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Enhanced efficiency and frequency assignment by optimizing the base stations location in a mobile radio network

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Abstract Most mobile radio networks have been planned based on the classical cellular concept. However, alternative planning strategies that lead to more efficient network configurations are necessary due to the fact that the traffic density is generally far from constant throughout the service area, making necessary the relocation of base stations inside the traffic hotspots. If the traffic is characterized in a discrete way, the optimization of base stations location resembles vector quantization, a well-known problem in signal processing. In this paper, we use this analogy to propose a mobile radio network planning algorithm. Simulation results show that higher trunking efficiency as well as improved frequency assignment can be obtained if an existing mobile radio network is redesigned using the presented strategy.

Keywords Base station location · Frequency assignment · Optimization · Trunking efficiency

1 Introduction

The classical cellular concept considers the structure of a mobile radio network as a regular hexagonal cell lattice with a periodic frequency reuse pattern. Most mobile radio networks have been planned based on this concept as have all techniques aimed at increasing their traffic capacity [1]. However, an interest to find alternative planning strategies that lead to more efficient network configurations has risen for a number of reasons such as [2]: traffic density cannot be assumed constant throughout the service area, radio wave propagation is practically never homogeneous and isotropic, base stations (BSs) sites usually cannot be chosen arbitrarily, etc.

After years of research it has been concluded that although for uniform traffic distribution a uniform network layout is best possible, for nonuniform traffic, BSs need to be relocated inside the hotspots [3]. Several research works aimed at optimizing the BSs location have been published (see [3, 4] for an exhaustive list of references), but just a few of them take into account the traffic distribution to satisfy the relocation condition mentioned above.

In this paper, we propose a mobile radio network planning strategy based on the analogy between the base stations location problem (BSLP) and vector quantization (VQ), a well-known problem in signal processing. This analogy allows an existing VQ algorithm to be applied to the solution of the BSLP, placing BSs inside traffic hotspots while optimizing other network parameters. A practical example shows that redesigning an existing mobile network in the proposed way provides better frequency assignment plans, higher homogenization of the number of required channels per cell, and therefore improved trunking efficiency.

2 Vector quantization

In signal processing, quantization means to convert a continuous-amplitude signal into a discrete-amplitude one [5, 6]. A source is defined as a stochastic process described by a probability density function, and a signal is a particular realization of such a process. Vector quantization is characterized by its dimension, equal to the number of data samples in a set, which are quantized jointly as a single vector. In other words, VQ means to approximate an infinite set of source vectors by a limited set of code vectors that constitute

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a codebook. This approximation can be characterized by its distortion, defined as the difference between a source vector and its associated code vector, commonly measured by the squared Euclidean distance for simplicity. In principle, the design of an optimal vector quantizer is a challenging task due to the need for multidimensional integration. However, the use of a training sequence [7] that best represents the statistical characteristics of the source bypasses the need for multidimensional integration allowing an easier formulation of the problem.

2.1 Vector quantizer design problem

The vector quantizer design problem can be stated as follows: given a vector source with its statistical properties known, given a distortion measure, and given the number of code vectors, find a codebook and a partition, which results in a smaller average distortion. Let there be a training sequence consisting of M source vectors:

$$X = \{\vec{x}_1, \vec{x}_2, \ldots, \vec{x}_M\} \tag{1}$$

where M is assumed to be sufficiently large so that all the statistical properties of the source are captured by the training sequence. We assume that the source vectors are k-dimensional, i.e.,

$$\vec{x}_m = (x_{m,1}, x_{m,2}, \ldots, x_{m,k}); \quad m = 1, 2, \ldots, M \tag{2}$$

Let N be the number of code vectors, and let us represent the codebook by:

$$C = \{\vec{y}_1, \vec{y}_2, \ldots, \vec{y}_N\} \tag{3}$$

where each code vector is k-dimensional, i.e.,

$$\vec{y}_n = (y_{n,1}, y_{n,2}, \ldots, y_{n,k}); \quad n = 1, 2, \ldots, N \tag{4}$$

Let S_n be the encoding region associated with the code vector $\vec{y}_n$ and let us denote the partition of the space as:

$$S = \{S_1, S_2, \ldots, S_N\} \tag{5}$$

If the source vector $\vec{x}_m$ is in the encoding region S_n, then its approximation, denoted by $q(\vec{x}_m)$, is $\vec{y}_n$; in general:

$$q(\vec{x}_m) = \vec{y}_n \quad \forall \vec{x}_m \in S_n \tag{6}$$

Assuming a squared Euclidian distance measure, the average distortion is given by:

$$D^2 = M^{-1} \sum_{m=1}^{M} |\vec{x}_m - q(\vec{x}_m)|^2 \tag{7}$$

In optimization terms, the vector quantizer design problem can be stated as follows: given X and N, find C and S such that D^2 is minimized. If C and S are a solution to the above minimization problem, then they must satisfy the following two criteria of optimality:

(1) *Nearest neighbor condition:* The encoding region S_n should consist of all the vectors that are closer to $\vec{y}_n$ than any of the other code vectors. This condition is satisfied by obtaining the Voronoi diagram [8, 9] of the k-dimensional codebook, $vo\,(C)$, which is the subdivision of the plane into N cells, one for each code vector in C, in such a way that S_n is defined as:

$$S_n = \{\vec{x} \in X | dist(\vec{x}, \vec{y}_n) < dist(\vec{x}, \vec{y}_{n'})\} \quad \forall \vec{y} \in C;\ n \neq n' \tag{8}$$

where *dist* is a distance function. Different distance functions can be used to define a variety of Voronoi diagrams. Using the L_2-metric (squared Euclidian distance) function, the encoding region S_n is given by:

$$S_i = \{\vec{x} \in X \| \vec{x} - \vec{y}_n|^2 < |\vec{x} - \vec{y}_{n'}|^2\} \quad \forall \vec{y} \in C;\ n \neq n' \tag{9}$$

(2) *Centroid condition*: The code vector $\vec{y}_n$ should be the average of all the training vectors that are in the encoding region S_n. It also must be ensured that at least one training vector belongs to each encoding region, i.e.:

$$\vec{y}_n = \frac{\sum_{\vec{x}_m \in S_n} \vec{x}_m}{\sum_{\vec{x}_m \in S_n} 1} \tag{10}$$

2.2 The LBG algorithm

The Lynde-Buzo-Gray (LBG) algorithm [10] provides a solution to the vector quantizer design problem fulfilling both criteria of optimality, based either on a known probabilistic model or on a long training sequence of data. As most of vector quantizer design techniques, this algorithm produces a quantizer meeting necessary but not sufficient conditions for global optimality. Usually, however, local optimality is assured. The algorithm consists of the following steps:

(1) Given $C_i = \{\vec{y}_n; n = 1, \ldots, N\}$, find the minimum distortion partition, i.e., the Voronoi diagram $vo(C_i) =$

$\{S_n; n = 1, \ldots, N\}$. Compute the average distortion D_i according to the distortion measure to be used, e.g., Eq. (7).

(2) If $(D_{i-1} - D_i)/D_i \leq \varepsilon$, halt with C_i final codebook. Otherwise continue.

(3) Find the optimal codebook for $vo(C_i)$, i.e., $C(vo(C_i)) = \{\vec{y}(S_n); n = 1, \ldots, N\}$.

(4) Set $C_{i+1} \equiv C(vo(C_i))$. Replace i by $i + 1$ and go to step 1.

Steps 1 and 3 together form the so-called Lloyd iteration [10], which guarantees to decrease the distortion error or at least leave it unchanged. The LBG algorithm converges in a finite number of Lloyd iterations to a local minimum of the distortion function.

3 Base stations location problem

This problem consists in finding the coordinates (x, y) of all the BSs of a mobile network that optimize parameters such as radio coverage, transmit power, etc. Most of these parameters get closer to optimality when BSs are placed inside the traffic hotspots. For example, if BSs are located as close as possible to the points where call attempts are more likely to occur, less transmit power will be required to provide them with an adequate radio coverage. Evidently, a precise description of the traffic characteristics within the service area is required in order to obtain a network configuration in which BSs are optimally located. This description must capture the long-term traffic statistical properties accounting for different time varying traffic patterns. Even though a number of traffic source models have been proposed, e.g., [11–14], their application to radio network planning is limited due to their high complexity. Moreover, most of these models are valid just for very specific cases. A more suitable traffic model for our radio network planning strategy is presented in [15–17]. This model is known as the demand node concept (DNC) and represents the spatial distribution of the traffic demand by discrete points. In order to obtain the most representative characteristics of the traffic, the model is reduced to a stationary case in which only the peak traffic, i.e., the traffic during the busiest hour, is considered. The drawback of the model is that the busy hour changes over time within the service area, forcing the network designer to decide how to weight the different traffic factors to satisfy the market requirements. Despite this fact, the model is useful since it provides traffic information for a worst-case design.

In the DNC model, a demand node represents the center of an area that contains a quantum of traffic expressed as a fixed number of call requests per time unit, e.g., calls per hour (calls/h). Based on available geographical and demographical data, the spatial traffic intensity is calculated within the service area by the use of sophisticated estimation methods and is stored in a traffic matrix. A partitional clustering algorithm [15, 18] generates a finite number of demand nodes using this traffic matrix. Hence, demand nodes are dense in areas of high demand (hotspots) and sparse in regions of low demand.

The DNC reveals a close analogy between the BSLP and the 2-dimensional VQ problem. Both are facility location problems, in which the main parameters to be optimized are the BSs locations and the code vectors values, respectively. The codebook given by (3) and (4) can be redefined as the set of all the BSs locations, $B = \{b_1, b_2, \ldots, b_N\}$, where $b_n = (x_n, y_n)$ are the coordinates of the n-th BS and N is the total number of BSs in the network. The set of M traffic demand nodes, $A = \{a_1, a_2, \ldots, a_M\}$, is analogous to the training sequence X of the VQ problem given by (1). Thus, the Voronoi diagram $vo\,(B)$ defines the theoretical coverage of every BS. However, for mobile radio networks planning, the distance function to compute the Voronoi diagram must be replaced by a model that predicts the propagation loss, L, as a function of the propagation path, R. For simplicity, we use the basic model that represents the propagation loss using an exponential law of decay [19], i.e., $L \propto R^{-\gamma}$, where γ is a propagation coefficient. Hence, the coverage area of the n-th cell is given by the following Voronoi partition:

$$S_n = \{\vec{a} \in A \| \vec{a} - \vec{b}_n|^{-\gamma} < |\vec{a} - \vec{b}_{n'}|^{-\gamma}\} \quad \forall \vec{b} \in B;\, n \neq n' \tag{11}$$

Hereinafter, a typical value of $\gamma = 4$ for urban environments is used. More sophisticated propagation models might be used in a straightforward way.

4 Benchmark example

In order to assess the benefits of the analogy previously described, we choose a benchmark example, the operational characteristics of which are known or at least can be computed from available data. The mobile radio network in the city of Würzburg, Germany [15–17], was selected since its spatial traffic distribution is already available in the form of demand nodes as depicted in Fig. 1.

The benchmark example network consists of nine BSs located in such a way that the radio coverage is maximized. The so-called set cover base station positioning algorithm (SCBPA) [15–17] produced the network configuration (hereinafter referred to as the original network configuration) depicted in Fig. 2. It can be seen that the cells are not of the same size and have irregular shape. Also, each cell covers a different number of demand nodes; therefore, every cell requires a different number of channels in order to serve its

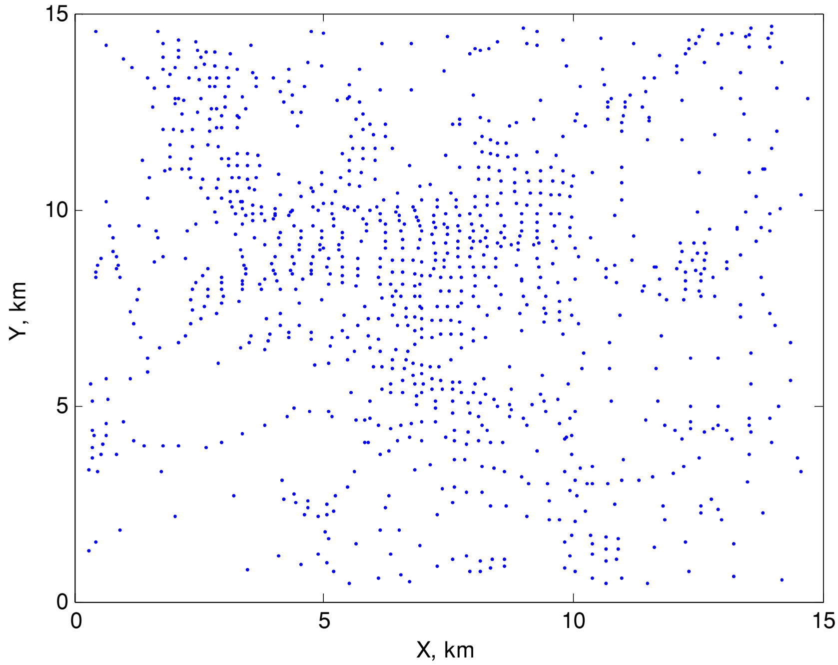

Fig. 1 Spatial traffic distribution represented by demand nodes

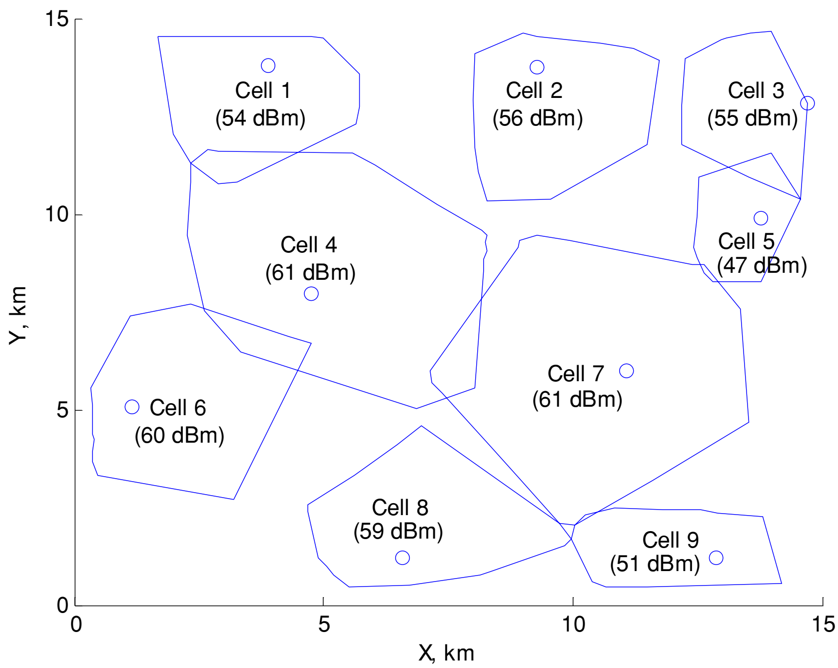

Fig. 2 Original network configuration

corresponding traffic load. By knowing the number of demand nodes that each cell covers, the total traffic load in every cell (and consequently the number of channels it requires) can be computed by applying the Erlang-B formula [20]. Assuming three different cases for the number of call attempts accounted per demand node: 1, 3, and 5 calls/h, and an average call duration equal to 180 seconds, the number of channels required per cell were computed for a grade of service (GoS), i.e., the probability of a blocked call, equal to 0.02 (Table 1).

An important parameter to characterize the performance of a mobile network is the *trunking efficiency*, which is determined by the amount of traffic per channel as [21]:

$$\text{Trunking efficiency}\,(\%) = \frac{\text{traffic in Erlangs}}{\text{number of channels}} \times 100 \qquad (12)$$

Table 1 Required channels per cell of the original network configuration

	1 calls/h	3 calls/h	5 calls/h
Cell 1	10	22	33
Cell 2	9	19	29
Cell 3	5	9	13
Cell 4	25	61	97
Cell 5	5	9	13
Cell 6	6	11	16
Cell 7	14	31	47
Cell 8	7	15	22
Cell 9	5	9	13
Total	86	186	283

Generally, a cell that operates with less than 15 channels, i.e., a trunking efficiency (computed with (12)) of less than 60% for a GoS = 0.02, is inefficient and less cost effective [21]. Hence, this value represents the efficiency threshold, below which any cell is considered to have a poor performance. The trunking efficiency of every BS in the original network configuration was computed and the results are summarized in Table 2.

4.1 Frequency assignment

Frequency assignment is another important problem that arises in mobile radio networks planning. The frequency assignment problem (FAP) is closely related to the BSLP because a poorly planned network configuration might waste spectrum and degrade the overall GoS [4]. Thus, both problems must be treated together while planning a mobile radio network, even though assigning frequency channels while minimizing interference is a hard task in itself. Due to the special characteristics of the original network configuration regarding cells size and shape irregularity, conventional frequency assignment techniques [22, 23] cannot be directly applied here because the network lacks a constant frequency reuse pattern. Classical channel separation constraints [22, 23] do not provide an adequate description of the interference limitations in this case. Therefore, we use a sequential algorithm that utilizes carrier-to-interference ratio (CIR) estimations [24] to solve the FAP. This algorithm arranges the BS transmitters (TXs) in descending order according to a degree of difficulty (DD). The DD is defined in terms of the interference from neighboring cells and the number of required channels per cell [24]. Then, the first available channel is taken and assigned to the first TX in the sequence, i.e., the one with the largest DD; after this, all the other TXs in the sequence are inspected in descending order to determine whether the channel can be reused or not. Only if a CIR constraint is satisfied, the channel reuse is allowed. After all the TXs have been inspected, the assignment sequence is reordered and then the second channel is considered. This process is repeated iteratively until all the channel requirements of the network have been satisfied. The aforementioned CIR constraint is given by:

$$\sum_{j \in \beta_i} \left(\frac{P_j d_{ij}}{P_i R_i} \right)^{-\gamma} \leq \frac{1}{\alpha} \tag{13}$$

where β_i is the set of all the cells that use the same channels as cell i (excluding cell i itself), and α is a CIR threshold, i.e., the minimum acceptable CIR value at any point within the cell boundaries. This CIR constraint differs slightly from the one in [24] because in this case we have taken into account the transmit power of the TXs in cell i and j, P_i and P_j, respectively. We introduced this modification [25] because each cell has a different size, which is determined by the transmit power; therefore, no simplification by assuming the same transmit power in all the cells can be made.

We computed the frequency assignment plan for a CIR threshold equal to 18 dB [24]. An additional constraint was imposed, which states that the spectrum separation between two channels assigned to the same BS must be at least 3 frequency channels in order to avoid cosite interference. Noise and adjacent channel interference were neglected. The minimization of the frequency assignment *span*, i.e., the difference between the lowest and the highest frequency channels used to construct the assignment plan, was used as optimization target. The processing time required to obtain the solution for each case was also registered. The results are summarized in Table 3.

Table 2 Trunking efficiency (%) of the original network configuration

	1 calls/h	3 calls/h	5 calls/h
Cell 1	48	65.5	72.7
Cell 2	45	63.9	69.8
Cell 3	28	46.7	53.9
Cell 4	67.4	82.9	86.9
Cell 5	27	45	51.9
Cell 6	32.5	53.2	60.9
Cell 7	53.6	72.6	79.8
Cell 8	40.7	57	64.8
Cell 9	29	48.3	55.8

Table 3 Frequency assignment plan of the original network configuration

	1 calls/h	3 calls/h	5 calls/h
Span	76	181	289
Processing time (s)	2.7	11.48	33.29

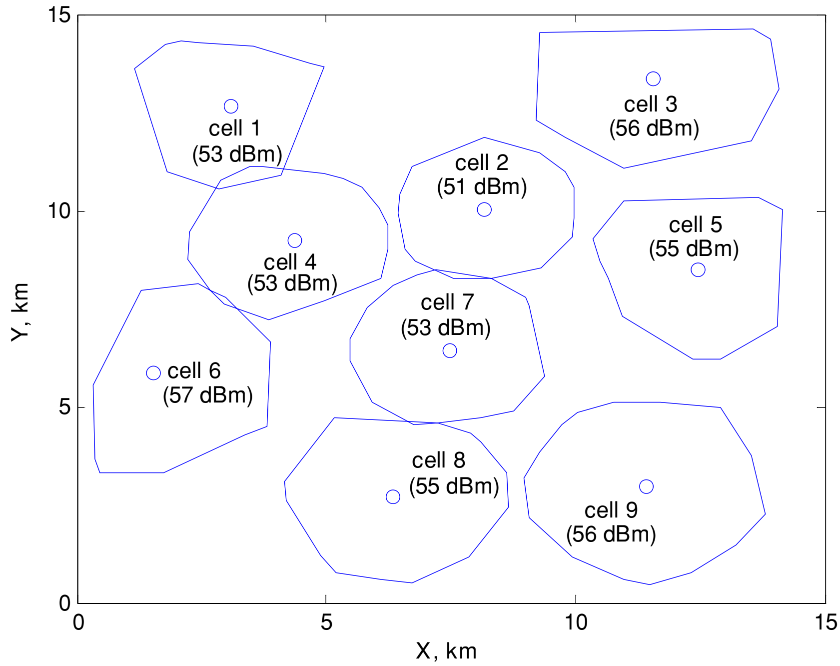

Fig. 3 Redesigned network configuration (75% coverage)

5 Results

We implemented the LBG algorithm incorporating the Voronoi partition given by (11) and applied it to the set of demand nodes A of the original network configuration (Fig. 1), assuming a distortion threshold value equal to $\varepsilon = 10^{-5}$. Figure 3 depicts the redesigned network configuration that was obtained. Notice that the BSs are located inside the traffic hotspots and smaller cell sizes are obtained in such regions. This fact reduces the distance from the BSs to the traffic sources, which consequently minimizes the propagation losses. In order to attain fair network performance comparisons with the original configuration, the redesigned network was forced to cover the same percentage of demand nodes as the original one, i.e., 75% of the total number of demand nodes [15–17]. To achieve this, in every cell only the 75% of the demand nodes (the closest ones to the BS) inside its corresponding Voronoi partition were used to determine the cell size. The required channels per cell were computed by applying the Erlang-B formula as in the original network configuration. The results are summarized in Table 4. By comparing Tables 1 and 4, one can notice an increase in the number of required channels to satisfy the same traffic demand in the redesigned network configuration. In fact, the total number of required channels in the redesigned network configuration increased 5.8%, 4.8%, and 3.5% with respect to the original one for the three cases considered, respectively. Intuitively, one might expect a larger frequency assignment span in order to satisfy a bigger number of required channels; however, as it will be seen later, this does not happen in the redesigned network configuration.

Table 4 Required channels per cell of the redesigned network configuration (75% coverage)

	1 calls/h	3 calls/h	5 calls/h
Cell 1	11	23	34
Cell 2	14	31	47
Cell 3	8	16	23
Cell 4	14	31	48
Cell 5	8	16	24
Cell 6	7	14	21
Cell 7	12	28	42
Cell 8	8	17	26
Cell 9	9	19	28
Total	91	195	293

5.1 Trunking efficiency

The trunking efficiency was computed for the redesigned network configuration (Table 5). A comparison with Table 2 shows that in most of the cases the efficiency of the BSs increased in the redesigned network configuration, even more than 10% in some cases, due to a higher homogenization of the number of required channels per cell. This can be seen more easily if we look at the trunking efficiency curve [21] of each network configuration. Figure 4 depicts the trunking efficiency of the nine BSs in the original and the redesigned network configurations for the highest traffic loaded case (5 calls/h), respectively. From the curve in Fig. 4(a), we see that the gap between the number of required channels in the least and the most loaded BSs in the original network configuration is 84 channels, which means that some BSs are excessively

Table 5 Trunking efficiency (%) of the redesigned network configuration (75% coverage)

	1 calls/h	3 calls/h	5 calls/h
Cell 1	46.4	66.5	75
Cell 2	53.2	72.1	79.3
Cell 3	38.8	58.1	67.4
Cell 4	54.3	73.5	79.2
Cell 5	40	60	66.7
Cell 6	38.6	57.9	64.3
Cell 7	54.6	70.2	78
Cell 8	44.4	62.6	68.3
Cell 9	43.3	61.6	69.6

Table 6 Frequency assignment plan of the redesigned network configuration (75% coverage)

	1 calls/h	3 calls/h	5 calls/h
Span	65	134	212
Processing time (s)	2.3	8.34	20.32
Span improvement (%)	14.5	26	26.6
Processing time improvement (%)	14.8	27.4	39

less efficient than others that serve a greater amount of traffic load. Thus, the efficiency curve ranges between 53.9% and 86.9%. In this case, three BSs operate under the acceptable threshold value. In the redesigned network configuration there exists a greater homogenization of the required channels per cell, which can be seen in Fig. 4(b) as the shrinkage of its corresponding efficiency curve. This is due to the fact that each cell serves a rather similar amount of traffic; therefore, the gap between the number of required channels in the least and the most loaded BSs is reduced to 27 channels. Here, the efficiency curve ranges between 64.3% and 79.3%. Only two BSs experienced a slight efficiency decrease whereas the rest experienced an increase even over 10%, which results in all the BSs working above the trunking efficiency threshold. Similar results were obtained for the other two cases with 1 and 3 calls/h per demand node.

5.2 Frequency assignment

The frequency assignment span was computed for the redesigned network configuration. In all the cases, there was a significant improvement with respect to the frequency assignment span of the original network configuration. Moreover, the processing time required to solve the FAP was reduced in all the cases. Table 6 summarizes these results.

The best span improvements (up to 26.6%) were obtained for the medium and heavy traffic loaded cases, respectively. Thus, redesigning a mobile radio network in the proposed way is worthwhile for medium and heavy loaded networks when spectrum scarceness becomes a critical issue. Regarding processing time, the best improvement (39%) was obtained for the heavy traffic loaded case. It is a well-known fact that the homogeneity of the required channels is a determining factor of the FAP complexity [26, 27], i.e., the greater the homogeneity, the lower the complexity required. This explains the improvement in processing time and therefore the improvement in the frequency assignment span in the redesigned network configuration, where

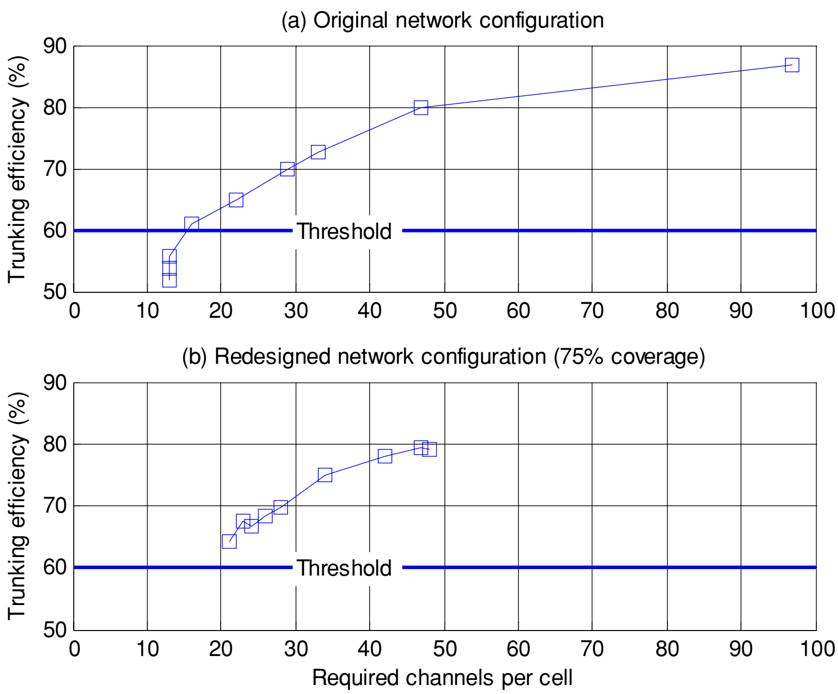

Fig. 4 Trunking efficiency of (a) the original and (b) the redesigned network (75% coverage) configurations for the 5 calls/h case

a greater homogenization of the required channels was obtained. These results show that smaller frequency assignment spans can be obtained in spite of an increase in the total number of required channels in the redesigned network configuration with respect to the original one. This suggests that the proposed planning strategy promotes also better *frequency reuse*. Let us define an empirical measure of the frequency reuse of a mobile radio network as the ratio of the total frequency assignment span to the total number of required channels, i.e.,

$$\text{Frequency reuse index} = \frac{\text{frequency assignment span}}{\text{total number of required channels}} \tag{14}$$

The lower the value of the frequency reuse index (FRI), the better the frequency reuse of the network. We computed the FRI of both the original and the redesigned network configurations and compared the results for all the cases (Table 7). We observe better frequency reuse in the redesigned network configuration for all the cases, although the best improvements (up to 29.9%) are achieved for the medium and heavy traffic loaded cases. This is due to the fact that the frequency reuse is limited by the interference from neighboring cells, and since the propagation distance between BSs and mobile stations (MSs) is minimized in the redesigned network configuration, so is the transmit power required in every cell; therefore, harmful interference is reduced as well.

5.3 Transmit power

The transmit power requirements of each BS were computed in both the original and the redesigned network configurations. For this, it is enough to know the sensibility threshold for the kind of communication service in the network, i.e., the minimum acceptable power at the input of the MS, which we assumed to be 80 dBm; a comprehensive table of typical thresholds for different communication services can be found in [4]. The total transmit power in the original network configuration is 5380.6 W, whereas in the redesigned one it is 2635.1 W. This represents a reduction of 51% of the power necessary to cover the same traffic load. This promotes better electromagnetic compatibility (EMC) conditions with other radio systems operating in the surrounding vicinity as well as a significant saving of power consumption.

Table 7 Frequency reuse index of both network configurations

	1 calls/h	3 calls/h	5 calls/h
Original configuration	0.88	0.97	1.02
Redesigned configuration (75% coverage)	0.71	0.68	0.72
Improvement (%)	19.3	29.9	29.4

5.4 Radio coverage

The original network configuration considered so far was planned so as to maximize radio coverage [15–17]. Maximizing coverage can be quite a different problem from the one of minimizing the frequency assignment span in a mobile radio network. In a low traffic loaded network, frequency reuse can be low so as to minimize interference and thus maximize coverage, without requiring a large frequency assignment span. On the other hand, in a heavy traffic loaded network, spectrum scarceness becomes a critical issue. In such a case, frequency reuse must be maximized (even if this means that radio coverage is decreased) in order to serve more users. However, 75% coverage is rather low for a well designed network. For this reason, we investigate the behavior of the redesigned network configuration for the heavy traffic loaded case when higher coverage is required.

Our planning algorithm has the capability of providing higher radio coverage in the redesigned network configuration by increasing the transmit power in every BS in order to cover a defined percentage of its corresponding demand nodes. Obviously, this has a direct impact on the frequency reuse due to an increase in interference. Therefore, the impact of higher coverage on the frequency assignment span, frequency reuse, and trunking efficiency are analyzed.

For 90% and 95% coverage, the required channels per cell (Table 8) and the frequency assignment plan (Table 9) were

Table 8 Required channels per cell of the redesigned network configuration (5 calls/h case) for 90% and 95% coverage

	90% coverage	95% coverage
Cell 1	37	39
Cell 2	51	53
Cell 3	25	26
Cell 4	49	51
Cell 5	25	26
Cell 6	22	23
Cell 7	45	48
Cell 8	27	29
Cell 9	30	31
Total	311	326

Table 9 Frequency assignment span and frequency reuse index of the redesigned network configuration (5 calls/h case) for 90% and 95% coverage

	90% coverage	95% coverage
Span	231	272
Frequency reuse index	0.74	0.83

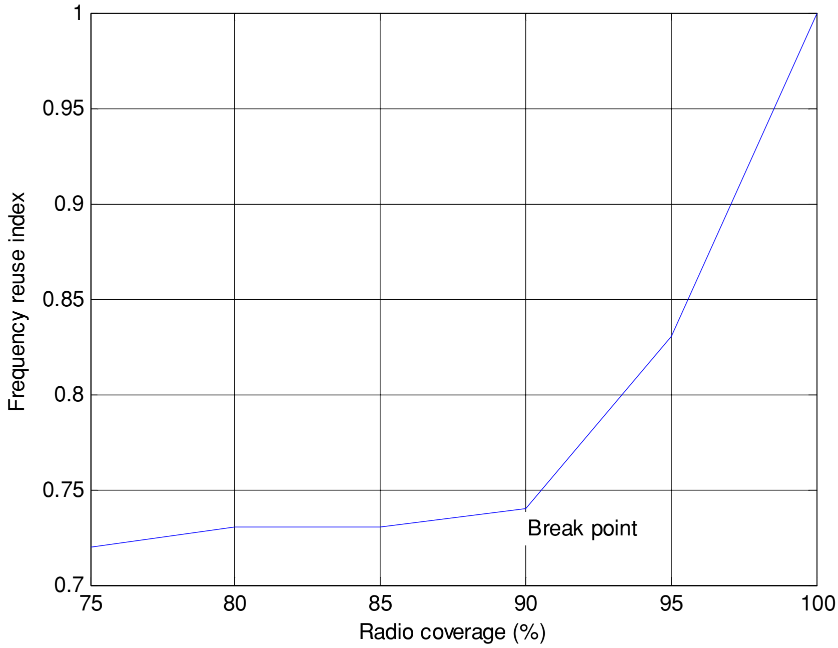

Fig. 5 Frequency reuse index as a function of radio coverage

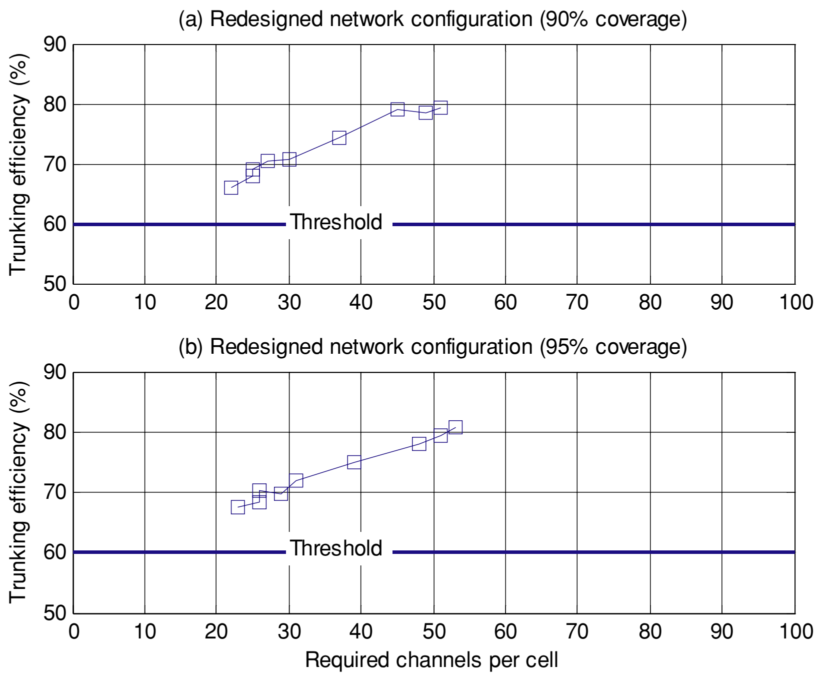

Fig. 6 Trunking efficiency of the redesigned network configurations (5 calls/h case) for (a) 90% and (b) 95% radio coverage

computed for every case. Although the increase in the total number of required channels was 6.1% and 11.3% with respect to the redesigned network configuration with 75% coverage, the frequency assignment span increase was 8.9% and 28.3%, respectively. This shows a rapid degradation of frequency reuse in the redesigned network configuration when higher coverage is demanded. In Fig. 5 the FRI is depicted as a function of radio coverage. Notice that the FRI increases drastically for coverage values greater than 90% (break point). This indicates that radio coverage cannot be increased indiscriminately without affecting the frequency reuse of the network. Hence, we suggest fixing the coverage to a value just before the break point, which results in the best compromise between radio coverage and frequency reuse.

Regarding trunking efficiency, there is practically no significant change in the efficiency curve (in comparison to the curve in Fig. 4(b)) when higher coverage is required (Fig. 6). This is obvious since trunking efficiency is mainly determined by the distribution of traffic load between all the cells (Voronoi partition); thus, it is independent of the percentage of covered demand nodes because this percentage is the same for all the cells.

6 Conclusions

We have presented a new approach to solving the base stations location problem. We show that this problem can be treated in an analogous manner to vector quantization. The proposed approach locates base stations in a traffic adapted way by placing them inside the traffic hotspots, providing a redesigned network configuration that promotes better utilization of the radio spectrum. Frequency assignment span and trunking efficiency were particularly analyzed, and in both cases we obtained significant improvements with the proposed planning strategy in comparison to an existing one. The best frequency assignment improvements were obtained for medium to heavy loaded traffic cases. Due to a greater homogenization of the number of required channels per cell, trunking efficiency was also improved making the redesigned network more cost effective. Moreover, this approach allows the network designer to determine the maximum radio coverage without affecting the frequency reuse of the network. Since the homogenization of required channels per cell seems to be a determining factor to obtaining more effective frequency assignment plans, and in general, more effective network configurations, future research work shall concentrate in the development of planning strategies that provide total homogenization.

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References

1. W.C.Y. Lee, *Mobile Communications Design Fundamentals*, 2nd ed. (Wiley, New York, 1993).
2. A. Gamst and E.-G. Zinn, Cellular radio network planning, IEEE Aerospace and Electronics Systems Magazine 1 (1986) 8–11.
3. A. Eisenblätter, A. Fügenschuh, T. Koch, A. Koster, A. Martin, T. Pfender, O. Wegel and R. Wessäly, Modelling feasible network configurations for UMTS, Technical Report 02-16, Konrad-Zuse-Zentrum für Informationstechnik, Berlin, Germany (March 2002).
4. S. Hurley, Planning effective cellular mobile radio networks, IEEE Transactions on Vehicular Technology 51 (2002) 48–56.
5. R.M. Gray, Vector quantization, IEEE ASSP Magazine 1 (1984) 4–29.
6. A. Gersho and R.M. Gray, *Vector Quantization and Signal Processing* (Kluwer, Boston, MA, 1992).
7. P.C. Cosman, K.O. Perlmutter, S. M. Perlmutter, R. A. Olshen and R. M. Gray, Training sequence size and vector quantizer performance, in: *Proceedings of Asilomar Conference on Signals, Systems, and Computers* (November 1991) pp. 434–438.
8. F. Aurenhammer, Voronoi diagrams—a survey of a fundamental geometric data structure, ACM Computing Surveys 23 (1991) 345–405.
9. M. de Berg, M. van Kreveld, M. Overmars and O. Schwarzkopf, *Computational Geometry: Algorithms and Applications* (Springer-Verlag, Heidelberg, Germany, 2000) pp. 145–162.
10. Y. Linde, A. Buzo and R.M. Gray, An algorithm for vector quantizer design, IEEE Transactions on Communications COM-28 (1980) 84–95.
11. D. Hong and S.S. Rappaport, Traffic model and performance analysis for cellular mobile radio telephone systems with prioritized and nonprioritized handoff procedures, IEEE Transactions on Vehicular Technology VT-35 (1986) 77–92.
12. S.A. El-Dolil, W.-C. Wong and R. Steele, Teletraffic performance of highway microcells with overlay macrocell, IEEE Journal on Selected Areas Communications 7 (1989) 71–78.
13. K.K. Leung, W.A. Massey and W. Whitt, Traffic models for wireless communication networks, IEEE Journal on Selected Areas Communications 12 (1994) 1353–1364.
14. G.J. Foschini, B. Gopinath and Z. Miljanic, Channel cost of mobility, IEEE Transactions on Vehicular Technology 42 (1993) 414–424.
15. K. Tutschku, T. Leskien and P. Tran-Gia, Traffic estimation and characterization for the design of mobile communication networks, Technical Report 171, Institute of Computer Science, University of Würzburg, Germany (April 1997).
16. K. Tutschku, Demand-based radio network planning of cellular mobile communication systems, Technical Report 177, Institute of Computer Science, University of Würzburg, Germany (July 1997).
17. K. Tutschku and P. Tran-Gia, Spatial traffic estimation and characterization for mobile communication network design, IEEE Journal on Selected Areas Communications 16 (1998) 804–811.
18. A.K. Jain and R.C. Dubes, *Algorithms for Clustering Data* (Prentice Hall, Englewood Cliffs, NJ, 1988).
19. T.S. Rappaport, *Wireless Communications: Principles and Practice*, 2nd ed. (Prentice Hall, Englewood Cliffs, NJ, 2001).
20. S. Qiao and L. Qiao, A robust and efficient algorithm for evaluating Erlang B formula, Technical Report CAS98-03, L8S 4L7, Department of Computing and Software, McMaster University, Ontario, Canada (August 1998).
21. S. Faruque, *Cellular Mobile Systems Engineering* (Artech House, London, 1996), pp. 194–197.
22. S. Hurley, D.H. Smith and S.U. Thiel, FASoft: a system for discrete channel frequency assignment, Radio Science 32 (1997) 1921–1939.
23. D.H. Smith, S.M. Allen, S. Hurley and W.J. Watkins, Frequency assignment: Methods and algorithms, in: *Proceedings NATO RTA SET/ISET Symposium on Frequency Assignment, Sharing and Conservation in Systems* (October 1998).
24. J.-L. C. Wu and L.-Y. Wey, Channel assignment of cellular mobile systems with nonuniform cells, IEE Proceedings Communications 145 (1998) 451–456.
25. R. Chávez-Santiago, E. Gigi and V. Lyandres, Channel assignment for cellular mobile networks with nonuniform cells—an improved heuristic algorithm, IEE Proceedings Communications 153 (2006) 61–68.
26. A. Gamst, Some lower bounds for a class of frequency assignment problems, IEEE Transactions on Vehicular Technology VT-35 (1986) 8–14.
27. R. Chávez-Santiago, E. Gigi and V. Lyandres, The time complexity cost of adjacent channel interference in a heuristic for frequency assignment, in: *Proceedings IEEE 2005 International Symposium on Microwave, Antenna, Propagation and EMC Technologies for Wireless Communications* (August 2005), pp. 674–677.

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