CLUSTERING AND BEAMFORMING FOR EFFICIENT COMUNICATION IN WIRELESS SENSOR NETWORKS

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ABSTRACT- Energy efficiency is a critical issue for the in Wireless Sensor Networks (WSNs) as sensor nodes have limited power availability. In order to address this issue, this paper tries to maximize the power efficiency in WSN by means of the evaluation of WSN node networks and their performance when both clustering and antenna beamforming techniques are applied. In this work, four different scenarios are defined depending on the number of WNS sensors considered: 20, 10, 5 and 2 nodes per scenario, and each scenario is randomly generated ten times in order to statistically validate the results. For each experiment, four different target directions for transmission are taken into consideration in the optimization process (phi=0º and theta=45º; phi=0º and theta=75º; phi=45º and theta=45º; phi=45º and theta=75º). Each scenario is evaluated for two different types of antennas, an ideal isotropic antenna and a conventional dipole one. Up to the authors' knowledge, it is the first time that beamforming and clustering have been simultaneously applied to increase the network performance in WSN. The analyzed cases in this document are focused on defining a fixed power for each node, static nodes (no movement after the random scenario generation), and 2D surface for the node location.

Keywords: Wireless Sensors Networks; Energy efficiency; Beamforming, Optimization techniques.

1. Introduction.

The next generation 5G wireless communications are currently being developed [1] [2]. Indeed, the first deployments of a 5G network are expected to be fully operating in 2020 [3]. The design goals of such systems are shown in Fig. 1. These system are conceived to provide very high data rates (typically of Gbps order), extremely low latency, manifold increase in base station capacity and significant improvement in users' perceived Quality of Service (QoS), compared to current 4G LTE networks [4]. There are many innovative technologies that will be used to satisfy the demands of massive volume of traffic and various devices: massive MIMO, orthogonal frequency-division multiple access (OFDMA), cloud radio access network (CRAN), software-defined networking (SDN), composite wireless infrastructures, flexible spectrum management, small cells, and heterogeneous network deployment, among others [5].

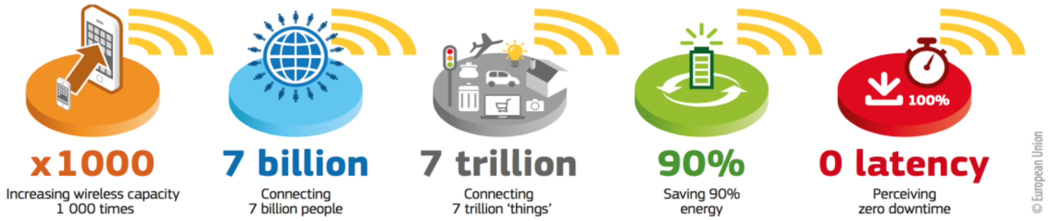

Fig. 1. Design goals and requirements for 5G networks. (from [3])

The research initiatives by industry and academia have identified eight major requirements [1] of the next generation 5G systems, being "the reduction in energy usage by almost 90%" one of them. Green technologies are thus being considered in the standard bodies. As a consequence, energy efficiency is therefore a key issue for the design of these networks [6]. Efficiency, in general, and energy consumption in particular, does clearly involve any sort of optimization. The required technologies for the developing of 5G systems as well as the application scenarios are quite numerous. One of the most potential cases of use of 5G [4] is the Wireless Sensor Networks. The expected number of connected "things" (IoT: Internet of Things) will be 7 trillion [3]. Therefore, it is clear that energy preservation for WSN is an issue of great concern in what related to network design and deployment, protocols and configurations, trying to maximize the performance of the nodes.

One option is to reduce the energy consumption by optimizing the way the wireless communications take place. The problem has to do with the air interface (the radio signals) and how the radiation pattern (beam) is set up to reach the desired QoS with minimal energy consumption. The technique that enables this energy-efficient wireless communications is beamforming [7], which consists of several coordinated antennas radiating jointly to generate a directive beam for covering a given area with a very accurate precision. The goal is to reduce the energy consumption of the sensors by performing collaborative beamforming. This is a very important problem as the sensor nodes have limited power, and saving energy is critical. In this paper, the objective is to show that beamforming can be used in the context of WSNs to perform energy efficient communications, allowing the lifetime of this kind of distributed infrastructure to be steadily increased. To the best of our knowledge, this is the first approach in which the gain of the beamforming is accurately computed, in relation to the number of nodes, organized in different clusters in the WSN.

The paper is organized as follows. Section 2 describes the beamforming model used for WSN. Section 3 shows the optimization algorithm. Section 4 provides the results and an analysis and discussion of the results obtained. The conclusions are outlined in Section 5.

2. Collaborative Beamforming in WSN.

WSNs usually have the nodes arbitrarily located in a defined area. In many cases, this distribution is a random one. This has influence in the data transmission when considering collaborative nodes, not being easy to maximize the global transmission capacity of the network. In this context, beamforming has arisen as a good strategy in WSN for the complete system optimization in terms of energy efficiency and network capacity and reliability. The first approaches on this are dated only a few years ago. In [8], the authors prove the existence of an optimum feeding configuration for each individual element of the network when trying to maximize the transmission gain in a desired space direction. Moreover, in the results in [9] it is stated that 80% of the network energy is saved when applying beamforming. In [10], the authors provide a theoretical proof of the gain improvement if beamforming is applied. In this work, we compute iteratively the beamforming in an array of sensors to calculate the possible gain improvement based on this approach[11-12]

2.A. Beamforming

The beamforming techniques are based on the definition of a highly directive pattern in a desired direction, depending on the network operation conditions and the network transmitting necessities. Based on it, it is necessary to consider the field of each individual element contributing constructively in the desired pattern directions and destructively in rest of them, even provoking transmission nulls in some critical directions. The general pattern is made of the aggregation of the elementary ones, and five variables define the antenna array that the nodes form. These variables can be classified into two different categories, which are the radiating element nature and the spatial location:

Radiating element:

1. The amplitude excitation of each unitary radiating element.
2. The phase excitation of each unitary radiating element.
3. The radiation pattern of each element, depending on the kind of antenna considered (dipole, slot, helix, patch array, bow tie, etc.).

Spatial location:

4. The separation among elements of the array, in terms of wavelength distance.
5. The antenna array geometry, which may be linear, circular, rectangular, or spherical, among other possibilities.

Considering classical array theory, the most convenient and affordable manner of placing the elements is a 1D line or 2D surface in which the elements are uniformly separated and with the same excitation in both amplitude and phase. This simple configuration let obtain a variation in the radiation direction when acting progressively over the phase of each element, preserving the Nyquist criterion which is related to the element separation (lower than half a wavelength). Unfortunately, this is not the case of WSN networks, whose nodes are distributed in space with distances that are much longer than a wavelength. However, there is still enough room to achieve benefits from applying beamforming, although it becomes a harder task to find the optimal configuration.

2.B. WSNs scenario model

The experimental setup considered in this work implies a random node deployment in a squared area. The node location is based on a uniform distribution in both 2D coordinates, with no movement once the nodes are settled down. This approach is widely used in the definition of WSN experimental scenarios, as it can be found in [7] or [8]. In this scenario, each node has a limited power autonomy, which must fulfil the operation requirements for both data transmitting to the HECN and environment sensing.

The nodes are also equipped with different antenna types providing different antenna patterns, as depicted in the preceding section. Although it is typically assumed that the total available power is the same at each sensor, the distribution of power devoted to sensing or to data transmission can be modelled to be diverse. In this work, it is assumed that the node consumption for each task is commanded by random uniformly distributed variable of value [0,1]. Thus, the available Energy at sensor *x* (*x = 1, 2,…, max_sensors*), Ea_x, is the following:

$$Ea_x = E_t * F_x \qquad (1)$$

where E_t is the total available sensor energy and F_x is the uniformly distributed variable described above. Additionally, the energy consumed by each sensor (Ec_x) is:

$$Ec_x = P_{tx\_x} * t_x \qquad (2)$$

where P_{tx_x} is the amount of power devoted to transmit the data in sensor *x* and t_x is the transmission time. Notice that the node consumption can be also expressed in terms of power. Thus, the available power, Pa_x, is provided by:

$$Pa_x = P_{tx\_x} * F_x \qquad (3)$$

As it can be noticed, the maximum lifetime, t_{life_x}, for the sensors as a whole is obtained when the energy consumption is equal to the available energy:

$$E_t * F_x = P_{tx\_x} * t_{life\_x} \qquad (4)$$

As a consequence, the lifetime of each sensor can be written as follow:

$$t_{\mathrm{life\_x}} = \frac{E_t * F_{\mathrm{x}}}{P_{tx\_\mathrm{x}}}; \tag{5}$$

At this point, it must be considered that P_{tx_x} is the power needed to transmit data without considering beamforming. However, when beamforming is applied, $P_{tx\_x,}$ which is related to the excitation in amplitude of each sensor is multiplied by a gain effect provided by the beamforming. This gain effect depends on the final radiation pattern and may induce gain in some directions and loss in others. Thus, the power to transmit data to the receptor is:

$$P_{tx\_\mathrm{x\_B\_A}} = P_{tx\_\mathrm{x}} * GB; \tag{6}$$

where $P_{tx\_x\_B\_A}$ is the excitation in amplitude of each sensor and GB is the global gain value at the different directions of transmission/reception. Thus, P_{tx_x} considering beamforming is:

$$P_{tx\_\mathrm{x}} = \frac{P_{tx\_\mathrm{x\_B\_A}}}{GB}; \tag{7}$$

Finally, the lifetime when adding beamforming, $t_{life\_x\_B}$, is:

$$t_{\mathrm{life\_x\_B}} = \frac{E_t * F_{\mathrm{x}} * \mathrm{GB}}{P_{tx\_\mathrm{x\_B\_A}}}; \tag{8}$$

The main interest in this work is focused on the maximization of the lifetime of the WSN as a whole, applying beamforming for the data transmission among the sensors. This is translated into a search of phase and amplitude configurations, $P_{tx\_x\_B}$, at each sensor that maximize the final outcome:

$$\max \{ t_{WSN} = min(t_{life\_x\_B}), \quad x \in [1,max\_sensors] \} \tag{9}$$

Notice that the lifetime of the WSN is fixed by the sensor that first runs out of battery.

2.C. Optimization algorithm

In order to address the problem defined above in Eq (9), a Genetic Algorithm (GA) has been adopted as the optimization algorithm because they have shown to perform quite well over a great variety of optimization problems [8]. GAs manage a pool of candidate solutions (the population), which represent tentative solutions of the target problem. In our case, these solutions are composed of the excitation (module and phase) of the sensors deployed in the WSN. The GA population is iteratively improved by using genetic operators (selection, recombination, and mutation) that follows the idea of “survival of the fittest”, i.e., new solutions are generated in each generation and replace worse solutions in the population. The process of iterating through successive generations is called evolution, and ends when a termination condition is fulfilled.

The GA included in the optimization toolbox of Matlab ® has been used. We want to note that we have not pay any attention to the parameterization of the GA, as it is not the goal of this paper to look for the best optimization algorithm for the problem addressed. Basically, the default configuration of this GA and rather standard settings are used: the population size has been set to 100; as genetic operators, Remainder selection, Heuristic crossover (with a probability of 0.8), and Uniform mutation (probability of 0.1); finally, the stopping condition is to perform 100 generations.

3. Results.

The radiation patterns and their gains when applying beamforming are computed with [13], a Matlab toolbox ®. Beamforming requires all the nodes in the cluster to be synchronized, and this issue takes time: the higher the cluster size is the longer the sync time needs to be. In this work we have fixed four different scenarios regarding the number of antennas implied: 20, 10, 5 and 2 nodes per scenario. Additionally each scenario is randomly generated ten times in order to statistically validate the results. For the scenarios of 20, 10 and 5 nodes, a transmission time of 40%, 30%, and 20% is used for synchronization, respectively. In each experiment, four different transmission directions are being considered for the optimization process (phi=0º and theta=45º; phi=0º and theta=75º; phi=45º and theta=45º; phi=45º and theta=75º). Then, the GA starts optimizing the antenna parameters installed in these sensors for performing the desired beamforming (a beam towards the HECN, which is located at the four different directions previously mentioned). Additionally, the number of node clusters in each WSN scenario is another optimization variable for achieving the best performance. Each scenario is evaluated for two different antennas, an ideal isotropic antenna and a conventional dipole one. In this set of experiments all the sensors are considered to be transmitting the same amount of power when acting in the network as a collaborative node.

3.A. Pattern results

Figs. 2 to 7 present the performance results. For all the figures, each row shows the results (normalized patterns) for five different randomly generated scenarios. At each subfigure, it should be noticed that, although the desired transmission direction implies a particular theta and phi value, the subfigures provide the radiation pattern results for the particular phi and the entire theta range (360º). In this theta range, the desired theta direction can be easily identified. When there is more than one cluster, the plots correspond to the performance of the first one.

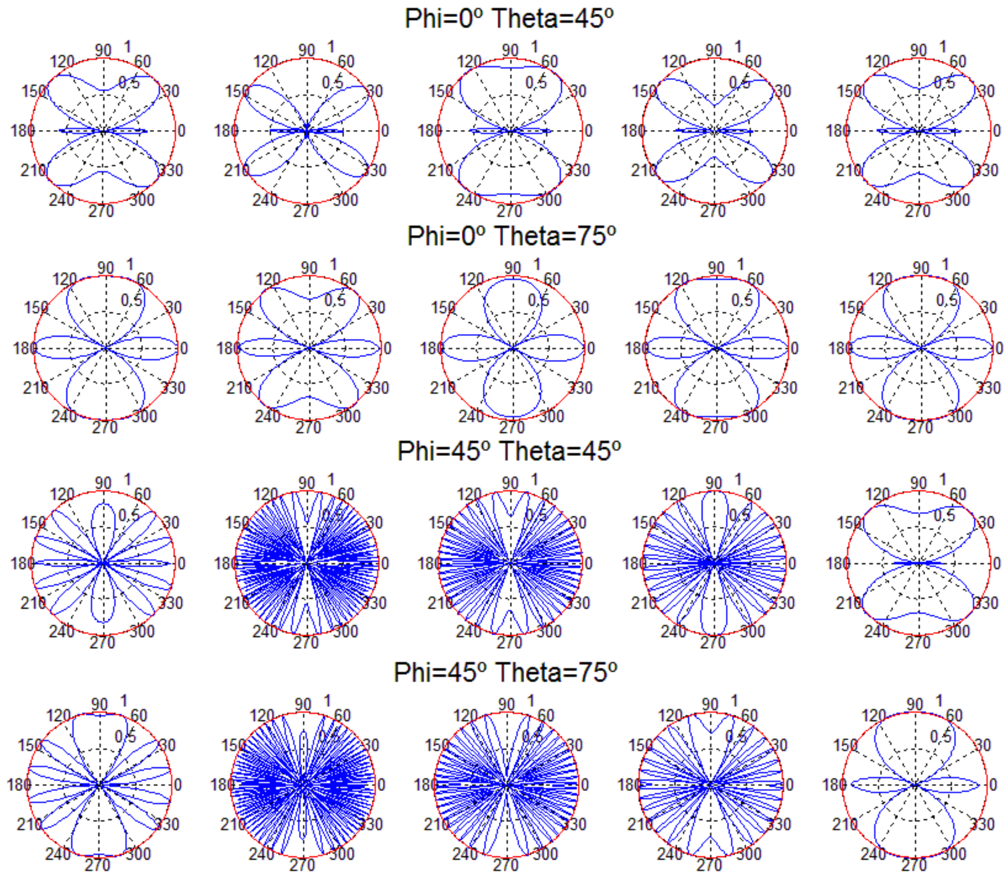

Fig.2. Radiation pattern for 2 sensors, different search angles: isotropic antenna.

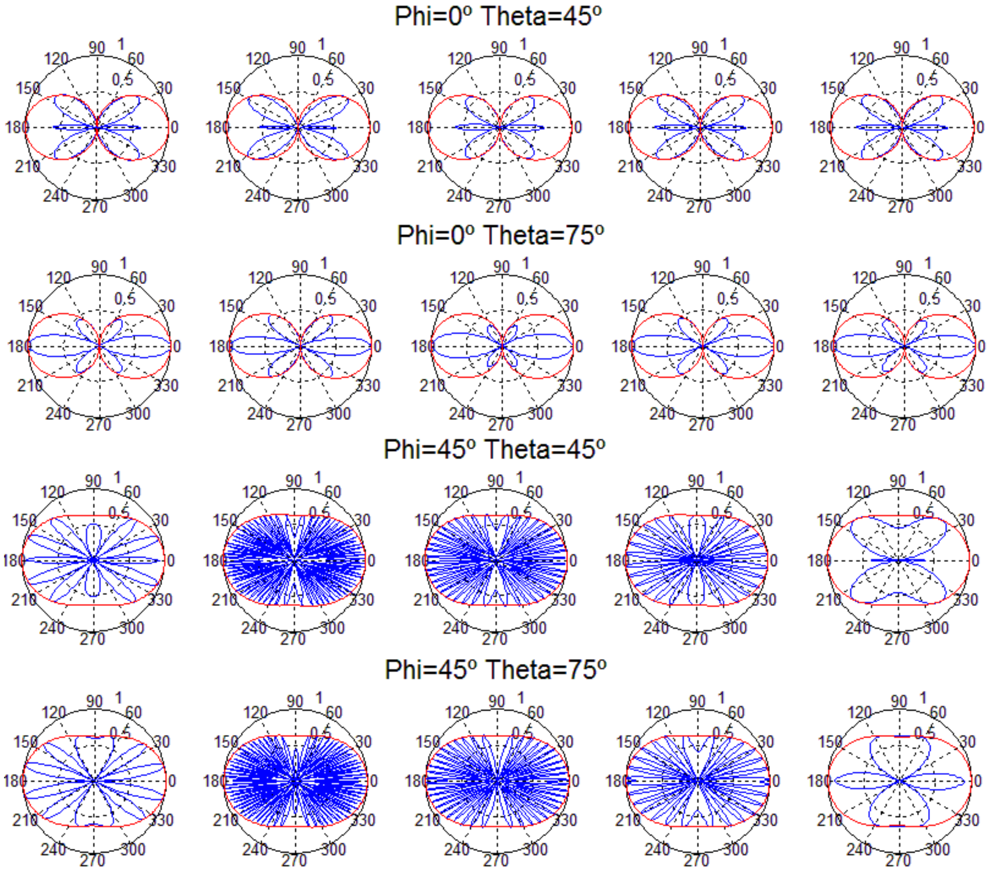

Fig.3. Radiation pattern for 2 sensors, different search angles: dipole antenna.

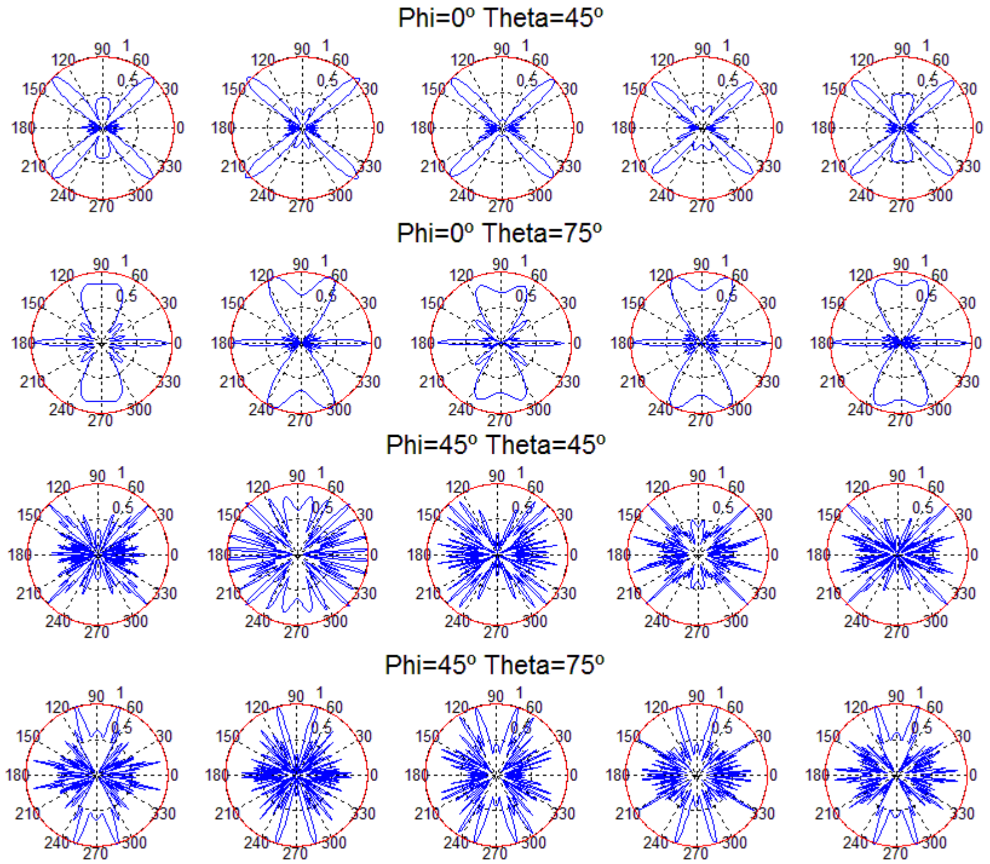

Fig.4. Radiation pattern for 5 sensors, different search angles: isotropic antenna.

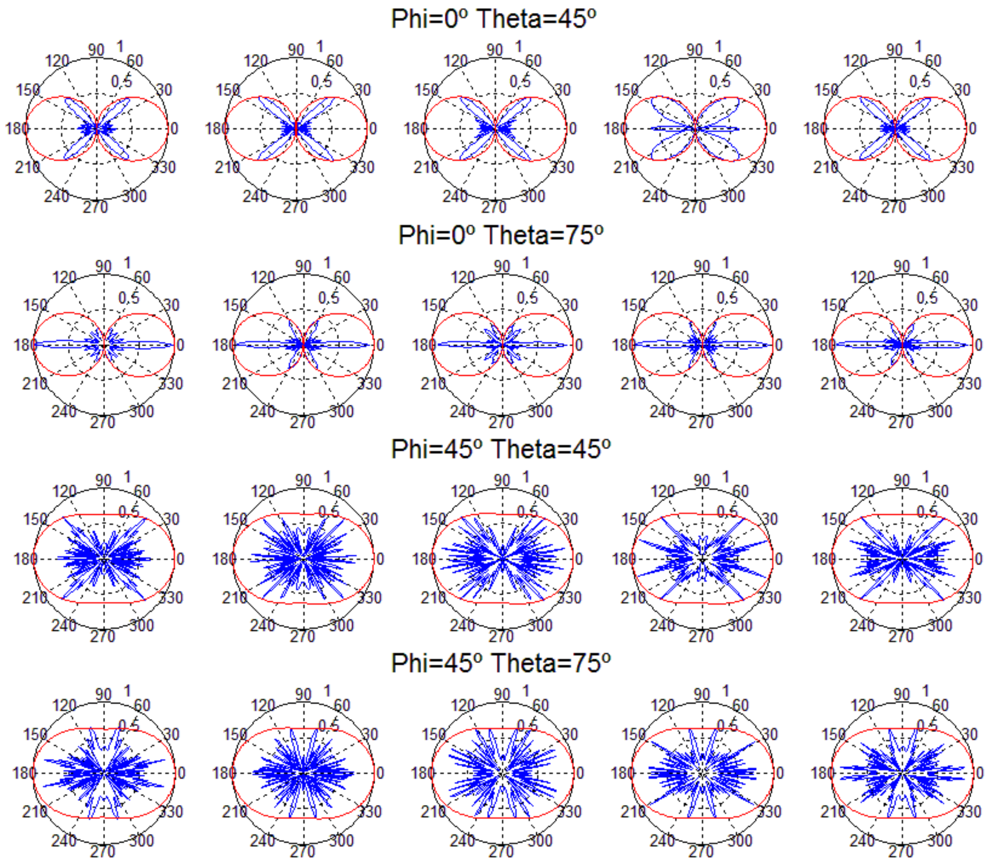

Fig.5. Radiation pattern for 5 sensors, different search angles: dipole antenna.

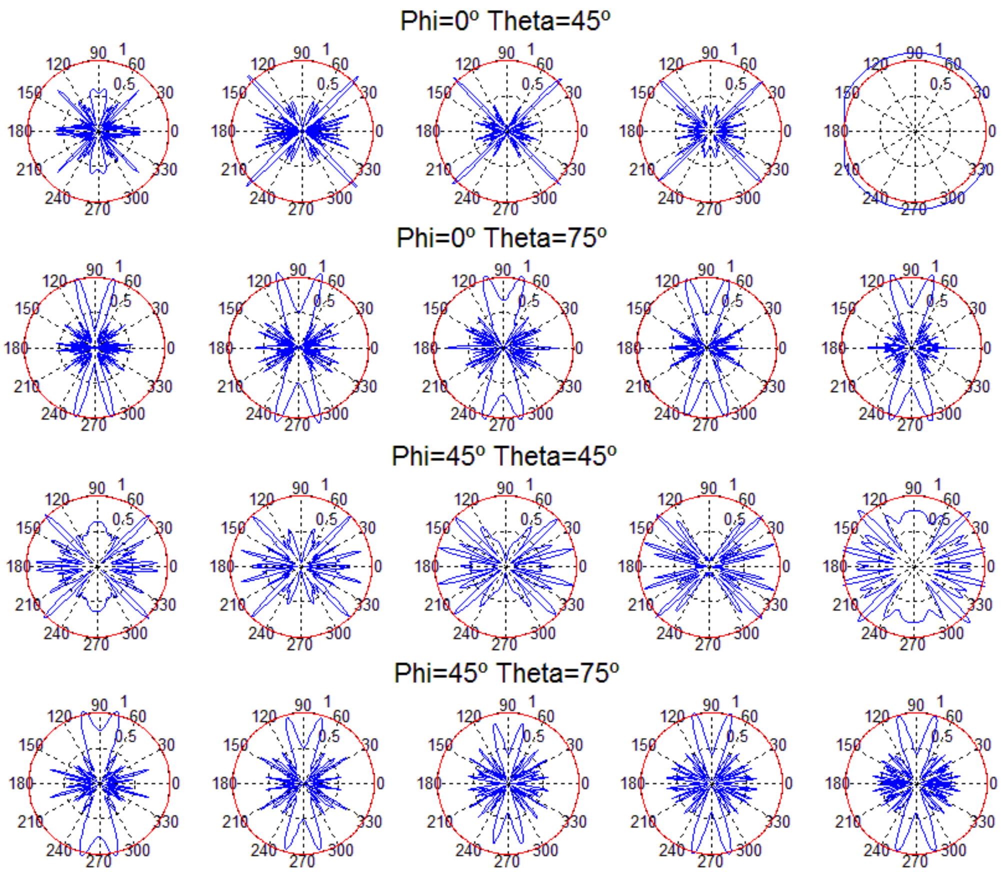

Fig.6. Radiation pattern for 20 sensors, different search angles: isotropic antenna.

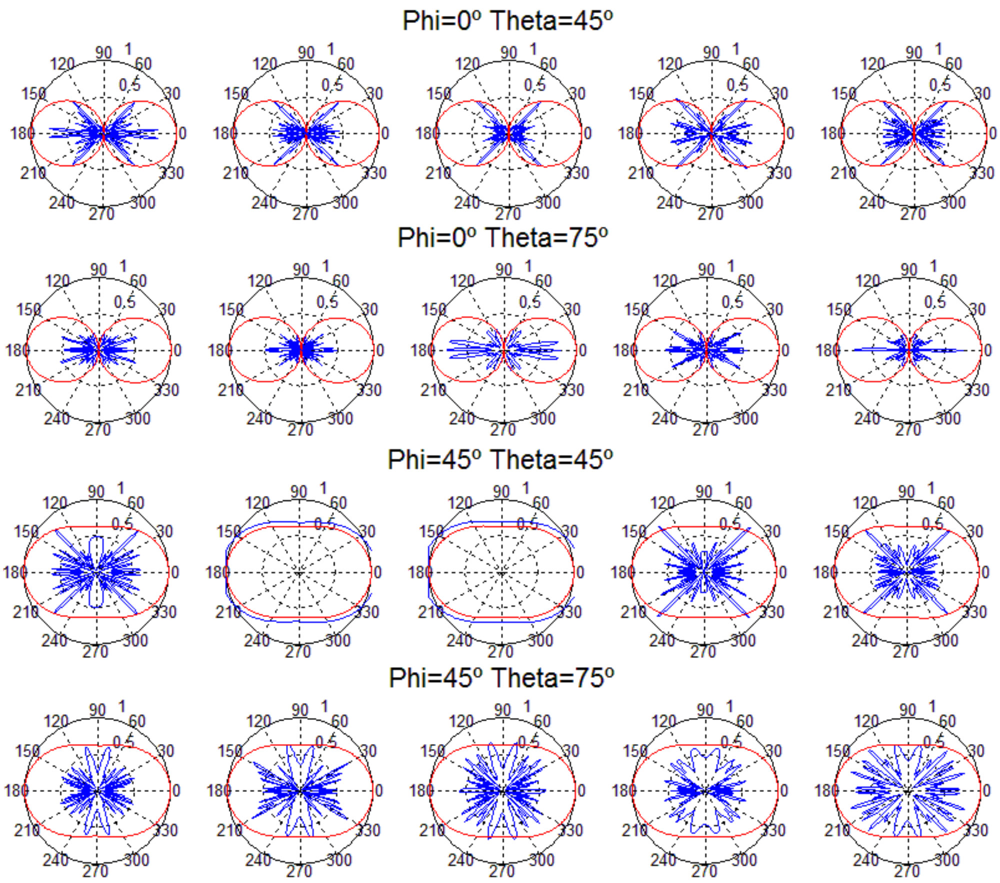

Fig.7. Radiation pattern for 20 sensors, different search angles: dipole antenna.

For all the figures, remember that the radiation patterns in each row are different because the inherent scenario has been randomly generated for each repetition of the five provided in a row.

Figure 2 provides the beamforming results of two sensors with isotropic antennas for the four different angular configurations. It is observed that, although the desired direction is always obtained, there is still a high amount of radiated power towards other directions. This limitation is logical regarding the reduced number of sensors considered. As the number of nodes is increased, the radiated power towards directions different from the desired one is reduced, as it is clearly identified in Fig. 4. In the case of using a dipole (Fig. 3 and 5), the dipole radiation pattern adds a limitation in the beam that points towards the desired direction. The final beam is, thus, affected by the radiation pattern of the dipole, reducing the global gain achieved, as expected. When the number of nodes is high (20 nodes, Figs. 6 and 7), the desired beam becomes more directive, the number of the rest of beams is reduced and also their gain. It must be identified that in the worst case of a highly fragmented scenario with a large number of clusters, containing only one node per cluster, the beam cannot be configured (see for instance Fig. 6, row one, fifth plot).

Notice that, for a reduced number of sensors (up to five), the optimization process selects only one cluster. For a larger number of sensors (Figs. 6 and 7), the clustering becomes quite important due to its influence in the final gain result of each scenario. When the number of sensors within the cluster is reduced and therefore, the number of clusters is high, the results provide a poor performance.

3.A. Gain results

Additionally, the gain results are analyzed. Figs. 8 to 11 provide the gain values for the four different desired search angles, all scenarios and both antennas. The gain values are computed in terms of the increment factor regarding the gain in the case beamforming is not used, that is the gain obtained for a unitary node for the desired direction and provided by its antenna pattern. In all the figures, each column of the gain plot is linked to the corresponding column of the number of cluster plot. For example, in Fig. 8, the columns 8 and 9 corresponding to isotropic antennas and five sensors (orange and red colors) have gain of 1.8 corresponding to a number of clusters of two.

For a reduced number of nodes (2 nodes), the gain increase factor is of around 1.8 and quite stable for all the repetitions and any direction. In the case of the five sensor scenarios, the gain factor is around 4 and also stable, mainly in the cases in which only one cluster is selected. In particular, in 10% of cases (6 out of 60), the gain is the same as in the case of the two nodes with only one cluster. This is expected because the scenarios with five nodes are divided into two clusters, one of them with two nodes, which is the worst case.

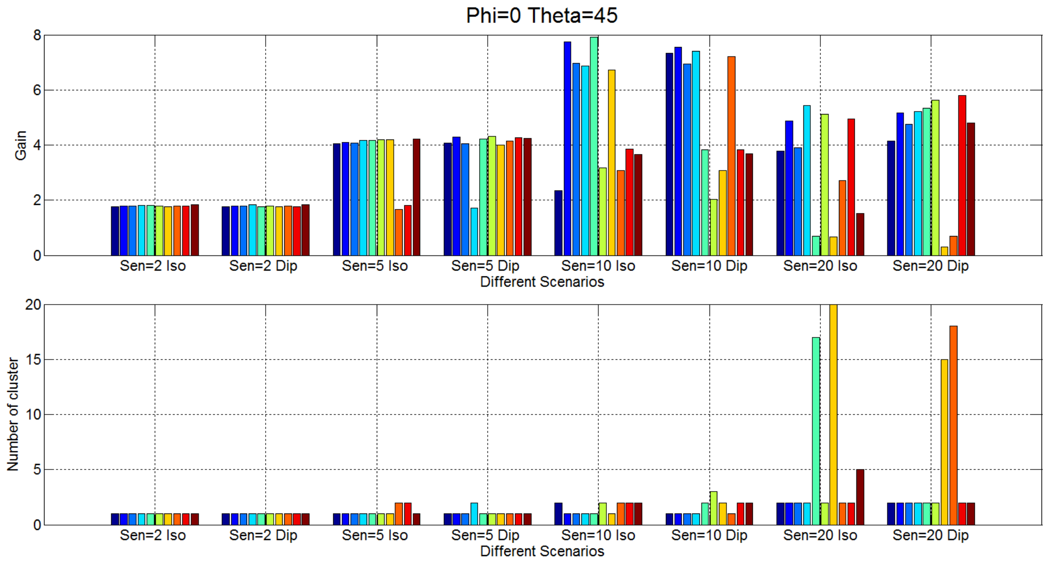

Fig.8. Results for search angle phi=0º, theta=45º, all scenarios and both antennas.

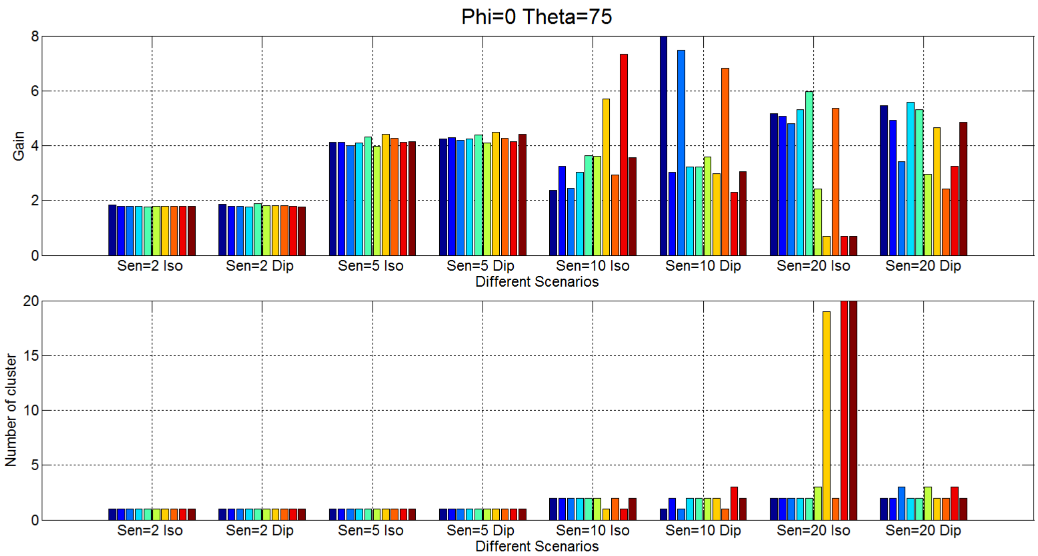

Fig.9. Results for search angle phi=0º, theta=75º, all scenarios and both antennas.

It is also identified that, for a reasonably high number of sensors (ten nodes), the gain factor is the best if only one cluster is defined. However, depending on the desired direction, antenna patterns and random positions of the nodes, only in 50% of cases one cluster is obtained, with gain factor values between 6.5 and 8. In the case in which the clusters are more than one, the gain factor is reduced (below 4), being even worse than the values for the scenario with only five nodes. In the case of a highly populated scenario (20 nodes), always two or more clusters are obtained and the gain values are between 4 and 6, corresponding to cases with clusters with lower nodes. In some cases, the optimization process identifies more than ten clusters which provide gain factors lower than 1, which means a gain reduction and therefore the optimization process must be corrected and improved to deal with this more demanding scenarios.

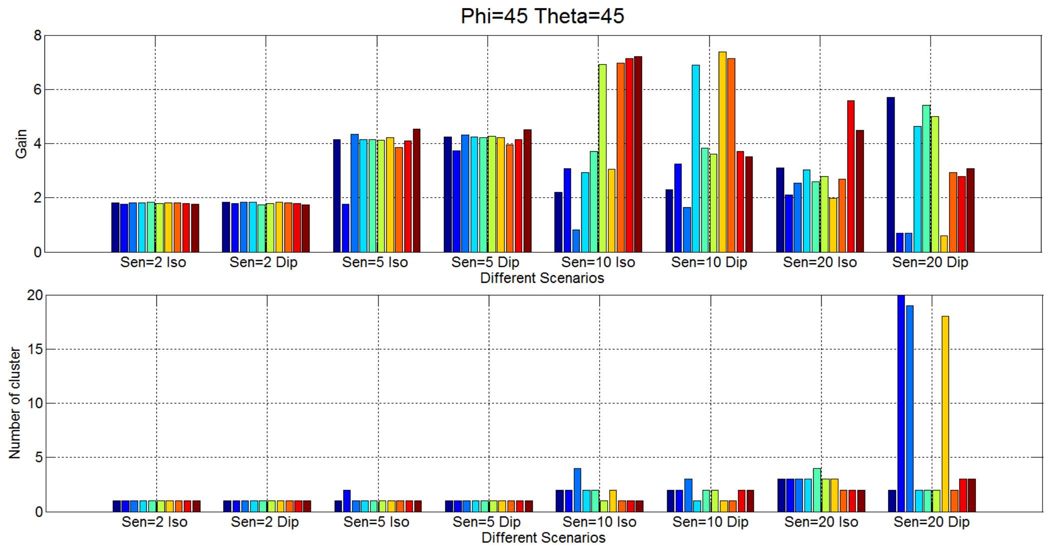

Fig.10. Results for search angle phi=45º, theta=45º, all scenarios and both antennas.

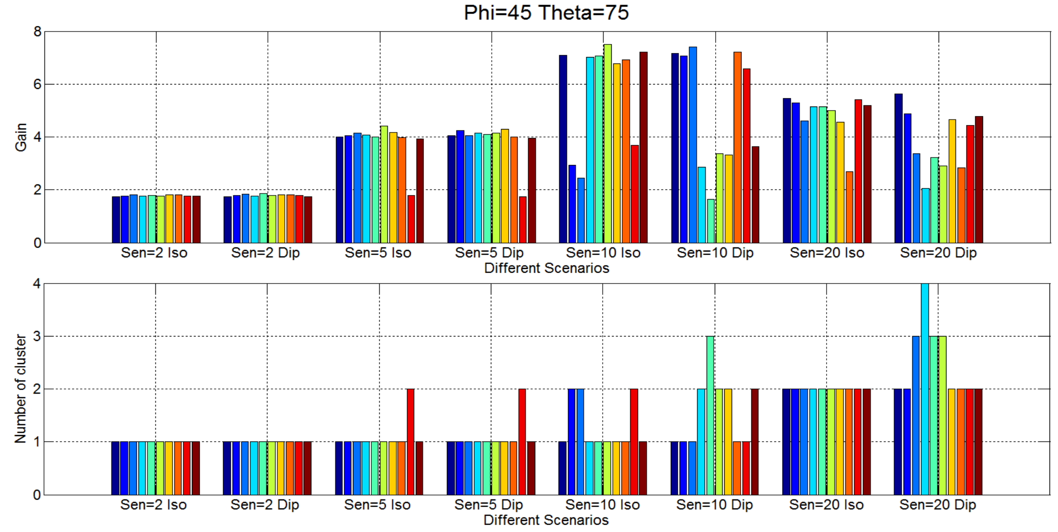

Fig.11. Results for search angle phi=45º, theta=75º, all scenarios and both antennas.

4. Conclusion.

This work provides the evaluation of WSN node networks and their performance when both clustering and antenna beamforming are applied. In this work we have fixed four different scenarios regarding the number of sensors implied: 20, 10, 5 and 2 nodes per scenario, and each scenario is randomly generated ten times in order to validate the result and their repeatability and reliability. For each experiment, four different transmission directions are considered (phi=0º and theta=45º; phi=0º and theta=75º; phi=45º and theta=45º; phi=45º and theta=75º) for the optimization process. Each scenario is evaluated for two different antennas, an ideal isotropic antenna and a conventional dipole one. In this set of experiments all the sensors are considered to be transmitting the same amount of power when acting in the network as a collaborative node. In the results, always the desired direction is obtained and almost at any case there is an increase in the gain factor compared to the one without beamforming and clustering (sole node). It is observed that the number of node clusters in each WSN scenario has a high influence for achieving the best performance, which occurs for reduced number of clusters containing large number of nodes on them. Up to the authors' knowledge, it is the first time that beamforming and clustering have been simultaneously applied to increase the network performance in WSN. The analyzed cases in this document are focused on fixed power for each node, static nodes (no movement after the random scenario generation) and 2D surface for the node location.

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