Hindawi Publishing Corporation
International Journal of Distributed Sensor Networks
Volume 2014, Article ID 965495, 9 pages
http://dx.doi.org/10.1155/2014/965495

Research Article

A Game Theory Based Strategy for Reducing Energy Consumption in Cognitive WSN

Elena Romero, Javier Blesa, Alvaro Araujo, and Octavio Nieto-Taladriz

ETSI Telecomunicación, Universidad Politécnica de Madrid, 28040 Madrid, Spain

Correspondence should be addressed to Elena Romero; elena@die.upm.es

Received 6 September 2013; Revised 28 November 2013; Accepted 19 December 2013; Published 28 January 2014

Academic Editor: Al-Sakib Khan Pathan

Copyright © 2014 Elena Romero et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Wireless sensor networks (WSNs) are one of the most important users of wireless communication technologies in the coming years and some challenges in this area must be addressed for their complete development. Energy consumption and spectrum availability are two of the most severe constraints of WSNs due to their intrinsic nature. The introduction of cognitive capabilities into these networks has arisen to face the issue of spectrum scarcity but could be used to face energy challenges too due to their new range of communication possibilities. In this paper a new strategy based on game theory for cognitive WSNs is discussed. The presented strategy improves energy consumption by taking advantage of the new change-communication-channel capability. Based on game theory, the strategy decides when to change the transmission channel depending on the behavior of the rest of the network nodes. The strategy presented is lightweight but still has higher energy saving rates as compared to noncognitive networks and even to other strategies based on scheduled spectrum sensing. Simulations are presented for several scenarios that demonstrate energy saving rates of around 65% as compared to WSNs without cognitive techniques.

1. Introduction

Global data traffic in telecommunications grows annually at a rate of 70%. The increasing number of wireless devices that are accessing mobile networks worldwide is one of the primary contributors to traffic growth. The number of mobile-connected devices will exceed the world's population in 2013 according to the CISCO report [1]. One of the main causes of this spectacular growth of mobile traffic is the increase in mobile-connected laptops and tablets and the emergence of smartphones whose use has increased by 82% in 2012. Handsets will exceed 50% of mobile data traffic in 2013. All of these devices (smartphones, tablets, and laptops) are usually connected via Wi-Fi or Bluetooth, which work on a 2.4 GHz unlicensed band.

Reexamining the CISCO report, machine to machine (M2M) communications are shown as one of the most important trends with a 90% annual growth between 2012 and 2017. Typical M2M applications include security and surveillance, health, or monitoring. These applications are usually supported by wireless sensor networks (WSNs) providing a wireless and flexible structure for the transmission of the data acquired by sensors to the rest of the network.

One of the problems with WSNs is certainly spectral coexistence. Regarding spectrum scarcity, most WSN solutions operate on unlicensed frequency bands. In general they use the industrial, scientific, and medical (ISM) bands like the worldwide available 2.4 GHz band. This band is also used by a large number of popular wireless applications, as mentioned before, or wireless networks based on IEEE 802.15.4. As a result, coexistence issues on unlicensed bands have been the subject of extensive research showing that IEEE 802.11 networks can significantly degrade the performance of 802.15.4 networks when operating on overlapping frequency bands [2]. To address the efficient spectrum utilization problem, cognitive radio (CR) [3] has emerged as the key technology, which enables opportunistic access to the spectrum.

One of the most important challenges with WSNs is energy consumption. Due to the number of nodes, their wireless nature, and, sometimes, their deployment in difficult access areas, nodes should not require any maintenance. In terms of consumption this means that the sensors must be energetically autonomous, the networks should not require human intervention, and therefore the batteries cannot be changed or recharged. In these kinds of scenarios, node

lifetime should last for years, making energy consumption a dramatic requirement to establish. If energy consumption has not been taken into account, nodes will eventually shut down.

The introduction of CR capabilities in WSNs provides a new paradigm for power consumption reduction offering new opportunities to improve it, but this also implies some challenges [4]. Specifically, sensing state, collaboration among devices—which requires communication, and changes in transmission parameters all increase the total energy consumption.

When designing WSN optimization strategies, the fact that WSN nodes are very limited in terms of memory, computational power, or energy consumption is not insignificant. Thus, light strategies that require low computing capacity must be found. In this way, different previous works, shown in Section 2, have demonstrated the feasibility and effectiveness of implementing game-theory-based strategies to optimize limited resources on WSNs. Since the field of energy conservation in WSNs has been widely explored, we assumed that new strategies should emerge from the new opportunities presented by cognitive networks.

In this paper a new game-theory-based strategy to optimize energy consumption in WSNs is presented. This strategy takes advantage of a new opportunity offered by cognitive wireless sensor networks (CWSNs): the ability to change the transmission and reception channel.

The organization of the paper is as follows. Section 2 presents the review of the state of the art. Assumptions about the network are exposed in Section 3. The game-theory-based strategy is presented in Section 4. Section 5 describes the baseline scenario and tools used in the simulations and the results are presented and discussed. Finally, Section 6 presents the conclusions from this work.

2. Related Work

CWSNs are a young technology and there is not a wide range of contributions in this area. Most works found in the literature on CWSNs introduce the general idea and promote research in this field. Zahmati et al. present in [4] an overview of CWSNs, discussing the emerging topics and the potential challenges in the area. Moving on to energy efficiency, there are several approaches to reduce power consumption for CNs but not specifically for CWSNs. Most of the research work focuses on achieving power-efficient spectrum use. In [5] a transmission power management is proposed to minimize interference with primary users and to guarantee an acceptable quality of service (QoS) level for cognitive transmission. In [6] the power constraint is integrated into the objective function which is a combination of the main system parameters of the cognitive network.

If we move to the specific area of consumption reduction in CWSNs, there is still much work to do. Focusing on low-power networks that exploit CR features, [7] notes the importance of CR features to improve power consumption, as in [8] where it is noted that CR could be able to adapt to varying channel conditions, which would increase transmission efficiency and hence help reduce power used for transmission and reception. These papers address the new opportunities offered but lack in specific solutions. In [9] two main problems related to energy consumption are listed: network lifetime maximization and energy efficient routing.

Specific solutions are given in [10] where authors propose a routing scheme optimizing the size of transmitted data and the transmission distance. Also, Stabellini and Zander center their work on reducing power consumption in the sensing step [11]. They use an energy constrained system comprising of two sensor nodes that avoid interference by exploiting spectrum holes in the time domain to prove its algorithm.

Given that the contributions in the field of reducing energy consumption in CWSNs are still scarce, it is possible to use the advances in WSNs to inspire new strategies for CWSNs. This way, it is possible to find a wide range of previous works in the area of algorithms based on game theory seeking energy optimizations in sensor networks. As stated in [12], more than 330 research articles related to game theory and WSNs were published from 2003 to 2011. Modeled games range from routing, task scheduling, or MAC energy efficient implementations.

Moreover, the use of game theory based algorithms is suited well to the characteristics of CNs. There are several studies based on game theory that model CN resources, from an overview presented in 2010 by [13] to models of channel selection [14], power allocation [15], or the mixture of both [16].

However, the introduction of intrinsic characteristics of WSNSs makes it essential to model energy consumption games. In addition, games designed for CWSNs should be lighter in terms of processing and energy consumption. In this area, a game-theory-based energy-efficient approach to power allocation in CWSNs is presented in [17]. Even if the approach takes energy efficiency into account, the game models power allocation instead of energy consumption.

Even though the research in this area looks to be very interesting, the use of CR to improve energy consumption in WSNs is not a mature research area. Some ideas are given but real proposals outside of the efficient sensing area or routing protocols are missing.

3. Assumptions and CWSNS Scenario

CWSNs are based on typical WSNs, improved with several features provided by cognitive networks. Thus, typical CWSNs are similar in components, distribution, and behavior to WSNs.

In this model, a CWSNS consists of a set $N = \{1, 2, \ldots, n\}$ of n cognitive wireless sensor nodes which could implement different final applications. Each node can communicate with others depending on their position and the transmission range. A typical CWSN consists of a number of nodes which can vary from tens to thousands of devices. These nodes are battery powered. CWSNS communicate over IEEE 802.15.4 specification with rates of up to 250 Kbps. However, typical CWSN rates are lower. Transmission power is limited due to energy consumption constraints. Nodes could perform in transmission mode, reception mode, or standby mode.

Typical current consumptions are 20 mA in transmission or reception mode and below 1 mA in standby mode [18]. Moreover, the mode usually described as sensing refers to a long-lasting reception mode.

As mentioned before, CWSN nodes communicate on an ISM band in coexistence with Wi-Fi or Bluetooth devices. Due to their bandwidth and their transmission power, each Wi-Fi channel can mask up to four 802.15.4 channels when both technologies coexist on the 2.4 GHz band.

Even if one of the main characteristics of CR is the existence of primary users (PUs) and secondary users (SUs), in this scenario no distinction shall be made between them. According to their formal definition, PUs are the "owner" of the spectrum band with right to communicate without restrictions, while SUs can use the spectrum if they do not jam PUs. Because of the CWSN use of unlicensed bands, the definition in this case refers to the information importance or relevance. Moreover, the strategy could apply to PUs and SUs improving their energy consumption in both cases.

4. Game Theory Strategy

As mentioned in Section 1, constrained resources are an intrinsic challenge related to WSNs. The additional complexity added to the nodes to enable cognitive capabilities makes nodes have higher energy consumption. Moreover, processing capability of WSN nodes is limited; thus, the strategies implemented should have low complexity.

There are many new different opportunities for reducing energy consumption in CWSNs. The proposal presented is to divide the opportunities for energy consumption optimization into three groups, namely, those that are obtained through spectrum sensing, those related to the capability to change transmission parameters, and those that depend on the ability to share network knowledge. The first two groups are directly derived from the cognitive capabilities added to the WSN nodes. However, the third one, related to the cooperation between devices, is one of the basic characteristics of WSNs, now enriched with cognitive information.

The proposed strategy addressed in this paper focuses on the ability to change transmission parameters based on sensed information. In addition, this strategy takes advantage of the cooperation in the network to share the information. In this work, a channel shift strategy to prevent unnecessary retransmissions has been selected. The use of less noisy channels avoids extra retransmissions and makes the global consumption reduction of the network possible.

As shown in Section 2, game theory is widely accepted for resource optimization in cooperative WSNs, and, now, with cognitive capabilities, it could fit even more. Although other approaches to optimize energy consumption such as genetic algorithms have been explored, their implementation in WSN nodes is expensive in terms of cost in computational resources and energy consumption [19, 20].

By its intrinsic nature, a sensor-network resource problem can be easily modeled like a game. In addition, games can be simplified enough without losing functionality to make them supported by a WSNS node, even if its processing capability is limited.

Table 1: Payoff matrix for player n.

Payoff for node n	m changes channel	m does not change channel
n changes channel	$-C_{ch}$	$-C_{ch} - C_n$
n does not change channel	$-C_n$	$-C_o$

A game is defined by several characteristics. The *resource* being modeled, the *players*, their *strategies,* and the *actions* they can take. Thereon, *costs* associated with each *action* will be defined, and, by combining this with the *odds* (suspected or known) of such *actions* occurring, the *payoff matrix and function* will be obtained.

In the approach described in this paper, the game is modeled as a finite resource game due to the battery-powered nodes, which provide them with a finite energy. The *resource* is the energy available in each node. *Players* are CWSN nodes $N = \{1, 2, \ldots, n\}$ and the *strategies* are those relating to the selection of the communication channel $S = \{s_1, s_2, \ldots, s_i\}$. The feasible *actions* that each one of the *players* can carry out are to change or not change the transmission channel. This *action* can arise from themselves or after a *move*—request—from another *player*. Energy consumption is modeled as the *resource* for which players compete. Thus, the *payoffs* and *costs* are those energy expenses associated with the *actions* taken. $P_n(s)$ where $n \in N$ is the nth payoff function.

This game can be described as a hybrid game because although it is noncooperative in game theory terminology, communication between nodes can lead to the common good. It is a non-zero-sum game, in which there is no correlation between one player's payoffs and another player's losses. In fact, there may be values that maximize the payoffs of every player. The game is sequential because actions are performed sequentially. This game is asymmetrical since payoffs are different depending on the players. In this case this dependence refers to the position of the players and the traffic between them. It is also an evolutionary game, since players can learn, adapt, and evolve their actions based on the information shared and the odds perceived from the rest of the nodes.

For the calculation of the *payoff* matrix of this game, the resulting *payoffs* coming from the combination of the *actions* taken by the *players* (to change or not to change the transmission channel) are taken into account.

The *payoff* matrix for *player n* that communicates with *player m* is shown in Table 1.

And the *payoff* matrix for node n could be expressed as

$$P_n = \begin{pmatrix} -C_{ch} & -C_{ch} - C_n \\ -C_n & -C_o \end{pmatrix}, \quad (1)$$

where C_{ch} is defined as the energy cost associated with a change of the communication channel. It is calculated as the addition of the extra energy cost associated with the sensing mode (C_{sensing}) and the cost of the transmission (C_{tx}) and reception (C_{rx}) caused by the agreement messages needed to

negotiate the channel change (n_msg). Thus, the energy cost of the action of change in this case is

$$C_{ch} = C_{\text{sensing}} + (C_{tx} + C_{tx}) \cdot n_\text{msg}. \quad (2)$$

C_o is the energy cost of transmission in noisy channels. It is calculated as the cost of a packet transmission taking into account that it requires a number of retransmissions named n_rtx. This n_rtx depends on the observed and stored number of retransmissions needed by previous packets and is calculated as the average of the needed message retransmissions for the previous k (parameterizable) messages:

$$C_o = C_{tx} \cdot n_rtx. \quad (3)$$

C_n is the energy cost associated to communications in a channel not shared with the receiver. Even though this situation is not very common, it could happen if several CWSNs perform the strategy without agreement. C_n is calculated as the cost of transmission when the number of retransmission has run out and consequently the maximum allowed has been reached (max $_rtx$):

$$C_n = C_{tx} \cdot \max_rtx. \quad (4)$$

Naming x the odds of node n and y the supposed probability of node m to take the action to change the communication channel and calculating the total *payoff* of node n result in

$$\begin{aligned} P_n = &- C_{ch} \cdot x \cdot y - (C_{ch} + C_n) \cdot x \cdot (1 - y) \\ &- C_n \cdot (1 - x) \cdot y - C_o \cdot (1 - x) \cdot (1 - y), \\ P_n = &(2 \cdot C_n - C_o) \cdot x \cdot y + (C_o - C_{ch} - C_n) \cdot x \\ &+ (C_o - C_n) \cdot y - C_o. \end{aligned} \quad (5)$$

To determine the optimal value of x, each node n stores the observed number of accepted and sent requests from its neighbor nodes. From this stored data it is possible to extract the supposed probability of change y. Evaluating C_{ch}, C_n, and C_o at the time of the channel change request, the optimal value of x that maximizes the payoff can be obtained.

Applying the maximization criterion of this simple algorithm in every device, it is possible to optimize the consumption of each node without impacting the breakdown of other nodes in the network. Thus, by maximizing the lifetime of each network node, the lifetime of the network as a whole is prolonged. Although this statement is not always true, the energy saved in each node has a positive effect on the overall operation of the network.

For the implementation of this strategy, it could be possible to always run the maximization of the payoff in the background, but in terms of energy conservation and computing capabilities it is more efficient to optimize only when the transmission channel is noisy enough. In this way, the strategy considers that the optimization will be triggered, taking into account other parameters such as the RSSI received in the communication channel, which is related to noise presence.

Optimization strategy performs as follows.

(1) Every node in the CWSN receives messages by the assigned channel and saves RSSI samples from each message received.

(2) If the RSSI value saved in node n is above a certain threshold (in a certain number of samples), node N activates the optimization algorithm that evaluates the payoff function to decide if changing the channel is interesting at that moment or not.

(3) If the result of this evaluation is a change, node N senses the spectrum and chooses the least noisy channel.

(4) Node N communicates its decision to the rest of the network nodes and the new chosen channel according to its sensing values.

(5) The rest of nodes evaluate this change and decide whether to change the channel depending on its payoff function. This decision is communicated back to other nodes in the network.

(6) The value of the stored accepted channel change requests is updated in order to calculate y in future situations.

Although in this work the sensing state only involves one node, this approach could be adapted to any type of sensing depending on the network features. To demonstrate the validity of this algorithm, only the triggered node is responsible for sensing. However, new collaborative techniques or channel negotiation in clusters could be included according to the location of the nodes.

5. Experimental Results

In this section results of different simulations are presented. First, the simulation tool used to perform them is presented. The baseline scenario and the different scenario configurations are shown. Finally, the simulations performed and the results obtained are presented and discussed.

5.1. Simulation Tools. In this work the architecture of cognitivity brokerage framework [21] is used. For simulation results the framework used is composed of two fundamental elements: a CWSN simulator and low power cognitive radio real devices. This framework [22] has been tested and referenced in previous works. Both the simulator (based on Castalia) and real nodes implement the cognitivity brokerage architecture mentioned.

The structure of Castalia simulator has been enhanced to provide cognitive features. The simulator can carry out sensing tasks in order to acquire and share spectrum information. This information may include received signal power, noise power, or time between packets. The information is processed, stored, and shared according to the implemented strategy. A virtual control channel (VCC) also exists to share sensed information, with no extra overhead over regular communications.

The simulator is also responsible for the scenario definition, the simulation of the spectrum state, and the communication between nodes from the physical to the application layer.

Real nodes are used just to confirm, as empirical testing, results for small-scale networks. So that all the results presented in this paper are extracted from the simulator.

5.2. Cognitive Baseline Scenario. The baseline scenario which carries out the simulation tests is deployed in a 100 m × 10 m area, such as an example of a WSN scenario. It contains two coexisting networks, a CWSN and a Wi-Fi network. In the baseline scenario 100 Wi-Fi nodes are assumed, but a simulation with a varying number of Wi-Fi nodes is performed (from 50 to 200 devices). CWSN results show the energy consumption of a cognitive device which communicates only with the network coordinator (as a WSN star topology).

CWSNs are modeled with a Texas Instrument CC2420 transceiver. Values of energy consumption are extracted from datasheet (for transmission, reception and idle modes, and energy costs of transitions between modes) and verified through experimental measurement. Sensing stage is modeled as a reception mode lasting for 200 ms.

CWSN nodes transmit common WSN packets of 50 bytes at −5 dBm while Wi-Fi network transmits the usual Wi-Fi packets of 2000 bytes at −3 dBm. Both networks use ISM band at 2.4 GHz. A maximum number of 20 retransmissions are set for CWSN and Wi-Fi nodes in the baseline scenario. However, it is interesting to check the behavior by varying the maximum number of retransmissions allowed. Therefore, a simulation for this is included.

For the baseline scenario, a RSSI threshold of −150 dBm taking into account 5 samples is assumed. Nevertheless, a simulation with a different number of samples and a variable threshold is also considered.

In order to facilitate simulations of different configurations, a reduction in simulation 10 times lower in every magnitude is assumed. For this assumption, a long-term simulation is performed, showing similar results to those presented in the paper. Thus, simulation time is 300 s, and network rates of 1 packet per second on CWSNs and 50 packets per second on Wi-Fi are chosen. The spectrum sensing period for CWSNs is 2 s.

In order to simulate new Wi-Fi configurations or the appearance of new Wi-Fi networks or nodes in the area, these simulated nodes change their communication channel every 30 s.

In all the results shown, figures show the energy consumption in accumulated Joules over time. For a real reference, typical batteries for CWSNs have a total energy of 18,000 J.

5.3. Results and Discussion. In this section results of different simulations are discussed. Even if the simulations do not last as long as the battery life, energy consumption reduction can be appreciated for enhancing the network lifetime. Presented results always show the energy consumption for a CWSN node.

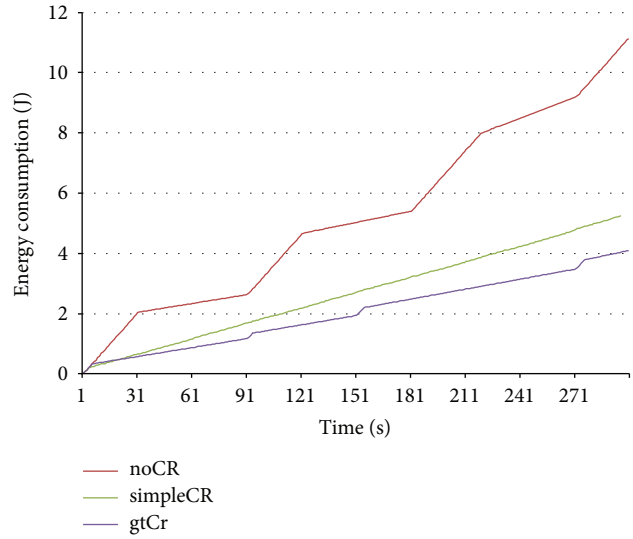


Figure 1: Baseline scenario.

For the first simulation, the baseline scenario is simulated with three different CWSN optimization strategies. The first one, marked in red, is a typical WSN without cognitive capabilities—noCR, which must remain on their initial channel even if this channel becomes very noisy. Green line—simpleCR, shows a first strategy approach to the CWSN, where cognitive nodes are able to sense the spectrum and change their transmission parameters accordingly. This first approach to the CWSN senses the spectrum every 2 s and changes the transmission and reception channel for the whole network. In this way, the least noisy channel is assured each 2 s. In the third CWSN strategy—gtCR, the proposed optimization strategy based on game theory explained in Section 4 is shown in purple. In order to compare energy consumption, the chosen sensing period is 2 s as well.

Figure 1 shows that even in the first 300 s gtCR strategy provides energy consumption savings of around 65% compared to the noCR scenario. Furthermore, these savings will increase over time as both noCR and simpleCR have steeper slopes in energy consumption. In relation to simpleCR, gtCR saves energy consumption by approximately 30% in the first 300 s. As in the previous case, these energy savings are increasing over time.

Figure 2 shows the energy consumed each second instead of the accumulated consumption over time for the baseline scenario. This figure shows the detailed energy consumption of the algorithm each time it is triggered.

Looking at the noCR line, energy consumption is lower than simpleCR when Wi-Fi channel does not overlap with the CWSN one. However, when the channel does coincide (0–30 or 90–120 seconds) energy consumption spikes.

Focusing on simpleCR energy consumption is almost regular throughout the simulation. This is due to the fact that energy consumption imposed by the sensing state is much higher than the energy consumption in transmission and reception modes in an ideal situation (without coexistence Wi-Fi) so the biggest amount of energy consumed comes from the sensing state.

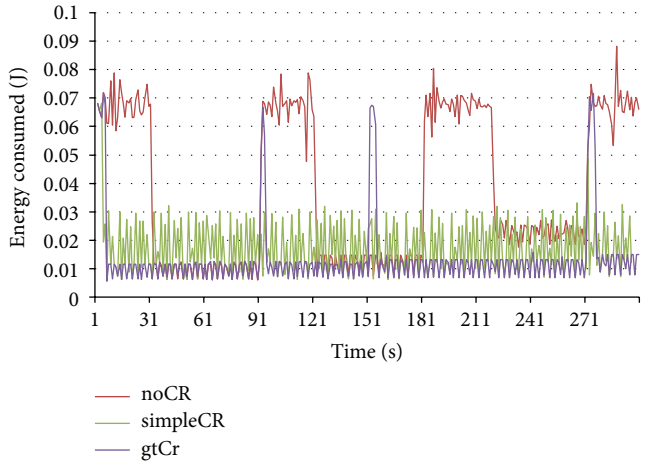


Figure 2: Instantaneous energy consumption for the baseline scenario.

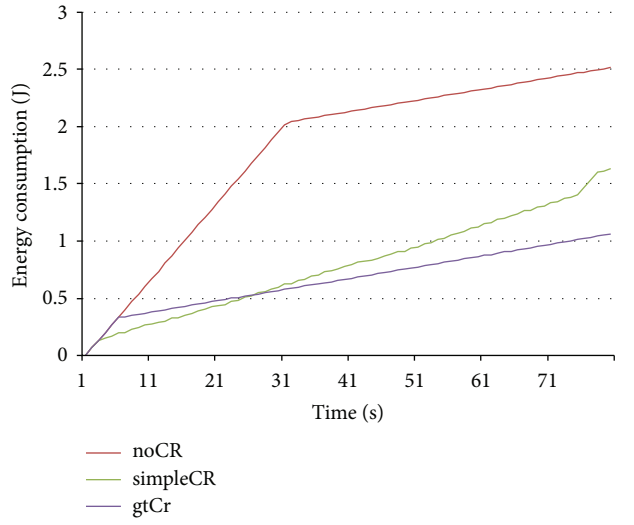


Figure 3: Baseline scenario with 50 Wi-Fi nodes.

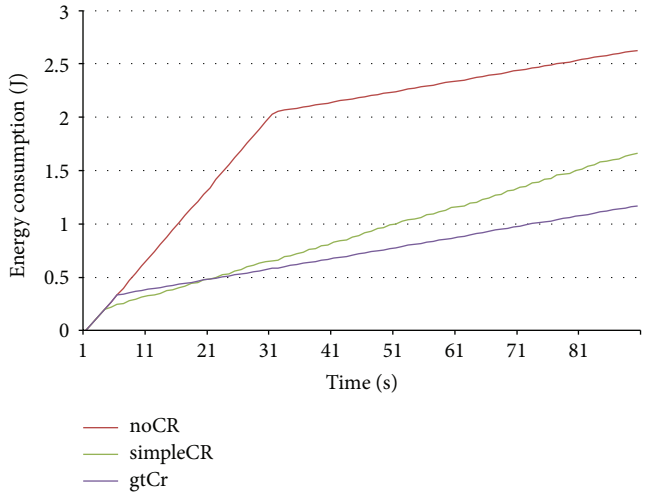


Figure 4: Baseline scenario with 200 Wi-Fi nodes.

Even though in some cases gtCR increases node processing consumption, for the strategy calculation, this energy cost is offset by the energy consumption savings by avoiding noisy channels.

The next simulations show the results of varying the number of Wi-Fi nodes on the baseline scenario in order to change noise in the area. These results can be seen in Figure 3, which uses 50 Wi-Fi nodes instead of 100 in the baseline scenario, and Figure 4, with 200 Wi-Fi nodes for a very noisy ambience.

As can be seen, both simulations are similar in shape and values as baseline scenario, so it can be concluded that the proposed algorithm is not influenced by the amount of noise present in the scenario.

The next scenario modifies the RSSI threshold used by the gtCR strategy as a first decision mechanism to show if this threshold influences the behavior of the strategy. In Figure 5, the behavior of the algorithm for different decision thresholds in dBm is shown.

As shown, algorithm performance is also not greatly influenced by the chosen threshold. This is because of the game-theory-based strategy design which takes into account subsequent corrections such as the number of retransmissions used to calculate the best moment to change the channel.

Small changes that are seen in the center values of the figure are due to the random character of the channel chosen by the Wi-Fi nodes, which makes CWSN nodes take the decision of change at 90 s or at 180 s depending on the existing noise in the channel. But energy consumption at 300 s is similar for every chosen threshold.

The next scenario changes the number of RSSI samples taken into account in order to calculate the RSSI value. The intention of these different values is to probe the strength of the strategy employed against anomalous measures of RSSI. For the simulation shown in Figure 6, different numbers of samples are taken.

The increased value of energy consumption shown in Figure 6 for 10 samples is due to the time waste produced by the sampling RSSI with every received packet. As the packet rate for the CWSN is 1 packet per second, it must wait longer to obtain more samples, thereby making the algorithm take longer to react to changes and trigger the game-theory-based strategy. Although increasing the number of samples protects the algorithm from possible erroneous samples, it is shown that the reaction time makes the CWSN node remain on a noisy channel longer; thus, the number of retransmissions increases, raising its consumption. The number of samples must be chosen depending on the WSN application scenario and the randomness of the noise.

For the next scenario it is interesting to vary the maximum number of retransmissions allowed by the CWSN nodes, as it is a parameter that depends directly on the decision to change the channel or not in the game-theory-based strategy design. Figure 7 shows the results.

As can be seen, the greater the maximum number of retransmissions set, the higher the energy consumption produced. In this case, it should reach a compromise between consumption and network reliability depending on the final

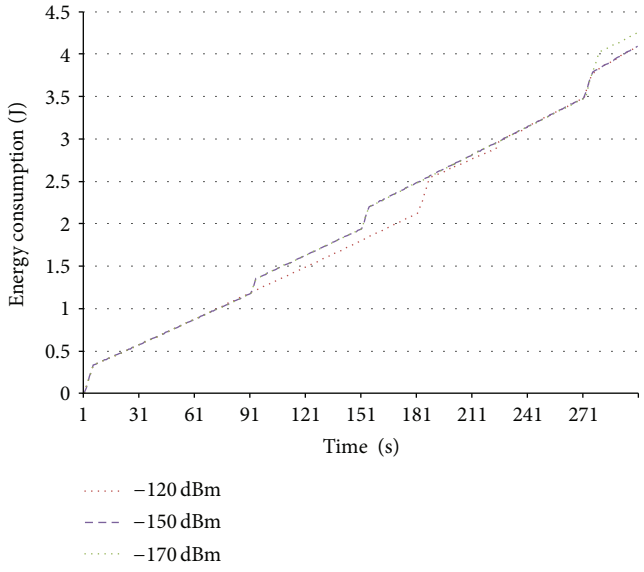


Figure 5: Scenario varying RSSI threshold.

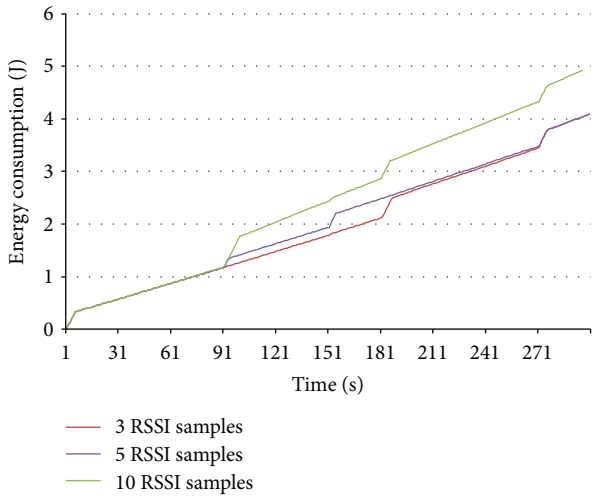


Figure 6: Scenario varying number of RSSI samples.

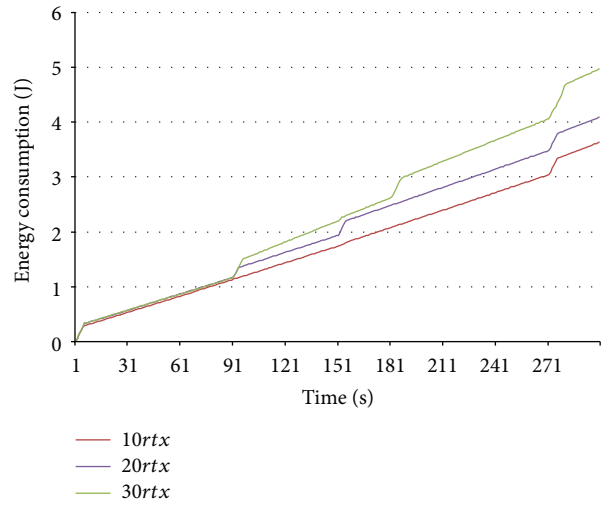


Figure 7: Scenario varying number of *rtx*.

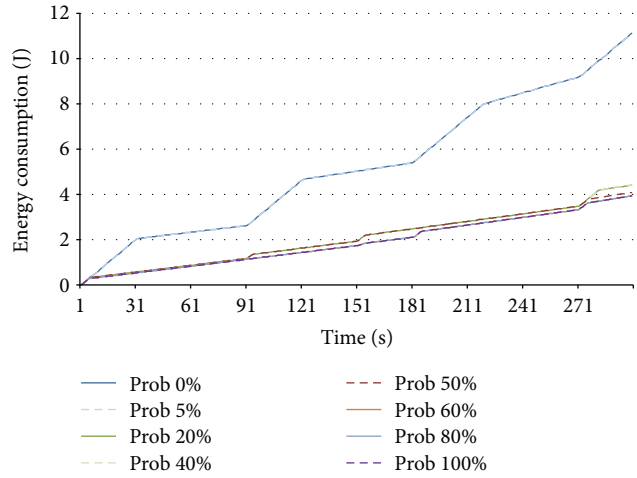


Figure 8: Scenario varying init probY.

application of the WSN or the importance of the data transmitted by the nodes.

One of the most interesting questions is how this strategy evolves depending on the initialization values of the probability of accepting the changes request y stored for the rest of the network nodes. This evolution could show if the strategy could adapt to real behavior or, instead, relies heavily on initialization values. In this case several experiments that include initialization values from 0 to 100% of change requests accepted are performed showing the following results.

Figure 8 shows that values from 0 to 5% demonstrate values similar to noCR techniques in energy consumption, shown in Figure 1. Moreover, 80% to 100% values are exactly the same, as are 50% to 60% and 20% to 40%.

In any case, it is shown that initialization values between 20% and 100% are quite similar in terms of long-term power consumption, indicating that the algorithm, regardless of its initialization, moves rapidly toward a stationary situation based on the sensed spectrum around the node and the behavior of the rest of the devices.

To summarize results, the algorithm shows improvement rates of over 65% compared to WSNs without cognitive techniques and over 30% compared to sensing strategies for changing channels based on a decision threshold. For the dependence of the values used in the payoff function, results are shown in Table 2.

6. Conclusions

WSNs are shown as one of the most important trends in wireless communication. Energy consumption became

Table 2: Results summary.

Parameter	Dependence	Factors
Number of nodes	No	
RSSI threshold	No	
RSSI samples	Yes	Application Data rate Sensing period
Number of *rtx*	Yes	Network reliability
Init probY	No (above 20%)	

an important problem to face in typical WSN application because of the use of batteries. The introduction of CN features opens up new interesting research challenges ranging from CR capabilities to WSN intrinsic features.

In this paper, a new strategy based on game theory for reducing energy consumption in CWSNs has been presented. This is a light optimization algorithm that enables its implementation in CWSNs although the nodes computing resources are limited. The strategy is applicable in conjunction with other energy consumption optimizations. This way the results can be further improved by incorporating routing protocols that have been proven efficient or MAC implementations for low consumption.

The developed algorithm has been tested on a framework based on Castalia adapted to incorporate cognitive capabilities. As seen in the results section, the algorithm shows improvement rates of over 65% compared to WSNs without cognitive techniques and over 30% compared to sensing strategies for changing channels based on a decision threshold.

It can also be seen that the algorithm behaves similarly even with significant variations in the number of noisy nodes. Likewise, RSSI decision threshold and the number of samples taken into account for their calculation do not influence the operation of the algorithm. In regard to the number of samples, the only relationship arises from taking a large number of samples, which increases the consumption as the node keeps in the noisy channel for too long.

Concerning the maximum number of retransmissions allowed for CWSN nodes, energy consumption increases along with them but is caused by the retransmissions itself and completely unrelated to the algorithm. In this case, a compromise should be reached between consumption and network reliability. The initialization value of the odds of change from other nodes does not significantly affect the performance of the algorithm for values above 20%, since this probability evolves based on the noise and not on its initialization.

Reducing energy consumption in WSNs is an interesting field in which there is much work to be done. CWSNs introduce new features to take advantage of and also new challenges to face. It would be interesting to see how this algorithm behaves on a larger network or a comparison with other game models.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgment

This work was funded by the Spanish Ministry of Economy and Competitiveness, under INNPACTO Program (Reference Grant IPT-2011-1197-370000, PRECOIL; IPT-2011-1241-390000, LINEO; IPT-2011-0782-900000, S2S).

References

[1] Cisco Systems Inc., "Cisco visual networking index: global mobile data traffic forecast update, 2012–2017," Tech. Rep., 2013.

[2] I. Howitt and J. A. Gutierrez, "IEEE 802.15.4 low rate—wireless personal area network coexistence issues," in *Proceedings of the IEEE Wireless Communications and Networking (WCNC '03)*, vol. 3, pp. 1481–1486, New Orleans, La, USA, 2003.

[3] J. Mitola, *Cognitive radio: an integrated agent architecture for software defined radio [Ph.D. thesis]*, Royal Institute of Technology, Stockholm, Sweden, 2000.

[4] A. S. Zahmati, S. Hussain, X. Fernando, and A. Grami, "Cognitive wireless sensor networks: emerging topics and recent challenges," in *Proceedings of the IEEE Toronto International Conference—Science and Technology for Humanity (TIC-STH '09)*, pp. 593–596, Ontario, Canada, September 2009.

[5] D. J. Kadhim, S. Gong, W. Xia, W. Liu, and W. Cheng, "Power efficiency maximization in cognitive radio networks," in *Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC '09)*, pp. 1–6, Budapest, Hungary, April 2009.

[6] I. Aissa, M. Frikha, and S. Tabbane, "A dynamic power management procedure in cognitive radio," in *Proceedings of the IFIP Wireless Days (WD '10)*, pp. 1–5, Venice, Italy, October 2010.

[7] G. Gür and F. Alagoüz, "Green wireless communications via cognitive dimension: an overview," *IEEE Network*, vol. 25, no. 2, pp. 50–56, 2011.

[8] O. B. Akan, O. B. Karli, and O. Ergul, "Cognitive radio sensor networks," *IEEE Network*, vol. 23, no. 4, pp. 34–40, 2009.

[9] G. Vijay, E. B. A. Bdira, and M. Ibnkahla, "Cognition in wireless sensor networks: a perspective," *IEEE Sensors Journal*, vol. 11, no. 3, pp. 582–592, 2011.

[10] I. Glaropoulos, V. Fodor, L. Pescosolido, and C. Petrioli, "Cognitive WSN transmission control for energy efficiency under WLAN coexistence," in *Proceedings of the 6th International ICST Conference on Cognitive Radio Oriented Wireless Networks and Communications (CROWNCOM '11)*, pp. 261–265, Yokohama, Japan, June 2011.

[11] L. Stabellini and J. Zander, "Energy-aware spectrum sensing in cognitive wireless sensor networks: a cross layer approach," in *Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC '10)*, pp. 1–6, Sydney, Australia, April 2010.

[12] H. Y. Shi, W. L. Wang, N. M. Kwok, and S. Y. Chen, "Game theory for wireless sensor networks: a survey," *Sensors*, vol. 12, no. 7, pp. 9055–9097, 2012.

[13] B. Wang, Y. Wu, and K. J. R. Liu, "Game theory for cognitive radio networks: an overview," *Computer Networks*, vol. 54, no. 14, pp. 2537–2561, 2010.

[14] N. Tang, J. Sun, S. Shao, L. Yang, and H. Zhu, "An improved spectrum sharing algorithm in cognitive radio based on game theory," in *Proceedings of the 12th IEEE International Conference on Communication Technology (ICCT '10)*, pp. 504–507, Nanjing, China, November 2010.

[15] E. del Re, R. Pucci, and L. S. Ronga, "Energy efficient non-cooperative methods for resource allocation in cognitive radio networks," *Communications and Network*, vol. 4, pp. 1–7, 2012.

[16] J. D. Deaton, S. A. Ahmad, U. Shukla, R. E. Irwin, L. A. Dasilva, and A. B. MacKenzie, "Evaluation of dynamic channel and power assignment for cognitive networks," *Wireless Personal Communications*, vol. 57, no. 1, pp. 5–18, 2011.

[17] B. Chai, R. Deng, P. Cheng, and J. Chen, "Energy-efficient power allocation in cognitive sensor networks: a game theoretic approach," in *Proceedings of the of IEEE Global Communications Conference (GLOBECOM '12)*, pp. 416–421, Anaheim, Calif, USA, 2012.

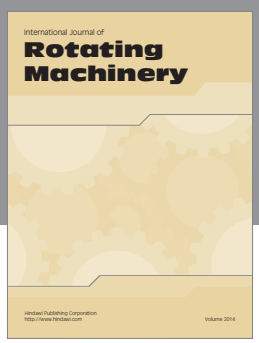
[18] CC2530 Datasheet. Texas instruments, http://www.ti.com/lit/ds/symlink/cc2530.pdf.

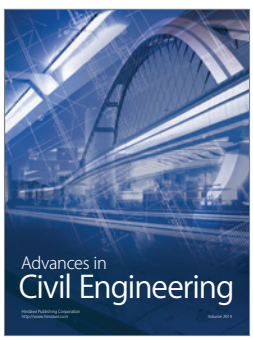
[19] J. Cooper and C. Hinde, "Improving genetic algorithms' efficiency using intelligent fitness functions," in *Developments in Applied Artificial Intelligence*, vol. 2718 of *Lecture Notes in Computer Science*, pp. 636–643, Springer, Berlin, Germany, 2003.

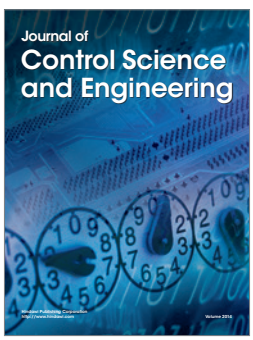
[20] A. E. Ohazulike and T. Brands, "Multi-objective optimization of traffic externalities using tolls. A comparison of genetic algorithm and game theoretical approach," in *Proceedings of the IEEE Congress on Evolutionary Computation (CEC '13)*, pp. 2465–2472, Cancun, Mexico, 2013.

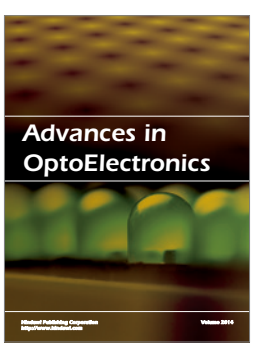
[21] J. Rabaey, A. Wolisz, A. Ercan et al., "Connectivity brokerage—enabling seamless cooperation in wireless networks," Tech. Rep., Berkeley Wireless Research Center, Berkeley, Calif, USA, 2010.

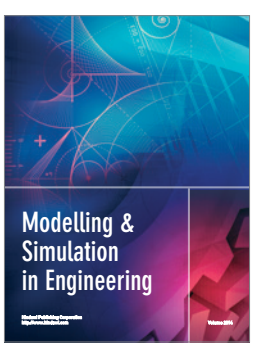
[22] A. Araujo, E. Romero, J. Blesa, and O. Nieto-Taladriz, "Cognitive wireless sensor networks framework for green communications design," in *Proceedings of the 2nd International Conference on Advances in Cognitive Radio (COCORA '12)*, pp. 34–40, Chamonix, France, 2012.

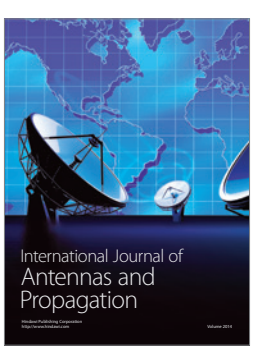


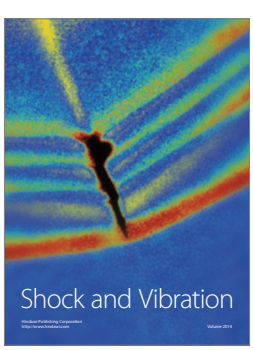


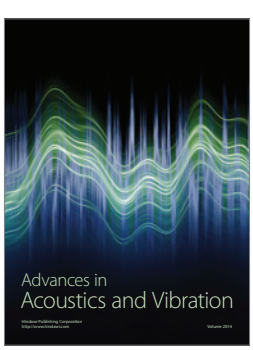












Hindawi

Submit your manuscripts at
http://www.hindawi.com