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In cellular mobile communication networks, the distribution of a customer population in a support area is often clustered. Considering this effect in network planning is an important aspect which strongly influences the Quality-of-Service (QoS) experienced subjectively by customers in the network. In this paper, we first discuss two-dimensional point processes and their application in mobile network traffic characterization. The inclusion of cluster processes in cellular traffic models is presented subsequently. The degradation of the subjective QoS the subject of the first model example, while additionally, the impact of repeated call attempts is investigated in the second model.

1 Introduction

In the development of the first generation of wireless telephone networks, due to the lack of systematic planning methodology, the network planning was done in a step-by-step manner, where pragmatic approaches were used.

The planning task started with the implementation of cell sites with subsequent measurements of the initializing system, followed by a step-wise adaptation until the desired network performance was reached. This approach often neglects the interactions between planning constraints, requires more equipment than necessary and tends to over-dimension the system. This approach, however, used to be the most suitable one, since required data for a systematic planning were not available.

Due to today's tremendous customer demand and network growths, with more and more carriers joining the market, the need of a systematic planning methodology has become essential. Furthermore, knowledge about customer behavior and measured traffic data have become more accurate to allow for a detailed planning procedure.

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Conventional cellular planning is based on the *analytical approach* [9, 3] to cellular network planning, the focus of which is laid on radio planning aspects, i.e., selection of cell sites, frequency planning, and antenna design. We describe the analytical approach in more detail in Section 2.2.1. Due to its algorithmic formulation the approach is widely found in todays cellular network planning [5] which is supported by tools like PlaNET [7] or GRAND [3]. These tools may be regarded as complex desktop calculators for trained radio engineers since the assistance of a human expert is required in each phase of the algorithm.

The major disadvantage of the analytical planning approach is that it focuses almost exclusively on radio design aspects of cellular network planning leaving considerations of the customers' demand somewhat underdeveloped. In consequence, there are activities to overcome this deficiency. An *integrated* approach to cellular network planning is proposed in [14]. In contrast to the conventional approach where the planning process is driven by coverage considerations, this approach is driven by customers' demand. The aim is not to cover as much area but to supply as many users as possible. Additionally, existing interactions between planning constraints are taken into account when resolving conflicting planning objectives. By doing so the approach automatically obtains planning solutions which are optimized under multiple aspects.

One of the key components common to all approaches is, of course, the performance evaluation of the planning solution. As in wire-line telephone systems, a typical performance

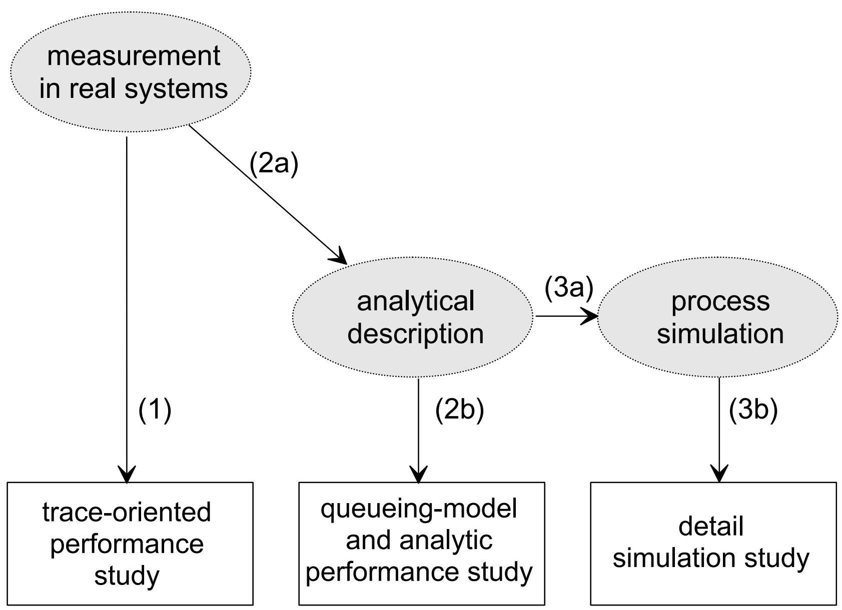

Figure 1: Cluster process and network planning

evaluation task in mobile network planning is based on the following steps (cf. Fig. 1):

- ▷ Measurements in real systems: Typical measures required for traffic process modeling are customer population and distribution, as well as mobility profiles of mobile stations. Currently, a lack of published data is obvious in the literature, and a standardized measurement method to obtain customer process patterns is not available.

- ▷ Teletraffic process description: Based on the measured data, a spatial process type may be chosen to represent the customer population and its distribution. As discussed in Section 2, a number of processes suited for analytic description can be found in standard literature on Stochastic Geometry. However, a more formal (and automatic) procedure to transform a measured data set into a process description (step (2a) in Fig. 1) is needed. For a few well-known processes from Stochastic Geometry (see [10, 2]), there exist methods to identify and to fit a spatial point process model to a given customer distribution.

  The algorithm to simulate two-dimensional stochastic processes (step (3a) of Fig. 1), is also a crucial point. Some basic algorithms for the two-dimensional binomial process and the two-dimensional Poisson process will be discussed in Section 2.

- ▷ Use of input process in performance models: Finally, analytic and simulative process descriptions must be usable as input processes of performance models of mobile networks. This step leads to rather abstract but easy-to-implement analytic models (step (2b) in Fig. 1) or to detail simulation studies (step (3b) in Fig. 1).

In the context of the method hierarchy shown in Fig. 1, the impact of customer clusters on mobile network performance will be studied, where attention is devoted to the following aspects:

- ▷ How to specify and describe two-dimensional cluster processes. Basically, already known results in Stochastic Geometry applicable to the wireless network planning, will be outlined. In Section 2 we describe some common spatial processes and how they can be simulated and analyzed in a performance model (step (3a) in Fig. 1).

- ▷ How does the cluster structure affect the performance of a cell in particular, and the entire network in general. We consider the subjective Quality-of-Service (QoS), i.e., the QoS experienced subjectively by a customer, in accordance to the cluster structure. This is done in Section 3, based on simple queuing models, which represent examples of step (2b) in Fig. 1.

2 Spatial Point Processes and their Application

2.1 Spatial Point Processes Overview

The intention of this section is to give a short introduction to spatial point processes. We do not aim at a strict mathematical description of these stochastic processes but fall back to a more informal description from a practical point of view. Comprehensive mathematical treatment can be found in the monographs of Stoyan [10] or Cressie [2].

We start with some definitions and basic properties of point processes with higher dimensions. The description will be restricted to the case of *planar* point processes, i.e., point processes in the 2-dimensional plane. A few basic point processes will be presented together with simulation methods to generate these.

2.1.1 Basic properties

In general a (planar) *point process* N is a random variable, which takes random choices of mappings $\mathbf{B} \mapsto N(\mathbf{B})$, where $\mathbf{B}$ is a Borel set (in the 2-dimensional plane) and $N(\mathbf{B})$ is a counting measure, the number of simple points contained in $\mathbf{B}$. A realization of N is called a *point pattern*. It should be noted that in this context the term "process" is somewhat misleading since it does imply a dynamic evolution in time, the notion of which is not present here.

As a random variable a point process induces a probability measure, the *distribution* of the point process N. For a point process, the analogues to the moments of a scalar random variable take the form of *moment measures*. The *kth moment measure* of point process N is defined by

$$\mu^{(k)}(\mathbf{B}_1 \times \cdots \times \mathbf{B}_k) \quad = \quad \mathrm{E}\left[N(\mathbf{B}_1), \ldots, N(\mathbf{B}_k)\right], \tag{1}$$

where $\mathbf{B}_1, \ldots, \mathbf{B}_k$ are Borel sets. If $\mathbf{B}_1 = \cdots = \mathbf{B}_k$, then we get the kth moment of the real-valued random variable number of points $N(\mathbf{B})$ in set $\mathbf{B}$,

$$\mu^{(k)}(\mathbf{B}^k) \quad = \quad \mathrm{E}\left[N^k(\mathbf{B})\right], \tag{2}$$

The first moment measure of a point process is called its *intensity measure*

$$\Lambda(\mathbf{B}) \quad = \quad \mu^{(1)}(\mathbf{B}) \quad = \quad \mathrm{E}\left[N(\mathbf{B})\right]. \tag{3}$$

If N is *stationary* (also termed *homogeneous*), i.e., its distribution is invariant under translation of its points by some vector $\mathbf{x}$, then

$$\Lambda(\mathbf{B}) = \lambda A(\mathbf{B}) \tag{4}$$

for some constant λ, which is called the *intensity* of N. Here, $A(\mathbf{B})$ denotes the area of set $\mathbf{B}$. Choosing $\mathbf{B}$ such that $A(\mathbf{B}) = 1$ shows that λ may be interpreted as the mean number of points per space unit, which is independent of the shape and location of $\mathbf{B}$ within the plane. If N is not stationary,then $\mathrm{E}\left[N(\mathbf{B})\right]$ depends on the location of $\mathbf{B}$ and the intensity is undefined.

In analogy to the variance and the coefficient of variation of a scalar random variable one defines the *variance measure* and the *coefficient of variation measure*

$$\begin{aligned} \mathrm{VAR}\left[\mathbf{B}^2\right] &= \mu^{(2)}(\mathbf{B}^2) - [\mu^{(1)}(\mathbf{B})]^2 \qquad (5)\\ &= \mathrm{E}\left[N^2(\mathbf{B})\right] - (\mathrm{E}\left[N(\mathbf{B})\right])^2 \\ c(\mathbf{B}) &= \frac{\sqrt{\mathrm{VAR}\left[\mathbf{B}^2\right]}}{\mathrm{E}\left[\mathbf{B}\right]}. \qquad (6) \end{aligned}$$

If N is stationary and *isotrop* (i.e., its distribution is invariant under rotations about the origin), then the point process is called *ergodic*. A consequence of ergodicity is that a single point pattern of the process is sufficient for statistical evidence. For ergodic point processes larger values of $c(\mathbf{B})$ indicate the existence of clusters of points, while, clearly, $c(\mathbf{B}) = 0$ if N is deterministic.

The *reduced Palm distribution* [8] of point process N with respect to a point $\mathbf{x}$ is the conditional distribution of N not counting $\mathbf{x}$ given $\mathbf{x}$ is a point of N. In our context the reduced Palm distribution may be used to calculate the probability that there are a certain number of active sources in the neighborhood of an active source. If N is stationary, then the reduced Palm distribution is independent of $\mathbf{x}$.

2.1.2 Basic Planar Point Processes

In the following, we present some basic planar point processes and algorithms for their simulation (cf. [11]). For simplicity, we will assume that the area covered by the process is the rectangle $\mathbf{W} = [0, a] \times [0, b]$. Any shape of $\mathbf{W}$ is possible with some minor changes, e.g. in simulation by applying the accept–reject method [6] after generating the point pattern on a rectangle.

Basically, one may divide planar point processes into point processes with a fixed number of points and point processes with a random number of points on the area observed. We start with an example of a process with a fixed number n of points, namely the Binomial process.

Binomial Process The number of points contained in set $\mathbf{B} \subset \mathbf{W}$ is distributed according to the binomial distribution (hence the name)

$$P\left(N(\mathbf{B}) = k\right) = \binom{n}{k} p_{\mathbf{B}}^{k}(1 - p_{\mathbf{B}})^{n-k}, \quad k = 0, \ldots, n, \tag{7}$$

where $p_{\mathbf{B}} = A(\mathbf{B})/A(\mathbf{W})$.
The intensity is $\lambda = n/A(\mathbf{W})$. Clearly, $c(\mathbf{B}) = \sqrt{(1 - p_{\mathbf{B}})/(np_{\mathbf{B}})} < 1$.

To generate a point pattern for simulation purposes one simply has to generate n pairs (x_i, y_i) where x_i is uniformly distributed in $(0, a)$ and y_i is uniformly distributed in $(0, b)$.

If we start by choosing the number of points n of a Binomial process according to a Poisson distribution, we arrive at the Homogeneous Poisson Process, as presented below.

Poisson Process The number of points contained in Borel set $\mathbf{B} \subset \mathbf{W}$ is distributed according to the Poisson distribution

$$P\left(N(\mathbf{B}) = k\right) = \frac{[\lambda A(\mathbf{B})]^k}{k!} \exp(-\lambda A(\mathbf{B})), \tag{8}$$

where λ is the intensity of the process. As with the Poisson distribution, $c(\mathbf{B}) = 1$. (The homogeneous Poisson process becomes inhomogeneous when λ is replaced by a function which depends on the location.)

The above remark makes the algorithm to simulate a two-dimensional Poisson process clear: simply choose the number of points from a Poisson distribution with parameter λab and generate a Binomial pattern with that number of points. Since sampling from a Poisson distribution is difficult if its parameter is large [6] the pattern generation method illustrated in Fig. 2 is more convenient.

The construction starts by generating a sequence $\{x_i\}$ of points on the x-axis whose inter-point distance is governed by a exponential distribution with parameter λb. Consequently the number of points contained in interval $[0, a]$ is Poisson-distributed with parameter λab. As with the Binomial Process the corresponding sequence $\{y_i\}$ is generated by uniform "dropping" on $[0, b]$. Finally, the Poisson pattern is given by pairing $\{x_i\}$ and $\{y_i\}$.

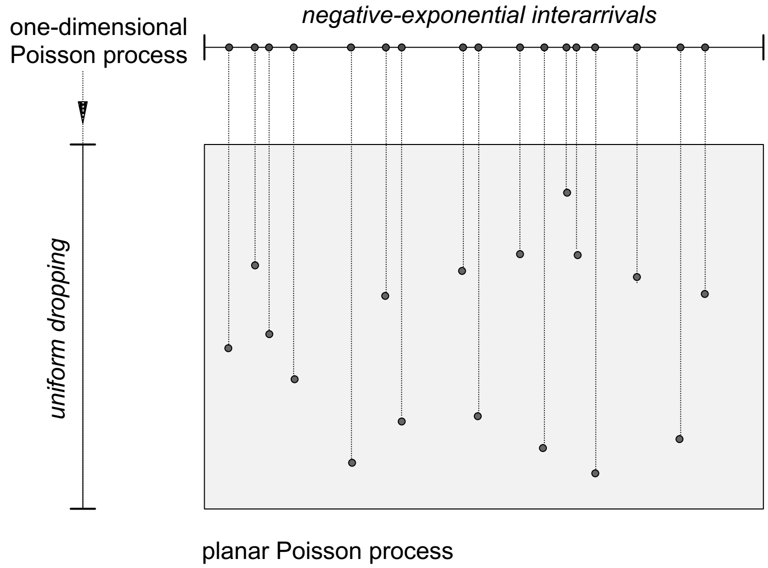

Figure 2: Generating a Poisson pattern

Due to its simplicity, the homogeneous Poisson process plays an important role among spatial point processes. The statistical properties of this process are very convenient for analysis, e.g. the reduced Palm distribution is identical to the distribution of the process. Furthermore, the process may serve as a generic building block when constructing more complex models like Cluster Poisson Processes.

Cluster Poisson Processes A Cluster Poisson Process is constructed from a homogeneous Poisson process using the points of the Poisson process as *parent points*. Now, each of the parent points is used as the center of a cluster of points (*children points*). Each cluster is generated independently of the others and the same construction rules apply for all of them. Within a cluster the points are placed independently according to the density function of cluster points. Only the children are points of the cluster point process.

With respect to the cluster point density a number of processes are distinguished; e.g. in our context are important

- ▷ *Matern* process
  The number of points per cluster is a Poisson random variable. The children are placed uniformly in a circle of radius R, which is constant for all clusters.

- ▷ *Thomas* process
  The number of points per cluster is a Poisson random variable. The cluster points are located according to a symmetric 2-dimensional normal distribution.

From the construction of cluster processes their simulation is straight forward, starting with a Poisson process as described above.

One of the problems with more complex point processes is that the distribution of the process in general is not known and even moments of the distribution are difficult to derive.

2.2 Application of Spatial Point Processes in Cellular Network Planning

2.2.1 Conventional Cellular Network Planning

Basically, the algorithm used in conventional cell planning has four phases: *Network Definition*, *Propagation Analysis*, *Frequency Allocation*, and *Radio Network Analysis*, which are iteratively passed several turns (cf. Fig. 3).

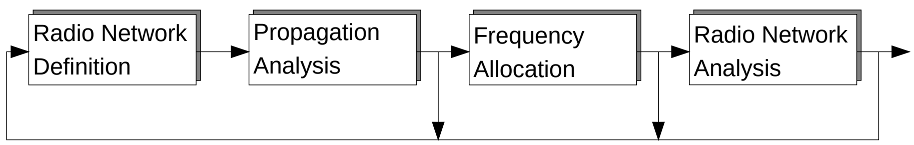

Figure 3: Conventional cellular network planning

In the *Radio Network Definition* phase, an experienced radio engineer chooses the cell sites. This decision is based on the geographical map of the area to be supplied, the radio engineering knowledge, and the planning experience of the human expert.

Starting from the transmitter positions laid down during radio network definition the *Propagation Analysis* evaluates the radio coverage of the area using field strength prediction methods. Here, several stochastic propagation models as well as more sophisticated approaches like ray-tracing techniques are applied. The decision which field strength prediction method to use is again up to an human expert. Computer tools offer little if any support for this decision.

If the coverage does not satisfy the coverage requirements, the algorithm restarts in phase one with choosing new transmitter positions and designs. Otherwise the algorithm proceeds with the *Frequency Allocation*. Here, the first step is to calculate the required number of traffic channels. This is done using a database of the expected traffic, which is usually derived from rough estimates based on land use data. The database assigns an amount of expected traffic to each pixel of the topological map. The expected traffic of the area covered by a cell is then computed by adding the values of all the pixels contained in that cell. Based on the expected offered traffic, the number of traffic channels required is then computed using landline capacity planning techniques like the well known Erlang formulae. Obeying interference distance constraints imposed by a given frequency re-use pattern the algorithms tries to find a valid frequency plan.

If such a plan can be found, the algorithm proceeds to radio network analysis. Otherwise the algorithm starts again in phase one. To evaluate the network performance the *Radio Network Analysis* calculates the Quality-of-Service of the area in the form of blocking and hand-over dropping probabilities. In doing so, stochastic channel characteristics and demand estimates from the database of expected traffic are used again. If QoS specifications are met the algorithm stops, else it starts again in step one.

2.2.2 Inclusion of Customer Traffic in Planning Process

From the above description it is apparent that the consideration of customer traffic is underdeveloped in the conventional planning approach. Thus, [14] not only explains ways of considering the customer traffic but even places the focus on it; the driving force of the planning algorithm is the customers' demand. The key concept to achieve this is the introduction of *demand nodes*.

A demand node represents the center of an area containing a quantum of demand from teletraffic point of view, accounted in a fixed number of call requests per time unit. Thus, demand nodes discretize the traffic demand in both space and demand domain. The definition implies that the demand nodes are dense in areas of high demand and sparse in areas where demand is low. One of the key components of the system model for network performance analysis is a model of the demand node pattern.

While the notion of demand nodes is advantageous during radio network definition and propagation analysis [14], there are some drawbacks when the influence of more detailed user behavior is under investigation. For instance, it is incompatible with the idea of having a finite number of traffic sources which is more realistic than assuming an infinite number of sources when cells are small. Effects of customers redialing when blocked cannot be modeled either.

2.2.3 Cluster Processes in Mobile Network Models

We propose to use spatial point processes to model the customers' demand Each point of the process represents a customer of the mobile network. In the standard literature on Stochastic Geometry [10, 2], there are methods for identifying and fitting a spatial point process model to such a customer distribution. Recently, a similar approach was followed by Bacelli et al. [1]. They propose a mobility model based on spatial point processes.

In Section 3, we assume that fitting the model identifies an ergodic spatial point process. With this type of process in mind there are two ways of interpreting cell placement. On the one hand, a cell is fixed and different customer patterns generated by the spatial point process model the volatility-in-time of the offered traffic. On the other hand, one may fix a customer pattern and randomly place a cell. From teletraffic point of view the deployment of a cell based on considerations on area coverage only is somewhat random.

Both cases induce a distribution of the number of traffic sources contained in the cell area. The traffic generated by these sources is the offered traffic of the cell model.

3 Modeling of Subjective QoS versus Cell Design

In this section, we present a basic model aiming at answering the question: How does the cluster structure influence the subjective QoS of a customer in a mobile network. A test customer (TC) in a mobile network is observed. If the TC is located in a clustered geographic environment and the network planning does not take into account this customer concentration, the subjective QoS experienced by this customer will decrease. To describe the degradation of the QoS due to cluster effects quantitatively, we first assume that the cell planning process neglects the customer cluster. This corresponds to a cell planning approach trying to cover geographical areas only and not customer population locations.

3.1 Model Description

We observe a TC in a mobile network with a clustered structure described by a two-dimensional point process. In this environment, an omni-cell covers and supports a number of customers. The cell covers the area F, to which a constant number of K channels are allocated. Due to the cluster structure, the number of customers will be described by the random variable X.

The customer traffic process is embedded in an finite source model, as shown in Fig. 4. A customer can be in one of the two states: Idle or Active. The time intervals the customer is in one of these states are assumed to be exponentially distributed. The random variable I with mean $1/\alpha$ denotes the soujourn time in the Idle state. After finishing a call a customer will stay in this state until generating the next call. If the call request is rejected, the customer

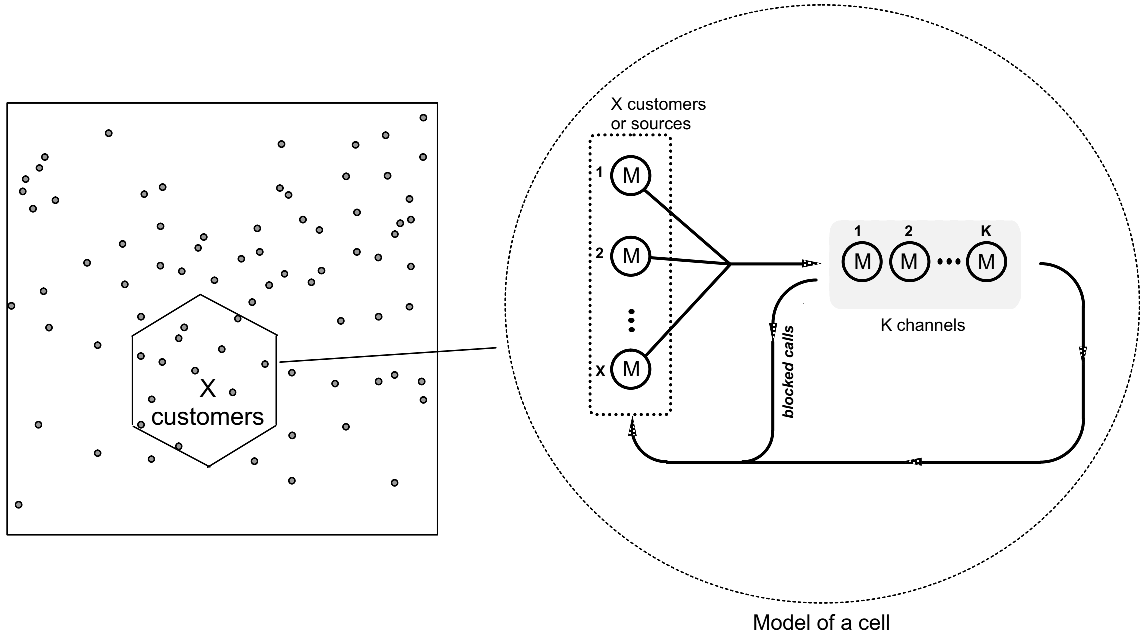

Figure 4: Omni-cell with customer clusters

remains in the Idle state. The time interval in the Active state is denoted by random variable B with mean $1/\mu$. This state represents the use of a channel. The customer is in this state while connected. At the end of a connection a customer will be back to the Idle state.

The offered traffic intensity of a customer, i.e. the probability that a customer is active when the blocking effect would be neglected, is given by

$$\rho_M = \frac{\alpha/\mu}{1+\alpha/\mu}. \tag{9}$$

We refer to ρ_M also as the customer activity factor. This parameter is often used as input of the mobile network planning and ranges from 0.015 (15 *mErl* [milliErlang]) to 0.05 (50 *mErl*).

Thus, the model of a cell is the standard loss system with K servers and a finite number X of sources. In this case X is a random number representing the number of customers randomly accounted. This customer population X is obtained if we position a cell of size F independently, i.e., without taking the cluster structure into account.

3.2 Clusters and Subjective QoS

We define the subjective QoS as the call blocking probability seen by an arbitrary test customer in the observed area. It is intuitively clear that in the case of uniformly distributed customer population we have the best-case QoS. We expect that when the cell design is done without taking into account the customer cluster structure, the QoS will decrease in more bursty or more clustered environments.

With $x(i) = P(X = i)$ the probability $x^*(i)$ of the test customer to be in a population of $X = i$ customers becomes

$$x^*(i) = \frac{i x(i)}{\mathrm{E}[X]}. \tag{10}$$

Applying the well-known Engset-formula [4] leads to the conditional blocking probability of the test customer being in a cell with $X = i$ customers:

$$\begin{aligned} p_B(i) &= P(\{\text{test customer rejected} \mid X = i\}) \\ &= \frac{\binom{i-1}{K}\left(\frac{\alpha}{\mu}\right)^K}{\sum_{k=0}^{K}\binom{i-1}{k}\left(\frac{\alpha}{\mu}\right)^k}. \end{aligned} \tag{11}$$

Taking Eqns. (10) and (11) together, we arrive at the blocking probability of an arbitrary test customer, which is also the subjective QoS described above:

$$p_B = \sum_{j=K+1}^{\infty} p_B(i)\, x^*(i). \tag{12}$$

Since the Engset–formula already gives the *subjective* blocking probability, i.e. the probability to be blocked as seen by an arriving customer, in Eqn. (10) the distribution of the point process is appropriate; otherwise, its reduced Palm distribution must be used.

3.3 System Performance vs. Customer Clustering Phenomenon

Figs. 5 and 6 show the subjective Quality-of-Service for a cell with $K = 7$ and $K = 15$ channels, respectively. These numbers arise from typical cells in GSM systems. The expected number of customers within a cell was chosen such that assuming $\rho_M = 50$ *mErl* of offered traffic per customer leads to QoS of 0.1% for a constant number of customers in the cell. The general behavior of both systems looks very similar for all types of customer distributions. It can be seen that the difference between the deterministic and the Poisson case is quite small such that there is no large error if one assumes a fixed number of customers in the cell while the actual number is Poisson distributed. However, the QoS largely degrades if the customer population in a cell follows a negative-binomial distribution. The QoS being one order of magnitude larger for the negative-binomial distribution with $c = 1$ compared to the Poisson distribution which also has $c = 1$ shows that there is an impact of higher moments of the customer distribution. Consequently, it is not sufficient to fit the model by means of the first two moments of the customer population only. The type of the distribution has also to be taken into account.

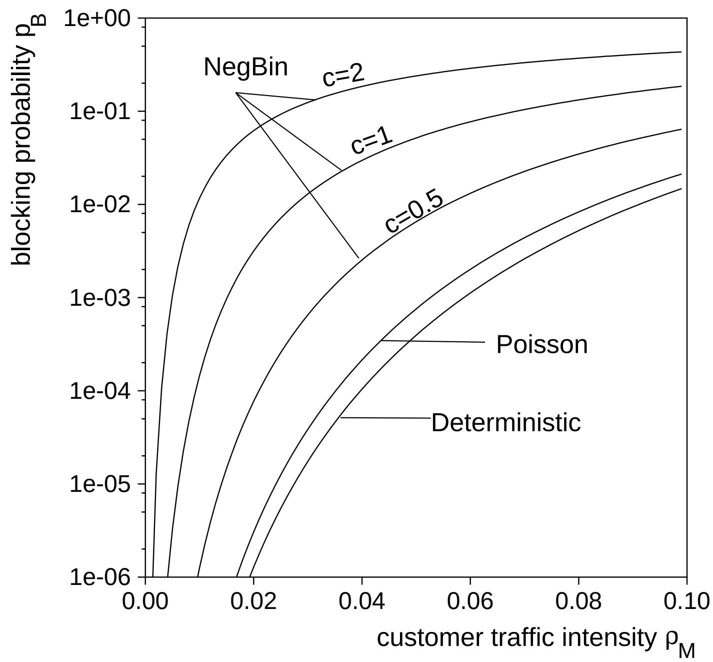

Figure 5: Impact of customer population on subjective Quality-of-Service ($\mathrm{E}[X] = 30,\ K = 7$)

3.4 Clusters and Customer Retrial

The cell model discussed in the previous section is now modified by replacing the two-state customer model with the repeated attempt model investigated in [12] and [13]. Now, a customer can be in one of the three states: Idle, Active and Wait-for-Reattempt (cf. Fig. 7). This new state models the time intervals between reattempts, which are shorter than those between fresh calls.

The customers stays in the Wait-for-Reattempt state for the time R with mean $1/\alpha_0$. If the call request is rejected, the customer will enter the Wait-for-Reattempt state with the retrial

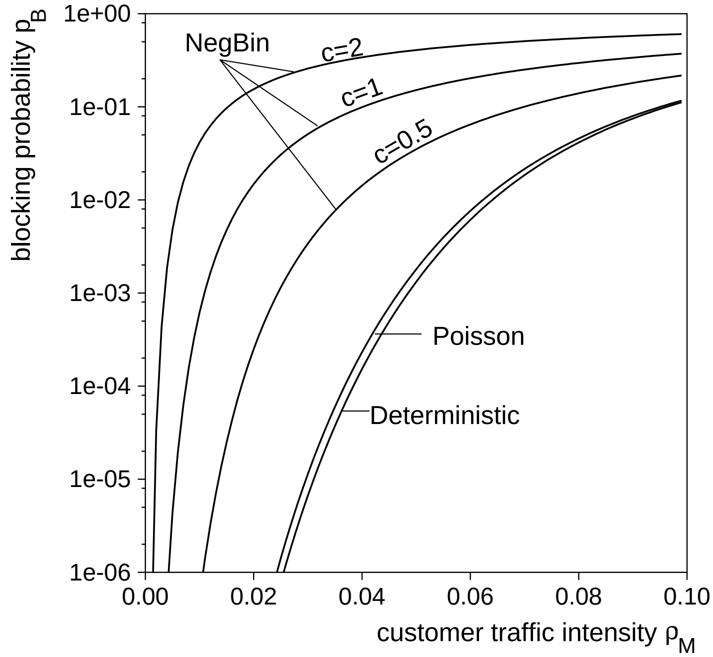

Figure 6: Subjective Quality-of-Service ($\mathrm{E}[X] = 130,\ K = 15$)

probability Θ or abandon the call and remain in the Idle state with the complementary probability $1 - \Theta$. When a call request has been rejected a customer will stay in this state before generating the next reattempt. When this reattempt is also rejected, the customer will reenter the Wait-for-reattempt state, again with the retrial probability Θ.

The detailed analysis of the subjective blocking probability of a customer in this case can be found in [12, 13], where the number of customers in a cell is constant. To obtain results for a clustered customer population, the probability of Eqn. (11) has to be replaced by the numerically obtained probability from [12].

Fig. 8 shows the QoS of a cell having $K = 7$ channels for retrial probabilities of $\Theta = 0.0, 0.3, 0.6, 0.9$ when the number of customers are distributed according to a Poisson and a negative-binomial distribution, respectively. Again, the expected number of customers in the cell was chosen such that the QoS is 0.1% if the number of customers is constant and the offered traffic per customer $\rho_M = 50$ *mErl*. The general behavior of the curves is similar to the case without reattempts. The reattempts start to affect the blocking probability in higher degree with the global load exceeding 1.0, which, in this system, is the case if $\rho_M > 0.19$.

The degradation of QoS can be seen more clearly in Fig. 9, which depicts the number of reattempts for all calls and completed calls, respectively, for $\Theta = 0.9$. Clearly, the minimum of attempts is 1. It can be seen that the number of attempts grows with the system load. This

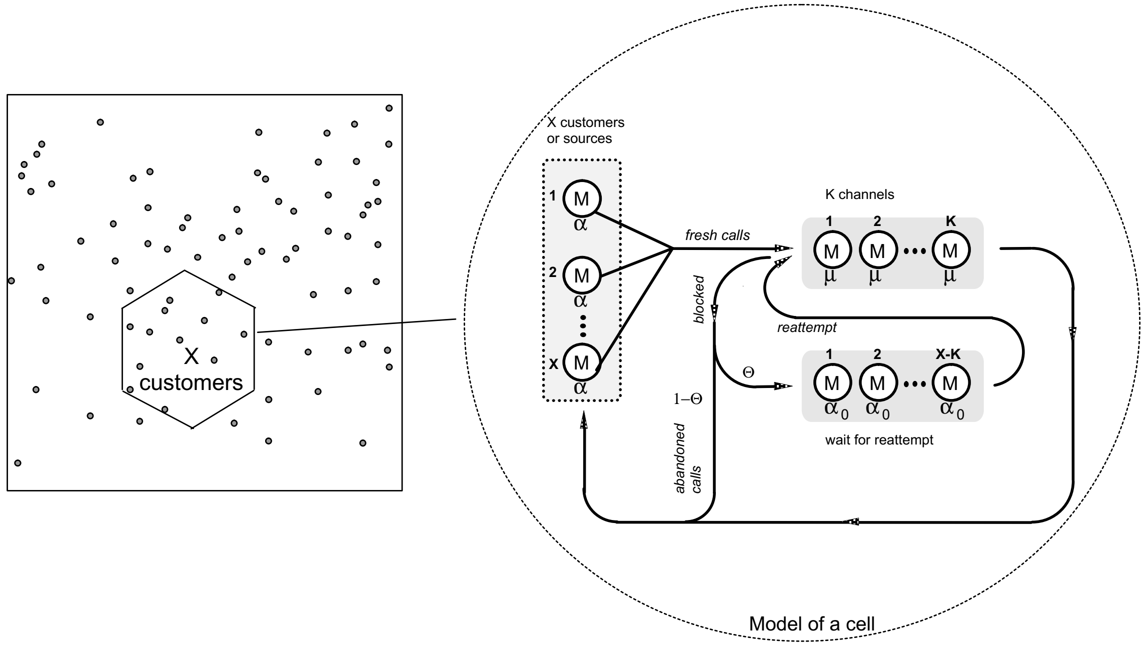

Figure 7: Repeated attempt model with clustered customer population

behavior is due to the fact that a growing load causes growing blocking probabilities which cause more reattempts which, in turn, rise the system load (avalanche effect). Incompleted calls have less attempts in the average compared to completed calls. The number of attempts to complete a call is much higher with a negative-binomial customer distribution with $c = 1$ compared to the Poisson distribution. Again, the type of distribution plays an important role.

4 Conclusion

In this paper we described the methodological aspects to include customer cluster effects in mobile network planning and the impact of clustered customer distribution patterns on network performance.

The first part dealt with basic questions, e.g. how to specify and describe two-dimensional cluster processes; a brief outline of results from Stochastic Geometry was given. The inclusion of cluster processes in cellular traffic models was presented subsequently.

The second part provides modeling examples to show how the cluster structure affects the performance of a cell in a mobile network. In this context, we considered the subjective Quality-of-Service, which is seen subjectively by a customer in a mobile network. Two model

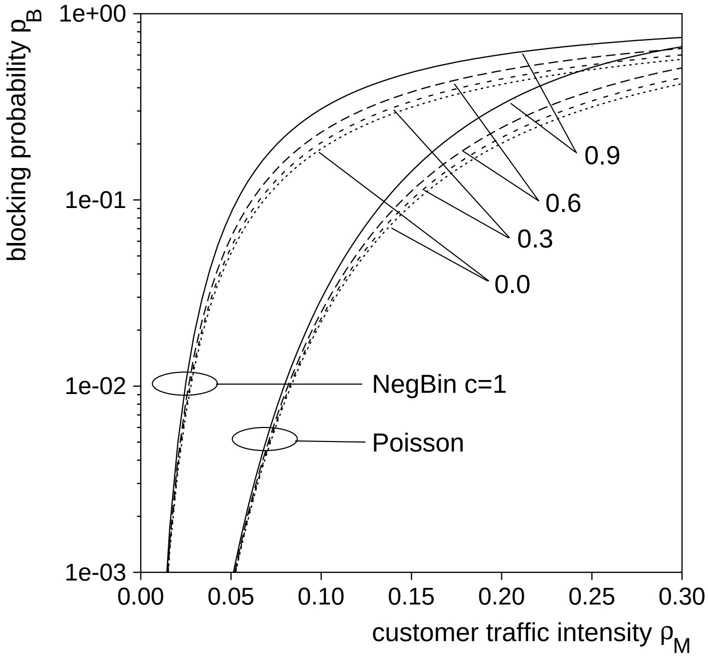

Figure 8: Customer cluster and retrial phenomenon vs subjective Quality-of-Service ($\mathrm{E}[X] = 30,\ K = 7$)

examples show the application of spatial point processes in traffic models. Both models indicate a degradation of the quality of service in terms of the blocking probability, when the customer population is clustered; in the case of the second model, a degradation in terms of the number of attempts to successfully complete a call is observed additionally. Furthermore, both examples show that for fitting a spatial point process model to a customer population it is not sufficient to fit the first two moments of the customer distribution only.

A drawback of the spatial point processes presented here is that they do not inhere a notion of time. For better traffic models one should fall back to space-time point processes which are discussed in stochastic geometry literature also (cf. [2]). Exploring ways to apply this processes in traffic models is subject to ongoing studies.

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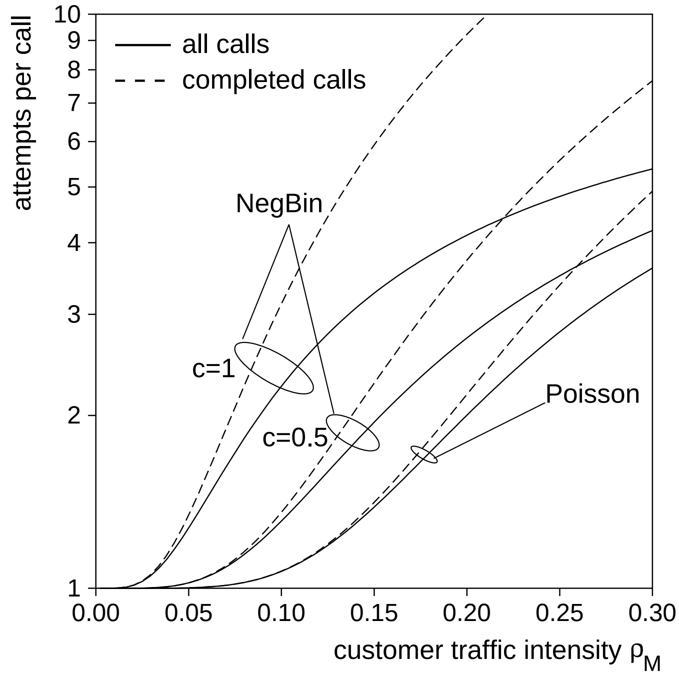

Figure 9: Influence of customer cluster distribution type ($\mathrm{E}[X] = 30,\ K = 7,\ \theta = 0.9$)

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