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Coordinated location-based self-optimization for indoor femtocell networks

A. Aguilar-Garcia*, R. Barco, S. Fortes

Universidad de Málaga, Andalucía Tech, Departamento de Ingeniería de Comunicaciones, Campus de Teatinos s/n, 29071 Málaga, Spain

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A B S T R A C T

Current indoor femtocell networks pose many challenges that could end up into a congested or non-operative cellular communication. In this context, widespread Heterogeneous Cellular Networks (HCNs) and smart devices can provide information that, if well-processed, could support the operation, administration, management and provision (OAM&P) procedures to improve the indoor network performance. Thus, a proposal based on the Self-Organizing Networks (SON) paradigm and context information is described in this paper in order to overcome network degradations and failures. In particular, a coordinated self-optimization system is proposed to enhance extremely overloaded indoor femtocell networks and to reduce the energy consumption. This approach, which is supported by geo-located measurements, automates the network OAM&P procedures and provides the intelligence to network elements for a quick adaptation. Finally, the system performance is analyzed in a realistic simulated environment, where the improvement in network capacity, coverage as well as the efficient use of energy, are discussed.

1. Introduction

Mobile cellular networks have become a standard infrastructure in human beings life, e.g., for services such as voice calls, text messages, video streaming, etc. Consequently, the demand for mobile network services has increased and wireless technologies have rapidly evolved. However, this growing demand, in terms of both coverage and capacity, is driving current mobile network deployments towards their limits. In order to overcome these problems, different solutions are being studied by operators and vendors to face the increasing data traffic and enhance network capacity, at the same time expanding coverage. On the one hand, whilst classical base stations (macrocells) covered areas of tens of kilometers, their combination with cells with various sizes (small cells) provides better signal quality and reduces problematic outage areas. On the other hand, the coexistence of multiple *Radio Access Networks* (RAN), e.g., GSM, UMTS and LTE, allows to choose the most suitable one depending on the demanded service. All these solutions create complex *Heterogeneous Cellular Networks* (HCNs). The automation and maintenance of mobile networks play a key role in HCNs. In this context, the concept of *Self-Organizing Networks* (SON) [1,2] classifies the self-x mechanisms into three areas [3]: *self-configuration* automatically configures new network elements, *self-optimization* enhances network performance by auto-tuning network parameters and self-healing automatically mitigates the network faults.

Nowadays, most cellular traffic is generated indoors (e.g., home, work or shopping malls), where there is often a lack of coverage or insufficient QoS. In these cases, network operators are offering small cells to overcome the indoor issues, being femtocells the main deployed base stations indoors. *Femtocell Access Points* (FAP) [4] are simple and small versions of standard macrocells, manufactured to be deployed at indoor environments. These low-cost and low-power devices cover areas of several meters and work in the licensed frequency band. Besides, femtocells are connected to the operator's network by a broadband connection (e.g., cable or xDSL), which makes it more prone to failures. They are plug and play devices, hence, operators could offer unplanned deployments, which means, the client is free to locate the femtocell anywhere.

The singularities of femtocells (short-range, unplanned deployments, restriction in the number of users per femtocell, etc.), the specific characteristics of indoor environments (number of people, multi-path reflections, etc.) and the mobility pattern of indoor users are challenges for current operators and vendors, which demand the development of new SON mechanisms for femtocell networks instead of making use of classical SON algorithms which manage macrocell networks. For example, classical SON mechanisms focused on macrocell networks that analyze wireless broadband resources in order to balance the network traffic may not properly work in femtocell deployments. The reason is that a

* Corresponding author.
E-mail addresses: aag@ic.uma.es (A. Aguilar-Garcia), rbm@ic.uma.es (R. Barco), sfr@ic.uma.es (S. Fortes).

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femtocell (e.g., with processing-capability: 8 users) could be full when the maximum number of active connections is reached (i.e., there are 8 connected users), even if there are available radio resources (e.g., these 8 users are consuming low throughput). Therefore, in case a classic SON mechanism analyzes this situation, it would conclude that this cell is not overloaded because it has free broadband resources to allocate new incoming connections. Thus, the network would not be optimized. New incoming connections would be rejected by the Admission Control (AC) algorithm because the maximum number of connected users has been reached. A simple and short-term solution could be oversizing indoor environments with many femtocells according to the peak traffic/users. Nevertheless, this solution would increase operator costs, would not take advantage of all available resources and would not be optimal in the long-term as indoor environments continuously change (new obstacles, new mobility pattern, occasional events, etc.). For these reasons, the development of new SON mechanisms focused on indoor mobile networks would be in charge of tuning parameters to manage and to update these networks.

Several SON mechanisms have been proposed in literature to tune network parameters in order to enhance network performance: Mobility Robustness Optimization (MRO) [5], Mobility Load Balancing [6], Energy Saving [7], Coverage and Capacity Optimization (CCO) [8], etc. However, the modification of these parameters, such as power transmission, handover margins, antenna tilt, etc. might be highly susceptible to logical or parametric dependencies. For example, a SON method based on mobility load balancing could change antenna tilt to offload a heavily loaded cell [6], while another SON method such as CCO would also modify antenna tilts to increase the spectral efficiency [8]. Hence, many types of conflicts could arise (e.g., tuning the same network parameter) during mobile network operation due to these dependencies, undermining the stability of the network performance. In consequence, the coordination of SON algorithms is an important challenge that must be addressed to ensure the highest network performance [9].

Traditional SON techniques analyze cellular network parameters and *key performance indicators* (KPIs) to decide the action to be taken in the network. However, this paper proposes to use additional information external to the network itself to support SON mechanisms because of three factors: the expansion of smart devices (smartphones, smartwatches, etc.), the high variety of sensors integrated into these devices (compass, accelerometers, etc.) and the continuous connectivity to the Internet. These context data such as geo-located measurements, mobility patterns, etc. provide supplementary information to the classical network performance indicators, opening new lines of research to improve SON algorithms.

The main contribution of this paper is the design and the coordination of novel *Mobility Load Balancing* (MLB) and *Energy-Savings* (ES) algorithms for self-optimizing temporary overloaded indoor femtocell networks based on newly defined coverage geometrical maps and users' topology (location-awareness). Regarding the load balancing mechanism, the optimal transmission power of femtocells is set immediately, avoiding slow adaptive processes. Although the proposed algorithm manages any traffic data type, it is aimed at prioritizing voice calls over any other kind of traffic. In turn, the energy-savings mechanism switches on/off or keeps in dormant mode those femtocells with/without close users. The coordination of these two SON mechanisms (i.e., load balancing and energy saving algorithms) enhances the overall cellular system, increasing users' satisfaction and network capacity and coverage, simultaneously reducing energy consumption.

The rest of this paper is organized as follow. Section 2 introduces the state-of-the-art. Section 3 presents the problem formulation. Section 4 describes the system inputs, internal procedures and the location-aware SON algorithms. Section 5 analyzes the system performance. Finally, Section 6 summarizes the conclusions.

2. Related work

One of the most important and studied use cases in self-optimization methods, *Mobility Load Balancing (MLB)* [10], is focused on moving traffic from congested cells to low loaded cells. Conversely, those cells with no close users could turn off its radio propagation activity and standby their internal procedures by keeping the cell in dormant mode or switched off. In consequence, a substantial reduction of mobile network energy consumption could be reached as *Energy-Savings (ES)* [11] use case defines. The coordination between these mechanisms is mandatory to avoid conflicts in the network parameters adaptation, hence, to ensure the system robustness and reliability [9].

Femtocells [4] are the main deployed base stations at indoor environments, challenging mobile network operators to well-manage those resulting HCNs due to their unplanned deployments. The literature has proposed several methods to address these two use cases in indoor scenarios.

Firstly, in MLB approaches, studies like [12,13] analyzed the persistent congestion problems on traffic distribution in LTE femtocells scenarios. They proposed several traffic sharing algorithms to tune femtocell handover margins and transmission power based on network indicators with the purpose of an automatic adjustment of femtocell parameters. However, these works did not take into account the femtocell processing-capability limitation. Moreover, they did not address temporary overloaded situation or context aware information, but permanent long-term situations and network KPIs. The authors in [14] studied the importance of analyzing the available radio resources as well as the maximum capability of users' connections for mobility load balancing in temporal overloaded situations. Nevertheless, that work did not consider the context aware information which could improve the algorithm performance. Some other mechanisms like [15,16] introduced the use of context information in optimization methods at indoor environments. More specifically, in location-awareness, a method that makes use of the *Received Signal Strength* (RSS) information from each terminal per position to resize the cell area and balance data traffic was studied in [17]. However, these methods are based on propagation models, which could provide a high RSS error due to the variability of channel conditions. Additionally, the work proposed in [18] introduced the users' location and the RSS information measured from the network to support the SON mechanisms. Nevertheless, the self-optimization algorithm made use of the geometrical distances between the users in order to estimate the new transmission power of femtocells. Those geometrical distances could not be always the optimal solution to focus the optimization efforts for calculating that new transmission power due to the influence of the wall, obstacles, etc. in the level of RSS (e.g., two close users could receive quite different RSS if there is a wall in the middle).

Secondly, ES mechanisms have also been widely investigated in the literature. From the point of view of femtocell scenarios, the challenges and opportunities of these systems are presented in [19]. The work proposed in [20] developed a novel distributed femtocell power adaptation algorithm which converges to the Nash equilibrium of a corresponding power adaptation game and reduces the energy consumption. Nevertheless, its implementation in a real network could be a challenge to work in real time due to its complexity and computational cost. Conversely, the authors in [21] introduced a simple energy saving method based on geometrical distances (Voronoi diagrams) to build localized algorithms. However, these regions could not really match with the coverage

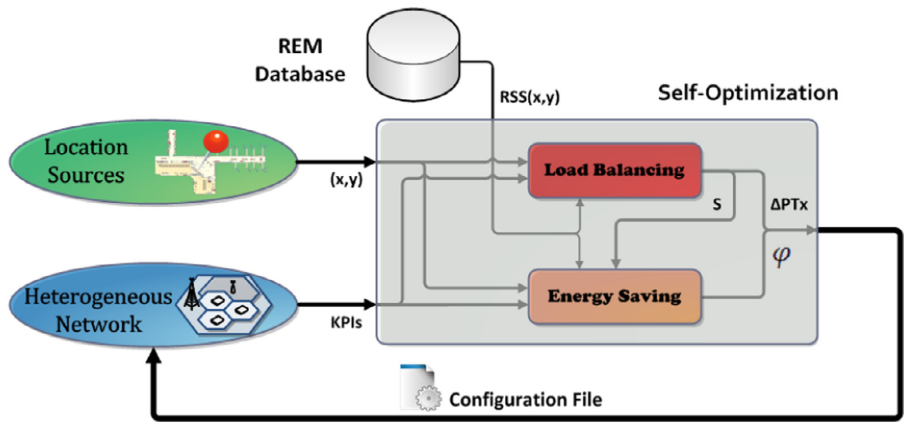

Fig. 1. Self-optimization scheme.

areas, especially in indoor scenarios because of the impact of the wall, occasional obstacles, etc. in the signal propagation.

Since both use cases (MLB and ES) are power related, these algorithms resize the cell area. This is done by changing or modifying the transmission power, antenna tilt, handover parameters, etc. in order to improve (or increase) energy efficiency (or network capacity/coverage). In consequence, they could negatively affect each other. Hence, their coordination is a challenge in current HCNs to avoid potential conflicts. European projects [22] and recent research [23,24] supported and studied this approach. A heuristic coordination framework for self-optimizing mechanisms is presented in [9]. Other works, like in [25], presented the interactions of a MLB method and another self-optimization algorithm that extended its functionalities to avoid conflicts by a combined use case. However, the coordination between MLB and ES use cases has not been studied in femtocell networks.

Some references related to location-aware SON, which are not focused in the use cases under study (MLB and ES), are discussed in [26,27,28].

For those reasons, the paper is focused on the design and coordination of novel location-based self-optimization techniques at indoor femtocell environments. In particular, coordinated methods for load balancing and energy saving are proposed.

3. Problem formulation

The proposed SON methods aim to manage femtocell networks and to optimize their parameters focusing on temporary overloaded situations in order to improve the users' quality of experience at the same time to reduce the energy consumption and operators' expenses. As a consequence, the following indicators must be analyzed to find a good trade-off between them.

First, from the MLB point of view, an indicator based on the network accessibility and retainability is measured to assess the *User Dissatisfaction Rate* (UDR) [12]:

$$UDR\ [\%] = BR + (1 - BR) \cdot OR \tag{1}$$

where the *Blocking Rate* (*BR*) is the number of rejected connections over the number of total attempt connections. The *Outage Ratio* (*OR*) is the sum of the time the calls are in outage (they cannot transmit but are connected) over the sum of the time of all the calls in the network. OR depends on the channel quality and the availability of network resources, i.e., a bad *Signal to Interference-plus-Noise Ratio* (SINR) (OR_q) or the lack of temporary resources (OR_s) increase that ratio: $OR = OR_q + OR_s$. UDR should be as low as possible, which means, few dissatisfied users.

Next, the quality of the signal received by the users is analyzed: the *Channel Quality Indicator* (CQI). This indicator is reported by the users to the base station. In this sense, the mean CQI (MCQI) is calculated as:

$$MCQI = \overline{CQI} = \frac{1}{N}\sum_{u=1}^{N} CQI_u \tag{2}$$

where N is the number of active users and CQI, for LTE technology, is a number from 0 to 15. A high value is desirable in this indicator.

From the energy-saving point of view, an indicator based on the percentage of active cells over the number of deployed cells in the scenario is computed as:

$$ACR\ [\%] = \frac{N_{active\_cells}}{N_{cells}} \cdot 100 \tag{3}$$

ACR (Active Cells Rate) provides an estimation of the energy consumption, although it does not measure or take into account the cell transmission power. Therefore, a significant indicator to measure the overall power saving is the power transmission ratio (PTR), calculated as:

$$PTR\ [\%] = \frac{\sum_{i=1}^{N_{cells}} PTx_i}{\sum_{k=1}^{N_{cells}} PTx_{max}^k} \cdot 100 \tag{4}$$

where N_{cells} is the number of deployed cells, PTx_i is the current transmission power of cell i and PTx_{max}^k is the maximum value of transmission power that cell k can be set. Hence, to reduce the energy consumption, low values of these indicators are desirable.

The number of handovers, $N_{handovers}$, over the number of users, N_{users}, has been also assessed as a key indicator to measure the signaling data necessary to manage the network (*User Handover Rate* – UHR). Keep similar values compared to the non-optimization situation is desirable:

$$UHR = \frac{N_{handovers}}{N_{users}} \tag{5}$$

Therefore, the proposed heuristic methods must share traffic and efficiently manage the energy consumption in the network. It will be carried out by moving users from overloaded femtocells to offloaded femtocells and by switching off those femtocells without near users.

4. System inputs

This section introduces the system inputs that the proposed SON algorithms will analyze in the next section. It is composed of network indicators, the information about the positions of the terminals and the data provided by a commercial repository (see the scheme in Fig. 1).

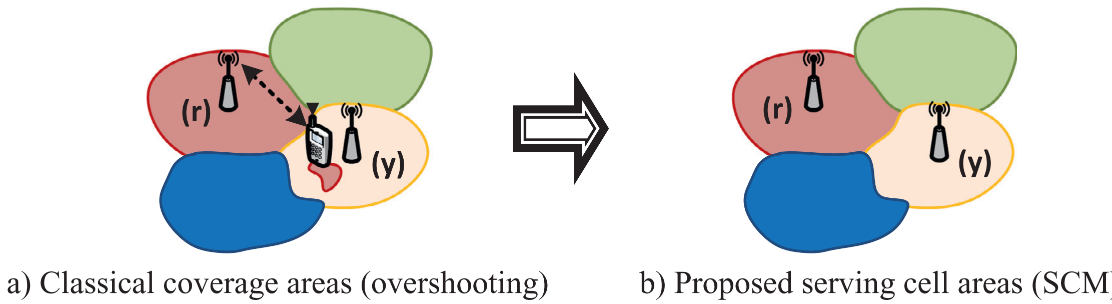

Fig. 2. Calculation of SCM.

4.1. Cellular network information

Network parameters and KPIs are supplied to the proposed SON system as a feedback about the status and the situation of the cellular network. This information is related to the current traffic, the transmission power of femtocells, etc.

4.2. Location sources

Multitude of indoor-positioning systems developed in the literature can provide information on the users' location, being one of the main inputs of the proposed SON system. An extensive summary of existing works on indoor localization can be found in [29]. The proposed context-aware SON systems will be deployed following the management architecture for positioning-aware SON detailed in [30].

Initially, the proposed location-aware SON system will be analyzed with accurate users' positons (no location error). Then, the emulated indoor positioning system will introduce different average location error (from 1 to 32 m) to assess the location-aware SON system under realistic conditions.

4.3. Radio environmental maps (REM)

Radio Environmental Maps (REM) [31] is a cognitive tool for environmental awareness. It consists of a dynamic procedure to store radio environmental information on wireless systems. This idea was defined by the Virginia Tech team as a database that contains different kinds of information such as environment radio signal, location of base stations, geographical features, etc. Furthermore, this tool is not just a simple database storing environmental data, but it is also able to process that information to implement spatial interpolation and temporal interpolation/processing mechanisms. These procedures could be either static or dynamic. For example, some positions of a scenario could be without RSS information. Hence, this lack of information would be interpolated based on the collected RSS samples and the intelligent entity in charge of spatial interpolation. Moreover, this information could be periodically updated through static well-located devices. The results are, among others, averaged RSS maps based on the processed geo-located data from the mobile networks [32,33].

REM could be either centralized (or global) which provides extensive processing capabilities and reduces signaling overhead, or distributed (or local) which increases the computational costs of each cell and reduces the delay. Focusing on femtocell networks, the most convenient solution would be to centralize all the information in a global entity as these indoor environments would be small size networks. Moreover, REM could be integrated in the operator's architecture or be part of a third party service provider, which would depend on the operator's policies and decision. The proposed SON system would integrate REM into the middle layers (e.g., domain manager) of the operator's OAM architecture.

5. Proposed approach

This section describes the proposed location-based MLB and ES algorithms and their coordination to ensure users' accessibility and retainability, at the same time reducing the overall power consumption. These mechanisms analyze the network indicators and the information about the positions of the terminals (see the scheme in Fig. 1). Both mechanisms, MLB and ES, tune the transmission power of the femtocells: the MLB method adapts the femtocells transmission power and the ES method switches on/off or turns to dormant mode the femtocells. MLB use case would be prioritized over ES use case. ES use case has to be on hold to finish till MLB provides it the required information (Cell Activity). In other case, the proposed value of the configuration parameter (femtocell transmission power) by the ES method could be opposed or different from the one proposed by the MLB method. For example, ES method proposes to switch off a femtocell because it considers no close users, but the MLB method requires that femtocell by increasing the femtocell transmission power to offload another femtocell. Moreover, these mechanisms will be deployed following a centralized OAM architecture for each femtocell network [30].

5.1. Internal procedures

These system inputs are proposed hereafter to create different *virtual maps* (VM): Serving Cell Maps (SCM) and Neighbor Cell Maps (NCM).

(1) **Serving cell maps**

A method is proposed to estimate coverage maps where some cellular irregularities such as overshooting cell issues are eliminated and the most suitable serving cell for each position is represented. Fig. 2a shows the classical coverage for femtocells (omnidirectional antennas). A typical indoor networks issue is illustrated: *overshooting*. It happens due to the geometry of these environments, multi-path reflections, wall obstacles, number of people, etc. Therefore, a femtocell (*red femtocell (r)* in Fig. 2a top left) could serve users out of its expected coverage area due to propagation channel conditions. These occasional small coverage areas could be a shortcoming for many self-optimization algorithms. That situation also presents problems to operators in terms of signaling cost because the number of handovers around the overshooting area will be increased. These situations are managed thanks to the so-called *Serving Cell Maps* (SCM).

Calculating SCM is a process composed of two steps. In the first step, the new coverage areas are defined based on geo-located RSS matrices supported by the REM tool. This procedure is based on the *Thiessen Polygons* [34] where, for each cell, an irregular polygon $A_{cell(k)}$that delimitates its coverage area as a serving cell is

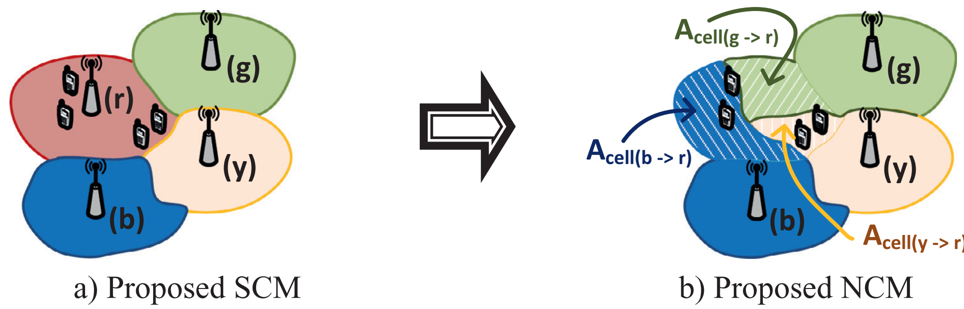

Fig. 3. Proposed neighbor cell list.

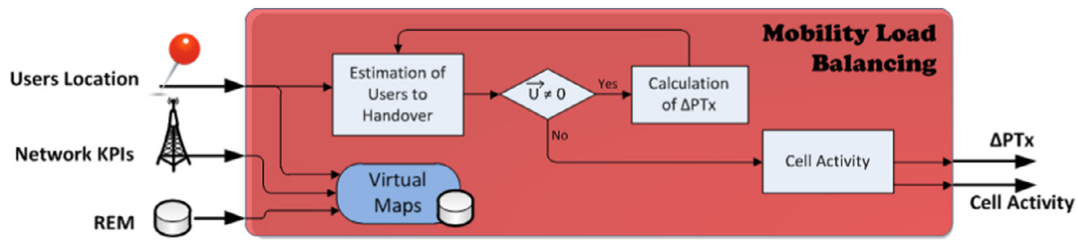

Fig. 4. Mobility Load Balancing scheme.

generated:

$$A_{cell(k)} = \{(x, y) \in (X, Y) |\ RSS(x, y)_{cell(k)} > RSS(x, y)_{cell(j)} \quad \forall\ j \neq k\} \tag{6}$$

where (*X*, *Y*) are the coordinates of the scenario. This procedure builds a network map as that presented in Fig. 2a, where for a certain femtocell (*r*) two disconnected coverage areas are presented. Therefore, the next step is to determine which the main area is. For that purpose, those areas $A_{cell(k)}$ that are split into *N* subareas, $A^i_{cell(k)}$, must be analyzed. Those subareas are compared to find the biggest one in order to remove overshooting and keep the most suitable area:

$$A'_{cell(k)} = max\{A^i_{cell(k)} |\ A_{cell(k)} = \sum_{j=1}^{N} A^i_{cell(k)}\} \tag{7}$$

In this sense, those removed areas must be joined to other/s area/s. Therefore, each area $A_{cell(p)}|p \neq k$ must be updated by including these discarded areas $A^i_{cell(k)}|A^i_{cell(k)} \neq A'_{cell(k)}$ according to:

$$A'_{cell(p)} = A_{cell(p)} + \sum_{h=1}^{M} A^h_{cell(p)} \tag{8}$$

where *M* is the number of new coverage subareas belong to *cell*(*p*) and $A^h_{cell(p)}$ is calculated as Eq. (1) but focusing on those discarded areas and avoiding the RSS information of *cell*(*k*):

$$A^h_{cell(p)} = \{(x, y) \in \left(X^i_{cell(k)}, Y^i_{cell(k)}\right) |\ RSS(x, y)_{cell(p)} > RSS(x, y)_{cell(q)}\ \forall\ q \neq p, k\} \tag{9}$$

This procedure is repeated till all subareas are joined to the main serving cell coverage areas. Finally, the proposed serving cells coverage areas are illustrated on Fig. 2b, where the small subarea of the red cell (r) is embedded into the yellow cell (y) area.

(2) **Neighbor cell maps**

A new virtual map, named *Neighbor Cell Maps* (NCM), is designed to estimate the neighbor cells of each serving cell. The aim of these maps is to create the *proposed neighbor cell lists*.

For that purpose, the same procedure to build SCM is followed now but, removing the RSS values of the serving cell *cell*(*k*). Then, Eqs. (6) to (9) generate the new NCM (see Fig. 3b). Those new areas which cover the original area $A'_{cell(k)}$ (from SCM) are denoted as $A_{cell(j \rightarrow k)}$, where $cell(j \rightarrow k)$ means that the cell *cell*(*j*) covers the area of the removed cell *cell*(*k*). Fig. 3b depicts an example where three cells ($j = \{b,\ y, g\}$) are adjacent to the serving cell ($k = \{r\}$). Finally, the *proposed neighbor cell list* is created as follows:

$$C_{cell(k)} = \{cell(j)\ |\ A_{cell(j\rightarrow k)} \in A'_{cell(k)} \forall\ j \neq k\} \tag{10}$$

5.2. Mobility load balancing algorithm

The proposed MLB method aims to ensure coverage and increase the network capacity at indoor femtocell networks, beyond the classical offloading of macrocells into femtocells. Since for most operators the overall users' satisfaction is more critical in voice calls rather than in any other kind of service, in the proposed algorithm data traffic users are handed over to macrocells when a femtocell is considered overloaded. After that, the MLB algorithm balances voice traffic among the femtocells. The periodicity to trigger the mechanism should be low to solve temporary overloaded situations. Additionally, two thresholds are defined for the load, defined in Eqs. (11) and (12) as the ratio of users in serving and neighboring cells respectively. These thresholds are configured based on a sensitivity study or on the operators' experience, policies or priorities:

- S_{th} is the minimum load (ratio of users) to consider a serving cell as highly loaded (see Eq. (11)). Its range goes from 0 (cell is always considered highly loaded) to 1 (cell is never considered highly loaded).
- T_{th} is the maximum average load in the neighboring cells of the studied cell (see Eq. (12) to consider the neighboring cells as low loaded and, consequently, available to catch users to offload the studied cell. Its range goes from 0 to 1.

The initial condition $S_{th} > T_{th}$ is mandatory to avoid ping-pong effects and oscillations in the MLB process.

The global scheme of the proposed MLB algorithm is depicted in Fig. 4. It shows an iterative mechanism to estimate the new

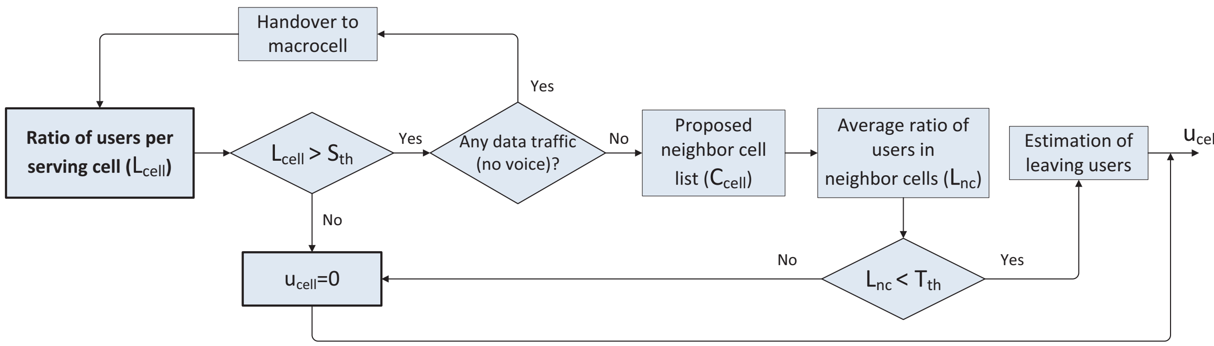

Fig. 5. Internal scheme of *Estimation of Users to Handover* block.

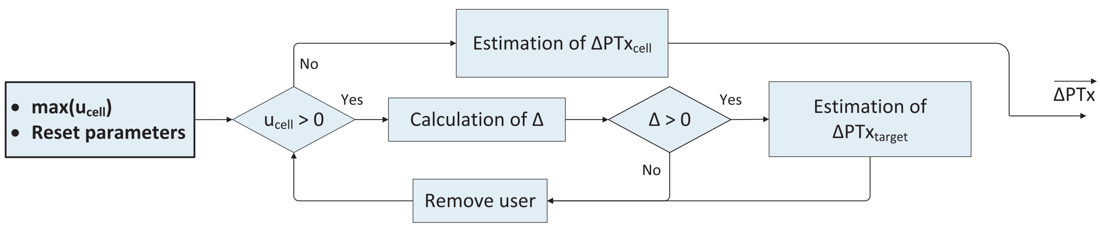

Fig. 6. Transmission power variation block.

transmission power variations of the femtocells, ΔPTx_{cell}. The iterations do not stop while the estimated new transmission power variation still causes overloaded situations. It should be noticed that the overload situations are estimated within this internal procedure without actually performing the power variations in the network. The system inputs are the information from REM databases, cellular network KPIs and the position of the terminals. The system output is the transmission power variation ΔPTx_{cell} that should be applied to the femtocell *cell*. Additionally, another output is the cell status of that femtocell (i.e., whether it has active users or not), which is subsequently used as input for the ES mechanism. The main modules of the MLB method are described in the next paragraphs:

- ***Estimation of users to handover***: The aim of this module is to provide an estimation of the number of users that should leave its serving cell, u_{cell}, to be handed over to a target cell.
  First of all, two indicators are calculated based on the SCM, the NCM and the users' locations:

◦ L_{cell}: the ratio of users (according to the SCM):

$$L_{cell} = \frac{users_{cell}^{SCM}}{max\_users_{cell}} \tag{11}$$

where $users_{cell}^{SCM}$ is the number of users in the coverage area of *cell* defined by the SCM and max_users_{cell} is the total number of users that the femtocell could allocate.

◦ L_{nc}: the ratio of users of its *proposed neighbor cell list* (according to the NCM):

$$L_{nc} = \frac{\sum_{i=1}^{NC_{cell}} L_{cell(i)}}{NC_{cell}} \tag{12}$$

where the numerator is the sum of the ratios of users for the cells in the *proposed neighbor cell list* and NC_{cell} is the length of this list.

The scheme of this module is shown in Fig. 5. The first step is to calculate the ratio of users in the serving cell, L_{cell} (see Eq. (11)). The condition $L_{cell} > S_{th}$ makes the algorithm continue, in other case, this procedure is finished and no users are forced to be handed over. In case the condition is accomplished, users are classified per service. Due to the interest of satisfying voice call users, a basic classification of traffic into two main services is taken into account: *voice connections* and *other services*. In case there are users with other services (data traffic), these users are forced to handover to macrocells one by one after evaluating the initial condition again, $L_{cell} > S_{th}$ (see Fig. 5). Note that, in most cases, there is no available macrocell coverage indoors, hence, most of these data traffic users could be in outage for a while till a femtocell is available. In other case, the procedure continues to the next module.

At this point, the *proposed neighbor cell list*, $C_{cell(k)}$, of the $cell(k)$ is determined (as described in Section 5.1). Afterwards, the ratio of users of the *proposed neighbor cell list*, L_{nc}, is calculated (see Eq. (12)). Then, if the condition $L_{nc} < T_{th}$ is accomplished, the number of users u_{cell} that should leave the cell can be calculated as follows:

$$u_{cell} = users_{cell}^{SCM} - max\_users_{cell} \cdot \left(\frac{L_{cell} + \sum_{i=1}^{NC_{cell}} L_{cell(i)}}{NC_{cell} + 1} \right) \tag{13}$$

where $users_{cell}^{SCM}$ is the number of users in the coverage area of *cell* defined by the SCM, max_users_{cell} is the total number of users that the femtocell could allocate, L_{cell} is the ratio of users per cell or neighboring cells and NC_{cell} is the number of neighboring cells. In the case u_{cell} is not an integer number, the next integer number is selected.

In other case ($L_{nc} \geq T_{th}$), the close area of the studied femtocell is overloaded and there are no close low-loaded femtocells to move the users forward. Under this unlikely situation, an event would be triggered to warn the network engineers about this problematic situation. They will study this case and evaluate the deployment of additional femtocells (if this case is repeated several times in the same place) or doing nothing because it is an isolate case or because S_{th} and T_{th} should be reconfigured (bad configuration or very restricted configuration).

Finally, a vector $\vec{U}$, composed of the number of users that should leave each femtocell is sent to the next block: $\vec{U} = (u_{cell(1)},\ u_{cell(2)} \ldots\ u_{cell(n)})$.

The next module *"Calculation of ΔPTx"* will depend on the vector $\vec{U}$. In case it is equal to 0, which means the network is considered balanced, the method finishes. In other case, the algorithm

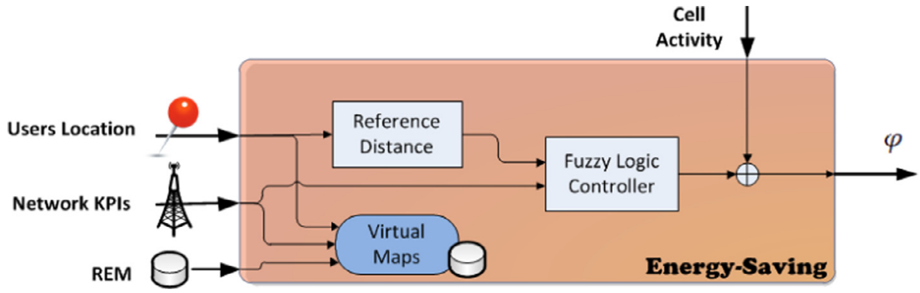

Fig. 7. Energy-savings scheme.

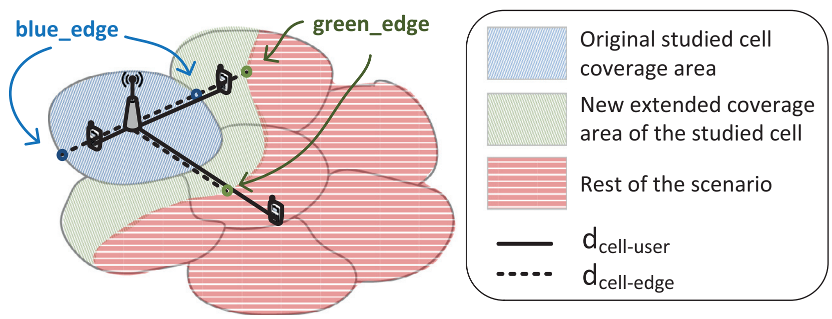

Fig. 8. Reference distance scheme.

continues to calculate the transmission power variations of femtocells.

- ***Calculation of*** ΔPTx: This module decides the transmission power variation that must be applied to each femtocell in order to move users and to avoid overloaded cells in the network. A conventional rule-based scheme, based on $\vec{U}$, is proposed in Fig. 6. It is executed for that *cell* which presents the maximum value of u_{cell}, till all the users u_{cell} are assessed.

First, the parameters of this block are initialized to zero (Δ and $\overrightarrow{\Delta PTx}$). These parameters are calculated by elementary equations: additions, and operators: maximum and minimum. It would reduce the computational complexity and costs. Then, the value of u_{cell} must be higher than zero to continue with the process. In that case, the calculation of Δ is. For each user $g(m)$ (where $m = \{1, 2, \ldots users_{cell}^{SCM}\}$) of the serving cell, the *RSS* value from its serving cell, $RSS_{cell}^{g(m)}$, and the maximum *RSS* from its neighboring cells (according to NCM), $RSS_{nc(m)}^{g(m)}$, are defined. Being $nc(m)$ the proposed neighboring cell with the highest value of *RSS* for the studied user m. The following two vectors composed of those values are created, $\overrightarrow{RSS_{cell}} = \{RSS_{cell}^{g(1)}, RSS_{cell}^{g(2)} \ldots RSS_{cell}^{g(users_{cell}^{SCM})}\}$ and $\overrightarrow{RSS_{nc}} = \{RSS_{nc(1)}^{g(1)}, RSS_{nc(2)}^{g(2)} \ldots RSS_{nc(users_{cell}^{SCM})}^{g(users_{cell}^{SCM})}\}$, respectively. After that, the minimum value of the difference between these two vectors is saved as $\Delta_{target} = \min\{\overrightarrow{RSS_{cell}} - \overrightarrow{RSS_{nc}}\}$ where *target* refers to the neighboring cell that minimizes previous equation (possible target cell for that user). In case that Δ_{target} is positive, the transmission power variation ΔPTx_{target} applied to that target cell is calculated as follows in Eq. (14), where ΔPTx_{target} is equal to $\frac{\Delta_{target}}{2}$ the first iteration because initial values of ΔPTx_{target} are set to zero. Otherwise, Δ_{target} is negative, this step is skipped.

$$\Delta PTx_{target} = \max\left(\Delta PTx_{target}, \frac{\Delta_{target}}{2}\right) \tag{14}$$

Finally, the system removes that user and u_{cell} decreases one unit. The process is repeated till u_{cell} reaches the zero value, when the serving cell transmission power variation $\Delta PTx_{cell}$is calculated as follows:

$$\Delta PTx_{cell} = -\left(offset + max\left\{\overrightarrow{\Delta PTx_{target}}\right\}\right) \tag{15}$$

where the *offset* is a network parameter defined to reduce ping-pong handovers between two cells and $\overrightarrow{\Delta PTx_{target}}$ is the vector composed of all the target neighboring cells transmission power variations. The output of this module is the vector $\overrightarrow{\Delta PTx} = \{\Delta PTx_{cell}, \overrightarrow{\Delta PTx_{target}}\}$.

The procedure (Fig. 4) emulates how the new network configuration, ΔPTx, impacts on the deployed femtocells by going back to the first block "*Estimation of users to handover*" . This block builds a new SCM according to the new changes of power and evaluates the network again.

- ***Cell activity***: It is the last step of the mechanism (Fig. 4). $\overrightarrow{\Delta PTx}$ is set in the network while *Cell Activity* (S_{cell}) is supplied to the ES algorithm according to the femtocells activity. S_{cell} is 1 if there is any user on that femtocell according to the SCM, otherwise it is 0.

5.3. Energy-Saving algorithm

This mechanism switches on/off or turns into dormant mode the femtocells depending on the users' location, the network KPIs and the information provided by the MLB mechanism. In dormant mode, the femtocell is recovered in a few seconds, whereas it takes tens of seconds when it is switched off. This algorithm will be triggered once the MLB algorithm had finished.

The ES system is illustrated in Fig. 7, which is mainly composed of two modules. The first module computes the *reference distance* based on the SCM. The second module introduces a fuzzy controller to evaluate the status of each femtocell. These modules are detailed below:

- ***Reference distance***: This module calculates an indicator named *reference distance* for each user and cell, which is proportional to the distance from the users' location to the studied cell.

For that purpose, a process similar to that defined for *Neighbor Cell Maps* (see Fig. 3) is applied in this method for each studied

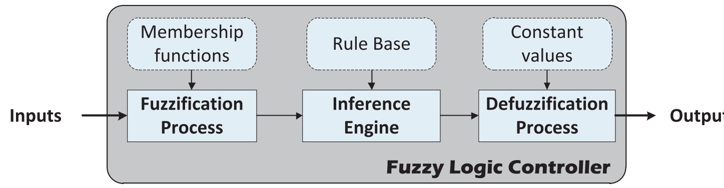

Fig. 9. Fuzzy Logic Controller scheme.

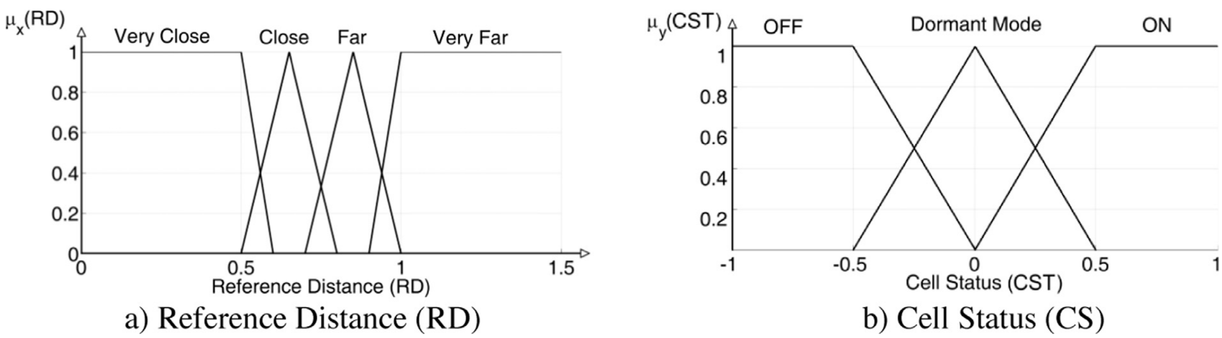

Fig. 10. Membership functions.

cell. In this case, instead of removing the studied cell, the femtocells of its *proposed neighbor cell list* (see Eq. (10)) are removed from the network. In consequence, a new layer is created with three different areas: (1) the original studied cell coverage area is defined as *'blue area'*, (2) the new extended coverage area of that cell is the *'green area'* and (3) the rest of the scenario is denoted as *'red area'* (see Fig. 8).

After that, a vector $\overrightarrow{\gamma_{cell}}$ is obtained with the *reference distances* of all users in the scenario for each studied cell. It is built as $\overrightarrow{\gamma_{cell}} = (f_{cell}(g_1),\ f_{cell}(g_2)\ldots\ f_{cell}(g_n))$, where g identifies the users, n is the total number of active users in the scenario and $f_{cell}(g)$ is described as follows:

$$f_{cell}(g) = \begin{cases} 0.5 \cdot \frac{d_{cell-user}}{d_{cell-blue\_edge}} & if\ g \in original\ cell \\ 0.5 \cdot \left(1 + \frac{d_{cell-user} - d_{cell-blue\_edge}}{d_{cell-green\_edge} - d_{cell-blue\_edge}}\right) & if\ g \in extended\ area \\ 1 & if\ g \in rest\ of\ scenario \end{cases} \tag{16}$$

where d_{a-b} is the distance from position a to position b. In consequence, the subindex *cell* identifies the position of the studied cell and *user* refers to the position of each terminal. The subindexes *blue_edge* and *green_edge* are calculated as the intersection between the line $(cell - user)$ and the area edge.

Finally, the minimum *reference distance*, $\theta_{cell} = \min\{\overrightarrow{\gamma_{cell}}\}$, is sent to the next module.

- ***Fuzzy logic controller (FLC)***: This module decides whether the femtocell should be switched on/off or kept in dormant mode. For that purpose, a FLC has been selected to evaluate the *reference distance* information. The main reasons to select a FLC are its simplicity in developing and managing rules based on the recommendations of expert as well as its low computational cost to be implemented in a real network.

The proposed FLC approach (see Fig. 9) is based on the Takagi-Sugeno-Kang (TSK) [35] method, which transforms the input parameters into particular outputs following specific membership functions and "IF-THEN" rules. FLCs are described in linguistic terms. In consequence, the experts' experience and knowledge can be easily transferred to the system. Furthermore, several rules can be triggered simultaneously, smoothing the controller actions.

Firstly, the input parameters are transformed into labels or linguistic terms based on fuzzy sets by means of membership functions. That process is called *fuzzification*. Several fuzzy sets could be implemented. The membership functions quantify the degree of membership of an input parameter p to a specific fuzzy set X. It is expressed as $\mu_x(p)$. Secondly, those labeled inputs are evaluated by the inference engine. This step is defined through the rule-base and it is built from the expert experience. Finally, the degree of truth for each rule r is calculated. This indicator is denoted by α_r and its analytical expression depends on the FLC implementation (e.g., AND/OR operators). Once that indicator is obtained, the output is evaluated following a *defuzzification* method (e.g., center of gravity).

Table 1
Fuzzy rules of FLC.

Reference Distance (RD)	Cell Status (CS)	Proposed Cell Status (PCS)
VC	–	ON
VF	–	OFF
C	OFF	DM
C	DM	ON
C	ON	ON
F	OFF	OFF
F	DM	OFF
F	ON	DM

In particular, in this work, the FLC is defined according to the requirements of the energy efficiency mechanism. The input parameters to the FLC are: the *Reference Distance (RD)*, which comprises of the θ_{cell} value for each studied cell; and the *Cell Status (CS)*, which presents the current status of the studied cell (on, off or dormant). The *Proposed Cell Status* (PCS) is the output of the system, whose possible values are: 'ON' (value = 1), 'Dormant Mode' (value = 0) and 'OFF' (value = -1). A membership function is defined for each input (see Fig. 10). RD possible values are: *'Very Close'* (VC), *'Close'* (C), *'Far'* (F) and *'Very Far'* (VF). Likewise, CS possible values are: *'ON'* (ON), *'Dormant Mode'* (DM) and *'OFF'* (OFF).

The fuzzy rules are described in Table 1, which are based on the AND operator, this means, all the conditions of the expression must be true. In this sense, for a better understanding, an example rule is described: 'IF RD is *'close'* AND CS is *'dormant mode'* THEN PCS is *'ON'*.The two membership functions are computed to get the degree of truth of each rule i:

$$\alpha_i = \mu_x(RD)^* \mu_y(CS) \tag{17}$$

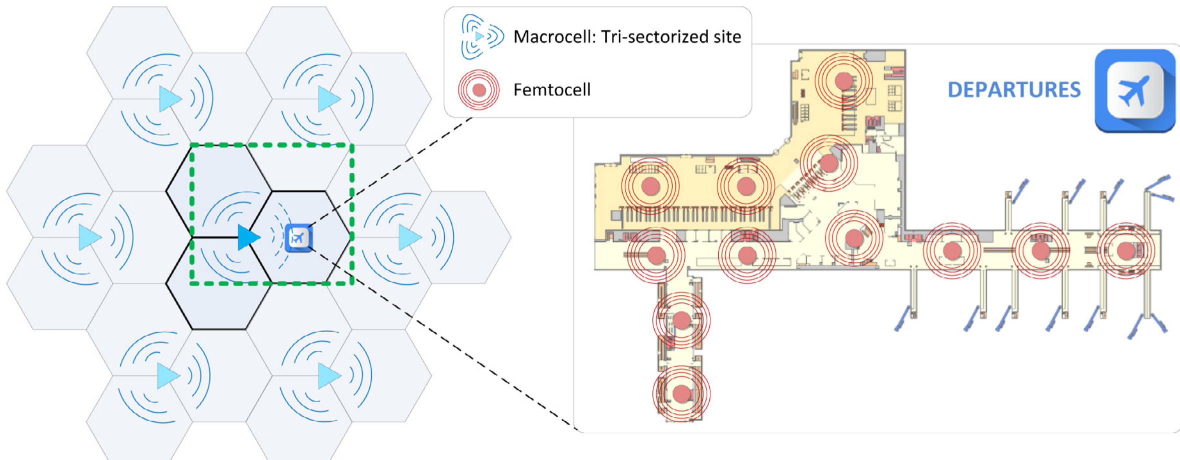

Fig. 11. Simulated scenario.

where * is the AND operation included in the antecedent of the rules. Finally, the FLC presents the output value, o_{cell}, based on the center-of-gravity method:

$$o_{cell} = \frac{\sum_{i=1}^{R} \alpha_i \times \ \omega_i}{\sum_{i=1}^{R} \alpha_i} \tag{18}$$

where α_i is the degree of truth for rule i (Eq. (17)), ω_i is the value of the constant output (1, 0 or −1) of rule i and R is the number of defined rules.

The last step of the ES algorithm is to integrate the output value of the FLC (o_{cell}) with the Cell Activity (S_{cell}) provided by the MLB mechanism, as the latter is more critical.

$$\varphi_{cell} = \begin{cases} -1 & if\ S_{cell} = 0\ and\ o_{cell} \in (-\infty, -0.5) \\ 0 & if\ S_{cell} = 0\ and\ o_{cell} \in [-0.5,\ 0.5] \\ 1 & otherwise \end{cases} \tag{19}$$

where φ_{cell} could take the same three values as PCS: -1, this mean the femtocell must be OFF, 0, the femtocell must be in dormant mode and 1, the femtocell must be ON.

6. Results analysis

6.1. Analysis set-up

A realistic simulation scenario has been designed to verify the proposed algorithms. This scenario models the Departure Lounge of Malaga Airport, which is a 265 m long and 180 m wide building (Fig. 11). Twelve open access femtocells have been placed in the building to increase cellular network capacity and coverage offered by the tri-sectorized macrocell deployed outside the building (see Fig. 11). The whole scenario is 3 km x 2.6 km (green dotted area) and, to avoid edge effects, the wrap-around technique has been implemented. This deployment presents a frequency reuse factor of 1. The developed scenario is introduced into the dynamic system-level LTE simulator described in [36]. The propagation model selected for this simulator is Winner II [37]. Likewise, shadowing is modeled following a spatially-correlated log-normal distribution with different standard deviation for outdoor and indoor users, as well as fast-fading is modeled by the *Extended Indoor A* (EIA) approach for indoor users [38].

Indoor users' mobility follows a random waypoint mobility model based on the work in [39]. Users' movements are defined to create a non-homogeneous user distribution and hotspots where network congestion may occur. Table 2. summarizes the main simulation parameters.

Fig. 12a presents an example of the classical coverage area. In turn, the proposed SCM is depicted in Fig. 12b.

Table 2
Simulation parameters.

Propagation Model	Indoor-indoor	Winner II A1
	Indoor-outdoor	Winner II A2
	Outdoor-outdoor	Winner II C2
	Outdoor-indoor	Winner II C4
Base Station Model	EIRP	13 (femto) / 43 (macro) dBm
	Directivity	Omni (femto) / tri-sector (macro)
Mobile Station Model	Noise Figure	9dB
	Noise Density	−174 dBm/Hz
Traffic Model	Calls	Poisson (avg. 0.43calls/user•h)
	Duration	Exponential (avg. 100 sec)
Mobility Model	Outdoor	3 km/h, random direction & wrap-around
	Indoor	Random Waypoint
Service Model	Voice over IP	16 kbps
	Full Buffer	
RRM Model	Bandwidth	5 MHz (25 PRBs)
	Access Control	Directed Retry (Threshold=−44 dBm)
	Cell Reselection	Criteria S, R
	Handover	Events A3, A5 (Offset = + 3 dBm)
	Scheduler	Voice: Round-Robin Best Channel Full Buffer: Proportional Fair
Time Resolution		100 ms
Self-Optimization Algorithms	Epoch Time	60 seconds
	S_{th}, T_{th}	0.7, 0.6

The value of S_{th} and T_{th} could be defined based on a sensitivity study of the UDR indicator or based on the operators' experience, policies or priorities. The proposed approach makes a sensitivity study during the network planning in the airport scenario where femtocell capacity is 32 users. The femtocell deployment is simulated to estimate the values of UDR for the different combinations of these thresholds with steps of 10. The best values for this scenario are $S_{th} = 0.7$ and $T_{th} = 0.6$ as Fig. 13 shows. Under this configuration, the algorithm reduces the UDR to 1%. This system would not require a complex study to select the optimal parameters as the performance of the system is not very sensitive to the parameter selection (it would be around 1.5% of UDR) when the value of the selected parameters is below 100 (100 means the method is not triggered).

In addition to the airport, the proposed techniques have been also assessed in a five floor building as depicted in Fig. 14. Four femtocells are deployed on the third floor. This scenario was set up with the same simulation parameters as Table 2.

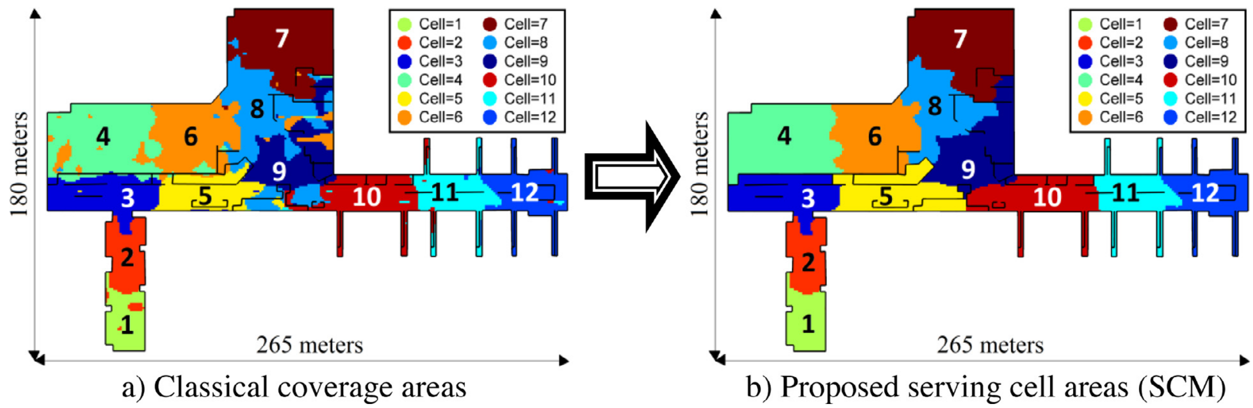

Fig. 12. Estimated SCM.

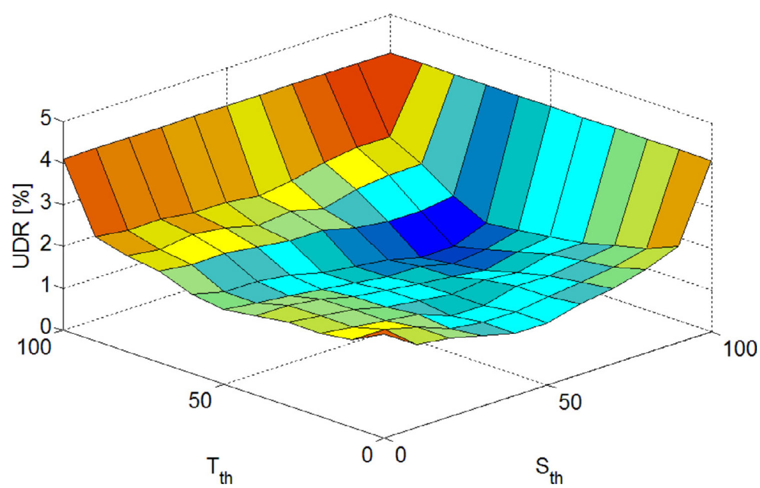

Fig. 13. MLB+LOC method - Sensitivity study of UDR based on S_{th} and T_{th}.

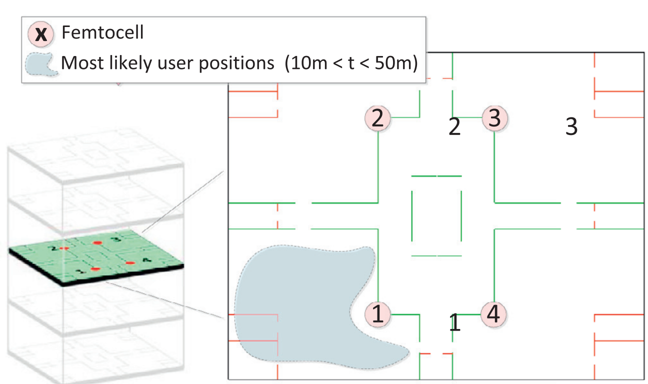

Fig. 14. Office scenario.

6.2. Assessment of the results

Initially, this system is evaluated with high accuracy users' location in both scenarios. Then, the performance of the methods is assessed to measure the feasibility of the proposed location-aware SON system under several location errors (up to 32 m) due to low accuracy of current indoor positioning techniques.

The *Power Load and User Sharing* (PLUS) optimization mechanism presented in [14] has been selected as the state-of-the-art reference method to compare the proposed algorithms. PLUS is aimed at traffic steering at indoor scenarios. It is carried out thanks to a *Fuzzy Logic Controller* based on experts' rules that modifies the femtocells transmission power according to a parameter related to blocked-calls and the current cell transmission power. Moreover, the proposed location-based SON methods have been adapted to gather RSS information directly measured by the users. This means, no users' location is required. Therefore, the assessed algorithm are referenced as: non-optimized network (NO OPT), the reference method (REF), the load balancing method (MLB), the energy-saving method (ES), the coordination of MLB and ES methods (COOR) and the location-based SON methods are named MLB+LOC, ES+LOC and COOR+LOC respectively.

The challenge faced by the proposed algorithms is threefold. First, the percentage of active voice calls must be as high as possible, handing over any other kind of service to macrocells in case the situation is considered congested. Second, a good *Quality of Service* (QoS) is expected to support the communication. Finally, the energy consumption must be reduced by switching off or keeping in dormant mode those femtocells with no users. The proposed mechanisms have been evaluated in four different indoor deployments depending on the femtocell limit in the maximum number of UE in connected mode (usually 4, 8, 16 or 32 users). Initially, one of them (32 users) for the first scenario (airport) is described in detail to finally summarize the average performance of the second scenario and the other configurations.

Therefore, the following evaluation is carried out with femtocells that are limited to 32 users in connected mode. In this case, since the proposed self-optimization algorithms prioritize voice

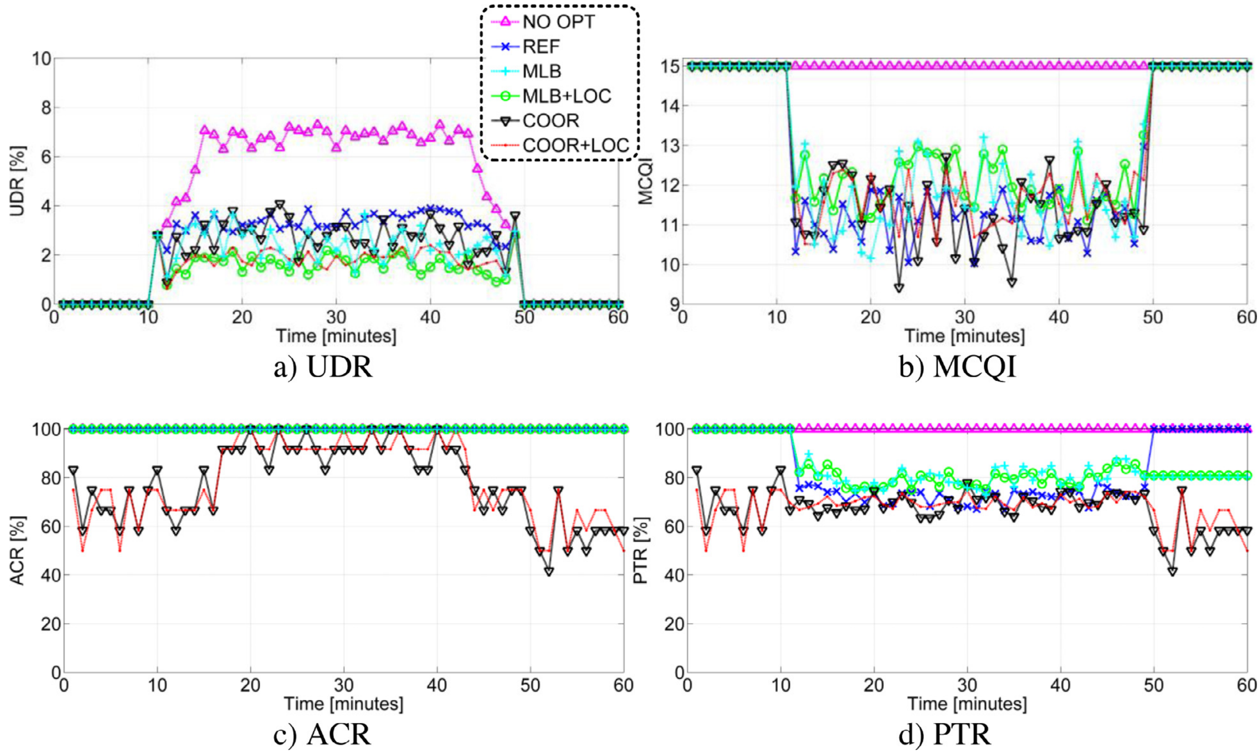

Fig. 15. Network performance at the airport.

connections, the execution of the algorithms must be done in the shortest possible period. Additionally, femtocells need a period to set the configuration file (i.e., to change the transmission power) which takes normally tens of seconds. For these reasons, the algorithms are triggered every minute while hotspots are created every hour. Furthermore, the normally unplanned deployment of femtocells forces their initial transmission power to be set to its maximum value.

Initially, the (not self-optimized) network is well-managed and there are no accessibility or retainability issues (i.e., all the attempted connections are accepted and none of them are dropped or in outage). However, after 10 minutes, the rate of users in the network starts to increase and a specific area of the scenario (a boarding gate) becomes overloaded. At this moment, femtocells closed to that area would reach their maximum capability and would have to reject/drop connections as Fig. 15a shows (*'magenta line'*). That situation persists during more than 30 minutes, being UDR around 7%. After that period, the rate of users is reduced and the network can then accept new requests. In average, the UDR is around 4% along one hour, which is over the maximum value accepted by most mobile operators' policies. Now, the same scenario is optimized by the REF method [14]. Fig. 15a shows that this method (*'blue line'*,) outperforms the non-optimized case when the network is congested (4% vs. 7%). The average value of UDR along one hour is reduced below 2%. The performance of the proposed MLB+LOC method is also shown in Fig. 15a (*'green line'*), which enhances UDR over 50% in comparison with the state-of-the-art REF method. In the case of the COOR+LOC (*'red line'*), UDR is also better than the REF method. However, due to the time femtocells need to be switched on or awake, the performance of this indicator is slightly lower compared with the MLB+LOC method. A shorter execution period for changing the status of the femtocell would help to fix this shortcoming. In case the RSS values are directly reported by the users, the MLB (*'cyan line'*) and COOR (*'black line'*) methods outperform the REF method but decrease the UDR performance compared to the location-aware SON methods. The main reason is related to the channel instability due to the shadowing, multi-path reflections, wall obstructions, etc., even if the terminal protocol stack (Layer 1 and Layer 3 [40]) would minimize the impact of fast-fading.

The channel quality is directly related with the previous UDR indicator. For the non-optimized case, the level of MCQI is the highest even if there are accessibility or retainability issues, as Fig. 15b shows. This is due to the fact that these users present the best CQI levels. Nevertheless, when they have to handover and the target femtocell is full, these users are dropped (mainly due to handover failures). Conversely, the self-optimization mechanisms have to sacrifice network resources per call (i.e., CQI is reduced) in order to avoid accessibility or retainability issues (i.e., enhance UDR). Besides, the level of MCQI is still good enough to ensure high quality connections for all of them. Note that, blocked/dropped calls are not necessary due to bad CQI, other issues could finish the calls keeping a good CQI (calls could abnormally finish because of a problem of missing neighbor cells, cell capacity, lack of radio resources, etc.). Analyzing this issue from the other side, bad CQI means the calls might be blocked/dropped and the mean performance of MCQI would be decreased.

From the point of view of the system energy consumption, Fig. 15c and Fig. 15d illustrate the network energy performance. On the one hand, the ACR shows how the COOR and COOR+LOC mechanisms either switches off or turns into dormant mode many femtocells of the scenario, while the other methods keep all femtocells awake. On the other hand, the PTR is lower for the REF, MLB and MLB+LOC methods. This is due to the fact that the femtocell transmission power is decreased to balance traffic (in comparison to the maximum transmission power level set by default). The REF algorithm tends to return to the maximum power level once the network is balanced while the MLB and MLB+LOC algorithms keep

Table 3
Overall network performance.

	NO OPT	REF Method	MLB Method	MLB + LOC Method	COOR Method	COOR + LOC Method
UDR [%]	4.1	2.2	1.8	1.1	1.9	1.2
MCQI	15	12.7	13.0	13.2	12.6	12.9
ACR [%]	100	100	100	100	80.2	78.4
PTR [%]	100	81.8	88.1	86.7	71.3	68.4
UHR	0.86	0.82	0.91	0.84	0.93	0.85

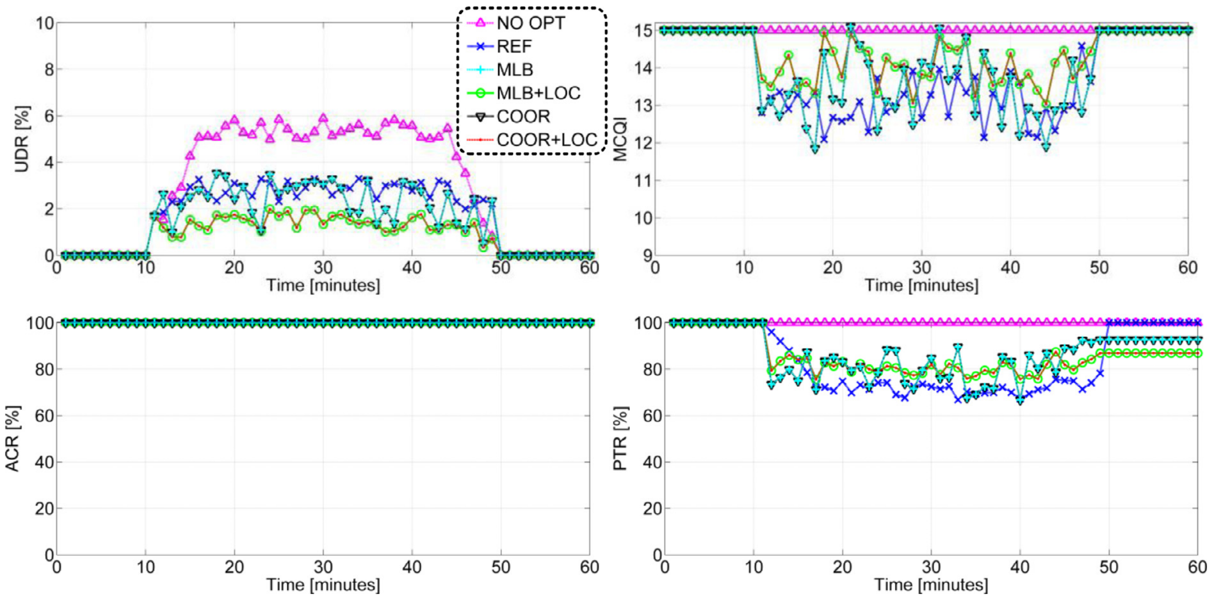

Fig. 16. Network performance at the office scenario.

the last power configuration. The COOR and COOR+LOC methods provide even higher energy-savings in the network because femtocells could be switched off.

Regarding the impact of the power changes on handovers, the average of UHR is around 0.85 for the non-optimized network. The REF method presents a UHR of 0.8, while the MLB and COOR methods increase the UHR to 0.9 and 0.91 respectively. The proposed location-based methods (MLB+LOC and COOR+LOC) have a UHR of 0.83. As expected, re-sizing the coverage area of femtocells involves an increase rate in the number of handovers per user when the self-optimization algorithm is triggered. But, once the network is optimized, the number of handovers is decreased compared to the non-optimized network. That is happening because less handovers are required when the traffic in the network is balanced.

Moreover, the algorithms were also evaluated during one day simulation where a hotspot was created in a different place of the airport each hour. Table 3. presents the average values of each indicator in that period. It could be observed that the results are comparable to the results of one hour simulation.

To show that the previous results are independent of the scenario, the proposed SON system is also assessed in a second scenario. Here, the user density is evenly distributed from t=0 minutes to t=10 minutes and from t=50 minutes to t=60 minutes. However, from t=10 minutes to t=50 minutes, the users' positions are more likely to be located in the blue-dashed non-uniform shape, closed to femtocell 1 (see Fig. 14). That situation would overload femtocell 1.

The same network indicators are measured in this office scenario. Fig. 16 illustrates the performance evaluation.

These results are similar to those described for the airport scenario. However, due to the low number of femtocells, most of the time there are users camped at each femtocell or they are close to those empty femtocells. For this reason, the ES methods are never triggered. Therefore, the MLB method and MLB+LOC method present the same results as the COOR method and the COOR+LOC method respectively. Regarding the UDR indicator, the proposed location-based SON methods outperform the REF, MLB and COOR methods. The benefit of location in the SON mechanisms can be observed. The level of MCQI is still good enough to ensure high quality connections. Conversely, as none of the femtocells are switched off, the ACR indicator is 100% for all the methods. However, the transmission power of some femtocells is decreased, as PTR indicator illustrates, in order to move users from overloaded femtocells to offloaded femtocells.

Finally, the same evaluation has been carried out with femtocells with different restrictions in the number of connected users (4, 8 and 16 users) and for both scenarios. The conclusion is that the restriction in the number of users per femtocell does not significantly change the previous results. That means, the proposed SON algorithms are independent of the type of femtocells and, a priori, from the type of scenario.

6.3. Impact of users' location error

The indoor positioning system could introduce some errors in the users' location. This situation is evaluated to assess the practicality and reliability of the proposed self-optimization methods. The evaluation has been performed under the same conditions as Section 6.2 at the airport scenario.

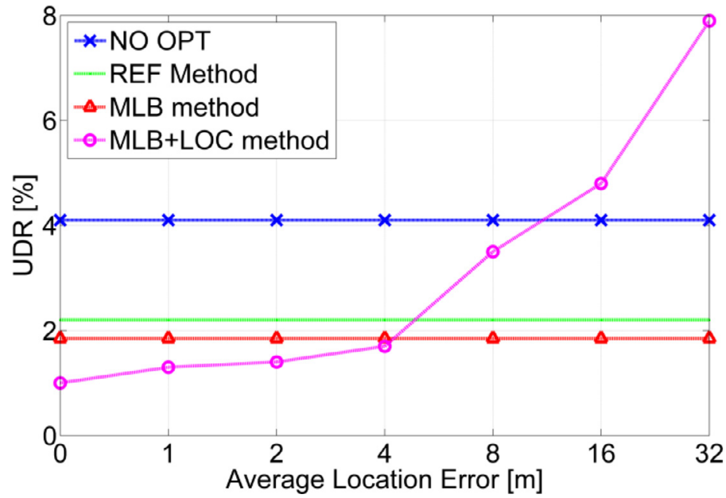

Fig. 17. Impact of average location error.

The average UDR values have been calculated for different average errors (1–32 m) as Fig. 17 shows. Compared to the non-optimized network case (NO OPT), to the reference method (REF method) and to the MLB method, where the average UDR values are 4.1%, 2.2% and 1.8% respectively, MLB+LOC algorithm enhances the system performance when the average location error is lower than 16, 8 and 4 m respectively. The impact that those errors have on the SON algorithms performance increases with the location errors, becoming unacceptable for the operators. In this sense, the accuracy of some of the current indoor positioning systems is lower than these location errors [26], which means, the performance of the proposed SON methods would enhance the network capacity, coverage and the efficient use of energy compared to the state-of-the-art.

Besides, the mobility pattern of users (i.e., the users' locations change in short periods) and large-scale deployments (i.e., estimation of thousands of users) could be a challenge for current indoor-positioning systems. However, the proposed SON system does not require a continuous estimation of the users' locations (i.e., the same periodicity of the SON methods is enough). In large-scale deployments, distributed indoor-positioning systems could be implemented to address the calculation of the users' locations. Moreover, in case of an indoor-positioning system based on RSS from cellular mobile infrastructure (e.g., femtocells), both positioning system and SON entities must be coordinated. Each time a SON algorithm tunes femtocells power transmission, this power change must be notified to the positioning system algorithm in order to update the fingerprint databases.

6.4. Analysis of performance metrics for real deployments

Additional performance metrics are measured and analyzed to ensure the viability of our approach in a real scenario.

- **Successful transmission rate:** The well-known Transmission Control Protocol (TCP) is selected as the communication protocol between systems. It would ensure 100% of successful transmission rate.
- **Signaling overhead:** The context-aware SON system receives information from the REM system and the indoor positioning system. That information is ASCII encoded and transmitted in JSON messages. Each message would size the communication headers (TCP+IP=40 bytes) plus around 440 bytes of information for a reported user position, while the message size from the REM system would be the communication headers plus around 310 bytes for RSS information per position and femtocell. Each additional RSS from a femtocell increases the text 240 bytes). Therefore, a scenario with 10.000m2 where RSS information is reported from 5 femtocells each m2, REM system would transmit 14 Mbytes each time the network conditions change (e.g., construction of a new wall, a new femtocell is deployed, etc.). Conversely, the indoor positioning system would transmit 96 Kbytes to supply the position of 200 active users. This information would be transmitted in few seconds in current communication technologies (DSL or optical fiber).
- **Delay:** The information could be received with a delay due to processing time issues in the sources systems, being the indoor processing system the most critical case. The time to estimate the users' location is configured to one second per user plus a few milliseconds to transmit the information. Hence, SON system would receive the users' positions with a minimum delay of one second. In case that information is received with a delay of few seconds or any of the users' position is missing, the SON system is not triggered in that period.
- **Computational cost:** The time to process all of that information would depend on the number of users and femtocells in the scenario. The "Big O notation" would describe the limiting behavior of these algorithms. The number of users is limited by the femtocell but the number of femtocells would depend on the deployment. The complexity of the MLB method would be related to $O(k \cdot n)$, where n is the number of femtocells deployed and k is the number of iterations the algorithm need to converge. Normally, $k < n$ because the algorithm quickly converges to the optimal value of the femtocells transmission power to balance the network load and very few femtocells would be overloaded each iteration. Conversely, the complexity of the ES method would be related to $O(m)$, where m is the number of femtocells deployed. Hence, as these mechanisms are processed in parallel and the complexity of $O(k \cdot n) > O(m)$, then, the global system complexity would be the worst case: $O(k \cdot n)$. For the described deployment of femtocells (max. 32 users/femto) in the airport (12 femtocells) and the number of users (around 200 active users), the time the SON system requires to propose the new network configuration parameters is around 65 milliseconds. This time is short enough compared to the configuration time of the femtocell.
- **Automatic values of S_{th} and T_{th}:** A periodical network analysis is necessary to automatically compute these thresholds due to the specific characteristics of indoor environments and users' mobility patterns. Each hour or day the algorithm would

change one of these thresholds in steps of X units and the new network performance would be analyzed

According to this, the *reference thresholds* ($\boldsymbol{S_{th}}$, $\boldsymbol{T_{th}}$) would be periodically changed $\pm\,\Delta \boldsymbol{S_{th}}$ and $\pm\,\Delta T_{th}$, to find if any of the new proposed thresholds around the *reference thresholds* would minimize the UDR. In that case, those new thresholds would be the *reference thresholds* and the procedure is repeated around these thresholds. In other case (none of the new combination of thresholds outperforms the UDR), initial reference thresholds would be the optimal thresholds.

That procedure could take several iterations (i.e., days or hours) to reach the optimal solution. Conversely, that solution could be obsolete in time due to environment changes (new walls), users' mobility patterns (more users in winter than in summer), etc. Thus, this procedure should be triggered regularly.

In case the context-aware SON system might degrade the network performance (due to delays of context data, missing information, etc.), it will be immediately detected and the context-aware SON algorithms will be temporarily disabled and the network would be managed by conventional SON mechanisms [14].

7. Conclusions and future work

This paper has introduced the current challenges of temporary overcrowded HCNs at indoor environments and has proposed a coordinated self-optimization system. The aim was to homogenously balance users in the network to increase its capacity and coverage, at the same time maintaining a high global quality in voice connections and reducing the power consumption.

The proposed location-based algorithms have been shown to enhance the network performance, from the point of view of the users' satisfaction and energy efficiency. On the one hand, the MLB + LOC algorithm provides optimal configuration parameters to reduce as much as possible accessibility and retainability issues, prioritizing voice connections. On the other hand, the COOR + LOC system tries to improve both aspects, reaching a compromise. This means that a slight UDR degradation is obtained compared to the standalone MLB + LOC method because of the high energy-saving. A shorter period in the execution of the COOR + LOC algorithm could enhance its performance. The coordination of these methods is mandatory to avoid conflicts in self-optimization mechanisms.

Future work will be focused on the development of new self-optimization methods to analyze additional context-aware information. Moreover, the evaluation of these algorithms will be assessed in other realistic simulated scenarios and real testbeds with indoor-positioning system.

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Alejandro Aguilar-Garcia graduated in Telecommunications Engineering in 2010 at Universidad de Málaga, in the fields of Telematics and Communications. He improved his mobile communications skills coursing an Expert Mobile Communications Course in 2009. He started his career at Sony European Technology Centre in the Speech and Sound Group, participating on an existing video classification system based on audio and image features. He is currently working towards his PhD developing novel SON mechanisms for small-cells in mobile networks at the Communications Engineering Department at the University of Málaga.

Raquel Barco holds a M.Sc. and a Ph.D. in Telecommunication Engineering from the University of Malaga. She has worked at Telefonica in Madrid (Spain), the European Space Agency (ESA) in Darmstadt (Germany) and Nokia Networks. In 2000 she joined the University of Malaga, where she is currently Associate Professor. Her research interests include satellite and mobile communications, mainly focusing on Self-Organizing Networks.

Sergio Fortes received his M.*Sc*. degree in Telecommunication Engineering from the University of Málaga (Spain) in 2008. He began his career in the field of satellite communications being through different positions in European space agencies (DLR, CNES, ESA) where he participated in various research activities. In 2010, he joined the satellite operator Avanti Communications, where he acted as consultant and coordinator of research projects with the European Space Agency and other partners. In 2012 he joined the Communications Engineering department at Universidad de Málaga, where he is currently pursuing his Ph.D. focused on the development of innovative SON techniques for mobile networks.