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A Hybrid Workload Model for Wireless Metropolitan Area Networks

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Abstract—**Wireless local and metropolitan area networks are en route to complement 2nd and 3rd generation cellular networks to provide for broadband wireless access for mobile users. The characterization and generation of realistic workload is important to allow for accurate network planning and traffic engineering. In this paper, we present the instantiation of a novel workload model, which is a hybrid of an empirical mobility model and a synthetic traffic model. We focus on the effects which are induced by user mobility. The model clearly separates the influence of mobility and traffic to allow for greater flexibility. Thus, we are able to integrate different traffic characteristics on top of our mobility model elegantly. We present results for the example of a real city and compare our model to existing synthetic models. Our findings are, that our model is able to cover the macroscopic effects of real world behavior more precise than currently available workload models.**

Keywords—Workload model; mobility model; simulation; radio access network.

I. INTRODUCTION

The characterization and generation of workload is crucial to allow for accurate network planning and traffic engineering. To allow for proper prediction of the load to be observed within wireless local and metropolitan area networks, we need to consider load fluctuations induced by traffic variability as well as induced by user mobility. Currently, there are fairly accurate models to describe traffic variations. However, there is a lack of mobility models which represent realistic user behavior for macroscopic scenarios, like for example for a city at large. The collection of statistical data from information related to personal mobility can aid in developing accurate mobility models. We believe, that these may overcome restrictions of synthetic workload models currently in use.

Our goal is to investigate the influence of user mobility for future wireless radio access networks. We are particularly interested in load balancing or quality of service issues to deal with the predicted traffic demand of future wireless networks. We concentrate on the effects induced on data traffic by user mobility. Our work is not about devising models to evaluate teletraffic properties in the traditional sense, like call arrival rate, call blocking rate, handoff rate, and rate of location updates, which are determined by the connection-oriented nature of telephony applications.

The contribution of this work lies in the instantiation of our macroscopic mobility model [1] which is performed for an area within central Darmstadt, a city of approximately 145.000 inhabitants. The results in the area of user mobility are combined with realistic traffic models to constitute the workload.

The paper is organized as follows. Previous and related work is surveyed in Section II. The theoretical foundations of our model are briefly explained in Section III. Section IV gives the detailed description of the instantiation process of the model using real world data. Section V contains the analysis of our results. This includes the evaluation of our model against existing synthetic ones as well as implementation issues. We finish by drawing conclusions and by pointing to possible future work.

II. RELATED WORK

Related work encompasses empirical and synthetic approaches to describe user mobility and workload. The empirical models are based on real network and mobility traces, while the synthetic approaches mostly use purely random behavior to characterize the movement of single users or groups of users. A fairly comprehensive survey on mobility modeling in wireless networks can be found in [2], a more detailed description of some synthetic models in [3].

Recent empirical models include the work of Tang and Baker [4] which is able to provide deep insights into user behavior for a metropolitan area wireless network. The work of Kotz and Essien [5] presents real world traces 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. Balanchandran et al. [6] concentrate on network performance of small scale networks which are not representative for the metropolitan scale.

Existing synthetic models for macroscopic usage often borrow concepts from transportation planning (see for example [7]). Recent approaches for such models, including the work from Lam et al. [8] and Nanda [9], focus on handoff rates and other parameters related to the number of handovers and user numbers within given cells. These do not differentiate between different classes of users and traffic demands. The activity

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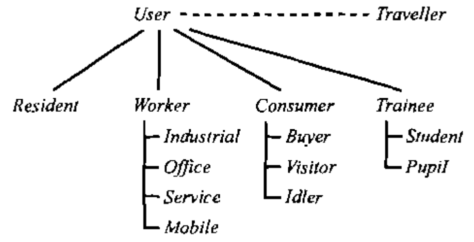

Figure 1: Classification of active user roles

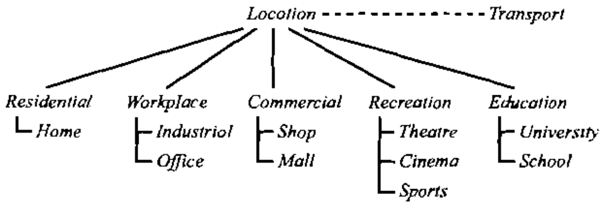

Figure 2: Classification of locations

based mobility models described in Scourias and Kunz [10], Rocha et al. [11], and Markoulidakis et al. [12] provide for some basic mechanisms which may be used for our purposes. The formulation of these models and their instantiation is however not optimized for data traffic analysis but for classical teletraffic applications.

The scope of synthetic models aims at microscopical user behavior and thus they mostly do not account for a city at large. Empirical models on the other hand only include users already "on-air" which use already deployed services (in current models mainly fixed bandwidth telephony within cellular networks), thus omitting future services and applications as well as users being currently "off-air".

Our model combines the realism of empirical mobility models with the flexibility of synthetic traffic models. This considerable gain in adaptability of the resulting hybrid workload model comes however at the expense of extensive empirical surveys to obtain the necessary statistical input data.

III. Macroscopic Workload Model

Our model [1] distinguishes between user and traffic related issues. We account for user mobility using movement patterns, so called trips, which define the movement of a user from an origin to a destination. The set of users is classified to describe their behavior.

Users may be active in one role (see Fig. 1) including residents at home, students, office or service worker, etc. or inactive during rest periods. Trips are based on the intended behavior of users which are attracted by certain locations (see Fig. 2). We divide the investigated region of interest into zones which represent homogeneous areas with respect to socio-economic characteristics. Zones are described by multiple properties: number of workplaces, number of residents, etc. as obtained by communal zoning plans.

Since the zones attract users—corresponding to their current role—we finally obtain the user distribution for all zones and

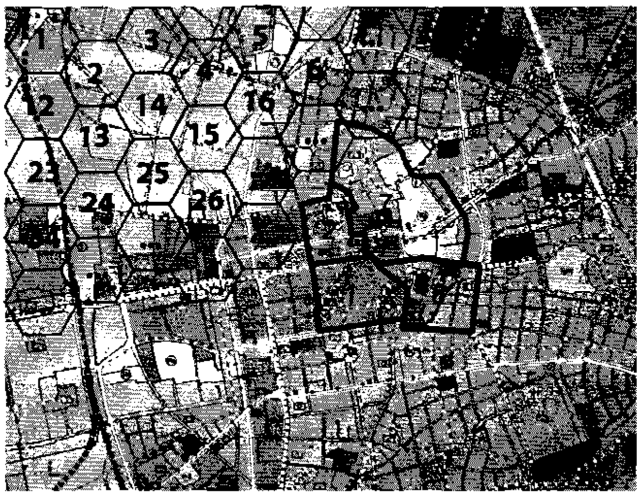

Figure 3: Modelled part of the city of Darmstadt; zones vs. cells

their variation over time. The combination of the user distribution with traffic models describing the traffic induced corresponding to the different roles results in the workload on the network. Hence, it is possible to independently investigate mobility and traffic related problems using the proposed model.

The model equations are given in [1]. The individual steps of the modeling process include:

- Classification of users and behaviors B.
- Classification of zones z, cells c and locations Ar.
- Calculation of the time-dependent number of users with behavior b within zone z.
- Calculation of the time-dependent activity a of users with behavior b in zone z.
- Transformation of the results from zone to cell level.
- Classification of traffic classes m per user behavior.
- Calculation of the workload matrix w_c^m.

IV. Instantiation of the Workload Model

We present a typical 24 hour day within our model. The instantiation of the model is performed using statistical field data. 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 on the numbers of workplaces, 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

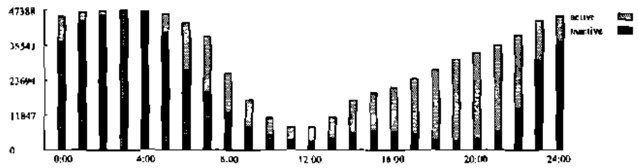
Figure 4: Overall number of active/inactive residents over 24 hours

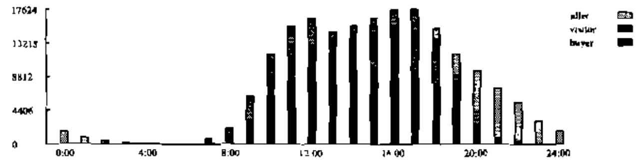
Figure 5: Overall number of consumers over 24 hours

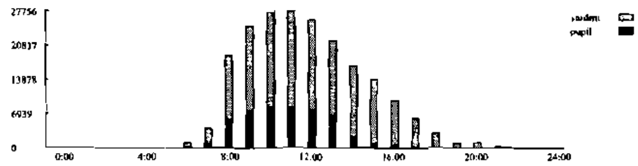
Figure 6: Overall number of trainees over 24 hours

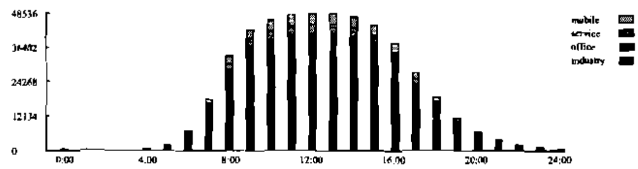
Figure 7: Overall number of workers over 24 hours

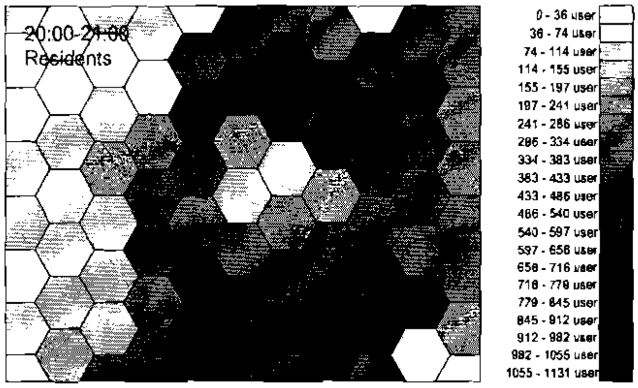
Figure 8: Active residents in Darmstadt from 20:00 to 21:00h

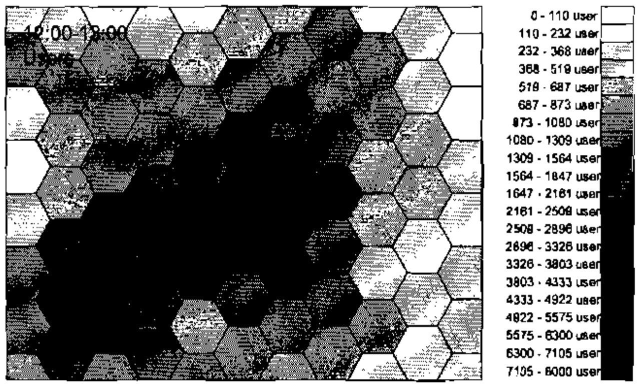
Figure 9: Active users in Darmstadt from 12:00 to 13:00h

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 from "Statistisches Bundesamt" are however of extremely fine-grained level of detail. Thus we used 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 140,000 inhabitants. The area covered is approximately 9.13 square kilometers. We use 83 cells with a size of 110,000 square meters each. The cell shape is hexagonal with the side length of the hexagon being 205.80m (height = 356.69m, width = 411.60m). We needed to perform significant post-processing overhead.

The zones available in the zoning plan are for example of arbitrary shape and size and need 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 turned out to be very labor intensive. Fig. 3 shows the zoning plan of the area modeled, the city center of Darmstadt. The shape of some zones from census data is drawn as well as the modeled grid of cells.

See Figures 4, 5, 6, and 7 for the predicted number of active users, categorized according to the user types depicted in Fig. 1. These numbers have been deduced for the scenario of Darmstadt using our model.

Combined with the attraction levels for the area of interest, we obtain the projection of the time varying number of users for all zones. Fig. 9 gives an example for the model prediction of the number of active residents during evening (20:00 to 21:00h). The main residential areas are clearly visible in a belt surrounding the center of the city. The center itself consists of office and shopping facilities while the region on the left is mainly covered by industrial areas - only populated with few residents at the time of the presented snapshot. Fig. 9 gives an example for the number of active users during noon (12:00 to 13:00h). It is clearly visible, that the city center and the nearby university attract most of the users.

To obtain a valid workload model, we combine the user densities obtained by means of the mobility model with traffic estimates per user class. To allow for proper treatment of QoS aspects while keeping the complexity manageable we introduce four traffic classes similar to the ones proposed in the 3GPP initiative: conversational, streaming, interactive and background traffic [13].

TABLE 1: INSTANTIATION OF TRAFFIC RATES PER USER CLASS

		Traffic				
User class	**User type**	***Conversational***	***Streaming***	***Interactive***	***Background***	***Sum***
Residents	Inactive	0.00 kbyte/s	0.00 kbyte/s	0 00 kbyte/s	0.04 kbyte/s	0.04 kbyte/s
	Active	2.70 kbyte/s	3.20 kbyte/s	8.10 kbyte/s	6.60 kbyte/s	20.60 kbyte/s
Consumer	Buyer	0.80 kbyte/s	0.30 kbyte/s	1.50 kbyte/s	0 60 kbyte/s	3.20 kbyte/s
	Visitor	1.20 kbyte/s	1.00 kbyte/s	2.30 kbyte/s	0.70 kbyte/s	5.20 kbyte/s
	Idler	1.50 kbyte/s	1.60 kbyte/s	3.60 kbyte/s	1.10 kbyte/s	7.80 kbyte/s
Worker	Industry	0.40 kbyte/s	0.20 kbyte/s	1.30 kbyte/s	0.50 kbyte/s	2.40 kbyte/s
	Office	2.90 kbyte/s	0.70 kbyte/s	4.40 kbyte/s	2.00 kbyte/s	10.00 kbyte/s
	Service	0.60 kbyte/s	0.20 kbyte/s	1.30 kbyte/s	0.50 kbyte/s	2.40 kbyte/s
	Mobile	2.30 kbyte/s	0.60 kbyte/s	5.30 kbyte/s	1.80 kbyte/s	10.00 kbyte/s
Trainee	Pupil	0.60 kbyte/s	0.80 kbyte/s	2.70 kbyte/s	1.10 kbyte/s	5.20 kbyte/s
	Student	2.50 kbyte/s	3.00 kbyte/s	6.00 kbyte/s	3.30 kbyte/s	14.80 kbyte/s
Traveller		1.80 kbyte/s	1.40 kbyte/s	3.50 kbyte/s	1.90 kbyte/s	8.60 kbyte/s

- Conversational denotes traffic like IP-telephony or video-conferencing. This implies constant bit rate (CBR) traffic with a low delay of at most 100ms. The aggregate of multiple conversational flows may be modelled as CBR, too.
- Streaming traffic accounts for video on demand, streaming audio delivery or for example a news ticker. We assume a variable bit rate (VBR) nature of the individual streams. The delay bound is 250ms. The aggregate of various streams can be modeled with self similar traffic.
- Interactive traffic models transactional traffic like for example web traffic. We assume the interactive traffic to be self-similar if we regard traffic aggregates.
- Background traffic accounts for traffic like for example email delivery or synchronization of files at arbitrary times. We assume a self-similar nature of background traffic.

See Table 1 for the instantiation of the traffic classes we have chosen for initial parameterization of our model. Within our investigations, we focused on scenarios for future radio access networks. Thus the respective traffic values give estimates of the average traffic rate of the active individuals within each user class which have been predicted using statistics of online behavior of German citizens.

We assign a traffic vector based upon these classes for each user class derived. The combination of user mobility data and traffic vectors results in the workload model. Please note, that we model the traffic aggregates on cell level. It is easily possible to combine the mobility model with additional traffic vectors to account for different scenarios.

V. IMPLEMENTATION AND ANALYSIS

We implemented the mobility model using a spreadsheet to collect and combine all user and location related input data. We smooth the resulting user densities and obtain values for each 5 minute interval of simulation time (288 samples per day) using gnuplot. Since the target simulation environment is ns-2 [14], we developed a set of scripts to generate the corresponding Tcl input data for the simulation directly from the spreadsheet data. Thus we are able to easily change traffic vectors to account for different scenarios. Moreover, we integrated various other helper scripts to parameterize the nodes and traffic agents.

Since the calculated amount of traffic only accounts for traffic which is generated from users of a given cell, we further need to distribute the traffic within the network. That is, we may want to direct all traffic to a central edge gateway or on the other hand may model a certain degree of localization. Using our scripts, we are able to specify a ratio of external/ internal traffic which is included in automated traffic generation.

Compared with traditional synthetic models like for example the random walk or the random waypoint model, our results differ significantly in terms of user and traffic distribution throughout the network: the works [15] and [16] analyze the stationary properties of the random waypoint model which can be summarized as follows: the distribution of the location of

TABLE 2: FRACTION OF AREA OF NETWORK VS. USERS AND TRAFFIC

Fraction of Area	Fraction of Users	Total Traffic (in kByte/s)	Fraction of Traffic
5%	19.45%	187,789.18	15.20%
10%	30.38%	321,763.70	26.04%
15%	40.13%	434,984.70	35.20%
20%	50.11%	548,248.78	44.37%
25%	56.79%	62,9051.43	50.91%
30%	61.91%	699,633.32	56.62%
40%	70.34%	826,558.32	66.89%
50%	78.12%	943,639.39	76.37%
60%	84.36%	1,032,264.42	83.54%
70%	89.56%	1,105,837.54	89.50%
80%	94.05%	1,165,484.01	94.32%
90%	97.93%	1,214,794.85	98.31%
100%	100.00%	1,235,631.40	100.00%

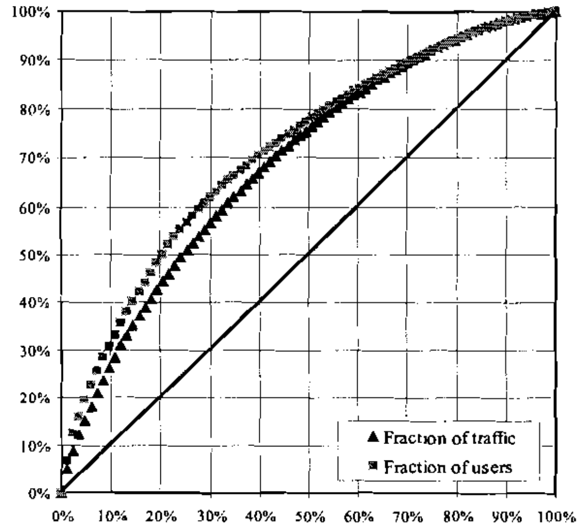

Figure 10: Fraction of users and traffic over fraction of area

nodes within a random waypoint model is concentrated near the eenter of the modeled area because nodes traveling between uniformly chosen points spend more time near the center than near the edges. The random walk model on the other hand eonverges to a nearly uniformly distribution of location of nodes in the stationary case, whieh is insufficent for the intended macroscopic usage, too.

However, to account for a city at large, we need to model areas of higher attraction as well as areas of lower attraction over day. The findings for our model are that we eannot assume uniformly distributed nodes. If we investigate the busy hour of the network for all individual modeled eells, we find, 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 expeet 78% of the active users causing 76% of the total traffic (see Table 2 and Fig. 10).

The calculated rate of our model varies substantially. While the average rate over all cells is 14,887.13 kByte/s, there are cells with a rate as high as 61,986.52 kByte/s and other cells with a rate of only 1,968.29 kByte/s. The standard deviation over the 83 cells being 11,002.80 kByte/s.

Visualizations of the resulting user and traffic fluctuations over place and time for the Darmstadt scenario can be found at [17].

VI. Conclusions and Future Work

This work presented the instantiation of a novel workload model which is a hybrid of an empirical mobility model combined with a synthetic traffic model. The results obtained can be used for further experimental analysis esp. for traffic engineering and network planning applications. In our case, we successfully applied the workload for a simulation study in the area of IP-based wireless metropolitan area networks to support user mobility [18]. The insights obtained using our model show major fluctuations of user density, which are induced by mobility.

Moving from traditional cellular networks to wireless local and metropolitan area networks results in smaller cells and traffic types other than voice. Thus we see an increasing need to deal with time varying traffie on multiple timescales combined with location-dependent load fluetuations. Our model is targeted to cover these aspects as well as the faeets of currently developed cellular networks operating on very small cell sizes.

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