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.

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 wireEs networks), that has among its main research objectives the cognitive and auto-optimising networks.

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.

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There is still an increasing need to assist engineers in 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.

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. Figure 1 shows how the optimisation of UMTS networks is related to the configuration of the radio parameters of the network. It is a cyclic process due to the fact that, after finding an optimised combination of the radio parameters, the experts change the system configuration of the expert system 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 block (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 process 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 encompasses the actual configuration of 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 generate base (a) and (b) from the space distribution of the calls made in the scenario and their corresponding propagation losses. To this end, a 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 instance, increase the antenna tilt or the common channel power. Each time a reputed engineer completes an optimisation process the new parameters 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., NoD UMTS. This system gathers data through call-tracking (monitoring calls in the network), probes (capturing data from the Lu and lub interfaces) and drive testing. The source of information used by NoD comes from the main signalising messages of the 3GPP standard protocols: RRC, NBAP, RNSAP and RANAP. NoD 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) measured 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.
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/N0 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.

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 it 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 coverage area while minimising the maximising the 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/N0 requirements are met. Traffic density maps allow 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 varies 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. In our 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 consider 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 how 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 of inputs. Hidden layer equals the number of inputs plus the number of neurons in the previous and next layer.
of either increasing or decreasing azimuth, tilt or CPICH power. The expert system just supplies this decision, of course with certain errors produced by the localisation algorithm.

The 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, \( \alpha \), in a total area, taking into account the \( E_{\text{c}}/N_0 \) criterion. This criterion has been weighted by the actual traffic density map in the scenario under study, \( \psi(x,y) \) 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:

\[
\text{cov}_{\text{obj}} = A_{\text{cov}} \cdot A_{\text{cov,initial}},
\]

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

\[
\text{cov}(x,y) = \psi(x,y) \cdot \phi(x,y).
\]

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 rejects 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.

The final cost function is:

\[
f_{\text{cov}} = A_{\text{cov}} + a \cdot f_{\text{power}} + f_{\text{traffic}},
\]

where \( a \) weights the importance of both terms. In this paper \( a \) is equal to 0.1.

Figure 5 represents, on the area under study, the areas that suffer a reduced coverage level – in this paper \( E_{\text{c}}/N_0 < -12 \text{dB} \) – 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.

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 back-propagation 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.
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 increases 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 only on one specific output – increase in Erlitic – 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 than testing the validity of the proposed system.

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Biographies

Vicente Osa (vicente.osa@upv.es) received his MSc. Degree in Telecommunications engineering from the Universidad Politécnica de Valencia (UPV) in 2005. He began his 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.

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