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Modeling mobility and workload for wireless metropolitan area networks☆

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Abstract

Research on large-scale wireless metropolitan area networks, which offer broadband capacity while supporting user and terminal mobility suffers from the lack of realistic mobility and workload models. There is a strong need for such models to be able to perform sound simulations supporting important yet difficult tasks like network planning and traffic engineering. In this paper, a novel approach towards realistic modeling of user mobility is proposed and studied. We formulate an analytical model, which is a hybrid of an empirical mobility model and a synthetic traffic model. The model clearly separates the influence of mobility and traffic to allow for greater flexibility. The mobility part is based on the combination of statistical zoning information with field data of movement patterns. This allows us to predict the density of users—classified into different groups—for a given area at a given time. We are able to integrate different traffic characteristics on top of our mobility model elegantly. The combination of user density with the predicted—synthetic—traffic of the modeled user groups gives the traffic and fluctuations of traffic throughout the network, thus describing the workload for the envisioned scenario. We present the instantiation of our model for the example of a real city. Analysis and simulations are provided which show that the proposed scheme is quite prospective. Our findings are, that our model is able to cover the macroscopic effects of real-world behavior more precisely than currently available mobility/workload models.

Keywords: Mobile communications; Wireless communication networks; Mobility modeling; Workload modeling; Metropolitan area radio access networks

1. Introduction

With the advent of the Internet, the quality of personal communications has changed significantly. The availability of a nearly ubiquitous communication platform and simple yet useful applications like e-mail, news or more recently instant messaging has attracted millions of users. Moreover, in a broader sense, the last century was significantly influenced by a trend towards personal mobility for the masses. The intersection of these trends gave birth to the area of mobile and wireless communication networks.

Today multiple technologies and frameworks compete for the market to support mobile communications: after the success of second generation cellular networks, the third generation specified within the IMT2000 framework is currently being deployed. On the other hand, there is a tremendous effort to build large-scale wireless networks based on wireless local area network technology—especially in the context of high-capacity usage. We think both technologies will proliferate—each one complementing the other for special applications—to fulfill both demands: personal mobility combined with ubiquitous communication capabilities at optimized traffic rates. These concepts are the foundation of fourth generation networks and the wireless Internet, embracing a heterogeneous set of radio access technologies, which gives rise to several interesting research challenges.

Induced by user and device mobility—while tightly coupled to usage and application-specific traffic

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patterns—future wireless metropolitan area networks will experience heavily varying loads on different timescales. Our goal is the investigation of resource management issues to deal with the predicted traffic demand of these networks. Here, we concentrate on solutions based on QoS routing mechanisms (see, for example, Refs. [1–3]). The system boundaries for our analysis are defined by the MobQoS scenario [4], which is derived from various concepts of the Internet communities and telecommunication industries [5–9].

We assume a three-tier architecture as depicted in Fig. 1(a). The mobile nodes (MN) or terminals are associated to wireless base stations, the so-called radio access points (RAP) representing the last hop of the provision network. The function of the first tier thus can be described as radio access. The second tier, the radio access network (RAN), comprises radio access servers (RAS), which are used to attach multiple RAPs. The RAS are meshed with neighboring systems and thus allow the start of resource management at this level. The core of the second tier is built by radio access routers (RAR). Between selected RAS and RAR there are uplinks. The transition to the third tier of the architecture, the core provider network, respectively, the Internet, is performed by one or more edge gateways (EGW).

This scenario reflects the paradigm change from strictly hierarchical topologies (see Fig. 1(c)), which are nearly homogeneous with respect to cell sizes and capacity in today's personal communication (PCS) networks, towards highly variable and meshed topologies including high bandwidth micro and pico cells. We assume our network to be a routing network beginning at RAS level as well (see Fig. 1(b)). Additionally, the set of applications used within such networks will yield different network traffic as in today's cellular networks—from constant bitrate voice communication towards a more Internet-like heterogeneous mix of traffic. Hence, we believe that today's mainly static resource management approaches need reconsideration.

Our work in the area of QoS routing protocols to allow for improved resource management concentrates on the effects induced on the data plane by user mobility. From these investigations, we derive the need for a more flexible and realistic mobility model than available in literature. As we will show, current mobility models suffer from various limitations: they are mostly restricted by the call- and connection-oriented paradigm of traditional cellular networks and lack the necessary degree of freedom and flexibility to reflect the future networks and services we want to investigate.

Our contribution lies in a novel mobility/workload model for wireless metropolitan area networks. We present in detail the fundamentals of our model, which is flexible with respect to parameterization of the user behavior while maintaining reasonable complexity. The model introduces a generic classification of locations and user behaviors, which allow the derivation of the aggregated effects of user mobility. We present the coupling of our mobility model with traffic predictions to form a workload model, as well. We provide the analytical description of the model. The formalization defines a toolset, which allows for easy implementation of our model in real metropolitan environments. The instantiation of our model is performed for an area within central Darmstadt, a German city of approximately 145,000 inhabitants.

The paper is organized as follows. In Section 2, previous and related work is surveyed. Section 3 describes the fundamentals of our model. This includes the modeling of locations and user behavior. Section 4 comprises the analytical description of our model. We give definitions as well as equations to exactly represent the model assumptions. In Section 5, we present the instantiation of our model and possible applications for networking

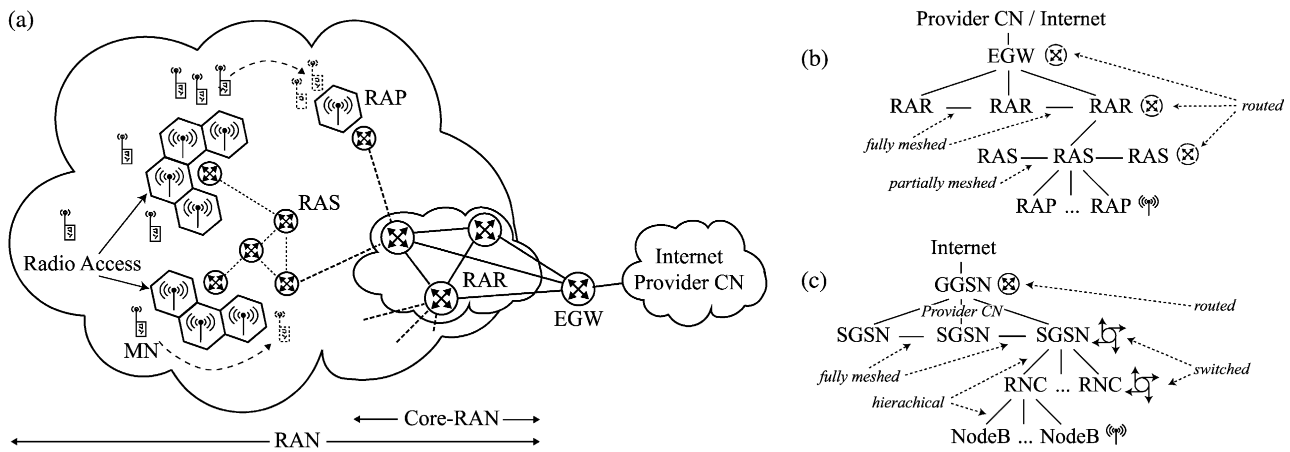

Fig. 1. (a) Scenario for a future wireless metropolitan area network. Conceptional model of: (b) the envisioned topology vs. (c) Traditional second and third generation topologies. Legend: CN, core network; EGW, edge gateway; GPRS, general packet radio service; MN, mobile node; RAN, radio access network; RAP, radio access point; RAR, radio access router; RAS, radio access server; RNC, radio network controller; SGSN, serving GPRS support node; GGSN, gateway GPRS support node.

research. The paper is concluded by summarizing the main results and discussing aspects of future research in Section 6.

2. Related work

There are different approaches towards realistic models for mobile communications. A fairly comprehensive survey on mobility modeling in wireless networks can be found in Ref. [10], a more detailed description of some random models in Ref. [11]. There is, however, no common scheme to categorize all dimensions of these models because they are so manifold. Within our work, we use a broad categorization into two classes: *microscopic* vs. *macroscopic* mobility models, since these two concepts cover the essential distinction with respect to our investigation.

- Microscopic mobility models describe the mobility behavior of individuals. They are often based on analytical descriptions of user movements. Most synthetic or random models fall into this class.
- Macroscopic mobility models describe the aggregated effects of mobility. They are often obtained using statistical data collection and thus inherently aggregate the behavior of individuals.

Within our context, we are interested to realistically model mobility at the scale of a metropolitan area. Given this viewpoint, we reviewed the following related work.

2.1. Microscopic mobility models

The class of random models is the most prominent example for microscopic models. Random models describe the movements of individuals. There are numerous models including the random walk model, the random gauss–markov model, the random mobility model, the markovian model, and the random waypoint model [11]. These models try to provide an exact analytical description of the behavior of individuals. Random models have been optimized for accuracy, [10] being one example. The characteristics of a generalized random model for cellular networks with respect to mobility patterns are studied in Ref. [12]. However, these models are not able to reflect macroscopic behavior and often exhibit undesirable properties if applied improperly [13].

Random models may operate on other levels to reflect group behavior as well [14]. However, the results, neither of individual mobility nor of group mobility do account for a city at large. This is mainly due to the mostly homogeneous nature of random models if aggregated thus leading to fairly equal distributions for large areas. If we, however, regard a real city, we observe numerous attractions and hot spots. These are likely to be crowded during short periods of time or over day while being empty during the night. It is, from our perspective, extremely unlikely, that pure random behavior fits such a scenario. There are some random models, which can be widely parameterized to match correct macroscopic behavior as well [15]. The correct instantiation for these depends on macroscopic models, nonetheless. Since the microscopic models violate our assumption of realism at metropolitan scale, we do not further investigate this class of models.

2.2. Macroscopic mobility models

Macroscopic mobility models try to match the aggregated user mobility within large areas. Models from transportation planning are often used as a basis for large-scale mobility models. TRANSIMS [16] is an example of a complex synthetical model. It creates a virtual region with complete representation of individuals and their activities. The transportation is modeled and trips are planned to satisfy the individuals' activity patterns. The behavior of individuals and the geometrical distribution of households is derived from census data. The focus of TRANSIMS is transportation planning. It would be possible to extend the framework to generate data that fits the needs of teletraffic modeling for wireless networks. However, this comes at the expense of a very complex overall framework which for example tracks the movements of all individuals and requires very hard calculations and extensive parameterization.

The comprehensive work of Lam et al. [17] presents and evaluates teletraffic models for metropolitan, national and worldwide scale. The work is based on results from transportation planning. The authors have been able to show that the model predictions can be validated using real world data. The focus lies—like in most work in the area of wireless teletraffic modeling—on the investigation of control plane issues like location management traffic. Therefore, the model does not include a distinction into multiple user types, effectively rendering it unusable for most parts of our intended model usage, which is coupled to data traffic.

A general work in the area of teletraffic models for urban environments can be found in Ref. [18]. The author investigates various types of cell structures and especially the influence of variation in the size of cells. Findings of Nanda [18] include the relation between handoff rate and cell size as well as between handoff rate and cell shapes. Despite the excellent results in the areas investigated, the work cannot be applied to our scenario, since it does not provide the necessary detail and flexibility of the user model. Ref. [19] limits its scope on the location management aspects of user mobility. However, the underlying mobility model presented makes uses of more detailed information of user behavior and activities, which are not further exploited. Moreover, the work borrows the concept of trips to describe the intention and whereabouts of users from work in the area of transportation modeling.

The work of Rocha et al. [20] uses a mobility model similar to the one in Ref. [19] and implements a graphical tool to support analysis of the results. The instantiation of areas and user behaviors is, however, very coarse and does not reflect realistic environments.

Ref. [21] describes a traffic model for "third generation cellular mobile telecommunication systems". Part of this model is a user mobility model described in Ref. [22], which is based on the average distance and average velocity of users. These parameters are estimated for certain environments including multiple classes of outdoor environments and different vehicles. The work is limited to the estimation of cell border crosses to predict handoff rates and call durations. While in Ref. [21] the geographical instantiation models a manhattan grid model of a city center using relatively coarse characteristics for zoning information, Ref. [22] presents background information on mobility modeling and a comparison to classic area zone models for teletraffic modeling including Ref. [23]. Other work in this area includes Refs. [24,25], which address additional aspects of area zone models and Ref. [26], which describes a novel stop-or-move mobility model to address some shortcomings of purely random models.

Another group of models for large-scale networks relies on the analysis of existing infrastructures and network traces. In particular, work which investigates large-scale wireless radio access topologies for data traffic with respect to user mobility has been proposed only recently. The work of Tang and Baker [27] is able to provide deep insights on user behavior for a metropolitan area wireless network. The work of Kotz and Essien [28] claims to be the largest and most comprehensive real world trace of a production Wireless LAN. The results, however, do account for a special campus style network and mainly focus on traffic analysis—the mobility aspect is restricted by the campus setup and thus cannot be transferred to public networks. Balachandran et al. [29] concentrate on network performance of small-scale networks, which are not representative for the metropolitan scale.

There are two critical points about trace-based methodologies. First, they only account for services already deployed and in use and particularly only count 'early adopters'. This is especially true if we regard wireless RANs for data communication at the time of writing. Second, the results often cannot be separated into mobility and traffic related parts, thus prohibiting the parametrization of individual factors for simulation.

2.3. Conclusions

While current approaches including Refs. [17,18] focus on handoff rates and other parameters coupled to the number of handovers and user numbers within given cells, they do not differentiate between different classes of users and traffic demands. The activity-based mobility models described in Refs. [19,20,22] provide for some basic mechanisms, which may be used for our purpose. The formulation of these models and their instantiation is, however, not optimized for data traffic analysis but for classical teletraffic applications.

In summary, random models do not account for mobility within large areas and the existing macroscopic models are either too restricted for our purpose or too complex for the intended application. The empirical studies of wireless LANs are limited with respect to the strict decoupling of mobility and traffic. Thus, we decided to develop a novel model to fit the needs of the described scenario. We borrow concepts from transportation planning to realistically cover macroscopic areas, such as, for example, a center of a large city.

3. Fundamentals

Our model is developed in the context of transportation and land use modeling [30,31]. We use the well-known travel demand modeling approach described in Ref. [30] and also used in previous work including Refs. [19,20,22].

The basic elements of activity based transport modeling are the *trip*, which defines the movement of a user from an origin to a destination, and the *zone*, which defines areas with a certain attraction level. Trips are based on the intended behavior of users while zones represent homogeneous areas with respect to socio-economic characteristics. The size of zones can range from a few hundred square meters to several square kilometers in size.

This basic model has been used since the 1960s to forecast travel demand and various techniques and submodels have been developed for determining the variables for each of the elements of travel demand modeling. It is important to keep in mind that the developed model represents aggregated information of users and zones only. Thus the model is well-suited for investigations covering macroscopic effects.

3.1. Trip generation

The trip generation estimates the total number of trips that depart and arrive in a specific zone. In particular, trips are classified by trip purpose, such as work or shopping, for example. The purpose is derived from the intended user behavior. The corresponding trip is scheduled to a location where this intention can be fulfilled, like, for example, a workplace or shopping mall. The generated trips need to be distributed to the destination zones according to the attraction of these zones, which is determined by socio-economic characteristics. Moreover, a modal split accounts for different transportation modes such as car, bike or subway. According to a trip assignment the individual trips are mapped to the transportation infrastructure and the best route is calculated.

We are primarily interested in the user densities for given zones. This allows us to omit the determination of modal splits, trip assignment, and route calculation, which reduces the model complexity significantly. To allow for the remaining trip generation and distribution, our model needs to classify locations and user behavior. Upon instantiation, real world data needs to be fitted to match this classification scheme. Finally, we are able to calculate the user densities for given zones.

3.2. Classification of locations

The classification of locations has to reflect their different attraction levels over time. A reasonable granularity can be reached by assigning a base attraction level to a zone. The base attraction level is set depending on basic characteristics of the location. *Residential areas* and *workplaces* (we distinguish into industrial and office workplaces) account for the major fluctuation of users. Moreover, the attraction of *commercial*, *recreation*, and *education* facilities is an important factor. These types of locations are further refined as follows. Commercial locations include shops and shopping malls; recreation includes theatres and opera, museums, cinema, sport events, bars, and pubs. Education places can be further classified into schools and universities. A special location called *transport* accounts for users on the move. We assume zones of reasonable size, like those given in most zoning plans for city development. Moreover, the zones should be homogeneous with respect to the attraction of the different locations within each zone, which is usually also true for public zoning information. See Fig. 2(a) for a detailed classification of locations. Please note that the classification is non-exhaustive to keep the level of complexity reasonable.

The accuracy of the approach may be increased if extra information about special places such as shopping malls, schools, universities, and sights possibly located in the zone is combined with the base attraction. This refinement comes at the expense of insider knowledge being necessary, though.

3.3. Classification of users

The most important criterion for the user classification is to adequately characterize the behavior of types of individuals. The intentions of the resulting groups need to match the attracting locations as well. The availability of information about the constitution and behavior of the derived groups to allow for proper instantiation is another crucial factor. This includes information to allow for case discrimination, in particular to predict state transition or inactivity of users. Resulting from this information, we are able to predict the aggregated impact of user mobility.

We differentiate the following types of users (roles): *residents*, *workers*, *consumers*, *trainees*, and *travelers*. Residents are the main group of interest during evening and at night. We distinguish between inactive residents (sleeping at home) and active ones (being at home). The role of a traveler accounts for the state transition between other states. For example, if a resident departs for a shopping district, he becomes to a traveler before finally taking the role of a consumer.

We discriminate consumers into buyers and visitors in order to separate shopping activity from leisure. The latter ones have to be distinguished into daily and nightly visitors (idlers) to model the different locations of recreation facilities as for example museums, swim-hall, and shopping during day or cinemas, theatres, and pubs in the evening. The numbers for daytime visitors includes tourists as well.

The number of trainees, namely pupils and students, usually cannot be neglected, nor can the number of workers. The class of workers is divided into different sub-classes which account for different zones in which they perform their job (commercial zone, industrial zone, etc.) and for expected differing professional communication behavior (e.g. mobile personnel use the communication network to carry out their job while an office or industrial worker communicates in breaks or on his way to/from work).

Besides their function as intermediate state, the travelers represent the number of people just crossing the investigated area by car, commuting to external work places or from external housings to internal workplaces/universities. See Fig. 2(b) for the classification of user behavior.

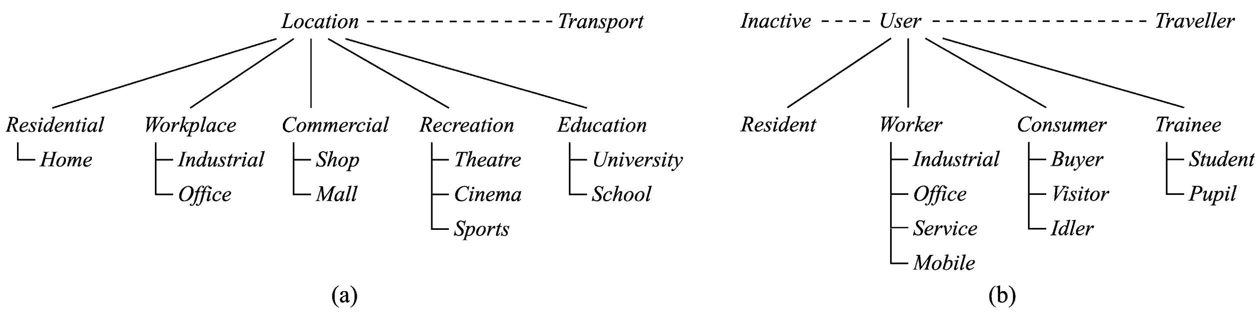

Fig. 2. (a) Classification of locations; (b) classification of user behaviors.

4. Model

Our model distinguishes between user and traffic related issues. It is based on the classification of zones, cells and locations (see Section 3.2) and the classification of users and behaviors (see Section 3.3). Using these prerequisites user mobility can be modeled as follows. Let

$Ar = \{residential, workplace, commercial, recreation, education, transport\}$ denote the set of types of locations.
$B = \{resident, worker, consumer, trainee, traveller, inactive\}$ denotes the set of behaviors.
$Z = \{z_1, z_2, \ldots, z_n\}$ denotes the set of zones. Zones do not overlap in space. The union of all zones z_i, $i = 1, \ldots, n$ covers the whole area of interest.

To allow for a mapping of locations to a cell-based network infrastructure let

$C = \{c_1, c_2, \ldots, c_m\}$ denote a set of cells.

The model should predict the number of users with behavior b, which can be expected in a zone/cell at given time t. Let

$U_b(t) =$ the total number of users with behavior b at time t. $u_{z,b}(t)$ denotes the time-dependent number of users with behavior b within zone z.

$$U_b(t) = \sum_{z \in Z} u_{z,b}(t) \text{ and } U(t) = \sum_{b \in B} U_b(t) \tag{1}$$

$U(t)$ might vary over time. During night, most users will be inactive, for example. They change their role to active residents after getting up and eventually to a worker, consumer, or trainee. In between they are modeled as travelers. To account for the *fraction of users* being active in a role b, we define a time-dependent split factor per behavior $f_b^u(t)$. In reality, the maximum number of users in the system is variable, because commuters and travelers may enter and leave the system over day. To simplify calculations, we assume a fixed maximum number of users U including all users possibly entering the system. If not present in the system, these users are modeled as inactive residents, which do not further contribute to the performed calculations. Please note, that $f_b^u(t)$ is independent from the location.

$$f_b^u(t) = \frac{U_b(t)}{U}, \text{ with } \sum_{b \in B} f_b^u(t) = 1 \text{ for all } t \tag{2}$$

Using $f_b^u(t)$ we calculate

$$U_b(t) = U f_b^u(t). \tag{3}$$

$A_b(t)$ denotes the activity of users (that is, they emit traffic) with behavior b at time t. $a_{z,b}(t)$ denotes the time-dependent activity of users with behavior b in zone z.

The user population $U(t)$ needs to be assigned corresponding to the *attraction* of locations within zones. We use a zone- and behavior-dependent split factor $f_b^a(z)$ to account for this property. With $f_b^a(z)$ we are able to calculate the number of users $u_{z,b}(t)$ within each zone.

$$u_{z,b}(t) = U_b(t) f_b^a(z) \tag{4}$$

To convert the number of users into the corresponding activity, we introduce the notion of intensity i_b, which models the fraction of time a user dedicates to communication purposes. Activity thus denotes the sustained number of communicating users. For the sake of simplicity, i_b may be combined with the traffic-part of a workload model and neglected in the mobility part. For maximum flexibility of the mobility model, it would be possible to introduce a time and zone dependent version of i_b, $i_b(z,t)$. The activity is

$$a_{z,b}(t) = u_{z,b}(t) i_b = U_b(t) f_b^a(z) i_b = U(t) f_b^u(t) f_b^a(z) i_b \tag{5}$$

with $\sum_{z \in Z} f_b^a(z) = 1$.
We obtain

$$A_b(t) = \sum_{z \in Z} a_{z,b}(t) = \sum_{z \in Z} u_{z,b}(t) i_b. \tag{6}$$

Moreover,

$$A(t) = \sum_{b \in B} A_b(t). \tag{7}$$

The next step is the transformation of the results from zone to cell level. We use a network model similar to Ref. [24]. The shape of cells is hexagonal. We assume that p cells are arranged in $(2r-1)$ columns. Fig. 3(a) shows that we obtain r columns of k cells and $(r-1)$ columns of $(k-1)$ cells. The total number of cells can be calculated as $p = rk + (r-1)(k-1)$. This cellular structure is overlaid on the zone-based area of investigation.

To be able to transform the results from zone to cell granularity, let s_z be the size of zone z and s_c be the size of cell c. Let $r_{c,z}$ denote the fraction of zone z, which is covered by cell c. Assuming an equal distribution of attraction levels within zones, we are now able to transform the results using

$$a_{c,b}(t) = \sum_{z \in Z} \frac{a_{z,b}(t)}{s_z} s_c r_{z,c}, \text{ with } \sum_{z \in Z} r_{z,c} = 1. \tag{8}$$

Using Eqs. (5) and (8) we can calculate the individual $a_{c,b}(t)$, which forms the user activity matrix $A_{c,b}(t)$.

$$A_{c,b}(t) = \begin{bmatrix} a_{1,\mathrm{resident}}(t) & a_{1,\mathrm{worker}}(t) & \cdots & a_{1,\mathrm{inactive}}(t) \\ a_{2,\mathrm{resident}}(t) & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots \\ a_{p,\mathrm{resident}}(t) & \cdots & \cdots & a_{p,\mathrm{inactive}}(t) \end{bmatrix} \tag{9}$$

Please note, that the model described above can easily be extended to reflect more details of user behavior or location attributes. For example, it would be possible to model

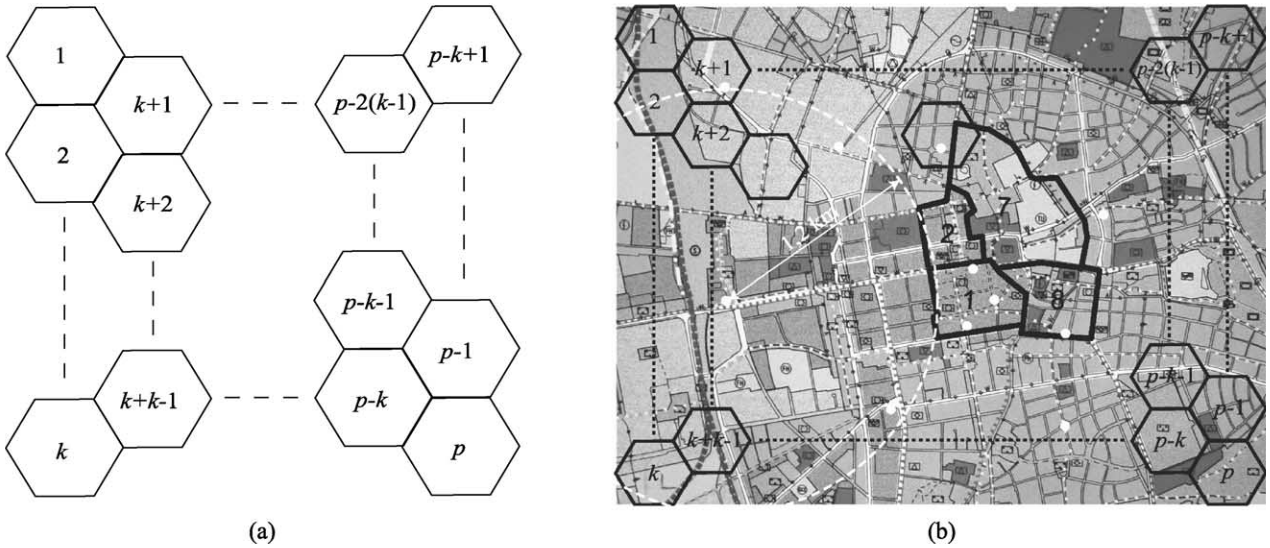

Fig. 3. (a) Network system model; (b) excerpt of the instantiation for Darmstadt, including the modeled cell vs. zone size and comparison to the coverage of the base stations of an actually deployed GSM network.

the time varying aspects of user activity by introducing $f_b^a(z,t)$. Another extension we do not describe within this paper is the adaptation of $f_b^u(t)$ to account for additional influences as for example workers being on sick leave, etc.

The user activity matrix $A_{c,b}(t)$ can be separated into time and location dependent factors. We are particularly interested in what we call the user activity and user density charts, which can be combined with a time-dependent traffic rate to form the workload for a wireless network. The user activity chart represents the number of active users per time-interval while the user density chart denotes the number of users for a given cell.

Since we use discrete cells and time-intervals during instantiation, we obtain the user activity chart as

$$A_b(t) = \sum_{c \in C} a_{c,b}(t) \qquad \text{for all time-intervals.} \tag{10}$$

The user density chart can be represented using

$$U_{c,b}(t) = U_b(t) f_{c,b}^a \text{ with } f_{c,b}^a = \sum_{z \in Z} \frac{f_{z,b}^a}{s_z} s_c r_{z,c}. \tag{11}$$

Let $M = \{m_1, m_2, \ldots, m_i\}$ denote a set of traffic classes and $r_b^m(t)$ be the time-dependent traffic rate of users with behavior b in traffic class m. We are able to augment traffic estimates for different classes of users to form a workload matrix $W_c^m(t)$ for each traffic class m.

$$W_c^m(t) = \sum_{b \in B} a_{c,b}(t) r_b^m \tag{12}$$

Using Eq. (12) we are able to calculate the daily workload as well as the time varying loads for each traffic class m. The resulting traffic accounts for the traffic initiated from specific cells. The distribution of the destinations of this traffic can be performed as appropriate.

5. Instantiation and application of the model

In this section, we give a brief introduction of the instantiation of the model. A detailed description of the instantiation for the city of Darmstadt, Germany and the resulting mobility and workload matrices can be found in Ref. [32].

5.1. Instantiation of the model

Modeling of locations is based on zoning information usually found in zoning plans for city development. The important property of zoning information is that the zones describe nearly homogeneous areas with respect to our location criterion. Most importantly, public data as well as census data usually applies to the level of granularity of zones. This gives exact information of numbers of work places, residents, etc. The granularity of data available suited our model nicely in most parts. In particular, public information included the number of residents with main and second address. Residents are additionally indexed by age (which can be used to classify pupils and students) and social state (working/not working). The detailed information about workplaces was available for all zones, too.

For the classification of user behavior, we needed more precise information than available solely using census data. While the distribution of users into the proposed classes can be achieved using public census records, we needed further information to characterize the time-dependent nature of trips. Fortunately, these shortcomings can be addressed using public time budget studies. The ones available for Germany provided by the German Federal Statistic Office are of extremely fine-grained level of detail, though. Therefore, we used

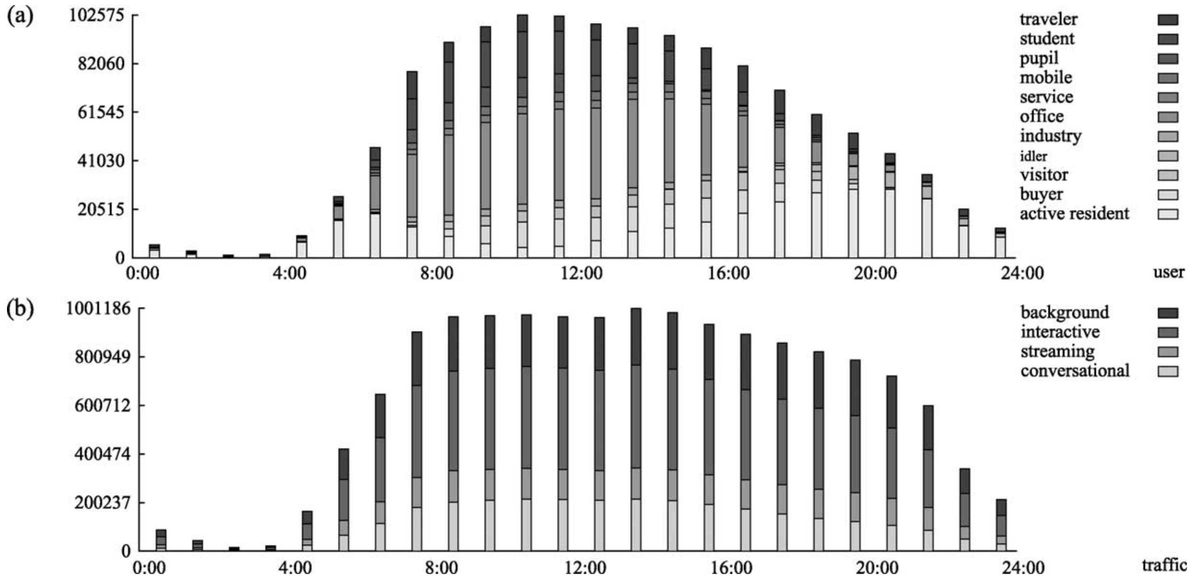

Fig. 4. (a) Summarized number of active users over time; (b) summarized workload over day (in kB/s).

secondary sources, which already interpreted these studies. In addition, we have been able to access trajectories of personal activities for various German cities. These have been available upon request at the municipality of Darmstadt for nonprofit use.

Using the above-mentioned sources, we have been able to instantiate our model for Darmstadt, a German city of around 145,000 inhabitants. We needed to perform significant post-processing. The zones available in the zoning plan are for example of arbitrary shape and size and needed to be manually processed to fit the proposed cell structure. Moreover, special locations have been modeled using our intimate knowledge of the city. Gathering data for these special places proved to be very labor intensive.

Some graphical results of the instantiation are given below. Fig. 3(b) shows the zoning plan of the modeled area—the city center of Darmstadt. The arbitrary shape of some zones (black) from census data is drawn alongside with the cells (black hexagons) of our model and the base stations of a currently deployed GSM network (white circles; we use an approximated cell radius of 1.2 km to depict the cell size).

A user activity chart for all users and user groups is depicted in Fig. 4(a). It shows the summarized number of active users over the day being modeled. We see low user activity in the early morning. Starting from 4:00 h in the morning, the number of active users increases as people get ready for work or are on their way to work. From 8:00 h on most people are up and active. We have observed that the geographical distribution of user density changes significantly over day, due to the different activities pursued by the different users. This shift in density can be seen especially from residential areas to workplaces. The decrease in the evening is not as abrupt as the increase seen in the morning. Nevertheless, the focus is changed from work to residential areas.

The combination of the user activity with the prediction of the traffic caused by this results in the summarized workload which is illustrated in Fig. 4(b). Because users in different classes produce different load, the peak traffic value does not correspond directly with the peak value of user activity.

As we noted earlier, our traffic distribution is dependent on the geographical location. Fig. 5 presents the corresponding density chart of user activity at cell level. The depicted values account for the projected aggregated user activity for all active users from 12:00 to 13:00 h. The activity is given in user-hours. The city center of Darmstadt consists of office and shopping facilities and large parts of the university while the region in the east is mainly covered by industrial areas. It is clearly visible, that the city center and the nearby university attract most of the users. Fig. 6 shows the density of active residents for the time period from 20:00 to 21:00 h. At that time, the main residential areas are clearly visible in a belt surrounding

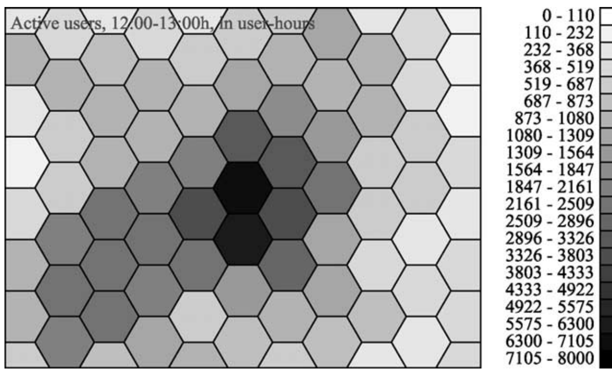

Fig. 5. Density of active users, 12:00–13:00 h (in user hours).

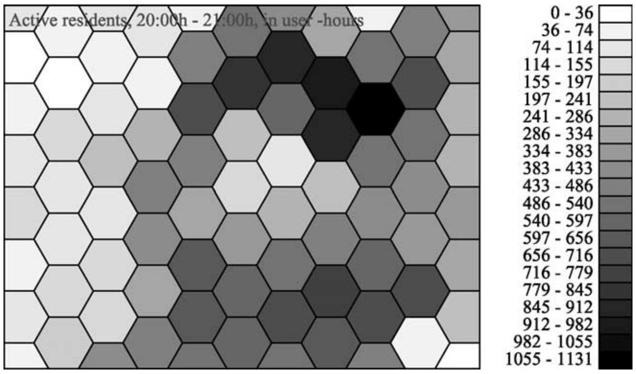

Fig. 6. Density of active residents, 20:00–21:00 h (in user hours).

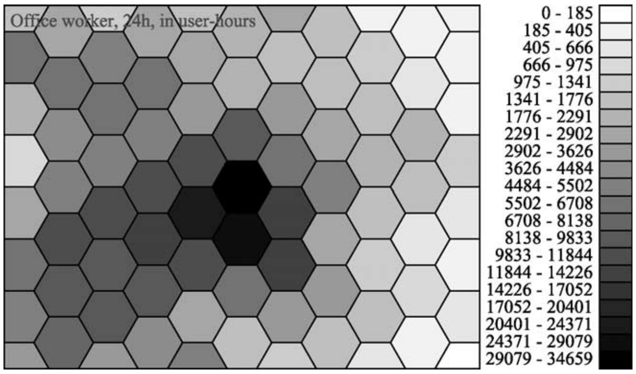

Fig. 8. Density of office workers over 24 h (in user hours).

the center of the city and in the west of the city. The center itself is only populated with few residents at the time of the presented snapshot.

Investigation of the busy hour of the network for all individual cells reveals, that within approximately 20% of the area we expect roughly 50% of the active users causing 44% of the total traffic. Within approximately 50% of the area, we expect 78% of the active users causing 76% of the total traffic. This clearly backs our initial assumption that the heterogeneity within fourth generation networks demands for adequate access technology like, for example, hot spots to provide for high capacity within selected areas. An animation of the time fluctuation of the user, respectively, traffic density over day can be found at Ref. [4].

Figs. 7–9 depict the activity values of some selected user groups for the complete day. While the consumers (see Fig. 7) are concentrated in the shopping areas of the city center, the office workers (see Fig. 8) are spread over the colocated office buildings in the same area and the district south east of the center. The image for the trainees (see Fig. 9) shows a different distribution: Darmstadt University of Technology, which is located in the city center and Darmstadt University of Applied Sciences located south east account for most activity while the pupils are nearly uniformly distributed throughout the city.

5.2. Application of the model

We used the workload model to perform an experimental analysis of a set of QoS routing protocols within a prototypical metropolitan wireless RAN [33]. The goal was to investigate the load-balancing capability of the routing strategies studied. The investigation included combinations out of the sets {static, dynamic}, {single-path, multi-path} and {distance, delay} algorithms. We used five different traffic distributions (external vs. internal traffic) with the four traffic classes {conversational, streaming, transactional, background} from Ref. [9]. We built a proprietary simulation environment which is based on ns-2 [34].

We now present some results of our study. The entire set of results can be found in Ref. [33]. We compare the delay of a measurement stream from a residential area to the city center. Fig. 10 depicts the scatter-plot of the delay of individual packets over 24 h for (a) a single-path algorithm and (b) a multi-path algorithm. Packets, which are dropped, are marked in gray. The single path algorithm 'fails' if the backbone is under heavy load. The loss increases and the delay is as high as 21 ms. The rise is relatively abrupt and the decline is smoother. This is due to the traffic load, which is similarly shaped. The delay-constraint multi-path algorithm has only short periods of time where the increase in delay and loss is considerable, albeit a few packets reach a delay of 33 ms due to the choice of prolonged paths.

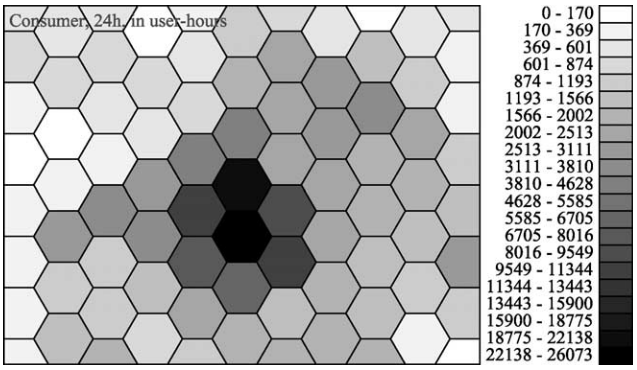

Fig. 7. Density of consumers over 24 h (in user hours).

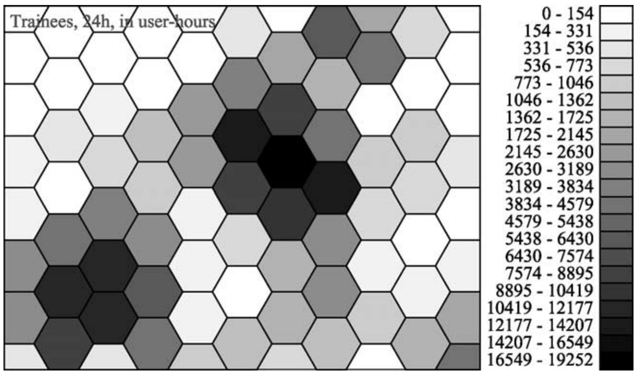

Fig. 9. Density of trainees over 24 h (in user hours).

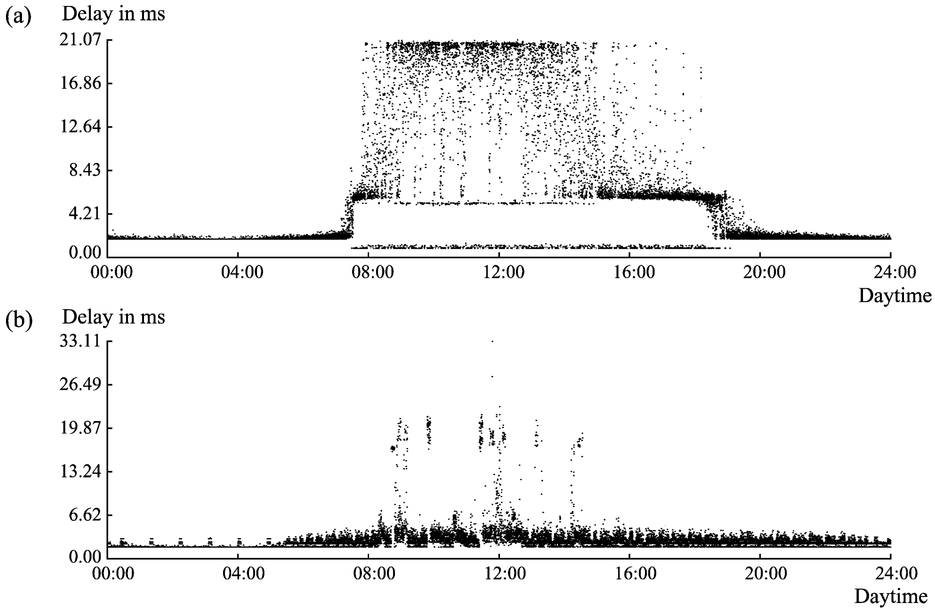

Fig. 10. Delay (in ms) of individual packets in a measurement flow from a residential area to the city center: (a) shortest path algorithm; (b) delay constraint multi-path algorithm.

6. Conclusions

We presented a novel approach towards a mobility model based on statistical data collection covering the macroscopic effects observed within metropolitan areas. After surveying the current state of the art approaches towards mobility modeling, we formulated a novel model to fit the special needs of metropolitan areas in the context of heterogeneous wireless RANs.

Our model borrows from models used for transportation planning while emphasizing the aspects needed for investigations on traffic related issues of wireless communication networks. The fundamentals of this model, the classification of the locations as well as the user behavior, have been described in detail.

Based on the above mentioned concepts, we derived and explained the analytical description of our model. We gave detailed definitions and equations to capture the model prerequisites and to allow for easy instantiation. Moreover, we gave information necessary to augment the results of the mobility model with traffic predictions to form a workload model for wireless metropolitan area networks. A transformation of the results to fit a cell-based networking infrastructure was presented, too.

In related work, we applied our model to serve as workload for a comparative analysis of quality of service routing strategies in wireless metropolitan area networks. The results of the investigation are based on the instantiation of our model for Darmstadt [32] and can be found in Ref. [33]. Lessons learned with respect to the instantiation of our model include that data which was not intended to serve as a basis for network traffic analysis needs significant post-processing, depending on the granularity of data available.

We perceive the combination of our approach with microscopic synthetic models as a further interesting research direction. One possible application would be the modeling of large-scale metropolitan ad hoc networks. The major advantage of such a model being the realism for both, microscopic and macroscopic analysis.

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