Expert Systems for the Automatic Optimisation of 3G Networks

Vicente Osa[1], Joaquín Matamales[1], Jose F. Monserrat[1], Javier López[2], Vicent Soler[2] and Narcís Cardona[1]
[1]Universidad Politecnica de Valencia, iTEAM Research Institute
Camino de Vera S/N, 46022 Valencia, Spain
[2]Ingenia Telecom, S.L.
Ronda Narciso Monturiol 4, 46980 Paterna, Spain
Corresponding author: jomondel@iteam.upv.es

Abstract

This paper presents a computer-aided optimisation process for operating UMTS network. First, the simulation-optimisation tool is analysed. Its main characteristic is the use of real measurements obtained directly from the network to adjust the simulation models. Besides, two different mathematical algorithms are used to find the optimised configuration of a specific set of the network parameters. Then, an expert system based on artificial neural networks is described. Its basic functioning depends upon the inputs provided by reputed optimisation engineers from the company Ingenia Telecom, S.L. The results show the better performance of the Simulated Annealing optimisation algorithm to get a valid solution and the effectiveness of the proposed expert system to assist in the decision. Given a real network scenario the computer-aided optimisation tool achieves a 98% improvement in terms of the reduction of non-served traffic.

Keywords Expert System, Optimisation, UMTS, Simulation, Call Tracing

1. Introduction

An important constraint of the 3G technologies is the high dependence of the radio access method, WCDMA (Wideband Code Division Multiple Access), on the cell interference level [1]. For this reason, in order to satisfy the required quality of service, it is basic to periodically execute system optimisation methods to guarantee the minimisation of the interference level.

In an operating UMTS network, continuous changes in the spatial-temporal traffic distribution and the quality of service requirements occur. This variability also affects the interference distribution and makes necessary to continuously reconfigure the network parameters in order to keep the interference as low as possible.

The system optimisation process consists of the network data collection, the problem detection after analysing the collected data, and the decision-making to solve the existing problems. Due to the fact that the effectiveness of the decisions making will be highly dependent on the experience of the radio engineering team responsible of this step, it is necessary to define the procedures to evaluate, quantify and discriminate between the different change decisions available. The logical evolution of the UMTS network optimisation processes is based on the avoidance of the high dependence on the human team by designing an automatic decision mechanism capable of determining the best configuration of the main network parameters [2].

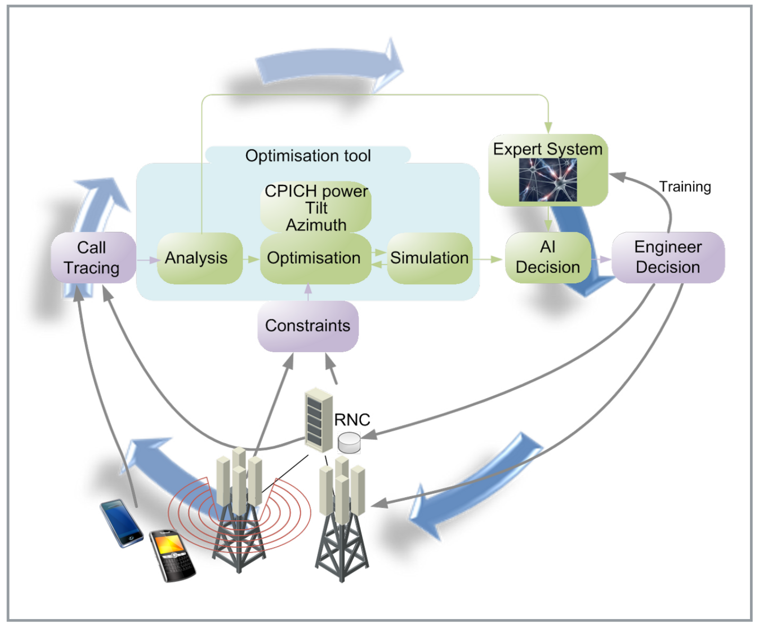
There is a lot of documentation regarding auto-optimisation of mobile communication networks (e.g. [2]-[4]). Besides, there are also several European research projects that have dealt with this problem. For example, the IST Momentum project, finalised in 2003, has treated this issue widely [5]. Nowadays, it is worth mentioning the current activity of the IST SOCRATES project [6] (Self-Optimisation and self-ConfiguRATion in wirelESs networks), that has among its main research objectives the cognitive and auto-optimising networks.

There is still an increasing need to assist engineersin the decision making process

The auto-optimisation mechanisms start not only from the specification of clear improvement objectives but also from the identification of a set of target parameters to optimise. Usually, the main target parameters for optimisation in UMTS networks are the location of the base stations, the antenna configuration, the pilot channels power level, the handover parameters and the definition of the neighbour lists (see, e.g., [2][3]).

The main handicap of the classical computer-aided optimisation process based on simulation and prediction is that this method has been able neither to substitute well-trained optimisation engineers nor to approximate predictions to reality. However this is not a reason to abandon this idea since not all optimisation engineers have the same skills and the final result is highly dependent upon their knowledge and experience. There is still an increasing need to assist engineers in the decision making process but current research trends point to the usage of Expert Systems that capture the know-how of highly-skilled engineers [7]. Moreover, the knowledge of optimisation is continuously evolving with the network updates and hence the Expert System must be refreshing its learning process with new incomes from the experts.

This document proposes a computer-aided optimisation (CAO) process that jointly integrates call-tracing, simulation fitted to actual measurements, optimisation search and expert systems based on neural networks. This practical experience has been carried out by Ingenia Telecom S.L. Company in collaboration with the Universidad Politécnica de Valencia, showing a huge impact of the final solution on the work flow of this optimisation company. Specifically, this paper first describes in Section 2 the current status of the optimisation of UMTS networks and how artificial intelligence can be included in the process. Then, Section 3 analyses the simulation set up and the subsequent optimisation. The expert system is explained in Section 4 whereas Section 5 presents some illustrating results. Finally, main conclusions are drawn in Section 6.



■ **Figure 1.** *CAO process*

2. Artificial Intelligence Applied to the Optimisation Loop

The objective of the proposed CAO process is to improve the performance of an operating UMTS network by tuning some of its radio parameters. It is a cyclic process due to the fact that, after finding an optimised combination of the radio parameters and applying the changes to the network, it is possible to execute the optimisation process again. Only applying a cyclic process the system configuration could be adjusted to the current radio access network conditions, as they are supposed to be continuously changing.

In this work the target optimisation parameters are the tilt and azimuth of the antennas and the power level of the common pilot channel (CPICH). These parameters are the most typically used in other works found in the literature related to the auto-optimisation of the radio access network [2].

Figure 1 shows the block diagram of the proposed computer-aided optimisation process. The central element of the diagram is the optimisation tool, which is able to find the optimum configuration for the radio parameters starting from the input data. This tool comprises basically three elements: (1) the analysis block, responsible for calculating (a) the user traffic density matrix and (b) the calibrated propagation loss matrices from each transmitter by using data collected from a call-tracing tool that monitors the Radio Network Controller (RNC) activity. This mechanism is described later on, in section 2.1. (2) the optimisation block, which finds the best combination of parameters given a maximum response time; and (3) the simulation block, which supports the optimisation block and provides the resulting propagation loss matrix and interferences of every cell that is modified in the optimum search process.

The input data of the optimisation tool encompass: the actual configuration of the radio parameters in the operating network, the list of target cells to optimise and their parameters subject to change, the possible set of values of these parameters and some information and statistics about user calls and traffic collected during a certain time period. The purpose of having the data of the user calls is to be able to generate (a) and (b) from the space distribution of the calls made in the scenario and their corresponding propagation losses. To this end, a user location algorithm has been employed. This algorithm uses the actual information available in the RNC to calculate the user trajectory with an average error of 100m. The resulting traffic density matrix modifies the cost function and, thus, affects the decision made by the optimisation algorithm, giving higher priority to those areas with higher traffic densities.

After the optimisation tool block there is a decision part comprising three different elements. The first one is an expert system based on neural networks that executes a continuous supervised learning. The current system state is introduced as neuron inputs and the output reflects the decision, for example, increase the antenna tilt or the common channel power. Each time a reputed engineer completes an optimisation process their outputs are used to train the expert system. This knowledge will be used by other engineers taking advantage of the system know-how. The outcomes of the expert system are combined with the simulation outputs in the artificial intelligence (AI) decision block. If both inputs agree on the decision the CAO tool reports the decision and the exact value the simulation suggest. On the contrary, the probabilistic output of the expert system is directly transferred indicating the level of likelihood of each decision. The last block represents the radio engineer task of choosing whether to apply directly the parameter configuration derived by the optimisation tool or rather to use it as a guideline to make gradual and conservative changes in the network, while monitoring the effects of such modifications.

3. The Optimisation Tool

3.1 Data Analysis

The analysis block processes the input data of the CAO in order to prepare useful information for the subsequent optimisation process. The CAO input data are collected by a monitoring tool integrated in a network analysis and optimisation system developed by Ingenia Telecom S.L, NeO UMTS. This system gathers data through call-tracing (monitoring calls in the network), probes (capturing data from the Iu and Iub interfaces) and drive testing. The source of information used by NeO comes from the main signalling messages of the 3GPP standard protocols: RRC, NBAP, RNSAP and RANAP. NeO also supplies information about the network topology, including location of the cells and initial configuration of the target parameters of the optimisation.

The main task of the analysis block is the localisation of a set of calls made in the area where the optimisation process is going to be applied. This task is done using a proprietary localisation algorithm that has proven a very good precision for the purpose of the optimisation process. Basically, this algorithm uses the Physical Random Access Channel (PRACH) propagation delay between the User Equipment (UE) and the cell where the call is started and the Received Signal Code Power (RSCP) measures contained in the measurement reports –sent by the UE to the network during the call – to estimate the initial localisation of the UE through geometric calculations.

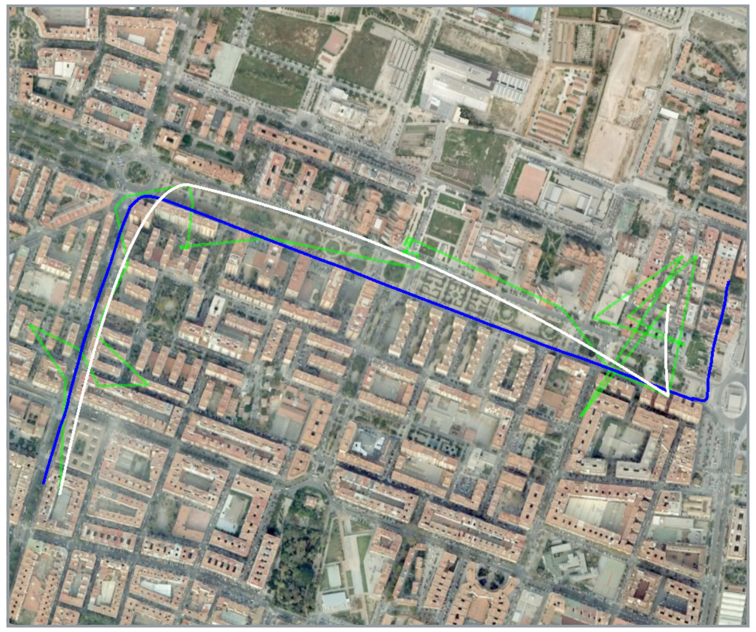
The overall process comprises other more sophisticated steps to increase the final accuracy. For instance, sliding window pre-processing of the values in the measurement reports, consideration of different propagation loss models depending on the area, detection of changes in the trajectory direction or trajectory approximation are some of the mechanisms applied in this process. Figure 2 shows an example of the potential of the implemented localisation algorithm. The blue line is the real path followed by the user during the call, the green line is the first output of the localisation algorithm and the white line the final approximation of the UE trajectory.

The objective of the process is to improve the performance of an operating UMTS network

3.2 Simulation fitted to real measurements

Once the localisation results are available after the execution of the data analysis, it is possible to use these results to generate useful information for the optimisation process. The simulation block of the optimisation tool assists the optimisation subsystem in the search of the optimal solution using real traffic density and propagation losses maps. This section describes how these two types of maps are derived.

It is worth recalling that the analysis block has previously processed all the measurement reports that users submit to the network, mapping each measurements report with the user geographic location. The traffic density is calculated based on these real measurements instead of using predictions. Considering the target area map as a grid, traffic density in each position or element in the grid is computed just counting the number of localisation points situated in that specific square area.



■ **Figure 2.** *Example of the localisation algorithm output*

To calculate propagation losses, for each grid position all real measurements are averaged

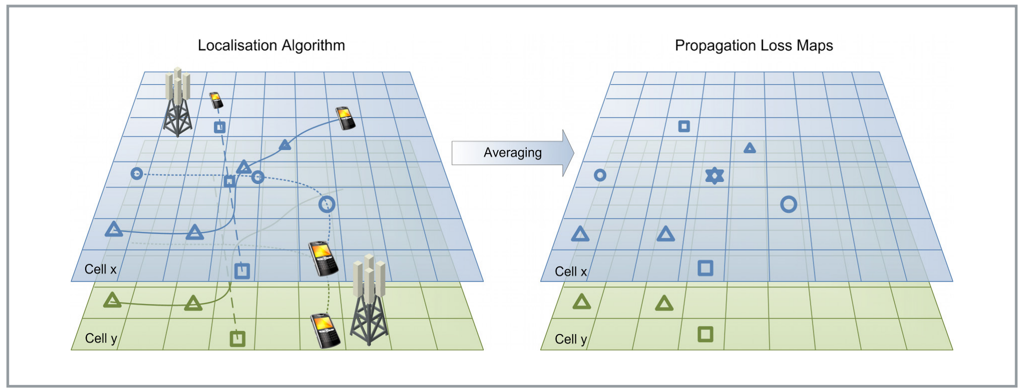


Figure 3. *Example of the localisation algorithm output*

On the other hand, to calculate propagation losses, for each grid position all available measurements are averaged whereas empty positions are filled using a propagation model calibrated with the available data. In order to be able to calculate the propagation losses from the RSCP values contained in the different measurement reports it is necessary to know the current CPICH transmission power of each cell, the radiation diagrams, the gain of the antennas and their actual values of tilt and azimuth.

After obtaining these maps – only once per deployed scenario – the simulation block evaluates the objective cost function, or energy, provided any modification in the radio parameters of any cell of the network. The evaluation of this cost function requires the calculation of the E_c/N_0 experienced by the CPICH channel of every cell in the whole scenario considering the transmitted power, the propagation loss matrix and all the power received from interferers. Assuming all these characteristics, it is possible to become aware of the magnitude of the computational cost required in the process. This is why optimum search algorithms are required.

3.3 Optimisation subsystem

The optimisation subsystem is the element responsible for searching the best configuration of the target parameters when trying to obtain the best performance for a given objective cost function. The aim of the process is to minimise or maximise a function – which depends on the target parameters – that is evaluated by the simulation block.

The inputs of the optimisation subsystem are: (1) the topology of the network, i.e. the position of the target cells and current values of the target parameters, (2) the set of possible values and restrictions of the target parameters and (3) the information needed for the simulation block, i.e. the traffic density map of the area under study and the propagation loss map of each cell.

In order to try to find the best values of the target parameters, the optimisation subsystem uses a local search algorithm, due to the fact that is not feasible to evaluate all possible combinations of all parameters. The algorithm goes through the search space looking for the best solution. Each iteration comprises the evaluation of the chosen objective cost function in order to see if the current solution is a good one. In this work, the objective cost function aims at maximising the covered area while minimising the transmission power over the CPICH. Propagation loss maps are needed by the simulation block in the objective cost function evaluation in order to check where the E_c/N_0 requirements are met. Traffic density map allows giving higher priority to heavy loaded areas. The two search algorithms considered in this work are described in the following.

Simulated Annealing

Simulated Annealing (SA) algorithm is an enhancement of the classical local search algorithms that allows movements towards states representing worse solutions, avoiding the possibility that the algorithm gets trapped in a local minimum too early. The name and inspiration come from the annealing process used in metallurgy. Its simplicity and good performance in a number of optimisation problems have made it become a very popular tool, with hundreds of applications in a wide variety of fields.

Classical local search algorithms start from an initial solution that is gradually adapted introducing small changes (for example, by change the value of only one variable) leading to different energy states. If the energy difference between two states, ΔE, is negative, the solution that the new state represents is supposed to be better than the previous solution. Therefore, this solution is substituted by the new one, continuing the process until reaching a stable state in which local search is unable to find a better solution. This means that the search process ends in a local minimum that may or may not be the global minimum.

In order to tackle this problem, movements towards states representing a worse solution than the current one are also allowed. However, these escape movements must be controlled in a certain manner in such a way that the search is lead towards the global minimum. In the SA case, this is made by controlling the frequency of the escape movements by means of a probability function, which provides lower movement probability to worse solutions as the search progresses. This probability is controlled by a temperature parameter, *T*, which initially has a high value and is gradually reduced. Specifically, the expression that represents the acceptance probability of a configuration change is:

$$P_{acc} = \begin{cases} 1 & \Delta E < 0 \\ e^{\frac{-\Delta E}{T}} & \Delta E \geq 0 \end{cases} \qquad [1]$$

Particle Swarm Optimisation

Particle Swarm Optimisation (PSO) is inspired by the social behaviour of bird flocking or fish schooling. The objective of the algorithm is to solve a problem in terms of maximising or minimising a fitness function. A population of individuals is defined initially, representing different random candidate solutions in the search space. The algorithm consists of an iterative process that varies these individuals depending on the fitness function performance of the current candidate solution and on the local and overall best performance. Each individual keeps track of its historically best candidate solution (local best) and a social network is defined so that every individual knows the best candidate solution among all local bests (global best).

4. The Expert System

The aim of expert systems is to capture the knowledge provided by a human expert and introduce it into a computer. The final system will act with enough intelligence as to solve a specific problem that otherwise should have been tackled by the expert. Of course, the expert system cannot infer this knowledge without the supervision of the human expert and machine learning must be used. In this paper, our machine learning block is a back-propagation artificial neural network trained directly from a set of inputs and the corresponding outputs provided by a set of reputed engineers.

The expert system analyses one by one all cells in the scenario. The list of inputs was established according to the information that experts consult to make the final decision. For any Cell Under Study (CUS) it is important to know its current configuration and its coverage distribution, which is provided by the call tracing tool. All the interferers of the CUS are sorted by level of overlap, and their main parameters are also inserted in the expert system. It is worth highlighting the relative azimuth that measures clockwise the beam pointing of both cells. Finally, output targets are the same as for the optimisation tool: tilt, azimuth of the antenna and the power level of the common pilot channel. Two neurons per concept are defined, one per direction change. One output is equal to 1 provided an absolute certainty of the decision whereas the output decreases with lower confidence levels. An output value of 0 represents that this changes is absolutely not recommended. Note that this design allows the expert system to manage uncertainty in a simple way. All details of the conceptual meaning of the inputs and outputs of the expert system are summarised in Table I

Concerning back-propagation, the proposed expert system uses Levenberg-Marquardt method, since there are not out-of-memory problems. According to this method the layers are fully connected, i.e. every neuron is connected to every other neuron in the next layer. Besides, the learning process has two phases. In the former, any training input is introduced in the network input layer. Then, the neural network propagates these inputs from layer to layer until the output is generated. In the second phase, the obtained output is compared with the human expert decision and is propagated backwards from the output layer to the input modifying the neuron weights. After processing an adequate number of training inputs-outputs the neural network will be automatically interconnected with the appropriate weights. The only open question is to determine the network topology, that is, the number of hidden layers and number of neurons per layer. The proper network architecture is usually chosen using heuristics or past experiences. As for the number of hidden layers, they are responsible for detecting the problem features. Any continuous function can be represented with one hidden layer, whereas discontinuous functions require at least two hidden layers. Therefore, a neural network has typically from three to five layers, account one for inputs and one for outputs. Concerning the number of neurons per layer, input layer equals the number

The aim of expert systems is to capture the knowledge provided by a human expert

	Neuron Input		Neuron Output	
1	CUS common power	1	↑ CUS common power	
2	CUS tilt	2	↓ CUS common power	
3	CUS mean coverage	3	↑ CUS tilt	
4	CUS 95th coverage	4	↓ CUS tilt	
5	I_1 distance	5	↑ CUS azimuth	
6	I_1 relative azimuth	6	↓ CUS azimuth	
7	I_1 common power			
8	I_1 level of overlap			
9	I_2 distance			
10	I_2 relative azimuth			
11	I_2 common power			
12	I_2 level of overlap			
	...			
37	I_9 distance			
38	I_9 relative azimuth			
39	I_9 common power			
40	I_9 level of overlap			
40	I_9 level of overlap		Uncertain terms [8]	
41	UTRAN CBR (%)	1	Definitely not	0
42	Reported cells	2	Almost certainly not	0.1
43	Cells to add	3	Probably not	0.2
44	Polluted MRs (%)	4	Maybe not	0.3
45	Polluting MRs (%)	5	Unknown	0.4-0.6
46	Avg EcN0 RACH	6	Maybe	0.7
47	Avg Prop. Delay (m)	7	Probably	0.8
48	Perc95 Prop. D elay (m)	8	Almost certainly	0.9
49	Perc98 Prop. Delay (m)	9	Definitely	1

Table 1. *List of neurons in the input and output layer.*

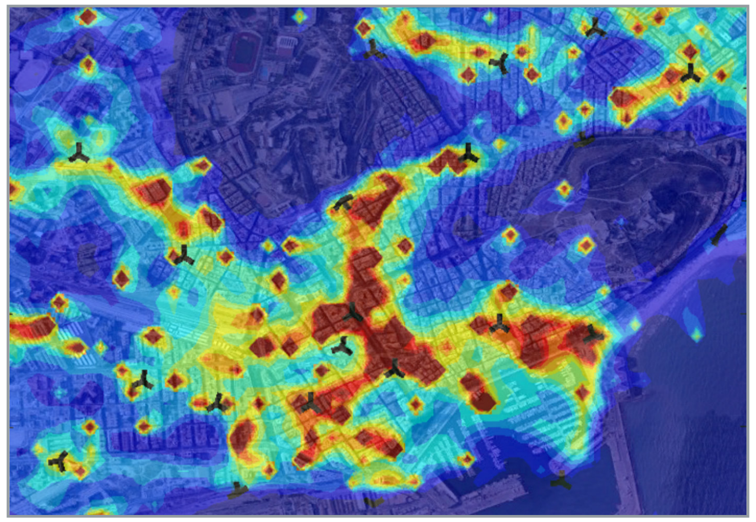


Figure 4. *Optimised scenario and traffic distribution.*

of inputs and the same happen with the output layer. Hidden layers comprise usually from 10 to 1000 neurons [8].

In order to design the Expert System, this paper proposes to check sequentially the optimum number of layers from three to five. For each case, a second step is to determine the optimum number of neurons per layer. With this aim, an optimum search algorithm based on simulated annealing is used. The input value is a vector with one, two or three element, each ranging from 10 to 1000 with steps of 1. The cost function to be minimized must estimate the performance of a given topology. The set of training examples is introduced in the network and then the sum of squared errors is calculated. The smaller the sum is the better the topology. The final architecture will be the optimum configuration of layers and neurons.

4.1 The artificial intelligence decision block

This is the last block of the CAO process. The objective of the AI decision block is to merge the optimisation tool and the expert system outputs. The optimisation tool generates a specific configuration of the system that, compared with the original one, implies a set of decisions of either increasing or decreasing azimuth, tilt and transmitted power. The expert system just supplies this decision, of course with certain reliability, but without indicating the concrete modification of each parameter. The AI decision block processes all this information in a simple way: if both sources coincide with the decision, the system indicates the action and the specific proposal of change. If they disagree, the system trusts the expert system more than the simulation tool, and derives the confidence level of all actions, i.e. passes all the outputs of the artificial neural network.

5. Results

The scenario under study, shown in Figure 4, covers the city centre of a European city, with sites positioned in real locations of a mobile operator and other radio configuration parameters, such as antenna heights, azimuth and CPICH power, obtained from the real deployment. Figure 4 also depicts the traffic density map where the red coloured areas represent high traffic density areas. As can be seen by visual inspection with the background city map, the localisation algorithm errors are cancelled when multiple inputs are averaged and the traffic map fits perfectly the areas without evident human activity. The large number of inputs allows eliminating the random errors produced by the localisation algorithm.

Next section analyses the functioning of the optimisation subsystem whereas results from the expert system are presented in section 5.2.

5.1 Optimisation subsystem

Two different optimisation techniques were tested, simulated annealing and particle swarm. They all use the same cost function which allows maximising the coverage area, A_{cov}, in a total area, taking into account the E_c/N_0 criterion. This criterion has been weighted by the actual traffic density map in the scenario under study, $A_0(x,y)$ shown in Figure 4, in order to give higher priority to those areas with higher density of users. The following objective function meets all the previous requirements:

$$f_{obj}^{cov} = \frac{A_{cov}}{A_{cov,initial}}, \qquad [2]$$

where the coverage area is calculated as the sum of all the elements of the following function:

$$cov^{traffic}(x,y) = cov(x,y)\cdot A_0(x,y), \qquad [3]$$

$$cov(x,y) = \begin{cases} 1, & (E_c/N_0)_{CPICH} \geq (E_c/N_0)_{CPICH,treshold} \\ 0, & (E_c/N_0)_{CPICH} < (E_c/N_0)_{CPICH,treshold} \end{cases}, \qquad [4]$$

and $A_{cov,\,initial}$ is obtained evaluating (3) for the initial configuration of the system.

However, this is not the only objective of the optimisation problem, since CPICH transmitted power must be also minimised. This second function is formulated as:

$$f_{obj}^{power} = \frac{1}{N}\sum_{i=1,N}\frac{P_{c\,i}-P_{c\,min}}{P_{c,max}-P_{c,min}}, \qquad [5]$$

being N the number of cells in the system, $P_{c,i}$ the CPICH power of the i-th cell and $P_{c,min}$ and $P_{c,max}$ the minimum and maximum value for this power, respectively.

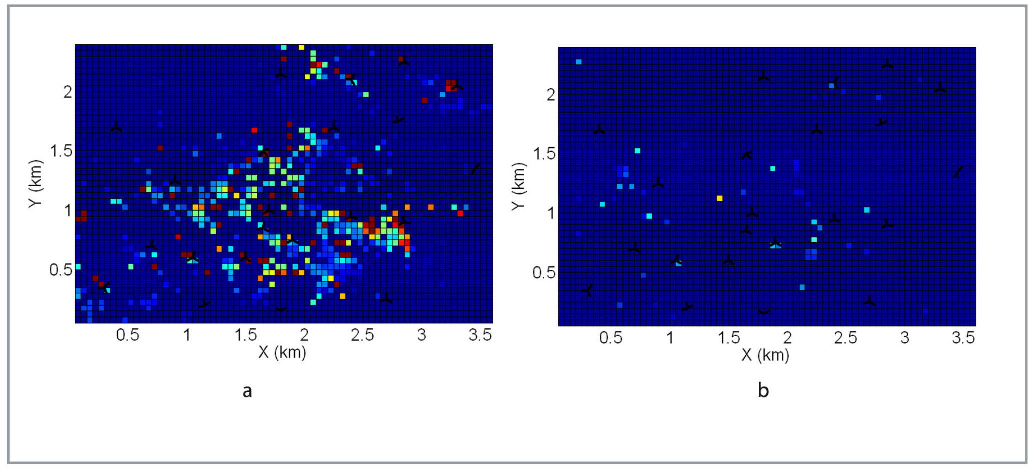


Figure 5 . *Points satisfying Ec/N0 criterion (dark blue) and traffic of non-covered points. Before optimisation (a) and after SA optimisation (b).*

The final cost function is:

$$f_{obj} = f_{obj}^{cov} + \alpha\cdot f_{obj}^{power}, \qquad [6]$$

where α weighs the importance of both terms. In this paper α is equal to 0.1.

Figure 5 represents, on the area under study, the areas that suffer a reduced coverage level – in this paper (E_c/N_0 < -12dB) – given the set of optimum radio parameters obtained. Colours represent the level of traffic of the non-covered point. On the left hand, it is depicted the initial configuration of the system with the real radio parameters. On the right hand, it is represented the improvement achieved with the simulated annealing solution. It can be seen the outstanding improvement of the carried traffic with good coverage. The non-carried traffic becomes more than 68 times lower as compared with the original configuration of the network.

Finally, Table II compares the performance of both studied algorithms in terms of computational burden, improvement of the final solution and power consumption. In terms of computational burden, SA is clearly better than the other algorithm. The reason for this is that the SA implemented in this work provides several mechanisms to allow saving execution time. In terms of the cost functions, although PSO requires more power consumption than SA and the initial configuration to get its best solution, it is not able to reach the performance of the SA.

5.2 Expert system

In this section, some results of the evaluation of the expert system executed for a specific target parameter and direction are given, specifically those obtained by the neural network (NN) responsible of deciding on a potential tilt increase in the CUS. Using Levenberg-Marquardt backpropagation algorithm, the NN has been trained employing 203 cases of cells optimised by an expert engineer, reserving 15% of the samples for validation and a 15% for testing. The best performance has been achieved with three hidden layers of 40, 20 and 10 neurons respectively.

Applying the trained NN to the same cells used by the auto-optimisation tool, both outputs are aligned in 77% of the cases, using 0.6 as the uncertainty threshold. That is, the decisions taken by both tools, in terms of increasing or not the tilt, match in 77% of the cells analysed. The comparison of the results of both tools is possible after converting the auto-optimisation output using the transfer function shown in Figure 6.

6. Conclusions

The proposed CAO tool automatically provides an optimum configuration of the radio access parameters of an operating UMTS network. The analysis block is essential for this success, since localisation information is the basis for the rest of steps. Comparing the search algorithms, the mechanism based on SA allows, by means of

	SA	PSO
Normalised execution time	1	2.17
Reduction of non-carried traffic (%)	98.53	92.54
Reduction of power use (%)	17.6	-7.16

Table 2. *Comparison of the different optimisation algorithms.*

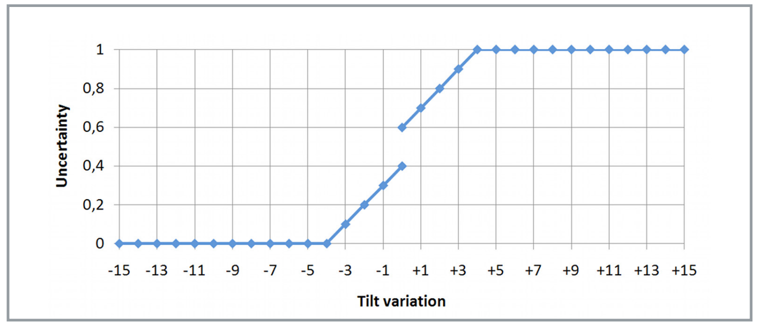


Figure 6. *Transfer function used to convert optimisation output in uncertainty terms.*

some computational cost reduction techniques, obtaining good results while saving 54% on the execution time, as compared with PSO. Besides, the SA percentage of improvement in the served traffic is better than PSO even consuming less power. As compared with the original configuration of the network – a realistic one – the non-carried traffic becomes more than 68 times lower. Finally, comparing the computational cost of both mathematical methods, the PSO algorithm takes 2.17 times more than the SA. Therefore, in order to choose one specific method it seems reasonable to make use of SA for this specific problem. As further work, other variants of the PSO could be investigated to check for better performance.

Concerning the expert system, results have focused on one specific output – increase tilt – since this is the only decision currently made by the optimisation company involved in this study. Results demonstrated a very good performance of the designed neural network with only 142 training cells. The proposed scheme is agnostic from the specific deployment since it analyses cells one by one. Anyway the presented results cannot be considered as definitive, since a trained network should be applied to another different scenario then testing the validity of the proposed system.

Acknowledgment

The authors would like to thank the funding received from the Ministerio de Industria, Turismo y Comercio within the Project number TSI-020100-2009-179 and the FEDER funds.

References

[1] Harri Holma and Antti Toskala, WCDMA for UMTS. Radio Access for Third Mobile Communications, 3rd Ed., John Wiley & Sons, 2004.
[2] Jaana Laiho. Achim Wacker and Tomas Novosad, Radio Network Planning and Optimisation for UMTS, 2nd Ed., John Wiley & Sons, 2006.
[3] Maciej J. Nawrocki, Mischa Dohler, A. Hamid Aghvami, Understanding UMTS Radio Network Modelling, Planning and Automated Optimisation, 1st Ed., Wiley & Sons, 2006.
[4] Christophe Chevallier et al. WCDMA (UMTS) Deployment Handbook: Planning and Optimization Aspects, 1st Ed., John Wiley & Sons, 2006.
[5] T. Kürner, A. Eisenblätter, H.F. Geerdes, D. Junglas, T. Koch, A. Martin, Final Report on Automatic Planning and Optimisation, IST-2000-28088-MOMENTUM-D47-PUB, October 2003.
[6] SOCRATES project, http://www.fp7-socrates.org/.
[7] Wu Jing, Li Lin and Lei Yi, "KDD in the optimization of GSM network", Applied Artificial Intelligence, vol. 16, no. 2, pp. 97 – 115, February 2002.
[8] Michael Negnevitsky. Artificial Intelligence A Guide to Intelligent Systems, 2nd Ed., Addison Wesley, 2005.

Biographies

Vicente Osa (viosgi@iteam.upv.es) received his MSc. Degree in Telecommunications engineering from the Universidad Politécnica de Valencia (UPV) in 2005. He began its career as a programmer analyst in private companies. In late 2008 he joined the Institute on Telecommunications and Multimedia Applications (iTEAM) as a researcher. Since then, his work in the Mobile Communications Group (MCG) has focused on the development of auto-optimisation tools for third generation mobile networks.

Joaquín Matamales (joamaca@iteam.upv.es) received the MSc. degree in Telecommunications engineering from the Universidad Politécnica de Valencia (UPV) in 2008. His work developed in the Mobile Communications Group (MCG) of the Research Institute on Telecommunications and Multimedia Applications (iTEAM) has focused on performance assessment and optimisation of third generation mobile networks.

Dr. Jose F. Monserrat (jomondel@iteam.upv.es) received his MSc. degree with High Honors and Ph.D. degree in Telecommunications engineering from the Polytechnic University of Valencia (UPV) in 2003 and 2007, respectively. He was the recipient of the First Regional Prize of Engineering Studies in 2003 for his outstanding student record receiving also the Best Thesis Prize from the UPV in 2008. He is currently an associate professor in the Communications Department of the UPV. His research focuses on the application of complex computation techniques to Radio Resource Management (RRM) strategies and to the optimization of current and future mobile communications networks. He is currently participating in two European Project, ICARUS and WINNER+. In the latter he is leading the research activities focused on the definition of Advanced RRM techniques for LTE-Advanced. He is also participating in one external evaluation group within ITU-R on the performance assessment of the candidates for the family of standards IMT-Advanced.

Javier López (javier.lopez@ingenia-telecom.com) Javier López is partner and project manager of Ingenia Telecom S.L. He received his MSc. Degree in Telecommunications engineering from the Universidad Politécnica de Valencia (UPV) in 2005. He was granted with a Socrates-Erasmus grant to carry out his Master Thesis in Strathclyde University, Glasgow (United Kingdom) in collaboration with the company Pollaroid UK. He began his career as a programmer analyst in Accenture España S.L. and in 2006 he joined the research team of the Institute on Telecommunications and Multimedia Applications (iTEAM). His functions there focused in the management of working teams responsible for the collaboration agreements with companies like Teltronic and Vossloh.

Vicent Soler (vicent.soler@ingenia-telecom.com) is founder partner and technical director of Ingenia Telecom S.L. He received his MSc. Degree in Telecommunications engineering from the Universidad Politécnica de Valencia (UPV) in 2001. He was the recipient of the National Prize for the best master thesis from the Universidad Politécnica de Madrid for the project 'Mobile System for Live Image Transmission over Internet'. In 2001 he joined the Institute on Telecommunications and Multimedia Applications (iTEAM) as a researcher and manager of the working team responsible for the collaboration agreement between Motorola España and UPV, developing a wide variety of projects related to mobile communications, mainly for UMTS, IMS and TETRA networks. Afterwards he also became the manager of other collaboration agreements with companies like Teltronic or Vossloh. Nowadays he also participates as a collaborator professor in the Mobile Communications Master (MUCOM) in the UPV.

Dr. Narcís Cardona (ncardona@iteam.upv.es) was born in Barcelona, Spain. He received the M.S. degree in communications engineering from ETSE Telecommunications, Polytechnic University of Catalunya, Barcelona, in 1990 and the Ph.D. degree in telecommunications from the Polytechnic University of Valencia (UPV), Valencia, Spain, in 1995.

Since October 1990, he has been with the Department of Communications, UPV, where he is the Head of the Mobile Communications Group, the Director of the Mobile Communications Master Degree, and the Assistant Director of the Research Institute on Telecommunications and Multimedia Applications (iTEAM). He has led several national research projects and has participated in some European projects, i.e., Networks of excellence, and other research forums in mobile communications. His current research interests include mobile channel characterization, planning and optimization tools for cellular systems, RRM techniques applied to personal communications, and broadcast cellular hybrid networks.

Dr. Cardona has been the Vice-Chairman of the COST273 Action and is currently in charge of the WG3 of COST2100 in the area of radio access networks. He was the Chairman of the Third International Conference on Wireless Communications Systems (ISWCS'06).

.