

# Energy Savings by Using Traffic Estimation for Dynamic Capacity Adaptation in Communication Network Operations

Andreas Ahrens<sup>1</sup>, Christoph Lange<sup>2</sup>, and Jelena Zašcerinska<sup>1</sup>

<sup>1</sup>Hochschule Wismar: University of Applied Sciences: Technology, Business and Design, 23966 Wismar, Germany

<sup>2</sup>Hochschule für Technik und Wirtschaft (HTW) Berlin, University of Applied Sciences, 10313 Berlin, Germany  
Email: {andreas.ahrens, jelena.zascerinska}@hs-wismar.de; christoph.lange@htw-berlin.de

**Abstract**—Energy efficiency of telecommunication networks plays an essential role in the context of sustainability and climate change – as those networks are large power-consuming distributed infrastructures. Furthermore, also an economical network operation calls for low energy demand. A challenging and crucial task for energy-efficient and sustainable network operation is the load-adaptive operation of network elements such as routers, switches and access multiplexers. Since the traffic is temporally fluctuating, load-adaptive control of the network requires a robust traffic demand estimation. This is also of overwhelming importance, as a stable network operation is a central task of network operators – since it is expected by their customers as the service they pay for. Here, Wiener filtering has been identified as a robust solution for reliable traffic demand forecasting on relevant time scales. The results presented in this paper show that the capacity dimensioning based on the proposed Wiener filtering traffic forecasting leads to reliable outcomes in terms of predicted traffic enabling sustainable and efficient network operation.

**Index Terms**—Network energy efficiency, load-adaptive network operation, traffic estimation, Wiener filtering

## I. INTRODUCTION

The European Union faces major challenges from the increased threats of climate change, with serious consequences in the energy sector [1]. Energy efficiency in general and particularly in the telecommunications sector, due to its large distribution as well as its tremendous and pervasive development, needs to be improved. In order to prevent dangerous climate change, the telecommunications sector is working to save energy in large-scale telecommunications networks.

According to the latest numbers of the International Telecommunication Union (ITU), the telecommunications sector contributes around 2 % to 2,5% of greenhouse gas emissions. Here, fixed and mobile telecommunications contribute an estimated 24 % of the

total. As the ICT industry is growing faster than the rest of the economy, this share may well increase over time [2], [3].

In large-scale (nationwide) communication networks there are two drivers of energy consumption: coverage and network capacity. Often, the first task of a network is to connect all endpoints that seek network connection. This leads to certain amount of energy demand for the active network equipment. In case the coverage is achieved and more capacity is needed the (excess) energy consumption is driven by the capacity to be installed. As today's network equipment is merely designed to follow the temporal fluctuating traffic demands with its provided capacity, this excess capacity is installed statically and thus leads to a (static) additional energy demand. The present work focuses on network capacity in relation to efficiency of energy consumption.

Large-scale telecommunication networks are utilized by consumers' and business applications, such as video and music streaming but also for large file transfers for e. g. data backups. The electricity consumed by the network operation depends essentially on the installed network capacity and affects the operators' energy bills considerably. In order to become more environmental-friendlier, network operators have recognized the ability for improvements throughout the recent past for reducing the network energy demand – and thus the operators' energy bill. The expected traffic amount in a network requires a certain network capacity to be installed and therefore determines the electricity demand of such a network via the necessary active network equipment.

A suitable measure for roughly estimating the energy efficiency of a network system or section is the energy per bit – describing the energy needed on average for the transmission of a bit by a particular technology or network section. With the technology progress to higher transmission rates, energy efficiencies can only be achieved by decreasing the energy per transmitted (or processed) bit.

The traffic observed in networks varies between weekdays and weekends, see e. g. [4]. The real observed traffic depends furthermore strongly on the particular geographical and functional network section under consideration. For example, the access network in a

---

Manuscript received February 4, 2020; revised September 20, 2020.  
Corresponding author email: andreas.ahrens@hs-wismar.de.  
doi:10.12720/jcm.15.11.790-795

residential area on a working day exhibits a traffic characteristic that is very different from a similar network section in a business park on the same day. However, the absolute differences between observed traffic characteristics are not the main focus of this paper. Here, we focus on a principle technique of estimating traffic patterns as an inevitable precondition for dynamic capacity provisioning that works independently of the concrete traffic curve.

A possible solution for improving the energy efficiency of networks is considered by load-adaptive operation where the network capacity follows the traffic demands. This is in contrast to the prevalent network design, where the network capacity is above the expected peak traffic plus a capacity reserve. In order to achieve any improvements in the network’s energy efficiency, it is essential to adapt the provided network capacity to the fluctuating traffic demands and thus, in turn, to estimate the traffic demand reliably for these capacity dimensioning purposes. Dynamic capacity provisioning – or load-adaptive operation – can be achieved by, e. g. switching on and off ports and links to provide the necessary network capacity — or it can be done on a per-link basis. Examples for such a kind of dynamic load-adaptive network operation on a per-link basis can be found as Energy Efficient Ethernet on Ethernet links [5], they are standardized as low power mode regimes for ADSL (Asymmetric Digital Subscriber Line) connections and furthermore they are discussed as radio access network management approaches [6]. Once a robust traffic prediction solution is found – that is needed for either type of load-adaptive network operation – load-adaptive network operation regimes can be considered a strong possible solution towards network energy efficiency improvements.

The aim of the work is to develop a simulation model for dynamic capacity adaptation based on the analysis of Wiener filtering for traffic prediction underpinning energy savings in communication network. The present research employs the qualitative methodology as model creation is a qualitative process. Qualitative process is a methodology mostly used within the interpretive approach [7]. Hence, the research is carried out within the interpretive paradigm. Interpretative paradigm is characterized by the researcher’s practical interest in the research question [8]. The researcher is the interpreter [9]. The novelty of this contribution is the simulation model defined by the method for traffic prediction based on the Wiener filtering [10]-[12] as it is known from statistical signal processing: The knowledge regarding traffic behaviour from the past, e. g. from previous hours or days, is used to estimate the future traffic characteristics.

The remaining part of this paper is structured as follow: In section II a traffic-related system model is constructed, following by the traffic prediction highlighted in section III. In section IV the application of traffic prediction to dynamic load-adaptive network operation is studied. The obtained results are introduced and analyzed in section V.

For verification purposes, the originally observed traffic is compared with the estimated traffic. Also, the energy consumption associated with the newly proposed capacity dimensioning strategy is calculated and compared to conventional procedures. The presented concept is verified by means of a statistical analysis where the stochastic traffic characteristics are varied, and the resulting capacity dimensioning and energy efficiency is analyzed. Concluding remarks are provided in section VI.

## II. TRAFFIC-RELATED SYSTEM MODEL

As a basis for establishing traffic prediction algorithms, real measured traffic data or a modeled traffic time function with suitable characteristics and statistics is necessary. Throughout this paper a traffic model is used that refers to an exemplary link in a network whose capacity is subject to load-adaptive switching regimes. The traffic function is constructed as follows: An underlying time function  $s(k)$  (e. g. mean traffic), with variations on a longer time scale, is used for modelling the average traffic fluctuation observed for an exemplary link throughout a day. To model the stochastic variations in the traffic on a shorter time scale, an additive white Gaussian noise  $n(k)$  with zero mean and the variance  $P_R$  is added. In consequence, the traffic function  $v(k)$  is obtained that is referred to an observed traffic throughout the paper. The observed (measured) traffic  $v(k)$  results in:

$$v(k) = s(k) + n(k) . \tag{1}$$

Fig. 1 shows exemplary curves of the observed (measured) traffic  $v(k)$  and the underlying averaged traffic function  $s(k)$ . The resulting system model is highlighted in Fig. 2.

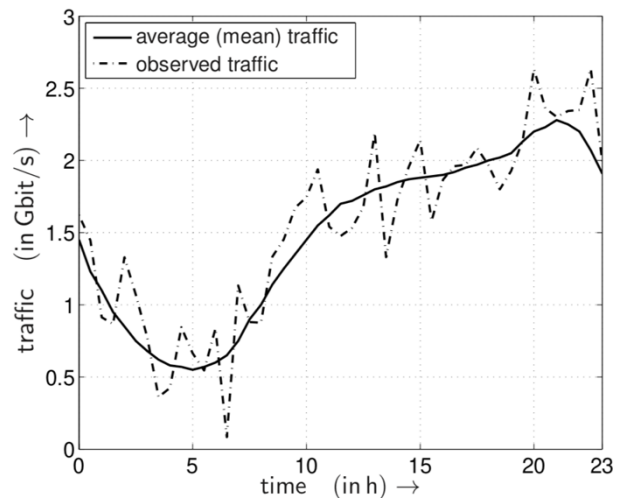


Fig. 1. Characteristics of exemplarily averaged (solid line) and observed traffic (dashed line)

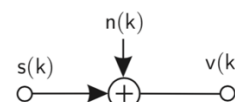


Fig. 2. Resulting system model for modelling traffic fluctuations

This modelled traffic contains the long-term traffic fluctuations over a day as well as the inherent stochastic nature of typical broadband data traffic. The complementary cumulative distribution function (CCDF) of the modelled traffic at noon is shown in Fig. 3. Assuming a throughput of 1,72 Gbit/s (averaged traffic observed  $s(k)$ ) at noon traffic fluctuations become obvious. In conclusion, in this way an appropriate traffic model has been obtained that can be described and adjusted by analytic parameters. In Fig. 3 exemplarily variances  $P_R$ , describing the short-term fluctuations, in the range of 0,1 ... 1,0 are selected. The noise is used to simulate the random fluctuations of the traffic in a network on a very short time scale that cannot be described by a deterministic function. The variance of that noise is chosen in a way that realistic orders of magnitude are met – that can be observed on real network links. The variance of a bit rate – that is measured in bit/s – exhibits the dimension of a bit rate squared, i. e. the variance describing the short-term traffic fluctuations has technically the unit (bit/s)<sup>2</sup>. In the interest of the clarity of the presentation in this work the units of this variance are omitted.

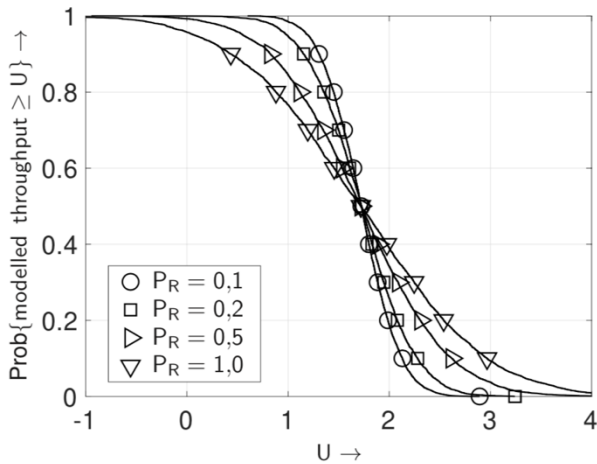


Fig. 3. CCDF of the throughput at noon taking different values of  $P_R$  into account

### III. TRAFFIC PREDICTION USING WIENER FILTERING

For a robust traffic estimation, a *Wiener* filter is used in this work, since it is suitable for tasks when minimizing the mean square error (MMSE, minimum mean square error) between the estimated (i. e. predicted) traffic and the real traffic. The Wiener filtering approach is in particular viable, when the mean traffic is affected by short-term fluctuations, that are modelled as Gaussian noise. Therefore, differences in the mean traffic such as between weekdays and weekends are not taken into consideration as these fluctuations are considered by the mean value – that differs between weekdays and weekend days and thus leads to different numerical values and results, but has no impact on the considered approach. A linear predictor can be used to estimate the traffic at the

time  $k$  by taking the last  $q$  traffic values  $v[k - q]$  into account and results in

$$\hat{v}[k] = \sum_{\mu=1}^q p_{\mu} \cdot v[k - \mu]$$

with the parameter  $q$  describing the order of the predictor. The coefficients of the predictor  $p_{\mu}$  (for  $\mu = 1, 2, \dots, q$ ) have to be defined by minimizing the energy of the error signal  $e[k] = v[k] - \hat{v}[k]$ . The error signal  $e(k)$  appears after linear filtering of the signal  $v(k)$  with the so far unknown filter coefficients  $b(k)$  (see Fig. 4) – which are related to the predictor coefficients by  $b[\mu] = -p[\mu]$  for  $1 \leq \mu \leq q$ ,  $b[0] = 1$  and  $b[\mu] = 0$  for all other  $\mu$ . Details on the derivation of this interrelationship are shown in [13].

Taking the stationary mean (averaged) traffic  $s(k)$  and the added noise  $n(k)$  into account, the observed noisy process  $v(k)$  forms the basis for the proposed traffic prediction. Using the Wiener filter the mean square error between the estimated traffic  $\hat{v}(k)$  and the mean (averaged) traffic  $s(k)$  can be minimized.

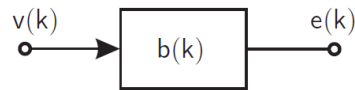


Fig. 4. Error signal  $e(k)$  as a function of traffic function  $v(k)$

In Fig. 5 the curves of the exemplary observed traffic  $v(k)$  and the predicted traffic  $\hat{v}(k)$  are shown: It becomes obvious that the estimated or predicted time function follows the observed traffic in tendency but is not directly useful for capacity dimensioning – as there are time periods where the traffic is under-estimated. Therefore, some modification or adaption of the Wiener filtering is necessary for capacity dimensioning purposes in order to take those deviations into account. The target is always a reliable network operation – meaning here sufficient capacity – and then somewhat downstream – the improved energy efficiency.

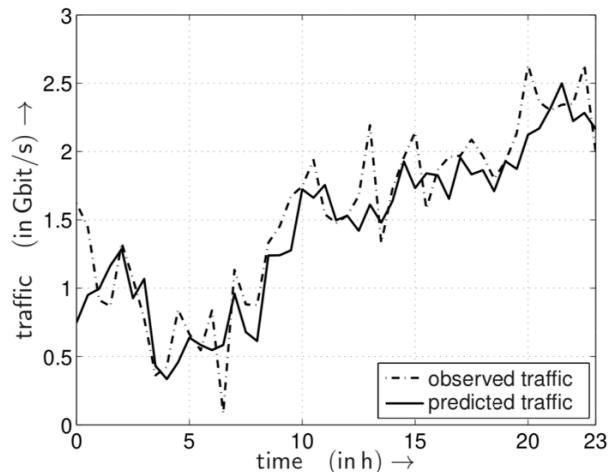


Fig. 5. Observed (dashed line) and predicted (solid line) traffic time functions

IV. CAPACITY DIMENSIONING AND ENERGY EFFICIENCY

Provided that there is a linear dependency between capacity and power ensured by the network elements, from the capacity time function  $c(t)$  a power time function  $P(t)$  is obtained by  $P(t) = K \cdot c(t)$ , where the factor  $K$  exhibits the dimension of an energy per bit (in J/bit or Ws/bit). The actual value and magnitude of  $K$  depends strongly on the system technologies and their generations. The energy consumed by a bit of data as it runs through a telecommunication network, e.g. the Internet, can be estimated by counting the number of network elements – e.g. switches, routers, amplifiers, transceivers – that the bit passes through, and adding all of these contributions to the energy consumption of that bit of data. According to [14] it is expected that a high-end core router consumes around 20 nJ/bit, while Ethernet switches consume less than 10 nJ/bit. These numbers depend strongly on the technologies and therefore are subject to improve as technology improves.

In this work the parameter  $K$  is assumed to be  $K = 10^{-6}$  Ws/bit. The value of energy per bit is determined by the communication system in use e. g. a switch, a router or an access multiplexer – or network section under consideration e. g. optical access network, core network or the radio link. A thorough investigation on this topic with typical numerical values can be found e.g. in [14]. The chosen value of  $K = 10^{-6}$  Ws/bit is a typical value out of a wide range of possible values.

Taking into account that the power consumption function  $P(t)$  follows the traffic function  $v(t)$ ,  $P(t)$  has to be adapted according to the traffic (Fig. 6). As highlighted by Fig. 6 load adaptiveness leads to energy efficiency improvements. Now temporal power consumption  $P(t)$  is no longer constant. To measure energy efficiency improvement of particular load-adaptive case  $n$ , energy efficiency parameter  $\epsilon_n = E_n/E_0$  is used, as defined in [15], [16]. Here,  $E_0 = P_0 \cdot T$  describes the reference case with no load-adaptiveness at all.

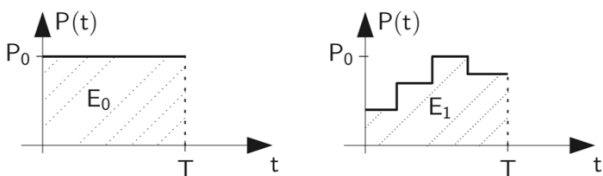


Fig. 6. Energy efficiency improvement by taking power traffic-dependent time function for load-adaptiveness (right) and non load-adaptiveness (left) into account.

V. ENERGY EFFICIENCY RESULTS

Based on the capacity dimensioning use cases in Fig. 7, the capacity follows directly the estimated traffic. As an example a noise variance  $P_R = 0,1$  is assumed for describing the short-term traffic fluctuations. In order to avoid a capacity bottleneck, a traffic reserve is added to the estimated traffic  $\hat{v}(t)$ , i. e.  $c(t) = \hat{v}(t) +$  to

ensure a sufficient capacity. This traffic reserve is especially needed for situations where the real traffic is under-estimated by the predictor. The energy efficiency of different cases of load-adaptive operation regimes is shown in Fig. 8. Hereby, scenario 0 describes the reference case employing no load-adaptiveness at all and scenario 1 represents the best-case limit, where the capacity follows the observed traffic ideally. Realistic load-adaptive regimes will exhibit energy efficiencies  $\epsilon_n$  between those boundaries. It becomes obvious that energy efficiency is increased when approximating the traffic curve more exactly. However, in scenarios where the traffic is under-estimated a capacity bottleneck could appear. The probability will doubtlessly increase for lower  $\Delta$ . Therefore, the parameter  $\Delta$  has to be selected carefully.

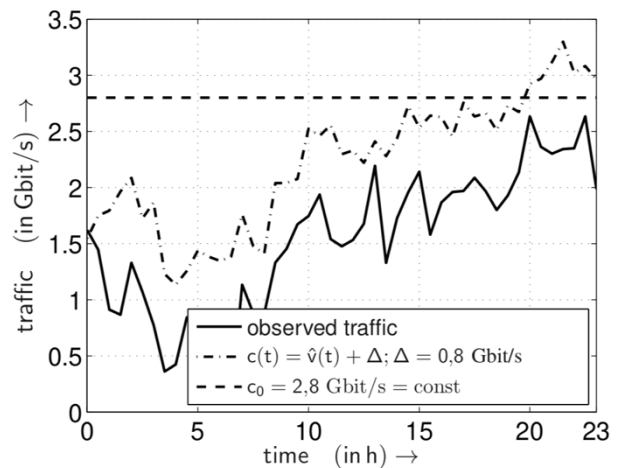


Fig. 7. Capacity as a function of the estimated traffic for different parameters of the traffic reserve

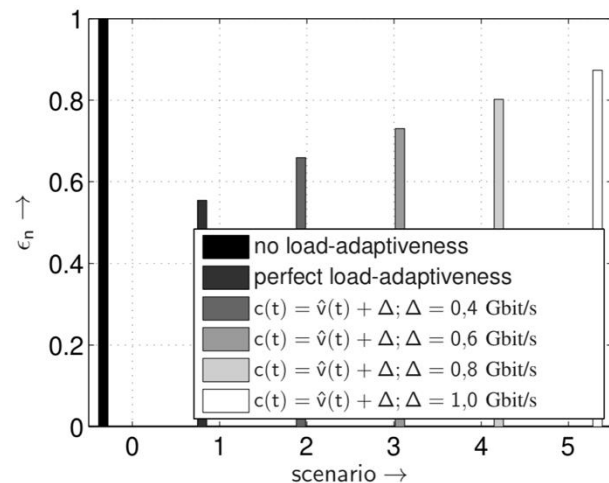


Fig. 8. Energy efficiency for different parameters of the traffic reserve based on  $c_0 = 2,8$  Gbit/s

VI. CONCLUSIONS

In this paper, a traffic prediction approach for temporally fluctuating network traffic based on Wiener filtering has been analysed. The findings of the theoretical analysis allow creating the simulation model of dynamic

capacity adaptation based on the analysis of Wiener filtering for traffic prediction underpinning energy savings in communication network.

Our approach can be useful in case the capacity will be provided basing on the temporally fluctuating traffic demands. If the excess capacity is provided as usual by statically adding more lines for additional capacity only the fact whether a port of a line is on or not will determine the energy consumption. Before the background of increased energy cost and increasing sensibility for environmental concerns capacity in the future should be provided load-adaptively – and then traffic prediction algorithms like discussed in this paper are indispensable and come in handy for network design and planning.

The presented work is limited by the creation of the simulation model only. Another limitation is the application of Wiener filtering for prediction of energy consumption on a communication network component or larger site based on past traffic capacity.

Future work will focus on validation of the proposed simulation model. Further on, validation of the simulation model will be implemented in different environments. Analysis of other prediction methods will be carried out, too. A comparative study of different prediction methods will be presented. Deep analysis of the interrelations between energy and traffic as well as network port will be implemented. Modification of network capacity based on the load will be analyzed. Treatment of traffic volumes on different days, e.g. weekday vs. weekend, will be detailed.

#### CONFLICT OF INTEREST

The authors declare no conflict of interest.

#### AUTHOR CONTRIBUTIONS

The paper was jointly developed by the three authors of this contribution. Prof. Andreas Ahrens and Prof. Christoph Lange conceived of the presented idea. Both developed the theory and performed the computations. Dr. Jelena Zašcerinska verified the analytical methods. All authors discussed the results, contributed to the final manuscript and approved the final version of the paper.

#### REFERENCES

- [1] G. Amanatidis, European policies on climate and energy towards 2020, 2030 and 2050. Policy Department for Economic, Scientific and Quality of Life Policies Directorate-General for Internal Policies. PE 631.047, 2019.
- [2] S. N. Roy, “Energy logic: A road map to reducing energy consumption in telecommunications networks,” in *Proc. Int. Telecommunications Energy Conference*, San Diego (USA), 2008, pp. 2–4.
- [3] P. Marsch, O. Bulakci, O. Queseth, and M. Boldi, *5G System Design: Architectural and Functional Considerations and Long Term Research*, John Wiley & Sons, Chichester, 2018.
- [4] A. Betker, I. Gamrath, D. Kosiankowski, *et al.*, “Comprehensive topology and Traffic model of a nationwide telecommunication network,” *Journal of Optical Communications and Networking*, vol. 6, no. 11, pp. 1038–1047, 2014.
- [5] P. Reviriego, K. Christensen, J. Rabanillo, and J. A. Maestro, “An initial evaluation of energy efficient ethernet,” *IEEE Comm. Letters*, vol. 15, no. 5, pp. 578–580, 2011.
- [6] A. Ambrosy, O. Blume, H. Klessig, and W. Wajda, “Energy saving potential of integrated hardware and resource management solutions for wireless base stations,” in *Proc. 22nd International Symposium on Personal Indoor and Mobile Radio Communications*, Toronto, Canada, 2011.
- [7] N. C. Thanh, T. T. L. Thanh, “The interconnection between interpretivist paradigm and qualitative methods in education,” *American Journal of Educational Science*, vol. 1, no. 2, pp. 24–27, 2015.
- [8] L. Cohen, L. Manion, and K. Morrision, *Research Methods in Education*, 5th ed., London and New York: Routledge/Falmer Taylor and Francis Group, 2005.
- [9] A. Ahrens, O. Purvinis, J. Zašcerinska, D. Miceviciene, and A. Tautkus, “Burstiness management for smart, sustainable and inclusive growth: Emerging research and opportunities,” *IGI Global*, Hershey, 2018.
- [10] N. Wiener, *Extrapolation, Interpolation, and Smoothing of Stationary Time Series*, Wiley, New York, 1949.
- [11] L. R. Vega and H. Rey, *A Rapid Introduction to Adaptive Filtering*, Springer, Heidelberg, New York, 2013.
- [12] S. V. Vaseghi, *Advanced Digital Signal Processing and Noise Reduction*, John Wiley & Sons, Chichester, 2009.
- [13] A. Ahrens, C. Lange, C. Benavente-Peces, “Traffic estimation for dynamic capacity adaptation in load adaptive network operation regimes,” in *Proc. International Conference on Pervasive and Embedded Computing and Communication Systems*, Lisbon, Portugal, 2016.
- [14] R. S. Tucker, “Green optical communications part ii: energy limitations in networks,” *IEEE Journal of Selected Topics in Quantum Electronics*, vol. 17, no. 2, pp. 261 – 274, 2011.
- [15] C. Lange and A. Gladisch, “Limits of energy efficiency improvements by load-adaptive telecommunication network operation,” in *Proc. 10th Conference of Telecommunication, Media and Internet Techno-Economics*, Berlin, Germany, 2011, pp. S5–1.
- [16] C. Lange, D. Kosiankowski, A. Betker, H. Simon, N. Bayer, D. V. Hugo, H. Lehmann, and A. Gladisch, “Energy efficiency of load-adaptively operated telecommunication networks,” *IEEE/OSA Journal of Lightwave Technology*, vol. 32, no. 4, pp. 571 – 590, 2014.

Copyright © 2020 by the authors. This is an open access article distributed under the Creative Commons Attribution License ([CC BY-NC-ND 4.0](https://creativecommons.org/licenses/by-nc-nd/4.0/)), which permits use, distribution and reproduction in any medium, provided that the article is properly cited, the use is non-commercial and no modifications or adaptations are made.



**Andreas Ahrens** received the Dr.-Ing. and Dr.-Ing. habil. degree from the University of Rostock in 2000 and 2003, respectively. In 2008, he became a Professor for Signal and System theory at Hochschule Wismar, University of Technology, Business and Design, Germany. His main field of interest

includes error correcting codes, multiple-input multiple-output systems, iterative detection for both wireline and wireless communication as well as social computing.



**Christoph Lange** received the Dipl.-Ing. degree (diploma) in electrical engineering and the Dr.-Ing. degree (doctorate) in communications engineering from the University of Rostock, Germany, in 1998 and 2003, respectively. From 2006 to 2018 he worked for different research and

innovation departments with Deutsche Telekom in Berlin. Currently he is a Professor of Communication Networks and Systems at Hochschule für Technik und Wirtschaft Berlin, University of Applied Sciences. His research interests include several aspects of communications engineering as well as design and energy efficiency of communication networks.



**Jelena Zašcerinska** was awarded the Dr. Degree by University of Latvia in 2011. In 2012 she became a leading researcher at Centre for Education and Innovation Research, Latvia. She received research grants. In 2012 she was bestowed expert rights by Latvian Council of Science, in 2013 - by Horizon 2020, in 2017 - by

National Science Centre, Krakow, Poland. Since 2013 she has been actively acting as Editorial Board Member and Reviewer in international scientific journals.