Insights into Cellular Networks: Anatomy of Traffic Profiles

Wieslawa Wajda
Bell Labs
Alcatel-Lucent Deutschland AG
Stuttgart, Germany
Wieslawa.Wajda@alcatel-lucent.com

Abstract—**Analysis of real telecommunication data can provide a fine grasp and good understanding of user behavior dynamics and can be used to improve network management strategies. Following this approach, we analyze actual wireless traffic and provide basis for a suitable network model with a given network traffic profile. Unlike previous approaches, we introduce criteria for intelligent network resources utilization and define metrics to discover optimization potential of wireless system architectures. Our traffic fluctuation analysis is of interest for traffic load prediction and can boost BS switching time strategies. Thus, this study provides hints into hardware realization of a future base station and basis for development of efficient network architectures.**

Keywords-base station; traffic profile; traffic fluctuation; cell categorization; effiiciency index.

I. INTRODUCTION

In the existing literature, traffic observation and resource utilization in real networks were analyzed in different context. Investigation how efficiently radio resources are used by different subscribers and applications in macro Base Stations (BS) were done by Paul et al. [1]. The observations are related to traffic spread, mobility and efficiency in connection to subscriber pricing, protocol design, spectrum allocation and energy savings. Gender-based traffic characterizations based on campus traffic data were done by Kumar and Helmy [2]. Much research has been devoted to traffic classification models and methods in context of network security and management. In this context, the analysis concerned different kind of traffic generated by single application flow and the real-time traffic data were used for verification of proposed methods by Khalife et al. and by Won et al. [3][4].

In this paper, we agree with Jiang et al. [7] and are convinced that only the analysis of real traffic measurements give a deeper understanding into the network and thus provides a basis for a suitable network model with a given network traffic profile. Unlike the mentioned approaches, we introduce criteria for intelligent network resources utilization and define metrics to discover optimization potential of wireless system architectures.

A. Contributions

Focusing on actual network data, we:

- Introduce criteria of BSs capacity utilization in a capital city centre, so called *Dense Urban Centre* (DUC) and in an extended circle of the capital city centre, so called *Greater Dense Urban* (GDU) area.
- Define a metric to assess optimization potential for energy saving in the specific areas.
- Define BS categories with regard to their traffic profiles.
- Provide details of traffic fluctuation.
- Contribute to better understanding of resource sharing.

The results of this study give hints for hardware (HW) realization of future BS, contribute to resource optimization of the BS and provide basis for development of future efficient network architectures and adequate methods for resource management.

B. Analysed data

Data at our disposal have been provided by a single European operator in an European city. The analyzed traffic data cover BS of different power and capacity for dense urban centre und greater dense urban areas. The traffic data has been sampled for down- (High Speed Downlink Packet Access) and for uplink (High Speed Uplink Packet Access) in 900 sec (15 min.) intervals over a period of a week.

Given intervals of 15 min. make traffic fluctuation of shorter time invisible. Due to the fact that our analysis is oriented toward system utilization, this represents no real disadvantage and does not reduce the quality of the data. Furthermore, short fluctuations are typically resolved with the help of store and forward technology and are not relevant for analyzed mechanisms.

The analyzed system covers about 400 pico, micro and macro UMTS-cells in dense urban area, as well as over 900 pico, micro and macro UMTS-cells in greater dense urban area. In the analyzed area, macro-cells were deployed with high mounted antenna at ca. 24 – 44 m and with 15 – 20 W transmission power. Micro-cells were deployed with ca. 0.85W and with low mounted antennas at ca. 5 - 6 m. In addition, some pico-cells were deployed.

 ISBN: 978-1-61208-347-6

C. *Structure of the paper*

This paper is organized as follows. Section II presents load dynamics in analyzed network in opposite to load dynamics in single cells presented in Section III. Section IV gives a general look at cell load, especially in DUC. Section V shows cells utilization in relation to their capacity and proposes metric discovering potential for energy efficiency in the cells. Based on the study, cells are characterized regarding their traffic profiles in Section VI. Section VII deals with traffic fluctuation and contributes to understanding of its basic structural elements. Hints for BS architecture and its possible advantage for energy saving in the network are presented in Section VIII. Finally, the paper is concluded in Section IX.

II. GLOBAL TRAFFIC PROFILE

Global traffic of the analyzed cell population was calculated as shown in (1).

$$F(t) = \sum_{i} f_i(t) \qquad (1)$$

with $f_i(t)$ being the cells individual relative traffic data. Diagrams of F(t) for DUC and GDU areas show sinusoid like shape and periodicity over a week (see Figure 1 and Figure 2). The fluctuation dynamic is within the range of about 13 dB. In the case of a DUC area, highest traffic load appears between 10:00 a.m. to 05:00 p.m., while in the GDU area the high traffic is by about 02:00 p.m. and decreases up to 10:00 p.m.

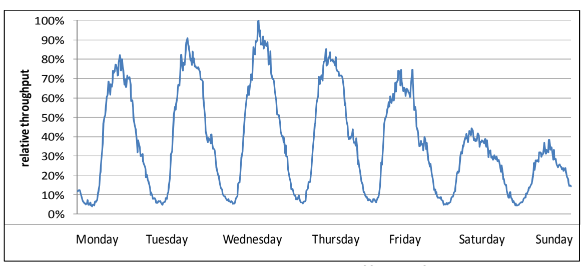

Figure 1. DUC weekly traffic profile.

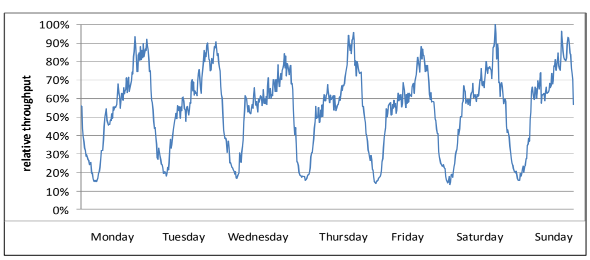

Figure 2. GDU traffic profile over a week.

Also, there is a difference on weekends between traffic density in the DUC and GDU areas. The hypothesis can be made that this difference results from population movement. Where the population in the GDU is dominated by inhabitants and therefore steady, the DUC has more office buildings and therefore its population drops on evenings and on weekends.

III. LOCAL TRAFFIC PROFILE

In some cases, an aggregated traffic profile is used by Gonzales et al. and Ambrosy et al. [5][6], but the load profiles of individual cells turn out to behave very differently from shown global profiles, as presented in the Figure 3.

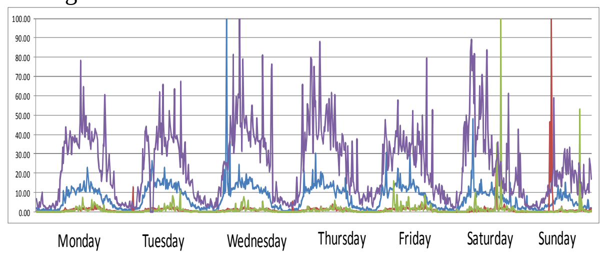

Figure 3. Traffic examples of cells in different areas.

Cell load profiles are different, even in cells of the same BS. They are extremely volatile and aperiodic. Depending on the BS location and served cell, load profiles can have very different utilization. Also, they can show some periodicity or be unpredictable. Summing up, elaboration and assessment of optimization measures for cells must be based on well understanding of a cell behavior and its traffic profile.

The considerable load dynamic justifies an optimization effort of BSs in analyzed areas. Some optimization examples can be: switching connections or hardware modules off, changing the transmission scheme, adapting the transmission speed of the backbone by slowing down clock frequency, selling released transmission resources to third party, while tuning off reserved resources can be controlled by actual time and date. The algorithms can be reinforced by self-learning procedures, to facilitate correct system reaction in case of nonstandard events and events not covered by a core algorithm.

IV. CELL LOAD

A general look at the traffic profiles of individual cells lets expect low cell utilizations because there are a few traffic peaks and the traffic load is low (see Figure 3). The Cumulated Density Function (CDF) calculated for all cells in DUC over the analyzed time period confirms this thought. Figure 4 shows high probability for low traffic in all analyzed DUC cells.

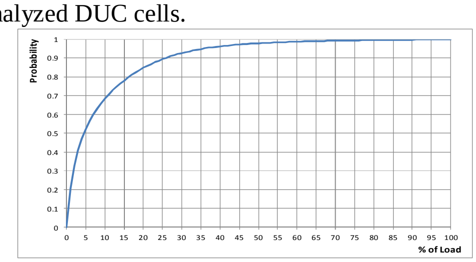

Figure 4. CDF of cells load in DUC.

According to this and to the fact that cell load profiles are greatly different, a closer look at their distribution, utilization, traffic oscillation and dynamics is essential for

ISBN: 978-1-61208-347-6

support decisions on design, deployment and operation of single BS, as well as of a whole wireless network.

V. UTILIZATION OF BS CAPACITY

First, we define what the BS capacity and the BS utilization is. The BS capacity is defined as the max. data traffic the BS can handle at once, which is, based on data we have, the highest absolute data rate of a particular BS in a week. Therefore, if we speak of 100% of BS capacity, it means its highest data rate in the measured time period. Furthermore, the resource utilization is the throughput the BS processes at a given time. For example, following the green solid line in Figure 5, about 90% of analyzed BSs (on the Y axis) in the GDU area have 90% traffic load by only up to 25% of its capacity (X axis). Similar, according to the violet solid line 90% of BSs in the GDU and according to the violet dotted line 60% of BSs in the DUC area are utilized by less than 20% for 85% measured traffic load. Finally, it can be recognized that the processed traffic of BSs in both regions does not exceed 50% of their capacity.

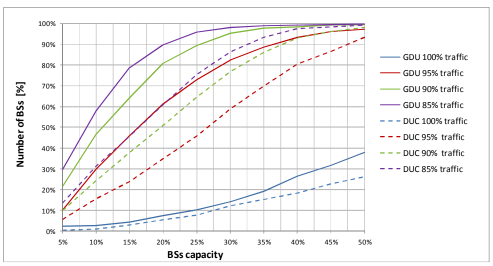

Figure 5. BSs utilization in DUC and GDU areas.

According Figure 5, it could be assert that the overall utilization of BS in the GDU is about 25% lower as those in the DUC area, and in both areas there is a big potential for improvements of the utilization factor.

A. Load distribution

Even though the load distribution in the time scale of a whole system is predictable, and has a shape with 24 h oscillation period influenced by a day of week as shown in Figure 1 and Figure 2, the load shapes of individual BSs are different and seem not to be bound to a periodic event. Figure 6 shows 5 different shapes for various cells in the GDU area between 07:00 a.m. and 06:00 p.m. on one day. We can see no similarity between them.

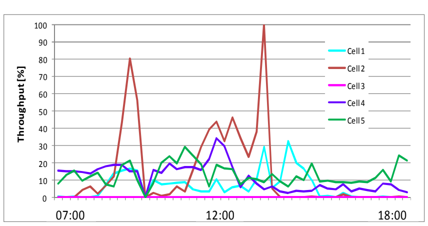

Figure 6. Load profiles of different BS between 07:00 a.m. - 06:00 p.m.

The CDF function of the traffic variance for all BSs in DUC area shows that more than 90% of evaluated BS population has a variance less than a half of the calculated variance max value (see Figure 7). It lets us assume that the spreading of values, i.e., the most oscillation of a load shape is low to middle. This in turn has an impact on BS construction and deployment planning.

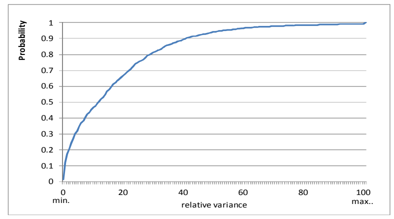

Figure 7. CDF function of load variance in DUC.

The above confirms also the Figure 8. It shows the view on the traffic load of a number of cells in the DUC area, where areas with low traffic at night and differences in the traffic of particular cells can be well recognized. Very interesting is also to see, that the traffic of a single cell is not steady but shaped by a short rising peaks which seems to be independent one from another.

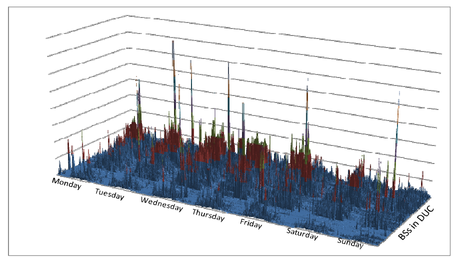

Figure 8. Traffic load over a week of exemplary BSs in DUC.

The discrete cross correlation function allows a closer look at the traffic divergence. The cross correlation function for two cells is defined as follow and has been used correspondingly for all cell pairs:

$$R = \sum_{-\tau}^{\tau} \frac{\frac{1}{T}\int_{-\infty}^{\infty} x(t)\, y(t+\tau)dt}{\sum_{-\tau}^{\tau} \frac{1}{T}\int_{-\infty}^{\infty} x(t)x(t+\tau)dt} \qquad (2)$$

The correlation value of compared traffic profiles of cell *x* and cell y is shown in relation to the autocorrelation function of the source cell *x* where τ is the correlation window time and T is the measured time period (one week).

Figure 9 shows the *R* values for all BSs in the DUC area for τ in the range of ±1 hour.

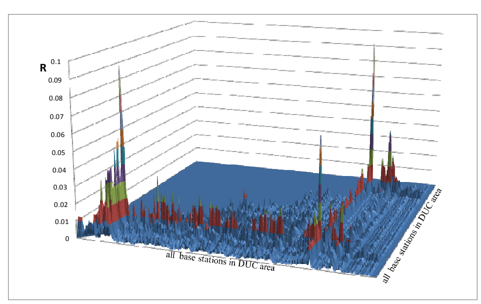

Figure 9. Cross correlation of cells in DUC area.

 ISBN: 978-1-61208-347-6

It can be seen that the R values are low, so there is no significant correlation of BSs traffic in the region. However, the high peaks show that there is some correlation between BSs traffic in the neighborhood.

B. *Metric to assess the potential for energy saving*

Observed low BSs utilization and low correlation value of their traffic profiles let expect reasonable saving potential for energy and for HW costs. Therefore, some calculations have been made to identify the energy saving potential more exactly. For this reason, a metric was defined which express an Energy Saving Potential Index (ESPI) based on a histogram of load values between 0% - 100% load with 5% steps (bins).

The value of the ESPI is *zero* if there is no potential for energy saving and *one* if the energy saving potential is high.

$$ESPI = \frac{\sum_i n_i (1-\alpha_i)}{\sum n_i} \qquad (3)$$

Here, n is the number of measures for a given load bin, α is the load fraction, e.g., 0% - 100%, and i the number of defined load bins.

Applying the ESPI metric to the DUC area and by consideration of 20 bins, each every 5% traffic load (see Figure 10) it can be identified, that the lowest ESPI value is 0.70. In total, 92% cells have saving potential between 0.81 – 0.95 and 60% cells had saving potential between 0.90 – 0.95.

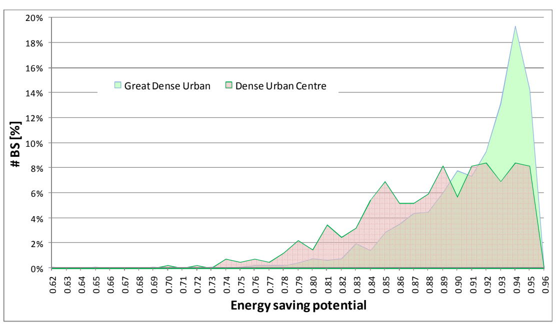

Figure 10. ESPI for DUC and GDU.

For the GDU area, most cells have saving potential index between 0.76 – 0.95 whereby 71% cells have saving potential over 0.9.

VI. BASE STATION CATEGORIES WITH REGARD TO THEIR TRAFFIC PROFILES

It was expected that the best way to save energy is to design a base station optimized to its traffic profile and further to adopt the network architecture to recognized traffic categories. Therefore, we analyzed the individual BS traffic to categorize traffic profiles of individual cells. As shown later in this section recognized categories of traffic profiles have corresponding energy saving potential. The BSs were analyzed regarding their traffic load during working days, emerged peaks, traffic load on the weekend and ESPI. At last, the studied traffic profiles were categorized into three generic traffic profiles in the DUC and two generic traffic profiles in the GDU area what is presented in Table I.

In the analysis, it was assumed that the highest throughput peak in the observed time embodies the maximum load or maximum resource utilization of the given BS, whereby that maximum resource utilization is typically in the range of 60% for macro BSs in dense urban areas as found in EARTH [10].

TABLE I. BS CATEGORIES

Dense Urban Centre				
BS Type	Traffic load	Peaks	Traffic on weekend	ESPI
1	Very low, Mostly < 5% of BS capacity	Random, sparse	Almost never	Typically 0.95
2	Medium to high load between 09:00a.m. – 05:00 p.m. 60% of the traffic load ≈ 5% of the. BS capacity	Less peaks up to max. load	Lower than during the week	Typically 0.85 – 0.89
3	High load, during most of the 24 h; 95% of the traffic load ≈ 60% of BS capacity	Many	Lower or similar to traffic during the working days	Typically 0.74
Greater Dense Urban				
BS Type	Traffic load	Peaks	Traffic on weekend	ESPI
1	Low; up to 10 % of BS capacity	Random, few high peaks	Yes	Typically 0.92
2	Mostly low traffic during a day and higher traffic in the night. The most traffic is up to 35% - 40% of the BS capacity	Many	Similar to traffic during the working days	Typically 0.70 – 0.80

As shown in Table I, recognized traffic profiles categories have corresponding energy saving potential.

VII. FLUX

The analysis of traffic profile requires understanding of its basic structural elements. These elements can be described by means of the term *flux* that corresponds to envelope of the traffic function with different levels of aggregation. The envelope of traffic function, i.e., a single

 ISBN: 978-1-61208-347-6

flux, is calculated as a linear approximation of consecutive growing and falling traffic profile sections with symmetry defined by constant ρ .

In the calculations, the ρ value was set to the level at which the fluctuation integrated down to the general shape can be simply compensated by hardware measures and would not influence traffic control algorithms.

The formulas for flux calculation are defined below.

a) *Rising edge*

$$t_i < t < t_k, \qquad f'(t) > 0 \tag{4}$$

b) *Falling edge*

$$t_{k+1} < t < t_m, \qquad f'(t) < 0 \tag{5}$$

c) *Flux criterion*

$$abs\left|\frac{f(t_i) - f(t_m)}{\max_t f(t) - \min_t f(t)}\right| < \rho \tag{6}$$

d) *Flux definition:*

$$F(x) = f(t_i) + n\frac{(f(t_k) - f(t_i))}{t_k - t_i} \tag{7}$$

$$for \qquad t_i \le n \le t_k$$

and

$$F(x) = f(t_k) - n\frac{(f(t_k) - f(t_i))}{t_m - t_k} \tag{8}$$

$$where \qquad t_{k+1} \le n \le t_m$$

where the t_i, t_k and t_m are described as in Figure 11.

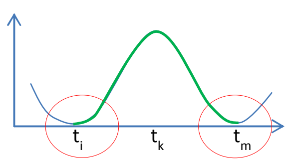

Figure 11. Parameters for flux definition.

An example for a traffic load fluctuation and the envelope for a given ρ is shown in Figure 12.

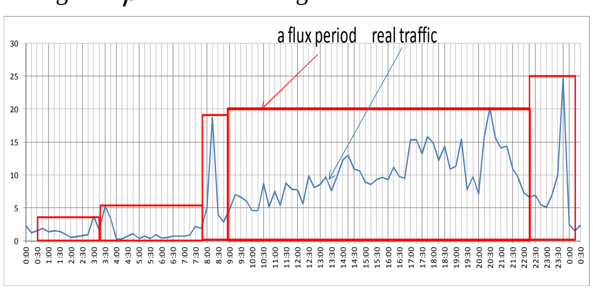

Figure 12. Traffic example and Fluxes.

The following flux parameters were calculated: flux duration, flux delta, i.e., the difference between the lowest and highest value of the flux, and slew rate.

The CDF functions for calculated parameters for the GDU area are shown in Figures 14, 15 and 16. Please note that traffic data has been sampled with 900 sec intervals. The results of flux duration calculation (see Figure 13) shows that traffic changes are relatively slow. About 50% of analyzed fluxes last up to 1 hour and 90% last up to 2, 5 hours.

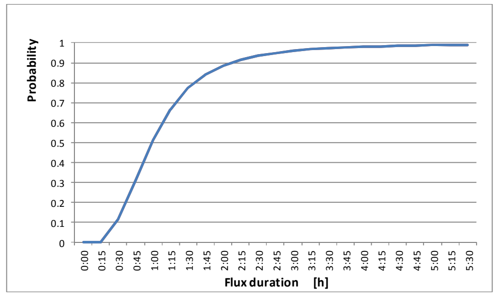

Figure 13. CDF of flux duration.

Figure 14 shows that the amplitude of 50% fluxes is up to 5% of max. load and 90% fluxes have the amplitude lower than 28% of max. load. It means that fluctuations with high amplitude are relatively seldom.

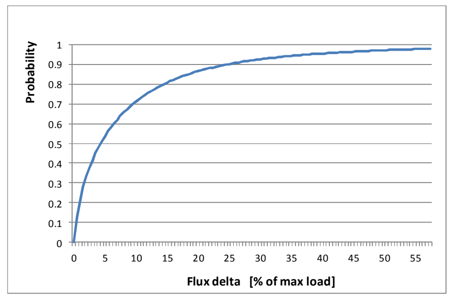

Figure 14. Flux delta.

Slew rate of rising and falling edges for the almost all fluxes is nearly the same (see Figure 15).

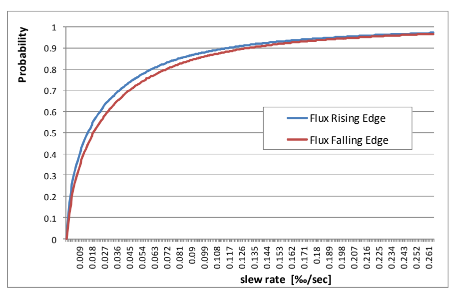

Figure 15. Flux edges.

The slew rate of low dynamics fluxes (with delta up to 50 % of max load) has the value of 0.5‰ of their peak value per second. This means that the slew time of the fluxes lasts about 30 minutes.

The 90% high dynamic fluxes (with delta higher than 50 % of the max load) have the slew rate of rising and falling edge by about 0.65‰ per second of the peak value.

Analysis of findings concerning traffic fluctuation can be used to estimate a number of design parameters for improved BS's local or network wide resource management, as, for example, required answer times, thresholds, safety margins for changes of system state and for short time traffic prediction.

The above results show that network optimization measures by hardware, as well as by software are feasible.

 ISBN: 978-1-61208-347-6

VIII. POSSIBLE SOLUTION ON BS ARCHITECTURE BASED ON THIS SURWEY

The above analysis of load distribution and traffic profile characteristics provides basics for architecture of scalable BS hardware as proposed by Wajda [8]. The analysis shown that there are a number of traffic load ranges it can be optimally performed by specialized hardware modules with working characteristics adapted to supported traffic range. For example, assume BS consisting of two modules, where the first one supports the range up to 10% of max. traffic load and consumes 1 kW per hour and the second module supports the traffic peaks up to max. load and consumes 10 kW per hour. If the second module, due to the traffic load characteristics, can be switched off during 80% of the BS working time than the energy consumption can be greatly reduced. To assess energy savings we estimated traffic ranges and corresponding processing modules as shown in Table II and in Table III.

TABLE II. RESULTS FOR THE ANALYZED DUC AREA

Traffic profile	Number of BSs in the analysed population (DUC) [%]	Energy Saving factor	Proposition for HW modules [% load]	Power consumption savings by modular HW
1	ca. 40 %	0.90 – 0.95	5%, 100%	70%
2	ca. 53 %	0.89 – 0.85	5%, 25%, 100%	58%
3	ca. 7 %	0.84 – 0.70	5%, 25%, 50%, 100%	55%

TABLE III. RESULTS FOR THE ANALYZED GDU AREA

Traffic profile	Number of BSs in the analysed population (GDU) [%]	Energy Saving factor	Proposition for HW modules [% load]	Power consumption savings by modular HW
1	ca. 90 %	0.81-0.95	5%, 25%, 100%	56%
2	ca. 10 %	0.70 – 0.80	25%, 50%, 100%	45%

The calculations are based on power model and simulator used in EARTH project and presented by Imran et al. and Desset et al. [9][10][11].

IX. CONCLUSION AND FUTURE WORK

Against well predictable global traffic profiles for DUC und GDU, traffic profiles of single cells are extremely volatile and not predictable. Therefore, optimization measures addressed to single cell must be well balanced and done separately from system wide optimization algorithms.

Traffic analysis of individual cells in DUC area had shown low utilization of cell resources and mostly low to middle oscillation of a load shape.

The developed metric, the Energy Saving Potential Index, confirmed the low utilization and, in consequence, a huge energy saving potential (over 0.9). Due to the estimated saving potential, it is worth to exploit low traffic utilization by BS architectural design.

Sophisticated network management strategies, for example those concerning resource sharing can benefit from this research, for example, common traffic management can help to reduce traffic dynamic of particular BS and increase its resource utilization.

Furthermore, the defined BSs categories provide basis for a suitable network model with a given network traffic profile and can be used for development of energy effective HW by means of configurable set of procedural and physical building blocks that can be assembled manually, as well as in an automated way.

Flux details will help to boost BS switching time strategies and provide hints for hardware realization, as well as improve quality of traffic load prediction.

In the next research work, based on above findings, different modular HW solutions, transceivers based on power amplifiers with optimized dynamics, and new network management strategies will be proposed.

ACKNOWLEDGMENT

I would like to give special thanks to my colleagues Andreas Wich and Ulrich Barth for the outstanding discussions. This work was supported in part by the German Federal Ministry of Economics and Technology funding program IT2Green (IntelliSpektrum).

REFERENCES

[1] U. Paul, A. P. Subramanian, M. M. Buddhikot, and S. R. Das, “Understanding Traffic Dynamics in Cellular Data Networks”, The 30th IEEE International Conference on Computer Communications (IEEE INFOCOM 2011), April 2011, pp. 882 – 890, ISSN: 0743-166X, ISBN: 978-1-4244-9919-9

[2] U. Kumar and A. Helmy, “Extract: Mining Social Features from WLAN Traces: A gender-based study”, The 13-th ACM International Conference on Modelling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM’10), ACM SIGSIM, Oct. 2010, pp. 240-247, ACM 978-1-4503-0274-6/10/10.

[3] J. Khalife, A. Hajjar, and J. Diaz-Verdejo, “A multilevel taxonomy and requirements for an optimal traffic-classification model”, International Journal of Network Management, vol. 24, issue 2, March/Apr. 2014, pp. 101-120, doi: 10.1002/nem.1855.

[4] Y.Won, BPark, M, and Won,J.Chung, Kim, “Fine-grained traffic classification based on functional separation”, International Journal of Network Management, vol. 23, Sep./Oct. 2013, pp. 350-381.

[5] M.J. Gonzalez, D. Ferling, W. Wajda, A. Erdem, and P. Maugars, “Concepts for Energy Efficient LTE Transceiver Systems in Macro Base Stations”, Future Networks and Mobile Summit 2011, Conference Proceedings, , June 2011, pp. 33-41, IEEE Catalog Number: CFP1134J-PRT, ISBN: 978-1-4577-0928-9.

[6] A. Ambrosy, O. Blume, D. Ferling, P. Jueschke, M. Wilhelm, X. Yu, “Energy Savings in LTE Macro Base Stations”, 7th IFIP Wireless and Mobile Networking Conference, Vilamoura, Algarve, Portugal, May 2014, in press.

[7] M. Jiang, M. Nikolic, S. Hardy, and L. Trajkovic, “Impact Of Self-Similarity On Wireless Data Network Performance”, IEEE International Conference on Communications (ICC 2001), Juni 2001, pp. 477 - 481 vol. 2, ISBN: 0-7803-7097-1

[8] W. Wajda “New concept of a modular wireless base station and benefits for network management and energy efficiency”, IET International Conference on Wireless Communications and Applications (ICWCA 2012), Conference Proceedings, Oct. 2012, p. 34, ISBN:978-1-84919-550

[9] EARTH (Energy Aware Radio and neTwork tecHnologies), EU funded research project FP7-ICT-2009-4-247733-EARTH, Jan. 2010 to June 2012, https://www.ict-earth.eu/

[10] Ed. M.A. Imran et al., Energy efficiency analysis of the reference systems, areas of improvements and target breakdown, EARTH EC deliverable D2.3, December 2010, Available from https://bscw.ict-earth.eu/pub/bscw.cgi/d71252

[11] C. Desset et al., “Flexible power modeling of LTE base stations”, IEEE Wireless Communications and Networking Conference (WCNC 2012), Apr. 2012, pp. 28858-2862, doi: 10.1109/WCNC.2012.6214289.

