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Automated W-CDMA Microcellular Deployment and Coverage Reconfiguration based on Situation Awareness

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Abstract: *This paper examines the implementation of an automated W-CDMA microcellular deployment and coverage reconfiguration algorithm based on the concepts of Situation Awareness (SA). A deterministic microcellular propagation model (Citrus) is used to provide the detailed site-specific propagation data. An initial network deployment is performed over one square kilometre of central Bristol using the Combination Algorithm for Total Optimisation (CAT). Buildings are then added or removed from the microcell to represent realistic time variations in the geographic environment. A new Situation Awareness (SA) algorithm is developed and applied to the modified W-CDMA microcell to automatically reconfigure the network's coverage and capacity based on the new propagation environment. Optimisation of coverage and capacity is achieved through the use of a Genetic Algorithm (GA). This paper presents the details of the underlying SA algorithm and the results obtained for the above scenario. These new algorithms are shown to automatically sustain a high Grade of Service as the microcellular environment evolves over time. Gains of up 203% in spectral efficiency were observed for the 144 kbps service.*

1. Introduction

Cellular W-CDMA networks differ significantly from second generation systems such as GSM. In particular, they will offer variable bit rate services with peak rates far in excess of those currently available. To meet these requirements, many thousands of basestations will need to be deployed using a hierarchical cell structure. Given this situation, there is a very strong need to design and deploy cost-effective networks. A well-designed system will make good use of traffic, propagation and collateral information to maximise spectral efficiency and optimise key parameters such as coverage and capacity. This leads to the efficient use of network resources and provides increased revenue for the network operator. From a user perspective, a well-planned network delivers high Quality of Service (QoS) to all geographic locations for a wide range of mobile applications.

The QoS delivered to users in a network can change significantly over time as a result of variability in both the traffic and the propagation environment (e.g. the construction of new buildings, the demolition of old buildings and changes in vegetation etc.). In the case of microcells, these fluctuations can result in major changes in cellular coverage and capacity. Adaptive or dynamic networks are now being proposed in order to drive down the cellular infrastructure cost while maintaining QoS in a time varying network. More specifically, Self-Organising techniques have been proposed to achieve dynamic network behaviour [1]. In order to implement Self-Organisation, previous research has focused on the implementation of 'Situation Awareness' (SA), which represents key enabling functionality [1][2]. SA requires basestations to monitor parameters such as pathloss (basestation to basestation and basestation to mobile), with this information shared across the network. These techniques maximise the use of the fixed cellular infrastructure by allocating resources when and where they are required. Adaptive algorithms for macrocells based on the concept of Situation Awareness have already been devised to reconfigure coverage for different scenarios (i.e. the addition or removal of basestations) [1][2]. These macrocell studies made use of the relatively simple COST 231-propagation model. For a microcellular environment, predicting and achieving geographic coverage is a far more complex affair that depends on site specific parameters such as building locations and local terrain features [3]. Given this situation, microcellular SA techniques must be based on coverage data obtained from more accurate, site-specific, propagation models.

Starting with a particular W-CDMA microcellular deployment, the aim of this paper is to determine whether Self-Organisation techniques can maintain QoS over an evolving geographic environment. For this purpose, site specific coverage prediction data is generated using a 3-D building, foliage and terrain database for a central region of Bristol. An initial deployment is performed using the Combination Algorithm for Total Optimisation (CAT) [4]. The CAT selects base sites that are optimised to meet initial coverage and capacity requirements [4]. The SA

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adaptive algorithm is then used to demonstrate how coverage can be automatically maintained despite significant changes in the propagation environment (i.e. the introduction of new high rise buildings and the demolition of existing structures).

2. Propagation Model and Initial Base site Optimisation

A well-developed fully three-dimensional deterministic propagation model is used to generate the time varying propagation data required in this study. The model uses geographic data (terrain, building, foliage and ground cover) to predict power as well as time, frequency and spatial dispersion in the radio channel [4]. It is optimised for intracellular coverage as well as inter-cellular predictions (interference) between different cells in a mixed-cell network.

Once coverage prediction is complete, the Combination Algorithm for Total Optimisation (CAT) is used to optimise the number and location of base sites required to meet operator defined coverage and capacity requirements [5]. The CAT algorithm analyses a list of all possible basestation locations and chooses the minimum sub-set required to meet the design criteria. As time passes, changes in the propagation environment will inevitably degrade the performance of the cellular network.

3. Reconfiguration using SA

Our cellular study is performed over a one square kilometre region of central Bristol. An aerial photograph of this district is shown in Figure 1. A microcellular UMTS W-CDMA FDD network is now simulated assuming non-homogenous traffic with a variable traffic mix (see Table 2 for details). As discussed previously, a number of basestations (10 6-sectored) are optimally deployed using the CAT algorithm. Different design targets are used based on the various loading conditions and traffic mixes shown in Table 2. The QoS in each case is determined from the outage probability for the specified C/I threshold. To simulate temporal variations in the environment, modifications are made to the 3-D geographic database. This takes the form of adding and/or removing building structures. The resultant outage probability will almost certainly rise once these changes have been made to the geographic database. However, results are expected to indicate that automated SA can enable a near constant outage probability to be maintained.

3.1 Adaptive Algorithm using SA

The problem of optimising coverage and capacity in a W-CDMA system is a classic case of a multiple objective problem. Inherently, such problems do not have a single

solution and optimisation techniques must evaluate a best possible solution. Genetic Algorithms have been used for some time in the literature for radio coverage optimisation. As reported by Lieska [6], the advantage of the Genetic Algorithm (GA) over other combinatorial or heuristic methods is that it directly processes the computer representation of the potential solutions, rather than manipulating mathematical formulations (object functions).

In this analysis the use of the GA is extended to include the concept of providing the Radio Network Controller (RNC) with SA functionality. As such, basestations can self-configure their coverage in order to provide a Grade of Service (GoS) that maximises the network operators' revenue and provides an acceptable QoS to subscribers.

The following technique could be implemented in a manner where mobile stations report their RSSI (received signal strength indicator) to the RNC, which would then direct basestations to adaptively adjust their transmit powers with a view to minimising key network parameters such as outage and blocking probability.
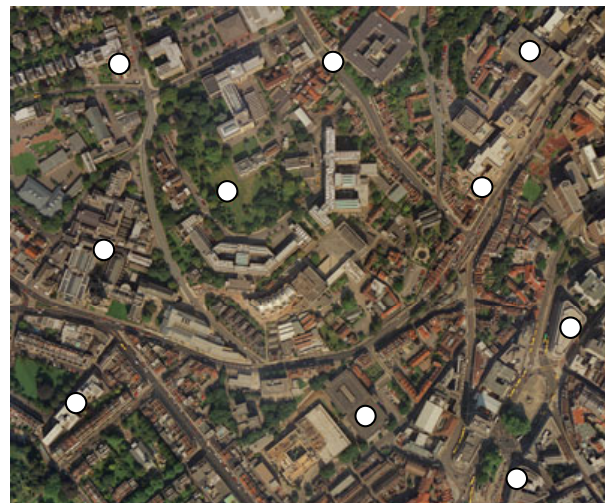

Figure 1: Coverage of a one square kilometre region of central Bristol using 10 UMTS Basestations

3.2 Genetic Algorithms (GA)

The GA is derived from evolution and genetics [7]. The term *chromosome* refers to a candidate solution to a problem encoded as a bit string. The *population* represents the search space of potential solutions. There are three main operators in GA: *Selection*, *Crossover* and *Mutation*. Selection selects chromosomes in the population for reproduction. The fitter the chromosome, the more times it is likely to reproduce. *Crossover* refers to the fact that 'high quality' parent chromosomes recombine to produce high quality offspring candidate solutions. Traits from the most dominant individuals will

therefore survive into the next generation. Finally, *Mutation* is the operator that randomly flips bits in a chromosome.

The canonical GA consists of an initial population of n randomly generated l-bit chromosomes. The fitness of each chromosome is evaluated using a fitness function $f(x)$. Subsequently, a pair of parent chromosomes is selected from the current population, the probability of selection being an increasing function of fitness. With probability p_c the pair of chromosomes is recombined to form two offspring. Finally, mutation of the two offspring occurs at each locus with probability p_m and the current population is replaced with the new population.

3.3 Problem definition

The problem objective is to maximise W-CDMA coverage and minimise outage probability and blockage. The solution consists of finding the optimum values of downlink transmit powers at the basestations to maintain a target GoS in the network.

3.3.1 Chromosome encoding and fitness function

The downlink transmit power values are represented as a power vector and converted to binary for bit string representation. An 8-bit representation is chosen to encode each transmitter level in the vector string.

The initial population is composed of 100 individuals and is generated so that each transmitter has a random power level ranging from 0 to28dBm (the latter value being the maximum downlink power for microcells).

The fitness function used in the GA is given below:

$$f(x) = \frac{\text{Total area covered by each solution chromosome}}{(\text{Blocking probability} + 1) + (\text{Outage probability} + 1)} \quad (1)$$

The numerator consists of parameter to be maximised while the denominator contains parameters to be minimised. Each chromosome solution is evaluated using equation 1. Figure 2 illustrates the fitness landscape for 100 deployed users and 100 generations. The parameter values are listed in Table 1.

Parameter	Value
Recombination probability	0.7
Mutation probability	0.001
Population size	100
Number of runs	100

Table 1: Parameter values

3.3.2 Grade of Service

The Grade of Service is defined as [8]:

$$GoS = \chi + P_{bl} \quad (2)$$

where χ represents the outage probability and P_{bl} the blocking probability. Figure 2 can be viewed as the average area per grade of service. Consequently, if equation 1 is multiplied by the number of users deployed, it is possible to determine the system capacity per unit area for a specified GoS.
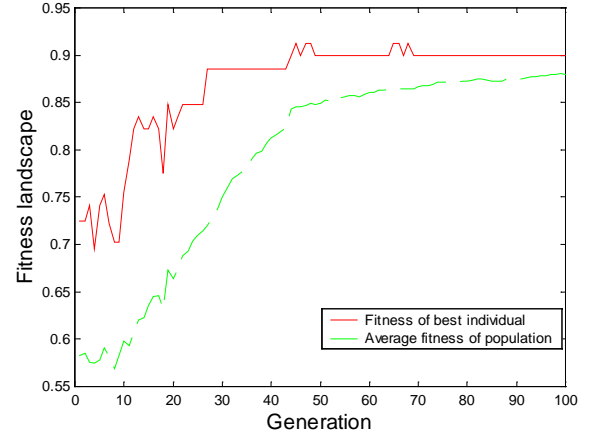

Figure 2: Fitness function for average of 35 users/cell

4. Simulation approach

A Monte Carlo simulation approach is used to generate snapshots for different user distributions and to evaluate different network parameters such as outage probability and blocking probability. For each simulation run, the GA iterates over 100 generations to converge to an optimum solution as seen from Figure 2.

The spectrum efficiency is a measure used to gauge the effectiveness of the SA algorithm for different traffic scenarios (Table 2). Table 3 provides a selection of simulation results obtained using sectored antenna patterns at the basestations.

Data rate(kbps)	15(voice)	144(data)	384(data)
Eb/No target (dB)	6.7	4.3	5.6
Mix 1	100%	-	-
Mix 2	-	100%	-
Mix 3	-	-	100%
Mix 4	75%	20%	5%

Table 2 Traffic scenarios

5. Simulation results

Figure 3 illustrates the GoS of the network for different loading conditions. For a specified GoS it is possible to use this data to establish the system soft capacity using equation 3 [9].

$$V_{cs} = \omega_{cs} \times \text{bit rate} \times \text{S.A.F} / \text{system bandwith} \quad (3)$$

where ω_{cs} represents the average load offered in Erlangs and S.A.F denotes the service activity factor.
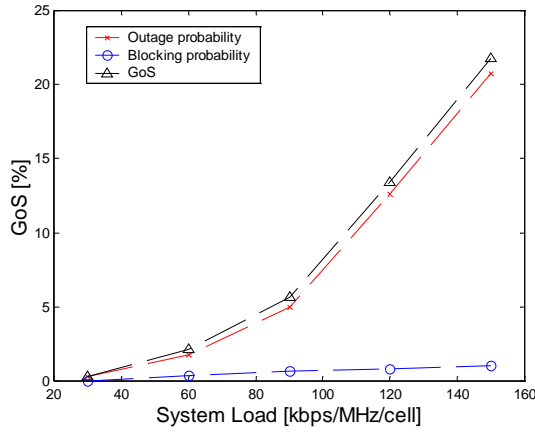
Figure 3: GoS curve for homogeneous voice services

From Figure 3 and assuming a specified GoS of 10%, the system capacity for a 15 kbps voice service is evaluated at 110 kbps/MHz/cell.

Traffic mix	Spectrum efficiency [kbps/MHz/cell]
Mix 1	115.1
Mix 2	201.0
Mix 3	380.0
Mix 4	162.5

Table 3 Spectrum efficiency for different traffic mix for initial database

A similar curve, as seen in Figure 4, is obtained for various service mixes for a network covered with ten six-sectored (60° beamwidth) basestations. It can be deduced from Figure 4 that at the specified GoS target (10%), the use of a 384 kbps data service results in the best spectrum utilisation from the traffic mixes considered.
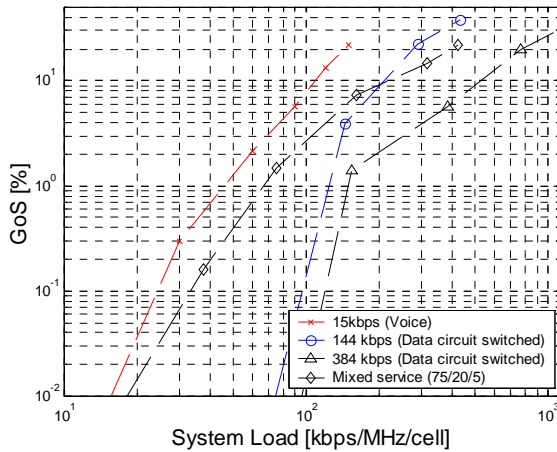

Figure 4: GoS curve for various traffic mixes

5.1 Temporal Variations

The microcellular database in Citrus is now modified in order to reflect evolutions in the local environment. These evolutions can result in significant changes in the propagation between mobiles and basestations. Outage values are evaluated for both the old and new databases using identical deployment schemes.

The SA algorithm detects the impact of the geographic evolutions (such as uncovered areas or regions of high interference) and engages the GA to calculate new basestation transmit power levels to remedy the situation. Figure 5 shows results obtained for the modified database with and without automatic GA updates.
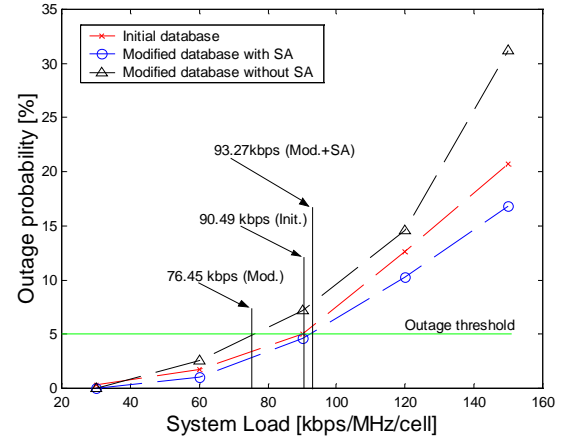

Figure 5: Outage probability for voice services

It can be seen that the outage probability rises much faster when the SA algorithm is not used to compensate for changes in the local environment.

Services	Initial database	Modified database	
		With SA	Without SA
	Spectrum efficiency [kbps/MHz/Cell] (GoS=10%)		
Voice (15 kbps)	115.11 (38.37)[1]	124.34 (41.34)	102.69 (34.23)
Data (144 kbps)	201 (6.98)	190 (6.58)	62.98 (2.186)
Data (384 kbps)	380 (4.95)	240 (3.125)	<100 (1)
Mix services (75/20/5)	162.5 (10/3/0)	163 (11/3/1)	156 (11/3/1)

Table 4: Benchmark results for spectrum efficiency

For voice services, SA results in a 21% increase in spectral efficiency. For 144kbps data services, a benefit of 203% can be derived as seen in Figure 6. For 384 kbps data services, figure 7 shows that without SA the target GoS cannot even be achieved. In the case of mixed services, a benefit of 4.48% is predicted from Figure 8. From Table 4, it can be seen that SA restores the network spectrum efficiency to values obtained at deployment except for the 384kbps, which appears extremely sensitive to pathloss.

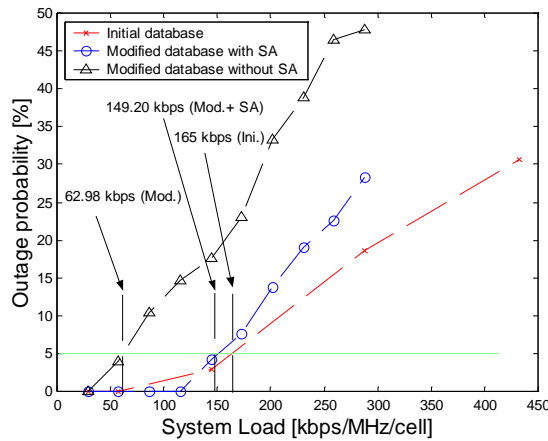[1] Expected number of subscribers using service per sector

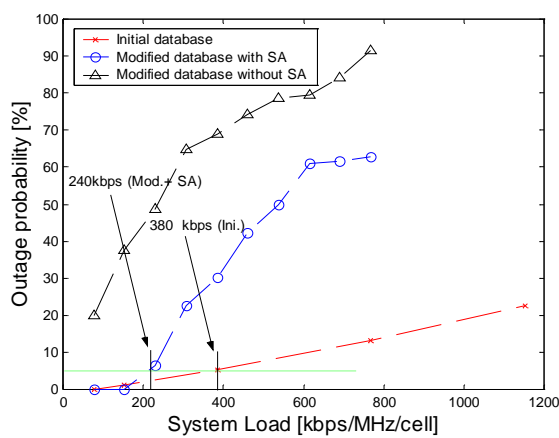**Figure 6: Outage probability for cs data (144 kbps)**

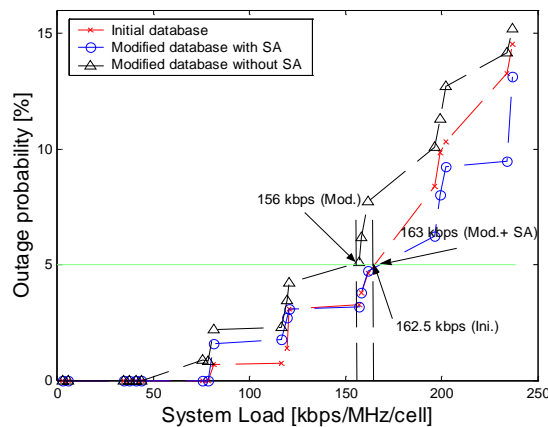**Figure 7: Outage probability for cs data (384 kbps)**

Figure 8: Outage probability for mixed services

6. Conclusions

This paper has investigated the use of GA and Situation Awareness algorithms to automatically support the deployment and configuration of a mixed traffic W-CDMA microcellular network. The ability of the basestations to monitor changes in the propagation conditions and QoS perceived by subscribers allows the network to efficiently self adapt. Results show that for different traffic mixes, SA can be used to reconfigure the network in terms of restoring a target GoS, following changes in the microcellular environment.

The coverage needs to be re-evaluated periodically and this could be performed in practice using location aware mobile terminals that report their RSSI levels to the surrounding basestations. The algorithm appears cost effective since it requires no additional hardware other than a server for processing purposes. Optimised parameters would then be downloaded to network elements during non-critical hours of operation.

Using detailed propagation models (such as Citrus) and optimum deployment algorithms (such as the CAT), an optimum deployment of microcellular W-CDMA was performed. Using the SA methods discussed in this paper, the network was then able to automatically self-configure to maintain these high levels of coverage and capacity even as the geographic environment evolved. Without the use of SA, the network capacity was seen to fall off in sympathy with changes in the local environment.

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