ANALYSIS OF MOBILE RADIO ACCESS NETWORK USING THE SELF-ORGANIZING MAP

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Abstract: Mobile networks produce a huge amount of spatio-temporal data. The data consists of parameters of base stations and quality information of calls. The Self-Organizing Map (SOM) is an efficient tool for visualization and clustering of multidimensional data. It transforms the input vectors on two-dimensional grid of prototype vectors and orders them. The ordered prototype vectors are easier to visualize and explore than the original data. There are two possible ways to start the analysis. We can build either a model of the network using state vectors with parameters from all mobile cells or a general one cell model trained using one cell state vectors from all cells. In both methods further analysis is needed. In the first method the distributions of parameters of one cell can be compared with the others and in the second it can be compared how well the general model represents each cell.

Keywords: Neural networks, self-organizing map, cellular network, performance optimisation.

1. Introduction

As the launch of third generation technology approaches, operators are forming strategies for the deployment of their networks. These strategies must be supported by realistic business plans both in terms of future service demand estimates and the requirement for investment in network infrastructure.

When provisioning 3G services the control for the access part can be divided into three levels. Two lowest layers are radio resource management (RRM) functionalities and the highest hierarchy level is control performed by the network management system (NMS). More about this control hierarchy can be found in [10]. The scope of this paper is the NMS level. The role of NMS is essential owing to the fact that major enhancements or new service roll-outs are planned by utilizing the measured long term performance data from existing network.

The multidimensional performance space in future cellular networks force the traditional operator processes to go through some major changes. Additional challenges arise from the fact that in the case of 3G there will be multiple services, customer differentiation (customers with different priorities) and multiple radio access technologies to be managed simultaneously, optimally, as one resource pool. Furthermore, the high competitive situation forces operators to fast changes in service provisioning. All this will move the focus of operators daily tasks from offline planning to rapid network performance evaluation, trend analysis and optimisation based on network measurements. Therefore new analysis schemes for 3G networks are presented in this paper. The strength of the proposed method is its ability to combine multiple measurements and thus provide the result in a simple format despite the fact that the input space is very complex. The method also aids the operator in visualizing the service performance and in classifying the cells. The cell classification (clustering) will aid the operator in setting the configuration parameters controlling the service provisioning. Furthermore, similarly behaving cells can be identified and thus problem solving in the network is more effective.

In this paper, the use of the Self-Organizing Map (SOM) in optimization process is proposed. The SOM is a widely used neural network algorithm [7]. It has several beneficial features that make it a useful tool in data mining and exploration. The SOM follows the probability density function of the underlying data and functions, thus, as an efficient clustering and data reduction algorithm. The SOM is readily explainable, simple and - perhaps most importantly - highly visual. SOM based methods have been applied in the analysis of processes data, e.g., in steel and forest industry [8]. In addition, the SOM has been used in analysis and monitoring of telecommunications systems. Applications include novel equalizer structures for discrete-signal detection and adaptive resource allocation in telecommunications networks. In this paper, wideband code division multiple access (WCDMA) mobile network has been analyzed using the SOM. The goal is to develop efficient adaptive methods for monitoring the network behavior and performance. Special interest is on finding clusters of mobile cells, which can be configured using similar parameters.

In [3], [5] and [13] examples of 3G optimization cases are represented. In general the availability of references related to 3G analysis and optimization is limited. This is owing to the fact that there are very few commercial networks deployed at the time of writing. In abovementioned references the approach has been parameter centric: how to measure and tune configuration parameters to obtain wanted performance. In the case of this paper the network status visualization is the main focus. This information can be further used in order to obtain optimization of correct parameter/parameter set of selected cells.

In the next section, the application domain which is mobile radio access network is described. Then the SOM algorithm is presented in Section 3 and two methods to classify mobile cells are described in Sections 4 and 5.

2. Mobile network and the data

The scope of this section is to describe the used network scenario and the parameters used in the simulations. The data used in this work has been generated using WCDMA radio network simulator [6]. The WCDMA radio network depicted in Fig. 1 has been planned to provide 64-kbps service with 95% outdoor coverage probability. The average site distance is around 910 m.

The network configuration used to produce the data consisted of 32 base stations in Helsinki city area. The users of the network were circuit-switched with 64-kbps and

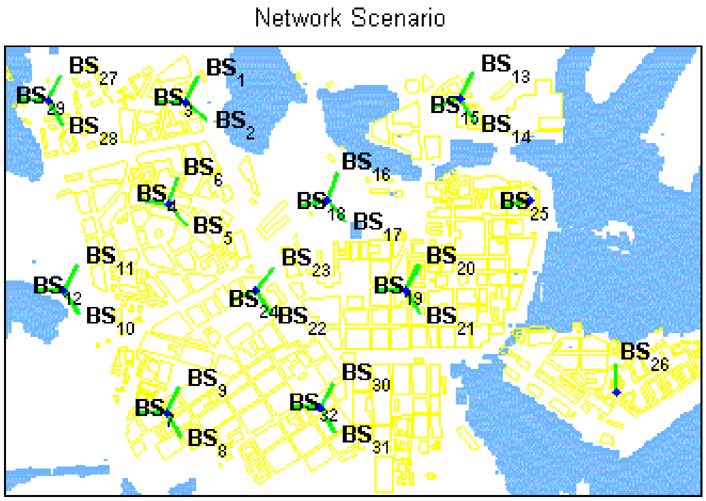

Figure 1. Helsinki city area with base stations.

the admission control was parameterized so that uplink interference had no impact on the admission process. The most important radio network simulation parameters are listed in Table 1.

Table 1. Important radio network parameters

Terminal maximum power	126 mW
Base station maximum power	20 W
Base station maximum power per link	450 mW
Target of UL/DL FER	5 %
Uplink system noise	-102.9 dBm
Downlink system noise	-99.9 dBm
Terminal speed	3 km/h

Used propagation model was Okumura-Hata with average area correction factor of -1.5 dB (excluding water areas). The multipath channel model was Vehicular A: five-taps with gains of -2.9, -5.2, -9.5, -13 and -15 dB respectively.

Slow fading deviation was 8 dB and the correlation distance was 50 m. Minimum coupling loss was 50 dB. Pilot power was 1 W. Softhandover was limited by saving maximum 3 links per terminal.

Power control is done once in a frame only to speed up the simulation. The power control step size is 0 to 15 dB depending on the difference between the average E_b/I_o over 10 previous frames and the target E_b/I_o [9]. Number of subscribers was 2112, which generate five 120 second calls on the average in an hour. Total simulation time was 1800 seconds.

The state of the network is characterized by 17 parameters of each base station which are saved every 100ms. The parameters include uplink noise raise in dBs, downlink average total transmission power in watts, number of users and average frame error rate (FER) of both uplink and downlink.

In this study, only uplink noise raise and uplink FER of each cell is used. A logarithmic scale with 10^{-2} as minimum FER is used.

3. Self-Organizing Map

The Self-Organizing Map forms a nonlinear topology preserving mapping from the input space to the output space. This means that patterns near each other in the input space are mapped to neurons which are close to each other in the neural net. In the original algorithm, the SOM is trained by the following unsupervised algorithm.

Each input vector $x(t)$ is compared with node vectors m_i to find the best-matching unit (BMU) c.

$$||x - m_c|| = min_i\{||x - m_i||\} \tag{1}$$

The best-matching node and the neighboring nodes are modified in the direction of the input data.

$$m_i(t+1) = m_i(t) + \alpha(t)h_{ci}(t)[x(t) - m_i(t)] \tag{2}$$

The neighborhood function h_{ci} is usually a Gaussian function, which is centered around node c and multiplied by decreasing learning rate $\alpha(t)$.

One step of the training algorithm of the SOM is illustrated in Fig. 2. The size of the SOM is 16 units, which have been arranged into a two-dimensional grid of 4 by 4 units. A data sample is marked with a cross; the black circles are the values of the prototype vectors before, and the gray circles after updating them towards the data sample. This kind of an update step is repeated iteratively during the training process.

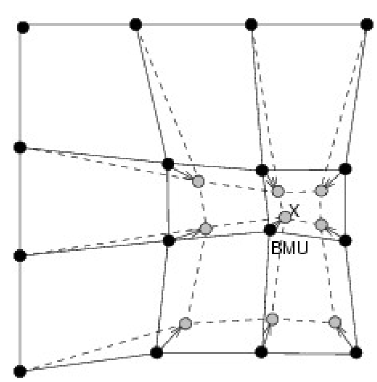

Figure 2. An illustration of the SOM training.

In this work, a batch version of the original algorithm is used, because it is computationally more effective. The samples collected from a fixed time interval are first averaged over the topological neighborhoods of the respective winner cells in the map. After that the node vectors are updated in one step using these averaged values, as in the classical K-means algorithm [11].

The SOM algorithm is able to perform both data clustering and visualization. The benefit of using SOM is in visualization of interesting parts of data. The algorithm moves the nodes of the map towards the areas of higher density of mapped input vectors. As a result, the SOM efficiently visualizes the clusters.

4. Classification of mobile cells using correlations of SOM component planes

Here a method for clustering mobile cells on the basis of covariance matrixes of SOM component planes is presented. The method utilizes the SOM algorithm twice. At first SOMs of one variable are built (see Sec. 4.1). Then the covariance matrixes of the SOM component planes are computed. Covariances of one or more variables are used as data to a second SOM. The outputs of the second SOM are the clusters of mobile cells (see Sec. 4.2). In Sec. 4.3 the classification of using several variables is demonstrated.

4.1 SOM of one variable

Data of each cell is masked so that one variable of each mobile cell is analyzed with the corresponding ones of the other cells. The data to be analyzed has been normalized to zero mean and unit variance as one data vector over all the cells. Here uplink noise raise and logarithm of uplink FER have been analyzed using the SOM. Hexagonal 2D neighborhood grid of 10 x 15 nodes is used. Fig. 3 shows the SOM component planes when the FER is studied. There is one component plane per each mobile cell. The parameter values of the mobile network state at one moment can be read from similar locations on component planes. For example, upper left corner gives one possible combination of network error rates.

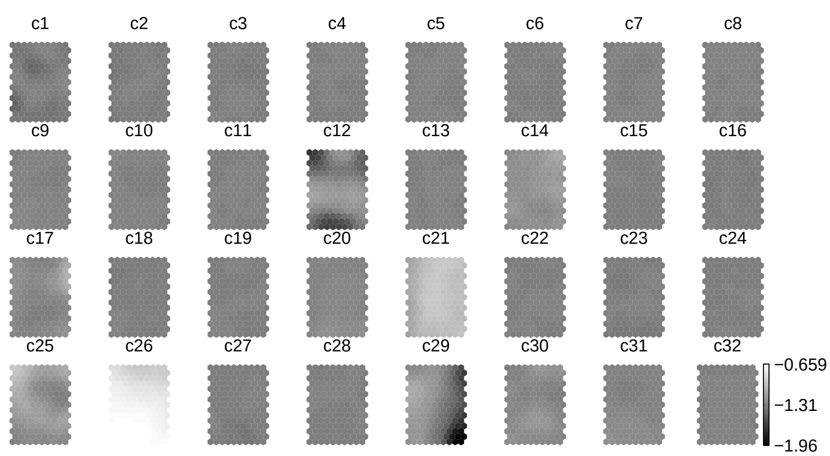

Figure 3. SOM component planes of the FERs. Minimum FER is fixed to 10^{-2}.

The component planes are visualized using a common color axis. This makes it possible to see the real error rates, but it also hides the smaller variations inside the cells. In the figure only some of the cells seem to differ from the common behavior. Cell 26 has a lot higher FER than all the others.

4.2 Reorganized SOM component planes

If we are interested in, for example, to find out which mobile cells have similar FER distribution, the task of human analyzer can be made easier by further processing the component planes of SOM. This kind of postprocessing is more important if the number of component planes is higher.

The component planes are considered as separate figures. Covariance matrix of the figures is computed by first converting the figure dot or node values c_{ij}^n to vectors a^n, where i and j are the coordinates on the map and n is the mobile cell number. The length of each vector a^n is the product of component plane dimensions.

The covariance matrix C of the planes a^n is the new data, which will be used in Sec. 4.3. This data has one row for each mobile cell. A new second level SOM is trained using the covariance matrix. The topology of the new SOM is 2D rectangular grid. Because 32 component planes are analyzed grid of size 8 x 8 nodes is used. The covariance matrix row of each cell is mapped on the second level SOM and the best-matching unit (BMU) for each mobile cell is found. The map nodes are labeled using the results of BMU search.

The second level SOM can be visualized using the labels or the corresponding first level SOM component planes. In the latter case the SOM component planes have been reorganized so that the similar ones locate near each other. This makes it easier to find correlations between SOM components.

The SOM planes reorganization method has been discussed earlier in [14] and [15]. In the latter paper several modifications of the algorithm have been represented. In Fig. 4 the SOM component planes of Fig. 3 have been reordered using the method above.

From the Fig. 4 we can see that cell 26 has higher error rate than the others and that also the FER distributions of cells 12, 14, 17, 21, 25, 29, 30 differ quite much from the others. The rest of the cells have similar FER distribution. The different behavior of cells can be partly explained with the help of the radio network plan: cells 26 and 21 suffer from bad interference situation (due to the fact that the water areas allow easy propagation for interfering signals), in case of cells 12 and 29 the difference can be explained with the position of the cell. These cells are located at the edge of the network, and thus only little data is available. Number of neighboring interfering cells is also lower compared to the other cells.

4.3 Classification using several variables

Several SOMs for different variables can be built and reorganized using the methods of previous sections. The covariance matrixes C_k of all first level SOMs can be combined so that we get a new data matrix $C = [C_k C_l \ldots]$, $k \neq l$. Matrix C has a row C^n for each cell n. The row is a concatenated vector of cell correlations of used variables.

When the SOM is trained using this new data, we are able to get a new ordering of the cells. The result (Fig. 5) is about the same as in Fig. 4. Only cells 14, 21, 25 and 26 differ from the others. It is obvious that in this case correlations of uplink noise raises

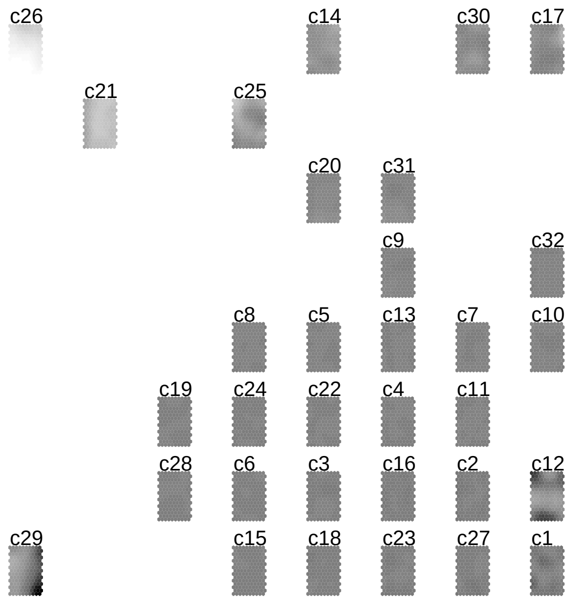

Figure 4. SOM planes representing error rates of the mobile cells are reorganized. Planes are also labeled using cell numbers. Color scaling is as in Fig. 3.

do not have a meaningful effect on clustering. The same cells differ from common behavior as before.

Clusters of mobile cells can be found using U-matrix presentation [12] or hierarchical clustering of SOM node vectors [16]. Hierarchical clustering can be either divisive or agglomerative [2]. In divisive hierarchical clustering data vectors are separated in finer groupings. Agglomerative hierarchical clustering methods add similar groups together starting from some initial base clusters. The base clusters can be either all SOM node vectors or some set of them like local minimas. Here, group-average hierarchical clustering is used with SOM node vectors as base clusters.

The number of clusters can be fixed manually on basis of the U-matrix or more sophisticated methods like Davies-Bouldin index can be used [1]. Here, the number of clusters is fixed manually to four. The clusters of the original data are shown in Fig. 6. The classification result combined with locations of the cells has been shown in Fig. 7. As it can be seen, cells can be characterized and divided into different clusters. In a radio network optimization process it is reasonable to assume that the configuration parameters for cells within a cluster are at least partly the same. The BMUs of the original data have been printed (in Fig. 6) using subscript 1 and the BMUs of the new data set with subscript 2 ($c1_1$ means cell 1 with original data). In the new data set, the pilot power of cells 21 and 26 have been decreased from the original 1W to 0.5W. The reason for this change was to reduce the physical size of these two cells to improve the overall quality of service. It can be seen in the following results that the change was not yet adequate.

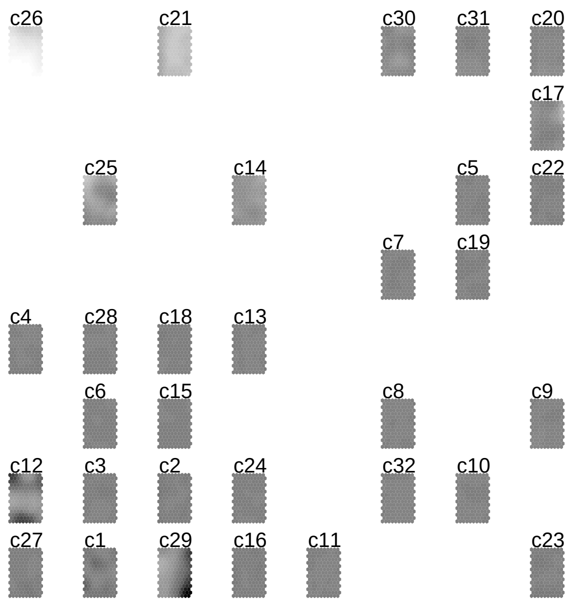

Figure 5. SOM planes representing error rates are ordered using correlations of both uplink noise raise and FER component planes.

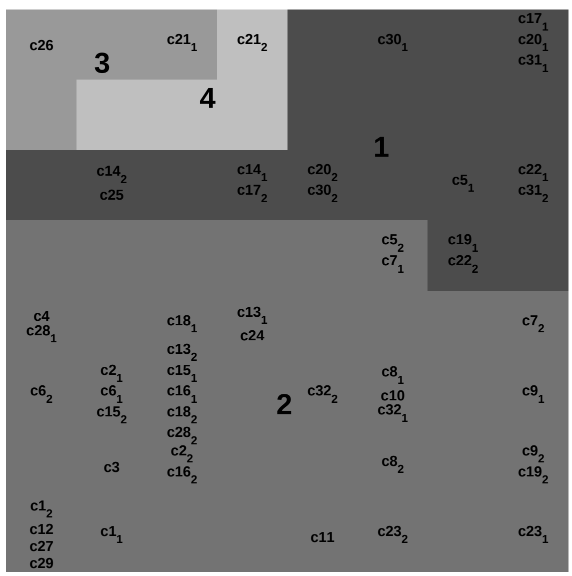

Figure 6. Four clusters of mobile cells. Cell clusters are found using correlations of both uplink noise raise and FER component planes.

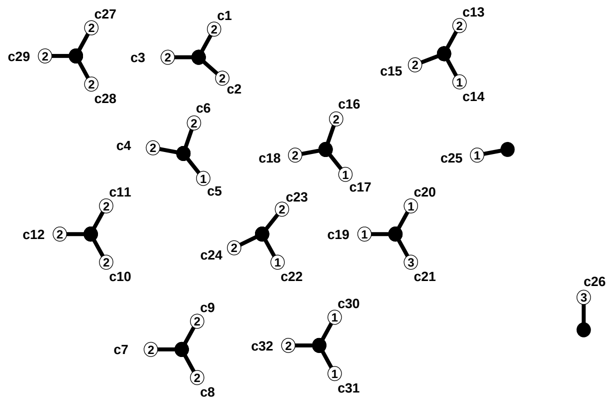

Figure 7. Locations and classes of mobile cells.

When new data is analyzed, SOM component plane representation of the data has to be constructed. The easiest way to do this is training the SOM again. When the SOM is trained, the new data can be used in the BMU search or it can be masked out. If the new data is masked out in the BMU search, but used when the neurons are updated we can obtain similar SOM as before, but in addition we get the component planes for the new data. From the component planes new covariance matrices can be computed, new clusters can be found and the BMUs of the new and the old data can be found.

The method described above classifies mobile cells on basis of correlations of selected variables. A model of mobile network which describes the relations between mobile cells has been built. This method analyses the correlations between cells i.e. does a bad performing cell have degrading influence also on the neighboring cells.

5. Classification of mobile cells using cluster histograms

In Section 4 method to form data clusters was presented. The input data was used to build a model of the network. In this section another method for classification of mobile cells is presented. Also this method uses two levels of SOMs. In order to analyze sequence of data samples instead of a single data point a histogram map is computed. Histogram consists of proportions of data samples falling in each of the data clusters. These histograms describe the long-term behavior of data sequences and they are used in the cell classification. A new SOM is generated using the histogram information as the training set. By using a clustering algorithm exact behavioral clusters can be generated. These behavioral clusters are found by hierarchical clustering method, here the Ward clustering [2] with local minimas of SOM node vectors as base clusters. Histograms for each mobile cell are computed using the clusters as bins. The histograms are the data, which are used to train the second SOM and to find the BMUs for each cell.

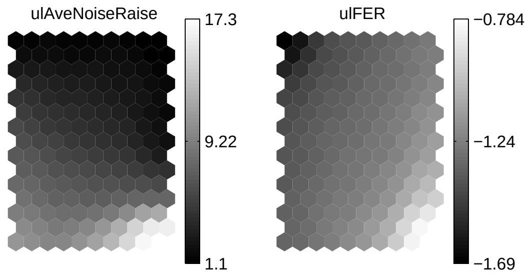

Figure 8. SOM trained by uplink noise raises and error rates of all the cells of the network.

5.1 General mobile cell model

In Fig. 8 the component planes of the general mobile cell model are shown. The optimal number of clusters minimizes Davies-Bouldin index [1]

$$\frac{1}{C}\sum_{k=1}^{C}\max_{l\neq k}\{\frac{S_c(Q_k)+S_c(Q_l)}{d_{ce}(Q_k,Q_l)}\} \tag{3}$$

where C is the number of clusters, S_c within-cluster distance and d_{ce} between clusters distance, Q_k and Q_l are the clusters. When Ward clustering is used, four clusters or states for mobile cells minimize the Davies-Bouldin index. In Fig. 9 state 4 represents the higher load state and the others normal state.

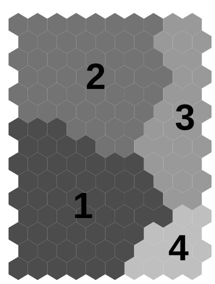

Figure 9. Four clusters of SOM node vectors given by Ward clustering and Davies-Bouldin index.

The BMUs of data vectors give the state or the class of the cell. From a sequence of states we can compute the class frequencies of mobile cells. Using these histograms as data to a second level SOM we get a SOM of histograms. The topology of the new SOM is 2D rectangular grid. Grid of size 8 x 8 nodes has been used as in 4.2. The BMU search of the map is based on Kullback-Leibler distance [4]. The Kullback-Leibler distance or relative entropy between two probability distributions $p_X(x)$ and $q_X(x)$ is defined by

$$D_{p||q} = \sum_{x \in \mathcal{X}} p_X(x) \log\left(\frac{p_X(x)}{q_X(x)}\right) \tag{4}$$

where the sum is over all states of the system (i.e., the alphabet $\mathcal{X}$ of the discrete random variable X).

The group-average hierarchical clustering with local minimas of SOM node vectors as base clusters gives new clusters of mobile cells. These clusters with mobile cell BMUs are shown in Fig. 10. The result is about the same as in the previous section. The shifts of states of cells when the pilot power of cells 21 and 26 is decreased are visualized using old clusters to label the new data and compute new histograms. As before the BMUs of the original data have been printed using subscript 1 and the BMUs of the new data set with subscript 2. The clustering information with spatial data is also shown in Fig. 11.

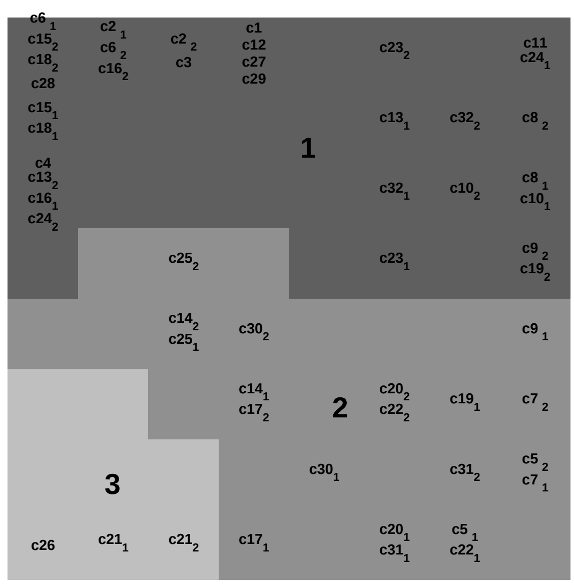

Figure 10. Three clusters of mobile cells. Cell clusters are found using cluster histograms of SOM trained by uplink noise raise and FER of each cell.

The method described above classifies mobile cells using class frequencies as models of mobile cell behavior. The distributions describe how much a particular mobile cell differs from a general cell model, which has been built using as much data as possible. General cell model is an absolute reference for cell performance. The position of the cell on the reference map reflects its actual performance.

6. Conclusion

In this paper two new methods to monitor mobile network state have been presented. In the first method, lower level SOMs of one variable are first build. Covariance matrices of the component planes of these SOMs are then used to train another

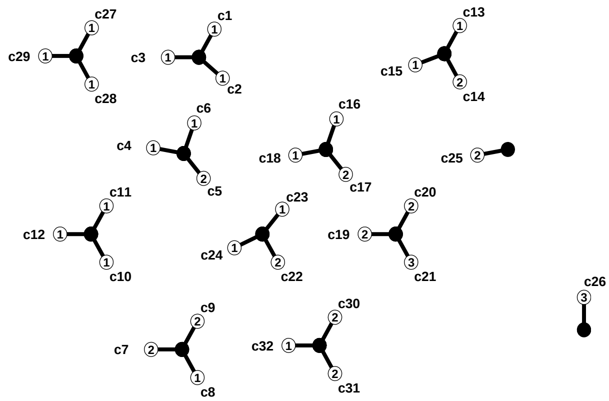

Figure 11. Locations and classes of base stations.

map, which reorders the mobile cells. In the second method, a lower level SOM, which represents general mobile cell model is built. Histograms of the states of the base stations are built using clusters of lower level SOM. The same clusters can be used later to find out histograms of new data. Thus, the operational mode of each cell and the whole network can be monitored. The first method is powerful when the correlation between the cells is of interest. The second method is used when information of the absolute performance of cells is required.

The data which is used to build the lower level SOM in the method based on class histograms should be selected carefully so that it represents well all the possible states of the cells. If it does not, the lower level SOM should be trained again using new set of data.

In this paper it has been demonstrated that SOM can be used in cell clustering. The possibility of finding similarly behaving cells will make the operators' optimization task more cost effective. Similar configuration parameter sets for cells within a cluster can be utilized. Furthermore, owing to the highly visual nature of SOM, the multidimensional performance space can be visualized more effective than with traditional tools. Thus the operators have means to get an interpretation of the service performance.

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