Mobility Robustness Optimization in Enterprise LTE Femtocells

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***Abstract*—Mobility robustness optimization has been identified as an important use case of Self-Organizing Network (SON). In this paper, a self-optimization algorithm for tuning handover (HO) parameters of a Long Term Evolution (LTE) femtocell network in an office scenario is presented. The algorithm is implemented by a fuzzy logic controller, which jointly tunes HO margin and Time-to-Trigger parameters. The aim of the algorithm is to improve the overall handover performance, given by the average number of HOs per call and the call dropping ratio. Simulation results show that, unlike existing algorithms, the proposed algorithm improves network performance for any situation of average network load.**

***Index Terms*—LTE, femtocell, handover, fuzzy logic, handover margin.**

I. Introduction

In recent years, mobile communications have experienced an important growth that has led to a rapid increase in the number of mobile users and services. To face these changes, more complex networks have been developed, comprising advanced technologies and a higher number of elements. This is the case of Long-Term Evolution (LTE), which is the evolution of the current Universal Mobile Telecommunications System (UMTS) radio access technology. LTE is the combination of the all-IP core network known as the evolved packet core (EPC) and the evolved UMTS terrestrial radio access network (E-UTRAN). The key benefits of LTE can be summarized in improved system performance, higher data rates and spectral efficiency, reduced latency and power consumption, enhanced flexibility of spectral usage and simplified network architecture [1].

Moreover, due to the complexity and size of future networks, operators demand equipment from manufacturers that allows the development of self-organizing networks (SON) [2]. Such a piece of equipment must be able to self-configure, self-optimize and self-heal its problems.

In parallel, femtocells have been proposed as a promising solution to improve capacity and coverage indoors. Femtocell access points are low-power base stations using cellular technology in licensed frequency bands providing service indoors over internet-grade backhaul under operator management [3][4]. Unlike in macrocellular scenarios, in femtocell scenarios, careful planning is not feasible due to the large number of base stations. Thus, an automatic parameter tuning during operation is extremely important for operators. Unfortunately, the limited functionality of legacy femtocell equipment, the limited capacity of backhaul link and, most importantly, the complexity of the indoor propagation environment makes this optimization process more complex than in macrocell networks.

In mobile networks, the handover (HO) mechanism has a strong impact on network performance. Thus, ensuring the best HO parameter settings is key for network operators, which justifies that mobility robustness has been identified as an important SON use case by the industry [5]. In femtocell networks, this can only be achieved by applying SON techniques.

In the literature, several HO parameter optimization algorithms have been proposed for LTE macrocells [6][7]. In the case of femtocells, most of the attention has been paid to residential scenarios with standalone femtocells. In [8] and [9], the enforcement of a minimum time interval is proposed to eliminate unnecessary handovers between macro and femtocells. Likewise, an adaptive algorithm for selecting the hysteresis margin based on user position in LTE is presented in [10]. However, as pointed out in [11], enterprise femtocell networks have important differences with residential scenarios, namely that: a) enterprise scenarios often have a three-dimensional structure, where neighbor cells are located everywhere around the serving cell, which leads to interference problems; b) a different, and probably more intense, user mobility pattern than at home; c) a higher concentration of users varying both in space (e.g., canteen) and time (e.g. coffee break, meeting end); and d) open access instead of closed (i.e., limited) access. It is thus expected that the best HO parameter settings might be different from those in other scenarios.

In this paper, a self-tuning algorithm for a standardized HO algorithm in an enterprise LTE femtocell scenario is presented. The proposed algorithm aims to improve the quality of service in terms of dropped call rate, while keeping signaling load in terms of number of HOs per call within reasonable limits. The algorithm is implemented as a Fuzzy Logic Controller (FLC), whose inputs are performance statistics in the network management system collected on a long-term basis. Assessment is based on a dynamic system-level simulator implementing a three-dimensional office scenario. The main contribution of this paper are: a) a sensitivity analysis of the impact of HO parameters on the performance of an LTE enterprise femtocell

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network, and b) a self-tuning algorithm for HO parameters that outperforms, in this specific scenario, those previously reported in the literature for macrocells [6][7].

The rest of the paper is organized as follows. Section II outlines the most relevant parameters in the HO algorithm and the criteria guiding the tuning process. Section III introduces fuzzy logic principles and the details of the designed controller. Section IV presents the experiments carried out to validate the algorithm. Finally, Section V summarizes the main conclusions of the study.

II. LTE Handover Algorithm

Similarly to other technologies, a HO can be triggered in LTE due to different reasons. Since the aim of this work is to improve the quality of network connections, attention is focused on a handover due to quality reasons. A quality HO is triggered if

$$SINR(c,i) < SINR_{th}(i) \ for \ TTT(i) \ , \text{ and} \quad (1)$$

$$RSRP_j(c,j) \geq (RSRP_i(c,i) + HOM(i,j)) \ , \quad (2)$$

where $SINR$ is the Signal to Interference and Noise Ratio experienced by a connection c to the serving cell i, $SINR_{th}$ is a SINR threshold value defined on a cell basis, TTT is the Time-To-Trigger value indicating the time during which Eq. (1) must be satisfied, $RSRP$ is the Reference Signal Received Power that indicates the received power value for a connection from the serving cell i or from the adjacent cell j, and $HOM(i,j)$ is the HO margin indicating the power margin value to be met by cells i and j for a HO to be executed. The latter is defined on a per-adjacency basis.

The optimization algorithm proposed here configures the HOM and TTT parameters. In this work, HOM takes values between 0 and 8 dB, with intervals of 0.5 dB, while TTT takes values between 100 and 800 ms, with intervals of 100 ms, due to the time resolution of the simulator used in the experiments. Both parameters are considered as two global variables across the stage, although the HOM parameter is defined on a per-adjacency basis.

Each pair of values of these control parameters (HOM, TTT) determine a network operating point. Its modification will alter network performance in terms of the average number of HO per call (HOR, for HO Ratio) and the Call Dropping Ratio (CDR). For instance, low TTT and HOM values lead to the user being connected faster to the best cell with abrupt changes of propagation conditions (e.g., when the user moves towards a neighbor cell). Such an effect helps to avoid dropped calls in the networks. However, this situation also facilitates triggering unnecessary HOs, which might lead to instabilities in the HO process (referred to ping-pong), translating into an increase of the number of HOs and, consequently, of signaling load in the network. In contrast, increasing HOM and TTT restricts the HO process, decreasing the number of HOs, but deteriorating connection quality as the user is not always connected to the best cell. This might end up with an increase of CDR.

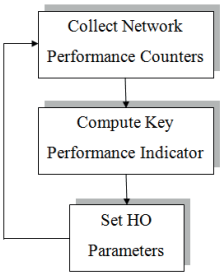


Fig. 1. Algorithm flowchart.

III. Design of Self-tuning Algorithm

The optimization algorithm for parameter tuning is designed as a fuzzy logic controller [12].The main advantage of fuzzy controllers, compared to classical proportional integrative and derivative (PID) controllers, comes from the simplicity of defining working rules based on operator previous knowledge.

A. Algorithm structure

Fig. 1 shows the flowchart of the proposed algorithm. For a certain period of time, referred to as *optimization loop*, a femtocell gathers performance measurements, such as number of HOs and dropped calls, from which HOR and CDR are computed. These indicators are used to assess the performance of current HOM and TTT settings. If indicators show a network performance improvement compared to previous settings, network parameters are kept unaltered as in previous loops. Otherwise, new values for HOM and TTT are calculated by the FLC, and a new *optimization loop* starts.

B. Fuzzy Logic Controller

As shown in Fig. 2, the controller has an incremental structure. The inputs of the FLC are HOR and CDR statistics, while the outputs are the changes in HOM and TTT, ΔHOM and ΔTTT, that will be downloaded into the network for the next loop. Inside, the FLC is divided into three blocks: fuzzificator, inference engine and defuzzificator. The *fuzzificator* qualifies the inputs (i.e., performance indicators) with values between 0 and 1 according to the degree of membership of these inputs to a qualifying class (e.g., ”high”, ”medium” or ”low”). Such a mapping is made by membership functions $\mu(HOR)$ and $\mu(CDR)$, shown in Fig. 3. These functions indicate the degree of membership of each value to each class. Note that a certain input value can be qualified simultaneously to different classes due to the overlapping of membership. The *inference engine* defines the behavior of the controller in linguistic terms by means of ”IF ... THEN ...” rules. Table I shows the *inference engine* rules defined in this work. For instance, rule 3 reads as “IF HOR is high and CDR is low THEN ΔHOM is very positive and ΔTTT is negative”. Finally, the *defuzzificator* translate the consequent of the rules fired in the inference machine, to a numeric value (in this work, the suggested parameter change). For this purpose, the center-of-gravity method [12] has been used

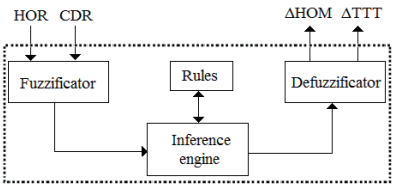
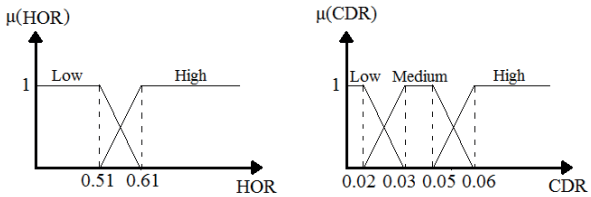


Fig. 2. Fuzzy logic controller scheme.



(a) HOR (b) CDR

Fig. 3. Input membership functions.

TABLE I
FUZZY LOGIC CONTROLLER RULES

N	HOR	CDR	ΔHOM	ΔTTT
1	High	High	Negative	Very Positive
2	High	Medium	Positive	Positive
3	High	Low	Very Positive	Negative
4	Low	High	Very Negative	Very Positive
5	Low	Medium	Equal	Negative
6	Low	Low	Positive	Equal

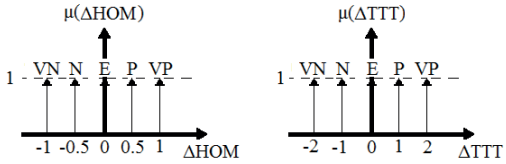
in this work. For simplicity, the controller is designed based on the Takagi-Sugeno approach, where output membership functions are constants, as shown in Fig. 4.

IV. SIMULATION ANALYSIS

This section tests the operation of the proposed algorithm by simulations. First, the methodology experimental is described and results are presented later.

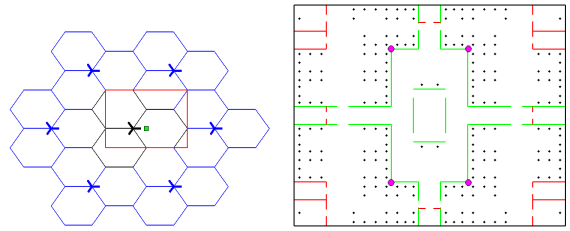
A. Assessment methodology

To assess the performance of the optimization algorithm, a dynamic system-level simulator implementing a three-dimensional office scenario has been used [13]. Fig. 5 a) shows the simulation scenario, comprising three co-sited and tri-sectorized macrocells (black cells in the figure). To avoid border effects during the simulation, a wrap-around technique is adopted by replicating the original scenario around itself



(a) ΔHOM (b) ΔTTT

Fig. 4. Output membership functions.



(a) Scenario layout (b) A floor diagram

Fig. 5. Simulation scenario.

TABLE II
SIMULATION PARAMETERS

BS model	EIRP	BS_{femto}=13 dBm BS_{macro}=43 dBm
	Directivity	femto: omnidirectional macro: tri-sectorial
MS model	Noise figure	9 dB
	Noise spectral density	-174 dBm/Hz
Traffic model	Arrival process	Poisson (avg. 0.22 calls/(user*hour))
	Duration	exponential (avg. 180 sec)
	Spatial distribution	Uniform
Mobility model	Outdoor	3 km/h, random direction & wrap-around
	Indoor	random waypoint
Service model	Voice over IP	16 kbps
RRM model	6 PRBs (1.4 MHz)	
	Cell Reselection	
	Access control	
	Handover:	PBGT, Qual, Umbrella HOM=6 dB, TTT=200 ms
	Scheduler: RR-BC	Time: Round-Robin (RR) Freq.: Best Channel (BC)
Average network load	50%	
Time resolution	100 ms	
Nbr. optimization loops	23	
Simulated network time	7200 s per network parameter setting	

(blue cells). Performance indicators are collected only inside the area under study (red square). An office building with dimensions 50m x 50m has been placed inside the coverage area of a center cell (green square). The number of floors in the building can be configured by the user (5 in this work). The floor plan is the same for all floors. Figure 5 b) shows the layout of one of the floors. Magenta circles show femtocells positions, lines are walls (different colors represent their thickness), and black diamonds are work stations. For simplicity, only Voice-over-IP (VoIP) service and the downlink are considered in the experiments. Table II summarizes the default values of the main simulation parameters. The reader is referred to [13] for a more detailed explanation of the simulation environment.

A sensitivity analysis is performed first to check the influence of tuning HO parameters (HOM and TTT). Later, the performance of proposed optimization algorithms is tested. Three different algorithms are simulated. The first two are those proposed in [6] and [7], which have been adapted for a femtocell environment. Algorithm in [6] has been adapted considering the number of HOs per call instead of raw number of HOs, as well as slight changes in membership functions used to classify performance indicators. Regarding algorithm in [7], the main change is enforcing that TTT values are

multiple of 100 ms. These are referred to hereafter as 1D and 1.5D, respectively, and will be used as a benchmark. The third algorithm is that proposed in Section III, referred to as 2D (for 2 degrees of freedom). The algorithm 1D (for 1 degree of freedom) modifies only HOM parameter, unlike the algorithm 2D which modifies both HOM and TTT. The algorithm 1.5D modifies both values, but only in a pre-defined set of pair values. Thus, it is not possible to modify independently HOM and TTT parameters in the 1.5D algorithm.

Two performance indicators are used to compare the three optimization algorithms, based on CDR and HOR statistics collected in the different optimization loops. Firstly, a Figure of Merit (FM) measures the quality of a network parameter configuration (i.e., a pair of values of HOM and TTT) from the values of CDR and HOR, as:

$$FM = \omega_1 * (\frac{CDR}{CDR_t})^{\alpha_1} + \omega_2 * (\frac{HOR}{HOR_t})^{\alpha_2} , \qquad (3)$$

where CDR and HOR are the network performance indicators obtained by the parameter configuration in a particular optimization loop, and CDR_t and HOR_t are performance target values defined by the operator, ω_1 and ω_2 are relative weights showing operator preference between network connection quality and signaling load, and α_1 and α_2 are constants to penalize the non-fulfillment of objectives. Hereafter, $\omega_1 = \omega_2 = 0.5$, $\alpha_1 = \alpha_2 = 2$, $CDR_t = 0.05$ and $HOR_t = 0.5$.

Secondly, the FM average, P (for Penalty), is used to measure the goodness of the optimization algorithm, not only in a particular time (e.g., at the end of the optimization process), but along the whole tuning process including all optimization loops. In this work, P is defined with an infinite-horizon discounted problem as:

$$P \approx (1-\gamma) \sum_{n=0}^{h-1} \gamma^n * FM_{(n)} + \gamma^h * FM_{(h)} , \qquad (4)$$

where h is the number of simulated optimization loops, $FM_{(h)}$ is the value of FM at the end of loop h, and γ is the factor that provides more or less importance to the FM that were obtained in the first simulation loops. The value of γ ranges from 0 and 1. The closer to 1 γ is, the higher weight is given to FM values in the last loops (steady state) compared to the first loops (transient response). Hereafter, γ=0.99 and h=23. The value of h is large enough to ensure that all methods reach the equilibrium state at the end of the simulation process.

B. Results

Fig. 6 presents the FM value for different combinations of HOM and TTT for 50% average network load. A smoothing filter has been applied to that surface to reduce stochastic fluctuations in the indicator. In the figure, a deep valley with the lowest (best) FM values is observed for medium HOM (i.e., 3-4dBs) and low TTT (i.e., 100-200 ms) values. Thus, such settings can be considered as the optimal working point. Optimal (i.e., lowest) results are also obtained for FM

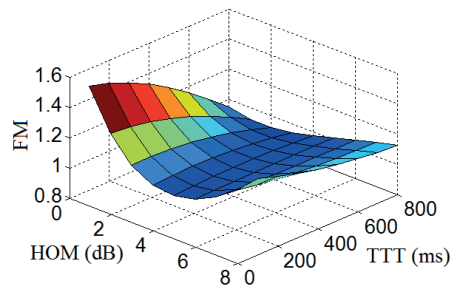


Fig. 6. FM sensitivity analysis.

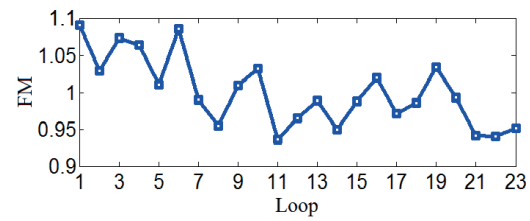


Fig. 7. FM evolution with time for 2D algorithm.

with low HOM values (0-2 dB) and high TTT (700-800 ms). However, FM experiences a high sensitivity to network parameter changes in this area, and therefore low HOM and high TTT values cannot be considered as adequate working points.

Fig. 7, 8 and 9 show, for the 2D algorithm, the evolution of FM, HOR and CDR performance indicators, and HOM and TTT parameters, respectively. The initial network configuration is HOM=6 dB and TTT=200 ms. It is observed how FM shows an overall improvement from 1.1 to 0.95 (i.e., over 13% of the initial value). The final network performance is reached with a network configuration of HOM=3 dB and TTT=100 ms. These network values are located inside the optimal area observed in Fig. 6. These network parameter settings obtain a CDR=4.5% (i.e., below the CDR_t target), and HOR=0.525 (i.e., higher than the target). Not satisfying

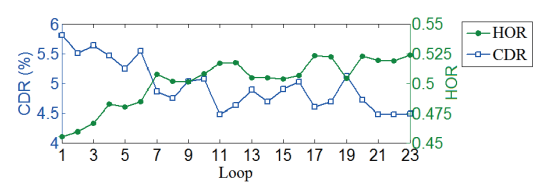


Fig. 8. HOR and CDR evolution for 2D algorithm.

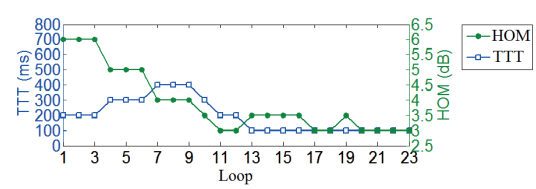
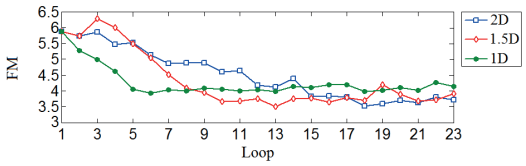
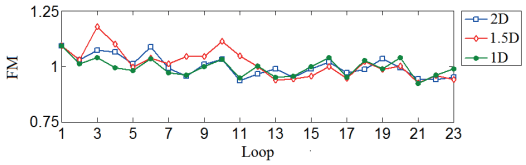


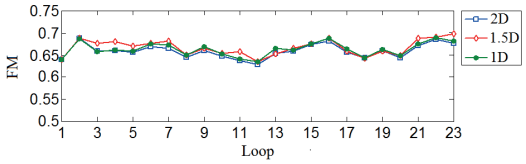
Fig. 9. HOM and TTT evolution for 2D algorithm.



(a) Average network load of 75%



(b) Average network load of 50%



(c) Average network load of 25%

Fig. 10. Comparison of the different self-tuning algorithms.

the latter target is explained by Fig. 6 and Eq. (3), where a better (i.e., lower) value of HOR would cause a worse (i.e., higher) value of CDR, leading to a worse overall FM result.

It should be pointed out that the fluctuations in FM are due to the stochastic nature of the simulation (and not caused by system instabilities from frequent parameter changes) since different values of performance indicators can be obtained for the same network parameter settings. This can be seen in loop 6, where, with similar HOM and TTT values to previous loop, there is an increase in the CDR and HOR values, thus increasing FM.

Fig. 10 depicts the figure of merit obtained for the different optimization algorithms with different average network load (25%, 50% and 75%). For low network load, lower interference levels will lead to a higher connection quality and less dropped calls. In contrast, for high network load, the probability of HO failure is large, leading to more dropped calls. For low and medium load, it is observed that final FM value is very similar for all methods. A more detailed analysis shows that all algorithms end up with same network parameter settings, but not all algorithms reach the best network settings at the same optimization loop. Specifically, algorithm 1.5D experiences the worst performance across time (P value), and 2D algorithm shows better stability. In contrast, for a 75% network load, it is observed that the 2D algorithm ends the optimization process in a better network configuration (i.e., lowest FM value). Such a better performance comes for its ability of tuning TTT and HOM independently (and hence the name 2D). This increased flexibility is achieved at the expense of a slower convergence to the steady state solution.

Table III shows the overall penalty, P, obtained by all algorithms along their trajectories. It is observed that the 2D algorithm shows the best result for a 75% network load. For low and medium load, network performance is similar to that observed with the other optimization algorithms.

TABLE III
TIME AVERAGE OF THE FIGURE OF MERIT

Average load	25%	50%	75%
2D	0.6727	0.9623	3.8952
1.5D	0.6916	0.9567	4.0002
1D	0.6775	0.9892	4.1649

V. CONCLUSIONS

In this paper, a self-tuning algorithm for time-to-trigger and handover margin parameters in an enterprise LTE femtocell network has been presented. The algorithm has been implemented by a fuzzy logic controller and later tested in a dynamic system-level simulator modeling an office building. With this tool, a preliminary analysis of the impact of HOM and TTT parameters on call quality and signaling load in these scenarios has been carried out. Later, the proposed algorithm has been compared against other algorithms previously reported in the literature. Results have shown that the call dropping rate can be decreased by up to a 25% in relative terms for large network loads.

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