Elsevier Editorial System(tm) for Pervasive and Mobile Computing
Manuscript Draft

Manuscript Number:

Title: Enhancing Energy Efficiency in CRSNs via Channel Selection based on Game Theory and Collaboration.

Article Type: SI: CRSNs

Corresponding Author: Ms. Elena Romero,

Corresponding Author's Institution: Universidad Politécnica de Madrid

First Author: Elena Romero

Order of Authors: Elena Romero; Javier Blesa, Master; Alba Rozas, Master; Alvaro Araujo, Doctor

Elena Romero Perales
Department of Electrical Engineering
Universidad Politécnica de Madrid
E.T.S.I.Telecomunicación – B-104
C.P: 28040 Madrid Spain
Phone: +34915495700
Fax: +34913367323
Email: elena@die.upm.es

Dear Editors,

Enclosed is a paper, entitled "Enhancing Energy Efficiency in CRSNs via Channel Selection based on Game Theory and Collaboration". Please accept it as candidate for publication in the Special Issue of Pervasive and Mobile Computing on "Recent Developments in Cognitive Radio Sensor Networks".

In this paper we present a new strategy to improve energy efficiency based on game theory and collaboration for CRSN. We consider energy savings a key issue in CRSN because of their intrinsic nature: mobility, dynamic and autonomy. Reducing energy consumption in these networks is an interesting field in which there is much work to be done. This approach takes advantage of a new opportunity offered by CRSN, the capability of change the communication channel. The presented strategy is a light optimization that enables its implementation in CRSNs although the nodes computing resources are limited. Simulations are presented for several scenarios that demonstrate its validity.

Finally, this paper, including figures, is our original unpublished work and it has not been submitted to any other journal for reviews.

Sincerely,

Elena Romero

Enhancing Energy Efficiency in CRSNs via Channel Selection based on Game Theory and Collaboration.

Elena Romero, Javier Blesa, Alba Rozas, Alvaro Araujo.

Electronic Engineering Department, Universidad Politécnica de Madrid, Avda/Complutense 30, 28040 Madrid, Spain

Abstract

Energy consumption in Wireless Sensor Networks is a historical problem which has been addressed from different areas. With the introduction of Cognitive Radio it is possible not only to increase the reliability of communications thanks to spectrum optimization, but also to reduce energy consumption. In this new scenario, a collaborative lightweight strategy based on game theory is proposed. It takes advantage of the two main capacities of Cognitive Radio Sensor Networks, the ability to adapt communication parameters and collaboration between nodes. Simulations have been carried out to validate the strategy in different scenarios with different noise schemes.

Keywords: Cognitive Radio Sensor Networks, Energy consumption, Game Theory, Collaboration, Optimization.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) have historically been a technology with numerous problems related to energy consumption [1]. Their intrinsic characteristics (low cost, few capabilities, mobile nature, and limited power source) make it mandatory to maximize their lifetime with very scarce resources. Furthermore, the implementation of complex algorithms that would help us to optimize energy consumption is not a valid approach due to the low processing capabilities of the nodes.

The subject of energy consumption in WSNs is therefore a known historical problem which has been addressed from different areas and levels. It has been approached from the specific physical implementation of the nodes themselves, to the application level, including routing protocols or MAC ad-hoc implementations.

In recent years, another problem, the spectrum saturation, has been added to the equation. WSNs usually operate in unlicensed spectrum bands such as the Industrial, Scientific and Medical (ISM) bands. These bands are shared with other networks (mainly those based on IEEE 802.11 or 802.15.1) and they have seen their occupation increased in the last years. One of the main causes is the increase of wireless-connected laptops, tablets and smartphones whose use has increased by 82% in 2012. According to CISCO report there will be more than 10 billion mobile-connected devices including Machine-to-Machine (M2M) modules by 2018 [2].

Therefore, the introduction of cognitive capabilities to WSNs allowing us to optimize their spectral occupation seems to be a good option. Cognitive Radio Sensor Networks (CRSNs) could not only increase the reliability of communications thanks to spectrum optimization, but also have a positive impact on parameters such as the Quality of Service (QoS), network security or energy consumption [3].

Taking advantage of the new cognitive capabilities of the network (such as channel selection) can have a great impact on energy consumption. These new opportunities introduced by CRSNs unveil a wide field in the energy consumption research area. However, this also implies some challenges. Specifically, the sensing of the radio spectrum, collaboration among devices -which requires extra communication- and changes in the transmission parameters, all increase the total energy consumption of the network.

When designing CRSN 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 a low computing capacity must be found. Since the field of energy conservation in WSNs has been widely explored, we assume that new strategies must emerge from the new opportunities presented by cognitive networks.

This work is supported by three main pillars: first, cognitive capabilities added to the WSN which provide the ability to know the state of the spectrum and change the transmission parameters; secondly, the ability to collaborate, both basic characteristics in CRSN. Finally, the third aspect for this work is game theory as a decision algorithm, which has been widely used in WSNs due to its characteristics of lightness and simplicity that make it valid to operate in these networks. The objective of this work is to propose a strategy to optimize energy consumption on CRSNs. The main contributions of the paper can be divided into:

- Proposing a collaborative game using cognitive capabilities for WSNs which can be implemented in low resources nodes.
- Proposing a new energy consumption optimization strategy for CRSNs based on the suggested game and collaboration among nodes.
- Evaluating the proposed strategy through simulations in several typical CRSNs scenarios.

Thus, this paper presents a game theory-based strategy using cognitive capacities (as channel selection) and collaboration between nodes allowing a significant reduction in the energy consumption of the network.

The rest of the paper is organized as follows: In Section 2 we present a state of the art in the area. Section 3 presents the assumptions and the typical scenario. The optimization is proposed in Section 4 (the game theory algorithm and the proposed collaborative strategy). Section 5 presents and discusses the results. Finally in Section 6 some conclusions are provided.

2. State of the art

CRSNs are still a developing field that has begun with investigations aimed at increasing the QoS in WSNs. The first papers encourage research in the area basing on the promising possibilities of the field. Kadhim et al., in [3], discuss the emerging topics and the potential challenges in the area and Akan et al. give a general presentation of the topic in [4], presenting feasible network architectures and a discussion of the existing communication protocols and algorithms. Both papers were published in 2009, which gives an indication of the state of this technology is in its early stages.

If we focus on the aspect of reducing energy consumption in CRSNs, it is possible to find some works that take into account energy consumption among the parameters to consider, but are designed and developed for the optimization of other aspects. Along this line, we can find [5] which presents a packet-size optimization taking into account energy efficiency, [6], which designs a routing protocol considering energy consumption as a cost, or [7] which proposes a channel assignment method that takes energy into account. But definitely, most works in this group deal with spectrum sensing protocols designed for low energy consumption [8][9][10]. In all of these papers, energy consumption is one of the aspects taken into account when evaluating the main parameters of the optimization, which gives an idea about the importance of energy consumption in CRSNs. This way they work on energy-sustainable optimizations of other parameters or at least on optimizations where energy consumption is not increased by the new algorithms.

Looking for researches where optimizing energy consumption in CRSNs is the main objective, the most used approach is to optimize power allocation [11]. However, there are many other possibilities to explore. Gür and Alagöz note the potential of cognitive features to optimize energy consumption in [12]. Cognitive radio is proposed in [4] as a solution adapting the nodes to channel conditions, which increases communication efficiency, and therefore reduces the energy consumption for transmission and reception tasks. These papers address the new opportunities but lack in specific proposals.

Looking for game theory strategies for low-resources networks, it is possible to find a wide range of previous works in the area. As stated in [13], more than 330 research papers related to game theory and WSNs were published from 2003 to 2011. They present a huge variety of games modeling MAC implementations, routing protocols or task scheduling.

Moreover, the use of game theory-based algorithms is well suited to the characteristics of cognitive networks. Several papers based on game theory are presented in [14]. Network selection [15], spectrum sharing [16] or power allocation [17] are modeled as a resource in these games.

With the introduction of cognitive capabilities in WSNs a new paradigm is open for energy consumption reduction. As Joshi et al. state in [18]: "CR wireless sensors may be able to change their operating parameters to adapt to channel conditions. Therefore, energy consumption due to a packet collision and retransmission can be mitigated. "

Although research in this area looks very promising, the use of CR to enhance energy efficiency in WSNs is not a mature research area. Some ideas related to optimizing the communication channel are given, but real proposals are still missing..

3. ASSUMPTIONS AND CRSN SCENARIO

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

A typical CRSN consists of a number of nodes, typically varying from tens to thousands, distributed in an environment in which they have to make measurements. These nodes are usually powered by batteries and can perform in transmission mode, reception mode or stand-by mode. CRSNs used to communicate using the IEEE 802.15.4 specification. Even though this standard allows rates up to 250 Kbps, typical CRSN rates are much lower. The transmission power is limited due to the energy consumption constraints.

Typical current consumptions of CRSNs nodes are 20 mA in transmission or reception mode and below 1 mA in stand-by mode [19]. Moreover, the usually called sensing mode refers to a long-lasting reception mode. In this paper the time required to sense is assumed to be 200 ms. This time has been chosen after several experimental measurements in our laboratory.

In this paper, a typical scenario with a WSN communicating in a noisy environment is assumed. Because CRSN nodes transmit on ISM bands coexisting with Wi-Fi or Bluetooth devices, we consider a scenario where multiple wireless technologies communicate simultaneously. This scenario is very common due to the growth of consumer electronics (such as laptops, tablets and smartphones) that communicate over these technologies. 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 in 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). According to their formal definition, PUs are the "owners" of the spectrum band and have the right to communicate without restrictions, while SUs can use the spectrum if they do not disturb PUs. In this scenario no distinction shall be made between them given that CRSNs operate on unlicensed bands. Moreover, the strategy can be applied for every network node improving their energy consumption in any case.

4. COLLABORATIVE GAME THEORY-BASED STRATEGY.

As mentioned before, constrained resources are an intrinsic challenge related to CRSNs. Applying cognitive techniques to sensor networks both increases the needs of computer capabilities and the energy consumption of the nodes. Given that these capacities are limited, it is necessary to design simple and lightweight optimization strategies adapted to low-resources networks.

Among the different possibilities offered by applying cognitive radio to WSNs, in this work the selection of the transmission channel has been chosen. An improper selection of the transmission channel produces an extra consumption due to the retransmission of packets and the loss of Quality of Service (QoS) due to delays, packet losses, etc. Thus, based on the ability to sense the spectrum and change the transmission parameters, a strategy for reducing energy consumption is presented. This strategy is also based on collaboration among nodes for information sharing and decision making.

As shown in Section 2, game theory is widely accepted for resource optimization in CRSNs. In addition, games can be simplified enough without losing functionality to make them suited to be run on WSN nodes, even if their processing capability is limited.

A. Game model

In game theory, a game is defined by different characteristics: the *resource* modeled, the *players* taking actions and their *strategies*. Based on these actors, the scenario and the feasible actions *payoffs* or associated *costs* can be defined.

In this approach, the game will be a finite resource game taking the energy available in the nodes as the *resource* to be modeled. The *players* are all of the individual CRSN nodes, and the *strategies* are related to the selection of the transmission channel. Specifically, the actions each player can take are either changing to a specific channel or remaining in the same transmission channel. This *action* can arise from themselves or after a *move* -request- from another *player*. This decision will be taken depending on the *player* that makes the request, the state of the spectrum and the history. *Payoffs*. in this model *costs*, are the energy expenses incurred by each *player* based on their *actions* and those of the other *players*.

A summary of the notations used in the modeling of the game can be seen in Table 1.

Although it is mentioned that this game is collaborative, it is necessary to clarify that the collaboration is carried out during the game, but the decisions about the actions are taken by the nodes selfishly. That is, the nodes collaborate by sharing spectrum-sensing information to try to improve their overall performance, but the decision of each node about the channel change depends only on its own costs. It is not a cooperative game.

Following game theory terminology, this game can be described as a non-zero-sum game, since there is no correlation between a player's payoffs and the losses of the rest of the players. In fact, there may be actions hat minimize the losses of every player. It is a sequential game in which actions are taken one after the other. When actions are taken, players know in which game round they are playing and some information about the decisions of other players. The game is asymmetrical because the costs are not the same for every player. Specifically, they depend on the location of the player (different influence of noise in different areas) and the data rate. Finally, we can say that it is an evolutionary game, since players can adapt and evolve according to the information exchanged.

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

The payoff matrix for the communication between player n_i and player n_j is shown in Table 2:

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 to 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:

$$C_{ch} = C_{sensing} + (C_{tx} + C_{rx}) \times n_{msg}$$

C_o is the energy cost of transmitting in noisy channels. It is calculated as the cost of a packet transmission taking into account that it requires a number of *n_rtx* retransmissions. The value of *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* (configurable) messages.

$$C_o = C_{tx} \times n\_rtx$$

C_n, is the energy cost associated to communicating in a channel not shared with the receiver. Even though this situation is not very common, it could happen if several CRSNs perform the strategy without an agreement. C_n, is calculated as the cost of transmitting when the number of retransmissions has run out and consequently the allowed maximum has been reached (*max_rtx*).

$$C_n = C_{tx} \times \max\ \_rtx$$

It is important to note that the values of these associated costs are variable over time due to the network context, so they must be calculated in dynamically. The variation of these values makes the game evolve.

Once the costs associated with the communication between two nodes are calculated, it is necessary to weigh the costs associated with the number of messages exchanged between the different network nodes. This information can be collected from the application directly or through history values. This way, a node should be more influenced by the nodes with which it communicates the most.

For a formal analysis of the game, we will rely on two important concepts in game theory: the Nash equilibrium and the Pareto optimality. Nash equilibrium is a strategy profile, where each player’s action is the Best possible Response taking into account the other players' actions at that moment. The Best Response (BR) can be defined as the action of a player that maximizes its utility taking into account the actions of the others.

Carrying out a formal analysis of Nash equilibrium in the proposed game, and taking into account that every cost is a negative value, it is possible to confirm that the pairs of actions belonging to the best response correspond to those found on the diagonal of the Table 2; that is, the cases when both nodes takes the same action.

Pareto optimality is a measure of efficiency. An outcome of a game is Pareto optimal if there is no other outcome that makes every player at least as well off and at least one player strictly better off. Looking at the proposed game, Pareto optimals match the Nash equilibrium pairs. Depending on the values of C_o and C_{ch} the Pareto optimality would be one pair or other.

Due to its sequential nature, a representation of the game in extensive form can be better suited. An extensive game is defined by:

$$Game = (N, A, H, Z, \chi, \rho, \sigma, \mathrm{u})$$

Where:

$N = \{n_1, n_2, n_3 \dots n_i\}$

$A = \{a_1, a_2, a_3 \dots a_i\}$

$H = \{h_1, h_2, h_3 \dots h_i\}$

$Z = \{z_1, z_2, z_3 \dots z_i\} \quad Z \neq H$

$\rho = \{\rho_{H1}, \rho_{H2}, \rho_{H3} \dots \rho_{Hi}\} \qquad \forall\, h \in H \quad \rho_{Hi} = \{n_i, n_j \dots n_k\}$

$\chi = \{\chi_{H1}, \chi_{H2}, \chi_{H3} \dots \chi_{Hi}\} \qquad \forall\, h \in H \quad \chi_{Hi} = \{a_i, a_j \dots a_k\}$

$\sigma(h_i, a_j) = h_k \ or \ z_k$

$\forall\, h_1, h_2 \in H;\ \forall\, a_1, a_2 \in A; \quad if \ \ \sigma(h_1, a_1) = \sigma(h_2, a_2) \implies h_1 = h_2 \ and \ a_1 = a_2$

There is only one possible path to get to h_k or z_k. Decision and final rounds form a tree.

$u = \{u_{Z1}, u_{Z2}, u_{Z3} \dots u_{Zi}\} \qquad Z \to \mathbb{R}$

The extensive form representation can be seen in Figure 1.

Analyzing the Nash equilibrium and the Pareto optimality in this extensive representation form, it is possible to confirm that they are the same pairs. In the notation of the

Figure 1, the Nash equilibrium corresponds to values u_{Z1}, u_{Z8}, u_{Z2} and u_{Z4}. Pareto optimality are those for u_{Z1} and u_{Z2}.

B. Description of the strategy

The collaborative strategy proposed in this paper is explained below. When designing an energy optimization strategy, the first step is to decide when to trigger the optimization algorithm. It is 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 has a certain amount of noise. The optimization is triggered when Received Signal Strength Indicator (RSSI) level detected in the communication channel exceeds a configurable threshold. This measure is related to the presence of noise in the channel.

Considering the Nash equilibrium and Pareto optimality formally obtained in section A, it could be expect that players take actions that lead to stabilize the game in one of the pairs obtained.

The collaborative strategy is executed as follows:

- Each CRSN node $\{n_1, n_2, n_3 \dots n_i\}$ receives and transmits its messages through the assigned channel normally. When a message arrives, the receiving node saves its associated RSSI sample.

- When the RSSI values stored in n_i surpass a certain threshold (some extra samples are taken in order to avoid false measurements), the node n_i activates the optimization algorithm.

- The node n_i enters into sensing state, saves the RSSI values of every available channel and determines the less noisy channel.

- The node n_i communicates the sensed information and the chosen channel to the rest of the CRSN nodes.

- The rest of nodes n_{-i} receive the request for changing the channel and the preference for which channel to change to. Each n_{-i} node evaluates the costs associated to each action and decides whether or not to change the channel depending on its payoff function. This decision will be communicated to the other nodes in the network.

- If the evaluation results in a change of the communication channel, this n_{-i} enters into sensing state and checks if the preferred channel is its best option. If it is not, n_{-i} responds with its own sensed spectrum information.

- After receiving the n_{-i} responses, n_i evaluates the sensed information received. If the preferred channels do not match, n_i weighs its payoff function according to the message exchanges.

- Every node informs the rest of the CRSN nodes about the final decision taken.

Although in this work every node can sense the spectrum, this approach can be adapted to any type of sensing strategy depending on the network features. To demonstrate the validity of this algorithm, every node in the CRSN senses the spectrum, which constitutes the worst case in terms of energy consumption. However, new collaborative techniques or distributed sensed information can be included taking into account the location of the nodes.

5. RESULTS AND DISCUSSION

In this section results of different experiments are presented in order to validate the proposed strategy. First the simulation tool used to perform them is presented. The basic scenario used as a reference and the different parameters modifications are exposed. Finally the achieved results are presented and discussed.

A. Simulation Tools

In this work the architecture of the Cognitivity Brokerage framework [20] is used. The framework used in the simulation is composed of two fundamental elements: a CRSN simulator and low power Cognitive Radio real devices. This framework [21] has been tested and referenced in previous works. Both the simulator (based on Castalia) and the real nodes implement the mentioned Cognitivity Brokerage architecture.

The structure of the 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, through which 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 just used to confirm, these results for small-scale networks as an empirical test. Therefore, all the results presented in this paper are extracted from the simulator.

B. Cognitive baseline scenario

The simulated scenario is composed by 100 CRSN nodes deployed in a 60x60 m area simulating a monitoring application installed in a building in an urban area. These nodes communicate following the IEEE 802.15.4 standard.

The 100 CRSN nodes include one network coordinator, 4 routers and 95 end devices (environment monitoring sensors). The total simulation area is divided into four equal regions. The coordinator and the routers positions are fixed, the coordinator in the center of the square, and each router in the center of each region. The end devices are uniformly deployed in each region.

In these simulations two coexisting networks are communicating, a CRSN and a Wi-Fi network. The baseline scenario has 4 Wi-Fi access points and 100 Wi-Fi devices (such as handheld devices). Access points are located in the center of each region, like the CRSN routers, and Wi-Fi devices are randomly deployed following a uniform distribution.

End devices transmit WSN packets of 50 bytes at -5 dBm to their region router. Routers send ACK messages after a sensor data reception and also notify the network coordinator time it collects 10 measurements from each sensor node.

The Wi-Fi network transmits Wi-Fi packets of 200 to 2000 bytes at -3 dBm. It is interesting to check the behavior by varying the noise level so a simulation for this is included. Both networks operate on the 2.4 GHz ISM band. A maximum number of 20 retransmissions are set for the CRSN and the Wi-Fi nodes in the scenario.

CRSN nodes are modeled by a Texas Instrument CC2420 transceiver. The values of energy consumption are extracted from its datasheet (for transmission, reception, idle modes and energy costs of transitions between modes) and verified through experimental measurement. The sensing stage is modeled as a reception mode lasting for 200 ms.

For the baseline scenario, a RSSI threshold of -150 dBm averaging 5 samples is assumed.

In order to facilitate simulations of different configurations, simulation time is 100 s, and network rates of 1 packet per second on CRSNs and 2000 packets per second on Wi-Fi are chosen. In order to simulate new Wi-Fi configurations or the appearance of new Wi-Fi networks or nodes in the area, the simulated Wi-Fi nodes change their communication channel every 10 s.

To validate this assumption, a long term simulation is performed (simulation time 1000s, 0.1 packet per second for CRSNs and 200 packets per second for Wi-Fi communication) showing similar results to those presented in the paper even if the rates sounds too high for the typical CRSN scenario.

In all the results presented, figures show the energy consumption in accumulated Joules over time. For a real reference, the typical 2AA batteries for CRSN nodes have a total energy of 18,000 J. The results show the energy consumption of both a router and an end device.

C. *Results and discussion*

In this section the results of different simulations are discussed. Even if the simulations do not last as long as the battery life, an energy consumption reduction can be appreciated .

In order to test the performance of the proposed strategy, it is compared with a previous work presented in [22]. This previous strategy is also conceived to improve energy consumption and is also based in game theory. However, there is no collaboration among the nodes. Nodes base their decision of changing or not the communication channel in an independent way, without taking into account the response or the spectrum-sensing information of the rest of the network nodes. This previous work will be marked as noCollab in the graphs and the new strategy presented in Section 4 will be named collabGTh. It has been proven that the previous strategy does not depend on the threshold values for the RSSI or the number of samples taken into account.

Figure 2 compares the performance of these two strategies for the end devices in the baseline scenario with a spatial uniform noise scheme (every Wi-Fi device communicating in the same channel) with two different rates (2000 bytes/s and 200 bytes/s).

Figure 3 compares the performance of these two strategies for end devices with another noise scheme. In this case, the 4 Wi-Fi access points communicate in different channels. That means that there are 4 different channels occupied by Wi-Fi communications.

In both cases the Wi-Fi channels change every 10 seconds.

In both figures, we can see that the results are quite similar for each strategy, independently of the noise level. It is important to observe the improvement in the energy consumption of the nodes which use the new collaborative approach.

In the case of the uniform noise, we can see that the energy consumption of both algorithms is lower than the case with different regions. However, the adaptation of the new strategy to the noise in different regions gives results similar to the case with uniform noise. Therefore we can say that the new collaborative strategy perform equally in more difficult scenarios where the previous strategy fails.

Next, we present in Figure 4 the results obtained for the routers, but only for the case where the noise is 200 bytes/s, because the variation caused by the level of noise is not very significant.

In this case, routers implementing the not collaborative approach are not able to adapt to the changing channel because find a free channel without collaboration it is quite improbable. The routers performance is much more damaged than those of end devices because their data rate is higher than that of the end devices (routers send ACK messages to each end device after a received measurement). The router results confirm that both noise patterns have a similar effect in the case of the collaborative algorithm.

The new collaborative strategy provides energy consumption savings of around 50% compared to the no collaborative strategy in the worst case (with different noise schemes in each region).

To verify the performance of the algorithm with different noise patterns (even more stable), the results shown in Figure 5 and Figure 6 represent scenarios where the Wi-Fi noise stays in the same channel for the whole simulation.

In both cases the difference in consumption between the different scenarios is barely noticeable, so we can ensure that the proposed collaborative strategy can be stabilized with different noise patterns.

Finally, it is desirable to evaluate the energy cost of performing this strategy even in a scenario without noise. To simulate this behavior, the same CRSN is deployed without introducing the Wi-Fi nodes. The results are shown in Figure 7.

As shown in the Figure 7, the energy cost is even lower. This is because CRSN nodes can interfere with the communications in their own network. The new collaborative strategy is able to adapt its transmission channel to decrease the noise level perceived by the other nodes of the network with which it does not communicate. This is possible thanks to the weighing done in the utility function calculation, which takes into account the messages exchanged between nodes. .

6. CONCLUSIONS

WSNs have historically been a paradigm with numerous problems related to energy consumption due to their intrinsic characteristics. Taking advantage of new cognitive capabilities introduced in WSNs (such as channel selection) can have a possitive effect on energy consumption. These new opportunities introduced by CRSNs unveil a wide field in the energy consumption research area However, this also implies some challenges.

In this paper, a new strategy based on game theory and collaboration for reducing energy consumption in CRSNs has been presented. This is a lightweight optimization algorithm that can be implemented in CRSNs although the computing resources of their nodes are limited. The optimization of this strategy relies on the modeled utility function. A formal analysis of the game has been conducted obtaining a convergence to a pair of values coincident with the Nash equilibrium and the Pareto optimal.

The developed algorithm has been tested and compared with a previous work in the area on a Castalia-based framework adapted to incorporate cognitive capabilities. As seen in the results section, the algorithm shows improvement rates of over 50% compared to the previous non-collaborative game theory algorithm.

It can also be seen that the algorithm behaves similarly even with significant variations in the level of noise. Likewise, the results of every node in the network independently of their role (both routers and end devices) are improved.

The strategy has also been validated in different noise scenarios. The strategy has been proved useful both for scenarios in which the noise stays in the same channel and for those in which the noise patterns change. Moreover, the spatial distribution of noise has also changed from a uniform noise in the whole area to multiple noisy zones in different channels. Also in the simulations performed in the absence of noise, the strategy presented has shown better results than the previous one. These data also provide an idea of the lightness of the designed strategy.

Even if the results for this optimizing respond to what logically might be expected, have a formal model and a systematization for decisions taken is an important step forward to improve energy efficiency.

Reducing energy consumption in CRSNs is an interesting field with abundant opportunities. CRSNs introduce new features to take advantage of but also new challenges to address.

7. ACKNOWLEDGEMENTS

This work was funded by the Spanish Ministry of Economy and Competitiveness under INNPACTO program (Reference grant SETH; IPT-2012-0703-380000)

8. BIBLIOGRAPHY

[1] G. Anastasi, M. Conti, M. Di Francesco, and A. Passarella, Energy conservation in wireless sensor networks: A survey in. Ad Hoc Networks. Volume 7 Issue 3, Pages 537-568. May 2009. DOI: 10.1016/j.adhoc.2008.06.003 URL: http://dx.doi.org/10.1016/j.adhoc.2008.06.003

[2] Cisco Systems Inc. Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2012–2017, White Paper, Feb. 2013. URL: http://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white_paper_c11-520862.pdf

[3] A.S. Zahmati, S. Hussain, X. Fernando, A. Grami, Cognitive Wireless Sensor Networks: Emerging Topics and Recent Challenges in. Proceedings of IEEE Toronto International Conference Science and Technology for Humanity (TIC-STH), 2009. pp 593–596. DOI: 10.1109/TIC-STH.2009.5444432. URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5444432&isnumber=5444349

[4] O.B. Akan, O. Karli; O. Ergul, Cognitive radio sensor networks in IEEE Network, vol.23, no.4, pp.34-40, July-August 2009. DOI: 10.1109/MNET.2009.5191144 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5191144&isnumber=5191135

[5] M.C. Oto, O.B. Akan. Energy-efficient packet size optimization for cognitive radio sensor networks.in IEEE Transaction on. Wireless Communication vol 11 pp.:1544–1553. 2012. DOI: 10.1109/TWC.2012.021412.021512.111398 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6155553&isnumber=6183384

[6] P. Spachos, P. Chatzimisios, D. Hatzinakos, Energy Efficient Cognitive Unicast Routing for Wireless Sensor Networks in IEEE 77th , Vehicular Technology Conference (VTC Spring), 2013 pp.1-5, 2-5 June 2013 DOI:: 10.1109/VTCSpring.2013.6692539 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6692539&isnumber=6691801

[7] X. Li; D. Wang; J. McNair; J. Chen, Residual energy aware channel assignment in cognitive radio sensor networks in Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC '11), pp. 398–403, March 2011. DOI: 10.1109/WCNC.2011.5779196 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5779196&isnumber=5779102

[8] S. Maleki, A. Pandharipande, G. Leus, Energy-Efficient Distributed Spectrum Sensing for Cognitive Sensor Networks, in IEEE Sensors Journal, vol.11, no.3, pp.565-573, March 2011 DOI: 10.1109/JSEN.2010.2051327 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5483151&isnumber=5697312

[9] S. Izumi, K. Tsuruda, T. Takeuchi, L.E.E. Hyeokjong, H. Kawaguchi, M. Yoshimoto A Low-Power Multi Resolution Spectrum Sensing (MRSS) Architecture for a Wireless Sensor Network with Cognitive Radio in Fourth International Conference on Sensor Technologies and Applications (SENSORCOMM), 2010, pp.39-44, July 2010 DOI:

10.1109/SENSORCOMM.2010.13. URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5558046&isnumber=5558025.

[10] L. Stabellini, J. Zander. Energy-Aware Spectrum Sensing in Cognitive Wireless Sensor Networks: a Cross Layer Approach in Proceedings of IEEE Wireless Communications and Networking Conference WCNC pp.1-6, April 2010, DOI: 10.1109/WCNC.2010.5506383 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5506383&isnumber=5506094.

[11] B. Chai, R. Deng; P. Cheng; J. Chen, Energy-efficient power allocation in cognitive sensor networks: A game theoretic approach, in IEEE Global Communications Conference (GLOBECOM), pp.416-421, Dec. 2012 DOI: 10.1109/GLOCOM.2012.6503148 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6503148&isnumber=6503052

[12] G. Gür and Fatih Alagöz. Green Wireless Communications via Cognitive Dimension: An Overview. in IEEE Networks. 2011 vol. 25 no. 2 pp: 50–56, DOI: 10.1109/MNET.2011.5730528 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5730528&isnumber=5730517

[13] H. Y. Shi, W. L. Wang, N. M. Kwok and S. Y. Chen, Game Theory for Wireless Sensor Networks: A Survey in . Sensors. Vol 12. Issue 7. 2012. DOI:10.3390/s120709055, URL: http://www.mdpi.com/1424-8220/12/7/9055

[14] B. Wang, Y. Wu, K.J. Ray Liu. Game theory for cognitive radio networks: An overview in Elsevier Computer Networks. vol. 54, no. 14, pp. 2537–2561. April 2010, DOI: 10.1016/j.comnet.2010.04.004, URL: http://dx.doi.org/10.1016/j.comnet.2010.04.004

[15] R. Trestian, O. Ormand, G.-M. Muntean, Game theory-based network selection: solutions and challenges, in IEEE Communications Survey & Tutorials, vol. 14, no. 4, pp. 1212-1231, 2012, DOI: 10.1109/SURV.2012.010912.00081 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6144681&isnumber=6341161

[16] Y. Xiao, K-C. Chen, C. Yuen, DaSilva, L.A, Spectrum sharing for device-to device communications in cellular networks: A game theoretic approach, in IEEE International Symposium on Dynamic Spectrum Access Networks (DYSPAN), 2014, pp.60-71, April 2014, DOI: 10.1109/DySPAN.2014.6817780 URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6817780&isnumber=6817768

[17] E. Del Re, R. Pucci,L. Simone Ronga, Energy Efficient Non-Cooperative Methods for Resource Allocation in Cognitive Radio Networks in Communications and Network. Vol. 4, pp. 1-7. 2012, DOI:10.4236/cn.2012.41001 URL: http://dx.doi.org/10.4236/cn.2012.41001

[18] G.P. Joshi, S.Y. Nam, S.W. Kim., Cognitive Radio Wireless Sensor Networks: Applications, Challenges and Research Trends in Sensors 2013, no. 9, pp. 11196-11228, DOI:10.3390/s130911196, URL: http://www.mdpi.com/1424-8220/13/9/11196

[19] CC2530 Datasheet. Texas Instruments. http://www.ti.com/lit/ds/symlink/cc2530.pdf (Accessed September 2014).

[20] J. Rabaey, A. Wolisz, A. Ercan, A. Araujo, F. Burghardt, S. Mustafa, A. Parsa, S. Pollin, I. Wang, P. Malagon, Connectivity Brokerage - Enabling Seamless Cooperation in Wireless Networks (A White Paper)., October, 2010, URL: http://www.tkn.tu-berlin.de/fileadmin/fg112/Papers/papers_all/rabaey10connectivity_brokerage_enabling.pdf.

[21] A. Araujo, E. Romero, J. Blesa, O. Nieto-Taladriz. A Framework for the Design, Development and Evaluation of Cognitive Wireless Sensor Networks in. International

Journal on Advances in Telecommunications, vol 5 no 3 & 4, 2012, URL: http://www.iariajournals.org/telecommunications/tele_v5_n34_2012_paged.pdf

[22] E. Romero, J. Blesa, A. Araujo, O. Nieto-Taladriz, A Game Theory Based Strategy for Reducing Energy Consumption in Cognitive WSN, in International Journal of Distributed Sensor Networks, vol. 2014, Article ID 965495, 9 pages, 2014. DOI:10.1155/2014/965495 URL: http://dx.doi.org/10.1155/2014/965495

Table 1. Notations used in the model.

Symbol	Description
C	Cost associated to a player taking an action.
C_o	Cost of transmitting in noisy channels.
C_n	Cost of communications in a channel not shared with the receiver.
C_{ch}	Cost associated with a change of the communication channel.
$C_{sensing}$	Cost associated with sensing tasks.
C_{tx}	Cost of transmitting one packet.
C_{rx}	Cost of receiving one packet.
n_rtx	Number of retransmissions in the history for this channel.
max_rtx	Maximum number of retransmissions allowed by a node.
n_{msg}	Number of needed messages to communicate a channel change.
N	Nodes (players). Each CRSN node.
A	Actions. Set of actions CRSN nodes can take.
H	Decisions rounds. At this point actions must be performed by some nodes.
Z	Final round. End of the iteration.
ρ	Players function. Assigns which players take actions in each round.
χ	Action function. Assigns which actions can be taken in each round.
σ	Next step function. This function assigns each pair (h,a) to a new h or z.
u	Utility function.

Table 2. Matrix representation of the game

Pi,j	Not change	Channel 1	Channel 2	…	Channel n
Not	C_o, C_o	$C_n, C_{ch} + C_n$	$C_n, C_{ch} + C_n$	$C_n, C_{ch} + C_n$	$C_n, C_{ch} + C_n$
Channel 1	$C_{ch} + C_n, C_n$	C_{ch}, C_{ch}	$C_{ch}+ C_n, C_{ch} + C_n$	$C_{ch}+ C_n, C_{ch} + C_n$	$C_{ch}+ C_n, C_{ch} + C_n$
Channel 2	$C_{ch} + C_n, C_n$	$C_{ch}+ C_n, C_{ch} + C_n$	C_{ch}, C_{ch}	$C_{ch}+ C_n, C_{ch} + C_n$	$C_{ch}+ C_n, C_{ch} + C_n$
…	$C_{ch} + C_n, C_n$	$C_{ch}+ C_n, C_{ch} + C_n$	$C_{ch}+ C_n, C_{ch} + C_n$	C_{ch},C_{ch}	$C_{ch}+ C_n, C_{ch} + C_n$
Channel n	$C_{ch} + C_n, C_n$	$C_{ch}+ C_n, C_{ch} + C_n$	$C_{ch}+ C_n, C_{ch} + C_n$	$C_{ch}+ C_n, C_{ch} + C_n$	C_{ch}, C_{ch}

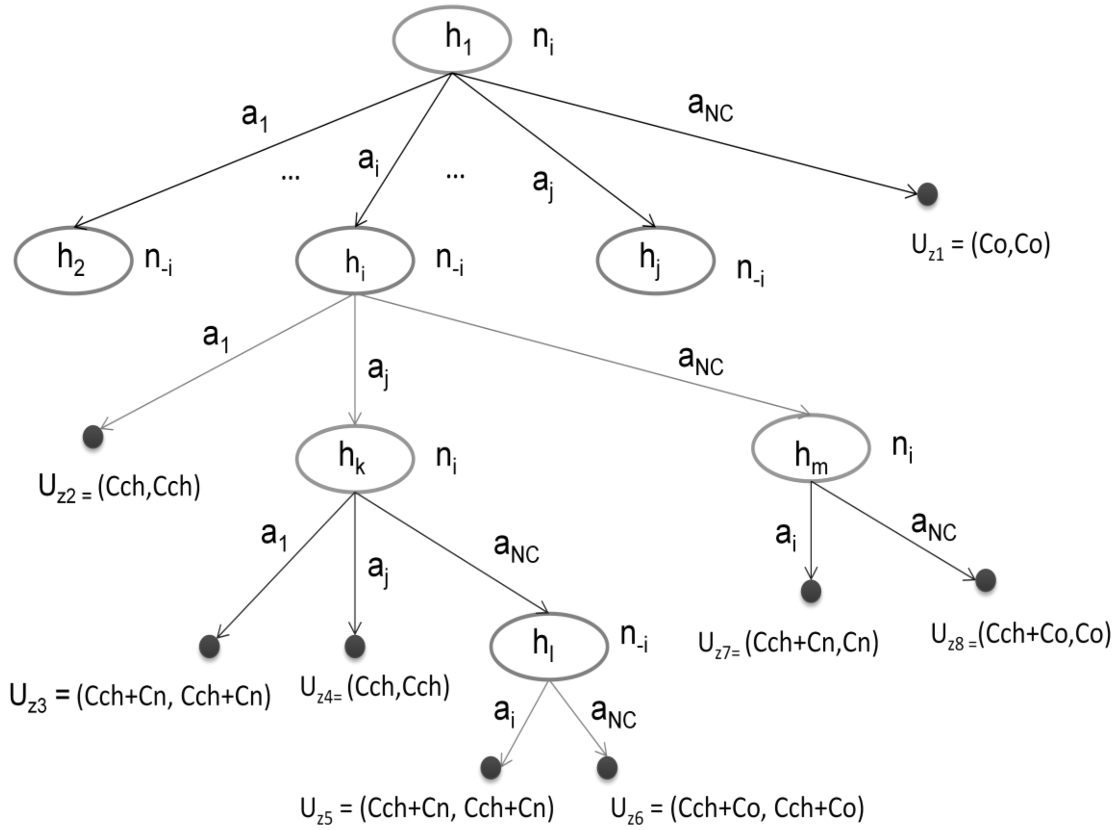

Figure 1. Extensive form representation of the game.

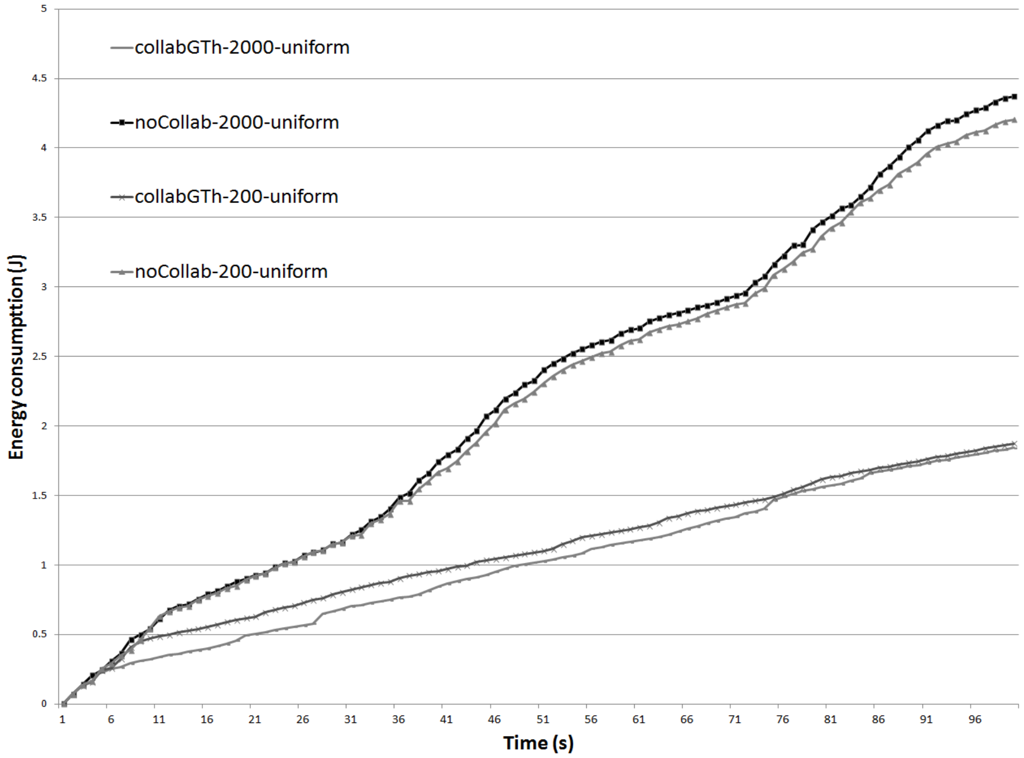

Figure 2. Baseline scenario in a uniform noisy scheme (end device).

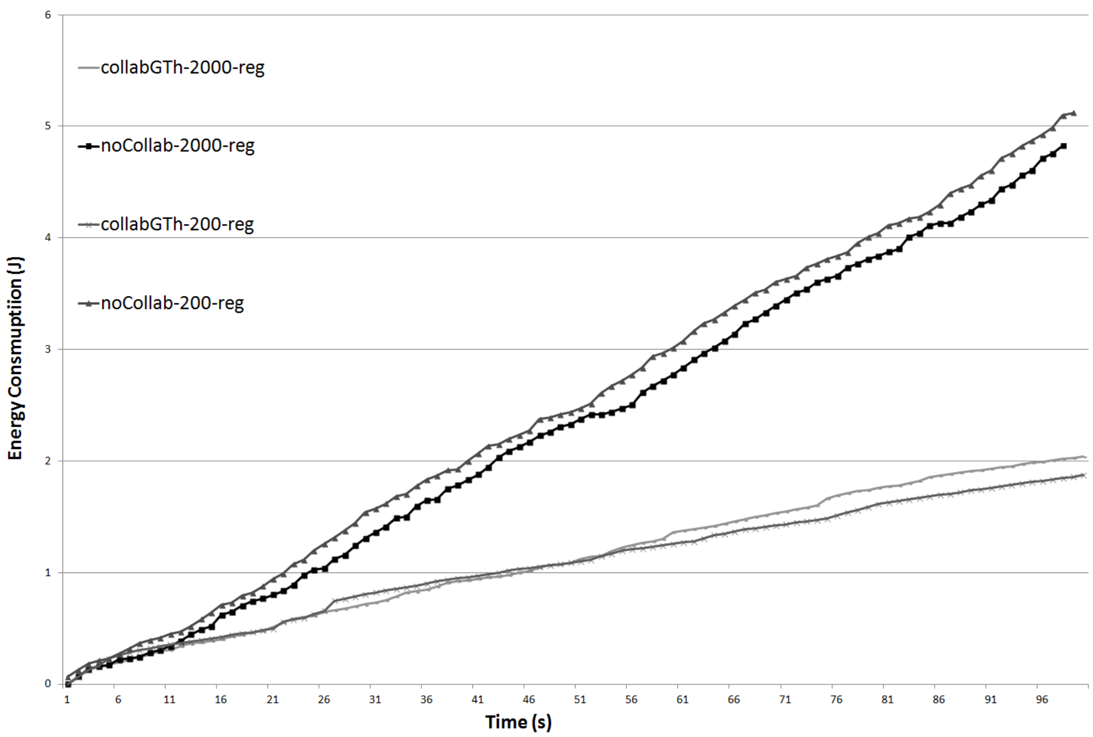

Figure 3. Baseline scenario in a not uniform noisy scheme (different in regions) (end device)

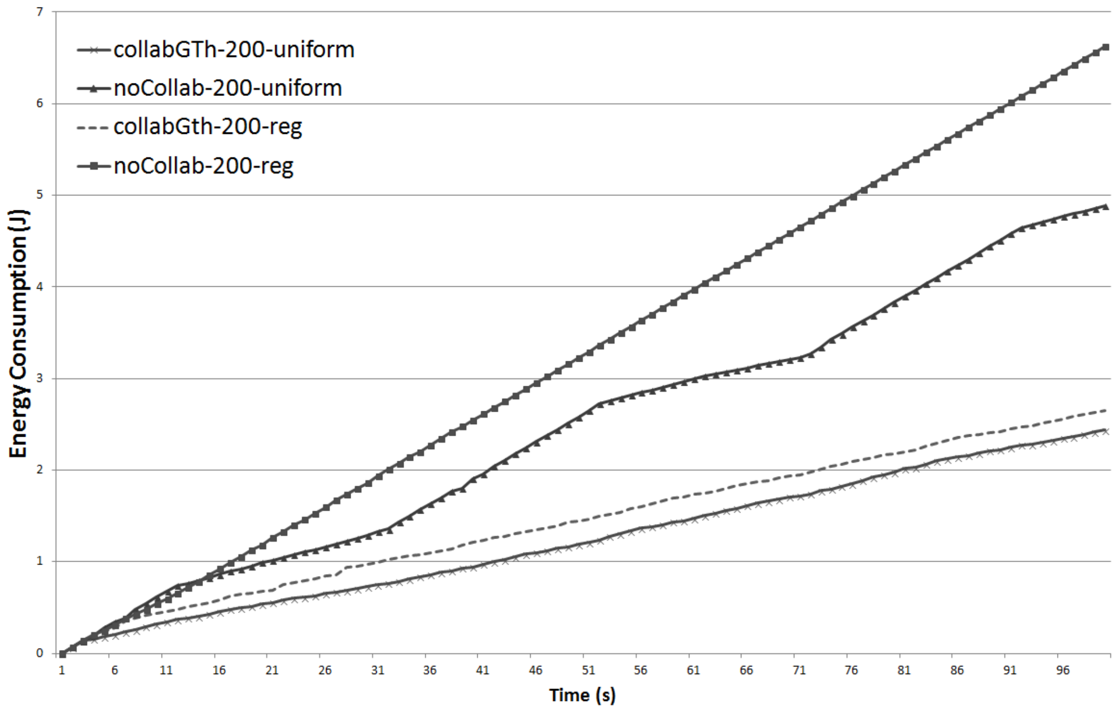

Figure 4: Baseline scenario in different noisy scheme (router)

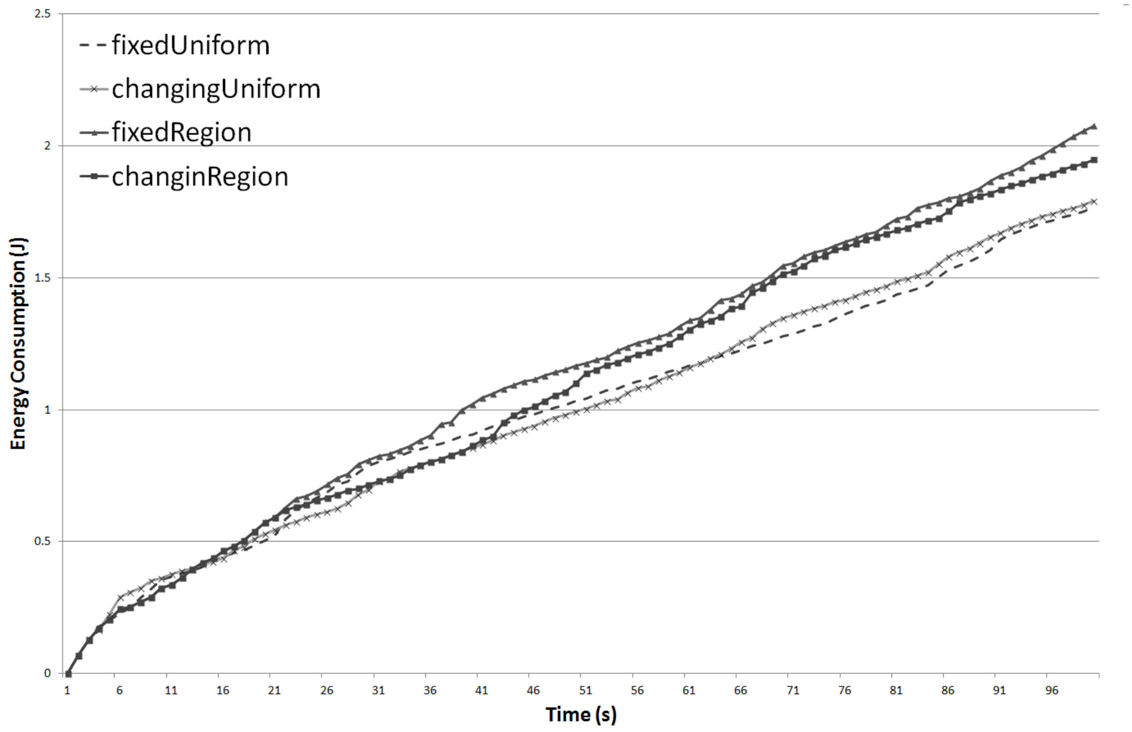

Figure 5. Collaborative strategy performance under different noise schemes (end device)

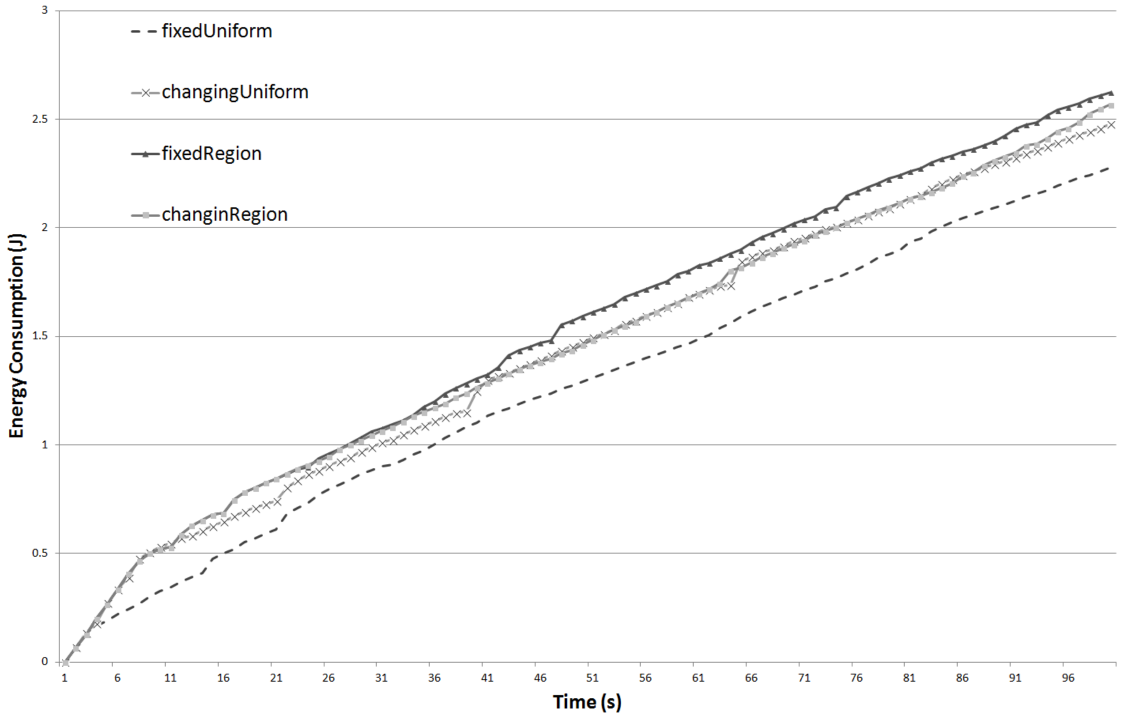

Figure 6. Collaborative strategy performance under different noise schemes (router)

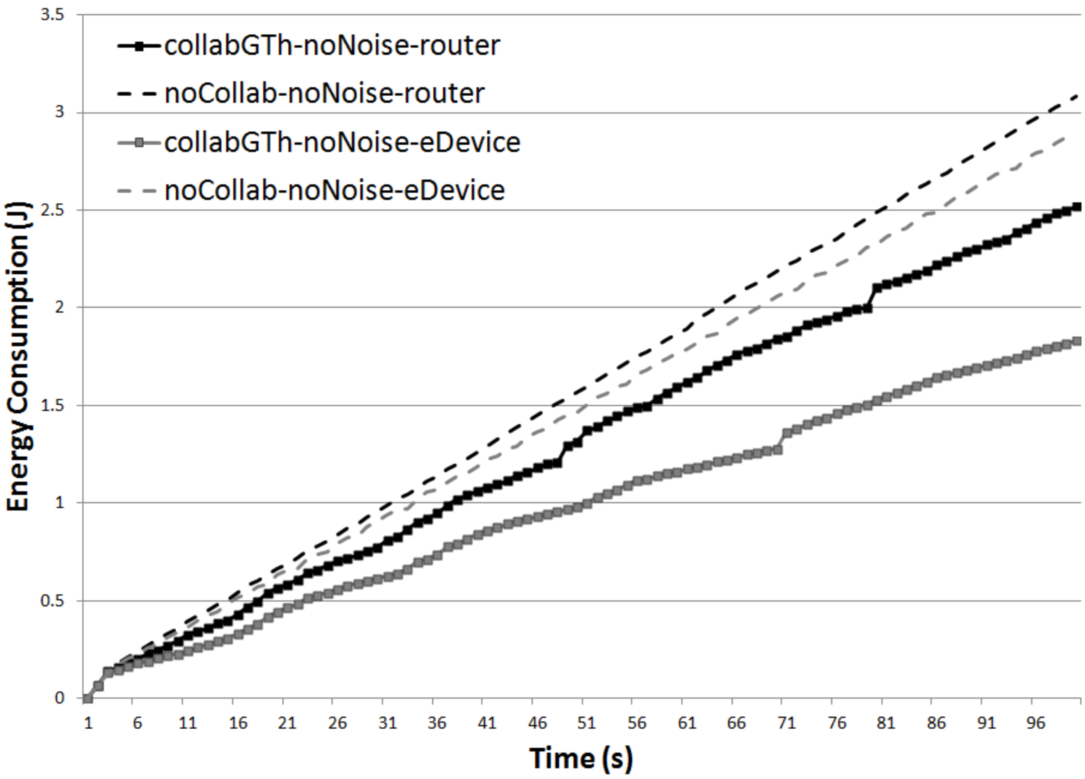

Figure 7. Comparison in a noise-free environment.