Distributed cognitive coexistence of 802.15.4 with 802.11

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***Abstract*— Thanks to recent advances in wireless technology, a broad range of standards are currently emerging. Interoperability and coexistence between these heterogeneous networks are becoming key issues, which require new adaptation strategies to avoid harmful interference. In this paper, we focus on the coexistence of 802.11 Wireless LAN and 802.15.4 sensor networks in the ISM band. Those networks have very different transmission characteristics that result in asymmetric interference patterns. We propose distributed adaptation strategies for 802.15.4 nodes, to minimize the impact of the 802.11 interference. This interference varies in time, frequency and space and the sensor nodes adapt by changing their frequency channel selection over time. Different distributed techniques are proposed, based on scanning (with increasing power cost) on the one hand, and based on increased cognition through learning on the other hand. These techniques are evaluated both for performance and energy cost. We show that it is possible to achieve distributed frequency allocation approaches that result only in an increase of** 20% **of the delay performance compared to ideal frequency allocation. Moreover, it is shown that a factor of two in energy consumption can be saved by adding learning to the system.**

I. Introduction

Interest in wireless technology has experienced an explosive growth over the last decades. The finalization of diverse standards has eased the development of wireless applications. As a result, the spectrum is getting used by a variety of heterogeneous devices, standards and applications. This is especially the case for the *Industrial, Scientific and Medical* (ISM) bands that are unlicensed and hence host the most heterogeneous range of networks.

In this paper we focus on the coexistence between two major wireless standards that operate in the 2.4*GHz* ISM band, namely 802.11g Wireless LAN [1] and 802.15.4 Sensor Networks [2]. Their overlapping frequency channels are shown in Fig. 1. The characteristics of both networks are very different, resulting in a problem that is asymmetric in nature. Indeed, the output power of 802.15.4 devices is typically as low as 0*dBm* [3], whereas the output power of 802.11g devices is 15*dBm* or above. Also, 802.15.4 sensor networks are designed to monitor the environment or buildings, and can be very large, while 802.11 networks are mostly local hotspots organized around an Access Point (AP). Finally, sensor network applications are not demanding in terms of throughput, but however require a high reliability and robustness against attacks or unknown events. They should also be self-organizing since it is impossible to maintain such large networks efficiently. In comparison, 802.11 networks are typically used by a limited number of throughput-intensive applications. There is in fact only one

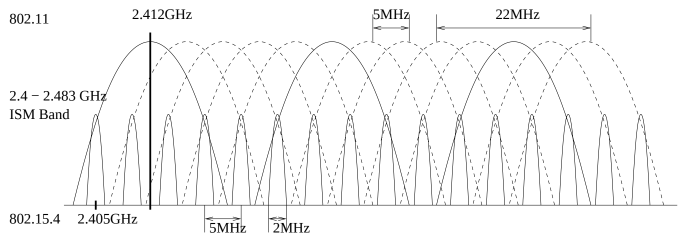


Fig. 1. 802.11 and 802.15.4 channels in the 2.4GHz ISM band.

common requirement: both 802.15.4 and 802.11 devices are battery-powered so that energy consumption is a major design criterion. Any algorithm for those networks should take the energy cost into account, including the non-negligible hardware power contribution associated with idle mode operation, scanning and receive processing.

The purpose is to introduce distributed algorithms to optimize the 802.15.4 performance under varying 802.11 interference patterns. The sensor network is indeed critically affected by the coexistence, since it's output power is much lower than that of 802.11 networks. The proposed algorithms should be fully distributed to improve scalability (since sensor networks are large), robustness (which is an important requirement for sensor network applications) and adaptability. More specifically, our goal is to design distributed channel selection algorithms that allow the sensor nodes to dynamically adapt their channel in response to the 802.11 interference. The energy cost of the proposed algorithms will always be taken into account.

Traditional approaches for coexistence of wireless devices focus on transmit power control. In [4], for instance, the allowable transmit power is determined in order to guarantee a protected radius to primary users that should not be interfered with. This is especially useful to enable spectrum sharing between systems with different levels of regulatory status, e.g., primary and secondary users. This type of sharing is typically referred to as *vertical sharing*, while *horizontal sharing* considers systems with equal regulatory status. Concerning the latter horizontal sharing between homogeneous devices, game-theoretic concepts are used in [5] to achieve distributed transmit power allocations. These can however not be used when the operating conditions of the considered networks are very asymmetric.

Another category of solutions focuses on dynamic frequency selection to avoid interference. In this context, the special case of vertical coexistence between 802.11 and 802.15.4 networks

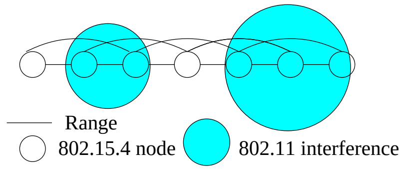


Fig. 2. Considered 802.15.4 network affected by 802.11 interference.

has started to receive attention since it has been shown in [6] that the impact of 802.11 on the sensor network is large and leads to above 92% of packet loss. An adaptive scheme using multiple radios has been proposed in [7] to overcome this, but this solution assumes that communication between nodes on a channel is possible, even after interference has been detected on that channel. This is not robust to the extreme interference patterns which are encountered in this context.

While the above presented classes of adaptation schemes optimize channel access by taking into account transmit power or interference constraints, none of them addresses the problem in a sufficiently distributed way. They rely on the availability of a dedicated control channel, which drastically limits the scalability and robustness of the sensor network. Moreover, they do not consider the system power cost of environment scanning. In this paper we will address these issues and propose new fully distributed algorithms that enable to increase the robustness of 802.15.4 networks in the presence of dynamic 802.11 interference, whith acceptable total power cost.

II. System Model

In this section we give a detailed overview of the models used for the sensor network and for the wireless LAN interference pattern. We also define the considered energy and performance metrics that are relevant for the investigated scenario. These metrics will be used to evaluate the proposed distributed adaptation algorithms.

A. 802.15.4 Network model

We represent the 802.15.4 network by a large number of nodes N that are arranged in a string or a rectangular topology. An $N \times N$ connectivity matrix $\mathbf{C}_{(N,N)}$ is used to denote which sensors can overhear each others. We assume that it is the case for all sensors in a range Rd from each other, where d is the internode distance and R is a parameter. In Fig. 2 a simple string topology is presented with $R = 2$. Each of the sensor nodes operates in one frequency channel among F possible ones, with $F = 16$ for 802.15.4 networks operating in the 2.4GHz ISM band. A N-dimensional vector $\mathbf{t}_N$ keeps track of the current frequency $f_i, (i \in [1, \ldots, F])$, which the different nodes are using to transmit. Although transmission is only possible on one frequency, we assume that nodes can be designed to scan or receive on multiple channels at the cost of increased scanning energy consumption and hardware.

The 802.15.4 medium access control can operate in different modes, depending on the use or absence of beacons. In this work, we will assume the beacon-enabled mode, which results in a so-called superframe structure [2]. Such a superframe typically consists of a beacon, a contention access period and a contention free period. More importantly, it is typically followed by an inactive period, during which the involved nodes are put asleep. It is assumed that sensors can change their channel without extra energy cost, when they wake-up from sleep mode. As a result, we can assume that the sensors potentially swap frequency every interbeacon period, which ranges from 15ms to above 4min according to the standard. The frequency swapping strategy will be determined by the proposed distributed adaptation algorithms.

On top of this medium access, three types of networks can be formed: star, peer-to-peer and cluster-tree. In this work, the 802.15.4 network is assumed to consist of nodes of equal importance that are connected in a mesh network through peer-to-peer connections. These connections are reflected in the connectivity matrix $\mathbf{C}$ introduced earlier in this section. Each of those connections in such type of networks is maintained by scanning for the beacons sent by the peer.

B. 802.11 Interference model

We consider a large 802.15.4 network, which is affected by 802.11 interference. As it will be described hereafter, this 802.11 interference can vary over frequency, time and space.

The variations in frequency result from the fact that different 802.11 networks can operate using different channels (Fig. 1). Dynamic frequency selection is a new functionality currently added to most of those 802.11 networks [8]. It is developed to optimize the frequency allocation of 802.11 networks that are subject to interference. As a result of this dynamic frequency selection, 802.11 interference is varying over time. It can be seen in Fig. 1 that each 802.11 network always covers four consecutive 802.15.4 channels. The power distribution over these channel is more or less flat, especially for the OFDM-based 802.11g which is currently getting widely used thanks to its throughput improvement w.r.t. conventional 802.11b networks [1].

The variation in time results from the fact that the use of 802.11 networks is varying over time since user activities vary over time. These variations result from 802.11 ad hoc networks that are opportunistically established to transfer a large file, or from 802.11 hot-spots that become operational when users join the network, as it was analyzed in [9]. It can thus reasonably be assumed that the 802.11 interference stays constant for several minutes to hours, and hence several (thousands) of 802.15.4 interbeacon periods.

The spatial variations result from the fact that 802.15.4 networks are typically deployed over a large area (e.g., for monitoring purpose). As a result, the 802.15.4 networks are expected to be large both in terms of the area they cover and the number of nodes they consist of. The theoretical transmission, and hence also interference, range of 802.11 networks is 100m to even 250m. Although this is a significant range, sensor networks can cover larger areas since they consist of a large number of nodes in a mesh topology. As a result, the 802.11 interference is assumed to affect large geographical subsets of the 802.15.4 nodes (Fig. 2).

We assume that an active or interfering 802.11 network will always be detected by the 802.15.4 nodes. In real systems, however, some noise should be considered in this detection of 802.11 interferers, since the 802.15.4 nodes could be scanning during a short inactive burst in between 802.11 packets. As the 802.15.4 beacon period is typically large compared to the 802.11 beacon or packet burst periods, this noise can be considerably reduced under the assumption that the 802.15.4 nodes scan during the whole period.

The 802.11 interference can thus finally be modeled as a $N \times F$ matrix $\mathbf{I}_{(N,F)}$. Each interfering network i then corresponds to a submatrix of dimensions $N_i \times 4$, where N_i denotes the number of nodes that are in the range of network i (depending on its output power), and where it is taken into account that every 802.11 interference pattern has a width of four 802.15.4 channels. Networks can swap frequency over time, disappear or appear, but this time variation is assumed to be slow compared to the 802.15.4 frequency adaptation.

C. Performance and energy measures

We consider delay as a relevant performance metric (throughput requirements in sensor networks are typically low). More precisely, assuming that sensors monitor a variable that should be communicated to a central sink, we consider the average number of periods required to forward a measurement to a fixed central sink as performance metric. This average is computed over time and over the nodes in the network. The more the network is affected by interference, the more periods will be required on average to reach the sink. We assume that every packet is forwarded only once during each period, to the node closest to the sink that can be reached during that period. As a result, nodes travel each period the largest possible distance.

As far as energy consumption is concerned, we can model the energy needed during every period independently of the actual packets sent, received or beacons overheard. This is a valid assumption since throughput is typically very low in sensor network applications. Moreover, since the full receive chain is typically required to be on for scanning, the power consumption in that mode is the same as the power consumption in the receive mode. During every superframe, each node is awake to listen at least to its current frequency channel. The quality of a frequency channel can be assessed by counting the number of overheard beacons of peers. If no beacons are heard, energy detection, which is part of the 802.15.4 specifications, can be used to detect harmful interference on the channel. As a result, the energy consumption only varies with the number of additional channels that are scanned (or listened to) in parallel. In the next section we will propose some distributed algorithms that require scanning on one or multiple channels, and evaluate if their increased energy cost actually leads to an improved performance.

III. Distributed adaptation and learning

In this section, we propose distributed channel selection algorithms to improve the 802.15.4 performance and robustness in presence of 802.11 interference. The proposed algorithms do not rely on any coordination between the nodes (which would otherwise require a dedicated interference-free channel). With random frequency selection as a reference point, we propose solutions based on scanning and more energy efficient solutions based on learning. The effectiveness of these approaches will be assessed in a time varying environment.

A. Random frequency selection

The simplest distributed frequency selection solution is a scheme where nodes randomly (following a uniform distribution) pick a channel every period. Packets are forwarded to any other node closer to the sink within communication range that happened to pick the same channel. It can of course be expected that the average delay in this scheme will be large. However, since it does not rely on any coordination between the nodes and does not rely on an environment model, it can adapt to any possible event.

B. Scanning based distributed approaches

It is possible to outperform the random frequency selection algorithm described above, since the considered 802.11 interference does not vary every 802.15.4 period (once an interference free channel is found for the whole network, the nodes should indeed continue using that channel until adaptation is required.) We propose here new scanning based approaches relying on the simulated annealing[1] optimization method, which can be elegantly implemented in the considered network setup. Simulated annealing is a very effective heuristic optimization strategy for finding a global optimum, developed by Metropolis et al [10]. The basic idea of the method is to sample the search space using a Gaussian distribution, and to *anneal* this distribution as the optimum is approached.

Applied to the present context (i.e., optimizing the frequency allocation over a large sensor network affected by dynamic interference), nodes have to keep looking for another channel (i.e., sampling the search space). Since the 802.11 interference probability over the 802.15.4 channels is uniformly distributed, this search space sampling can be done uniformly. Every period, next to the node i's current frequency channel f_i, another channel f_{random} is considered and its performance is assessed. This is done according to a given channel quality metric G. The latter metric is computed based on the one hand on the output of the built-in 802.15.4 energy detector [2] that enables to capture the presence of 802.11 interference, and on the other hand on the number of beacons heard in the scanned channel. It is assumed that no beacons can be heard in the presence of 802.11 interference. The metric G is defined as:

$$G = \begin{cases} \sum \text{beacons heard} + 1 & \text{if no energy detected,} \\ 0 & \text{if energy detected.} \end{cases} \quad (1)$$

When 802.11 interference is present, the channel quality is assumed to be equal to 0 (worst case). When no 802.11

[1] We have chosen simulated annealing instead of other heuristic optimization techniques such as Tabu search or genetic algorithms. Tabu search is based on steepest descent, which inherently requires scanning or sampling a large set of neighboring solutions at each iteration step, which is not a desired property from an energy perspective. Genetic algorithms are not well suited to solve dynamic problems, as it is the case for the considered varying interference.

interference is present, the channel quality is assumed to be proportional to the number of heard beacons, augmented by one to distinguish from the aforementioned worst case.

In simulated annealing, exploration is embedded in the algorithm to allow the system to *jump* out of a local optimum. This means that a new channel f_{random} can be accepted even if it is measured to be worse than the current channel f_i according to the quality metric G. This happens with a certain probability that should be decreased (i.e., annealed) when the system converges to its optimal solution. Typically, this annealing follows an exponential distribution. Obviously, the higher the quality metric G, the better the current solution and the closer the system is to the global optimum (i.e., full connectivity in a channel free of 802.11 interference). In the proposed algorithm, f_{random} is accepted with probability:

$$\exp(-G(f_i)/A) \times \{G(f_{random}) > 0\}, \tag{2}$$

where A is a normalization factor and where the second condition $(G(f_{random}) > 0))$ avoids the system to swap to a new channel where 802.11 interference is present (corresponding to $G = 0$). Further exploring a channel that is known to be bad is indeed clearly a waste of resources.

As far as energy is concerned, the proposed algorithm requires to scan the current channel f_i and an extra channel f_{random}, so that the energy cost is doubled with respect to the random frequency selection algorithm. Obviously, it is possible to increase the number of channels to sample simultaneously in the proposed algorithm, and continue the basic algorithm with the best one in terms of G. [2] In the sequel, we will also evaluate the performance gains in the case two random channels are selected at every iteration of the algorithm, at the cost of an increased energy consumption.

C. Learning based distributed approaches

We propose here learning based approaches to make a decision based on experience rather than based on scanning. The proposed learning scheme is based on a simplification of the *Q-learning* learning algorithm that does not need a model of the environment and can be used online [11]. The Q-learning algorithm tries to find the policy that optimizes the expected return R_w, which is typically expressed as a sum of discounted rewards over time. Since we operate in a dynamic environment, we only focus on near term reinforcement (by setting the discount value to 0 in the algorithm).

In Q-learning, a policy is represented by a two-dimensional lookup table indexed by states and actions. In the considered problem statement, both a current state and action correspond to a channel frequency: f_s and f_a. With discount factor zero, the Q-function (Q^*) represents for each state and action the expected rewards R_w when taking that action:

$$Q^*(f_s, f_a) = R_w(f_s, f_a) = G(f_a). \tag{3}$$

This means that the expected reward, which is expressed by the quality function G, only depends on the action and not on the current state. The problem is now that the Q^* function should be approximated (*learned*) online by an estimate $\hat{Q}^*$. To do so, for every possible action (channel selection f_a), we update the available estimate $\hat{Q}^*$ as:

$$\hat{Q}(f_a)^* = (1-\alpha)\hat{Q}^* + \alpha G(f_a), \tag{4}$$

where α is a learning parameter. The estimate of the Q-function implicitly defines a greedy policy that selects the action f_a with the largest expected reward:

$$f_a = \max \hat{Q}^*(f_a). \tag{5}$$

It is important to note that the Q-learning algorithm updates the estimate for each action, but in fact does not specify what actions should be taken. The Q-learning allows arbitrary experimentation while at the same time preserving the current best estimate of states' values. This is an important property in a time varying environment and allows decoupling the learning phase from the decision policy.

We propose the following algorithm to select the next channel. When experimentation (i.e., *learning*) is allowed, we select a random frequency f_a with a probability similar to Eq. 2 used for the simulated annealing algorithm. Since we did not scan the frequency f_a before selecting it, we cannot add the second factor of Eq. 2. This probability writes thus:

$$\exp(-G(f_i)/A). \tag{6}$$

When no experimentation is allowed (i.e., *experience*), we employ the greedy policy defined in Eq. 5.

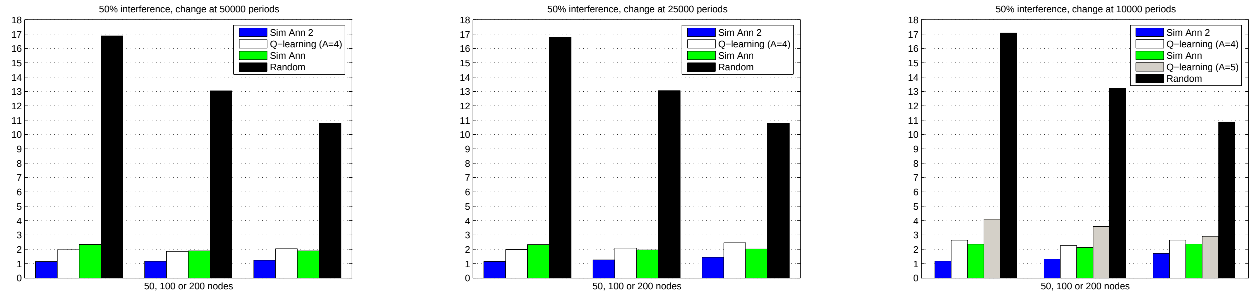
To sum up, the Q-learning algorithm selects a frequency f_a for the next period that is expected to maximize the reward or quality G. This optimal policy is learned online and some exploration is allowed to adapt to varying interference patterns. It is clear that every superframe period only one frequency is scanned, so that the energy consumption is similar to that of the random selection algorithm. In the results section we will investigate how the predictions based on learning compare with the more costly approaches based on scanning.

IV. Simulation results

We now evaluate the proposed schemes through simulation. We consider networks of different size ($N \in [50, 100, 200]$) in a simple string topology, varying average interference (25% or 50% of affected nodes) and different time-variations. Each of the results is averaged over 10 simulations that each last 10^8 802.15.4 algorithm steps. Traffic is generated randomly in the sensors, and forwarded to the sink node located at the end of the string topology. The connectivity range of each node is assumed to be $R = 10$. The performance measure is the average number of periods it takes for each packet to reach the sink, compared to the expected delay in case of ideal channel allocation (which could only be achieved by a central entity that can monitor the whole network interference). For the considered R and N, this ideal average number of periods can be shown to be of 3, 5.5 and 10.5 for N respectively equal to 50, 100 and 200. When not otherwise stated, the algorithm parameters are set to $A = 4$ and $\alpha = 0.1$.

We first look at a heavy interference scenario. Results are shown in Fig. 3, where the interference dynamics is

[2] We note that when multiple solutions are sampled, other techniques that are based on steepest descent, such as for instance Tabu search, could be used.



(a) 50000 periods static (b) 25000 periods static (c) 10000 periods static

Fig. 3. Normalized delay increase compared to ideal channel allocation.

increasing over the different plots. It can be seen that the simulated annealing algorithm with parallel scanning clearly outperforms the other solutions. However, this scheme results in a significant additional scanning cost (3 times the energy cost of the learning based approach, 1.5 time the energy cost of the simple simulated annealing solution). Also, it can be seen that the Q-learning scheme performs very well for the static interference scenario compared to the basic simulated annealing, while saving a factor two in energy cost. The performance achieved with random channel selection is low.

Regarding the impact of the interference dynamics, it can be seen in Fig. 3(c) that the performance of the Q-learning scheme decreases when the interference changes frequently. In this case it is indeed more difficult to maintain a correct estimate of the expected reward of an action f_a. On the contrary, simulated annealing is quite insensitive to the time-variations of the interference pattern, since it does not rely on estimates but on energy expensive instantaneous scanning. We can also note that the performance of Q-learning with increased exploration ($A = 5$ in Eq. 6) is lower.

Results corresponding to an amount of interference decreased to 25% are provided in Fig. 4. It can be seen that, compared to Fig.3(b), the performance of the Q-learning scheme has improved with respect to the simulated annealing algorithm. This can be understood as follows: the simulated annealing scheme scans the chosen random frequency before selecting it effectively. This has resulted in an additional factor in Eq. 2 compared to Eq. 6, to avoid that channels with interference are further explored. Clearly, the impact of this factor is larger when the average interference in the system is large, and investing more energy in scanning pays off when the probability to encounter interference is large.

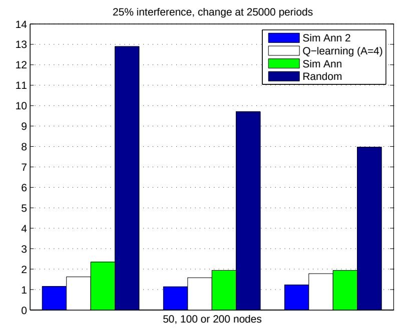


Fig. 4. Normalized performance in terms of % of the performance achieved compared to ideal off-line channel allocation for 25% of average load, 25000 periods static.

V. Conclusions

In this paper we have proposed some fully distributed channel selection algorithms for 802.15.4 networks in presence of dynamic 802.11 interference. The proposed algorithms are based on increased spectrum scanning (at the cost of energy consumption and additional hardware requirements) or increased learning. It is shown that adding learning to the distributed algorithms outperforms the schemes that rely on scanning in some scenarios, while saving a factor two in energy consumption. It is hence a promising direction to investigate more sophisticated learning schemes for spectrum sharing. The algorithms proposed in this paper should be extended to allow for a better tuning of the algorithms as function of the environment and its dynamic behavior. Also, the schemes should be embedded into real protocols to be used in those wireless networks under interference.

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