ARQ-based Cross-layer Optimization for Wireless Multicarrier Transmission on Cognitive Radio Networks

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Abstract

The primary feature of cognitive radios for wireless communication systems is the capability to optimize the relevant communication parameters given a dynamic wireless channel environment. Recently, several research groups have presented promising preliminary results on the benefit of extending the cognitive process at the system level, capable of perceiving current network conditions and then acting according to end-to-end goals. System optimization however implies some challenging tasks: 1) Current network state information has to be known at all transmitters. This dramatically increases the amount of overhead as the number of parameters becomes large; 2) System optimization is often a nonlinear problem with inter-parameter dependencies; 3) The optimization process should also support a dynamic quality of service (QoS) management scheme depending on the available network resources. In this paper, we invoke genetic algorithms (GAs) for iteratively finding the optimum parameters based on the acknowledgment (ACK) signal only. Neither network state information nor channel estimation is required. The set of accurate objective functions that we derive in our GA implementation control the optimization process at the system level toward any QoS. Simulation results show that our implementation achieves comparable performance to an exhaustive search over the whole set of parameters for which perfect network state information at the transmitter is assumed. It also outperforms the conventional scheme for which parameters are optimized at each layer separately.

Key words: Cross-layer optimization in cognitive radio networks, Impact of OFDM techniques for cognitive radio networks, WLAN applications of CR technology, Routing and association in cognitive wireless network, Genetic Algorithm.

1 Introduction

The tremendous success of wireless and data communications is driving us to find new enabling technologies to increase efficiency of wireless communications. The paradigm of cognitive radios was introduced by Joseph Mitola III less than a decade ago in 1999 Mitola, III and Maguire, Jr. (1999) (see also Mitola (2000)). Whereas most of the work so far has focused on considering the cognitive radios as a new technology for spectrum sharing, and the cognitive radio term is sometimes used also with more limited scope to denote spectrum agile radios, (see for instance Buddhikot (2007) and references therein), we consider, throughout the paper, Mitola's cognitive radio in which every possible parameter observable by a wireless node is taken into account to make it adaptive and context sensitive. Cognitive radio is an ideal extension for software-defined radio as it provides machine-learning based and efficient *automatic* optimization for a fully reconfigurable wireless black box that automatically changes its transmission or reception parameters in response to current network state and user demands.

The cognitive radios themselves are only a narrow aspect of a larger context, if one is considering the optimization of the overall capacity and QoS. A single radio-centric approach is not enough in the situation where cognitive and intelligent methods are used to enhance all system aspects in the context of wireless networks. Recently a number of authors have started to consider the issues related to Cognitive Wireless Networks (see for example works of Petrova et al. (2006), Nolan and Doyle (2007), Thomas et al. (2005), Thomas et al. (2006), Petrova and Mähönen (2007a), and Mähönen (2004)).

Petrova et al. (2006) introduced a cross-layer paradigm for cognitive radios in a form of the Cognitive Resource Manager (CRM). One of the main motivations of CRM has been to advance the cognitive radio work towards an all-OSI-layers approach. The concept of the Cognitive Resource Manager was introduced as an architecture and practical implementation project towards experimenting with networked cognitive radios (cf. earlier discussion by Petrova et al. (2006) and later general description by Petrova and Mähönen (2007a)). The CRM couples together several architectural blocks, such as well-defined interfaces and a toolbox for advanced optimization methods, as shown in Fig. 1. One should note in Fig. 1 that we consider the overlay case where cognitive radios may operate among other non-cooperative radios. The CRM concept is, as far as we are aware, quite novel. There is, however, a similar approach introduced by Rieser (2004) at Virginia Tech., known as Cognitive Engine (CE). There are some clear differences between the approaches; ours being currently more higher-OSI-layers and cooperative-networking based. The work with CRM and CE concepts has also progressed recently towards different implementations (see also work done by Sutton et al. (2006) and Minden et al. (2007)).

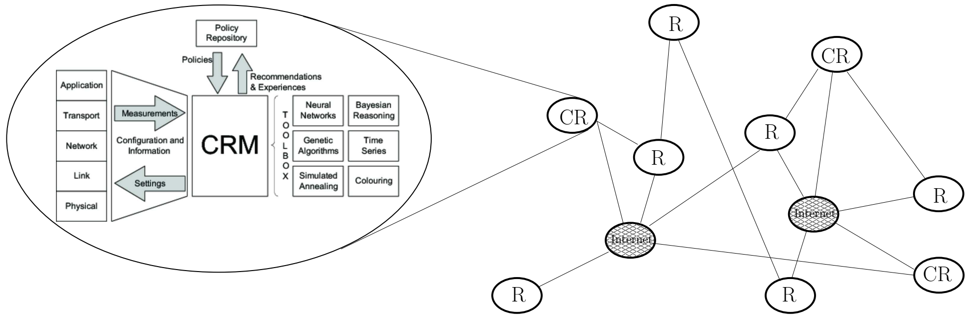

Fig. 1. Functional architecture of the Cognitive Radio Manager with the interfaces to different entities.

Instead of concentrating on physical layer as many previous cognitive radio studies (see Newman et al. (2007) and Rieser (2004) for instance), CRM strictly follows the approach of enabling cross-layer optimization with artificial-intelligence-based learning and adaptation. The key idea behind CRM is that it closely coordinates the interplay between cross-layer optimization functionalities and machine-learning-based algorithms. One of the corner stones for CRM is to follow the approach proposed by Song and Li (2005) based on *utility functions* that tradeoff the fairness and efficiency of resource allocation based on the QoS requirements of each user. Hence the application layer can negotiate with CRM the QoS requirements, e.g., delay bounds, throughput, depending on the available network resources and the physical resources available at the transmitter. For other relevant discussions on using a cross-layer approach with cognitive networks the reader should note work by Baldo and Zorzi (2007), and more generally by Johansson et al. (2006), and a review on decomposition methods by Mung Chiang et al. (2007). Additional examples are provided by Kawadia and Kumar (2005), who also discuss the possible pitfalls of cross-layer optimization.

Whereas CRM and CE frameworks may dramatically enhance overall performance when applied to point-to-point wireless links or towards full cognitive radio networks, there are, however, several potential drawbacks and design issues that must be overcome especially in the *networked environment*:

(1) Current full or partial network state information (NSI) has to be known at each transmitter. NSI estimation requires large overhead, especially in a time-varying environment and for large wireless networks. In fact, CRM may decrease the overall throughput due to high overhead, unless the design of the system takes in account the overhead of state information exchange,
(2) Since CRM performs non-linear optimizations over large-dimension spaces, the computational complexity may become a major burden for hardware implementation and it is not a trivial issue to ensure that CRM can reduce the power consumption overall,
(3) Moreover, non-linear optimization methods traditionally require numer-

ous internal tuning parameters; For instance, genetic algorithms with multiple objective functions require weights determination, crossover, mutation, elitism rates, just to mention a few main parameters. If these parameters are not well set due, for example, to a poor NSI estimation, the CRM approach can lead the system to an unstable state and traditional approaches lead to better performance,

(4) Finally, CRM implies the need to develop a set of complex and efficient decision making units that estimate NSI, and control the relevant communication parameters to optimize system performance. If the decision units are not well designed, CRM may take suboptimal decisions and in fact deteriorate performance compared to a conventional approach.

Moreover one should note that the utility-based optimization in the networked wireless environment is not a straightforward issue. The main problem is to find the utility function for optimization. The simplistic approach for optimizing just one parameter between two wireless devices, e.g., maximizing link throughput or minimizing bit-error rate might have adverse effects for other users or might effect the overall capacity of the network in unknown ways. Even in the case of a single wireless link, there is often a combination of different, and competing, goals to be taken in account in order to achieve suitable quality for communications (see also Newman et al. (2007)). The problem of knowing NSI at the right level has been pointed out recently in different modeling contexts; Petrova and Mähönen (2007b) introduced it through Value of Perfect Information (VPI) models, and Thomas et al. (2007) independently found a complementary description as the price of ignorance.

In this paper, we present a simple strategy for a cognitive radio system which attempts to alleviate these potential problems. Throughout the paper, we focus, without loss of generality, on the wireless orthogonal frequency-division multiplexing (OFDM) system with Medium Access Control (MAC) layer that is based on the Carrier Sense Multiple Access (CSMA) with Collision Avoidance (CA) protocol as for example in IEEE 802.11 (1999) standard, but our approach can be extended to other wireless systems.

The choice of OFDM as an underlying physical layer technology is well justified as many current and future commercial standards are based on this technology. Furthermore, the use of OFDM enables more direct comparison of our results with other techniques. At the MAC layer, the CSMA/CA protocol is chosen as it is quite generic and also widely used in 802.11-based systems. However, our approach can be extended to other MAC protocols. Specifically, we propose an Automatic Repeat reQuest (ARQ)-based protocol for cognitive radio system that controls the transmission QoS in terms of delay, throughput, packet loss rate and transmission power consumption along the lines of Ying Jun Zhang and Letaief (2006).

This work is invoking GAs as a cross-layer optimization methodology (see Whitley (1994) for a tutorial about GAs) and it can operate under our CRM framework. Our approach is unique by the fact that it is using only ACK signalling for exchanging feedback and due to this avoids many problems related to NSI exchange. Particularly, we show that all optimal transmission parameters can be determined through our GA implementation with the acknowledgment signaling (ACK or NAK) of the prior transmitted packets as the lone external input, and no transmission model is required for the optimization process. Moreover, our proposed method is able at once to dynamically handle different optimization goals in the cross-layer context that includes the Physical, Data Link and Network Layers. This makes our approach directly suitable for emerging cognitive radio networks, and as such our algorithm is not limited to point-to-point link optimization between cognitive radios. This work is analyzing specifically the situation where the cognitive radio link is operating among other non-cooperative radios (see Fig. 1). The analysis of the fairness and capacity maximization among the cooperative cognitive radios that form cognitive wireless networks is left for further work.

The remainder of this paper is organized as follows. In Section 2, we carry out the determination of the cognitive radio parameters and the four objectives that we consider throughout the paper. The genetic algorithm based on these objectives is introduced in Section 3. We then present the simulation results and some discussion in Section 4. We close this paper with conclusions in Section 5.

2 Cognitive radio Parameters

A primary feature of a cognitive radio is its ability to adapt to the surrounding environment. This feature defines a critical input to the system - a representation of the environment. In the conventional approach with feedback mechanism, the relevant environmental parameters of the CSMA/CA–OFDM transmission are evaluated at the destination which feeds them back to the transmitter. Clearly, this overhead penalizes the system throughput and requires a special protocol design to support this feature.

As illustrated in Fig. 2, we propose a different approach: we develop a genetic algorithm which utilizes the ACK signal as the only environmental parameter from the receiver side. Since most of the communication protocols include ACK control signaling, our approach is compatible with most standards and does not require any further modification. Another important set of inputs to any GA implementation are the decision variables that give the degrees of freedom in the optimization process. For cognitive radio implementation, these variables represent the transmission parameters that can be controlled by the

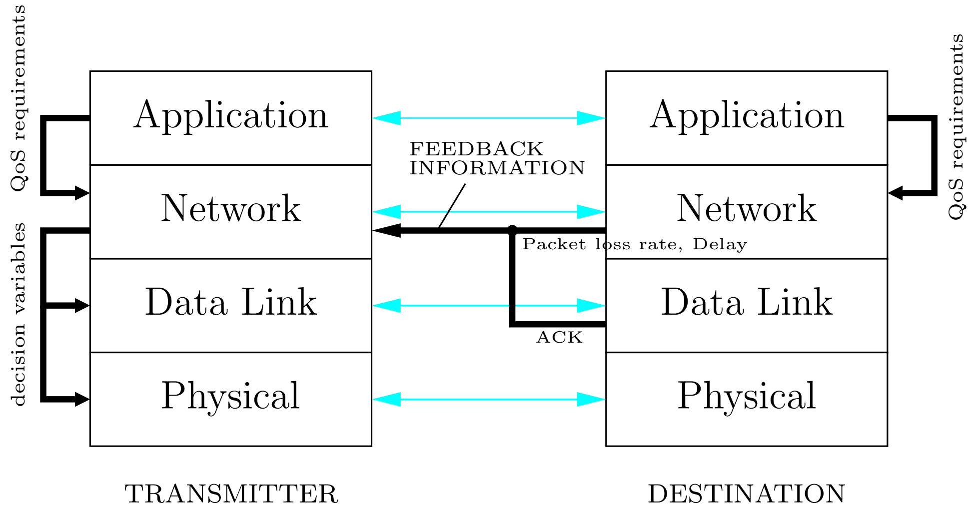

Fig. 2. Cognitive radio principle studied in this paper: the transmitter stores the ACK value (positive ACK or negative NAK) for each transmitted packet. Based on theses values, our genetic algorithm described in Section 3 iteratively optimizes the decision variables such that QoS requirements at the application layer are satisfied. The decision variables are (i) at the physical layer: transmission power and modulation order for each subcarrier; (ii) at the data link (MAC) layer: frame size, minimum and maximum contention windows sizes; (iii) at the network layer: variable transmission range and index of the associated access point. For a more detailed description of the parameters, see Section 2.2. Once the optimal parameters have been determined, the modulation order and the frame size are sent to the destination via the control channel before the payload is transmitted.

system. In addition to the environmental and transmission parameters, several objectives must also be determined to define how the cognitive radio should operate. The objectives of the system are the road map for determining the fate of the system. They allow the controller to steer the system to a specific QoS state. In this study, we define four objectives that represent extremely common wireless radio goals:

(1) Reliability based on the Packet Error Rate (PER),
(2) Power consumption (W),
(3) Throughput normalized as number of bits per symbol period and user (bits/symbol period/user),
(4) Delay bound (s).

Whereas these objectives are very representative cases of real-life fitness functions, it is worth noting that our GA-based approach can support any other objective functions that adequately suit specific QoS requirements.

2.1 Environment Parameters

Environmental variables inform the system of the characteristics of the surrounding environment. This information is used to aide the cognitive controller in making decisions. These variables are primarily used as inputs to GA, so it is essential to accurately estimate them. As aforementioned, we restrict the set of environmental parameters that are determined at the destination, to ACK signaling. If there is no ACK signal in the protocol, our approach can also use an estimate of the transmission packet error probability which can be provided, for instance, at the output of the error-correcting decoder at the physical layer. In our protocol, we assume the knowledge of the following set of parameters at the transmitter:

(1) ACK signal (positive ACK or negative NAK),
(2) Number of occurrences that a packet transmission has been successful. Denote τ as the ratio between this number divided by the total transmission time in term of time slot; the parameter τ can be evaluated with a basic counter which is incremented each time a positive ACK is received. In order to accurately evaluate τ for the current network state, we assume that the counter is periodically reset to zero,
(3) Number of occurrences that a packet transmission has been unsuccessful. Denote τ' as the ratio between this number divided by the total transmission time in term of time slot. Note that τ' can be determined directly from τ.

If additional information about the current network status, e.g., the propagation channel impulse response(s) or the current number of active users in the network is available at the transmitter, the GA can employ this information to ameliorate the optimization process of the transmission parameters.

2.2 Decision Variables

Cognitive radios become possible when the radio components permit the modification of the transmission parameters. These decision variables are set by the cognitive component once an optimal decision has been formulated using the GA. Defining a complete list of decision variables to generate a generic fitness function usable by all radios is difficult. A goal of this paper is to define a set of decision variables at the physical, link and network layers, large enough to guarantee that it is a representative sample for most cognitive radios. The transmission parameters used as outputs in our GA implementation are shown in Table 1.

Table 1
List of the transmission parameters in our GA implementation at the physical layer (uncoded OFDM transmission), the link layer (CSMA/CA with exponential backoff) and the network layer.

Network layer	Variable transmission range d Index of the access point to be associated
Link layer	Packet size L Minimum contention window size $\mathrm{CW}_{\min}$ Maximum backoff stage m
Physical Layer	Transmission power per subcarrier P_i, $i = 1, \ldots, N_c$ Modulation order per subcarrier M_i, $i = 1, \ldots, N_c$

2.3 Multiple Objective Functions

At the beginning of this section, we defined four objectives for our system: reliability, power consumption, throughput and delay bound. Next, we derive the corresponding objective functions of our GA implementation in order to lead the system to an optimal state [1] . In order to facilitate the selection of the weights of the objective functions, we normalize each objective function score to the range $[0, 1]$. The four objective functions in our GA implementation are respectively:

1) Minimize Power Consumption, i.e., decrease the amount of transmission power:

$$f_{\text{min\_power}}^{(\text{PHY})} = 1 - \sum_{i=1}^{N_c} P_i / N_c P_{\max} \tag{1a}$$

where N_c is the number of subcarriers in our OFDM system, $P_i,\ i = 1, \ldots, N_c$ is the transmission power on subcarrier i and $P_{\max}$ is the maximum possible transmission power for a single subcarrier. P_i can take values within $[P_{\min}, P_{\max}]$ but can also be zero, i.e., no transmission on subcarrier i if the channel fading coefficient in this band is smaller than a pre-determined threshold as in Sonalkar and Shively (2000). The function $f_{\text{min\_power}}$ is equal to 1 when no signal is transmitted over any subcarrier and equal to 0 when all subcarriers are transmitting with maximum power $P_{\max}$. At the link layer, the power consumption depends on the protocol. For CSMA/CA protocol with exponential backoff, the total transmission power also includes the power used

[1] The reader should note that we adopt here the term objective function, although the term utility function could also be used.

in packet retransmission. This yields:

$$f^{(\mathrm{MAC})}_{\mathrm{min\_power}} = 1 - (1 + \tau'/\tau) \cdot \sum_{i=1}^{N_c} P_i / N_c P_{\max} \tag{1b}$$

with τ and τ' defined in Section 2.1. Strictly speaking, $f^{(\mathrm{MAC})}_{\mathrm{min\_power}}$ can be negative for large transmission power and high retransmission rate. However, $f^{(\mathrm{MAC})}_{\mathrm{min\_power}}$ is monotonically decreasing function with respect to τ and we observe in our simulations, Section 4, that using (1b) in our GA implementation does not deteriorate the performance. Whereas (1a) or (1b) penalizes system states with higher power consumption, it might be not enough to guarantee that the current power consumption is equal to or lower than a certain threshold P^*. In order to ensure this, we modify (1b) as follows:

$$f^{(\mathrm{MAC})}_{\mathrm{min\_power}} = \begin{cases} 0, \text{ if } \sum_i P_i > P^*, \\ 1, \text{ if } \sum_i P_i \le P^*; \end{cases} \tag{1c}$$

2) Maximize Throughput, i.e., increase the overall data throughput transmitted by the radio. At the physical layer, the throughout per user T can be expressed in number of bits per symbol period as $T = \sum_{i=1}^{N_c} \log_2(M_i)/N_c$, where $M_i,\ i = 1, \ldots, N_c$ is the number of bits per symbol emitted on subcarrier i, $M_{\max}$ is the maximum modulation order with typical values 64 or 256 in wireless networks. M_i can take values from 1 to $M_{\max}$ with 1 special case occurring when subcarrier i is shut down. $M_i = 1$ means that the rate $\log_2(M_i)$ is equal to zero; no information is transmitted. In this particular case, the corresponding transmission power P_i is set to zero. Clearly, we have: $0 \le T \le \log_2(M_{\max})$, where the value $\log_2(M_{\max})$ is achieved when all subcarriers are loaded with symbols modulated with the largest available modulation order. Therefore, the objective function for the throughput is simply:

$$f^{(\mathrm{PHY})}_{\mathrm{max\_throughput}} = \frac{1}{N_c \log_2(M_{\max})} \cdot \sum_{i=1}^{N_c} \log_2(M_i). \tag{2a}$$

The function $f^{(\mathrm{PHY})}_{\mathrm{max\_throughput}}$ is equal to 1 when all subcarriers transmit with largest modulation order and equal to 0 when all subcarriers are switched off.

At the link layer, the saturation throughput T can be expressed as in Bianchi (1998)

$$T = \frac{\tau \cdot P \sum_{i=1}^{N_c} \log_2(M_i)/N_c}{(1 - \tau - \tau')\sigma + \tau T_s + \tau' T_c},$$

where P is a packet duration and σ denotes a slot duration. We adopt for T_s and T_c the same definitions as Bianchi (1998), i.e., T_s is the duration between the end of a packet transmission and the reception of the corresponding ACK signal, and T_c is the maximum delay after each packet transmission before declaring that the packet is lost.

An upper bound on the throughput T occurs if the highest modulation order $M_{\max}$ is used for all subcarriers and if all packet transmissions are successful which yields $T_{\max} = (P \cdot \log_2 M_{\max})/T_s$. Therefore, the objective function for the CSMA/CA throughput can be expressed as the ratio between T and $T_{\max}$

$$f^{(\mathrm{MAC})}_{\mathrm{max\_throughput}} = \frac{\tau \cdot T_s \cdot \sum_{i=1}^{N_c} \log_2(M_i)}{[(1-\tau-\tau')\sigma + \tau T_s + \tau' T_c]\, N_c \log_2(M_{\max})}. \tag{2b}$$

Whereas (2a) or (2b) penalizes system with lower throughput, it might be not enough to guarantee that the current throughput exceeds a certain threshold T^*. As for the transmission power, we therefore modify (2b) as follows:

$$f^{(\mathrm{MAC})}_{\mathrm{max\_throughput}} = \begin{cases} 0 \text{ if } T < T^*, \\ 1 \text{ if } T \geq T^*; \end{cases} \tag{2c}$$

3) Minimize Bit/Packet-Error-Rate, i.e., improve the reliability of the transmission. One possible objective function for characterizing the reliability of the system is:

$$f_{\mathrm{min\_ber}} = 1 - \log(0.5)/\log(\overline{P}_e), \tag{3a}$$

where $\overline{P}_e$ is the average bit-wise probability of error per subcarrier. This objective function which was initially proposed by Newman et al. (2007), has two drawbacks in our context. First, the receiver estimates the probability of error of the transmission and forwards a quantized version of it to the transmitter. This additional overhead should be included in the protocol and requires modification of the IEEE 802.11 standard. Second, it does not fit well with the usual QoS requirement. QoS usually requires a maximum tolerated bit or packet error probability. Above this threshold, the communication is disrupted. In this paper, we propose two new objective functions for the reliability of the transmission: the first function ensures that packet error probability is equal to or lower than a target PER denoted as PER*, i.e.,

$$f_{\mathrm{min\_ber}} = \log(\max(\mathrm{PER}^*, \mathrm{PER}))/\log(\mathrm{PER}^*). \tag{3b}$$

This objective function penalizes only the sets of decision variables that yield PER $>$ PER*; otherwise, $f_{\mathrm{min\_ber}} = 1$ as long as PER $\leq$ PER*. In other words, any set which satisfies PER $\leq$ PER* would be optimal from the PER minimization viewpoint independently if PER = PER* or PER =PER*/1000. The second objective function that we propose here is a binary version of (3b), i.e.,

$$f_{\text{min\_ber}} = \begin{cases} 0 \text{ if PER} > \text{PER}^*, \\ 1 \text{ if PER} \leq \text{PER}^*. \end{cases} \tag{3c}$$

As (3b), (3c) also ensures that packet error probability is equal to or lower than PER*. In addition, it requires at the transmitter the knowledge that the packet has been successfully transmitted or has been lost (collision with other users or transmission error due to the transmission channel distortion). Therefore, (3c) can be estimated from the acknowledgment signaling value only.

4) Minimize Transmission Delay, i.e., decreasing the time interval between two successful packet transmissions. The objective function for characterizing the delay bound of the system is

$$f^{(\text{PHY})}_{\text{min\_delay}} = \frac{L \cdot \log_2(M_{\max})}{L_{\min} \sum_{i=1}^{N_c} \log_2(M_i)}, \tag{4a}$$

where L and $L_{\min}$ are the current and minimum packet lengths, respectively. At the link layer, packet retransmissions have to be taken into account. The objective function becomes

$$f^{(\text{MAC})}_{\text{min\_delay}} = \frac{L \cdot \log_2(M_{\max})\lceil 1/\tau \rceil}{L_{\min} \sum_{i=1}^{N_c} \log_2(M_i)}. \tag{4b}$$

2.4 A Weighted Approach

Using the four objectives (1), (2), (3) and (4) as sole inputs to the GA fitness function will not suffice. In a wireless communication environment, there are several desirable objectives that the radio system may want to achieve. It is ambiguous to have, for example, the system maximizing the throughput while also minimizing PER. At the physical layer, this creates a conflict due to the single parameter, the modulation order M_i as is illustrated in Fig. 3. The optimal set for both objective functions lies on what is known as the Pareto optimal front, Fonseca and Fleming (1998a). This front represents the set of solutions that cannot be improved upon in any dimension. The solutions on the Pareto front are optimal and coexist due to the tradeoffs between the multiple objectives. In this example, the Pareto optimal front corresponds to the curve with maximum transmission power (−0.10 dBm). In many optimization problems, when no global criteria for the parameters

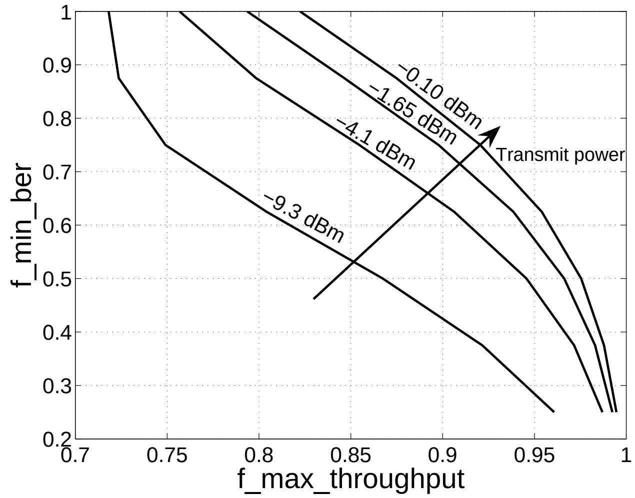

Fig. 3. Search direction example. Both objectives $f_{\max\_\text{throughput}}$ (2b) and $f_{\max\_\text{ber}}$ (3b) conflict with each other for any transmission power.

exist, objectives are often combined, or aggregated, into a scalar function. This aggregation optimization method has the advantage of providing a single scalar solution for the fitness function in the GA. This work proposes to use a simple weighted sum approach that has been presented by Fonseca and Fleming (1998a) and successfully implemented by Newman et al. (2007). The weighted sum approach attempts to maximize the sum of the positively normalized, weighted, single objective scores of the parameter set solution $\mathbf{x} = [P_1, P_2, \ldots, P_{N_c}, M_1, M_2, \ldots, M_{N_c}, CW_{\min}, CW_{\max}, L, d]$:

$$
\begin{aligned}
f(\mathbf{x}) = & \, w_1 f_{\text{min\_power}}(\mathbf{x}) + w_2 f_{\text{max\_throughput}}(\mathbf{x}) \\
& + w_3 f_{\text{min\_ber}}(\mathbf{x}) + w_4 f_{\text{min\_delay}}(\mathbf{x}).
\end{aligned}
\tag{5}
$$

This method suits the cognitive radio scenario well as shown by Newman et al. (2007) since it provides a convenient process for applying weights to the objectives. When the weighting for each objective is constant, the search direction of the evolutionary algorithm is fixed. This is the desired property when trying to find a single optimal solution for a given environment. Changing the objective direction of the fitness function requires only a simple change of the weighting vector. The problem is that the direction is not necessarily known in advance for a given QoS. For example, assume that PER$\approx 10^{-1}$ with current settings and that the target PER$^* = 10^{-3}$. In order to satisfy the PER requirement, it seems obvious to increase the weight related to (3) but the problem is to find the incremental value. In addition, if the weight related to the maximization of the throughput is too dominant, the QoS in term of PER is satisfied but at the expense of the other objectives. In this example,

Table 2
Example weighting scenarios — w_1, w_2, w_3 and w_4 are the weights for the objective functions $f_{\text{min\_power}}$, $f_{\text{min\_ber}}$, $f_{\text{max\_throughput}}$ and $f_{\text{min\_delay}}$, respectively.

QoS requirements	w_1	w_2	w_3	w_4
High throughput with target PER*	0.1	0.1	0.8	—
Real-time with target PER* and throughput T*	0.1	0.1	0.1	0.7

the throughput will be too low or the power consumption too high. A basic strategy would consist in updating the weights iteratively until a solution close to the requirements is reached. However, the convergence to the optimal set of weights may be (very) slow and the approach inefficient. The strategy that we adopt in our GA implementation exploits the discrepancy of the solutions in (1c), (2c) and (3c). Indeed, those objective functions may take only binary values, 0 or 1, so whatever the weights are, the overall fitness function score (5) is very likely low if one or several objective function scores are equal to 0. In Section 4, we validate this approach by means of simulations. Table 2 summarizes these example weight vectors for several QoS requirements.

3 Proposed Genetic Algorithm

The optimization problem (5) involves non-linear functions. Additionally, this implies that it is not possible to treat each parameter as an independent variable which can be solved in isolation from the other variables. There are interactions such that the combined effects of the parameters must be considered in order to maximize or minimize the solution set. As mentioned by Whitley (1994), a genetic algorithm is suitable to solve that kind of optimization problem. GAs are a family of computational models inspired by evolution. An implementation of GA begins with a population of random chromosomes. One then evaluates these structures and allocates reproductive opportunities in such a way that those chromosomes which represent a better solution to the objective function are given better chances to reproduce than those chromosomes which are poorer solutions. We assume that the variables representing the set of parameters $\{P_1, P_2, \ldots, P_{N_c}, M_1, M_2, \ldots, M_{N_c}, CW_{\min}, CW_{\max}, L, d\}$ can be typified by bit strings. This means that the variables are quantized in an a priori fashion and that the range of the quantization corresponds to some power of 2.

The first step in our GA implementation is to generate a *single* initial random bit string representing a possible solution $\mathbf{x} = [P_1, P_2, \ldots, P_{N_c}, M_1, M_2, \ldots, M_{N_c}, CW_{\min}, CW_{\max}, L, d]$ to the optimization problem (5). A first payload packet is transmitted with respect to these parameters. After receiving in return the acknowledge signal (positive ACK or negative NAK), the string is then evaluated and assigned the fitness value $f(\mathbf{x})$ given by (5). If optimization at the physical layer is considered, the objective functions to evaluate (5) are (1a) or (1c), (2a) or (2c) and (3c) depending on the QoS requirements. If cross-layer optimization is considered, then (5) is evaluated with (1b) or (1c), (2b) or (2c) and (3c). The principle of the optimization procedure employing the genetic algorithm is depicted in Fig. 4. A new random bit string

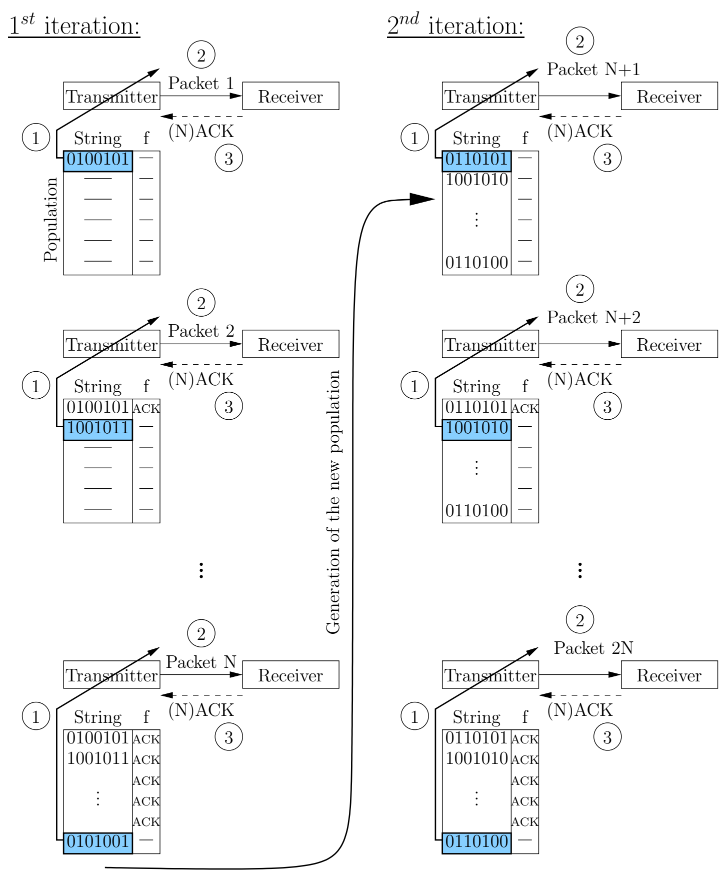

Fig. 4. GA Principle based on acknowledgment signaling. At the first iteration, (1): generate a random string and update the transmission parameters accordingly; (2): transmit packet 1; (3): update the fitness function f based on the received ACK; (1): generate a new random string and update the transmission parameters accordingly; (2): transmit packet 2; (3): update the fitness function f based on the received ACK. Continue the same procedure until transmission of packet N. Then apply GA to generate a new population (a better one). This completes the first iteration. At the second iteration, (1): use the new string 1 to updating the transmission parameters; (2): transmit packet $N+1$; (3): update the fitness function f based on the received ACK. Repeat the procedure for each next set of N packets.

representing another possible solution to the optimization problem (5) is used for the second packet transmission. Based on the value of the ACK signal for this packet, this string is evaluated and assigned the fitness value $f(\mathbf{x})$ given by (5). The population after two packet transmissions is 2. For the next packet transmission, this process repeats. Hence, the population grows linearly with the number of transmitted packets independently if the transmission fails or succeeds until it reaches a maximal value N. Then, selection is applied to the current population of N strings to create an intermediate population. Then recombination and mutation are applied to the intermediate population to create the next population, also of N strings. The process of going from the current population to the next population constitutes one generation in the execution of a genetic algorithm and is performed after each new set of N transmitted packets. Selection process that will more closely match the expected fitness values is "remainder stochastic sampling". There are several ways to make this selection. An efficient implementation described by Whitley (1994) uses a method known as "Stochastic Universal Sampling". Assume that the population is laid out in random order as in a pie graph where each individual is assigned space on the pie graph in proportion to fitness. Next an outer roulette wheel is placed around the pie with N equally spaced pointers. A single spin of the roulette wheel will now simultaneously pick all N members of the intermediate population. The resulting selection is also unbiased as shown by Whitley (1994). After selection has been carried out the construction of the intermediate population is complete and recombination can occur. This can be viewed as creating the next population from the intermediate population. Elitism is considered: A percentage (10% for instance) of the strings with best fitness function scores are duplicated in the new population set. For generating the other strings of the new population, crossover with single recombination point is applied to randomly paired strings with probability $p_c = 0.6$. After recombination, we apply a mutation operator. For each bit in the population, mutate, i.e., flip the bit `x` to `1-x` with probability $p_m = 1 - 1.8^{-\frac{1}{N}}$, where N is the size of the population as proposed by Fonseca and Fleming (1998b, page 40). After the process of recombination and mutation is complete for the selected N strings, the new population is re-evaluated through the transmission of the N next packets. The process of evaluation, selection, recombination and mutation forms one iteration in the execution of a genetic algorithm. We iterate until convergence to a stable solution for the set of parameters $\mathbf{x}$.

4 Simulation results

In this section, we characterize the performance of the proposed Genetic Algorithm for ARQ-based link adaptation for multicarrier transmission in various scenarios. In all cases, we simulate a multicarrier system with $N_c = 64$ subcarriers using the Matlab simulator. Sufficient cyclic prefix is assumed. Each subcarrier is assigned a random attenuation value $|H_i|^2$, $i = 1, 2, \ldots, N_c$ with chi-square distribution. Hence, the signal-to-noise ratio (SNR) varies independently from one subcarrier to another and induces a need for the power and rate adaptation for each individual subcarrier. The channel was assumed to be “block-invariant”, implying that the transmission channel impulse response remains constant or undergoes only minor changes over several consecutive packet transmissions. We assume regular Quadrature Amplitude Modulation (QAM) signaling (4-QAM, 16-QAM and 64-QAM) but our approach can readily be extended to arbitrary modulations. We also permit switching off some subcarriers if the fading is too deep for the corresponding bands. The transmission power P_i can take 16 values ranging uniformly from 0.1 mW to 2.56 mW. These are example values of course and do not represent any limitation for our GA based approach. At the link layer, adaptive contention window size is considered as suggested by Bianchi (1998). We assume no RTS/CTS mechanism. The minimum contention window size $CW_{\min}$ can take four possible values between 4 and 32. The maximal contention window size $CW_{\max}$ can take 8 values between 32 and 4096. The packet also has adaptive size L from 18 bytes to 2304 bytes. Finally, at the network layer, we assume multihop transmission with adaptive transmission range $\in \{d, d/2, d/4, d/8\}$. The network topology, i.e., the positions of the nodes that are assumed to be uniformly randomly distributed over a given area, is taken into account by the Rayleigh distributed channel coefficients. For high quality transmission channel, direct transmission over distance d is performed. For poor channels, however, transmission has to be done hop by hop separated from each other by distance $d/2$, $d/4$ or $d/8$ depending on the transmission noise level. For practical reasons, we assume half-duplex transmission, i.e., any node cannot transmit and receive simultaneously. We also assume for the considered network topology the presence of several access points within the transmission range. Our GA approach selects the access point which provides the best QoS. Overall, with 16 possible values for the transmission power, 4 possible modulation indexes, this gives 16×4 possible values for each subcarrier. With 4 (respectively 8) possible minimal (respectively maximal) contention window sizes, 8 different packet sizes and 4 transmission ranges, and 64 subcarriers, this gives a total search space of $64 \times 16 \times 4 \times 4 \times 8 \times 8 \times 4 = 4,194,304$.

4.1 Scenario 1: ARQ-based Discrete Waterfilling Algorithm

In the first example, we focus on the transmission parameters optimization for the physical layer. Whereas next examples will demonstrate the importance of cross-layer optimization, this example permits us to compare performance of our ARQ-based genetic algorithm against the performance obtained with optimal bit-loading algorithm. Our GA is compared to the bit loading algorithm proposed by Fischer and Huber (1996), which is near-optimal at moderate computational complexity. It serves us as a benchmark for this example but also for all the other examples of this section. Additionally, we compare our GA algorithm against the solution provided by Newman et al. (2007) which is also based on a genetic algorithm. The main difference resides in that the fitness function given by (5) is evaluated by using (3a) in Newman et al. (2007) instead of (3c) in our case. Also the weights are different. The only way to meet the QoS requirement, say target PER* using (3a) is to adapt the weights of the objective functions.

Newman et al. (2007) proposed several sets of weights that advantage either the system reliability or the power consumption or the throughput. In our simulation, we choose their most advantageous weight set, i.e, the set that satisfies the QoS constraint while providing the highest throughput. The final comparison in this example is carried out with the adaptive modulation scheme used in IEEE 802.11 standard. In this scheme, the modulation order is identical for all subcarriers. The highest order is chosen such that it satisfies the average target PER*. Fig. 5 shows the throughput performance achieved by the four considered algorithms as a function of SNR. In this example, target PER* is equal to 10^{-3}.

Three conclusions may be made. First, GA performs very close to the optimal bit-loading algorithm as long as the number of iterations in GA is large enough. The gap between GA with 100 iterations and bit-loading algorithm is approximatively 8 decibels at all SNR values. The gap is reduced to 1.5 decibels if GA performs 500 iterations. This loss is mainly due to the high percentage rate for the elitism in GA. Whereas elitism of 10% dramatically increases the convergence speed of GA, it penalizes the search toward the global optimal solution. Duplicating the best but still suboptimal solutions among the population in GA may prevent finding a new better solution. Second, our GA implementation outperforms the solution in Newman et al. (2007). The loss is mainly due to the fact that the GA implementation in Newman et al. (2007) uses the objective function (3a) rather than (3c). Indeed, three sets of weight were proposed: i) the multimedia mode which favors the throughput at the expense of the power consumption and the reliability, ii) the low-power mode which lower the power consumption and iii) the emergency mode which favors the reliability at the expense of the throughput and power consumption. As expected, the set corresponding to the multimedia mode (high throughput, lower reliability) leads to a better solution than the emergency mode set (high reliability, lower throughput) at high SNR. At low SNR, the emergency mode set performs better than the multimedia mode set. The operational SNR range is rather small for both sets, that is, if the SNR is smaller than 30 decibels, the multimedia mode cannot find any solution that satisfies PER*. On the other hand, for SNR larger than 30 decibels, the multimedia mode provides a solution with much better PER than PER* at the expense of the throughput. Finally, the conventional approach is penalized by the fact of using the same modulation order over all subcarriers. In this case, performance are dictated by the transmission error over the subcarrier(s) with the deepest fading.

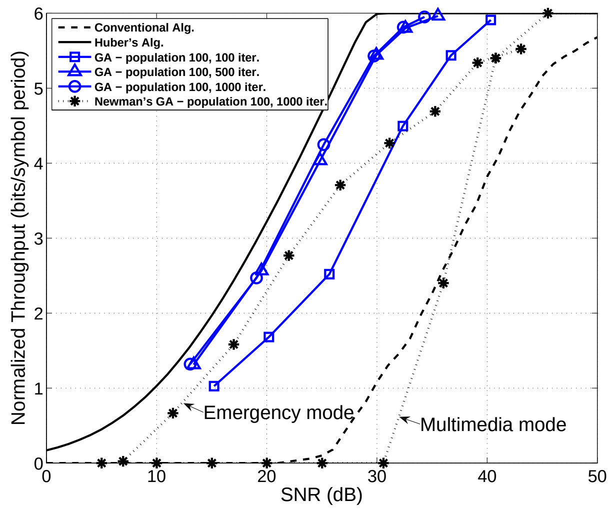

Fig. 5. Joint Power Optimization / Bit-loading Algorithm for OFDM system. Target $\mathrm{PER}^* = 10^{-3}$. The conventional algorithm performs adaptive rate as in the IEEE 802.11 standard; algorithm proposed by Fischer and Huber (1996) is a near optimal power allocation/bit-loading algorithm with computational complexity order of $N_c \log N_c$; we use this algorithm as a benchmark for our GA-based algorithm; Newman'algorithm denotes the GA-based bit-loading algorithm proposed by Newman et al. (2007).

4.2 Scenario 2: ARQ-based Cross-Layer Optimization with Adaptive Contention Window Size

Fig. 6 shows the throughput performance achieved by GA for cross-layer optimization. In addition to the parameters of the physical layer P_i and M_i , $i = 1, \ldots, N_c$, the minimal contention window size and maximum exponential backoff stage are also considered. Optimization over all these parameters with respect to (5) requires finding the optimal tradeoff between conflicting entities: Maximizing the minimal contention window size reduces the number of retransmission per packet and therefore the power consumption. However, it does not necessarily increase the throughput as shown by Bianchi (1998) for large network load. In this example, the target packet error rate PER^* is set to 10^{-3} and a network with 10 or 25 users is considered. We compare with the conventional scheme with pre-determined initial contention window size $CW_{\min} = 32$ and maximum backoff stage $m = 5$. For the conventional scheme, the modulation order is determined as in Scenario 1. We also compare with the scheme referred as "PHY then MAC" which consists of separately optimizing the parameters of the physical layer and the link layer. The parameters of the physical layer are optimized with the algorithm proposed by Fischer and Huber (1996) and the parameters at the link layer are optimized through an exhaustive search of all possibilities of $CW_{\min}$ and $CW_{\max}$.

Two conclusions can be made. First, GA with optimal $CW_{\min}$ and $CW_{\max}$ outperforms the conventional scheme by approximatively 20 decibels. The loss essentially occurs at the physical layer. Indeed, the gap between both schemes in Scenario 1 was already around 20 decibels. The fact of using a fixed contention window size $CW_{\min} = 32$ and maximum backoff stage $m = 5$ seems to have little effect on the performance. However, in different scenarios, this might not be the case. Second, GA also outperforms the "PHY then MAC" approach at SNR larger than 15 decibels. Although the bit-loading algorithm performs slightly better than GA at the physical layer (scenario 1), the "PHY then MAC" approach optimizes the minimum and maximum contention window sizes based on target PER* and not the current PER value. Whereas the loss is negligible at lower SNR values (SNR < 15 decibels), it becomes significant for SNR values greater than or equal to 15 decibels. Indeed, PER is significantly smaller than PER* and considering PER* instead of PER leads to non-optimal contention window sizes.

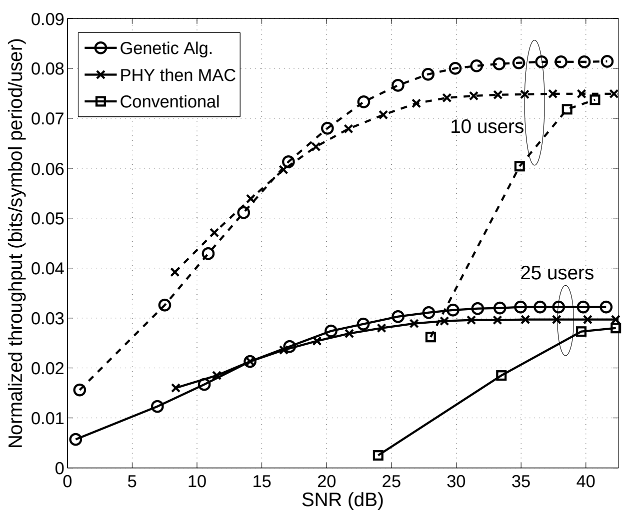

Fig. 6. Cross-Layer Optimization for OFDM-based CSMA/CA system: Joint Power Optimization / Bit-loading Algorithm / Minimum Contention Window Size / Maximum Backoff Stage. Target $\text{PER}^* = 10^{-3}$.

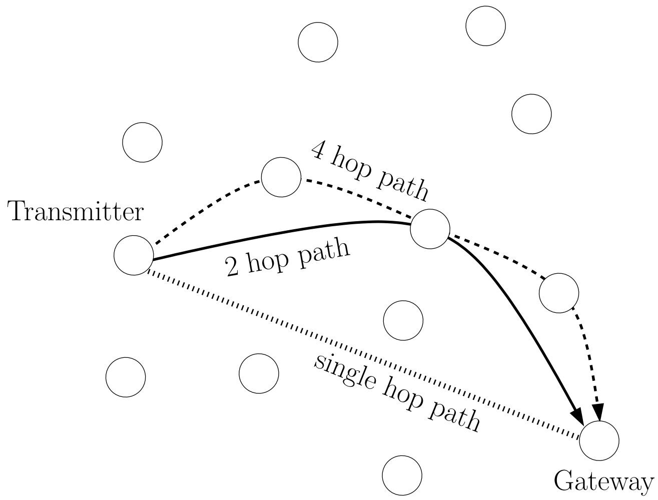

Fig. 7. System model for Scenario 3: Variable range routing for multihop transmission in a wireless mesh network. A transmitter transmits data to the gateway node via multihop transmission. There are several possible paths. Dotted line: direct transmission; solid line: 2-hop transmission; dashed line: minimum transmission range.

4.3 Scenario 3: ARQ-based Cross-Layer Optimization for Multihop Transmission with Variable Range Routing

In addition to the transmission parameters at the physical and link layers, we consider the transmission range d as a parameter at the network layer for multi-hop transmission. The tradeoff for d is illustrated in Fig. 7. In order to minimize the number of one-hop transmissions and therefore increase the throughput, it is better to use large values for a transmission range d. On the other hand, choosing smaller values of d improves the reliability of a single hop link which can support a higher data rate, but more intermediate nodes have to forward the packet until the destination is reached. Therefore, the optimal transmission range highly depends of the current network state. The results are shown in Fig. 8. The weights for the GA objectives functions are those in the first row of Table 2. In all simulations, we invoke GA to optimize the parameters at the physical layer, the link layer and the network layer, i.e., all parameters listed in Section 2.2 except the access point indices that are supposed, here, to be pre-determined. At low SNR, higher throughput can be achieved with smaller transmission ranges. Despite the fact that the throughput decreases linearly with the number of hops, this solution is preferable since the SNR for each single-hop transmission is much higher as plotted on the top x-axis. We ran simulations for all possible transmission ranges. This provides us with a benchmark for our GA implementation with variable transmission range. For low and high SNR, performance of GA with variable transmission range matches with the optimal solution. For medium SNR, say SNR= 15 decibels in Fig. 8, GA performs suboptimally. Indeed, most of the population that is satisfying the target PER* corresponds to multihop transmission with at least two hops, at the early stages. This means that there are a very few chromosomes (or maybe even none) in this population with maximum transmission range that satisfy PER<PER*. Even if there are a few, these elements are likely to vanish within the next iterations and the optimal solution (with transmission range $d = 1$) can be recovered only through a mutation operation.

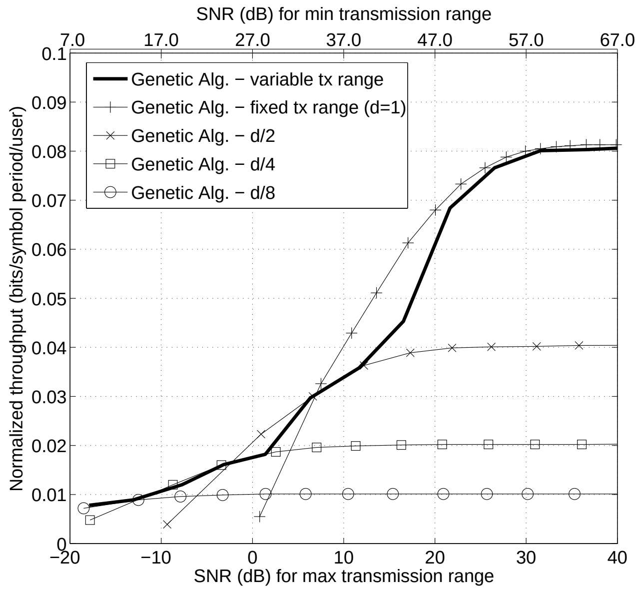

Fig. 8. Cross-Layer Optimization for OFDM-based CSMA/CA system with multihop transmission: Joint Power Optimization / Bit-loading Algorithm / Minimum Contention Window Size / Maximum Backoff Stage / Variable Range. Target $\text{PER}^* = 10^{-3}$. System load = 10.

4.4 Scenario 4: ARQ-based Cross-Layer Optimization for Frequency-Agile Multi-Channel Transmission

Along the lines of Dong Zheng and Junshan Zhang (2006), we take a cross-layer approach to study a frequency-agile medium-access control design for wireless networks. Particularly, we consider three opportunistic multi-channel MAC protocols (OMC-MAC) for single hop transmission (we assume here that the transmission cannot occur via multihop), which in fact make use of the channel conditions across multiple frequency channels to boost the system throughput and its reliability. We assume that the transmitter is within the transmission range of several APs. The OMC-MAC protocol has to determine an AP such that the transmitter can communicate at a high transmission rate. In contrast with more sophisticated schemes that take into account the interference due to the channel overlapping as in Ramachandran et al. (2006), we

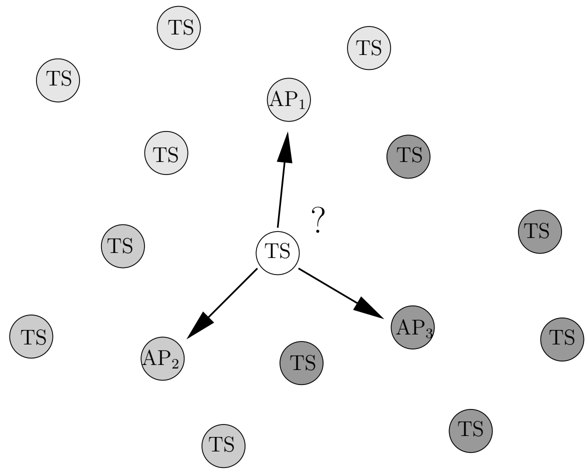

Fig. 9. System model in Scenario 4: A newcoming terminal station seeks to establish connection with one of the access points AP_1, AP_2 and AP_3 that are within its transmission range. Each transmission link from TS to AP_i, $i \in \{1, 2, 3\}$ is modeled as having additive white Gaussian noise with flat fading coefficient a_i. In this example, the current load is 4 for AP_1, 3 for AP_2 and 5 for AP_3.

assume that APs use orthogonal channels without interfering each other. In IEEE 802.11g standards, two or four orthogonal channels within the same area are realistic numbers. For instance, there is no overlap between channels 1, 5, 9 and 13 in realistic scenarios as shown by Dunat et al. (2004) and Fuxjager et al. (2007). We also simulated the case of 8 APs in order to gauge the performance from a cognitive radio perspective as it might occur in the IEEE 802.22 standard (see Cordeiro et al. (2005), for instance). The physical transmission channel between AP and the transmitter of interest is modeled with a single attenuation Rayleigh-distributed coefficient that is constant over a packet duration but varying randomly from one packet to the next. Moreover, attenuation coefficients are supposed to be uncorrelated between all channels. The first OMC-MAC protocol referred to as “max SNR”, uses the ACK signaling to measure the propagation channel condition for rate and power adaptation. By selecting the channel with the best current signal-to-noise ratio, the transmitter can send packets at higher rates. We also evaluate the performance of an alternative protocol denoted “min load”. This protocol selects the AP with the smallest number of active users and therefore minimizes collisions between packets. Both protocols may be combined into a third protocol such that the AP with the best overall throughput is chosen. This offers an interesting tradeoff between the current number of active users of each AP and the current channel realizations as depicted in Fig. 9.

For all three protocols, we invoke GA to optimize the parameters at the physical layer and the link layer. Moreover, selection of the best AP in the third protocol is done by GA as well. Performance results are compared against the results obtained with the basic protocol which consists in randomly selecting an AP independently of its channel conditions. The results are shown in

Fig. 10. We assume that (16 × the number of APs) users are uniformly distributed among the APs. This means that the current number of users among APs may significantly vary around the average value 16. The weights for the GA objective functions are those in the first row in Table 2. At low SNR, the best strategy consists in selecting the AP with the best transmission SNR. Although the potential high load of the chosen AP may significantly reduce the throughput, the selection based on best SNR is the only strategy which efficiently mitigates deep channel fading. As shown by Dong Zheng and Junshan Zhang (2006), the average throughput gain grows logarithmically with respect to the number of reachable APs. However, the simulated throughput gains are smaller than the theoretical gains. This is mainly due to the fact that in both the random access and the "best SNR" protocols, the minimum contention window size $CW_{\min}$ and the maximum backoff stage m are optimized (through GA). This optimization enhances the performance of both protocols equivalently and therefore reduces their overall performance gap. At high SNR, the protocol "min load" outperforms the max SNR-based strategy. Indeed, almost all transmitter-AP links have large SNRs to guarantee reliable transmission with the highest modulation order, 64 in our case. The throughput is then maximized for the AP with the smallest number of active users. At high SNR, GA-based "max throughput" protocol performance is slightly worse than that of the "min load" protocol. This behavior can be explained as follows. At high SNR (30 decibels), we use the same weights as in the low SNR regime (first row in Table 2). In that case, weight w_3 related to the throughput maximization is too low with respect to weight w_2 which is related to the transmission reliability. In this case, a significant proportion of the initial population of GA has some large fitness function values for "max SNR" while some other elements have some low values for "min load". Therefore, it may occur that solutions corresponding to higher throughput just vanish from the population through the iterations and GA performs suboptimally. However, whereas the "max throughput" protocol performs slightly worse than "min load" at high SNR, it outperforms the "max SNR" protocol. A detailed analysis on the average throughput gain can be found in de Baynast et al. (2007).

4.5 Scenario 5: ARQ-based Cross-Layer Optimization with QoS requirements

In the four previous scenarios, we use GA to maximize the throughput at given transmission power consumption and target PER*. In this section, we propose to evaluate GA performance with other QoS requirements. We start with transmission power consumption. Whereas we display GA performance after convergence in the previous scenarios, it might also be interesting to check the tracking properties of our GA implementation.

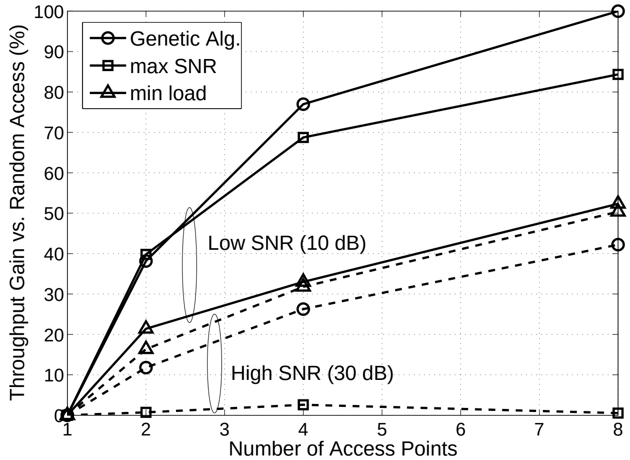

Fig. 10. Comparison between the three protocols for association for the frequency-agile multi-channel system described in Section 4.4: "max SNR" selects the access point with best SNR, "min load" selects the access point with the lowest load and the third GA-based protocol "max throughput" selects the access point which maximizes the throughput. For all three protocols, cross-Layer optimization is performed through GA and includes as parameters: power optimization, bit-loading, minimum Contention window size, maximum backoff stage. Target PER* $= 10^{-2}$ and the average system load per access point is equal to 16.

Case 1: Power consumption. Let us consider the following scenario: for the first 3000 time slots (0.15 seconds), full power is used (2.50mW), then the transmitter detects that the batteries are half-empty and the power controller lowers the power consumption to 1mW. After 6000 time slots (0.30 seconds), the system is asked to switch to the minimum power consumption 0.15mW. In order to satisfy the power consumption requirements, we use the objective function (1c) instead of (1b). In this case, the values of the weights are given in first row in Table 2 and the results are plotted in Fig. 11. The light gray curve shows the transmission power. As we can see, as soon as the power constraint changes, the optimal solution of our GA implementation satisfies the power constraints within a few time slot periods. Moreover, the throughput (black curve) is maximized in tens or hundreds of time slots. For a very low power constraint, say, 0.15mW, GA struggles to maximize the throughput and needs more than 1000 iterations to reach optimal throughput.

Case 2: Delay bound for data streaming (video or audio). Another important parameter in wireless networks is the transmission latency which is crucial for real-time audio and video streaming applications. In Fig. 12, we display the delay bound as a function of the number of active users such that all their transmissions experience a delay less than or equal to this delay bound. Target PER* is 2% and the target throughput T* is set to 640Kbps, 1.28Mbps or 2.56Mbps. The weights for GA are those in the second row of Table 2. Our GA implementation almost matches performance of the "PHY then MAC"

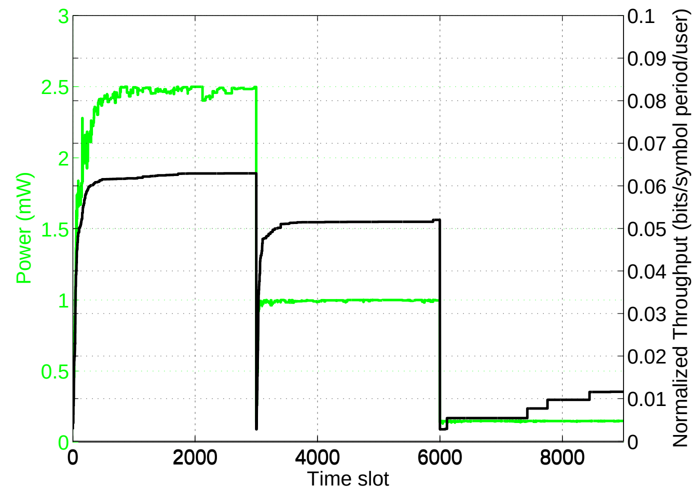

Fig. 11. Power adaptation in OFDM-based CSMA/CA system with decreasing power constraints: Start with full power utilization (Target POWER = 2.50 mW) for the first 3000 time slots, then switch to 1 mW mode for the next 3K time slots, then lower power (0.15 mW). Target PER* = 10^{-3}. Network load = 10.

approach. Basically, it means that GA selected the smallest packet sizes such that the throughput is greater or equal to T^*. Moreover, the delay bound with GA is twice as small as the delay bound for the conventional scheme. For large load, the delay reduction is even more important.

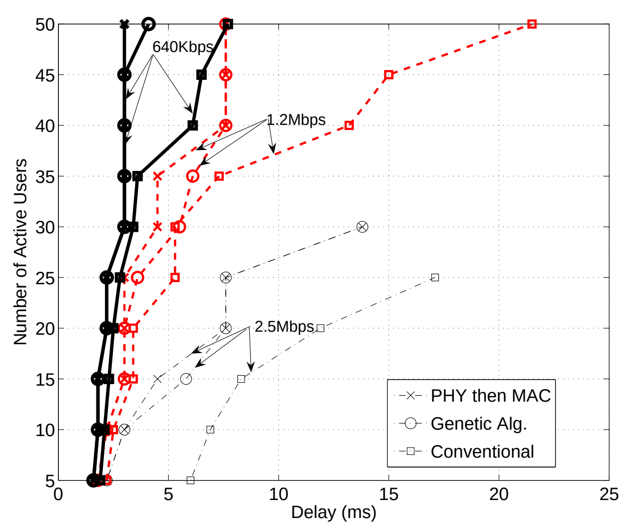

Fig. 12. Maximum number of active users in the network with respect to the delay bound. Target packet error rate of 2% in OFDM-based CSMA/CA system for high data rate streaming transmission (video).

5 Conclusion

We have addressed cross-layer optimization for wireless multicarrier systems in the context of cognitive radios and cognitive radio networks. Optimization involves search over large discrete spaces. Traditionally, this optimization requires full or partial network state information at the transmitter. In this work, we invoked a genetic algorithm to perform this optimization. We showed that the optimal transmission parameters can be iteratively determined with the acknowledgment signaling of the prior transmitted packets as the lone external input. No other network state information is required, and the fact that we are able to piggyback the information over ACK signaling makes the solution attractive as no separate signaling channel is required. Moreover, the optimization process does not require any transmission model. Simulations with a large variety of QoS requirements validated our approach. Simulation results showed that our ACK signal-based GA implementation achieves comparable performance to an exhaustive search over the whole set of parameters which requires perfect network state information at the transmitter.

The results show that GA-based cognitive methods can provide true benefits in the context of wireless communication networks. Future work requires more extensive studies with large-scale networks. In that domain we are currently experimenting not only with simulations, but also by using gnuRadio-based testbeds. One of the main benefits of our method is that it can concurrently and dynamically handle optimization towards different goals, and it does not require complex exchange of network state information. As future research, we are also considering issues of overall network capacity constraints and understanding the limits of VPI.

Acknowledgments

This work has been in part supported by DFG (Deutsche Forschungsgemeinschaft) and RWTH Aachen University through the UMIC excellence cluster funding.

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