Radio Environment Map Estimation
based on Communication Cost Modeling
for Heterogeneous Networks

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Abstract—Radio environment maps can be a powerful tool for achieving efficient context-aware resource allocation in 5G heterogeneous networks. In this paper, we consider an heterogeneous network formed by a traditional cellular network and a wireless sensor network. The role of the wireless sensor network is to estimate the radio environment map of the cell using a geostatistical interpolation technique named Kriging. A distributed clustering algorithm was proposed in a previous work in order to decrease the complexity of the estimation. In our contribution, the clustering formation process is modified to include the communication cost as a metric to determine which nodes are included in each cluster. Simulation results show that the proposed algorithm improves the estimation quality for sparse wireless sensor networks, and preserves the network lifetime by forming clusters with an average of 5 nodes.

I. INTRODUCTION

Heterogeneous Networks (HetNets) have received increasing attention over the last years as one of the potential technologies to be included in future 5G mobile communications standards [1]. HetNets have been proposed as a solution to deal with the enormous traffic growth predicted for the upcoming years, generated not only by traditional mobile users, but also by new paradigms such as the tactile internet [2] and the internet of things (IoT). By definition, an HetNet should combine different radio access technologies using different carrier frequencies in a smart way, including traditional macro-cell Base Stations (BSs), pico-cells, Wireless-Fidelity (Wi-Fi) or relays.

One of the open questions is how 5G mobile communications could benefit from the heterogeneity provided by HetNets. Basically, context or side information is needed in order to perform an appropriate context-aware resource management at the different layers of the HetNet. In this paper, we consider a HetNet which combines a traditional macro-cell BS with a Wireless Sensor Network (WSN) and explore Radio Environment Maps (REMs) [3], [4] as a key tool for providing this context or side information to the macro-cell BS.

WSNs are systems comprising a large number of sensors with the objective of monitoring a spatial physical

phenomenon. Traditional WSNs applications require a high density network topology in order to obtain spatially correlated data. In our case, the REM is formed by the spatial power spectrum radiated by the macro-cell BS. The role of the WSN is to estimate the value of the field at the positions where the sensors are located, and to provide spatial interpolations of the field values at the remaining locations where no sensors are available. This knowledge will be forwarded to the BS for context-aware resource allocation.

In this paper, the spatial interpolation for field estimation is performed using a geostatistical tool called Kriging [5]-[10], and more precisely, the ordinary Kriging version, which does not require the mean of the spatial field under estimation to be known and presents a lower complexity. References [5] and [6] are used as a basis of this work. In these references, two distributed algorithms based on Kriging are proposed for field estimation, which work on two phases. In a first step, the semivariogram, describing the spatial correlation among field values, is calculated in a distributed manner using an iterative algorithm. In a second step, sensor nodes apply Kriging to obtain the field value estimate. Reference [6] extends the work on [5] by adding a clustering algorithm that allows the semivariogram and kriging calculations to be performed distributively by clusters of nodes. Initial clusters are formed based on the Euclidean distance to the location where the field value is unknown. The second metric of interest is the Kriging variance, which can be seen as an approximation of the estimation error. New nodes are added to the initial cluster as long as the Kriging variance decreases (and the field estimation is improved) and the candidate nodes are in distance range with the initial cluster nodes. The proposed distributed framework is compared by means of simulations with a more traditional centralized approach.

In this paper, we modify the clustering algorithm proposed in [6], where nodes were added to a cluster exclusively based on a distance criterion, by a more realistic metric based on a communication cost model, which effectively takes into account the random nature of the propagation channel. Several communication cost models are extracted from the literature and compared in order to choose the more appropriate for our
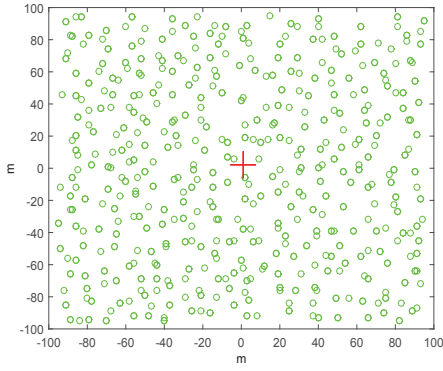
Fig. 1: HetNet combining a base station (red cross) with a WSN of 200 nodes

HetNet. Simulation results are provided to compare the performance of the communication cost based clustering algorithm with the original one from [6].

The remaining of the paper is organized as follows. In section II, the problem statement is formulated. Section III reviews different communication cost models available from the literature. Section IV describes the modified clustering algorithm and V presents the simulation results. The paper concludes with section VI.

II. PROBLEM STATEMENT

The HetNet is modeled as a set of N nodes $\mathbf{V} = \{1, 2, ..., N\}$, randomly located following a uniform distribution over the macro-cell area, where each node i is located at position $\mathbf{x}_i$, with $\mathbf{x}_i \in \mathbb{R}^2$, $\forall i$. The macro-cell BS is located at the center of the area (see Fig. 1). Due to transmission power limitations, the range of transmission for each node is limited to a distance R. Therefore, connectivity between nodes i and j only occurs if the Euclidean distance fulfills $d_{i,j} \leq R$. The field measured by a node located at $\mathbf{x}_i$ is denoted by $V(\mathbf{x}_i)$, $i = \{1, 2, ..., N\}$. Note that nodes are assumed to be able to calculate inter-node distances.

In order to estimate the REM, estimates of field value $\hat{V}(\mathbf{x}_0)$ at locations $\mathbf{x}_0$ where the field is unknown are obtained by means of the Distributed Clustering Algorithm (DCA) [6]. The field value at location $\mathbf{x}_i$ is obtained as:

$$V(\mathbf{x}_i) = P(\mathbf{x}_i) + S(\mathbf{x}_i), \qquad (1)$$

where $P(\mathbf{x}_i)$ is the average received power depending on the path-loss model and $S(\mathbf{x}_i)$ is the shadow fading following a log-normal distribution [11]. The received power at location $\mathbf{x}_i$ from N_t single antenna transmitters is calculated by the simple path-loss model:

$$P(\mathbf{x}_i) = K_{dB} + 10\alpha \log_{10} d_0 + 10 \log_{10} \left(\sum_{t=1}^{N_t} d_{i,t}^{-\alpha} \right), \quad (2)$$

where K is the constant path-loss factor, α is the path-loss exponent, d_0 is a reference distance for antenna far field and

$d_{i,t}$ is the distance between node location $\mathbf{x}_i$ and transmitter location $\mathbf{x}_t$.

The DCA algorithm from [6] builds upon two steps: semivariogram analysis and Kriging prediction. The semivariogram measures the correlation between field samples. The Empirical Semivariogram (EV), $\hat{\gamma}(\mathbf{h})$, is defined as follows:

$$\hat{\gamma}(\mathbf{h}) = \frac{1}{2|\mathcal{N}(\mathbf{h})|} \sum_{\mathcal{N}(\mathbf{h})} (V(\mathbf{x}_i) - V(\mathbf{x}_j))^2, \qquad (3)$$

where $\mathbf{h} = \mathbf{x}_i - \mathbf{x}_j$ is the lag distance, and $V(\mathbf{x}_i)$ and $V(\mathbf{x}_j)$ are field values at spatial locations $\mathbf{x}_i$ and $\mathbf{x}_j$, respectively. $\mathcal{N}(\mathbf{h})$ is the set comprising all location pairs $(\mathbf{x}_i, \mathbf{x}_j)$ such that $\mathbf{x}_i - \mathbf{x}_j = \mathbf{h}$ and $|\cdot|$ denotes its cardinality. Kriging technique replaces the EV by a semivariogram model, which in this case is the spherical model given by expression:

$$\overline{\gamma}(\mathbf{h}) = \left\{ \ c_1 + c_2 \left\{ \frac{3}{2} (\frac{\mathbf{h}}{c_3}) - \frac{1}{2} (\frac{\mathbf{h}}{c_3})^3 \right\}, \right.$$

where c_1, c_2 and c_3 are nugget, sill and range variables, respectively. In a second step, ordinary Kriging prediction is performed, where the Kriging interpolator at target location $\mathbf{x}_0$ is given by:

$$\hat{V}(\mathbf{x}_0)|_N = \sum_{i=1}^{N} w_{i|N}(\mathbf{x}_0) V(\mathbf{x}_i), \qquad (4)$$

where N is the number of nodes, $w_{i|N}$ is the weight assigned for node i from an estimation performed using N nodes and $\hat{V}(\mathbf{x}_0)|_N$ is the estimated value. These weights can be obtained by solving the following equations:

$$\mathbf{A}\lambda = \mathbf{b}, \qquad (5)$$

where

$$\mathbf{A} = \begin{cases} \overline{\gamma}(\mathbf{x}_i - \mathbf{x}_j), & i, j = 1, \dots, N, \\ 1, & i = N+1, \ j = 1, \dots, N, \\ & j = N+1, \ i = 1, \dots, N, \\ 0, & i, j = N+1, \end{cases} \qquad (6)$$

$$\lambda = [w_1, w_2, \dots, w_N, \mathcal{L}]^T, \qquad (7)$$

$$\mathbf{b} = [\overline{\gamma}(\mathbf{x}_0 - \mathbf{x}_1), \overline{\gamma}(\mathbf{x}_0 - \mathbf{x}_2), \dots, \overline{\gamma}(\mathbf{x}_0 - \mathbf{x}_N), 1)]^T, \quad (8)$$

and $\mathcal{L}$ is the Lagrangian.

III. COMMUNICATION COST MODELING

In reference [6], REM estimation is achieved by means of the DCA, which adaptively builds clusters of nodes in order to improve the field value estimation. The metrics involved in the cluster formation are the Kriging variance, which can be calculated as:

$$\sigma^2(\mathbf{x}_0)|_N = \sum_{i=1}^{N} w_{i|N}(\mathbf{x}_0) \overline{\gamma}(\mathbf{x}_i, \mathbf{x}_0) + \mathcal{L}(\mathbf{x}_0), \qquad (9)$$

and the Euclidean distance between sensor nodes or between nodes and the location where the field value is unknown, $\mathbf{x}_0$. Basically, once an initial cluster is build with the t sensor nodes which are in-range and closest to the target location $\mathbf{x}_0$, new nodes are added one by one as long as the Kriging

variance decreases and they are in-range with the cluster nodes.

In this paper, we modify the clustering formation algorithm by introducing the communication cost between sensor nodes as a criterion to adaptively modify the initial cluster. Communication cost in WSNs has been widely explored in the literature, e.g. [12]-[17]. One of the most well-known reference in the field is [12], where the objective is to reduce the energy dissipation required to communicate between nodes. To this end, expressions for the energy required to transmit and receive messages of K bits are derived, taking into account aspects such as the power amplifiers, the transmitter or receiver circuitry and the distance between nodes. The same authors extend their work in reference [13], where the energy consumption expressions are modified to consider free space (proportional to $d_{i,j}^2$, where $d_{i,j}$ is the distance between node location $\mathbf{x}_i$ and node location $\mathbf{x}_j$) or multipath models (proportional to $d_{i,j}^4$).

Authors in [14] consider the problem of minimizing the total communication cost of a WSN with a sink responsible of gathering data sensed by network nodes. The WSN is modeled as a network graph, where each link has a positive weight $w_{i,j}$ and a data rate $r_{i,j}$ assigned. The communication cost function is given by:

$$g(r_{i,j}, w_{i,j}) = r_{i,j}, w_{i,j}.$$

In the case of wireless communication links, $w_{i,j} = d_{i,j}^\alpha$, where α is the path-loss exponent $2 \leq \alpha \leq 4$.

Reference [15] proposes an algorithm to set up and maintain a network between nodes that are randomly deployed over an area with capability to move guaranteeing a minimum energy usage. The power consumption model includes three terms: the power needed to transmit, the power needed to receive (when a node needs to relay a packet) and the power needed to process (negligible compared to the other terms). The dominant contribution is the power needed to transmit, which the authors model as:

$$P_{Tx} = td_{i,j}^\alpha,$$

where t is a constant that indicates the predetection threshold at each receiver.

In references [16],[17], the following communication cost model is derived:

$$f_c = \frac{N_0(2^B - 1)\text{SNR}}{g_{i,j}\mu}, \tag{10}$$

where $g_{i,j} = x_{i,j}d_{i,j}^{-\alpha}$ is the channel gain between nodes i and j and $x_{i,j}$ is a constant chosen randomly following an exponential distribution with mean equal to one. The total number of bits is defined by B. μ ($\mu > 0$) is a parameter that depends on the particular modulation scheme. SNR is the desired Signal-to-Noise ratio, while N_0 is the power spectral density of the noise.

When analyzing all four models we observe that all the parameters (except distance) in [12], [14] and [15] will be constant in every node. This means that when calculating

communication cost between 2 nodes, the only parameter that will produce different costs between pairs of nodes will be the distance. In these three models, pairs of nodes with larger distances will show higher communications costs. Therefore, introducing any of these models when modifying the DCA would be the same as forming clusters of nodes based on the distance, which is one of the criteria in the DCA case. Considering this fact and that communication cost model in (10) includes parameters, besides distance, that do change in each pair of nodes as a consequence of taking into account the random nature of the propagation channel, model (10) was the one chosen to modify the original DCA. However, since the DCA requires the exchange of messages with different number of bits and this characterization is out of the scope of this paper, expression (10) is simplified as:

$$f_c = \frac{N_0\text{SNR}}{g_{i,j}}, \tag{11}$$

where the μ parameter depending on the modulation scheme is assumed to be common to all transmissions.

IV. DISTRIBUTED CLUSTERING ALGORITHM BASED ON COMMUNICATION COST

In this section, the DCA algorithm from [6] is modified to include the communication cost model from expression (11) as one of the criteria to adaptively build the clusters of nodes. In the original DCA, an initial set of t nodes, the ones in-range and closest to the target location $\mathbf{x}_0$, obtain the initial Kriging estimation $\hat{V}(\mathbf{x}_0)|_t$ (details on distributed semivariogram and kriging computation can be found in [5]) and compute the initial Kriging variance from (9). After this process, a new node, which is the one in-range and closest to initial cluster nodes, is added to the cluster, if exists, only if the updated Kriging variance decreases (which means that the estimation is locally improved).

The proposed Distributed Clustering Algorithm based on Communication Cost (DCA-CC) replaces the distance criterion by the communication cost model from (11). First of all, a communication cost threshold needs to be set according to the HetNet parameters in order to avoid forming clusters with a large number of sensors, which directly impacts on the battery life of the sensors. For each target location $\mathbf{x}_0$ in the area of interest, an initial cluster is formed with the t nodes showing the lowest communication cost, as long as this cost is below the predefined threshold. After this, we obtain the initial Kriging estimation $\hat{V}(\mathbf{x}_0)|_t$ from (4) and the initial Kriging variance from (9). Candidate nodes to be included in the cluster are nodes which show a communication cost with respect to the target location and nodes in the initial cluster below the predefined threshold. If such candidates exist, the node showing the lowest communication cost is added to the cluster and the Kriging variance updated. If the Kriging variance decreases, a new node will be added to the cluster. Otherwise, this means that the estimation cannot be improved and the process stops.

Algorithm 1 DCA-CC

N: Number of nodes in the network // t: Initial number of nodes in the cluster // f_c^{th}: communication cost threshold // $f_c^{i,j}$: communication cost between sensors located in $\mathbf{x}_i$ and $\mathbf{x}_j$ // f_c^i: communication cost between sensor located in $\mathbf{x}_i$ and $\mathbf{x}_0$.

1: f_c^{th} calculated according to HetNet parameters
2: **for** all $\mathbf{x}_0$ **do**
3:     Find set $\mathcal{T}$ with $t = |\mathcal{T}|$ nodes fulfilling $\min_{f_c^i \leq f_c^{th}} f_c^i$
4:     Initial field estimation $\hat{V}(\mathbf{x}_0)|_t$
5:     Initial Kriging variance $\sigma^2(\mathbf{x}_0)|_t$
6:     **for** $k = t + 1$ **to** $N - t - 1$ **do**
7:       Find set of candidate nodes $\mathcal{C}$ such that $f_c^i \leq f_c^{th}$ and $f_c^{i,j} \leq f_c^{th}$, $j \in \mathcal{T}$, $i \in \mathcal{C}$
8:       Add node which $\min f_c^i$, $i \in \mathcal{C}$ and $\min f_c^{i,j}$, $j \in \mathcal{T}$
9:       Estimate field value $\hat{V}(\mathbf{x}_0)|_k$
10:      Calculate Kriging variance $\sigma^2(\mathbf{x}_0)|_k$
11:      **if** $\sigma^2(\mathbf{x}_0)|_{k-1} \leq \sigma^2(\mathbf{x}_0)|_k$,
       then
12:        Updating process is terminated
13:      **else**
14:        Process is restarted from line 7
        $k = k + 1$
15:      **end if**
16:     **end for**
17: **end for**

Fig. 2: MSE versus communication cost threshold.
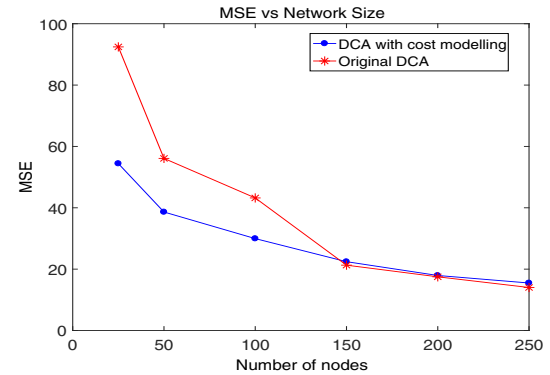
Fig. 3: MSE versus number of nodes for the DCA and DCA-CC algorithms.

As a result, and due to the random nature of the propagation channel, clusters of nodes can be formed with nodes which are not the closest ones in Euclidean distance to the target location $\mathbf{x}_0$. In principle, this could be a drawback for the DCA-CC and more details are given in Section V. The proposed DCA-CC is summarized in Algorithm 1.

V. SIMULATION RESULTS

Simulations were performed considering the scenario depicted in Fig. 1, where N sensor nodes are randomly deployed in a square area of 190×190 m. The REM is generated following equations (1) and (2). Path-loss exponent takes the value α=3, reference distance d_0=10 m, $N_t = 1$, standard deviation of shadow fading is 6 dB and $K = 38$ dB. The BS maximum transmit power is 24 dBm, whereas sensor nodes transmit at -10 dBm maximum, following LTE (Long Term Evolution) standard parameters.

The first step is to obtain the predefined communication cost threshold. In order to determine this value, the DCA-CC was evaluated in a network of $N = 100$ nodes for communication cost values ranging from 0 to 60 dB. Then, the Minimum Square Error (MSE) between each estimated REM and the original one was computed. Fig. 2 shows how the MSE decreases with the increase of the cost threshold. This means that as the threshold relaxes, more nodes can participate in the estimation process and therefore, the quality increases. From the figure, and considering that the lowest the threshold
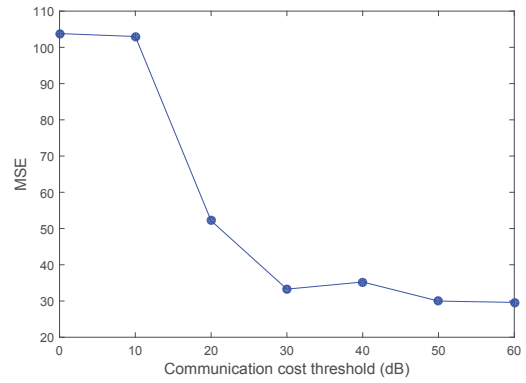
the least number of nodes participating in the estimation, a communication cost of 50 dB was predefined.

The quality of the estimation of the REM has been evaluated for different sizes of WSNs. To this end, the MSE between the original and the estimated REMs is calculated and shown in Fig. 3 for the DCA and DCA-CC algorithms. Recall that the original DCA forms clusters with nodes that are in the radius of the unknown location. It can be seen that the MSE generally decreases in a fast manner with the increase in the network size. This figure shows that for a network size that is inferior to 150 nodes, the DCA-CC achieves a lower MSE than the original DCA. On the other hand, for a network of $N > 150$ nodes, the values for both scenarios are very close to each other.

Fig. 4 shows the original REM and the estimations obtained by the DCA-CC for $N = 50$, 100 and 250 nodes. Following the results in Fig. 3, as the size of the network increases, the REM estimation quality increases as well. This is aligned with the Kriging theory which indicates that if data locations are densely located throughout the area of study, a high estimation quality will be obtained. The REM estimated with 50 nodes shows very small resemblance with the original map. Regardless of this, it can be noticed that it correctly locates the areas with higher power spectral density.

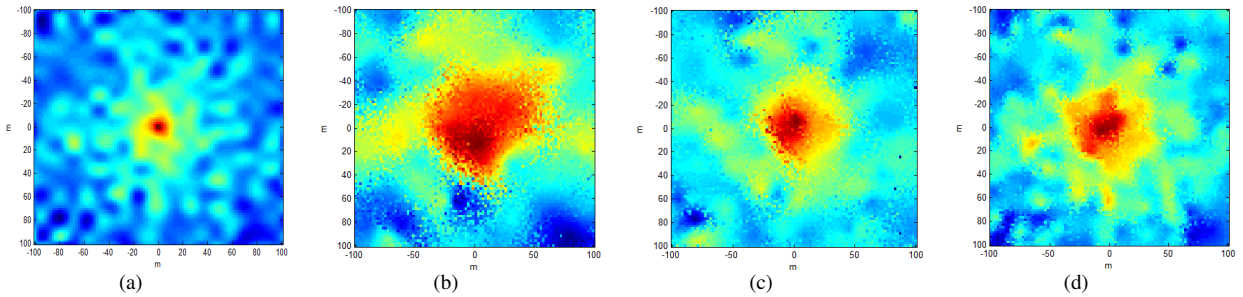HetNets, and in general 5G networks, require very precise

Fig. 4: (a) Original REM (b) Estimation with $N = 50$ (c) Estimation with $N = 100$ (d) Estimation with $N = 250$.

REMs to be able to allocate network resources as efficiently as possible. As a consequence of this, estimation quality is an important metric when reconstructing the REM. On the other hand, there is network lifetime. In WSNs, the lifetime is defined by the battery capacity. Since battery capacity is usually very low and the possibilities of changing or charging the nodes are very low as well, nodes must act as efficiently as possible to avoid wasting energy unnecessarily. Considering this, it is interesting to understand the size of the clusters that were created to perform the estimations for every network size.

Simulations results showed that for all network sizes, there were a few clusters containing up to 20 nodes. This indicates that in those particular cases, many nodes had to be added to the initial cluster until finding a node that increased the Kriging variance, since a very high Kriging variance was already obtained with the estimation performed by the initial cluster. Fig. 5 shows the cluster that was formed to estimate the value at location $\mathbf{x}_0 = (-87, -39)$. This figure indicates that all nodes surrounding $\mathbf{x}_0$ were included in the cluster. Consecutively, the order in which these nodes were added to the cluster was studied and revealed that nodes farther away from $\mathbf{x}_0$ were being added before closer nodes. If nodes far away are included before nodes that are closer, it is natural for the Kriging variance to be so high. Recall that the Kriging variance is the estimate of the estimation error and then, obtaining a big Kriging variance is equivalent to having a very poor estimation. A very poor estimation is obtained because if $\mathbf{x}_0$ is estimated with nodes far away, since these nodes are not spatially related to it, they highly impact the interpolation and provide a bad estimation. The theory behind Kriging explains that Kriging technique will assign a high weight to nodes close to the unknown location and a very low weight to nodes far away. Then, since nodes far away will have a minimum impact in the estimation, the theory suggests to remove these nodes from the calculations.

To understand why nodes far away were included in the cluster before closer nodes, we need to review the communication cost model. Recall that the communication cost is the metric that is used to define which nodes can be considered candidates for the cluster and in which order these nodes are added to it. When analyzing the cost model and reviewing
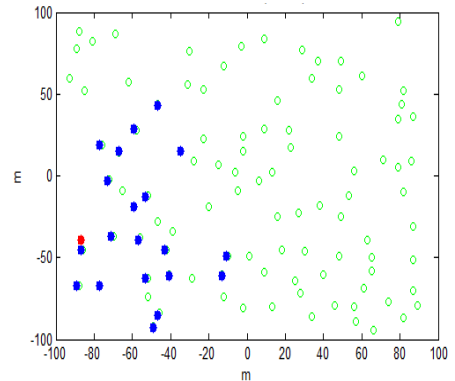

Fig. 5: Example of a cluster of 20 nodes formed to estimate location (-87,-39). The red dot is the target location, whereas blue dots are the nodes included in the cluster.

TABLE I: Average cluster size

N	50	100	250
Average cluster size	5.49	5.44	5.25

the spatial distribution of the cost, we found out that in some cases, nodes close to the $\mathbf{x}_0$ would receive a much higher cost than nodes far away. This is caused by the fact that the communication cost model includes a shadow fading component related to the received power and a parameter that is chosen randomly from an exponential distribution. These factors vary in such a way that they result in calculating, in some cases, a higher communication cost for close nodes. Therefore, even though these nodes are closer to the unknown location, they are included into the cluster after nodes that are far away but with a lower communication cost.

Regardless of these unusual situations in which clusters contain a big number of nodes, Table 2 shows that for different network sizes the average cluster size is close to 5 nodes, which is similar to the results for the DCA in [6]. This table and the results shown in Fig. 4 indicate that reconstructing a REM by using a distributed clustering algorithm based on communication cost modeling gives good results from both perspectives, estimation quality and network complexity.

VI. Conclusions

A distributed clustering algorithm based on communication cost has been presented for the estimation of radio environment maps. This algorithm builds clusters of nodes for distributed estimation via Kriging interpolation as long as the links between those nodes and between the nodes and the location of the field to be estimated show a communication cost below a predefined threshold. Simulation results indicate that the proposed algorithm outperforms a distance-based previous version for scenarios with sparse networks, achieving a good estimation quality for dense networks and keeping the average number of sensor nodes included in each cluster in a feasible number from the point of view of battery life. In future work, the impact of the predefined communication cost threshold will be further explored, and an analytical framework will be derived.

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