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Traffic Estimation and Characterization for the Design of Mobile Communication Networks

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Abstract: In this paper, we present a new method for the estimation and characterization of the expected teletraffic in mobile communication networks. The method considers the teletraffic from the network viewpoint. Its traffic estimation is based on the *geographic traffic model*, which obeys the geographical and demographical factors for the demand for mobile communication services. For the spatial teletraffic characterization, a novel representation technique is introduced which uses the notion of discrete *demand nodes*. We show how the information in geographical information systems can be used to estimate the teletraffic demand and validate the results by a real cellular design. Additionally, we outline how the discrete demand node representation enables the application of automatic mobile network design algorithms.

Keywords: traffic estimation, mobile network planning, clustering algorithm, facility location

1 Introduction

The design of third generation mobile communication networks faces three major challenges: first, there is the tremendous world wide increase in the demand for mobile communication services. Second, the main resource in wireless systems, i.e. the frequency spectrum, is extremely limited. And third, new access technologies like *Space Division Multiple Access (SDMA)* and *Code Division Multiple Access (CDMA)* require new mobile network planning methods. Since these challenges are strongly interconnected, they can only be addressed by an *integrated concept*, cf. Tutschku et al. (1996), in order to obtain an efficient, economic and optimal mobile network configuration.

The primary task of mobile system planning is to locate and configure the facilities, i.e. the base stations or the switching centers, and to interconnect them in an optimal way. To achieve an efficient and economic system configuration, the design of a mobile network has to be based on the analysis of the *distribution of the expected teletraffic demand* in the complete service area. In contrast, the traffic models applied so far for the demand estimation, characterize the teletraffic only in a single cell or they are too complex for practical use in the planning process. Therefore, the demand based design of mobile communication systems requires a traffic estimation and characterization procedure which is simple as well as accurate.

The paper is organized as follows. In Section 2 we first describe the traffic source models used so far in mobile network design and define a *geographical traffic model* which obeys the geographical and demographical factors for the expected teletraffic in a service region. Subsequently, we introduce the *demand node concept*. This is a novel technique for the representation of the spatial distribution of the teletraffic, which uses discrete points. In Section 3 of our presentation we outline a *traffic characterization procedure* which can provide a demand node distribution from publicly available geographical data. To generate the demand nodes, we introduce a *recursive partitional clustering* algorithm. In Section 4 we validate the demand node concept by data from a cell structure of an operating mobile network. Section 5 outlines how the demand concept can be applied for locating base stations and finally Section 6 summarizes the presentation.

2 Traffic estimation

In mobile communication networks the teletraffic originating from the service area of the system can be described mainly by two traffic models which differ by their view of the network. *a)* The *traffic source model*, which is also often referred to as the *mobility model*, describes the system as seen by the mobile unit. The traffic scenario is represented as a population of individual traffic sources performing a random walk through the service area and randomly generating demand for resources, i.e. the radio channel. An overview on these models is provided in Section 2.1. *b)* In contrast, the *network traffic model* of a mobile communication system describes the traffic as observed from the non-moving network elements, e.g. base stations or switches. This model characterizes the *spatial* and *temporal* distribution of the *traffic intensity* E, measured in *Erlangs*, in the two-dimensional service area. Both traffic models are used in mobile communication system design. Particularly the latter model is of principal interest when determining the location of the main facilities in a mobile network, i.e. the base stations and the switching centers. These components should be located close to the expected traffic in order to increase the system efficiency. Therefore, this paper will focus in Section 2.2 in greater detail on this type of models.

2.1 Traffic source models

Due to their capability to describe the user behavior in detail, *traffic source models* are usually applied for the characterization of the traffic in an individual single cell of a mobile network. Using these models, local performance measures like *fresh call blocking probability* or *handover blocking probability* can be derived from the mobility pattern. Additionally, these models can be used to calculate the subjective quality-of-service values for individual users.

Overview on traffic source models

A widely used single cell model was first introduced by Hong and Rappaport (1986). Their model assumes a uniformly distributed mobile user density and a non-directed uniform velocity distribution of the mobiles. Under this premise, performance values like the *mean channel holding time* and the *average call origination rate* in a cell can be computed.
El-Dolil, Wong, and Steele (1989) characterize the mobile phone traffic on vehicular highways by assuming a one-dimensional mobility pattern. They derive the performance values by applying a stationary flow model for the vehicular traffic. A similar one-dimensional highway model with a non-uniform density distribution was investigated by Leung, Massey, and Whitt (1994). For the traffic characterization, fluid flow models with time-nonhomogeneous and time-homogeneous traffic have been used, as well as a approximative stochastic traffic model.
A limited directed two-dimensional mobility model was investigated by Foschini, Gopinath, and Miljanic (1993). The model assumes a spatially homogeneous distribution of the demand and an isotropic mobility structure. Chlebus (1993) investigates a mobility model with a homogeneous demand distribution but assumes a non-uniform velocity distribution. The traffic orientation is non-directed and equally distributed.

The application of these traffic source models in real network planning cases is strongly limited. Some models, like the highway model proposed by Leung, Massey, and Whitt, give a deep insight on the impact of the terminal mobility on the cellular system performance, however they are rather complex to be applied in real network design. Other models, like the one suggested by Hong and Rappaport, due to their simplification assumptions, can only be applied for the determination of the parameters in an isolated cell.

2.2 Traffic intensity

Since the mobile network planning process requires a comprehensive view of the expected load, a network teletraffic model has to be specified. Therefore, we define the *traffic intensity* function $E^{(t)}(x, y)$. This function describes the offered teletraffic, as seen by the fixed network elements, in a unit area element at location (x, y) and at time instant t. The coordinates (x, y) of the area element are integer numbers. Due to the definition given above, the traffic intensity function is a matrix of traffic values representing the demand from area elements in the service region, cf. Figure 1(b). The traffic intensity $E^{(t)}(x, y)$ can be derived from the location probability of the mobile units.

Under the premise that this probability $p_{\text{loc}}^{(t)}(\chi, \psi)$ is known, the average number of mobile units $\#\overline{mob}^{(t)}(x, y)$ in a certain area element at time t is:

$$\#\overline{mob}^{(t)}(x, y) = \int_{x}^{x+\Delta x} \int_{y}^{y+\Delta y} p_{\text{loc}}^{(t)}(\chi, \psi) dy\, dx\,. \tag{1}$$

Here, $p_{\text{loc}}^{(t)}(\chi, \psi)$ is the probability that, if the system is viewed from the outside, there is a mobile unit at location (χ, ψ). The location (χ, ψ) is a coordinate in $\mathbb{R}^2$ and $\Delta x \times \Delta y$ is the size of the unit area element.

Using the assumption that every mobile unit has the same *call attempt rate* $r(t)$ at time t, the traffic intensity $E^{(t)}(x, y)$ can be readily obtained:

$$E^{(t)}(x, y) = \#\overline{mob}^{(t)}(x, y)\, r(t)\,. \tag{2}$$

Since in reality it is almost impossible to directly calculate the location probability $p_{\text{loc}}^{(t)}(\chi, \psi)$ from the mobility model, the traffic intensity has to be derived from indirect statistical measures.

2.3 The geographic network traffic model

The offered traffic in a region can be estimated by the *geographical* and *demographical* characteristics of the service area. Such a demand model relates factors like *land use*, *population density*, *vehicular traffic*, and *income per capita* with the calling behavior of the mobile units. The model applies statistical assumptions on the relation of traffic and clutter type with the estimation of the demand. In the *geographic network traffic model*, the intensity $E_{geo}^{(t)}(x,y)$ is the aggregation of the traffic originating from these various factors:

$$E_{geo}^{(t)}(x,y) = \sum_{\text{all factors } i} \eta_i \cdot \delta_i^{(t)}(x,y), \tag{3}$$

where η_i is the traffic generated by factor i in an arbitrary area element of unit size, measured in *Erlangs per area unit*, and $\delta_i^{(t)}(x,y)$ is the assertion operator:

$$\delta_i^{(t)}(x,y) = \begin{cases} 0 & : \text{ factor } i \text{ is not valid at location } (x,y) \\ 1 & : \text{ factor } i \text{ is valid at location } (x,y) \end{cases} . \tag{4}$$

So far the planning of public communication systems uses geographic traffic models which have a large granularity. A typical *unit area size* is in the order of square kilometers, i.e. in public cellular mobile systems this is the size of *location areas*, cf. Grasso et al. (1996). For the determination the positions of base stations a much smaller value is required. The locations of these facilities have to be determined within a spatial resolution of one hundred meters. An unit area element size in the order of $100m \times 100m$ is therefore indicated.

Traffic parameters

The values for η_i, which are the traffic intensity originating from factor i per area element, can be derived from measurements in an existing mobile network and by taking advantage of the known causal connection between the traffic and its origin. A first approach is to assume a highly non-linear relationship. A general structure to model this behavior is to use a parametric exponential function. In the geographic model, proposed within this paper, the traffic-factor relationship is defined to be:

$$\eta_i = a \cdot b^{x_i} \tag{5}$$

where a is constant and b is the base of the exponential function. For the validation of Eqn. 5, presented in Section 4, a value of 10 has been used for the basis b.

To reduce the complexity of the parameter determination we introduce the normalization constraint:

$$\frac{E_{\text{total}}}{A_{\text{service area}}/a_{\text{unit element}}} = \sum_{\text{all factors } i} \eta_i \,, \tag{6}$$

where $A_{\text{service area}}$ is the size of the service area, $a_{\text{unit element}}$ is the size of an unit area element, and E_{total} is the total teletraffic in this region. The value of E_{total} can be measured in an operating cellular mobile network.

The structure of the geographical traffic model given in Eqn.3 and Eqn. 5 appears to be simple. However, it will be shown in Section 5 that this model is accurate enough to describe the traffic in cells of an operating mobile network. Moreover, due to its structure the model can easily be adapted to the proper traffic parameters. This capability enables its application for mobile system planning.

Stationary geographic traffic model

The above proposed model $E^{(t)}_{geo}(x,y)$ includes also the temporal variation of the traffic intensity in the service area. Since communication systems must be configured in such a way that they can accommodate the highest expected load, the time index t is usually dropped and the traffic models are reduced to *stationary* models describing the peak traffic. The maximum load is the value of the traffic during the *busy hour*, cf. Mouly and Pautet (1992).

A pitfall for the network designer remains: the busy hour varies over time within the service area. In downtown areas the highest traffic usually occurs during the business hours, whereas in suburban regions the busy hour is expected to be in the evening. Therefore, the network engineer has to decide how to weight the different traffic factors, i.e. how to obey the different market shares of the various user groups in the traffic model of the network.

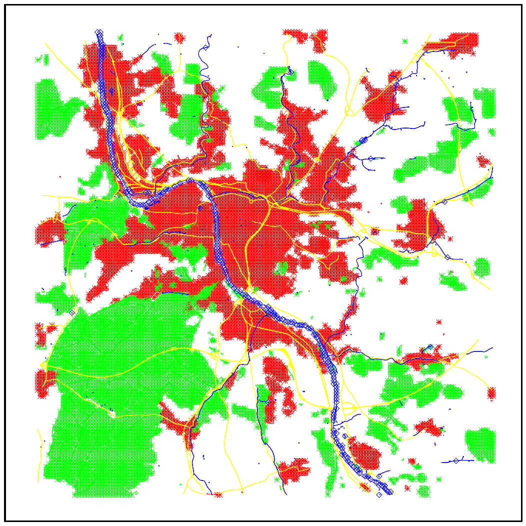
2.4 Traffic discretization

The core technique of the traffic characterization proposed in this paper is the representation of the spatial distribution of the demand for teletraffic by discrete points, called *demand nodes*. Demand nodes are widely used in economics for solving facility location problems, cf. Ghosh and McLafferty (1987).

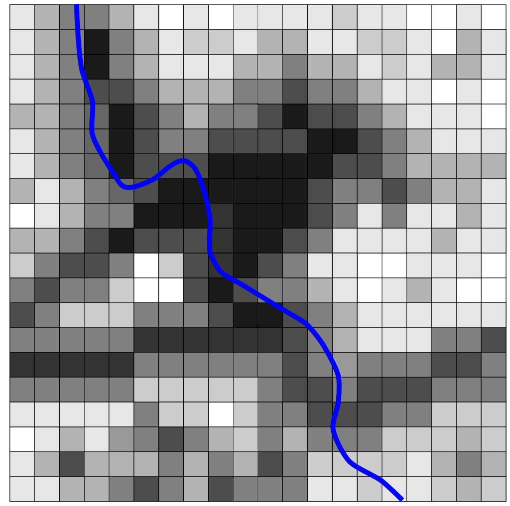
Definition: A demand node represents the center of an area that contains a quantum of demand from teletraffic viewpoint, accounted in a fixed number of call requests per time unit.

The notion of demand nodes introduces a discretization of the demand in both space and demand. In consequence, the demand nodes are dense in areas of high traffic intensity and sparse in areas of low traffic intensity. Together with the time-independent geographic traffic model, the demand node concept constitutes a *static population model* for the description of the mobile subscriber distribution.

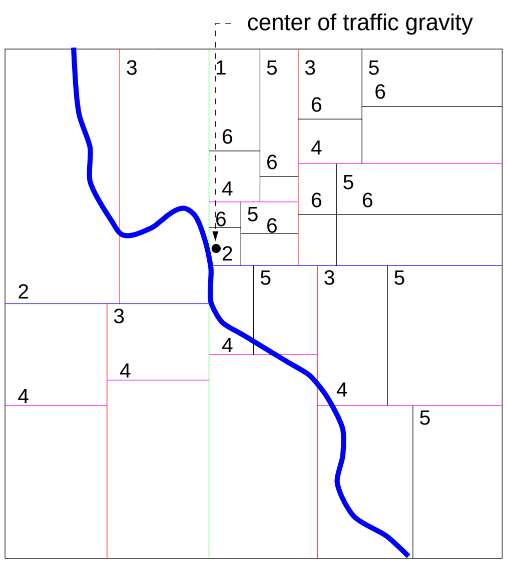
An illustration for the *demand node concept* is given in Figure 1: part (a) shows publicly available map data with land use information for the area around the city of Würzburg, Germany. The information was extracted from *ATKIS*, the official topographical cartographical data base of the Bavarian land survey office, cf. ATKIS (1991). The depicted region has an extension of $15km \times 15km$. Figure 1(b) shows the traffic intensity distribution in this area, characterized by the traffic matrix: dark squares represent an expected high demand for mobile service, bright values correspond to a low teletraffic intensity. Part (d) of Figure 1 depicts a simplified result of the demand discretization. The demand nodes are dense in the city center and on highways, whereas they are sparse in rural areas.



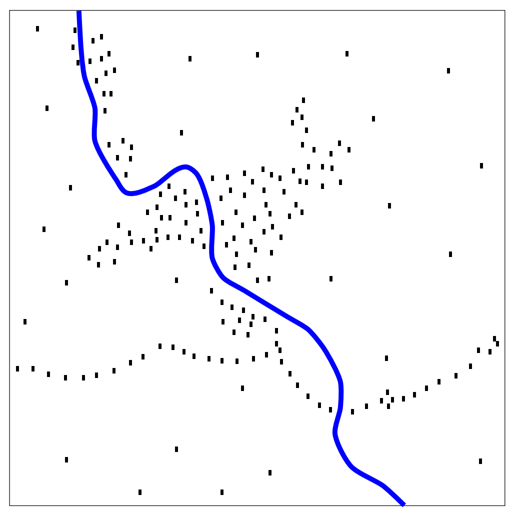
(a) Geographical and demographical data



(b) Traffic matrix



(c) Service area tessellation



(d) Demand node distribution

Abbildung 1: Demand node concept

3 Traffic characterization

3.1 Traffic characterization procedure

Based on the estimation method introduced in the previous section, the traffic characterization has to compute the spatial traffic intensity and its discrete demand node representation from *real world* data. In order to handle this type of data, the complete characterization process comprises four sequential steps:

Step 1 **Traffic model definition:**
Identification of traffic factors and determination of the traffic parameters in the geographical traffic model.

Step 2 **Data preprocessing:**
Preprocessing of the information in the geographical and demographical data base.

Step 3 **Traffic estimation:**
Calculation of the spatial traffic intensity in the service region.

Step 4 **Demand node generation:**
Generation of the discrete demand node distribution by the application of clustering methods.

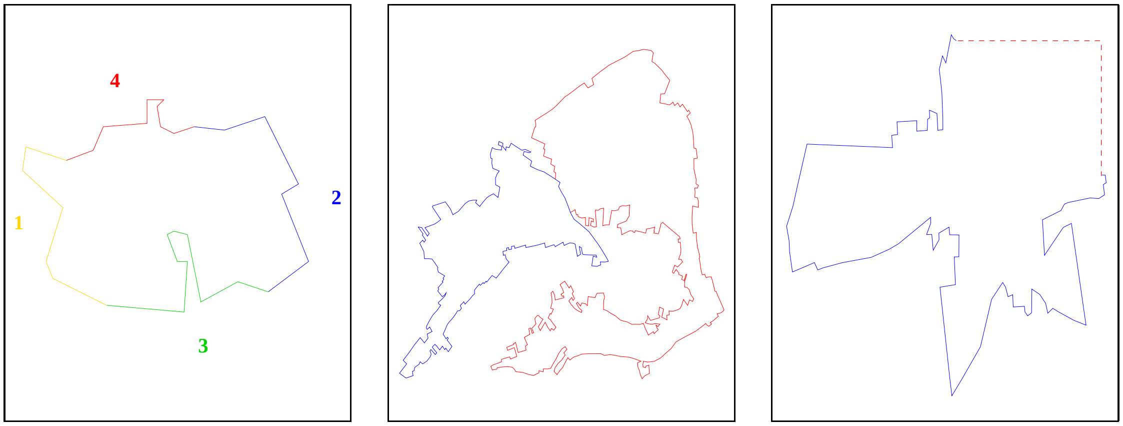
Traffic model definition

The definition of geographical traffic model in *Step 1* of the characterization procedure is based on the arguments given in Section 2.3. A simple but accurate spatial geographic traffic model is the base for system optimization in the subsequent network design steps.

Data preprocessing

The data preprocessing in *Step 2* is required since the data in geographical information systems are usually not collected with respect to mobile network planning. For example, ATKIS' main objective is to maintain map information. It uses a vector format for storing its drawing objects.

To determine the clutter type of a certain location, one has to identify the land type of the area surrounding this point. This requires the detection of the closed polygon describing the shape of this area. Since maps are mostly printed on paper, the order of drawing the lines of a closed shape doesn't matter, see Figure 2(a). To identify closed polygons, one has to check if every ending point of a line is a starting point of another one. If a closed polygon has been detected, the open lines are removed from the original base and replaced by its closed representation. Additionally, due to the map nature of the data, two adjacent area objects can be stored by a closed and an open polygon, see Figure 2(b). It also can happen that some data is missing, see Figure 2(c). In this case, line closing algorithms have to applied, cf. Leskien (1997). After the preprocessing step only closed area objects remain in the data base and the traffic characterization can proceed with the demand estimation.



(a) Unordered lines

(b) Adjacent open and closed polygons

(c) Closing lines

Abbildung 2: Dirty map information data

Demand estimation

Step 3 of the traffic characterization process uses the geographical traffic model defined in *Step 1* for the estimation of the teletraffic demand per unit area element. The computed traffic values are stored in the *traffic matrix*. To obtain the traffic value on a certain unit area element, the procedure first determines the traffic factors valid for this element and then computes the matrix entry by applying Eqn. 3.

3.2 Demand node generation

The generation of the demand nodes in *Step 4* of the characterization process is performed by a *clustering method*. Clustering algorithms are distinguished into two classes, cf. Jain and Dubes (1988): *a)* the *Partitional Clustering* methods, which try to construct taxonomies between the properties of the data points, and *b)* the *Hierarchical Clustering* methods which derive the cluster centers by the agglomeration of input values.

The algorithm proposed for the demand generation is a recursive partitional clustering method. It is based on the idea to divide the service area until the teletraffic of every tessellation piece is below a threshold θ. Thus, the algorithm constructs a sequence of bisections of the service region. The demand node location is the center of gravity of the traffic weight of the tessellation pieces.

The demand node generation algorithm is shown in Algorithm 1. The function `left_area`() divides the *area* into two rectangles with the same teletraffic and returns the left part of the bisection. The function `right_area`() returns the right piece. In every recursion step, the orientation of the partitioning line is turned by 90^o. The recursion stops, if every rectangle represents a traffic amount less than

Algorithm 1 (Generate Demand Nodes)

variables:

dnode_set	*global variable for the set of generated demand nodes*
orient	*orientation of partitioning line*
θ	*traffic quantization value*

algorithm:

```
proc gen_dnodes(area, θ, orient = 0) ≡
  begin
    if (traffic(area) < θ)
      then
            dnode_set ← center_traffic(area);
            return;
       else
            orient ← (orient + 90°) mod 180°;     /* turn partitioning line */
            a_l = left_area(area, orient);
            a_r = right_area(area, orient);
            gen_dnodes(a_l, θ, orient);            /* do the recursion */
            gen_dnodes(a_r, θ, orient);
    fi
  end
```

Algorithm 1: Demand node generation

the minimal quantization value θ. The function `traffic()` evaluates the amount of expected teletraffic demand in the area.

An example for the bisection sequence of the algorithm is shown in Figure 1(c). The numbers next to the partitioning lines indicate the recursion depth. To make the example more vivid, not every partition line is depicted in the example. The upper left quadrant of the Figure 1(c) shows only the lines until the recursion depth 3, the lower left part the lines until the depth 4, the lower right quarter the lines until depth 5 and the upper right quadrant of the region the lines until depth 6.

The partitional clustering algorithm of Algorithm 1 is a fast but simple clustering method. However, its accuracy depends strongly on the quantization value θ, which gives only an upper bound for the traffic represented by a single demand node. Moreover, since the algorithm constructs a sequence of right-angled bisections, the shape of the tessellation pieces is always rectangular. To overcome these drawbacks, we investigate also hierarchical agglomerative clustering algorithms. These methods are able to obtain tessellation pieces of arbitrary shape and of a predefined traffic value.

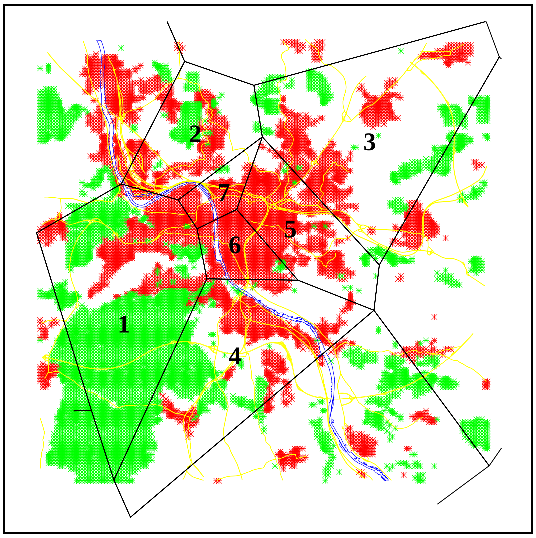


Abbildung 3: Cell boundries

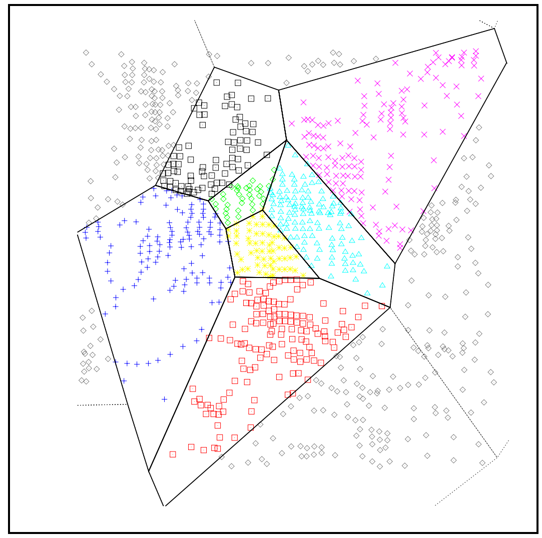


Abbildung 4: Demand node approximation

4 Validation of the traffic estimation

To evaluate the capability of the traffic estimation and characterization of Section 3, the traffic approximation of this procedure was compared with the traffic distribution measured in cells of the GSM-based D1 system of the German network operator DeTeMobil. Figure 3 depicts the approximated cell boundaries of the D1 system superimposed on the land use of the investigated area around Würzburg.

The traffic estimation of the demand node concept was based on the geographical network model as defined by the Equations 3 and 5. For the validation, the model considered as the traffic factors the five clutter types which were available for this area in the ATKIS data base: *vehicular traffic*, *urban*, *open outdoor*, *water*, and *forest*. Table 1 shows the values of the exponents used for the calculation of η_i in Eqn. 5. The parameter a was calibrated from measurements and constant for every traffic factor i. The demand node representation of the estimated traffic in this region, generated by Algorithm 1, is depicted in Figure 4. As expected the demand nodes are dense in the city center and on highways and are sparse in rural areas.

clutter type	$x_i = log_b(\frac{\eta_i}{a})$
vehicular traffic	3
urban	2
open outdoor	1
water	0
forest	-1

Tabelle 1: Parameter of the traffic clutter relationship

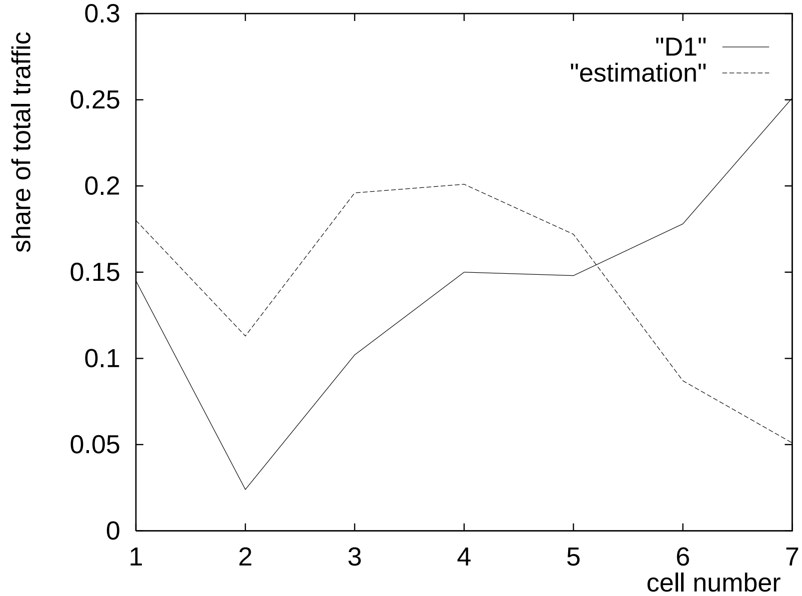


Abbildung 5: Cell traffic distribution

The share of the teletraffic of the cells in this area is shown in Figure 5. The solid line represents the proportion of each of the seven D1 cells of the measured total teletraffic. The dotted line in Figure 5 is the estimation of the geographic network traffic model. Both graphs are qualitatively almost the same for the cells with numbers 1, 2, 3, and 4. However, for the cells 5, 6, and 7 the estimation differs strongly from the measured distribution. The cause for the wrong approximation in these cells is the limited distinction of the traffic factors. Due to the use of ATKIS, the model does not distinguish between "urban" and "dense urban". However, the cells 5, 6, and 7 are located in the city center of the Würzburg. The high traffic demand due to the high user density in this area is not reflected in the model.
This example demonstrate that the geographical network traffic has the ability to estimate the traffic quite accurate (cf. cells 1, 2, 3, and 4). However, it has to be extended in some cases (cf. cells 5, 6, and 7).

5 Demand based mobile network design

To prove the capability of the demand estimation and to show the feasibility of the integrated design concept, *ICEPT* - a prototype of a planning tool for cellular mobile networks was implemented at the University of Würzburg, cf. Tutschku et al. (1997). The tools' core components are the automatic network design algorithm *SCBPA (Set Cover Base Station Positioning Algorithm)* and a traffic characterization procedure as described in Section 3.

The SCBPA algorithm is a GREEDY heuristic which selects the optimal set of base stations that maximizes the proportion of *covered* traffic, i.e. the ration of the

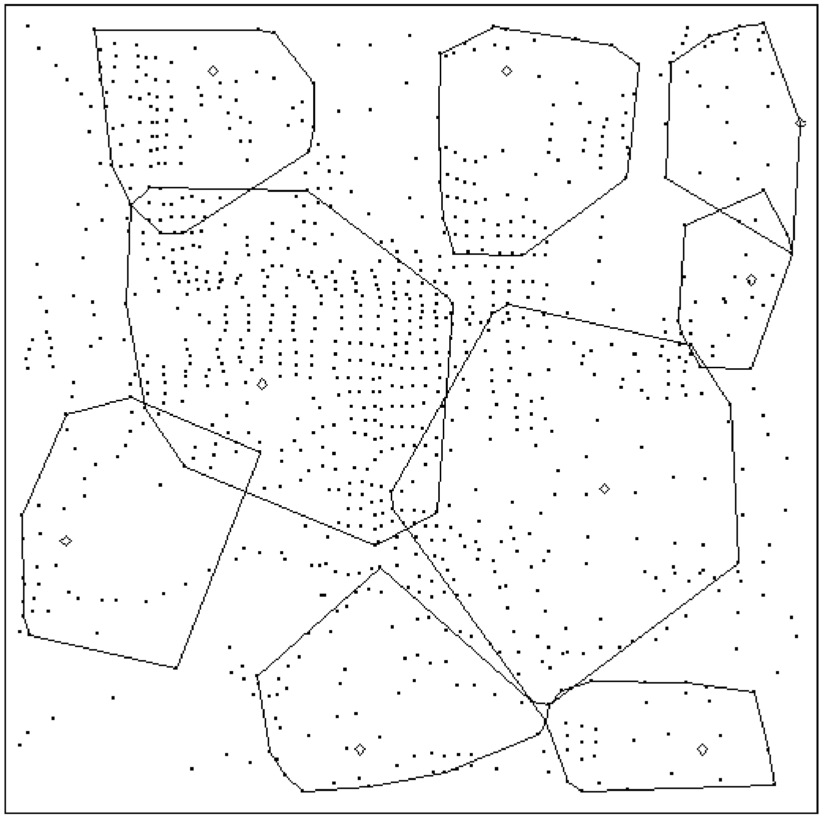


Abbildung 6: ICEPT planning result: base station locations

demand nodes which measure a pathloss on the forward/reverse link above the threshold of the link budget, cf. Tutschku et al. (1996).

SCBPA was tested again on the topography around the city center of Würzburg. The task was to find the optimal locations of nine transmitters in this terrain. The result of the algorithm is depicted in Figure 6. The base station locations are marked by a $\diamond$ symbol. The lines indicate the convex hull around the set of demand nodes which are supplied by the base station. The SCBPA algorithm was able to obtain a 75% coverage of the teletraffic of the investigated area. The total computing time for the configuration, including the traffic characterization, was 4min on a SUN Ultra 1/170.

6 Conclusion

This paper has presented a new method for the estimation and characterization of the expected teletraffic in mobile communication networks. The method considers the teletraffic from the network's viewpoint. Its traffic estimation is based on the *geographic traffic model*, which obeys the geographical and demographical factors for the demand for mobile communication services. For the spatial teletraffic characterization, a novel representation technique was introduced which uses the notion of discrete *demand nodes*. We demonstrated how the information in geographical information systems, like ATKIS, can be used to estimate the teletraffic demand in a service region and we validated the results with measurements from a real cellular network. Additionally we outlined how the discrete demand node representation enables the application of automatic mobile network design algorithms.

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