Improving Energy-efficiency with a Green Cognitive Algorithm to Overcome Weather's Impact in 2.4 GHz Wireless Networks

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Abstract: The necessity of energy-efficient systems in order to protect our environment, cope with global warming, and facilitate sustainable development is paramount for the researching world because the survival of the planet is at stake. Thus, optimizing the energy efficiency of wireless communications not only reduces environmental impact, but also cuts overall network costs and helps make communication more practical and affordable in a pervasive setting. This paper is focused on a solution to enhance the energy efficiency in outdoor wireless local area networks using the standard IEEE 802.11b/g. So, from a previous study about the weather's impact on the number of control frame errors and retransmissions, we propose a green cognitive algorithm that adapts wireless transmissions to the channel conditions caused by the weather. The goal is to reduce retransmissions and control errors in order to save energy and to enhance network performance. Our proposal is based on a mathematical analysis in which we see how the frame error rate is related to the power consumption according to the modulation scheme and data rate used by transmitters. Finally, several simulations show that the green cognitive algorithm presented in this paper involves significant energy savings for outdoors WLANs.

Keywords: Energy Efficiency, MAC layer, Green Cognitive Algorithm, Outdoor WLAN, IEEE 802.11, Weather's Impact

1. Introduction

Nowadays, telecommunications systems lead to a challenging tradeoff in terms of energy consumption. On the one hand, information and communications technologies are considered to be a facilitator for global energy savings thanks to initiatives such as teleworking, smart logistics, smart buildings, etc. However, on the other hand, the volume of network traffic is increasing day to day, and more and more communications systems have been deploying around the world, so it is involving huge energy consumption. Indeed, a significant part of the worldwide energy consumption today is caused by the network infrastructure.

Therefore, many researchers are focused on deploying green technologies in order to reduce carbon footprint and contribute to a sustainable environment. That is essential for a healthy planet and to guarantee its future. According to several studies [1] [2], information and communications technologies (ICTs) have a major role to play in tackling this problem. Nowadays, worldwide electrical demand in ICTs is estimated around 10% of the world electricity generation due to its non-stop growth. That is the reason why many scientists and official institutions are directing their efforts towards developing energy efficiency approaches [3]. Wireless networks are an important part of the ICT sector, which is believed to be one of the major consumers. Their inherent mobility and radio access entail higher power consumption than the ones done by wired networks. Therefore, green wireless networking is being researched to meet the expected future demands in an energy-efficient manner.

To find solutions that improve energy efficiency in wireless networks [4], it is essential to first identify the main sources of energy consumption in wireless devices, and understand how wireless protocols and operations affect the energy demand. In the case of wireless local area networks (WLAN) scenarios, they are of special interest [5] since they are one of the most popular wireless technologies around the world and they consume an important amount of energy due to their radio access nature [6].

Leaving aside their "baseline" power consumption, i.e., when the devices neither send nor receive traffic, energy consumption is mainly derivate from the computation and protocol communication processes [7] at all layers of the protocol stack. Consequently, energy conservation has been largely considered in the hardware design of wireless devices and by incorporating low-power strategies into the design of network protocols used for data communication [8].

Regarding the communication process, the energy consumption of an IEEE 802.11 wireless network interface is determined by the power consumed in the transmitting, receiving, and doze states and depends on the operation time in each of them. Although all stacks protocols promote energy efficiency approaches, medium access control (MAC) layer is particularly sensible as it employs a contention-based MAC protocol, called carrier sense multiple access with collision avoidance (CSMA/CA) [9], which is an energy-consuming protocol. That is because it is based on a timing structure to sense the channel and to avoid thus collisions.

Moreover, to solve the problem of hidden terminals, wireless devices can perform the RTS/CTS frames (Request to Send/Clear to Send) exchange before transmitting. Therefore, although all this mechanisms help to reduce collisions and transmit data successfully on a WLAN IEEE 802.11, it comes at a price since this high contention consume much higher power [10].

RTS and CTS frames are together with the acknowledgement frame, the three control frames considered at MAC layer in order to avoid collisions and guarantee successful receptions during transmissions. However, control frames may fail due to poor channel conditions and retransmissions would be necessary which lead to more energy consumption.

In previous works has been measured the weather's impact on such control frames errors and retransmissions at MAC layer on a real WLAN scenario [11] and in a point-to-multipoint link IEEE 802.11b/g [12]. These researches show a significant correlation between the number of control frame errors and weather conditions [13]. Therefore, this paper proposes a green cognitive algorithm to improve the performance of MAC protocol IEEE 802.11 by minimizing such impact through different actions based on the protocol operation, and reducing thus control frame errors and retransmissions. Our objective is to improve the energy efficiency of outdoor WLAN devices by reducing retransmissions and control frame errors due to the weather's impact on wireless channel. Moreover, our proposal is validated through simulations, showing that our approach is a good strategy to save energy and to overcome the weather's interference.

The rest of the paper is organized as follows. In Section 2 we explain the different approaches presented in literature that deals with improving the energy efficiency in WLANs and proposing green cognitive algorithms for this purpose. In Section 3 we introduce our experimental weather's impact research over outdoor links IEEE 802.11b/g and we show the main results obtained on MAC layer. In Section 4 we detail our green cognitive algorithm to overcome the weather's impact and to reduce the energy consumption by minimizing retransmissions and control frame errors. The accuracy of the algorithm and the effectiveness of the proposed actions are extensively evaluated by simulations in Section 5. Finally, Section 6 concludes the paper.

2. Related Work

One of the main goals of green wireless communications is to reduce the energy consumption for transmitting packets. Moreover, energy saving is one of the most important issues in wireless devices that have limited battery power. The vast majority of portable and mobile devices are currently equipped with IEEE 802.11 WLAN adapters, and recent studies have shown that the WLAN interface constitutes a major source of energy consumption in a mobile device [14].

There are several ways to reduce energy consumption for transmitting packets. One of the most used variables is the packet size but it requires some considerations. On the one hand, it is directly connected to the transmission time as smaller packet sizes, lower transmission times and so lower energy consumption. Therefore, although packet fragmentation in access points could be a way to improve energy efficiency [15], it also involves more packet transmissions to send the same volume of data. Moreover, for low values of the message size, the overhead related to the MAC header becomes predominant, and so more control traffic is transmitted too. Obviously, it also leads to an increase in the measured consumed power. Finally, shorter packets are less likely to experience collisions [16], consequently reducing retransmissions and control data traffic exchanged, which involve less power consumption. Therefore, these inherent tradeoffs have to be analyzed thoroughly in several works.

In [17], authors analyze the energy efficiency for Wi-Fi IEEE 802.11b multi-hop networks using NS-3 simulator. They show that energy efficiency decreases as the size of the transmitted packet is getting bigger because the value of energy consumption will grow in line with the increase of the size of the packets that are sent. However, the number of packets sent is constant (10000 packets) in their simulations and they only change the packet size. So, the overhead of MAC layer, the number of transmissions and the generated control traffic are not considered as variables because the number of packets is always the same. Therefore, we consider that it is not a real WLAN scenario since fragmentation is not considered.

Considering these aspects, another work [18] relates the power consumption of WLAN IEEE 802.11g devices to the traffic sent/received by the node, the modulation and coding schemes used and the size of the session level data units. In order to send the same volume of data, they confirm by experimental measurements that really both packets extremely large or small entail more power consumption than packet sizes among 1024 and 2048 bytes which are the lengths with the lowest energy consumption. It is due to the overhead introduced by MAC layer in small packets and the fragmentation in large packets.

As abovementioned works, the frame length at MAC layer presents the same problems. Sweedy et al. [19] evaluate the IEEE 802.11 MAC protocol according to the effect of the frame length, fragmentation and

RTS/CTS mechanism. Although the fragmentation process involves to transmit more control traffic (one ACK per fragment) and it is a time consuming (more waiting intervals SIFS), the occurrence of collision is getting lower with smaller fragment length since the medium is less busy. Another advantage of the fragmentation process is that if a fragment is lost due to collisions, it is the only one retransmitted instead of the whole frame. It enhances the energy efficiency of the system.

Another work [20] performs measurements in a WLAN in order to study the performance and the energy efficiency according to the packet size and offered load at application level. Authors show that flows using low data rates and small packets are not energy-efficient. Therefore, they propose that if an application operates in a scenario with low delay and/or low loss, the operational parameters of the application should be adapted by increasing the packet size to improve energy-efficiency. In contrast, if packet loss is found to be high, this could be corrected by re-adjusting the flow construction to achieve a better energy/performance tradeoff based on the energy-efficiency envelopes.

Krishnan et al. [21] apply a complete packet loss model and propose a local packet length adaptation algorithm whereby each node dynamically adjusts its packet length based on estimates of the probabilities of each significant type of packet loss. In their technique, the access point periodically broadcasts channel occupancy information, which each node uses in conjunction with its own local observations in order to estimate current network conditions. These are used to estimate the derivative of throughput with respect to packet length at each node under the current network conditions and to adapt the packet lengths accordingly. They demonstrate throughput gains of up to 20% via NS-2 simulator, and so they reach a higher energy efficiency network performance.

An analysis about the impact of channel fading, and direct collisions on MAC layer packetization in IEEE 802.11 WLANs is presented in [22]. They conclude that on one hand a large packet size is preferred to minimize protocol header overhead, but on the other hand, in the presence of hidden terminals, the transmission packets need to be small enough to reduce packet loss due to both channel fading and staggered collisions. So, authors propose an iterative algorithm to search for the optimal packet size in order to achieve a reasonable tradeoff for minimizing header overhead, fading errors, and staggered collisions, and increasing thus the efficiency.

An algorithm for optimal frame length prediction in the sending system according to channel conditions is presented in [23]. This proposal is based on that the optimal choice should be found between two opposite trends. On one hand, for an error-free communication channel, the increase of user data length promotes the channel efficiency due to increasing the ratio of the payload size to the total frame length; and for a high-error rate communication channel, the increase of user data length decreases the channel efficiency, as a result of erroneous frames retransmission.

Serrano et al. [7] have conducted a thorough measurement analysis of the power consumption of IEEE 802.11 devices that provides a detailed anatomy of the per-packet consumption and characterizes the total consumption of the device, and not only of its wireless interface. This works reveals that a substantial fraction of energy is consumed when packets cross the protocols stack and it is called the cross-factor. This study concludes that this energy consumed by such protocol stack operations does not depend on the frame size, as opposed to the network-related operations accounted for abovementioned literature.

Another approach to reduce the transmission time and so the power consumption is to associate an access point at higher transmission rates [24]. However, this implies the use of less robust modulation and coding schemes, which may result in a higher frame error rate (FER) under poor channel conditions. If a packet is lost, retransmission also consumes energy. Therefore, identifying the most energy-efficient rate, which minimizes the packet loss rate and transmission time is a very important research topic. A number of studies have worked on this issue [25], selecting different energy-efficient rates under different assumptions and scenarios for multi-objective optimization [26].

As we can see, the power consumption or energy efficiency in WLANs IEEE 802.11 has been widely studied, and there are several studies that focus this issue on the fragments length (fragmentation process at MAC layer) and data rate used at physical layer. However, as abovementioned there is a tradeoff between reducing the transmission time and increasing the overhead at MAC layer. Moreover, it always depends on the channel conditions as more retransmissions and control data traffic also decrease the energy efficiency.

In order to improve the energy saving in outdoor WLANs IEEE 802.11, we propose a cognitive green algorithm based on some previous studies about the weather's impact on the number of control frame errors and retransmissions at MAC layer. Our algorithm addresses the energy conservation from minimizing such retransmissions and failures during outdoor data transmissions. It is based on a cognitive loop that allows adapting the fragments length and data rate used in order to overcome the channel pitfalls cause by the weather conditions. This is an actual problem today as the number of outdoor wireless service providers, and portable devices with IEEE 802.11 interfaces are increasing and the weather's impact is not negligible. We present the improvements provided by our proposal in terms of energy saving and transmission performance.

3. Weather's Impact over 2.4 GHz Wireless Networks

There are several standards under the IEEE 802.11 standard for wireless LAN technology, and they are defined and updated by the Working Group for WLAN standards IEEE 802.11 [27]. The most deployed around the world are the standard variants IEEE 802.11a, IEEE 802.11b, and IEEE 802.11g since they were the first implemented ones. They use different physical layer technologies, and so they are different in terms of frequency, transmission rate, modulation and behavior against interferences. However, they can work together because they share the same medium access protocol CSMA/CA [28]. As this research is focused on the 2.4 GHz frequency range, the standard variants considered are IEEE 802.11b and IEEE 802.11g due to their wide deployment around the world. In this sense, although there are more recent standard variants such as IEEE 802.11n or IEEE 802.11ac, much of the available hardware is not still supporting IEEE 802.11 MIB (management information base) by SNMP (simple network management protocol) management. Therefore, it is not possible to perform our research. Moreover, the main difference between IEEE 802.11n and IEEE 802.11b/g is the amount of bandwidth supported by utilizing multiple wireless signals and antennas (called multiple in multiple out –MIMO- technology) instead of one. It is not a relevant issue that concerns in this research since the weather's impact is regardless of considering only one or several streams. However, what it is really decisive is how the modulation and coding scheme works, and it is really the same for all standard variants. Therefore, we have considered performing our research in the most mature WLAN technology deployed around the world: IEEE 802.11b/g.

IEEE 802.11g uses OFDM (orthogonal frequency division multiplexing) that works by breaking the radio signal into multiple smaller sub-signals that are then transmitted simultaneously at different frequencies to the receiver. OFDM reduces the amount of co-channel interference in signal transmissions and allows reaching data rate up to 54Mbps. In contrast, IEEE 802.11b uses DSSS (direct sequence spread spectrum) that uses a much higher than necessary spectrum bandwidth to communicate information at a much lower rate. Each bit is replaced or spread by a wideband spreading code. Moreover, their modulation schemes present a sparse constellation that allows reducing the probability that a symbol is mistaken for another. In spite of DSSS allows reaching data rates up to 11 Mbps, it has the ability to operate in low SNR (signal-to-noise ratio) channel conditions [29] due to abovementioned features.

Wireless channel conditions in IEEE 802.11 technologies can change due to ISM band interference from external sources as well as attenuation, shadowing, fading and multipath propagation. Weather conditions are one of the most severe external sources that impact on outdoor wireless transmissions. Radio wave propagation is affected by atmospheric gases (dry air, water vapor, oxygen) [30] and other weather conditions (hydrometeors) [31] [32] as the higher frequency, the more signal attenuation [33]. From the ITU-R (International Telecommunication Union - Radiocommunication) Recommendations [34] [35] [36], it is extracted that attenuation due to weather conditions on frequencies of few GHz is around 1-2 dB. Therefore, the weather's impact over outdoor IEEE 802.11b/g networks is considered relatively low. However, as end-users it is really noticed a worse function when we are connected to an outdoor access point IEEE 802.11b/g under adverse weather conditions. Therefore, the motivation to perform this research is to study in depth if despite of low attenuation, upper layers such as data link layer really notice it as more control frame errors and retransmissions. It is clearly related to quality of user's experience and link quality. Moreover, many protocol approaches to enhance wireless networks are based on the transmission successful or not of MAC frames (ACKs, CTS, RTS) and fragment retransmissions to estimate the wireless link quality and to adapt their function. So, performing this analysis on this layer is of special interest to know how the weather impact exactly on MAC layer performance in order to be able to propose a new green cognitive algorithm that allows improving the energy efficiency by reducing control frame errors and retransmissions. This algorithm is based on these previous studies.

Before deploying a specific scenario to measure the weather's impact on the number of control frame errors, we carried out an initial study on an already installed WLAN IEEE 802.11b/g [13]. The objective was to check if there were or not some evidence of such relation previously. We analyzed the outdoor WLAN of our university campus and we showed that really the weather affected its performance. This study was based on the number of control frames errors. Management frame errors were not included since we showed in another previous work that the weather affects them in a weak way [37]. However, we had to face some problems that came from studying a real WLAN such as changeable number of users, traffic variations, and uncontrolled sources of interferences. So, we decided performing an analysis on a specific scenario deployed just for this purpose in order to reach results more precise and reliable. In this way, data analysis presented in this paper is as accurate as possible because it is an environment totally controlled and managed for us. Therefore, although a single link is not comparable with a whole network in terms of designing and deploying like channel assignment, access point's distribution, average amount of users etc., it allows to study the transmission process in IEEE 802.11b/g systems in depth isolating problems derived from a real WLAN scenario.

This research is based on assessing how the weather impacts on the number of control frame errors and retransmissions over a point-to-multipoint link working under the standard IEEE 802.11b/g. Our setup consists of a main link point placed at our University Campus which connects to another point in CRAI building by one wireless link of 100 meters (short distance link). The same main point link also connect to another further point located at Azimut Electronics Company through a longer wireless link of 2200 meters (long distance link). So, network topology is composed of a main point link working as a common access point to which are connected two remote wireless clients (see Fig. 1). As they all use directional antennas, the furthest wireless client is a hidden terminal for the nearest one since it is not in its coverage range. Therefore, it is essential to perform the RTS/CTS handshake in order to avoid collisions between them. RTS Threshold is set to zero in order to turn on the RTS/CTS handshake for all data transmissions. During data collection period (April 2013), the link's environment was insulated from man-made electromagnetic interferences by setting it up on the roof of all buildings. There were not people with personal devices walking around and there was not any interfering machine. Moreover, the selected wireless channel was the least used in the area. The goal is to be able to conclude that any variation detected on the number of control frame errors is caused by variations on weather conditions. Two different link distances were considered in order to study how modulation and data rate influence on analysis as well.

Figure 1. Point-to-Multipoint Link and Weather Station Location

The number of control frame errors and retransmissions are recorded in the WLAN management information base (WLAN-MIB) of the D-Link access points (D-Link AirPlusXtreme G DWL-2000AP) in different counters. The selected counters to perform this research were:

✓ *dot11RTSFailureCount*, it is a counter that increments each time a CTS frame is not received in response to a RTS.
✓ *dot11ACKFailureCount*, it is a counter that tracks the number of times a data or management frame is sent to an individual address and does not result in the reception of an ACK frame from the destination.
✓ *dot11FCSErrorCount*, it is a counter that tracks the number of frames received of any type that resulted in a frame check sequence (FCS) error. Increasing load and increasing error rate will both result in this counter increasing more rapidly.
✓ *dot11RetryCount*, it is a counter that tracks the number of frames that required at least one retransmission to be delivered successfully.
✓ *dot11MultipleRetryCount*, it is a counter that tracks the number of frames that required more than one retransmission to be delivered successfully.
✓ *dot11FailedCount*, it is a counter that tracks the number of transmission attempts that are abandoned because they have exceeded either the dot11ShortRetryLimit (7 attempts in our case) when the length of frame is less than or equal to dot11RTSThreshold (in our case 0 octets) or dot11LongRetryLimit (4 attempts in our case) when the length of frame is greater than dot11RTSThreshold.
✓ *dot11FameDuplicateCount*, it is a counter that tracks the number of duplicate frames received.

They were collecting by the SNMP v2 through a querying process. Weather conditions were measured from a weather station located few meters away from the analyzed link. Both types of data (MAC layer counters and weather data) were gathered per minute. In order to generate control frames, stable ICMP (internet control message protocol) traffic was transmitted constantly through point-to-multipoint link. Then, they were preprocessed in order to remove outliers' values and prepare data to analyze them jointly. Moreover, weather conditions considered (temperature, humidity, dew point, and atmospheric pressure) were group into ranges in order to analyze the weather's impact according to them. Although, wind speed was also analyzed, its variation was not sensitive of being grouping since it was only significant (strong enough) at some moments.

Results from the correlation study performed between MAC layer counters and weather conditions for each link length are presented in Table I. We performed a Spearman's rank correlation study, as collected data are not normally distributed [38]. Hence, non-parametric methods are recommended instead [39]. The Spearman's correlation is based on ranks, that is, each item of each variable is replaced by the rank to which it belongs according to its ordinal position. Using ranks rather than data values produces two new variables (the ranks). Spearman's correlation can be thought of as the regular Pearson product moment correlation coefficient, that is, in terms of proportion of variability accounted for, except that Spearman is computed from ranks. From this coefficient and taking into account the level of significance, we can conclude whether two variables are related or not and the strength of the association. We chose the SPSS software package, owned by IBM, in order to analyze the data [40]. Table I shows Spearman's correlation coefficient, significance value, and the number of cases with non-missing values (N). The correlation coefficients vary from 0 to 1 in Table I as they are presented in absolute value to simplify since the green cognitive algorithm presented only takes into consideration the association grade. Moreover, the correlation study was carried out considering weather conditions grouped into four ranges (see Table II). The two main cut-points are placed at ±1 standard deviation from the average value of each weather condition distribution. The tails are the other two groups. SPSS software based on such aggrupation searches the correlation coefficients for all the possible cases.

As each MAC counter is mainly related to one weather condition, Table I shows these highest significant correlation coefficients (> 0.59) found at the short distance link and some lower values to allow us comparing both links. Cells marked as "N/A" indicate that either there are not samples for that grouping combination in such case or the correlation coefficient is too small (< 0.3). Table I also presents the groups of weather conditions for the corresponding coefficient since these results are decisive to design the green cognitive algorithm proposed in next section. Short distance link is referred as SDL and long distance link as LDL in Table I.

Table I. The highest correlation coefficients between MAC layer parameters and grouped weather conditions

MAC layer Counter	T	H	DP	AP	WS	N	Weather conditions Groups			
							Tª	H	DP	AP
Failed_SDL	0.693[1]	0.722	0.687	N/A	0.726	264	2	2	2	4
	N/A	N/A	N/A	0.616	N/A	229	2	3	3	1
	N/A	N/A	N/A	0.654	N/A	622	1	3	2	1
	0.632	0.525	N/A	N/A	N/A	263	1	1	1	3
Failed_LDL	N/A	0.510	N/A	N/A	N/A	58	3	2	3	4
	N/A	N/A	N/A	0.486	0.338	100	3	2	2	2
	N/A	N/A	N/A	N/A	0.320	68	4	1	1	2
FrameDuplicate_SDL	0.547	0.614	N/A	0.627	N/A	319	4	1	2	2
	0.505	N/A	N/A	N/A	N/A	263	1	1	1	3
FrameDuplicate_LDL	0.456	0.440	N/A	N/A	0.431	47	3	3	4	2
	N/A	0.662	0.468	0.696	N/A	56	1	1	1	2
	N/A	N/A	N/A	0.567	N/A	58	3	2	3	4
	0.388	0.427	N/A	0.399	0.508	117	3	3	3	2
	N/A	N/A	N/A	0.539	N/A	100	3	2	2	2
ACKFailure_SDL	0.646	0.528	N/A	N/A	N/A	263	1	1	1	3
	N/A	N/A	N/A	0.775	0.678	314	3	3	3	2
	N/A	N/A	N/A	0.660	N/A	196	2	1	1	2
	0.573	0.701	0.673	N/A	0.594	264	2	2	2	4
ACKFailure_LDL	0.378	N/A	N/A	0.303	N/A	86	3	2	3	3
	N/A	0.338	0.377	N/A	N/A	59	2	2	2	4
	N/A	N/A	N/A	0.452	0.393	100	3	2	2	2
	N/A	N/A	0.484	N/A	N/A	68	3	2	2	4
Retry_SDL	0.687	0.588	N/A	N/A	N/A	263	1	1	1	3
	N/A	N/A	N/A	0.688	N/A	622	1	3	2	1
	N/A	N/A	N/A	0.655	N/A	222	3	2	2	2
Retry_LDL	0.461	0.408	0.439	N/A	0.496	39	2	4	3	4
	N/A	N/A	N/A	0.404	0.415	100	3	2	2	2
	N/A	N/A	0.498	N/A	N/A	68	3	2	2	4
MultipleRetry_SDL	0.665	0.422	N/A	N/A	N/A	263	1	1	1	3

[1] All correlation coefficients are significant at the 0.01 level (2-tailed)

	N/A	N/A	N/A	0.783	0.681	314	3	3	3	2
MultipleRetry_LDL	N/A	N/A	0.498	N/A	N/A	29	1	3	2	2
	N/A	N/A	N/A	0.442	N/A	39	2	4	3	4
	0.333	N/A	N/A	0.404	0.364	100	3	2	2	2
RTSFailure_SDL	0.508	N/A	N/A	N/A	N/A	263	1	1	1	3
	N/A	0.505	0.536	N/A	0.505	226	3	1	1	2
	N/A	N/A	N/A	0.776	0.757	314	3	3	3	2
	N/A	N/A	N/A	0.576	N/A	196	2	1	1	2
RTSFailure_LDL	0.362	N/A	N/A	0.339	N/A	86	3	2	3	3

Table II. Weather conditions groups

Group	Temperature (ºC)	Humidity (%)	Dew point (ºC)	Atmospheric Pressure (hPa)
1	$T^a \leq 12.4$	$H \leq 58$	$DP \leq 6.6$	$AP \leq 1010.6$
2	$12.5 \leq T^a \leq 15.3$	$59 \leq H \leq 74$	$6.7 \leq DP \leq 10.3$	$1010.7 \leq AP \leq 1015.8$
3	$15.4 \leq T^a \leq 18.2$	$75 \leq H \leq 91$	$10.4 \leq DP \leq 14.1$	$1015.9 \leq AP \leq 1020.9$
4	$T^a \geq 18.3$	$H \geq 92$	$DP \geq 14.2$	$AP \geq 1021$

As we can see in Table II, the number of samples (N) is significant smaller at the long distance link. That is because less fragments are received at the furthest link point, and so less number of samples for each combination of grouping of weather conditions. However, the weather's impact on those which are successfully received is lower (smaller correlation coefficients) than samples taken from the short distance link. All of that despite of covering a higher distance and taking into account that smaller sample size (N) allows higher accuracy. Therefore, we can conclude that lower order modulations (IEEE 802.11b) used to transmit data at the long distance link (based on the sensitivity level) entails lower data rates and so higher transmission times. However, they are really more robust and less resilient against interferences caused by the weather conditions running at the transmission time than higher-order modulations used in IEEE 802.11g (short distance link). However, there are two exceptional cases for the frame duplicate counter. As abovementioned, transmission time is higher in the long distance link, so it increases the possibility that some frames are retransmitted because ACK frames do not arrive within the set timeout. So, they arrive at the receptor as duplicate frame later. Therefore, we can conclude that the weather's impact affects mainly the long distance link delaying frames and so increasing retransmissions.

Although the counter of FCS errors was also considered, statistical analysis did not present significant correlations. It is the only counter that tracks a specific field of frames (bit-level). Therefore, we can point out that the weather's impact is mainly perceived at frame-level rather than at bit-level.

4. Green Cognitive Algorithm

The cognitive networks' (CNs) goal is to reach self-aware networks, which are able to dynamically adapt their operational parameters in response to user needs or changing environmental conditions. Another important aspect is that they learn from these adaptations and use this knowledge to make future decisions. Therefore, it is said that these networks have the ability to think, to learn and to remember in order to reduce as much as possible the human intervention and maximize their self-configuration and maintenance. In order to meet this new paradigm, a cognition loop is the key and it features the following states: observe, orient, plan, decide, act and learn [41]. It can be defined as a cognitive process that can sense current reality, plan for the future, make a decision and act accordingly.

Typical technologies limit network ability to adapt their working using only local and reactive approaches, as network state is not shared for the different network elements. In contrast, cognitive networks seek to fulfill certain end-to-end goals of a data flow and to perform proactive actions learning and gathering solutions for future decisions [42]. Therefore, cognitive networks encompass the entire network stack in order to nodes intelligently select and optimize parameters based on the end-to-end requirements of the network. Their motivation is to enhance next generation of networks more complex, heterogeneous, and dynamic helping for their self-organization and making easier to meet user and application objectives jointly.

Cognitive Networks consider that it can be accomplished with the use of a Knowledge Plane (KP) that transcends layers and domains to make cognitive decisions about the network. The KP will add intelligence and weight to the edges of the network, and context sensitivity to its core. A KP could help the cognitive network in order to learn about its own behavior over the time, making it better, being able to analyze problems, tune its operation, and generally increase its reliability and robustness.

Fig. 2 shows the four phases required in a learning machine in order to be used as method in a cognitive network. The first one is environment; we need take into account this element because it will be responsible of the changes in network performance. This element is directly connected to performance phase. Performance stage is related to how is working our network in any of monitored elements. Knowledge will give us enough information to activate the learning process. This learning process will be the most intelligent box on our system, because it has to perform the appropriate actions to improve network performance through the information of knowledge and environmental elements. The general goal of learning is to improve performance on whatever task the combined system is designed to carry out.

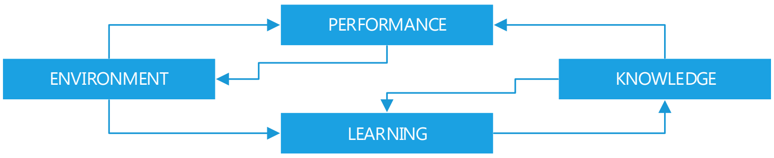

Figure 2. Phases on machine learning for cognitive networks

Therefore, cognitive networks are the best option to overcome the weather's impact taking into account energy consumption. Indeed, nowadays there are many efforts to approach this issue from the cognitive perspective [43].

4.1. Power Consumption Mathematical Analysis

This subsection presents a network model to explain a wireless communication between two devices. Furthermore, we show an analytical study to verify which data rates are more vulnerable to interferences and thus we will be able to take correct actions in our green cognitive algorithm. Finally, we present a power consumption model to check the required power of each rate when there are probable retransmissions and MAC-level fragmentation.

To carry out this analysis we have to define our wireless network model analytically. It allows us to know how they are structured and how the nodes are connected. There are two types of connections used in wireless networks: infrastructure and ad-hoc. We are going to focus on infrastructure connections, in particular in point-to-multipoint connections.

4.1.1. Frame Error Rate in IEEE 802.11b/g

IEEE 802.11b/g [9] works at 2.4 GHz and it has 12 transmission rates (4 of them from IEEE 802.11b and the others from IEEE 802.11g). The standard IEEE 802.11b employs DSSS while IEEE 802.11g employs OFDM as PHY layer access scheme, as we have seen in Section 3. Some information from IEEE 802.11 b/g are summarized on Table III.

Table III. IEEE 802.11 b/g PHY layer information

Rate (Mbps)	Modulation Scheme	FEC Rate	Receive Sensitivity (packet error rate < 10%) - dBm	Coding Gain - dB	IEEE 802.11
1	DBPSK	1/11	-89	10.4	b
2	DQPSK	1/11	-86	10.4	b
5.5	CCK	4/8	-85	8	b
6	BPSK	1/2	-82	-	g
9	BPSK	3/4	-81	-	g
11	CCK	8/8	-82	8	b
12	QPSK	1/2	-79	-	g
18	QPSK	3/4	-77	-	g
24	16-QAM	1/2	-74	-	g
36	16-QAM	3/4	-70	-	g
48	64-QAM	2/3	-66	-	g
54	64-QAM	3/4	-65	-	g

In order to quantify the robustness of each rate to noise we are going to calculate the probability of MAC frame fails in a communication between two nodes without taking into account any interference. To carry out this evaluation we have considered an Additive White Gaussian Noise (AWGN) to model the wireless channel. Moreover, we have fixed the SNR and the transmission rate.

In order to analyze the FER in every data rate of IEEE 802.11b we have followed the empirical equations presented in [44]. The following equations show the relation between *BER* (bit error rate) and the bit *SNR* (S_{bit}) at the PHY layer. *BER* at PHY layer is represented by equations (1), (2), (3) and (4) for 1 Mbps, 2 Mbps, 5.5 Mbps and 11 Mbps, respectively.

$$BER_{PHY-1Mbps}(S_{bit}) \leq Q\left(\sqrt{11 S_{bit}}\right) \quad (1)$$

$$BER_{PHY-2Mbps}(S_{bit}) \le Q\left(\sqrt{5.5S_{bit}}\right) \quad (2)$$

$$BER_{PHY-5.5Mbps}(S_{bit}) \le \frac{8}{15}\left(14Q\left(\sqrt{8S_{bit}}\right) + Q\left(\sqrt{16S_{bit}}\right)\right) \quad (3)$$

$$BER_{PHY-11Mbps}(S_{bit}) \le 24Q\left(\sqrt{4S_{bit}}\right) + 16Q\left(\sqrt{6S_{bit}}\right) + 174Q\left(\sqrt{8S_{bit}}\right) + 16Q\left(\sqrt{10S_{bit}}\right) + 24Q\left(\sqrt{12S_{bit}}\right) + Q\left(\sqrt{16S_{bit}}\right) \quad (4)$$

Where *Q(x)* is the probability that a normal (Gaussian) random variable will obtain a value larger than *x* standard deviations above the mean. It is more common to use the SNR instead of S_{bit}. There is a direct relation using equation (5). Where *B* is the bandwidth of the radio channel (20 MHz) and *R* is the bit-rate in Mbps.

$$S_{bit} = SNR\frac{B}{R} \quad (5)$$

In order to calculate the BER at MAC layer, it is required to add the coding gain presented in Table III. Relating equations of BER_{PHY} with equation (5) and adding the coding gain in each bit-rate, we obtain equation (6) where *j* is 1 or 2 Mbps and equation (7), where *i* is 5.5 or 11 Mbps. They show the relation of BER with SNR at MAC layer.

$$BER_{MAC-jMbps}(SNR) = BER_{PHY-jMbps}\left(SNR\frac{B}{R}10^{1.04}\right) \quad (6)$$

$$BER_{MAC-iMbps}(SNR) = BER_{PHY-iMbps}\left(SNR\frac{B}{R}10^{0.8}\right) \quad (7)$$

A similar calculation of BER at MAC level as a function of SNR is performed with IEEE 802.11g variant for its different modulation schemes (BPSK, QPSK and N-QAM). Following the theoretical calculation presented in [45] all modulation schemes used in IEEE 802.11a/g rates with an AWGN channel can be derived their symbol error rate (SER) function in N-ary pulse-amplitude modulation (N-PAM) from equation (8).

$$SER_{N-PAM}(SNR) = 2\left(1-\frac{1}{N}\right)Q\left(\sqrt{\frac{6SNR}{N^2-1}}\right) \quad (8)$$

BPSK is the same as 2-PAM, so the SER of BPSK is represented in equation (9). Other modulation schemes used in IEEE 802.11g are N-QAM, including QPSK that is the same of 4-QAM. For these modulations, SER is calculated using equation (10).

$$SER_{BPSK}(SNR) = SER_{2-PAM}(SNR) \quad (9)$$

$$SER_{N-QAM}(SNR) = 1 - \left(1 - SER_{\sqrt{N}-PAM}\left(\frac{SNR}{2}\right)\right)^2 \quad (10)$$

On PHY layer, the binary symbols are transmitted using Gray code. If we want to calculate the BER at this level we have to use the equation (11), where *k* is the number of bits per symbol, $k = \log_2(N)$.

$$BER_{PHY}(SNR) = \frac{1}{k}SER(SNR) \quad (11)$$

The FEC of IEEE 802.11g should be taken into account in order to calculate the error rate at the MAC layer. BER at MAC layer is presented in equation (14). Where d_{free} is the free distance of the convolutional code, a_d is the total number of error events of weight d and $P_d(SNR)$ is the probability that the decoder chooses an incorrect path with distance *d* from the correct path. It depends on BER_{PHY} defined in equation (12). All values are defined in [46].

$$BER_{MAC}(SNR) = \sum_{d=d_{free}}^{\infty} a_d \cdot P_d(SNR) \quad (12)$$

Based on these previous formulae, selecting the correct BER_{MAC} in each date rate of IEEE 802.11b/g and assuming that a loss of data frame occurs when one or more bits are corrupted. The probability that a data frame fails is defined by equation (13) where *L* is the payload length in bits.

$$FER_{MAC} = 1 - \left(1 - BER_{MAC}(SNR)\right)^L \quad (13)$$

Fig. 3 shows the frame error rate (FER) curves vs. signal to noise ratio (SNR) for the IEEE 802.11b/g PHY modes. These curves have been derived theoretically assuming an AWNG environment with packet size of 1000 bytes. In this scenario, we suppose that there is no interference; therefore, the errors are only due to the background noise. The propagation delays are also considered negligible. These curves demonstrate that higher-order modulations involve worse performance (more FER) in a low SNR scenario than lower-order modulations. Therefore, data rate adaptation is one of the best actions to face the weather's impact at MAC level.

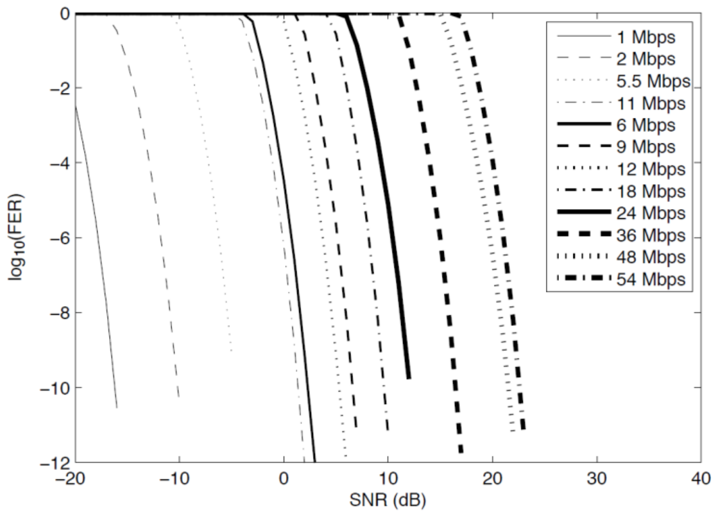

Figure 3. FER for every date rate of IEEE 802.11b/g.

4.1.2. Power Consumption Model in IEEE 802.11b/g

As we have seen in the previous section, the modulations used in the data rates belonging to the IEEE 802.11b standard are more robust than those used in IEEE 802.11g. It means there will be fewer errors in the wireless communication between two network nodes. This issue causes fewer retransmissions and so greater energy savings since less control packets are sent as well. The fact of using lower bit rate does not mean a direct relationship between the energy needed to transmit certain information. This is because there is an inverse relationship between the time required to send certain information and data rate used. For this reason, we are going to modeling the power consumption in IEEE 802.11b/g with RTS/CTS.

Let a network of nodes be *W=(N, L)*, where *N* is the set of nodes and *L* is the set of direct wireless connections between nodes. Link between a source node *s* and a destination node *d* is defined by duple *(s,d)* and the distance between both nodes is *d(s,d)*. The network traffic on the link *(s,d)* is represented by *D(s,d)* and the PHY rate as *DR(s,d)*. With this model, we can see the relationship between every parameter that affect the power consumed by a wireless node in a communication. In Table IV the mathematical notation used in our model is detailed.

Table IV. Mathematical notation

Variable	Definition	Variable	Definition
RTx_{sucess}	Number of retransmissions	T_{ACK}	ACK time
T_{DIFS}	DIFS time	CW	Content Window
T_{BO}	Backoff time	n_{frag}	Number of fragments
T_{RTS}	RTS time	*Header*	Header
T_{SIFS}	SIFS time	$DR(s,d)$	Data rate
T_{CTS}	CTS time	$DR_{base}(s,d)$	Basic data rate
T_{RTO}	Retransmission time out	RTS	RTS size
CTS	CTS size	ACK	ACk size
P_i	Power in idle mode	P_{TX}	Transmission power
P_{RX}	Reception power	E^{DR}	Energy in a data rate

Basing on the study presented in [47] the average number of retransmissions (RTx_{sucess}) until a receiver receives successfully the data frame is given by equation (14).

$$RTx_{sucess} = \lim_{x\to\infty}\sum_{n=1}^{x} n\cdot FER_{MAC}^{n-1}(1-FER_{MAC}) = \lim_{x\to\infty}\left(\sum_{n=1}^{x} n\cdot FER_{MAC}^{n-1} - \sum_{n=2}^{x+1}(n-1)\cdot FER_{MAC}^{n-1}\right) = \frac{1}{1-FER_{MAC}} \tag{14}$$

Time required in a frame transmission without losses is modeled by equation (15). Where, five different times are spent in transmitter (*Tx*) and the other ones in receptor (*Rx*).

$$T_{frame\_sucess} = \underbrace{T_{DIFS}+T_{BO}+T_{RTS}}_{Tx} + \overbrace{T_{SIFS}+T_{CTS}}^{Rx} + \underbrace{T_{SIFS}+T_{DATA}}_{Tx} + \overbrace{T_{SIFS}+T_{ACK}}^{Rx} \tag{15}$$

The length of backoff time (T_{BO}) is given by a random within the range $[0, CW]$ multiplied by a time slot (T_{slot}). CW value varies according to the number of successive retransmissions. The value of CW for the *i*-th retransmission is calculated in equation (16).

$$CW_i = min(2^{i-1}CW_{min}, CW_{max}) \qquad i \geq 1 \tag{16}$$

Knowing the times involved in transmission and reception process (see eq. (15)), now we are going to split up every time in order to calculate the power consumed for the transmission of *D(s,d)*. They are calculated in equations (17), (18) and (19) using variables explained in Table IV. We denote the time for transmission, reception and idle for source node ($T_{TX}^s, T_{RX}^s, T_{idle}^s$) and destination node ($T_{TX}^d, T_{RX}^d, T_{idle}^d$). According to [48] a wireless node spends less energy (it's in idle mode) in its waiting times (T_{DIFS}, T_{BO}, T_{SIFS}). In case of there are retransmissions we have to add a retransmission time out (T_{RTO}).

$$T_{TX}^s = T_{RX}^d = \frac{1}{1-FER_{MAC}}(T_{RTS} + T_{DATOS}) = \frac{1}{1-FER_{MAC}}\left(\frac{RTS}{DR_{base}(s,d)} + \frac{D(s,d) + n_{frag}\cdot Header}{DR(s,d)}\right) \tag{17}$$

$$T_{RX}^s = T_{TX}^d = \frac{1}{DR_{base}(s,d)(1-FER_{MAC})}(CTS + n_{frag}\cdot ACK) \tag{18}$$

$$T_{idle}^s = T_{idle}^d = \frac{1}{1-FER_{MAC}}\left\{T_{DIFS} + (1-FER_{MAC})T_{BO} + \left(2 + \frac{1}{n_{frag}} + 2FER_{MAC}\right)n_{frag}T_{SIFS} + FER_{MAC}\left(T_{RTO} - \frac{D(s,d) + n_{frag}\cdot Header}{DR(s,d)}\right)\right\} \tag{19}$$

Depending on data rate (*DR*) available in IEEE 802.11b/g, the power consumed per time unit is given by equation (20). It is noticed a clear difference among idle state, transmission state and reception state. This is due to every state needs an energy level to carry on the action.

$$E^{DR} = P_i\cdot(T_{idle}^s + T_{idle}^d) + P_{TX}\cdot(T_{TX}^s = T_{RX}^d) + P_{RX}\cdot(T_{RX}^s + T_{TX}^d) = 2\cdot P_i\cdot T_{idle}^s + (P_{TX} + P_{RX})(T_{TX}^s + T_{RX}^s) \tag{20}$$

As we can see in Fig. 4, as the probability of error is increasing (higher FER), the power consumption is increasing too. It is explained by the fact that there are more retransmissions and more control data traffic exchanged. Moreover, it shows that transmissions at smaller data rates consume more energy, as the transmission time is higher. But they cover wider ranges and they are more robust against wireless channel interferences. Finally, it is important to highlight that from 5.5 Mbps the differences on the energy consumption are very low. In order to plot Fig. 3, the power $P_{i,}$ P_{TX} and P_{RX} have been assumed from a real device datasheet [49].

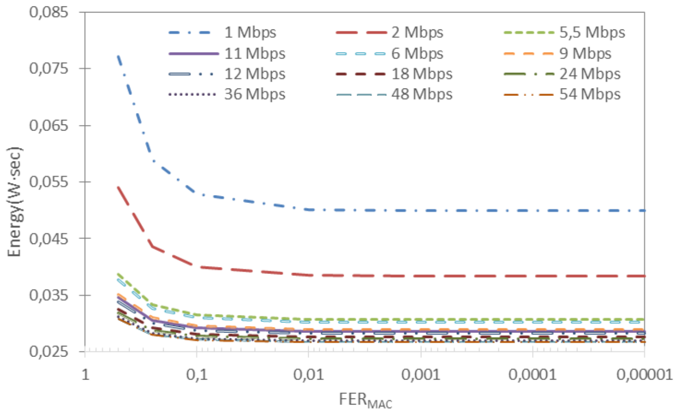

Figure 4. Energy consumption versus frame error rate at MAC layer according to data rates

Results presented in this section have defined the chosen actions and connections of our green cognitive algorithm presented in next sections.

4.2. Green Cognitive Algorithm

In this section, we explain in depth the green cognitive algorithm designed in order to reduce the energy required in a wireless communication. This energy saving will be given by the reduction of retransmissions and control frame errors caused by the weather's impact on IEEE 802.11b/g outdoor links.

Taking into account the weather's impact information presented in section 3, we design a KP for developing a green cognitive algorithm, which considers the weather as another input to improve MAC layer performance. Hence, it will entail energy savings when the weather's impact is considered an energy-consuming agent. Our proposed KP consists of the elements showed in Fig. 4. Some elements take weather data from their environment and others collect network performance data from time to time. Next, a green cognitive module according certain defined rules processes this information in order to decide if some changes should be applied or not to the network function. Finally, if it is required, the same module sends orders to the involved access points in order to perform some changes and actions to improve the wireless communication. Fig. 5 shows the elements that make up our knowledge plane.

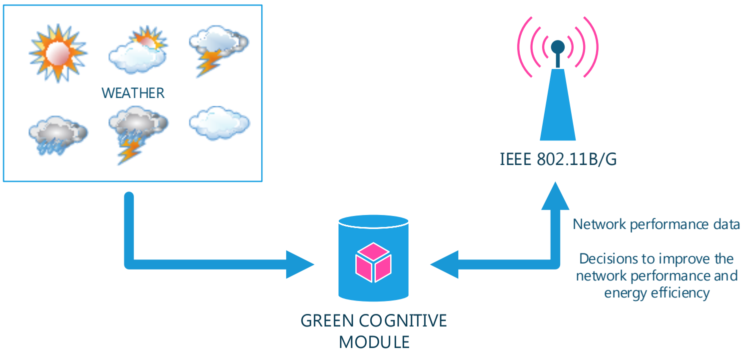

Figure 5. KP's agents involved in our green cognitive wireless network

Main modules that form our green cognitive module and their connections are shown in Fig. 6. The explanation about this cognitive module is performed sequentially. Firstly, our cognitive module starts its cognitive process. This cognitive process makes two sub-processes, one for taking data of the weather and another one for taking network data (control frames). According to these data combination, our algorithm will create the appropriate actions the making actions process. Then, according to the combination of network and weather data, one action or a combination of several actions will be chosen in the selecting actions module taking into account the energy efficiency and the throughput required by final user. Then, such action will be executed by the doing action module and monitored to carry out the demands by the throughput and energy efficiency module. Finally, there will be a learning process, which is storing actions performed for each data set. This will allow our algorithm to improve its performance automatically and to be faster creating actions.

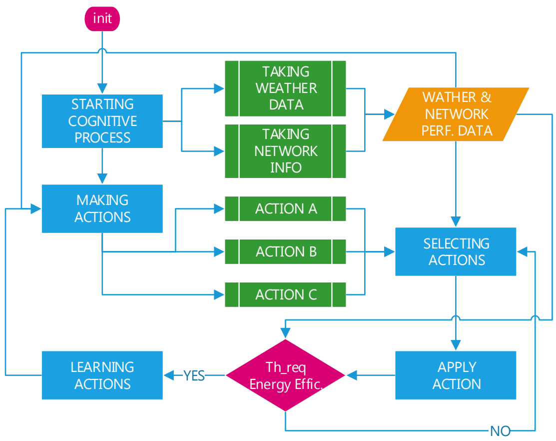

Figure 6. Green cognitive module

In order to go into detail about the algorithm we are going to focus on Fig. 6. We assume that our algorithm runs every t instant and it has memory, for example, it is capable of storing the information read in $t-1$. Moreover, this algorithm will work in synchronous mode, in this way data collected from the weather and network performance will correspond to the same instant of time. Data collecting from weather are temperature (*T*), humidity (*S*), dew point (*DP*) atmosphere pressure (*AP*) and wind (*W*). According to our previous study presented in section 3, our weather parameters have a high correlation coefficient when *T*, *H*, *DP* and *AP* are divided into groups and *W* (without group division). The first step is to check if the weather data taken is inside a significant group (see section 3). If this weather parameter is inside a significant group, it will go to the process of combination of significant groups. This process helps to the algorithm to focus only on the MAC control frames (*CF*) that have a significant correlation level according to section 3. If weather parameter is not inside of significant group, this will mean that every MAC control frame will be taken into account for processing control frames.

From the control frames selected, the processing control frames will active the process of making actions. These actions could be decreasing/increasing data rate, decreasing/increasing data packet length, decreasing/increasing *CW*, etc. Due to the proposed possible actions to take by our green algorithm are related to parameters of PHY and MAC layers, our algorithm is considered as part of the cognitive network approach. However, if under certain conditions, it only takes actions on PHY layer, it could be considered as part of cognitive radio approaches [50]. The module called processing control frames will do a task in order to place each control frame evaluated in a range. Each range will define the performance of the network, where performance A means the network work very well, performance B means the network works correctly, performance C means network have a lot retransmissions, errors, etc. The last case means that it needs to improve its behavior to spend less energy and respecting the throughput required by the final user. The way that this process will select every control frame is inside one group or other is given by equation (21), (22) and (23). Where *E[x]* represents the average of a *CF* in *t* and σ is the typical deviation of the control frame evaluated. Variables *j* and *k* allow the algorithm to adjust the amplitude ranges. Values satisfying equation (21) will be included in performance A, values of equation (22) will be included in performance C and other values will be included in performance B. See Fig. 7.

$$E[CF_i(t)] < E[CF_i(t-1)] - j \cdot \sigma_i(t-1) \tag{21}$$

$$E[CF_i(t)] > E[CF_i(t-1)] + k \cdot \sigma_i(t-1) \tag{22}$$

$$E[CF_i(t-1)] - j \cdot \sigma_i(t-1) \geq E[CF_i(t)] \leq E[CF_i(t-1)] + k \cdot \sigma_i(t-1) \tag{23}$$

Next module is called selecting actions, according to the performance range activated this module will select an action. The action selected always tries to satisfy the throughput required by the end-user being as efficient as possible in terms of energy. After selecting the action, this is applied to the network. Through network performance information, our algorithm will check if we are applying the correct actions to improve energy efficiency taking into account the throughput required by the final user. If these actions are appropriate, this information should be sent to module called processing control frames in order to improve the algorithm. This will be faster when creating actions for given *CF*. Otherwise, it will alert the selecting actions module to select more aggressive actions to achieve the objectives.

Finally, our algorithm updates the significant groups and the combination thereof. This will happen only with new non-significant input within the performance C range. This algorithm will be smarter and will include new significance information and it can automatically adapt to changes that may have our wireless network.

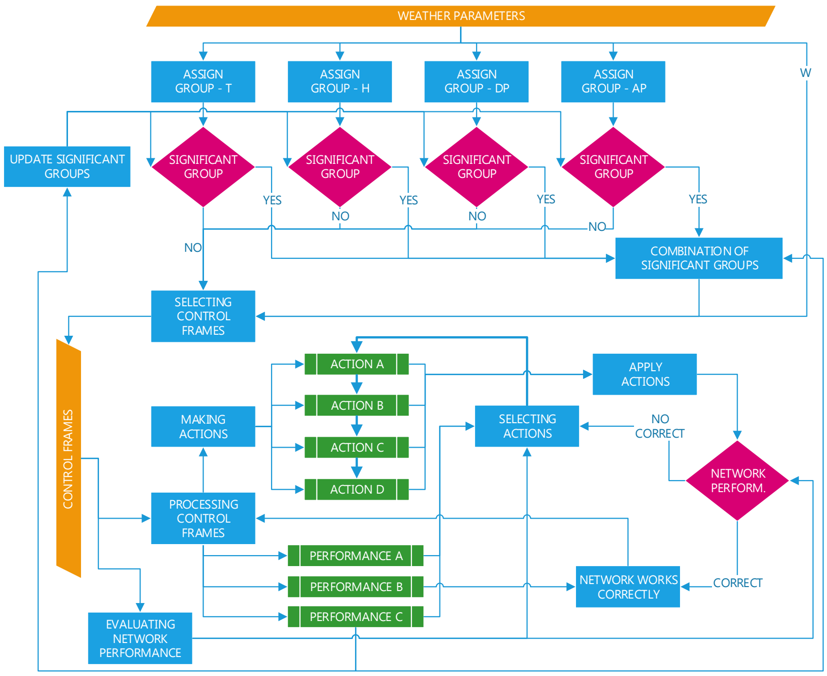

Figure 7. Detailed scheme of green cognitive module.

5. Simulations

In this section, we are going to show the simulations done to check that our algorithm works properly and it introduces a better behavior in terms of energy efficiency and less control traffic.

5.1. Test bench

In order to test the performance of our proposal we have made several simulations using Riverbed Modeler Wireless simulator [51]. We have simulated a scenario for each IEEE 802.11 b/g data rate. Each scenario has three access points making a point-to-multipoint connection. Access points are placed in a strategic positions in order to have a scenario with the feature of hidden terminal.

The simulation of weather conditions in this network simulator is not possible. For this reason, we have made some changes on the wireless channel conditions for the data transmission. Therefore, we have introduced a random interference noise between 1 to 2.5 dB. This data have been correlated with real weather parameters taken previously. With this method of reverse engineering, we can introduce meteorological data to our algorithm and this information will be related to network data simulated.

About wireless LAN parameters, we have fixed data rate in each scenario. In every scenario we have used distributed coordination function (DCF) with RTS/CTS as MAC technique. We have included the power threshold of Table III in each data rate. The fragmentation threshold has been 2304 bytes. The access point beacon interval is equal to 0.02 seconds and the maximum receive lifetime has been 0.5 seconds. We have used different wireless channels in order to avoid co-channel interferences.

The traffic load used for the simulations is best effort traffic generated by the simulator. We inject this traffic 40 seconds after the beginning and it will finish with the simulation. The traffic follows an exponential distribution (for the arrivals) with a mean time between arrivals of 20 milliseconds. The packet size follows an exponential distribution with a mean value of 256, 512, 1024, 1536, 2048, 3072 and 4098 bytes. The injected traffic has a random destination address, to obtain a simulation independent of the traffic direction. This traffic is represented in Fig. 7, where can see that the average traffic included in our simulations has been very similar in every IEEE 802.11b/g PHY-modes.

Figure 8 shows total higher layer data traffic (bits/sec) dropped by the all the WLAN MACs in the network as a result of consistently failing retransmissions. This statistic reports the number of the higher layer packets that are dropped because the MAC could not receive any ACKs for the (re)transmissions of those packets or their fragments, and the packets' short or long retry counts reached the MAC's short or long retry limit. Figure 9 shows these values on average in order to make easier their comparison. In this case, we can appreciate that 54 Mbps, 48 Mbps and 36 Mbps produces more data dropped. The lowest data rates introduce less data dropped and therefore less retransmission. Although, as we have appreciated in Fig. 3, the highest data rates consume less energy for the same FER and number of retransmissions. In a simulated environment, closer to the real, these high data rates are more vulnerable to effects on the wireless channel. According to this information (see fig. 8), we have not decided to perform all IEEE 802.11b/g PHY-mode since some of them such as 6 and 9 Mbps present more data dropped than 11 Mbps. Moreover, they involve less throughput and energy efficiency. Therefore, we consider that the best IEEE 802.11b/g PHY-modes to adapt the data rate in our green cognitive algorithm are 54, 36, 18, 11, 5.5, 2 and 1 Mbps.

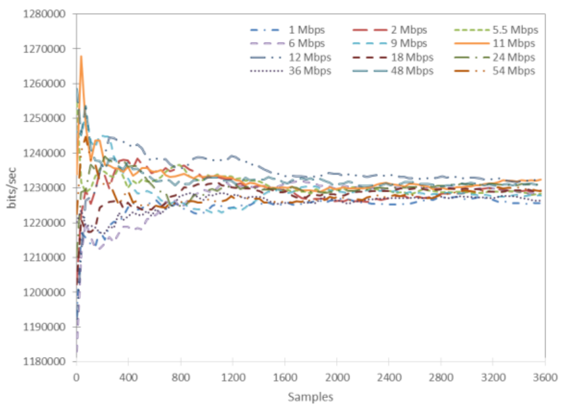

Figure 7. Traffic injected in each IEEE 802.11b/g PHY-mode with a packet size of 1024 bytes.

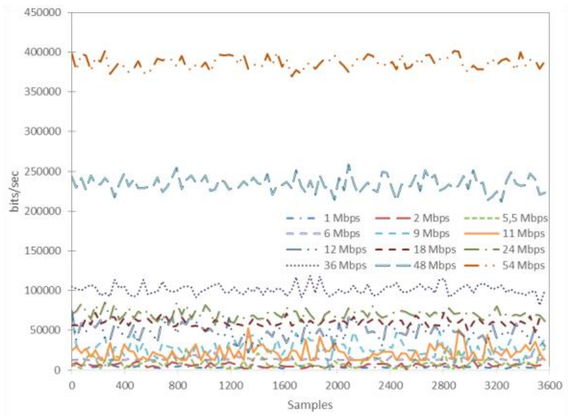

Figure 8. Data dropped by retry threshold exceeded in each IEEE 802.11b/g PHY-mode.

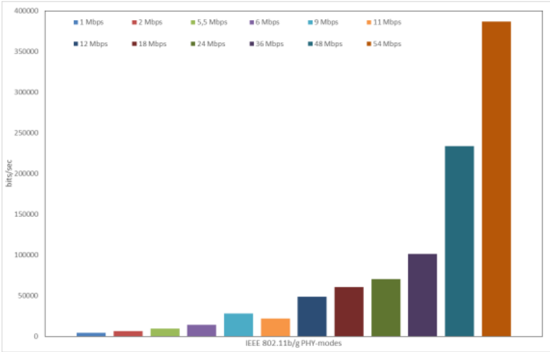

Figure 9: Data dropped on average by retry threshold exceeded in each IEEE 802.11b/g PHY-mode

5.2. Results

In Fig. 10, we have studied the variation of the data packet size in the data rates selected. In this figure, we can see as data size is related to control traffic introduced by a station. This WLAN control traffic includes RTS, CTS and ACK. In 1 and 2 Mbps the best data size of 4096 bytes, while in the others data rates the best is around 2048 or 1536 bytes. This phenomenon is due to fragmentation at high speeds introduces more traffic control since the radio channel can be free soon. Taking into account this phenomenon our green cognitive algorithm will select an appropriate data packet size to the data rate used.

In Fig. 11 is depicted the SNR of our simulation without taking into consideration weather parameters (blue line). This SNR decreases 2 dB in some samples when introducing meteorological phenomena (red line). When we have a low SNR we assume that weather conditions are affecting further communication. For that reason, we can see that data dropped at 36 Mbps increases and it decreases in the opposite way.

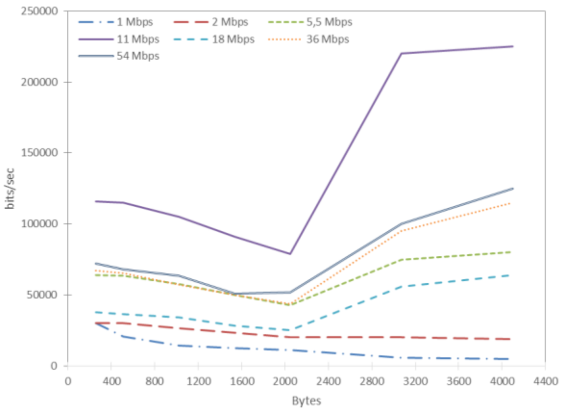

Figure 10. Data packet size variation vs. control traffic introduced for a wireless station in several IEEE 802.11b/g PHY-mode.

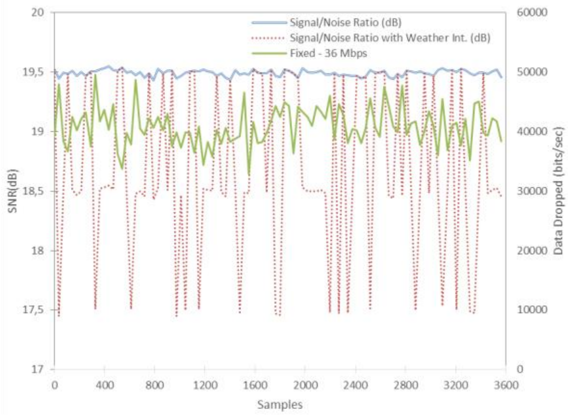

Figure 11. SNR vs. data dropped by retry threshold exceeded in 36 Mbps for a wireless station.

Lastly, we will operate our green cognitive algorithm. In this case, firstly our algorithm increased data packet size from 1024 to 2048 bytes. The following task was to verify the energy efficiency, it was not improved and the end-user throughput was decreased to 24 Mbps. The result of these actions can be seen in Fig. 12. This figure compares the data dropped in a normal operation with data dropped using our green algorithm. As we can be seen in Fig. 12, there are fewer data dropped which involves fewer retransmissions and a better network performance from the point of the final user.

Finally, we compare the energy level required in a normal communication at 36 Mbps applying our green algorithm and without it (see Fig. 13). Our algorithm presents higher energy efficiency especially in some maximum peaks (see samples from 1600 to 2400 in fig. 13). Our algorithm has an average consumption of 0.0715 W·s and the standard communication of 0.083 W·s. This means that our algorithm provides an improvement of 14% in terms of energy-efficiency respecting the throughput required by the final user.

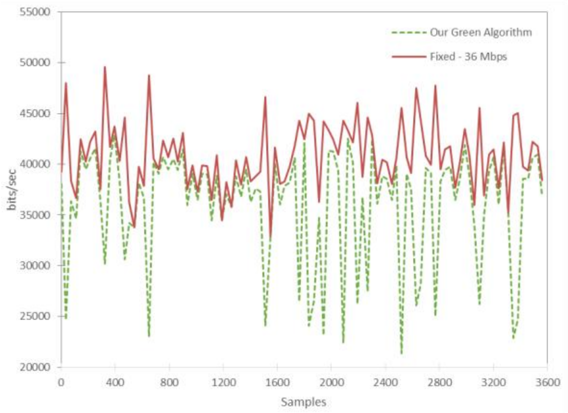

Figure 12. Comparison of data dropped by retry threshold exceeded in 36 Mbps for a wireless station.

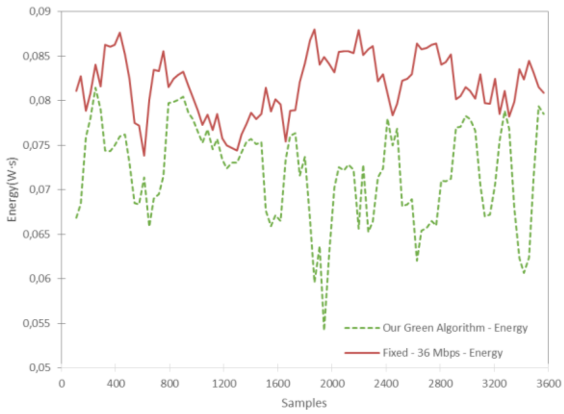

Figure 13. Comparison of energy required in 36 Mbps for a wireless station.

6. Conclusion and Future Work

Research presented is this paper deals with the current problem of energy consumption in wireless networks. Specifically, it is focused on outdoor WLANs IEEE 802.11b/g. WLAN interfaces are one of the most consuming issue on a portable device and those standards are ones of the most deployed around the world. So, they are of special interest. We approach this issue from the weather's impact on outdoor networks. We show that it is really involved with the number of control frame errors and retransmissions at MAC layer and so, it is essential to take it into account in order to save energy. We show such impact from a statistical analysis performed over an experimental setup composed of an outdoor point-to-multipoint link. Moreover, we model the energy consumption in WLANs and according to those results; we propose a new green cognitive algorithm to overcome the weather's impact and to enhance the energy efficiency. We show by simulations that our proposal entails significant energy savings and so it is a good option for outdoors WLANs.

As future work, we will study to introduce others possible features in our algorithm such as content window size in order to improve communications performance and energy efficiency. Moreover, we will analyze the applicability of our algorithm in recent standards IEEE 802.11 and also to be included in radio cognitive networks [52].

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References

[1] Ad-hoc Advisory Group Report, "ICT for Energy Efficiency," DG-Information Society and Media, European Commission, Brussels, 2008.

[2] M. P. Mills, «The Cloud begins with Coal, Big Data, Big Networks, Big Infraestructure and Big Power,» Digital Power Group, 2013.

[3] J. Rodrigues, "Green Communications and Networking," *Network Protocols and Algorithms,* vol. 5, no. 1, pp. 37-40, 2013.

[4] P. Serrano, A. de la Oliva, P. Patras, V. Mancuso and A. Banchs, "Greening wireless communications: Status and future directions," *Computer Communications,* vol. 35, pp. 1651-1661, 2012.

[5] S. L. Tsao and C. H. Huang, "A survey of energy efficient MAC protocols for IEEE 802.11 WLAN," *Computer Communications,* vol. 34, no. 1, pp. 54-67, 2011.

[6] J. Lloret, S. Sendra, H. Coll and M. Miguel Garcia, "Saving Energy in Wireless Local Area Sensor Networks," *Computer Journal,* vol. 53, no. 10, pp. 1658-1673, 2009.

[7] P. Serrano, A. Garcia Saavedra, G. Bianchi, A. Banchs and A. Azcorra, "Per-frame Energy Consumption in 802.11 Devices and its Implication on Modeling and Design," *IEEE/ACM Transactions on networking,* 2014.

[8] S. Sendra, J. Lloret, M. Garcia and J. F. Toledo, "Power saving and energy optimization techniques for Wireless Sensor Networks,," *Journal of Communications,* vol. 6, no. 6, pp. 439-459, 2011.

[9] IEEE, *IEEE Std 802.11™-2012 (Revision of IEEE Std 802.11-2007) Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY) Specifications,* New York: IEEE Computer Society, 2012.

[10] V. K. Khanna, H. M. Gupta and S. Maheshwari, "A high throughput and low power ad-hoc wireless LAN protocol," *Wireless Networks,* vol. 14, no. 1, pp. 1-16, 2008.

[11] D. Bri, P. Ramos, J. Lloret and M. Garcia, "The influence of meteorological variables on the performance of outdoor wireless local area networks," in *IEEE International Conference on Communications*, Ottawa, Canada, 2012.

[12] D. Bri, M. Garcia, J. Lloret and J. Misic, "Measuring the weather's impact on MAC layer over 2.4 GHz outdoor radio links," *Measurement,* vol. 61, p. 221–233, 2014.

[13] D. Bri, M. Fernandez-Diego, M. Garcia, F. Ramos and J. Lloret, "How the Weather Impacts on the Performance of an Outdoor WLAN," *IEEE Communications Letters,* vol. 16, no. 8, pp. 1184-1187, 2012.

[14] A. Lombardo, C. Panarello and G. Schembra, "EE-ARQ: a Green ARQ-Based Algorithm for the Transmission of Video Streams on Noise Wireless Channels," *Network Protocols and Algorithms,* vol. 5, no. 1, pp. 43-70, 2013.

[15] L. Wang and J. Manner, "Energy Consumption Analysis of WLAN, 2G and 3G interfaces," in *In Proceedings of the 2010 IEEE/ACM Int'l Conference on Green Computing and Communications & Int'l Conference on Cyber, Physical and Social Computing (GREENCOM-CPSCOM '10)*, Washington, DC, USA, 2010.

[16] C. Noda, S. Prabh, M. Alves and T. Voigt, "On Packet Size and Error Correction Optimisations in Low-Power Wireless Networks," in *IEEE International Conference on Sensing, Communications and Networking (SECON)*, New Orleans, USA, 2013.

[17] Nasaruddin, M. Andriani, Melinda and M. Irhamsyah, "Analysis of Energy Efficiency for Wi-Fi 802.11b," in *IEEE International Conference on Communication, Networks and Satellite (COMNETSAT)*, Yogyakarta, Indonesia, 2013.

[18] K. Gomez, R. Riggio, T. Rasheed and F. Granelli, "Analysing the energy consumption behaviour of WiFi networks," in *Online Conference onGreen Communications (GreenCom)*, 2011.

[19] A. M. Sweedy, A. I. Semeia, S. Y. Sayed and A. H. Konber, "The effect of frame length, fragmentation and RTS/CTS mechanism on IEEE 802.11 MAC performance," in *10th International Conference on Intelligent Systems Design and Applications (ISDA)*, Cairo, Egypt, 2010.

[20] M. Tauber, S. N. Bhatti and Y. Yu, "Application Level Energy and Performance Measurements in a Wireless LAN," in *IEEE/ACM International Conference on Green Computing and Communications (GreenCom)*, Chengdu, China, 2011.

[21] M. Krishnan, E. Haghani and A. Zakhor, "Packet Length Adaptation in WLANs with Hidden Nodes and Time-Varying Channels," in *Global Telecommunications Conference (GLOBECOM 2011)*, Houston, Texas, USA, 2011.

[22] W. Song, M. N. Krishnan and A. Zakhor, "Adaptive Packetization for Error-Prone Transmission over 802.11 WLANs with Hidden Terminals," in *the 11th international workshop on multimedia signal processing (MMSP'09)*, Rio de Janeiro, Brazil, 2009.

[23] G. A. Naydenov and P. S. Stoyanov, "Bit Error Period Determination and Optimal Frame Length Prediction for a Noisy Communication Channel," *AU Journal of Technology,* vol. 11, no. 1, pp. 7-13, 2007.

[24] B. Balaji, B. Tamma and B. Manoj, "A Novel Power Saving Strategy for Greening IEEE 802.11 Based Wireless Networks," in *Global Telecommunications Conference (GLOBECOM 2010)*, Miami, USA, 2010.

[25] J. Zhou, M. Jacobsson and I. Niemegeers, "Link Quality-Based Transmission Power Adaptation for Reduction of Energy Consumption and Interference," *EURASIP Journal on Wireless Communications and Networking,* vol. Open Access, pp. 1-17, 2010.

[26] B. Le, T. W. Rondeau and C. W. Bostian, "Cognitive radio realities," *Wireless communications and mobile computing,* vol. 7, no. 9, p. 1037–1048, 2007.

[27] T. W. G. f. W. Standards, "IEEE 802.11 Wireless Local Area Networks," [Online]. Available: http://grouper.ieee.org/groups/802/11/. [Accessed August 2014].

[28] D. Vassis, G. Kormentzas, A. Rouskas and I. Maglogiannis, "The IEEE 802.11 g standard for high data," *IEEE Network,* vol. 19, no. 3, pp. 21-26, 2005.

[29] L. Scalia, J. Widmer and I. Aad, "On the side effects of packet detection sensitivity in IEEE 802.11 interference management," in *IEEE International Symposium on a World of Wireless Mobile and Multimedia Networks (WoWMoM)*, Montreal, Canada, 2010.

[30] C. Boano, J. Brown, Z. He, U. Roedig and T. Voigt, "Low-Power Radio Communication in Industrial Outdoor Deployments: The Impact of Weather Conditions and ATEX-Compliance," *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering,* vol. 29, pp. 159-176, 2010.

[31] S. Cakaj, "Rain Attenuation Impact on Performance of Satellite Ground Stations for Low Earth Orbiting (LEO) Satellites in Europe," *Int. J. Communications, Network and System Sciences,* vol. 6, pp. 480-485, 2009.

[32] M. Luccini, *Joint Use of On-board Reconfigurable Antenna Pattern and Adaptive Coding and Modulation in Satellite Communications at High Frequency Bands, Ph.D. dissertation,* Dept. Electrical and Computer Engineering, University of Western Ontario, 2013.

[33] R. K. Crane, Propagation Handbook for Wireless Communication System Design, CRC Press, 2003.

[34] ITU, "Recommendation ITU-R P.676-10 Attenuation by Atmospheric Gases," ITU, Geneva, P Series, 2013.

[35] ITU, "Recommendation ITU-R P.840-6 Attenuation due to Clouds and Fog," ITU, Geneva, P Series, 2013.

[36] ITU, «Recommendation ITU-R P.838-3 Specific Attenuation Model for Rain for use in Prediction Methods,» ITU, Geneva, P Series, 2005.

[37] D. Bri, S. Sendra, H. Coll and J. Lloret, "How the Atmospheric Variables Affect to the WLAN Datalink Layer Parameters," in *The Sixth Advanced International Conference on Telecommunications*, Barcelona, Spain, 2010.

[38] N. S. Chok, "Pearson's versus Spearman's and Kendall's correlation, Thesis," University of Pittsburgh, 2010.

[39] D. J. Sheskin, Handbook of Parametric and Nonparametric Statistical Procedures: Third Edition, CRC Press, 2003.

[40] IBM, "SPSS Statistical Software," [Online]. Available: http://www-01.ibm.com/software/es/analytics/spss/. [Accessed February 2015].

[41] R. W. Thomas, L. A. DaSilva and A. B. MacKenzie, "Cognitive networks," in *1st IEEE International Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Baltimore, 2005.

[42] R. W. Thomas, D. H. Friend, L. A. DaSilva and A. B. MacKenzie, "Cognitive networks: Adaptation and learning to achieve end-to-end performance objectives," *IEEE Communications Magazine,* vol. 44, no. 12, pp. 51-57, 2006.

[43] G. Gür and F. Alagöz, "Green Wireless Communications via Cognitive Dimension: An Overview," *IEEE Network,* vol. 25, no. 2, pp. 50-56, 2011.

[44] IEEE Std 802.15.2, «Coexistence of wireless personal area networks with other wireless devices operating inunlicensed frequency bands,» IEEE, 2003.

[45] A. Goldsmith, Wireless communications, Cambridge: Cambridge University Press, 2005.

[46] IEEE Std. 802.11a, «Supplement to IEEE Standard for Information Technology - Telecommunications and Information Exchange Between Systems - Local and Metropolitan Area

Networks - Specific Requirements. Part 11: Wireless LAN Medium Access Control (MAC) and Physical Layer (PHY),» IEEE, 1999.

[47] W. Toorisaka, G. Hasegawa y M. Murata, «Power consumption analysis of data transmission in IEEE 802.11 multi-hop networks,» de *ICNS 2012, The Eighth International Conference on Networking and Services*, St. Maarten, Netherlands Antilles, 2012.

[48] L. M. Feeney y M. Nilsson, «Investigating the energy consumption of a wireless network interface in an ad hoc networking environment,» de *IEEE INFOCOM 2001. Twentieth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings.*, Anchorage, Alaska USA, 2001.

[49] I. Texas, "CC3000 IEEE 802.11b/g Solution Module," CC3000 IEEE 802.11b/g Solution Module , [Online]. Available: http://www.ti.com/product/CC3000/technicaldocuments.

[50] C. Fortuna and M. Mohorcic, "Trends in the development of communication networks: Cognitive networks," *Computer Networks,* vol. 53, no. 9, pp. 1354-1376, 2009.

[51] Riverbed, «Riverbed Modeler Wireless Suite,» [En línea]. Available: http://www.riverbed.com/products/performance-management-control/network-performance-management/network-simulation.html.

[52] K. P. Patil, S. Barge, K. E. Skouby and R. Prasad, "Spectrum Occupancy Information in Support of Adaptive Spectrum Sensing for Cognitive Radio," *Network Protocols and Algorithms,* vol. 6, no. 1, pp. 76-86, 2014.

[53] O. Jumira and S. Zeadally, Energy Efficiency in Wireless Networks, Wiley, 2013.

[54] H.-T. Wu, C.-W. Tuan and M.-T. Chuang, "A New EIFS Strategy for Performance Improvement of IEEE 802.11 Wireless LANs," *Network Protocols and Algorithms,* vol. 1, no. 1, pp. 7-15, 2009.