A Multi-cell Multi-objective Self-Optimisation Methodology based on Genetic Algorithms for Wireless Cellular Networks

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Abstract— **Self-Organising Networks (SON) are seen as one of the hottest topics in telecommunication network research and development, eagerly awaited by network operators to achieve a reduction in operational expenditures. However, there are still many challenges and difficulties when moving from the SON concept to practical implementation. In this context, this paper firstly provides a general formulation of the automated optimisation problem and a detailed description of the main challenges and difficulties ahead. Then, a generic multi-cell multi-objective self-optimisation methodology based on genetic algorithms is proposed. The proposed framework is formulated in detail for a joint coverage and overlap optimisation problem in a multi-cell scenario. A case study using real measurements of a UMTS network deployed in a medium-size European city is presented to illustrate the proposed methodology. In the presented case study, the pilot power, the antenna tilt and the antenna azimuth of the different cells are optimised according to certain cell coverage and cell overlap targets. Results reveal that the genetic-based approach is able to provide optimised solutions that efficiently achieve the desired targets accounting for inter-cell coupling effects.**

Keywords: Automatic optimisation, self-optimisation, pilot power, antenna tilt, antenna azimuth, genetic algorithms.

I. Introduction.

Third-generation (3G) mobile networks based on Universal Mobile Telecommunications System (UMTS) technology are one of the most widely deployed cellular networks in the world. Due to the increasing demand for wideband services in a competitive market, network operators are always investing large budgets to deploy and upgrade their networks. The increasing density of small cells (with the introduction of femto-cells) and the necessity to reduce costs clearly indicate that the process of network deployment and reconfiguration/optimisation must be carried out more efficiently. In this respect a Self-Organising Network (SON) is defined [1] as a communication network which supports self-x functionalities, enabling the automation of operational tasks, and thus minimizing human intervention. Self-organisation functionalities should be able not only to reduce the manual effort involved in network management, but also to enhance the performance of the wireless network. Several key notions of the self-organising concept can be found in the literature [2]. As an example, Spilling et al. introduced the idea that a self-organising network may be seen as an adaptive functionality that detects changes in the network and makes intelligent decisions to minimise or maximise the effect of these changes [3]. On the other hand, Yanmaz et al. defined it as a system that allows the cooperation of different nodes in response to changes in the environment in order to achieve certain goals [4]. The SON concept is seen as a way to reduce operational expenditures (OPEX) by automating functionalities (such as network optimisation) usually performed manually with extensive human work time. Furthermore, SON may also reduce capital expenditures (CAPEX), e.g. to minimise the number of sites to be initially deployed, still ensuring the requested coverage with the expected quality of service for the subscribers. For these reasons, the application of the SON concept is even much more attractive for the deployment and optimisation of future mobile networks such as Long Term Evolution (LTE)[5]. Consequently, SON has received a lot of attention in recent years. Self-organisation of wireless networks includes self-configuration (covering pre-operational phases such as planning and deployment), self-optimisation (optimisation during operational phase), and self-healing (recovering from faults such as the failure of a cell or site). Within each of these areas, several use cases with individual goals and requirements have been defined in [6]-[11]. Related to self-optimisation, which can be seen as an advanced automated optimisation, some contributions in the field of admission control and handover parameter optimisation, coverage and capacity optimisation, interference coordination and load balancing can be found in the literature [12][13].

The SON concept at the largest extent of a totally automatic network, able to operate with minimum human intervention, is quite ambitious and challenging, so that it can be anticipated that SON will continue as a hot research topic in coming years requiring further research efforts to facilitate its practical implementation, covering the long way from the current manual configuration/optimisation in 3G networks to reach a pure SON. This process will require changes on all aspects of an operator's radio engineering department (operational procedures, O&M software tools, radio engineer's skills, etc.). There are different ways to implement SON solutions. In the case of centralised solutions, the SON functionality resides in small number of entities at a high level in the architecture, i.e. the Network Manager (NM) or the Domain Manager (DM) in the 3GPP context [14]. Node-Bs do not take independent actions apart from the exchange of Key Performance Indicators (KPI), measurements and signalling messages with the central node in charge of the SON process (NM or DM). In the distributed SON case, the self-organising functionalities reside in many locations at a low level in the architecture (e.g. Node-Bs). A combination of the distributed and centralised solutions, denoted as Hybrid SON solution, may be useful when many SON tasks can be performed by the Node-Bs but some tasks (especially complex tasks where many cells are affected) need to be managed in a central node.

Focusing on the optimisation of a wireless network, two different aspects can be distinguished [15]: RF optimisation, which is in charge of optimising the setting of RF parameters (such as pilot power, antenna down-tilt, etc.) and service parameters optimisation, which includes the setting of admission and congestion control thresholds, maximum downlink power per connection, events to change to compressed mode, channel switching, etc. The self-optimisation process can be seen as the automatic determination of the most adequate values of several network configuration parameters in order to optimise the network performance in terms of specific targets such as the avoidance of coverage holes, reduction of cell overshooting effects, etc. [15]. The configuration of a cell typically involves a multiplicity of different options (e.g. the number of possible antenna azimuth values times the number of possible antenna tilts times the number of possible transmitted pilot power values, etc.). Furthermore, due to inter-cell coupling effects, the changes done in one cell may influence on the performance observed in the area of another cell. Correspondingly, when considering large cellular networks consisting of hundreds of cells, the resulting number of possible network configurations increases dramatically [16]. As a consequence, the use of self-optimisation algorithms becomes necessary since it is very hard for an engineer to cope manually with this level of complexity.

A wide range of possible optimisation strategies have been proposed in the literature in order to find the optimum or at least some acceptable sub-optimum solution for a particular optimisation problem. The selection of the optimisation strategy typically depends on the complexity of the problem, the time available to develop and implement the optimisation technique and the necessity to obtain solutions with an optimum objective value. Some simple optimisation methodologies such as greedy algorithms, local search techniques or Tabu Search have been commonly used for optimisation [17]-[19]. In turn, other methodologies such as simulated annealing, genetic algorithms or particle swarm algorithms provide in general better solutions at the expense of increasing the computation time and the algorithm complexity [20]-[22]. Several works that make use of these algorithms for the optimisation of mobile communication networks can be found in the literature [23]-[28]. As an example, simulated annealing is used in [23] for an automated optimisation of the main antenna configuration parameters. In [24] an optimisation strategy based on combining reinforcement learning and fuzzy logic is proposed to optimise tilt settings. Genetic optimisation techniques are based on an iterative process inspired by natural evolution [21][22]. These evolution principles allow obtaining better solutions as the number of iterations increase. In contrast to other search methods, which work with only one current solution at a time, genetic algorithms keep a collection of several possible solutions and work on all of them in a single iteration. This helps the algorithm to provide an extensive exploration of the search space and, as a consequence, it can rapidly locate good solutions. Genetic algorithms have been widely used in different areas of research for the optimisation of complex systems. Recent works in the field of mobile communications network optimisation raise the use of genetic algorithms as a promising framework [25]-[27].

Within this context, the first contribution of this paper is to provide a general framework for the self-optimisation process in a wireless cellular network. Then, the second contribution is the formulation of a generic automatic optimisation strategy based on genetic algorithms considering multiple optimisation targets in a multi-cell scenario. The third contribution is the formulation in detail of the optimisation for the cell coverage and cell overlap targets and its evaluation in a case study using real measurements obtained from a UMTS network. In contrast to previous works, mostly based on theoretical/simulation approaches that make use of network models, the use of real measurements obtained from e.g. drive tests, measurement reports, etc., can provide the optimisation techniques with a more accurate network characterisation. Although it is envisaged that the SON concept will be implemented in future mobile communication systems such as LTE, the availability of real data in UMTS and the lessons learnt from real UMTS case studies may constitute a solid basis for the future development and implementation of LTE SON. The rest of the paper is organised as follows. Section II presents the general framework for the proposed self-optimisation process making use of real network measurements and describes the proposed genetic algorithm. Section III particularises the proposed framework for the optimisation of cell coverage and cell overlap and Section IV shows the obtained results in a real scenario. Finally, conclusions are summarised in Section V.

II.- Proposed Self-Optimisation Framework.

A general network consisting of N cells with P tuneable parameters per cell is considered. Then, the network configuration is represented by the $P \times N$ matrix $\boldsymbol{\psi}=[\psi_{p,n}]$ where the term $\psi_{p,n}$ denotes the value of the p-th tuneable parameter of the n-th cell. The proposed self-optimisation procedure is illustrated in Figure 1 and consists in a continuous loop that interacts with the real network based on *observations* and *actions* 5, in order to determine the most adequate network configuration ψ to simultaneously achieve M optimisation targets. At the *observation* phase, certain measurements are collected from the network. The available set of measurements, corresponding to the current network configuration $\boldsymbol{\psi}$, is denoted as $\Pi(\boldsymbol{\psi})=\{\pi_{q,n}(\boldsymbol{\psi})\}$ and consists of specific metrics q=1,...,Q associated to the different cells n=1,..., N. From a general perspective, these metrics can come from measurement reports provided by mobile terminals, from network statistics and counters measured by the different network elements, or from drive-tests using a test mobile equipped with network monitoring software that follows predetermined routes. Then, each metric $\pi_{q,n}(\boldsymbol{\psi})$ can be a vector of different *samples*, where each sample is a different value of the same metric associated in general to different time instants and/or different geographical positions.

The self-optimisation framework will process the observed measurements in accordance to a set of M optimisation targets specified by the operator policies (e.g. avoidance of coverage holes, reduction of cell overshooting, optimisation of the cell overlap among cells, etc.) to detect if any of these targets is not properly fulfilled with the current configuration $\boldsymbol{\psi}$. If this occurs, the self-optimisation procedure will perform an optimisation search to find a new optimised network configuration $\boldsymbol{\psi}'$. The *action* will then consist in setting the configuration parameters of the different cells according to the new network configuration $\boldsymbol{\psi}'$.

Figure 2 depicts the general processes involved in the self-optimisation block. This process is carried out in a centralised way in which the measurements done by the mobile equipments and the different Node-Bs are collected in a central node (e.g. the DM or the NM in the 3GPP architecture [14]) which is in charge of running the self-optimisation process. Then, the *network performance monitoring* stage analyses the collected set of measurements $\Pi(\boldsymbol{\psi})$ in accordance with the M operator specific optimisation targets. This process is carried out for each cell and the result will be the $M\times N$ performance matrix $S(\psi)=[S_{m,n}(\boldsymbol{\psi})]$ in which the term $S_{m,n}(\boldsymbol{\psi})$ ($0\leq S_{m,n}(\boldsymbol{\psi})\leq 1$) reflects the performance obtained by the n-th cell in terms of the m-th optimisation target with the current network configuration $\boldsymbol{\psi}$. The higher the value of $S_{m,n}(\boldsymbol{\psi})$, the more likely that the m-th target is not sufficiently optimised in the n-th cell. Based on the elements of matrix $S(\boldsymbol{\psi})$ a trigger condition will be evaluated to decide if the measured performance is sufficiently satisfactory or if the network needs to be further optimised. In case the network performance is satisfactory, the current configuration $\boldsymbol{\psi}$ is kept and no changes in the network will be carried out. Otherwise, the *optimisation search* will be executed to find a better configuration $\boldsymbol{\psi}'$. In this case, when the optimisation search phase is finished and the new configuration $\boldsymbol{\psi}'$ is determined, the new network configuration parameters are sent to the corresponding Node-Bs. In the following, the network performance monitoring and the optimisation search processes will be further elaborated.

A. Network Performance Monitoring.

An expansion of the network performance monitoring block depicted in Figure 2 is provided in Figure 3. The process is executed on a cell by cell basis, to obtain for each cell n=1,..,N the performance indicators $S_{m,n}(\boldsymbol{\psi})$ associated to each m=1,...,M optimisation target and thus building matrix $\boldsymbol{S(\psi)}$. The steps shown in Figure 3 correspond to the performance monitoring of the n-th cell with respect to the m-th optimisation target. The process starts with the filtering of the measurement set $\Pi(\boldsymbol{\psi})$. It consists in selecting the subset of measurements $\Pi_f(\boldsymbol{\psi},m,n)$ with the metrics and samples that are relevant to the evaluation of the m-th target in the n-th cell under analysis. Measurements in this subset are then evaluated to check the fulfilment of a number of statistical conditions $c_{m,j}$ j=1,...,J_m for the m-th optimisation target. Each condition evaluates a given metric (or combination of metrics) against a specific threshold. Based on the result of these evaluations the performance indicator is computed as:

$$S_{m,n}(\psi)=\sum_{j=1}^{J_m}\alpha_m^j R_{m,n,j}\left(\Pi_f(\psi,m,n)\right) \tag{1}$$

where $R_{m,n,j}(\Pi_f)$ denotes the result of evaluating $c_{m,j}$ for the n-th cell and is a normalised soft-value $0\leq R_{m,n,j}\leq 1$. In turn, α_m^j are the weights given to each condition depending on specific operator policies. These weights are normalised so that their summation for all j=1,...,J_m equals 1. Finally, considering all the N analysed cells and M optimisation targets, the matrix $\boldsymbol{S(\psi)}=[S_{m,n}(\boldsymbol{\psi})]$ can be built as output of the performance monitoring process.

B. Optimisation search process.

The optimisation search problem can be formulated as the search of the network configuration parameters in matrix $\boldsymbol{\psi}=[\psi_{p,n}]$ that optimise the network performance given by matrix $\boldsymbol{S(\psi)}$. This is a multi-cell and multi-objective problem since N cells and M optimisation targets are involved. In general, optimisation targets can be partly contradictory (e.g. an increase in the transmitted power devoted to the pilot channel may improve coverage but may cause an increase in the cell overlap and interference [29]). For this reason, the network operator has to specify a trade-off criterion among the different optimisation goals. There are two general approaches to multi-objective optimisation [30]. The first one is to combine the different individual optimisation objectives into a single composite function (based on utility theory, weighted sum method, etc.). The other approach is to determine the Pareto optimal set of solutions. A solution belongs to the Pareto optimal set if there is no other solution in the solution space that has better performance for at least one target and the same (or better) performance for the rest of targets [30]. In real wireless networks consisting on hundreds of cells with several tuneable parameters per cell and many optimisation targets, the complexity of the optimisation problem may become extremely high. For this reason, the option of treating the problem by means of Pareto optimisation becomes extremely expensive from a computational point of view. Then, the most usual approach in these situations is the former approach in which a joint objective or cost function is defined as a linear combination of the different quality measures with certain weights β_m assigned to each m-th optimisation target, given by:

$$C(\psi)=\sum_{m=1}^{M}\beta_m C_m(\psi)=\sum_{m=1}^{M}\beta_m\sum_{n=1}^{N}S_{m,n}(\psi) \tag{2}$$

The optimum solution is thus given by the configuration matrix $\boldsymbol{\psi^*}$ that minimises the cost, that is:

$$\psi^* = \arg\min_{\psi} C(\psi) \quad (3)$$

In the following, a description of the proposed optimisation search methodology using genetic algorithms is presented. The overall procedure is shown in Figure 4. The genetic optimisation algorithm uses as inputs the current network configuration $\boldsymbol{\psi}$, the set of measurements $\Pi(\boldsymbol{\psi})$ obtained with this configuration and the M optimisation targets.

Genetic algorithms are based on the analysis of a set of N_{POP} possible solutions each one corresponding to a network configuration matrix, denoted as $\boldsymbol{\psi}^i$ i=1,...,N_{POP}. Following certain rules that mimic the genetic evolution, these solutions are varied in the successive iterations of the algorithm based on their associated performance. Each of the possible solutions $\boldsymbol{\psi}^i$ is called *chromosome* or *individual*, and each configuration parameter of an individual (i.e. each one of the elements $\psi^i_{p,n}$ of the network configuration matrix $\boldsymbol{\psi}^i$) is called *gene*. All the N_{POP} individuals considered in a given iteration, constitute the *population* of the genetic algorithm while each iteration is called *generation*. When the optimisation search is triggered, the algorithm starts with the initialisation of the N_{POP} individuals of the population corresponding to the first generation. The current network configuration is one of these individuals (i.e. $\boldsymbol{\psi}^1=\boldsymbol{\psi}$). For the rest of individuals i=2,...,N_{POP} the network configuration parameters are chosen randomly with uniform distribution within a certain defined search space for each parameter that includes constraints in terms of maximum and minimum values and resolution in the parameter adjustment. A correct definition of the search space is fundamental to assure an exhaustive analysis of all the potentially good solutions without increasing too much the algorithm computation time. For each of the individuals the algorithm needs to evaluate the corresponding performance matrix $\boldsymbol{S}(\boldsymbol{\psi}^i)$. Given that it is not feasible to perform the modification of the network configuration in real time according to $\boldsymbol{\psi}^i$ and obtain the corresponding measurements $\Pi(\boldsymbol{\psi}^i)$, the evaluation of $\boldsymbol{S}(\boldsymbol{\psi}^i)$ is based on an estimation of how the currently available measurements would change when setting the network configuration to $\boldsymbol{\psi}^i$. This is done by a process that takes as input the analysed configuration $\boldsymbol{\psi}^i$ and the current measurements $\Pi(\boldsymbol{\psi})$ and uses a transformation model $f\{\cdot\}$ to relate each network configuration parameter with the specific metrics. As a result, the estimated measurements $\Pi^*(\boldsymbol{\psi}^i)$ are obtained. This estimation process is a critical point since it requires an adequate modelling of the network to anticipate the effect of a modification of a parameter over the considered metrics. Using the estimated measurements $\Pi^*(\boldsymbol{\psi}^i)$, the process estimates the performance $\boldsymbol{S}(\boldsymbol{\psi}^i)$ that would be obtained with the configuration $\boldsymbol{\psi}^i$ following the steps that were presented in sub-section II.A (see Figure 3). Finally, the associated cost $C(\boldsymbol{\psi}^i)$ of individual $\boldsymbol{\psi}^i$ is computed according to (2) using the elements of matrix $\boldsymbol{S}(\boldsymbol{\psi}^i)$.

Once all the individuals in the initial generation have been evaluated, the algorithm determines the individual with minimum cost. If this minimum cost is below or equal to a certain threshold *Th_Cost*, the individual is proposed as the solution of the genetic algorithm and the algorithm is finished. Otherwise, if the maximum number of iterations has not been reached, the algorithm proceeds with a new generation and creates N_{POP} new individuals by applying the *selection*, *recombination* and *mutation* operators over the individuals of the previous generation. These operators model the evolution process using some rules that help the algorithm to provide better solutions as the generations evolve [22]. They are described in the following:

- *Selection operator*: It determines which individuals of the current generation are chosen for the creation of the individuals in the following generation. Among the existing possibilities for this selection process, the one considered here is the so-called "cost proportional selection" (sometimes referred to as *roulette-wheel selection*) [31]. In this methodology, two individuals are chosen randomly following a selection probability depending on the cost of each individual, so that better individuals (i.e. those with lower cost) are selected with higher probability. In particular, an individual i with configuration matrix $\boldsymbol{\psi}^{\boldsymbol{i}}$, is selected with a probability given by:

$$P_S(i) = \frac{\dfrac{1}{C(\psi^i)}}{\displaystyle\sum_{j=1}^{N_{POP}} \frac{1}{C(\psi^j)}} \tag{4}$$

- *Recombination operator*: This process consists in making a combination of the different genes (i.e. the network configuration parameters) of the two individuals selected in the previous step (called *parents*) to generate two new individuals (called *children*). The rationality of this process is to search for new solutions similar to the best individuals of the previous generation by combining their genes. The recombination process considered here is the so-called "1-point crossover" [22], illustrated in Figure 5. Considering the genes of the two *parents* denoted as $\boldsymbol{\psi}^{\boldsymbol{i}}$ and $\boldsymbol{\psi}^{\boldsymbol{j}}$, a crossover point is defined randomly and all the genes beyond this crossover point are swapped between both parents to obtain the children $\boldsymbol{\psi}^{\boldsymbol{i}*}$ and $\boldsymbol{\psi}^{\boldsymbol{j}*}$.
- *Mutation operator*: This is used to make small random changes in the genes (i.e. configuration parameters) of the two individuals obtained after recombination. The probability of performing a mutation in a given gene is $1/N_{genes}$ where $N_{genes}=P\times N$ is the number of genes in the individual. As a result, very few genes of an individual are usually modified in the mutation. When a gene is selected for mutation, the new value is either an increase or a decrease (with equal probability) in one resolution unit within the defined search space of the configuration parameter corresponding to the selected gene.

Note that, as a result of the selection, recombination and mutation process, a total of two new individuals will be obtained. Then the process is repeated $N_{POP}/2$ times until getting the N_{POP} individuals of the new generation. With the newly generated N_{POP} individuals, the algorithm executes again the evaluation procedure and computes the associated costs. The procedure is repeated iteratively until reaching a configuration with a cost below the specific threshold *Th_Cost*, thus providing a recommendation for a new parameterisation, or until reaching a maximum number of iterations. In the later case, it means that the algorithm has not been able to provide a sufficiently optimized solution by adjusting the configuration parameters $\boldsymbol{\psi}$ and other solutions (e.g. deployment of a new cell) should be considered.

III.- Multi-cell coverage and overlap self-optimisation.

The general framework presented in section II is particularised for the case where two optimisation targets ($M=2$) are considered in a UMTS network: m=1 is the optimisation of cell coverage and m=2 is the optimisation of cell overlap. The coverage of a cell is related to the ability to establish a communication in the cell's service area. Cell overlap exists in the areas where access to the network is possible through multiple cells. A certain degree of cell overlap is useful to facilitate the handover process. However, a large overlapping may generate excessive interference and soft handover overheads. The proposed solution in this section focuses on the Capacity and Coverage Optimisation (CCO) use case defined in 3GPP. For this use case, the centralised SON process may be located either in the DM (Domain Manager) or in the NM (Network Manager) [14].

A. Considered metrics.

In the following, it is assumed that the metrics $\pi_{q,n}(\boldsymbol{\psi})$ in the whole set of available measurements $\Pi(\boldsymbol{\psi})$ are organised in *samples*. Each sample k corresponds to a different value of the same metric obtained in a different geographical position and will be denoted in the following as $\pi_{q,n}(\boldsymbol{\psi},k)$. This would be the case when the metrics are obtained either from measurement reports or from drive tests carried out by mobile terminals equipped with e.g. a Global Positioning System (GPS).

The metrics $\pi_{q,n}$ $q=1,\ldots,Q$ that are considered relevant for the optimisation of cell coverage and cell overlap in the n-th cell are the following [32]:

- $\pi_{1,n}(\boldsymbol{\psi},k)$: *CPICH RSCP (Common Pilot Channel Received Signal Code Power):* This metric is the measured received power at the mobile terminal from the CPICH channel of cell n in the geographical position of sample k.
- $\pi_{2,n}(\boldsymbol{\psi},k)$: This is the Active Set list of a mobile connected to cell n in the geographical position of sample k. In UMTS terminology, the set of cells that the mobile is simultaneously connected to during soft handover is denoted as the *Active Set (AS)*. The AS is updated dynamically according to measurements of the CPICH RSCP of the different cells and has a specified maximum size AS_{max}.
- $\pi_{3,n}(\boldsymbol{\psi},k)$: *UE (User Equipment) transmitted power:* This metric is the power transmitted by the mobile terminal while in connected mode to cell n in the geographical position of sample k.
- $\pi_{4,n}(\boldsymbol{\psi},k,n^*)$: *CPICH Ec/Io degradation:* This is the reduction in the received CPICH energy per chip over total received power spectral density for cell n associated to the downlink interference coming from neighbouring cell n^*. In order to isolate the RF considerations from traffic effects, this paper evaluates this degradation in terms of the *Ec*/*Io* that would be measured if no traffic existed and only pilot channels were transmitted. In the Appendix I, the way to compute this metric is presented.

B. Configuration parameters.

The list of configuration parameters $\psi_{p,n}$ that are known for each cell n are the following ones:

- $\psi_{1,n}$: CPICH transmitted power by the n-th cell.
- $\psi_{2,n}$: Antenna tilt of the n-th cell, corresponding to the angle of the main beam of the antenna relative to the horizontal plane.
- $\psi_{3,n}$: Antenna azimuth of the n-th cell, corresponding to the pointing direction of the main beam in the horizontal antenna pattern.
- $\psi_{4,n}$: Cell location coordinates.
- $\psi_{5,n}$: Antenna height of the n-th cell with respect to the ground level.
- $\psi_{6,n}$: List of neighbour cells of cell n, denoted as $neigh(n)$.
- $\psi_{7,n}$: Soft Handover margin for cell n. It is used to decide when the cell has to be added to the AS of a given mobile. More specifically, it is a threshold relative to the

highest CPICH RSCP among the cells currently in the AS, denoted as $RSCP_{best}$. Then, cell n will be added to the AS when its RSCP is above $RSCP_{best}$ (dBm)-$\psi_{7,n}(dB)$ and the maximum number of allowed cells AS_{max} has not been exceeded.

C. Cell coverage: Performance Monitoring.

Following the general process of Figure 3 for the analysis of the cell coverage (optimisation target m=1) for the n-th cell, it firstly selects the subset of measurements and samples to be considered, $\Pi_f(\boldsymbol{\psi},1,n)$, out of the whole set of input measurements available for the overall optimisation process, $\Pi(\boldsymbol{\psi})$. Among the possible metrics listed in section III.A, the selected ones for the coverage analysis are $\pi_{1,n'}(\boldsymbol{\psi},k)$, $\pi_{2,n'}(\boldsymbol{\psi},k)$ and $\pi_{3,n'}(\boldsymbol{\psi},k)$ corresponding to any cell $n'\in\{n,neigh(n)\}$ including the cell n under study and all its neighbour cells. For a given cell, the samples to be analysed are selected in this paper according to Voronoi's tessellation 33 that consists in associating each sample to its closest cell taking into account the geographical location of the sample and the locations and pointing directions of the different cells. Then, the subset of measurements $\Pi_f(\boldsymbol{\psi},1,n)$ is composed by the samples of metrics $\pi_{1,n'}(\boldsymbol{\psi},k)$, $\pi_{2,n'}(\boldsymbol{\psi},k)$ and $\pi_{3,n'}(\boldsymbol{\psi},k)$ associated to locations in which the n-th cell is the closest cell [32]. The performance evaluation step is executed on the subset $\Pi_f(\boldsymbol{\psi},1,n)$ by checking the fulfilment of the following J_1=6 statistical conditions:

- $c_{1,1}$: It evaluates the probability that the CPICH RSCP of the n-th cell under study is below a threshold $RSCP_{cov}$ in the selected samples. Then, the condition is fulfilled if $Prob(\pi_{1,n}(\boldsymbol{\psi},k)<RSCP_{cov})>Th_{RSCP}$.
- $c_{1,2}$: Same as $c_{1,1}$, but considering a lower threshold $RSCP_{cov1}$, that is $Prob(\pi_{1,n}(\boldsymbol{\psi},k)<RSCP_{cov1})>Th_{RSCP1}$.
- $c_{1,3}$: Same as $c_{1,1}$, but considering a lower threshold $RSCP_{cov2}$ compared to $c_{1,2}$, that is $Prob(\pi_{1,n}(\boldsymbol{\psi},k)<RSCP_{cov2})>Th_{RSCP2}$.
- $c_{1,4}$: It evaluates the probability that the CPICH RSCP is below $RSCP_{cov}$ for all neighbour cells $n'\neq n$, that is $Prob(\pi_{1,n'}(\boldsymbol{\psi},k)<RSCP_{cov}\ \forall n'\neq n)>Th_{RSCP3}$.
- $c_{1,5}$: It evaluates the probability that the uplink transmit power is above a certain threshold P_T^* in the selected samples. This condition is fulfilled if $Prob(\pi_{3,n}(\boldsymbol{\psi},k)>P_T^*)>Th_{PT}$.
- $c_{1,6}$: It evaluates the probability that, in a given sample k, a cell n' should be in the AS but it is not, i.e. $Prob((n'\notin\pi_{2,n}(\boldsymbol{\psi},k))$ AND $(\pi_{1,n'}(\boldsymbol{\psi},k) > RSCP_{best}(\boldsymbol{\psi},k)-\psi_{7,n'})$ AND (number of cells in $\pi_{2,n}(\boldsymbol{\psi},k) < AS_{max}$) $\forall n')>Th_{AS}$.

Based on the result of evaluating each condition $c_{1,j}$ for the n-th cell, the term $R_{1,n,j}(\Pi_f(\psi,1,n))$ used in equation (1) to determine the values of $S_{1,n}(\psi)$ in matrix $\boldsymbol{S(\psi)}$ is computed. In the simplest case, the value $R_{1,n,j}(\Pi_f(\psi,1,n))$ could be 1 or 0 depending on whether the j-th condition is fulfilled or not. However, this would lead to a low granularity in the resulting values of $S_{1,n}(\psi)$. Correspondingly, in this paper a more sophisticated computation method has been used taking into account the spatial distribution of the samples where the conditions are fulfilled. Further details about the computation of $R_{1,n,j}(\Pi_f(\psi,1,n))$ are given in Appendix II.A.

D. Cell overlap: Performance Monitoring.

Let consider now the cell overlap (optimisation target m=2) generated by the n-th cell. In this case, the set of filtered measurements $\Pi_f(\boldsymbol{\psi},2,n)$ contains the samples of metrics

$\pi_{1,n'}(\boldsymbol{\psi},k)$, $\pi_{2,n'}(\boldsymbol{\psi},k)$ and $\pi_{4,n'}(\boldsymbol{\psi},k,n)$ associated to locations outside the theoretical coverage area of cell n (based on Voronoi's tesellation) in which cell n is detected with a CPICH RSCP $\pi_{1,n}(\boldsymbol{\psi},k)$ higher than $RSCP_{best}(\boldsymbol{\psi},k)-\psi_{7,n}$. The metrics are obtained for any cell n' measured in these locations.

The performance evaluation for the cell overlap optimisation target is executed over the filtered measurements $\Pi_f(\boldsymbol{\psi},2,n)$ by checking the fulfilment of the following J_2=3 statistical conditions:

- $c_{2,1}$: Let consider a sample k and denote as v the closest cell to the location of this sample based on Voronoi's tessellation. Then, this condition evaluates the probability that the CPICH RSCP of cell v ($\pi_{1,v}$) is higher than the coverage threshold ($RSCP_{cov}$) in the selected set of samples, that is $Prob(\pi_{1,v}(\boldsymbol{\psi},k)>RSCP_{cov})>Th_{RSCP}(\%)$. Note that, since $\pi_{1,n}(\boldsymbol{\psi},k)>RSCP_{best}(\boldsymbol{\psi},k)-\psi_{7,n}$, if $\pi_{1,v}(\boldsymbol{\psi},k)>RSCP_{cov}$, it reflects that cell v is received at a proper level in the position of sample k and also cell n is observed at a sufficiently high level (i.e., cell n is overlapping cell v in that position).
- $c_{2,2}$: It evaluates the CPICH Ec/Io degradation in the cell v due to the n-th cell. This is formulated as $Prob(\pi_{4,v}(\boldsymbol{\psi},k,n)>Ec/Io_{deg})>Th_{deg\text{-}overlap}$.
- $c_{2,3}$: It checks if cell n generating the overlap is not included in the AS at a sample k, that is $Prob(n \notin \pi_{2,v}(\boldsymbol{\psi},k))>Th_{AS}$.

Based on the result of evaluating each condition $c_{2,j}$ for the n-th cell, the term $R_{2,n,j}(\Pi_f(\psi,2,n))$ which is used in equation (1) to determine the values of $S_{2,n}(\psi)$ in matrix $\boldsymbol{S(\psi)}$ is computed. Details on how the term $R_{2,n,j}(\Pi_f(\psi,2,n))$ is computed are given in Appendix II.B.

E. Optimisation search.

Among the list of configuration parameters per cell $\psi_{p,n}$, the self-optimisation procedure in this paper focuses on the tuning of $\psi_{1,n}$ (CPICH transmitted power), $\psi_{2,n}$ (antenna tilt) and $\psi_{3,n}$ (antenna azimuth), which are some of the most usual tuned parameters during network optimisation [15].

The tuning of the CPICH transmitted power $\psi_{1,n}$ in UMTS networks is crucial to control the cell coverage and the size of the overlap regions among cells. A too low value of CPICH transmitted power may cause coverage holes while a too high value may generate excessive cell overlap and interference. Pilot power can be adjusted remotely and avoids additional costly site visits by technical personnel. The tuning of the tilt $\psi_{2,n}$ is another usual approach to control the coverage. When increasing the tilt, less power is received in the neighbouring cells thus reducing the inter-cell interference. However, this can be at the expense of introducing some coverage problems at the cell edge, so a trade-off exists in the appropriate tilt setting. In modern radio networks, remote electrical tilt antennas are used to ease tilt changes and reduce reconfiguration costs. Finally, changing the antenna azimuth $\psi_{3,n}$ can also help in re-adjusting the cell coverage footprint. For practical reasons, i.e., to limit the number of possible solutions and reduce the computation time to find the optimum or close-to-optimal solution, the following constraints are defined on the solution search space:

- The CPICH transmitted power can vary between 25dBm and 35dBm in steps of 1dB.
- The antenna tilt can vary between 0º and 10º in steps of 1º.

- The antenna azimuth can vary between -25º and +25º with respect to the original antenna orientation in steps of 5º.

As stated in section II.B, the optimisation search algorithm needs to estimate how the network measurements would change for the different network configurations that are evaluated. Thus, the estimated measurements $\Pi^*(\psi^i)$ are obtained applying a transformation function $f\{\cdot\}$ over the available measurements $\Pi(\psi)$. In this paper, and without loss of generality, the transformation model makes use of the linear relationship existing between RSCP, CPICH transmit power and antenna gain. Then, for a measurement in a certain position, an increase/reduction in the transmit power will lead to the same increase/reduction in the RSCP, and the same occurs with an increase/reduction in the antenna gain due to a modification of the antenna azimuth or tilt. Correspondingly, when adjusting the CPICH transmitted power, this transformation consists in modifying the RSCP in the real measurements with the same increase or decrease applied to the CPICH transmit power. In turn, the transformation of the RSCP after a change in the antenna tilt or antenna azimuth of the n-th cell is done using the n-th cell location coordinates $\psi_{4,n}$, the n-th cell antenna height with respect to the ground level $\psi_{5,n}$ and the geographical coordinates of each measurement, together with the antenna radiation pattern. Making use of this information and doing simple geometrical computations, the increase or reduction in antenna gain in the direction of the measurement position observed after the tilt or azimuth adjustment can be computed. Then, this increase or reduction is directly added to the current RSCP value to obtain the transformed value. It is worth mentioning that other more sophisticated transformation models could also be considered in the proposed methodology if more detailed information about the environment is available, such as data terrain information, geometrical and electrical characteristics of the buildings in the area, etc.

IV.- Results

The performance of the proposed self-optimisation methodology is illustrated with a case study in an urban area of a European city. The case study considers a region covered by $N=18$ cells distributed in 6 tri-sectorial Node-Bs. Each cell is identified as *Cell_n (n=1…N)* as shown in Figure 6. The network measurements are collected by means of drive test measurements carried out along certain streets as indicated in Figure 6. These measurements consist of the different metrics $\pi_{q,n}$, described in section III.A associated to different positions depending on the route. The geographical coordinates of each measurement are also obtained. During the network performance monitoring phase, these measurements are processed according to the algorithms described in sections III.C and III.D. In case the optimisation search is triggered, the genetic algorithm described in sections II.B and III.E is executed to evaluate the different configurations. The considered parameters for the network performance monitoring and the optimisation search processes are given in Table 1. For the case of the RSCP threshold setting the values have been based on [15], while the rest of algorithm parameters have been set after performing several tests.

The result of the network performance monitoring stage identifies some regions where coverage and overlap targets are not properly optimised (see Figure 7). The Voronoi regions which represent the theoretical coverage regions are represented in Figure 7. Furthermore, Table 2 shows the values of the terms $S_{m,n}$ for each cell for both optimisation targets. The trigger condition of the optimisation process is that the total cost $C(\boldsymbol{\psi})$ as a result of the network performance monitoring stage is above 0.1. In the considered case this condition is fulfilled and then the optimisation search process is executed.

In order to illustrate the performance of the algorithm, in this particular case study the algorithm only adjusts the network configuration parameters of Cell_9, Cell_10, Cell_14 and Cell_18 (see Figure 7). The population size in the considered genetic algorithm is initially set to $N_{POP}=20$. The algorithm is finished either when a solution with cost $C(\psi)=0$ is found or when a maximum of 30 generations have been run, as indicated in the parameters of Table 1. For a better understanding of the effects of the different tuneable parameters, three different cases are discussed in the following depending on the parameters that are adjusted.

A. Only the pilot power is adjusted.

In this case, the optimisation search algorithm only makes adjustments of the CPICH power $\psi_{1,n}$ in the four considered cells, while the antenna tilt and azimuth are not changed. Table 3 shows the initial configuration parameters and the final solution found by the genetic algorithm. To illustrate the evolution of the genetic algorithm to reach the final solution, two intermediate solutions are also presented. For each configuration, the total cost $C(\boldsymbol{\psi})$ defined in (2) and the individual contributions of the coverage $C_1(\boldsymbol{\psi})$ and overlap $C_2(\boldsymbol{\psi})$ to the total cost are presented. As the configuration is changed (see Table 3), the terms $S_{m,n}$ of some cells and optimisation targets are reduced and consequently, the total cost is also reduced. Although it is not shown in the paper for the sake of brevity, it has been observed that the reduction in the cost achieved by intermediate solution 1 (associated to the increase in the pilot power $\psi_{1,14}$) occurs thanks to totally removing the coverage holes in Cell_14 and Cell_10 while reducing the value of $S_{1,18}$ in Cell_18. In turn, the subsequent cost reduction achieved by intermediate solution 2 (associated to a pilot power decrease in the parameter $\psi_{1,9}$) is achieved thanks to totally removing the overlap caused by Cell_9 to Cell_18. The final solution found by the algorithm additionally increases the pilot power $\psi_{1,18}$ to enhance coverage in Cell_18 and correspondingly the total cost. Figure 8 presents the estimated network performance associated to the configuration provided by the final solution of the genetic algorithm. The comparison with Figure 7 illustrates the improvements: the overlap situation is solved and almost all the detected coverage holes are completely removed (i.e with the final solution found, only the term $S_{1,18}$=0.029 is different from zero). It is worth mentioning that an exhaustive search among all possible solutions in this particular case has revealed that there is no other solution that reduces the value of $S_{1,18}$=0.029 (i.e. the solution found is the only one that belongs to the Pareto optimal set) and, a as a consequence, it can be said that the obtained solution is the optimum one, which validates the algorithm performance.

B. The pilot power and the antenna tilt are adjusted.

In this case, the optimisation algorithm makes adjustments in both pilot power $\psi_{1,n}$ and antenna tilt $\psi_{2,n}$, keeping unchanged the antenna azimuth. Table 4 presents the solution found in this case. Notice that this solution is the same that was obtained in the case when only the pilot power was changed. Consequently, in this scenario, including the antenna tilt adjustment does not provide any additional improvement in terms of cost reduction.

C. The pilot power, the antenna tilt and the antenna azimuth are adjusted.

In this case, the optimisation algorithm makes adjustments in the pilot power $\psi_{1,n}$, antenna tilt $\psi_{2,n}$ and azimuth $\psi_{3,n}$ in the four considered tuneable cells. Table 5 presents the configuration found in this case in comparison with the original configuration. In this case, the genetic algorithm decided to adjust the antenna azimuth of the different cells, pointing them to the location of the coverage hole in Cell_18 that persisted when only the pilot power was changed (as seen in Figure 8). Also some antenna tilts are adjusted to avoid possible coverage/overlap problems due to the previous antenna azimuth adjustments. Note that, in this case, the solution found solves all the problems initially identified in Figure 7 and, as a consequence, the cost of this solution is reduced to zero. Note that, in this case, the solution found is also the only one in the Pareto optimal set since $S_{m,n}=0$ for all combinations of m and n. To further analyse the configuration adjustments made by the proposed methodology, Figure 9 presents the Cumulative Distribution Function (CDF) of the CPICH RSCP in the coverage hole detected in Cell_18 (see Figure 7) before and after optimisation. Notice the increase in CPICH RSCP achieved in both Cell_18 and Cell_14 thanks to the pilot power and antenna parameter adjustments (tilt and azimuth). As a consequence, the coverage hole detected in this region is removed.

On the other hand, Figure 10 shows the CDF of the CPICH RSCP in the region with overlap caused by Cell_9 to Cell_18 (see Figure 7). Note that before executing the optimisation search algorithm, the observed CPICH RSCP of Cell_9 in this region is considerably higher than that of Cell_18, reflecting the overlap situation. The adjustments made by the proposed methodology solve the overlap by reducing the CPICH RSCP of Cell_9 and increasing that of Cell_18 as shown in Figure 10. Concerning the algorithm convergence and the computational cost, Figure 11 presents the evolution of the minimum, the average and the maximum cost for the individuals evaluated in each generation. All three statistics progressively decrease as the number of generations increase and the optimum solution with cost equal to zero is found after 9 generations of 40 population members each. This reflects that the algorithm is able to achieve a fast convergence in this scenario in which the solution search space contains 11^{12} combinations (there are 4 cells x 3 parameters/cell=12 tuneable parameters, each one taking 11 possible values). In any case, it is worth mentioning that the number of generations required for finding the optimum solution is very much dependent on the specific scenario, so that increasing the number of tuneable parameters and/or the number of tuneable cells, would increase the required number of generations.

The impact of the population size (N_{POP}) on the computational complexity of the genetic algorithm is evaluated in the following. The number of individuals analysed by the algorithm before reaching convergence is taken as a representative indicator of this complexity, since the larger this value is, the larger the execution time will be. Figure 12 presents this indicator as a function of N_{POP}. An optimum solution (with cost equal to zero) is found in all the cases but, as shown, the population size is an important parameter to be adjusted in order to guarantee a fast algorithm convergence. With a low value of N_{POP} the solution space may not be properly explored, leading to a slow convergence and increased complexity. On the contrary, if a too high value of N_{POP} is chosen, the genetic algorithm needs too much time to evaluate all the individuals in a generation which also leads to a slow convergence. One of the clear advantages of genetic algorithms with respect to other optimisation search algorithms is that the individuals of a given generation can be evaluated independently. As a consequence, this allows the parallelisation of the procedure using multiple processors, leading to considerably high reductions in the computation time.

V.- Conclusions.

This paper has presented a general framework for the self-optimisation process in a wireless cellular network. It is composed of two main stages, namely the performance monitoring based on real measurements collected by the network and the optimisation search to identify the most adequate solution by configuring different tuneable network parameters. This second stage follows an automatic multi-cell and multi-objective optimisation methodology based on genetic algorithms. The framework and the methodology have been formulated first from a quite general and technology agnostic perspective and it has then been particularised to the multi-cell coverage and overlap self-optimisation for UMTS. A case study using real data of a UMTS network deployed in a medium-size European city has been presented to illustrate the capabilities of the proposed framework in a specific scenario. Results reflect the influence of the progressive inclusion of several tuneable parameters in the optimisation search. It has been obtained that, when the pilot power and antenna parameters (tilt and azimuth) are varied, the algorithm is able to find an optimal solution that solves the coverage and overlap problems identified in the considered scenario. An evaluation of the convergence and computational complexity of the proposed algorithm has also been provided, by analysing the adequate setting of the population size to enable a proper exploration of the solution search space.

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Appendix I.

In order to evaluate the degradation in terms of Ec/Io caused by the interference of a neighbouring cell, let consider a situation where cell n^* generates intercellular interference to cell n. The *CPICH Ec/Io* observed by a mobile equipment connected to cell n in the geographical position of sample k is defined as:

$$\left(\frac{E_c}{I_0}\right)_n(\psi,k)=\frac{\pi_{1,n}(\psi,k)}{\sum_i \pi_{1,i}(\psi,k)+\sum_i P_{R,traffic,i}(\psi,k)+P_N} \tag{5}$$

Where $\pi_{1,i}(\boldsymbol{\psi},k)$ corresponds to the CPICH RSCP of the i-th cell, $P_{R,traffic,i}(\boldsymbol{\psi},k)$ is the received power corresponding to the information sent in the rest of channels of the i-th cell and P_N represents the noise power. Note that this metric depends on the total power sent in the traffic channels which in general cannot be determined by means of drive tests. Then, the proposed alternative metric $\pi_{4,n}(\boldsymbol{\psi},k,n^*)$ makes use instead of the Ec/Io in the hypothetical case when no traffic existed and only pilot channels were transmitted ($P_{R,traffic,i}$=0). This can be easily obtained from the values of CPICH RSCP available in the set of measurements $\boldsymbol{\psi}$ as follows:

$$\left(\frac{E_c}{I_0}\right)_{n,wt}(\psi,k)=\frac{\pi_{1,n}(\psi,k)}{\sum_i \pi_{1,i}(\psi,k)+P_N} \quad (6)$$

Then, metric $\pi_{4,n}(\boldsymbol{\psi},k,n^*)$ reflecting the impact of the interference caused by cell n^* to cell n is defined as the ratio between the value of $(Ec/Io)_{n,wt}(\boldsymbol{\psi},k,n^*)$ that would be observed in cell n if cell n^* was not present, with respect to the value actually observed $(Ec/Io)_{n,wt}$ $(\boldsymbol{\psi},k)$. That is:

$$\pi_{4,n}(\psi,k,n^*)=\frac{\dfrac{\pi_{1,n}(\psi,k)}{\sum_{i\neq n^*}\pi_{1,i}(\psi,k)+P_N}}{\dfrac{\pi_{1,n}(\psi,k)}{\sum_i \pi_{1,i}(\psi,k)+P_N}}=\frac{1}{1-\left(\dfrac{Ec}{Io}\right)_{n^*,wt}(\psi,k)} \quad (7)$$

Note that the last part of equation (7), obtained through some algebraic operations of the first part, allows determining this degradation in the Ec/Io of cell n simply by computing the Ec/Io without traffic in cell n^* using (6).

Appendix II.

A. Computation of $R_{1,n,j}(\Pi_f(\psi,1,n))$ for the cell coverage optimisation target.

As previously explained in section II.C, the filtered set $\Pi_f(\psi,1,n)$ comprises the samples associated to geographical locations in which cell n is the closest cell. Then, for the first condition $c_{1,1}$, $R_{1,n,1}(\Pi_f(\psi,1,n))$ equals 1 if the condition is fulfilled and 0 if it is not fulfilled, taking into consideration all the samples in the filtered set $\Pi_f(\psi,1,n)$. Before applying the rest of conditions $c_{1,j}$, , j=2, ..., 6, the algorithm selects only the samples that fulfil $\pi_{1,n}(\boldsymbol{\psi},k)<RSCP_{cov}$ and groups those samples that correspond to adjacent geographical locations. Then, conditions $c_{1,j}$, , j=2, ..., 6 are applied separately for each group g. Specifically, the value $r_{1,n,j}(g)$ equals 1 if condition j is fulfilled for group g and 0 otherwise. The resulting value of $R_{1,n,j}(\Pi_f(\psi,1,n))$ for j=2,..., 6 is obtained as:

$$R_{1,n,j}\left(\Pi_f(\psi,1,n)\right)=\sum_{g=1}^{G(\Pi_f(\psi,1,n))} r_{1,n,j}(g)\frac{N_g\left(\Pi_f(\psi,1,n)\right)}{N_S\left(\Pi_f(\psi,1,n)\right)} \quad (8)$$

where $G(\Pi_f(\psi,1,n))$ is the number of groups, $N_g(\Pi_f(\psi,1,n))$ the number of samples of group g and $N_S(\Pi_f(\psi,1,n))$ the total number of samples in the filtered measurement set $\Pi_f(\psi,1,n)$.

B. Computation of $R_{2,n,j}(\Pi_f(\psi,2,n))$ for the cell overlap optimisation target.

In this case, the samples of the filtered set $\Pi_f(\boldsymbol{\psi},2,n)$ correspond to locations outside the theoretical coverage area of cell n in which this cell is detected with a CPICH RSCP above $RSCP_{best}(\boldsymbol{\psi},k)$-$\psi_{7,n}$. Then, the algorithm groups those samples that correspond to adjacent geographical locations and the different conditions $c_{2,j}$, j=1,..3 are applied separately for each group. Let $r_{2,n,j}(g)$ equal 1 if condition j is fulfilled for group g and 0 otherwise, and let $G(\Pi_f(\psi,2,n))$ be the number of groups, $N_g(\Pi_f(\psi,2,n))$ the number of samples of group g and $N_S(\Pi_f(\psi,2,n))$ the total number of samples in the filtered measurement set $\Pi_f(\psi,2,n)$. The resulting value of $R_{2,n,j}(\Pi_f(\psi,2,n))$ for j=1,..., 3 is obtained as:

$$R_{2,n,j}\left(\Pi_f\left(\psi,2,n\right)\right)=\sum_{g=1}^{G\left(\Pi_f\left(\psi,2,n\right)\right)} r_{2,n,j}\left(g\right)\frac{N_g\left(\Pi_f\left(\psi,2,n\right)\right)}{N_S\left(\Pi_f\left(\psi,2,n\right)\right)} \quad (9)$$

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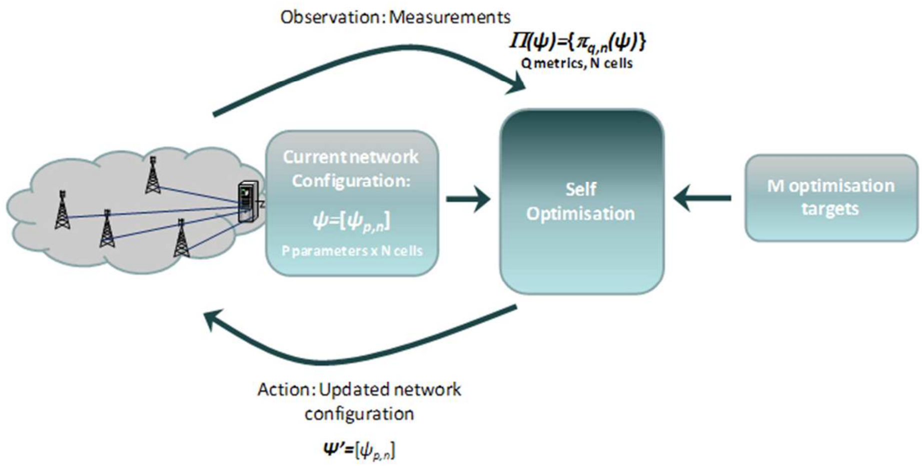

Figure 1.- Network self-optimisation loop.
207x104mm (96 x 96 DPI)

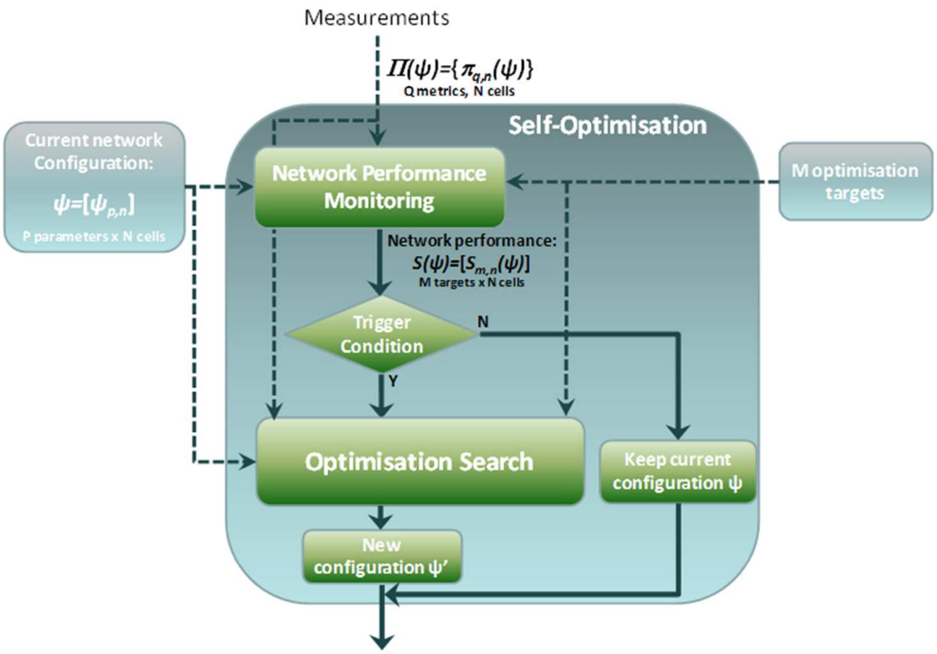

Figure 2.- Self-optimisation stages.
209x139mm (96 x 96 DPI)

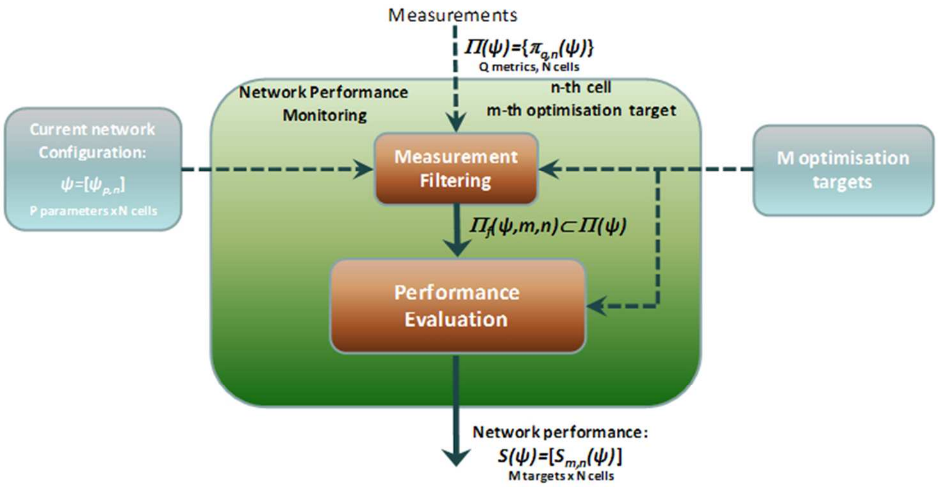

Figure 3.- Performance monitoring process
206x110mm (96 x 96 DPI)

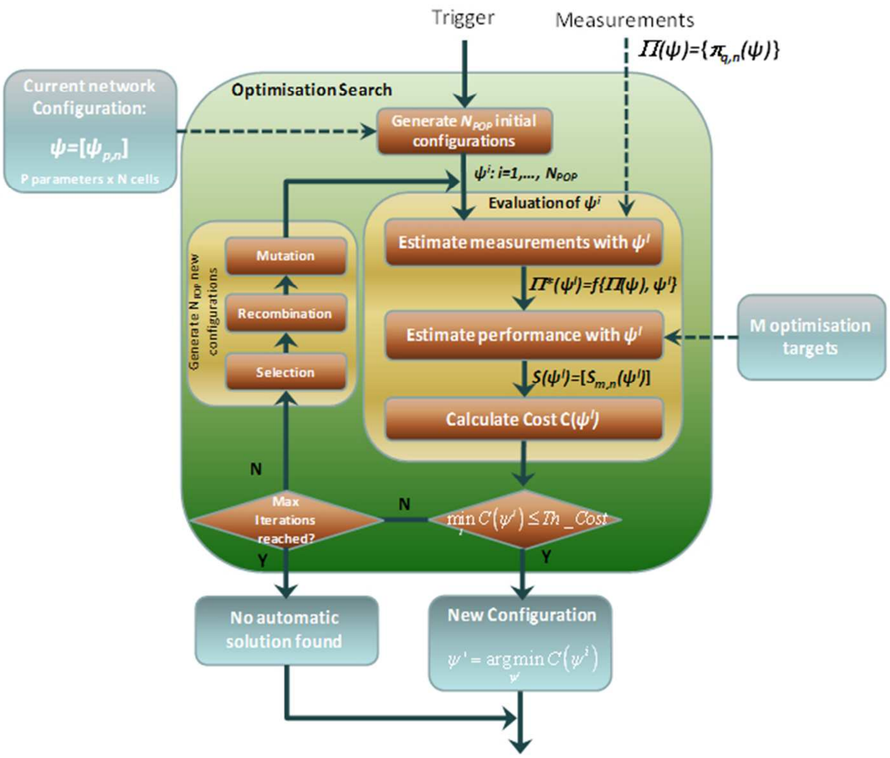

Figure 4.- Optimisation search based on the genetic algorithm.
199x154mm (96 x 96 DPI)

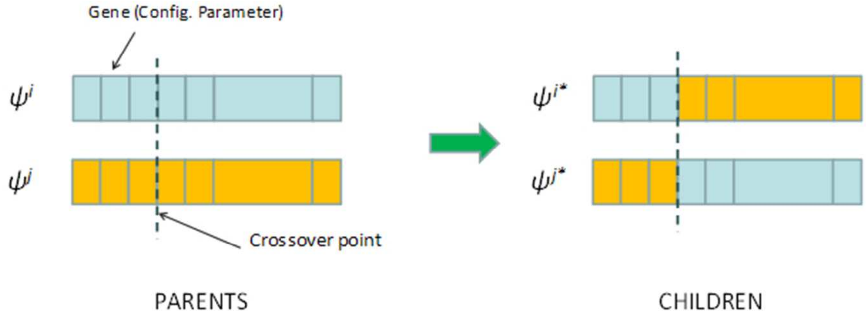

Figure 5.- Example of 1-point crossover
185x70mm (96 x 96 DPI)

Parameter	Value
$RSCP_{cov}$	-88dBm
$RSCP_{cov1}$	-98dBm
$RSCP_{cov2}$	-108dBm
Th_{RSCP}	5%
Th_{RSCP1}	50%
Th_{RSCP2}	50%
Th_{RSCP3}	50%
P_T*	-1dBm
Th_{PT}	50%
Soft HO margin ($\psi_{7,n}$)	3dB
AS_{max}	3
Ec/Io_{deg}	3dB
$Th_{deg\text{-}overlap}$	50%
Th_{AS}	50%
α_1^j, j=1,...,6	1/6
α_2^j, j=1,...,3	1/3
$\beta_1=\beta_2$	1
Th_Cost	0
Max_Iterations	30
N_{POP}	20

Table 1.- Considered parameters
78x121mm (96 x 96 DPI)

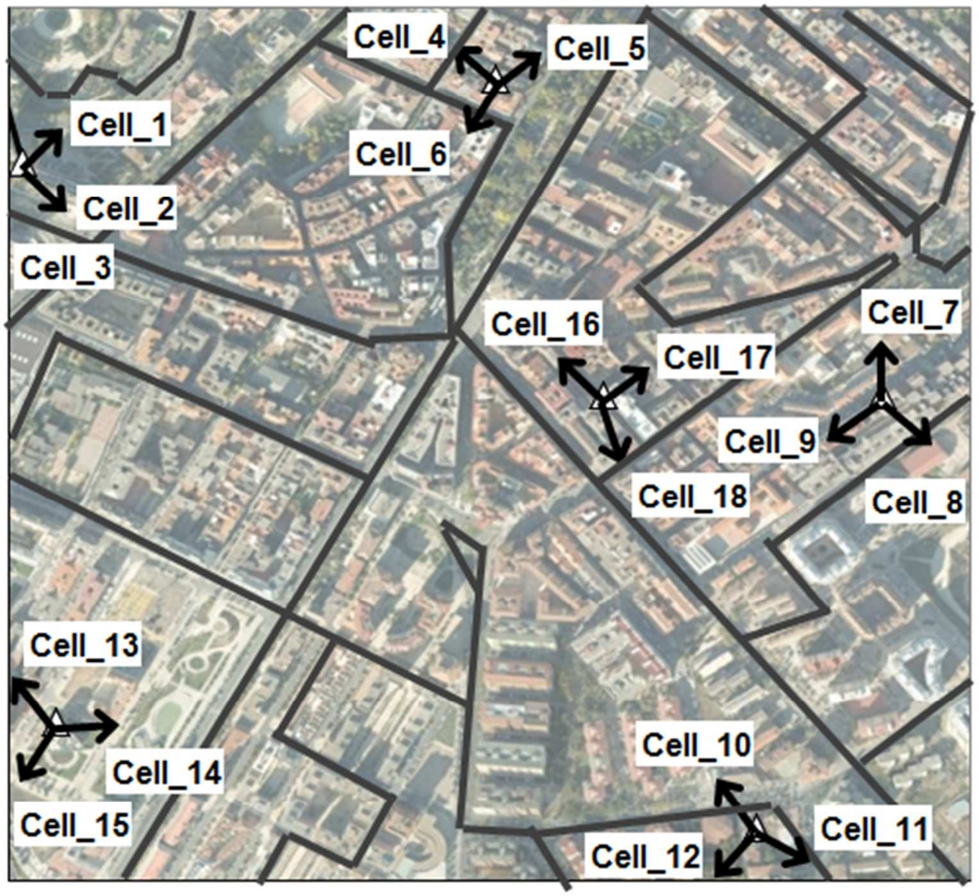

Figure 6.- Regions with available measurements
134x122mm (96 x 96 DPI)

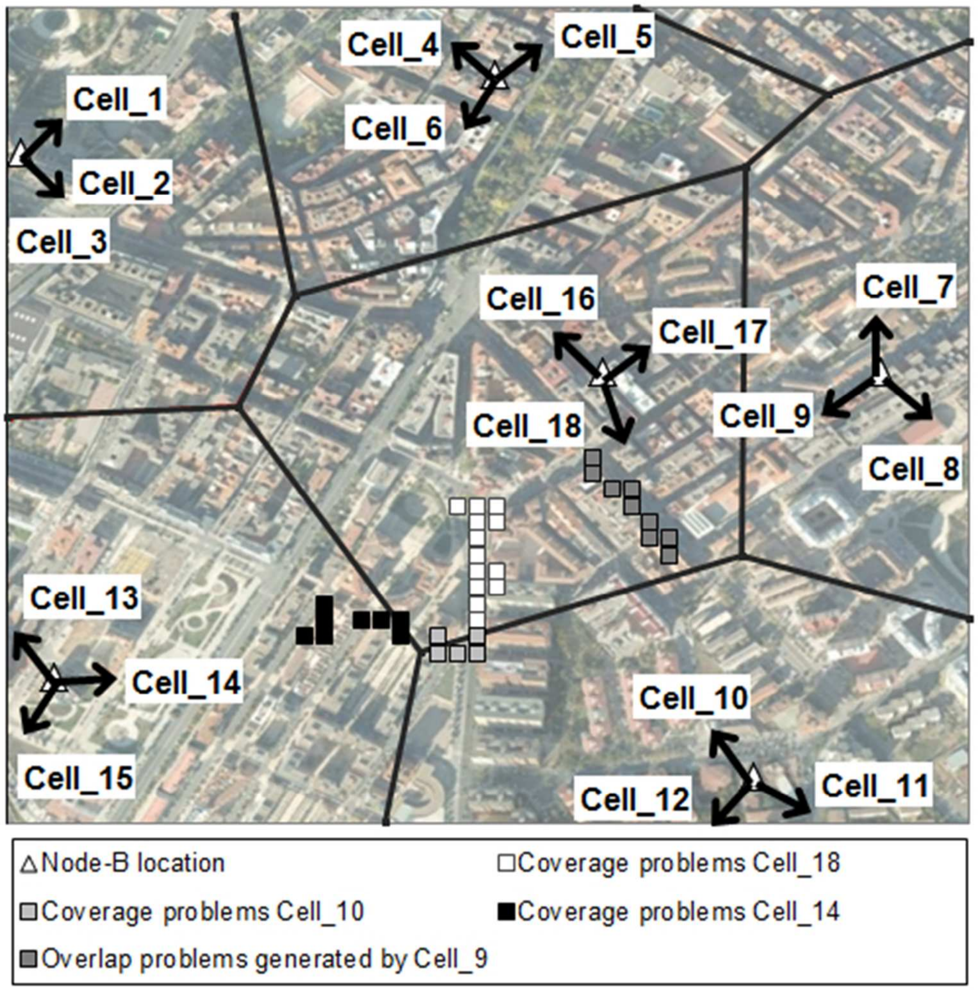

Figure 7.- Regions where coverage and overlap are not properly optimised.
135x134mm (96 x 96 DPI)

Optimisation of cell coverage (m=1)	
Parameter $S_{m,n}$	Value
$S_{1,18}$	0.126
$S_{1,10}$	0.068
$S_{1,14}$	0.014
Optimisation of cell overlap (m=2)	
Parameter $S_{m,n}$	Value
$S_{2,9}$	0.019

Table 2.- Values of the different Sm,n before optimisation.
114x52mm (96 x 96 DPI)

Parameter $\psi_{p,n}$ (p-th tuneable parameter for the n-th cell)	Initial solution	Intermediate solution 1 (found at generation 1)	Intermediate solution 2 (found at generation 3)	Final solution (found at generation 4)
$\psi_{1,18}$ (dBm)	30	30	30	34
$\psi_{1,9}$ (dBm)	30	30	28	28
$\psi_{1,14}$ (dBm)	30	35	35	35
$\psi_{1,10}$ (dBm)	30	30	30	30
Coverage cost $C_1(\psi)$	0.208	0.065	0.065	0.029
Overlap cost $C_2(\psi)$	0.019	0.019	0	0
Total cost $C(\psi)$	0.227	0.084	0.065	0.029

Table 3.- Results of the self-optimisation methodology when only the pilot power is tuned.
176x67mm (96 x 96 DPI)

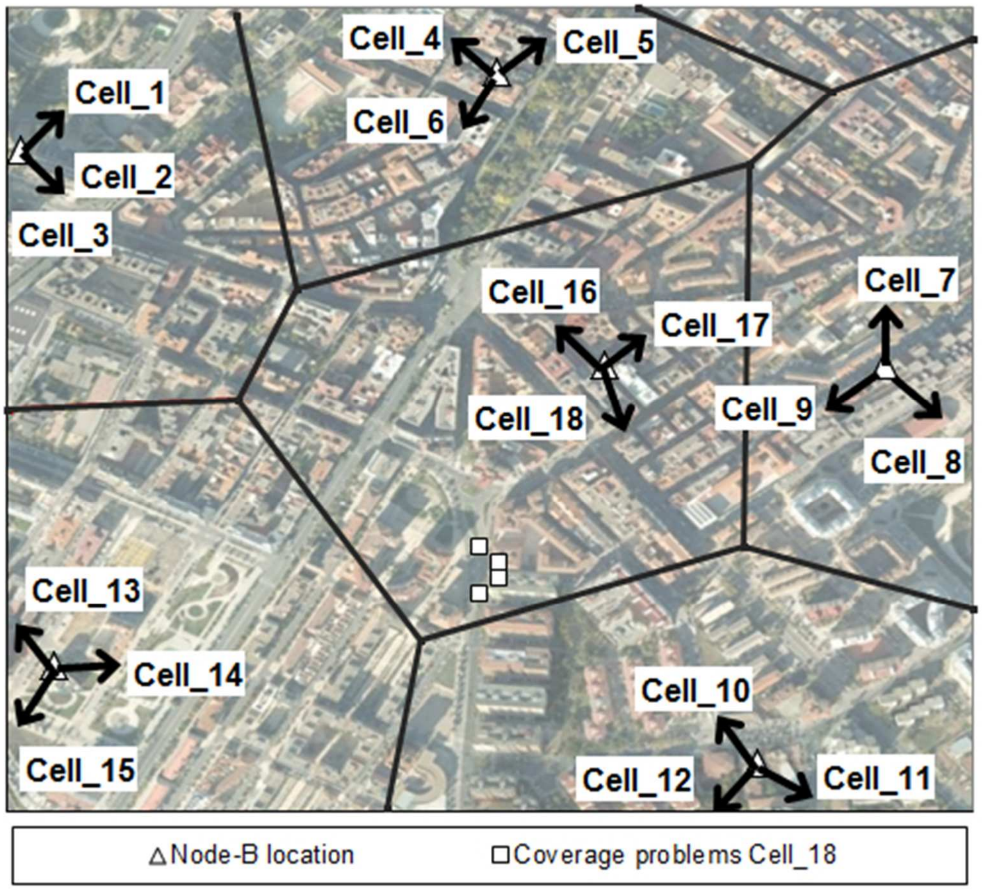

Figure 8.- Outcome of the solution found when adjusting only the pilot power.
135x123mm (96 x 96 DPI)

Tuneable parameter	Parameter $\psi_{p,n}$ (p-th tuneable parameter for the n-th cell)	Initial solution	Final Solution (found at generation 6)
CPICH transmitted Power	$\psi_{1,18}$ (dBm)	30	34
	$\psi_{1,9}$ (dBm)	30	28
	$\psi_{1,14}$ (dBm)	30	35
	$\psi_{1,10}$ (dBm)	30	30
Antenna Tilt	$\psi_{2,18}$ (º)	2	2
	$\psi_{2,9}$ (º)	4	4
	$\psi_{2,14}$ (º)	4	4
	$\psi_{2,10}$ (º)	4	4
Total cost $C(\psi)$		0.227	0.029

Table 4.- Results of the self-optimisation methodology when both pilot power and antenna tilt are tuned.
177x79mm (96 x 96 DPI)

Tuneable parameter	Parameter $\psi_{p,n}$ (p-th tuneable parameter for the n-th cell)	Initial solution	Final Solution (found at generation 9)
CPICH transmitted power	$\psi_{1,18}$ (dBm)	30	34
	$\psi_{1,9}$ (dBm)	30	28
	$\psi_{1,14}$ (dBm)	30	35
	$\psi_{1,10}$ (dBm)	30	30
Antenna tilt	$\psi_{2,18}$ (º)	2	4
	$\psi_{2,9}$ (º)	4	4
	$\psi_{2,14}$ (º)	4	3
	$\psi_{2,10}$ (º)	4	4
Antenna azimuth	$\psi_{3,18}$ (º)	170	185
	$\psi_{3,9}$ (º)	240	250
	$\psi_{3,14}$ (º)	90	80
	$\psi_{3,10}$ (º)	330	330
Total cost $C(\psi)$		0.227	0

Table 5.- Results of the genetic algorithm when pilot power, antenna tilt and antenna azimuth are tuned.
174x94mm (96 x 96 DPI)

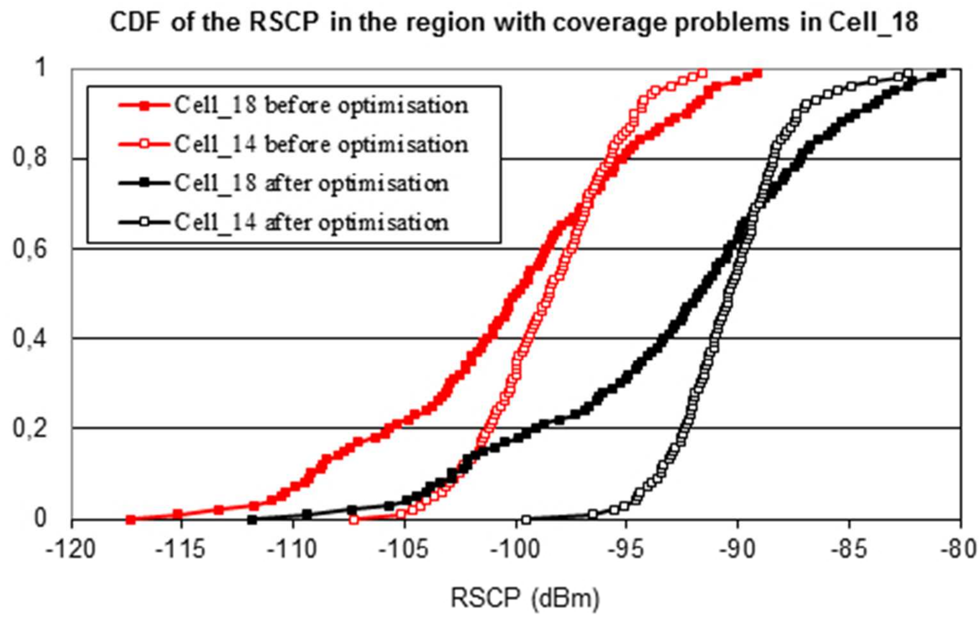

Figure 9.- RSCP in the coverage hole in Cell_18.
135x88mm (96 x 96 DPI)

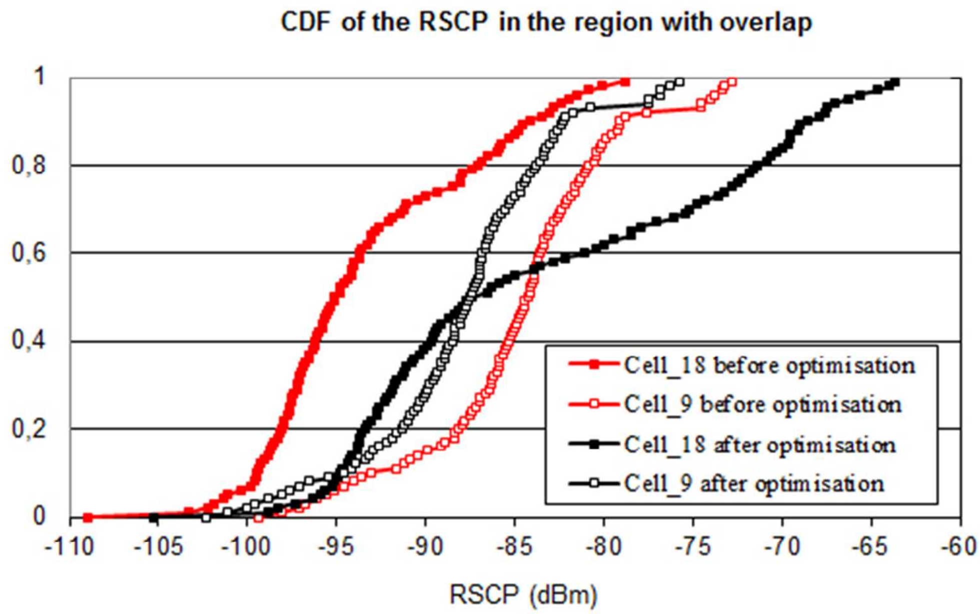

Figure 10.- CDF of the RSCP in the region with overlap.
136x88mm (96 x 96 DPI)

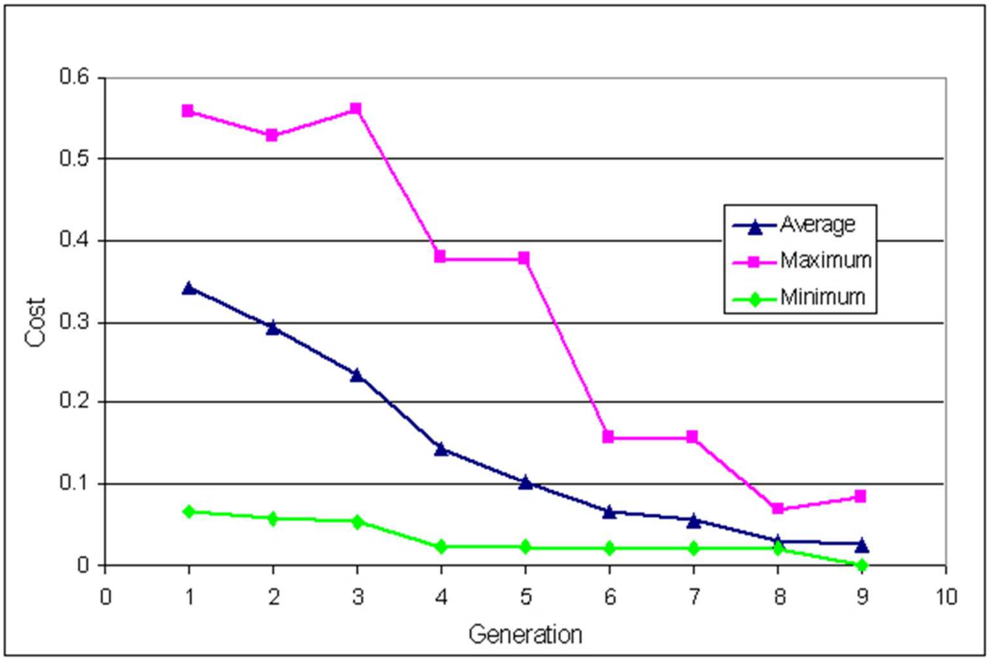

Figure 11.- Algorithm convergence.
163x110mm (96 x 96 DPI)

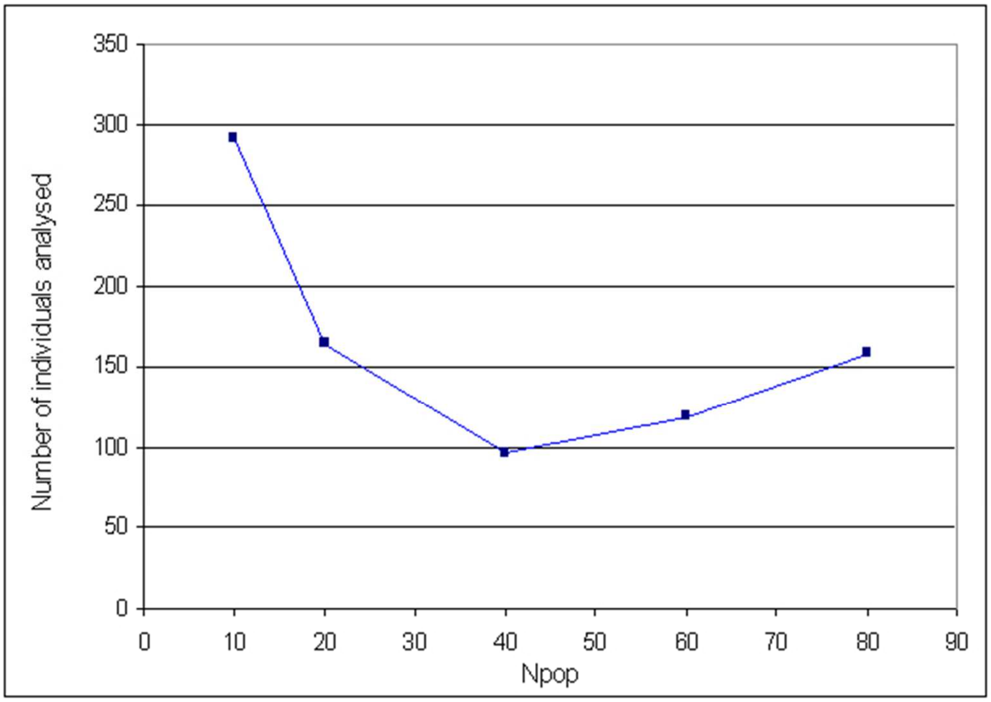

Figure 12.- Impact of the population size (N_{POP})
163x116mm (96 x 96 DPI)