined as the ratio of the number of the data packets which are successfully received at their destinations to the number of data packets which are sent out by their sources. The cross-layer framework is best for the scenarios with moderate network density, for example, networks with a width range from 200m to 400m. In this case, the most efficient routes are obtained with the cross-layer algorithm.

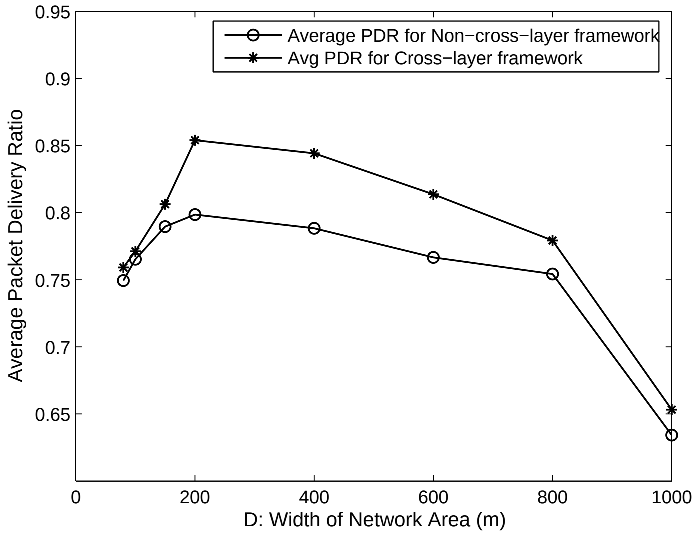


Fig. 1.8. Average Data Packet Delivery Ratio as a function of the network width D.

Another performance metric considered in the simulation is end-to-end data packet delay defined as the average delay for a data packet to be delivered from its source to its destination across the network. Fig. 1.9 illustrates that the cross-layer framework results in less delay at higher network density with $D < 400m$. For the scenarios with lower network density, the cross-layer framework suffers from an increased delay, due to the longer iterative route request process over wider spread nodes.

As analyzed in Section 1.4, the control overhead introduced by the iterative cross-layering algorithm consists in the signaling packet load and the routing maintenance overhead. In Fig. 1.10, the total number of control packets exchanged in the network is demonstrated for both of the cross-layer and non cross-layer frameworks. It is clear that the performance gain of the cross-layer framework is obtained at the cost of extra control overhead in the network. But as highlighted in Fig.1.5, the gain in energy for better coordinating the layers in a cognitive network balances this cost and even provides significant gains for dense networks.

As illustrated in the simulation results, a cross-layer framework trades

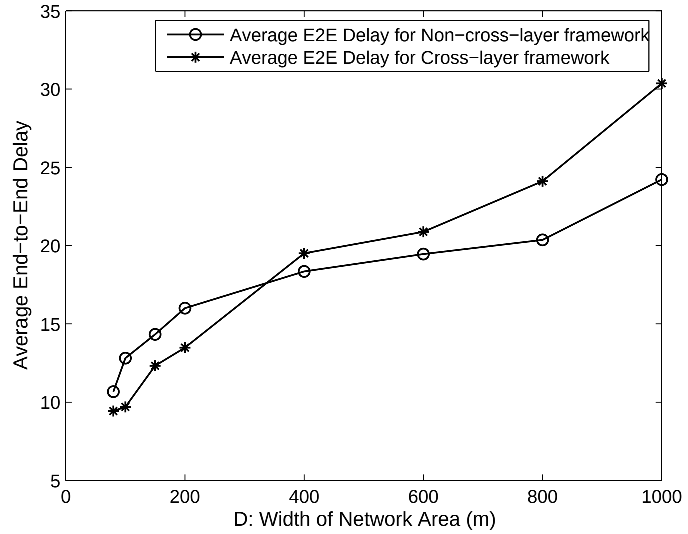


Fig. 1.9. Average End-to-End Data Delay as a function of the network width D.

off system control overhead for gains on the energy consumption for data transmission. However, for networks with stable topologies and continuous data traffic, this overhead pays off given the long term benefits on the energy savings, since most of the control overhead is spent at the initial stage, when the nodes build up their operating profile (i.e. transmission frequency, power and data forwarding path).

It also can be seen that the cross-layer framework is beneficial for the networks with higher densities, if the data services supported by these networks are delay sensitive and throughput tolerant. For networks with lower densities, cross-layer design may be beneficial for delay tolerant data services, since it yields considerable gains on data throughput in terms of improved packet delivery ratio and also results in significant energy savings.

1.6. Conclusions

In this chapter, we have explored the tradeoffs involved in cross-layering for cognitive radio networks. To this extent we have proposed a hierarchical cross-layer distributed framework for integrating power control, channel al-

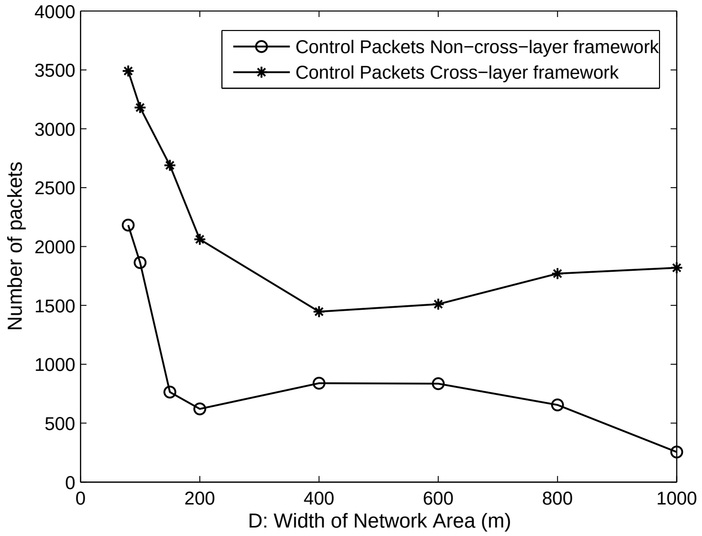


Fig. 1.10. Average Number of Overall Control packets ($O_R + O_{SP}$) as a function of the network width D.

location and routing. The objective of this framework is to reduce energy consumption, while providing QoS (BER, end-to-end delay and throughput) for all nodes across the network. Based on this framework, and using a combination of analytical and simulation results we were able to quantify the gains, as well as the increased overhead associated with cross-layering for our particular solution. We have shown that cross-layering is particular beneficial (despite the increased overhead) for dense networks, but can also be beneficial for delay tolerant traffic in lower density networks. Overall, the benefits outweigh the increased overhead when networks are quasi-static or static, as the increased overhead is characteristic for the initial set-up phase of the network.

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