SURVEY

Energy-Efficient OFDM Radio Resource Allocation Optimization With Computational Awareness: A Survey

BARTOSZ BOSSY, **PAWEŁ KRYSZKIEWICZ**, (Senior Member, IEEE), **AND HANNA BOGUCKA**, (Senior Member, IEEE)

Faculty of Computing and Telecommunications, Institute of Radiocommunications, Poznan University of Technology, 60-965 Poznań, Poland

Corresponding author: Bartosz Bossy (bartosz.bossy@put.poznan.pl)

ABSTRACT In this paper, we review radio resource optimization methods for energy-efficient wireless communication in links and networks using the Orthogonal Frequency Division Multiplexing (OFDM) and Orthogonal Frequency Division Multiple Access (OFDMA) techniques. We first consider the energy-efficiency metrics and optimization goals. We discuss the increasingly complex systems, starting from (i) a single OFDM link, (ii) an OFDMA single-hop network to (iii) multi-hop relay OFDMA interference networks. In each case, we elaborate on the transmission rate estimation, power consumption modelling, existing optimization constraints and the optimization solutions. Specifically, in the power-consumption modelling, we include the signal-processing (and related computing) power. We discuss the practicality of the considered solutions. We also touch upon the problem of nonlinear power amplifier characteristics (causing distortions typical for OFDM signals) to be taken into account for energy-efficient resource allocation. We discuss trade-offs and provide recommendations for future energy-efficient OFDM networks design. We also discuss the future works and challenges in the context of energy efficiency resource allocation for OFDM/OFDMA and their derivative techniques. We conclude that the presented design practices should include computational awareness in the networks to trade-off between information communication, information processing and the required network management energy-efficiency.

INDEX TERMS Energy-efficiency, green communication, optimization, orthogonal frequency division multiple access (OFDMA), power consumption estimation, relay networks, resource allocation, transmission rate estimation.

I. INTRODUCTION

In the era of ubiquitous Internet access, exponential growth of telecommunication traffic can be observed every year. According to Cisco predictions there will be 4.8 billion of global Internet users in 2022 and 28.5 billion networked devices and connections [1]. Moreover, the mobile data traffic will increase to 930 eksabytes in 2022. According to the Ericsson Mobility Report [2], communication of 26,9 billions of machines and devices that are expected by 2026 to

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comprise the Internet of Things (IoT) poses challenges, never encountered before. One of these challenges is an increase of energy consumption associated with the data-traffic growth worldwide. That is why reduced-energy wireless communication has been in the focus of research and industry interest for the recent years, aiming at achieving 10 times the energy efficiency (EE) in the Fifth Generation (5G) radio systems compared with the Fourth Generation (4G) of these systems [3]. Moreover, so-called *zero-energy* radios are envisioned for future Sixth Generation (6G) systems as their technology enablers [4]. According to this vision, drivers from society, including the United Nations sustainability goals, will

shape 6G communication systems. Moreover, high energy efficiency to reduce the overall network energy consumption will be a critical requirement for these future systems.

On the completion of 3GPP Release 15 [5] and Release 16 [6] (as of today, Release 17 being under way), the set of 5G standards has been defined. As in 4G Long-Term Evolution (LTE) standard, the Orthogonal Frequency Division Multiplexing (OFDM) has been proposed for 5G systems. Moreover, OFDM has been also successfully applied in other radio communication systems, such as Wireless Local Area Networks (WLANs), including IEEE 802.11a/g/n, Wireless Metropolitan Area Networks (WMANs), including World-wide Interoperability for Microwave Access (WiMAX) standard, Wireless Personal Area Networks (WPANs), including MultiBand-OFDM in the 3.1–10.6 GHz band, as well as in the terrestrial Digital Audio- (DAB) or Video Broadcasting (DVB-T) systems. Popularity of the OFDM technique results from its known advantages: high spectral efficiency compared to other double sideband modulation schemes, flexibility and adaptation potential to channel conditions, robustness against intersymbol interference (ISI), efficient implementation using Fast Fourier Transform (FFT), low sensitivity to time synchronization errors and facilitation of the Single Frequency Networks (SFNs) [7]. Finally, Orthogonal Frequency Division Multiple Access (OFDMA) is the popular OFDM-based method for Medium Access Control (MAC) layer to facilitate multiple users network access. Therefore, this paper focuses on the energy-efficient resource allocation in OFDM/OFDMA systems instead of NOMA (Non-Orthogonal Multiple Access), Slotted ALOHA, TDMA (Time Division Multiple Access). The use of NOMA techniques allows for higher spectral efficiency and lower latency but each of the users needs to decode the information of all the other users even if one has the worst channel gains. This leads to complexity in the receiver. Moreover, energy consumption is higher. In the case of the TDMA technique, the battery consumption is low but the guard interval between time slots and synchronisation is required. The synchronisation is also required in slotted ALOHA technique which is simple and decentralized protocol but due to frequent collisions, the maximum throughput of the slotted Aloha is only 0.368.

Motivated by the increased mobile communication traffic, required high data-rates and associated energy-consumption on one hand, and the applicability of the OFDM/OFDMA techniques in contemporary and prospective radio communication systems on the other, here below, we review approaches and promising methods to optimize wireless OFDM/OFDMA links and networks. Contrarily to the traditional approach to minimize the transmission power for the assumed target bit-rate, we look at advanced power-consumption models and optimization of the defined energy-efficiency metric. This is because depending on the link quality, power consumption of different causes, e.g. RF signal radiation, or signal processing, may dominate over each other, and may be worth minimization for overall energy-efficiency. Moreover, non-linear Power

Amplifier (PA) characteristic and high Peak-to-Average Power Ratio (PAPR) are well known issues of OFDM-based systems and they should also be taken into account (jointly with other sources of power-consumption model) when optimizing the energy-efficiency of those systems. Finally, the optimization algorithm itself also consumes energy, that needs to be taken into account.

Therefore, here below, we survey existing works that relate to energy-efficiency in OFDM/OFDMA networks, and we put a special emphasis on *computational awareness* of the presented solutions, i.e., on energy-consumption models that include energy consumed by digital and analog signal processing, not just by radio signal emission.

The paper is organized as follows. First, in Section II, we overview other surveys and tutorials that might be related to ours to show in what aspects our work is original and more focused. Then, in Section III, we provide definition of energy-effiency, and consider the main optimization goals related to energy-efficient wireless OFDM/OFDMA communication. We also review realistic power-consumption models of an OFDM link. In Sections IV, V and VI, we overview computationally-aware energy-efficiency optimization solutions for OFDM links, OFDMA single-hop and relay networks respectively. Section VII presents example results of energy-efficiency optimization for representative, carefully selected use-cases. Then, in Section VIII, we discuss energy-efficiency optimization that takes non-linear PA characteristic into account. In Section IX, we discuss practicality of the considered solutions, taking their computational complexity, and other related costs into account. We also provide recommendations for future energy-efficient OFDM networks design. The discussion about future works and challenges in the context of energy efficiency resource allocation for other techniques based on OFDM/OFDMA is provided in Section X. Finally, in Section XI, we summarize key findings of our survey and considerations.

II. RELATED SURVEYS AND TUTORIALS

There are a few survey papers that relate to our topic. Let us now overview these published surveys, and compare them with the content of our work within the following aspects that we undertake: (a) the considered radio communication techniques and scenarios (b) completeness of the power-consumption models, (c) considered methods for energy-efficiency optimization and (d) formal energy-efficiency radio resource management algorithms and optimized solutions for radio communication network.

In [8], Feng *et al.* discuss key enablers for energy-efficient wireless communication: resource management exploiting low traffic loads and service differentiation, network deployment strategies, utilizing diversities of heterogeneous networks and cooperative communications, as well as MIMO, OFDMA and cross-layer design options. The paper is not focused on OFDM/OFDMA radio resource optimization for energy-efficiency, and does not provide complete

transmitter-to-receiver power-consumption models. Similarly, as in [8], the authors of [9] briefly review some international projects and indicate key challenges related to green communications. Thus, [8] and [9] are different (more general and less focused) from our work in all aspects (a)-(d). Note that [8] indicates that energy-efficient resource allocation in OFDMA systems with appropriate relay strategies is still an open issue. It is in fact addressed in our paper below.

In [10] and [11], energy-efficiency of 5G networks is addressed. The first paper presents very general view on future networks before 5G era, focusing on renewable energy resources for 5G base stations (BSs). The second presents challenges of resource allocation, network planning, energy harvesting and hardware design for 5G. It does not focus on OFDM-specific problems. Thus, papers [10] and [11] differ significantly from ours in the considered scenarios, i.e. in aspect (a). Moreover, they do not address optimization methods (our aspect (c)), neither present formal or practical design solutions of energy-efficient radio networks (our aspect (d)).

In magazine paper [12] by Li *et al.*, the authors discuss general issues of energy-efficiency in wireless communication, in particular in OFDMA, multi-antenna and multi-hop networks indicating trade-offs between energy- and spectral-efficiency, as well as signalling overhead required for energy-aware networks. The paper does not touch upon computational awareness of networks, narrowing power consumption to transmit (radio emission) power. Moreover, it does not consider energy-efficiency optimization methods and their complexity. Likewise, in [13], Zhang *et al.* discuss fundamental trade-offs that must be taken into account in green wireless networks design: energy efficiency versus spectrum efficiency, deployment efficiency, latency and bandwidth. In this paper, the authors address energy-efficiency of OFDM. However, the considered power consumption model is limited to radio-emission power, no optimization methods are considered and solutions are not presented. Thus, similarly as [12], survey paper [13] is different from ours in aspect (b) and does not address aspects (c) and (d).

In [14], the EARTH project results are discussed, in particular, beam forming and MIMO techniques for energy-efficiency of LTE cellular systems. There, BS power consumption breakdown among major transceiver blocks, power supply and a cooling system is presented. Although an LTE system uses OFDMA in a downlink, no OFDM/OFDMA radio resource optimization is discussed. Consequently, this paper is not addressing our aspects (c) and (d).

In [15], resource allocation strategies (rate-adaptive and margin-adaptive algorithms) in the downlink OFDMA systems are considered. The focus of this paper is on resource allocation efficiency vs. fairness. Likewise, the authors of [16] overview resource allocation optimization in the uplink direction of OFDMA systems. However, the goals of the optimization methods considered in both papers are not the energy-efficiency. Moreover, the power

consumption model is simplified (narrowed to the radio-emission power). Thus, these survey papers differ from our work in aspects (b)-(d).

In [17], scenarios of multiple base stations co-existing in the same area and sharing the available radio resources are considered. The focus of the paper is on optimization and game-theory-based (equilibrium) solutions for interference coordination between base stations in homogeneous, heterogeneous and cooperative cellular networks. There, the power related to base-band signal processing is not taken into account, rather the power allocated to coexisting base stations. Thus, this paper is different in the considered scenarios (our aspect (a)) and energy-consumption model (aspect (b)) from our survey.

In [18], Zappone *et al.* review optimization methods for energy efficiency maximization in wireless networks and provide example numerical results. They consider maximization of network energy-efficiency metrics defined in different ways (as global energy-efficiency, weighted minimum energy efficiency, weighted sum energy efficiency and weighted product energy efficiency). The paper is not considering resource allocation for OFDM/OFDMA networks, and assumes a different power model than our work does. It presents optimization strategies (either monotonic or sequential optimization merged with fractional programming) for power control in a network with multiple links, each characterized by a specific circuit power independent of a bit rate. Considering a different technique and a different power model, this paper is different from our work in aspects (a) and (b).

Finally, it is worth mentioning that high PAPR in OFDM/OFDMA transmitters translates to inefficient power utilization. In [19] and [20], PAPR minimization techniques in OFDM systems are surveyed, however, these papers do not touch upon the problem of link- or network energy-efficiency optimization, nor the global power-consumption model. Thus, these surveys are narrowed with respect to our aspect (a) and not addressing aspects (b)-(d).

To summarize, our survey presented below concerns optimization methods of resource (subcarriers, resource-blocks, transmission power levels, modulation and coding schemes, relays) allocation for energy-efficiency maximization in OFDM/OFDMA links and networks. The power-consumption model considered here encompasses transmission (electromagnetic emission) power as well as the circuit- and base-band signal processing (computational) power dependent on the transmission bit-rate. This is why we call such methods *computationally aware*. To the best of our knowledge, no prior papers tackle systematic overview of the problems of OFDM/OFDMA networks global energy-efficiency optimization and dynamic resource allocation with computational awareness. The major contributions of this paper are as follows:

- In this paper, the state of the art with the original classification of the key aspects of energy-efficient resource allocation in the context of OFDM is presented.
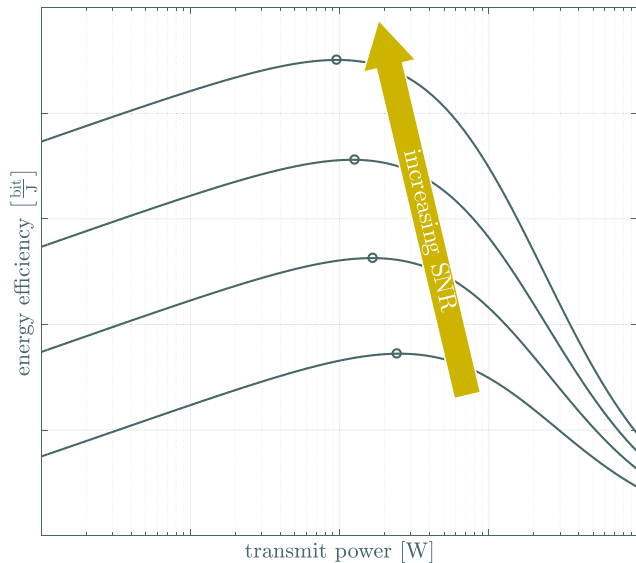
FIGURE 1. Relation between the energy efficiency and transmit power for different values of the Signal to Noise Ratio (SNR).

The definition of the EE metric with the ways its maximization are presented. Moreover, the analysis of each aspect and the relation between them have been discussed.

- The investigated aspects, energy-efficient resource allocation methods and solutions are presented for a single OFDM link, multiuser OFDMA and multiuser OFDMA relay networks.
- The practicality of the energy-efficient resource allocation is discussed. We touch upon the problem of nonlinear PA characteristics (causing distortions typical for OFDM signals) to be taken into account for energy-efficient resource allocation.
- In this paper, we discuss the design trade-offs, and formulated recommendations for the energy-efficiency maximization accounting for the optimization complexity, required information availability, signalling overhead and the available degrees of freedom in OFDM/OFDMA resource allocation.

Thus, in the contrast to the existing papers, our paper provides comprehensive knowledge about energy-efficient resource allocation in the OFDM/OFDMA systems. In this paper the approaches of the key aspects of energy-efficient resource allocation with pros, cons and trade-offs are provided. The methods and techniques used in the design of energy-efficient resource allocation are presented and finally the practical aspects of energy-efficient resource allocation, recommendations for energy efficiency as well as future works and challenges are provided.

III. DEFINITION AND ASPECTS OF ENERGY EFFICIENT RESOURCE ALLOCATION IN WIRELESS COMMUNICATIONS

Energy-saving or energy-efficient operation of communication and computing networks is typically evaluated using metrics related to either a total energy-consumption figure or the expected performance per energy unit. The later is called energy-efficiency, and can be expressed in the number of successfully transmitted bits per Joule or the number of computational operations (clock cycles) per Joule or the number of transported and processed computational tasks per Joule. In this paper, we concentrate on wireless networks exploiting OFDM/OFDMA flexiblity for energy-efficient communication. For such networks, the energy-efficiency metric η is commonly defined as a benefit-cost ratio, where the achieved data rate is divided over the associated power consumption:

$$\eta \left[\frac{\text{bit}}{\text{Joule}} \right] = \frac{\text{data rate [bit/s]}}{\text{power consumption [W]}}. \qquad (1)$$

Thus, this EE metric determines the number of successfully transmitted, received and processed bits per energy unit and should be maximized. Here, processing of bits refers to signal processing at the transmitter and at the receiver, which is required for successful transmission and reception of information. In Figure 1, the relation between the energy efficiency and transmit power for different values of the Signal to Noise Ratio (SNR) is presented. Let us observe that there exist the optimal point for the transmit power that maximizes EE. It means that there exists a trade-off between the data rate and power consumption which allows for energy-efficient transmission. Moreover, for the higher SNR values, the optimal point is reached for lower transmission power. Thus, in order to maximize the energy efficiency of wireless communications systems, one of three ways can be chosen:

(i) The maximization of the data rate, whilst minimizing the total power consumption. This approach is practically infeasible because the achievable data rate strictly depends on the transmit power (and the overall power consumption) and vice versa.

(ii) The maximization of the data rate with a minimum possible increase in power consumption (e.g., minimum increase of the transmit power can cause a significant gain in the date rate, particularly for low SNR values).

(iii) The minimization of the power consumption with a minimum reduction of the data rate (e.g. by applying less advanced coding decoding energy can be reduced, particularly at short communication distances).

In the context of the energy-efficient resource allocation exploiting OFDM/OFDMA techniques, the second and third approaches are usually chosen because in OFDM/OFDMA based networks, the total available bandwidth and power are partitioned into a number of subcarriers (SC) or resource blocks (RB). For each of them, the transmission parameters can be determined and adopted, depending on the channel conditions. Moreover, the short time-scale approach can be applied to maximize the energy-efficiency metric. It means that the resource allocation is realized in the frequency domain for a given time slot.

Here, by *resources* we mean energy-related communication means (such as transmit power, basic resource blocks, modulation and coding schemes (MCS) and other
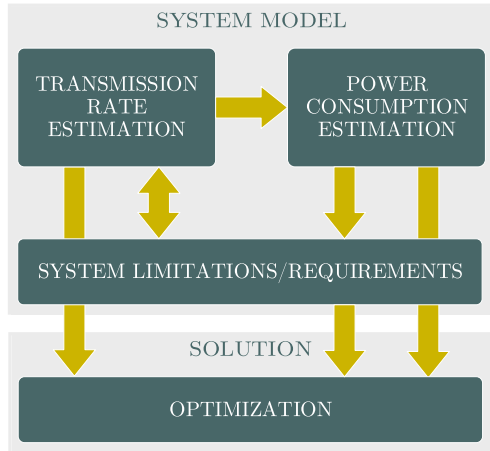
FIGURE 2. Interaction between the tasks of energy efficient resource allocation in wireless communication systems.

transmission parameters) and network means (such as relying nodes) that can be adjusted, depending on channels and network conditions. Optimization of resource allocation for energy efficiency involves estimation of the transmission rate and power consumption as well as taking all transmission limitations and network requirements into account what has been elaborated in the following subsections, in detail. Regarding the first two tasks, namely *transmission rate*- and *power consumption estimation*, they are required for the energy-efficiency metric definition. Based on the literature review, we distinguish different approaches to estimate the data rate and power consumption, and analyze them. Regarding the system *limitations/requirements* identification task, we concentrate on the system and network constraints and requirements which have to be fulfilled, and we demonstrate their impact on the energy efficiency. Finally, in the *optimization* task, the challenges and problems related to the design of the resource allocation algorithm for optimal energy efficiency have to be solved.

Figure 2 shows how the considered tasks interact with each other. specifically, the power consumption is determined by the transmission rate estimation (e.g. if coded transmission is considered, the power consumed by the encoder and decoder should be taken into account). The system limitations and requirements have an impact on transmission rate estimation (for example, when the fairness constraint or/and subcarriers grouping into resource blocks are considered). The transmission and power consumption estimations determine how the system limitations/requirements are met, while all aspects have an impact on the solution of the optimization problem which allows for energy-efficient resource allocation.

A. TRANSMISSION RATE ESTIMATION

The crucial aspect of the energy-efficient resource allocation is estimation of data rate and power consumption - the numerator and denominator of (1) respectively. In this subsection, the main approaches to the transmission rate estimation are

described. Having in mind the diversity of wireless communication systems, the transmission rate estimation is not a trivial task. In the literature (not just that related to energy-efficient resource allocation), three main approaches of transmission rate estimation can be distinguished:

(i) based on the Shannon formula,
(ii) estimated by the Shannon formula with scaling factors,
(iii) based on the error-rate function and the spectral efficiency of the applied MCS.

The Shannon formula for transmission rate estimation is the most commonly used approach. In general, the data rate described by Shannon formula is given by:

$$R\left[\frac{\text{bit}}{\text{s}}\right] = W \cdot \log_2\left(1 + \frac{P_{\text{R}}}{\sigma_{\text{N}}^2 + \sigma_{\text{I}}^2}\right), \tag{2}$$

where W is the channel (and the signal) bandwidth, P_{R} is the average received signal power over that bandwidth, while σ_{N}^2 and σ_{I}^2 are the average powers of the noise and interference respectively over bandwidth W. The Shannon formula can be easily adapted to OFDM/OFDMA subcarrier-channels as well as to different network scenarios e.g. multi-cell, heterogeneous or cooperative network. Moreover, according to (2), R for $\sigma_{\text{I}}^2 = 0$ is the concave function of the signal power P_{R}, while when $\sigma_{\text{I}}^2 \neq 0$, there exist techniques which allow to transform it into the concave one. (Note that concavity of this function results in relative low computational complexity of its optimization, as well as optimization of the energy-efficiency, which is in the focus of this paper.) The Shannon formula formulates the upper bound of the data rate which is not achieved by any practical wireless system. Therefore, using (2) for data rate estimation can be treated as idealistic approach which does not take the limitations of practical communication systems (e.g., such as a limited set of the modulation and coding schemes) into account.

In order to account for practical limitations of a wireless communication system, the data rate can be estimated by:

$$R\left[\frac{\text{bit}}{\text{s}}\right] = \xi \cdot W \cdot \log_2\left(1 + \frac{\nu \cdot P_{\text{R}}}{\sigma_{\text{N}}^2 + \sigma_{\text{I}}^2}\right), \tag{3}$$

where ξ and ν are the scaling factors fitting the Shannon formula to a practical system. The scaling factors can fit Shannon formula to the single MCS and spectral efficiency or to the whole set of them. Such an approach for rate estimation has been first considered in [21] where scaling factor ν depending on the bit error probability has been introduced. Based on [21] and the assumed code rate, the coding gain and bit error probability for various MCSs, the data rate has been estimated in [22]. Similar approximations for a whole range of the modulation and coding schemes can be found in [23], [24], and [25]. In the last case (in [25]), the Shannon formula is scaled just by factor ξ (assuming $\nu = 1$). The Shannon formula with scaling factors (formula (3)) reflects achievable rate in a practical communication system, and can still be the concave function of the signal power if the factors are appropriately chosen. Thus, using it for rate estimation is
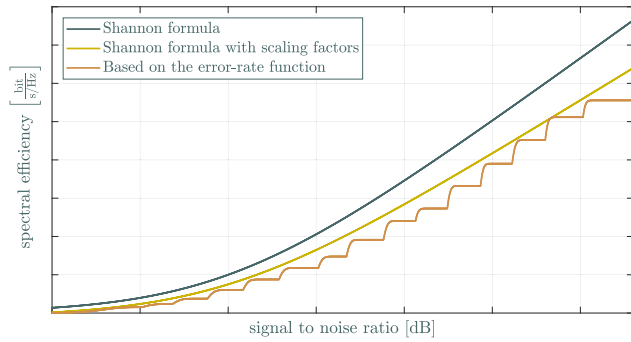
FIGURE 3. The spectral efficiency as a function of SNR for three approaches of the data rate estimation.

FIGURE 4. Trade-off observed in the data rate estimation.

TABLE 1. Pros and cons of the data rate estimation.

	Pros	Cons
Shannon formula	• the universal approach allows for describing the different systems • allows for determining the upper bound of the energy efficiency in the system • allows for applying optimization techniques with low complexity	• the ideal case which does not take the aspects of the practical wireless communication systems into account
Shannon formula with scaling factors	• brings the Shannon formula closer to the practical wireless communication systems • allows for applying optimization techniques with low complexity • better representation of the practical communication systems than Shannon formula without scaling factors • scaling factors can consider different aspects of the practical wireless communication systems	• does not take all aspects of the practical wireless communication systems into account • worse representation of the practical communication systems than approaches based on error rate function • the need to obtain the scaling factors • the scaling factors depend on the considered system
based on error rate function	• the best representation of the practical communication systems • take the aspects of the practical wireless communication systems into account	• makes the optimization problem non-convex which is very difficult to solve • the need to find the mathematical function which describes the error-rate function • the error-rate function highly depends on the parameters of the modulation and coding scheme

more accurate than using (2) and results in acceptable computational complexity of the considered optimization tasks.

The third approach to data rate estimation which is considered as accurately characterizing practical wireless communication systems is based on the spectral efficiency and the error rate function of the applied MCS e.g. the block-error rate (BLER), the packet error rate (PER) or bit error rate (BER). This approach depends on the parameters of the modulation and coding scheme, e.g., on the applied (de)modulation and (de)coding algorithms, the packet size, the number of decoder iterations, etc. In general, the data rate in this approach can be expressed by [26], [27], [28], [29]:

$$R\left[\frac{\text{bit}}{\text{s}}\right] = W \cdot \zeta_{\text{SE}} \cdot [1 - \text{err}(\mathbf{x})], \qquad (4)$$

where ζ_{SE} is the spectral efficiency in bit/s/Hz, err $(\cdot)$ is the function of error rate, while $\mathbf{x}$ is the vector of the parameters on which this function depends e.g. SNR, modulation and coding scheme. The data rate estimation by BLER function can be found in [27] where BLER curves have been approximated by the complementary error function erfc $(\cdot)$ with two scaling factors in a function of effective signal to interference and noise ratio (SINR). Moreover, in [29], the scaling factors for the MCS set of Long-Term Evolution (LTE) network are provided. The approximation of PER based on the noncentral chi-square distribution has been introduced in [30], and then applied in [31] in the context of the energy-efficiency maximization for hybrid automatic repeat request (HARQ) in a Rician fading channel. Other approximations of PER in systems applying HARQ be found in [32] and [33].

In Figure 3, the spectral efficiency as a function of SNR for transmission rate estimation based on the Shannon formula, estimated by the Shannon formula with scaling factors and based on the block-error rate are plotted. It can be observed that the Shannon formula deviates significantly from the real communication system. On the other hand, the data rate resulting from the block error-rate is non-convex function of the signal power (and SNR) making the prospective energy-efficiency optimization problem very difficult to solve. In Figure 4, the trade-off between the accuracy of data rate estimation and the complexity of the optimal,
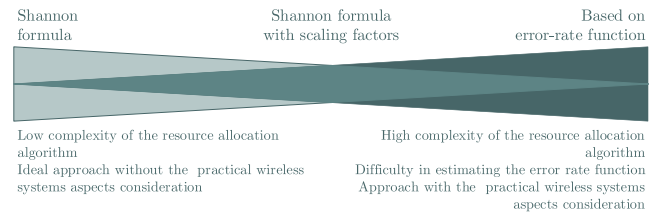
energy-efficient resource allocation algorithm is illustrated. Note that for the low accuracy of data rate estimation (according to the Shannon formula), usually, the energy-efficient resource allocation algorithm with low complexity can be designed. On the other hand, the estimation with high accuracy causes high complexity of the energy-efficiency optimization problem. Therefore, the Shannon formula with scaling factor seems to be a good trade-off between mapping practical system data rates and the complexity of solving the considered optimization problem.

Finally, the pros and cons of data rate estimation for the three described approaches are summarized in Table 1.
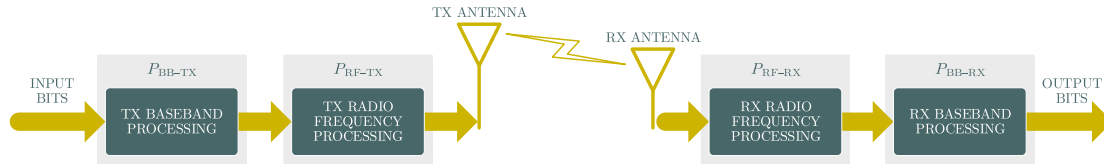
FIGURE 5. The general block diagram of the transmitter and receiver with the power consumption description related to each element.

B. ESTIMATION OF THE POWER CONSUMPTION

Estimation of the power consumption (the denominator in (1)) in a network is the crucial aspect in designing the energy efficient wireless communication systems. In general, the power consumption models consist of the power required to transmit the signal P_T and the power consumed by the circuits P_C which can be divided into power consumed by the baseband signal processing P_{BB} and by the radio-frequency (including intermediate-frequency) signal processing P_{RF} (see Figure 5):

$$P \, [\text{W}] = P_T + \underbrace{\underbrace{P_{BB-TX} + P_{BB-RX}}_{P_{BB}} + \underbrace{P_{RF-TX} + P_{RF-RX}}_{P_{RF}}}_{P_C}.$$

$$(5)$$

In case of the OFDM/OFDMA technique, the transmission power is equal to the sum of powers allocated to subcarriers which are determined by the designed resource allocation algorithm that responds to instantaneous channel conditions. The issue is more difficult in the case of the estimation of power consumed by the transmitter and receiver circuits. The main difficulty results from different types of transmission and reception techniques, applied technologies, standards, algorithms implementations, etc. In the literature, three approaches of power consumption modeling can be distinguished:

(i) high-level power consumption model,
(ii) estimating power consumption based on the measurements,
(iii) the estimation of the power consumed by each transmitter and receiver components.

Their pros and cons are presented in Table 2.

The high-level models can determine the power consumption of different techniques in a universal way but at the expense of the low accuracy of estimation. The simplest total power consumption model can be found in the early papers focusing on the energy-efficient resource allocation [34], [35]. In these papers, the total power consumption model consists of the constant circuit power and the transmit power allocated at each OFDM subchannel. The constant circuit power includes the power consumed by the baseband- and radio-frequency signal processing at the transmitter and at the receiver, while the transmit power dynamically changes according to instantaneous channel conditions.

TABLE 2. Pros and cons of the power consumption estimation.

	Pros	Cons
high-level model	• easy to define • the universal approach allows for describing the different systems • allows for applying optimization techniques with low complexity • low-dependent on the implementation, systems, parameters etc. and mathematically simple	• does not take all aspects of the real systems into account
based on measurements	• better representation of the real systems than high-level model • takes some aspects of the real systems e.g. data rate, path loss into account	• the measurements of the power consumed by the transmitter and receiver are required • the power consumption model depends on the implementation, system, parameter etc. • the energy consumption of the individual components of the transmitter and receiver is unknown
each component power estimation	• the best representation of the real systems • takes the aspects of the real systems e.g. parameters of transmission into account	• very difficult to determine the power consumption model of each component • the power consumption model depends on the implementation, system, parameter etc.

In [22], [36], and [37], the power dissipation in a chip is modelled as the sum of a static term and a dynamic term. The latter depends on, among other parameters, the supply voltage, the clock frequency and the circuit capacitance. It is assumed that the dynamic term depending on the clock frequency is scaled with the data rate. Thus, the circuit power is modelled as the linear function of the achieved data rate:

$$P_C \, [\text{W}] = \alpha + \beta \cdot R, \qquad (6)$$

where α is the static term, and β is the implementation-dependent factor determined in W/ (bit/s). These high-level power consumption models are commonly used in the energy efficient resource allocation optimization.

The second approach to estimate the power consumption of wireless devices is based on measurements. Such an approach guarantees high accuracy of power estimation but it highly
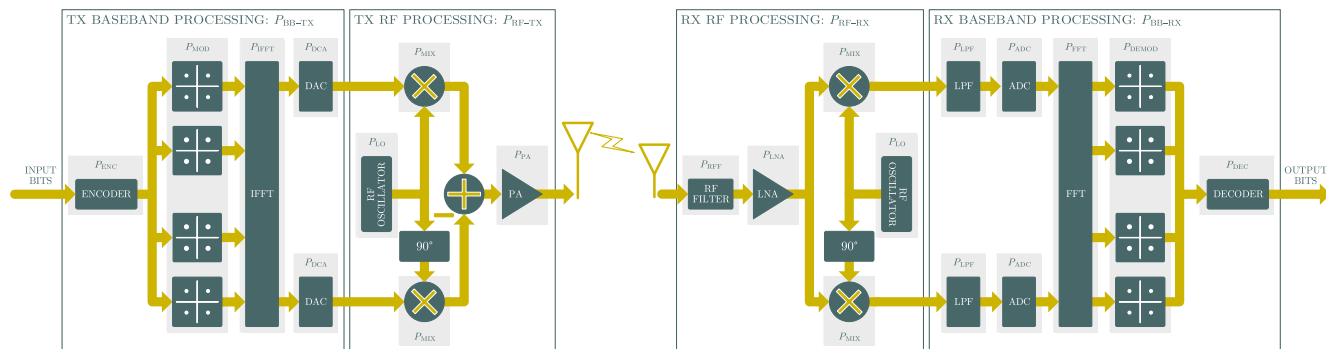
FIGURE 6. The block diagram of OFDM transmitter and receiver with the power consumption description related to each element.

depends on the equipment/link/network configuration, implementation, vendors, etc. In this approach, the total consumed power (including transmission power) is measured. It means that the transmission power allocation algorithm can not be applied with such models because the transmit power and the circuit power are not separable, thus the relation between them can not be determined a posteriori (after measurement). In [38], [39], [40], [41], and [42], the authors describe measurements of the power consumption of a set of commercially available devices, in the number of configurations. In [39], the stochastic power consumption models have been proposed based on measurements of a range of transceivers offered by various vendors. The authors of [39], [40], [41], and [42] have focused on the WiFi standards while in [38] the set of measured devices includes cellular network USB modem e.g. LTE as well as WiFi USB modem. Moreover, these papers provide the analytical models of the power consumed by devices. Although the power consumption modelling based on measurements highly depends on the devices hardware and software implementation, application techniques, vendors, etc., they can be useful to design the high-level models by the means of interpolation of measurement points or statistical approach.

The most accurate but also the most complex approach is to estimate the power consumption of each transmitter- and receiver-component separately. Having in mind the fact that the transceiver is integrated into one chip, the measurement of each its component is very difficult and practically impossible. Therefore, in the literature, the estimation of each transceiver component power consumption is usually based on its architecture. (The block diagram of the coded OFDM transmitter and receiver is presented in Fig. 6.) In this approach the power consumption model by circuits is given by:

$$
\begin{aligned}
P_{\mathrm{C}}\,[\mathrm{W}] \\
= \underbrace{P_{\mathrm{ENC}} + P_{\mathrm{MOD}} + P_{\mathrm{IFFT}} + P_{\mathrm{DAC}}}_{P_{\mathrm{BB-TX}}} \\
+ \underbrace{P_{\mathrm{LPF}} + P_{\mathrm{ADC}} + P_{\mathrm{FFT}} + P_{\mathrm{DEMOD}} + P_{\mathrm{DEC}}}_{P_{\mathrm{BB-RX}}}
\end{aligned}
$$

$$
+ \underbrace{P_{\mathrm{PA}} + P_{\mathrm{MIX}} + P_{\mathrm{LO}}}_{P_{\mathrm{RF-TX}}} + \underbrace{P_{\mathrm{RFF}} + P_{\mathrm{LNA}} + P_{\mathrm{MIX}} + P_{\mathrm{LO}}}_{P_{\mathrm{RF-RX}}},
$$

$$
(7)
$$

where P_{PA}, P_{LNA}, P_{LO}, P_{RFF} and P_{MIX} describe the power consumption of the power amplifier (PA), low noise amplifier (LNA), local oscillators (LO), radio frequency (RF) filter and mixer, respectively. The power consumed by baseband (BB) processing includes power consumption of the analog-to-digital converter P_{ADC}, the digital-to-analog converter P_{DAC}, modulation P_{MOD} and demodulation P_{DEMOD}, encoding P_{ENC} and decoding P_{DEC}, low-pass filter P_{LPF}, inverse fast Fourier transform P_{IFFT} and fast Fourier transform P_{FFT}. It can be observed that depending on the structure of a transceiver, the power consumption model can be different. Nevertheless, some elements are common for the most digital transmission systems. The power consumption models of these components consuming most considerable amount of power can be found in [43], [44], [45], and [46]. There, the total power spent in the communication link is the sum of power consumed by the power amplifier, the low noise amplifier, the analog-to-digital converter and the error-correcting decoder. More system-level energy models for the radio frequency front-end components of a wireless transceiver with the exemplary power consumption values from most commonly refereed publications can be found in [47]. The components include ADC, DAC, the reconstruction and anti-aliasing filters, the mixers, the frequency synthesizer, PA, LNA, and the baseband amplifier. In [48], more exemplary power consumption values are listed in the context of Long Term Evolution (LTE) technology. The power consumption models from the papers cited above have been adapted to multi-user massive MIMO (multiple-input and multiple-output) scenario in [49] and [50]. In addition to adapting existing models of energy consumption, the model has been extended by elements specific to the presented scenario, such as energy consumption by the channel estimation process, by the load-dependent backhaul or linear processing at the base station.

In most of the papers cited above, the authors focus on the power consumption of the RF front-end and channel
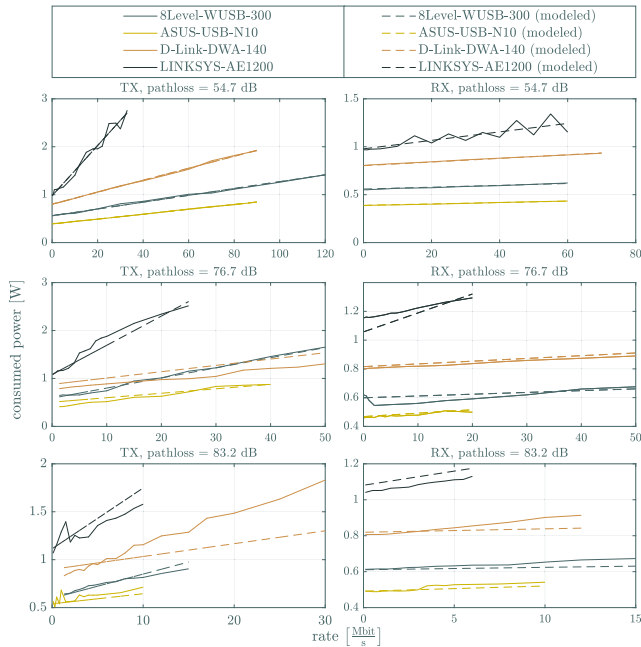
FIGURE 7. Measured and modelled power consumption of the USB transceivers as a function of the rate.

FIGURE 8. The consumed power for high-level power consumption model and based on the estimation of the power consumed by each transmitter and receiver components [25].

coding, neglecting the power consumed by other baseband signal processing algorithms which have a significant share in power consumption, in case of short links. In [51], [52], [53], [54], and [55], more attention is put to this aspect. In [51] and [52], the number of operations needed to encode or decode the information bit for the channel coding algorithms was determined. Then, knowing the energy consumption per operation, the total power consumed by channel coding can be determined. In [53], a dynamic power estimation methodology for Field Programmable Gate Arrays (FPGA) based system has been presented. The methodology has been evaluated on the LTE downlink physical layer and provides fast and accurate power estimation. Similarly as in the general power consumption model presented in [36], the power consumed by FPGA is also divided into static and dynamic power. In the proposed methodology, the total dynamic power is determined by the power estimations of each sub-element in the system e.g. in the wireless communication scenario, the power is estimated for channel coding, modulation, Fast Fourier Transform (FFT) etc. That work has been continued in [54] and [55] where the more advanced scenarios are considered, and the power consumption values of each system element are presented. Moreover, the extension to other FPGAs by introducing a scaling factor has been introduced. As overviewed above, diverse power consumption models can be considered for distinct transmitter and receiver components. In Table 3, key parameters of the power consumption models for distinct transmitter and receiver components known from the literature are summarized.

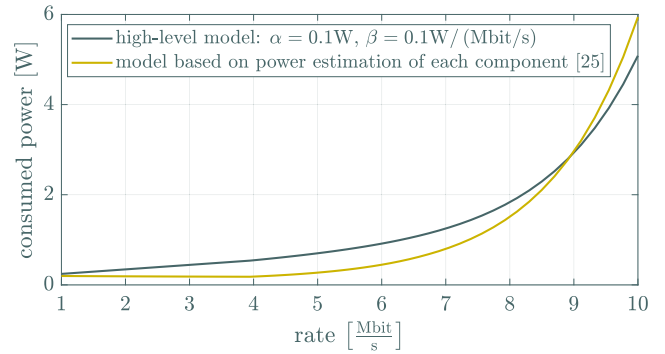Furthermore, in Figure 7 our measurement results for different USB transceivers and based on them the power

consumption model are presented [56]. The consumed power was measured on the transmitting and receiving sides for different values of pathloss. Moreover, all measured transceivers work in IEEE 802.11g standard and were selected so that the WiFi chipset was different. It can be observed that the power consumption increases with the rate and the values of the consumed power and curve slope highly depend on the vendor. There is also a noticeable impact of pathloss on the power consumed, particularly on the receiving side, which is related to the increasing power of transmission. Moreover, in Figure 8 the consumed power for high-level power consumption model and based on the estimation of the power consumed by each transmitter and receiver components [25] is presented. Note that in both approaches, the power consumed grows exponentially with the throughput, in contrast to the measurement-based approach where the power increased linearly. In addition, for a given system configuration, the power consumed by the transmitter and receiver components is in most cases constant. For the power consumption model presented in [25], only the power consumed by channel coding, the power amplifier and the transmit power change dynamically depending on the channel conditions. Therefore, both curves follow a similar course.

Finally, Figure 9 illustrates the trade-off between the accuracy of the power consumption models and the difficulty in defining them. It can be observed that if the power consumption model is easy to define, the representation of the real system is low. On the other hand, if the accuracy of the power consumption model is high, the model is really difficult to determine, for example, due to the fact that all transmitter/receiver components are integrated in a single chip. Therefore, the power consumption based on the measurements and augmented with the interpolation or stochastic modelling seems to be a good trade-off.

C. CONSTRAINTS
The maximization of energy efficiency metric as defined by (1) without constraints is not practical for multiple reasons.[1] In the optimization, physical limitations of the network

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[1]One might achieve the maximum energy efficiency, if no transmission takes place.
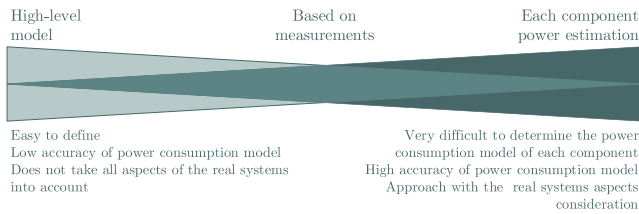
FIGURE 9. Trade-off observed in the power consumption estimation.

TABLE 3. The review of the power consumption models of the transmitter/receiver components.

Power	Model parameters	Reference
P_{PA}	class A power amplifier; parameters: the peak-to-average power ratio (PAPR) and the drain efficiency of the power amplifier	[43]–[46]
	class A power amplifier; parameters: PAPR, the proportionality constant and the output power proportional to the detected signal power at the receiver	[47]
	class A, AB and B power amplifier; parameters: PAPR, the drain efficiency of the power amplifier and the transmit power factor	[48]
P_{LNA}	the power gain, the noise figure, the operating bandwidth, the thermal noise and the figure-of-merit	[43]–[46]
	the gain, the noise figure and some proportionality constant parameter	[47]
P_{MIX}	the gain, the noise figure and some proportionality constant	[47]
P_{LPF}	the proportionality constant depending on the filter topology and the active elements used, the quality factor, the corner frequency and SNR	[47]
P_{LO}	the parasitic capacitance loading of the RF circuits, the reference frequency, is the supply voltage, the LO frequency, the proportionality constants	[47]
P_{ADC}	the resolution, the bandwidth, the thermal noise and some proportionality constant depending on the ADC architecture	[43]–[46]
	the minimum channel length for the given CMOS technology, the power supply, the signal and sampling frequency and the resolution which depends on PAPR and the signal-to-quantization-noise ratio (SQNR)	[47]
P_{DAC}	the parasitic capacitance of each switch, the oversampling rate, the signal bandwidth, the power supply, the unit current source per least significant bit and the resolution which depends on PAPR and SQNR	[47]
P_{ENC}	the number of operations needed to encode or decode the information bit	[52]
	the clock frequency, CBS (not explained in the paper)	[54]
P_{DEC}	LDPC codes; parameters: the number of ones in each column, the number of iterations, the data rate, the bandwidth and the constant parameter	[44], [45]
	the number of operations needed to encode or decode the information bit	[51], [52]
P_{MOD}	QAM modulator; parameters: the clock frequency and the number of the quantization bits	[54]
P_{IFFT}	the clock frequency, the number of the quantization bits and IFFT size	[54]

such as the maximum transmit power, minimum guaranteed throughput or particular standard requirements (e.g. the emission spectrum mask) have to be taken into account. Therefore, the energy efficiency optimization problem is usually defined as the objective function with constraints. Moreover, some limitations of wireless communication systems can be included in the objective function, e.g., grouping the subcarriers into resource blocks. The most common constraints known from the literature are listed below:

- *the maximum transmission power constraint* ensures that the sum of the transmission power allocated to the subcarriers is lower than or equal to the maximum assumed value. In the case of downlink transmission, this constraint typically limits the transmission power of the base station while, for the uplink, the transmit power of each end-user is limited. This constraint results from practical aspect of designing wireless communication systems where the total transmission power is limited by standards.

- *the requirement on the minimum data rate* aims at providing the end-user quality of service. In this case, the achieved data rate has to be higher than or equal to assumed threshold. In the literature, this constraint is typically considered in the short-term context. It means that in a given time slot, the resource allocation algorithm has to provide the required data rate. From the energy efficiency point of view, the data rate for a user with poor channel conditions can be extremely low, even zero, if this constraint was not applied. Thus, such constraint is necessary in the practical radio communication networks.

- *the subcarrier/resource block allocation constraint* which guarantees that the same subcarriers can be assigned to a certain, limited number of users. This constraint is relevant in the case of a multi-user scenario in order to avoid interference between users. In the case of homogeneous network, it means that a subcarrier can be assigned to at most one end-user. However, there exist scenarios, e.g. heterogeneous or relay networks, where the same subcarriers can be utilized by more than one user, resulting in interference between users. Note that a properly designed resource allocation algorithm, in an interference network, can increase the energy efficiency compared to the network without users interference. From the optimization point of view, this constraint requires the introduction of binary decision variables (representing each subcarrier assignment or no-assignment to a particular user) making the optimization problem a Mixed-Integer Nonlinear Fractional programming problem which is very difficult to solve in its original form.

- *the fairness constraint* is introduced to maintain the transmission rate among users with a predetermined proportion. Thus, it is considered in the multi-user system model.

D. OPTIMIZATION
The design of the energy-efficient resource allocation algorithm usually comes down to solving the optimization problem defined as the maximization of the energy efficiency

TABLE 4. The comparison of the methods to solve the fractional optimization problem.

| Dinkelbach method	Charnes-Cooper method	Quasiconcave optimization	Suboptimal solution
• transform the objective function into a new parametrized concave function • an iterative algorithm which solve the parameterized problem in each iteration is required • superlinear convergence of the Dinkelbach algorithm • standard optimization techniques can be used to solve the subproblem in each iteration	• the fractional problem transforms into an equivalent convex problem with one additional variable and two constrains • if the numerator is affine, the fractional problem transforms into an equivalent convex problem with one additional variable and one constrains • a single convex problem must be solved • standard optimization techniques can be used to solve the optimization problem	• the proof of quasiconcavity is required • the proof that the local maximum is also the global optimum is required in order to provide the global optimum • the special algorithm or heuristic has to be designed to solve the optimization problem	• the global optimum is not guarantee • the special algorithm or heuristic has to be designed to solve the optimization problem • low complexity solution can be provided
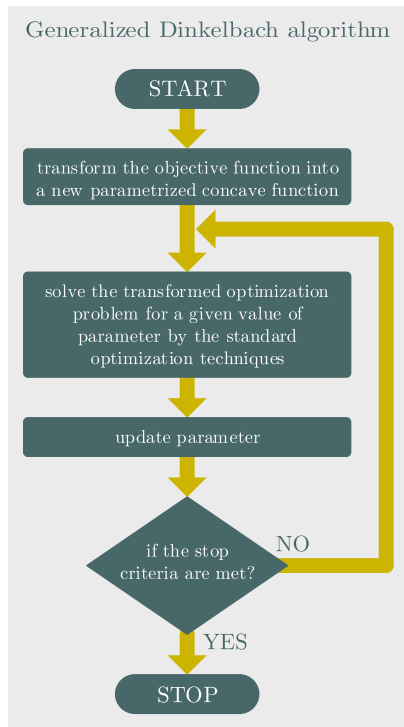
FIGURE 10. Generalized Dinkelbach method.

metric. Because of the fractional form of the energy efficiency metric, the optimization problem belongs to a broad class of fractional problems:

$$\mathbf{x}^{\star} = \arg\max_{\mathbf{x}} \frac{R(\mathbf{x})}{P(\mathbf{x})}, \tag{8}$$

$$\text{subject to: } f_i(\mathbf{x}) \leq b_i, \quad i = 1, \ldots, m. \tag{9}$$

Here, the vector $\mathbf{x}^{\star} = (x_1^{\star}, \ldots, x_n^{\star})$ contains the *optimal* values of the *optimization variables* $\mathbf{x} = (x_1, \ldots, x_n)$, the ratio of functions $R : \mathbb{R}^n \to \mathbb{R}$ and $P : \mathbb{R}^n \to \mathbb{R}^+$ is the *objective function*, the functions $f_i : \mathbb{R}^n \to \mathbb{R}$, $i = 1, \ldots, m$ are the (inequality) *constraint functions*, and the constants $b_1, \ldots, b_m$ are the limits, or bounds, for the constraints.

Since the objective function in (8) is in general non-concave, standard convex optimization algorithms are not guaranteed to converge to global optimum and specific algorithms are required. In the literature, four approach to solve the fractional programming problem can be found:

(i)   the Dinkelbach's method [57],
(ii) the Charnes-Cooper transform method [58],
(iii) solution of the quasi-concave optimization problem,
(iv) suboptimal solution of the optimization problem.

The Dinkelbach method and the Charnes-Cooper method can be used if the numerator of the objective function is concave while the denominator is convex or if the numerator is affine, the denominator does not have to be restricted in sign. Otherwise, if the optimization problem can not be transformed into concave one, the designing of the special algorithm or heuristic to solve the optimization problem is required. In the case of the Dinkelbach method the objective function is transformed into a new parameterized concave function which can be solved by the iterative Dinkelbach algorithm with the superlinear convergence. The generalized form of Dinkelbach algorithm is presented in Figure 10. In the Charnes-Cooper method, the fractional problem is transformed into an equivalent convex problem with one additional variable and two constrains (if the numerator is affine only one constraint is added). Finally, in Table 4, the comparison of the methods to solve the fractional optimization problem is presented.

IV. SINGLE OFDM LINK FLEXIBILITY FOR ENERGY-EFFICIENCY

In this section, we focus on the energy-efficient resource allocation in the context of a single OFDM link. Visualization of the example single link transmission with the related power consumption is presented in Figure 11. It can be observed that the user achieves some transmission rate as a result of per-subcarrier power allocation in response to the instantaneous channel conditions (visualized in Fig. 11 as the magnitude of the instantaneous channel characteristic). In the presented example, the resource allocation algorithms come down to determine the values of transmission powers
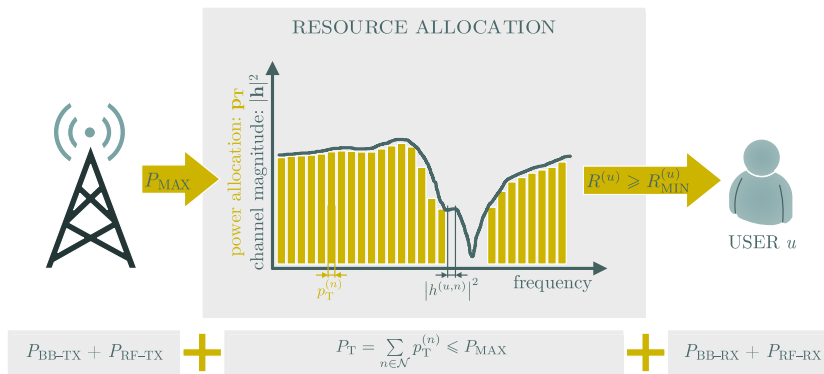
FIGURE 11. The single link scenario, where $p_T^{(n)}$ determines the power allocated on SC $n \in \mathcal{N}$, the channel coefficient in the link is defined by $h^{(u,n)}$ while $R^{(u)}$ is the data rate achieved by user u. The variables related to the system constraints are denoted as P_{MAX} and $R_{MIN}^{(u)}$ which define the maximum transmit power and the minimum data rate achieved by user, respectively.

allocated to subcarriers. However, more degrees of freedom can be identified in the single link scenario. Depending on the considered system scenario, the transmit power can be allocated per subcarrier, per resource block consisting of many SCs or per user. Moreover, in practical wireless communication systems, modulation and coding schemes and other transmission parameters can be adaptively selected in order to maximize the energy efficiency. Here below, the aspects of energy efficiency optimization are reviewed in the context of a single link scenario.

A. ESTIMATION OF THE OFDM SINGLE LINK TRANSMISSION RATE

In the context of the single, uth user OFDM link transmission rate $R^{(u)}$ is determined by the sum of the rates $r^{(u,n)}$ achieved using the allocated resource units:

$$R^{(u)} = \sum_{n \in \mathcal{N}} r^{(u,n)}, \qquad (10)$$

where $\mathcal{N}$ is the set of allocated resources In the literature, the first two approaches to the data rate estimation mentioned in Section III-A are usually considered for a single link scenario. While in [36], [37], [58], and [59] the data rate achieved per subcarrier is determined by the Shannon formula, the transmission rate in [22], [34], and [35] is estimated using Shannon formula with a scaling factor related to an adopted modulation and coding scheme and a target bit-error probability.

Most importantly, the data rate estimation methods can have various complexity as a result of the number of degrees of freedom available in a given system. In [22], the scaling factors for the Shannon formula-based rate estimation depending on the code rate, the coding gain and the target bit-error probability are determined per subcarriers which means that the modulation and coding schemes can vary among subcarriers. Such an approach allows theoretically for relatively the highest bitrate and EE. However, this assumes that at each subcarrier different MCS can be used. This requires potentially many parallel coding and decoding

blocks to be run in a single user equipment (UE), a solution infeasible in many hardware implementations. Two other limiting factors are: the wireless channel characteristic and the available amount of control information. The wireless channel is assumed typically to be invariant within time-frequency block limited by the coherence time and the coherence bandwidth. This block (often called *Basic Resource Block* - BRB) usually contains several subcarriers and OFDM symbols that should be assigned the same MCS. The MCS allocation has to be preceded by the channel impulse response estimation, typically using pilots, and feedback reporting quantized channel quality reported by a UE to the BS. These two processes need some time-frequency resources to accommodate pilots or control messages, reducing available resources for user data. The problem of finding the balance between the accurate channel estimation and the reduction in data rate has been discussed in [60]. Thus, in many real-world OFDM-based systems, the available degrees of freedom in resource allocation are limited and the data rate can be estimated per block of several subcarriers. The authors of [34], [35] have considered grouping subcarriers into subchannels described by the effective power-gain of a channel. The data rate has been estimated by Shannon formula with the scaling factors which have been obtained for the M-QAM transmission with Gray mapping coherently detected in an AWGN channel depends on a data interval, a signalling interval, the number of transmitted symbols, the number of subcarriers in the subchannel and SNR gap dependent on modulation and coding scheme.

B. POWER CONSUMPTION ESTIMATION FOR A SINGLE LINK

As shown in Figure 11 in the case of a single OFDM link the total power consumption consists of the power consumed by BB and RF signal processing on the transmitter and receiver side as well as the transmit power being the sum of powers allocated on subcarriers. Observe that, while the wireless channel frequency response has an influence on the
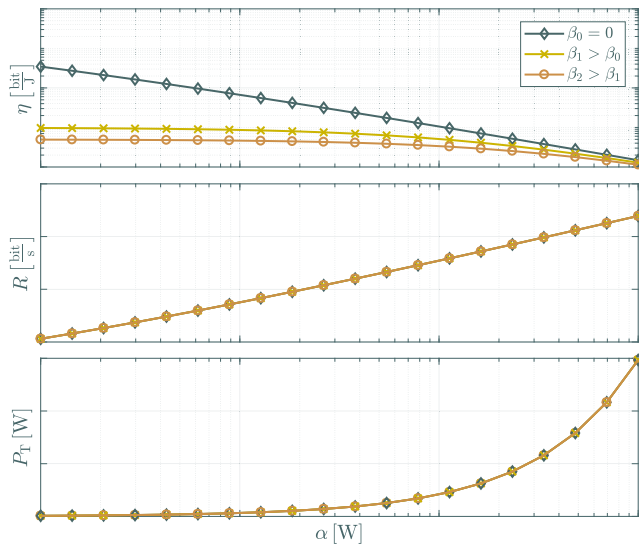
FIGURE 12. The energy efficiency, the data rate and the transmit power as a function of the circuit power for different value of the parameter β.

optimal allocated powers, its sum is typically fixed. It influences indirectly the consumed power. Moreover, as shown in Section III-B the power consumed by the circuits depends on many system parameters, e.g., the modulation and coding schemes, implementation, technology etc. However, these phenomena are in many cases not considered to simplify the model. The high-level power consumption model is usually used in the context of the single link scenario. One of these power consumption models considered in the literature assumes that the power consumption of BB and RF signal processing is expressed by one constant value. For example in [34] and [35] the authors assumed that this value is constant, equal to 0.1 W, though the adaptive QAM scheme has been used wherein the power consumption can vary for different modulation orders. Nevertheless, the adaptive QAM scheme has an impact on the transmit power because of different scaling factors in the data rate estimation among the modulation orders.

In [58] the circuit power (understood as the sum of power consumed by BB and RF signal processing) is assumed to be constant, but the transmission power is scaled by the parameter that expresses power amplifier inefficiency. A fixed value of PA efficiency is another simplification. It heavily depends on the utilized power amplifier, if it works with fixed or adjustable supply voltage or the transmitted signal itself. This problem will be discussed in Sec. VIII. Nevertheless, the values of the circuit power and the power amplifier inefficiency as well as the numerical results have been not provided in this paper (only analytical analysis has been considered).

Another high-level power consumption model considers variations in the circuit power [36], [37]. In this approach the circuit power is modelled as the sum of a static term and a dynamic term where the second of them depends on the sum rate. Moreover, the transmission power is scaled by

the parameter related to the efficiency of the power amplifier which is given by the Peak-to-Average Power Ratio (PAPR) divided by the drain efficiency of the power amplifier. There the maximum, rarely observed PAPR, equal to the number of subcarriers for an OFDM system, is assumed. Although, the authors have not provided the value of the power consumption model parameters, they have shown the impact of these parameters on the energy efficiency metric.

In [22] the modulation and coding scheme-dependent circuit power in the fast adaptive OFDM system has been considered. It means that the power consumption model does not depend only on the data rate and β parameter (as shows equation (6)) but also on the coding rate of applied modulation and coding scheme. Moreover, the data rate achieved per subcarrier has been estimated using Shannon formula with scaling factor which depend on the modulation and coding scheme as well. Therefore, the optimal transmit power can vary among the modulation and coding schemes for the same channel impulse response. The parameter describing the constant circuit power is equal 0.1 W while parameter $\beta = 5 \cdot 10^{-5}$ W/ (Mbit/s).

Another high-level power consumption model consisting of the fixed circuit power and the variable power increasing with the number of utilized subcarriers has been presented in [59].

It can be observed that the above models present increasing complexity in order to reflect rising number of relations influencing an OFDM link power consumption. Though, the models are rather high-level and general, independent of specific transceivers architectures. This can be treated as an advantage of these models, making the derived resource allocation algorithm independent from the hardware platform. A set of transceiver-dependent parameters, e.g., β, can be adjusted individually without a need for reformulation of the optimization problem or its' solving algorithm.

The above-cited papers use the high-level power consumption models to optimize the energy efficiency. Sample results for maximization of EE have been generated in the single link scenario with the linearly rate-dependent circuit power consumption model (described by equation (6)) are presented in Figure 12. The energy efficiency, data rate and transmit power in a function of the static part of circuit power consumption model are plotted. Let us observe that the data rate and transmit power are the same for different value of the parameter related to the dynamic part of the circuit power consumption (β). It means that the dynamic part does not affect transmit powers allocated on subcarriers but only energy efficiency value. Moreover, the transmit power increases with the static part of the circuit power (α) in order to eliminate the domination of static power over the transmission power.

However, there are some more detailed power consumption models considered in the literature as well. A single link transmission where the BB power consumption is modelled as the power consumed by each component is presented in [54]. The authors do not consider EE optimization. In [53] and [54] the authors propose the dynamic power estimation
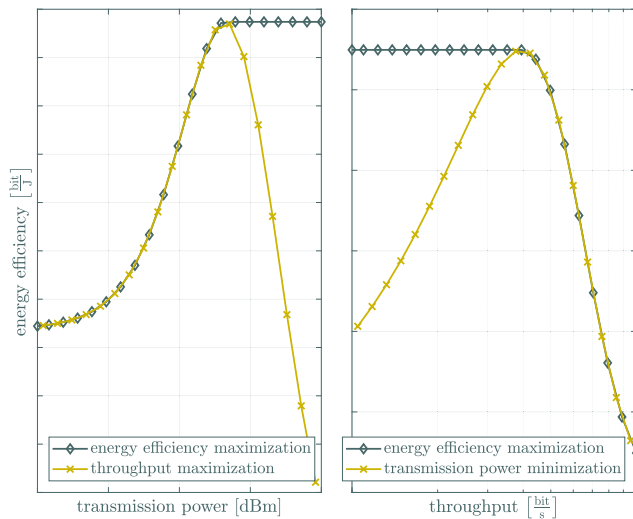
FIGURE 13. The energy efficiency as a function of available transmission power for the EE and throughput maximization (left subfigure), or as a function of the minimal throughput for the EE maximization and transmission power minimization (right subfigure).

methodology for FPGA-based OFDM transceiver. Moreover, in [54] the authors proposed measurement-based power consumption models for the considered FPGA implementation.

C. CONSTRAINTS FOR A SINGLE LINK
In Figure 11 it can be observed that the system can be limited by the maximum transmission power and the minimum required data rate. The important thing here is that if both constraints are considered the maximal transmission power has to be enough to provide the required data rate. Otherwise, the resource allocation is non-feasible.

The maximum transmission power constraint which ensures that the sum of the transmission power allocated on the subcarriers is less than or equal to the maximum assumed value has been considered, e.g., in [22], [34], and [35]. Figure 13 illustrates the optimized energy efficiency for the constrained OFDM link. On the left side the energy efficiency as a function of available transmission power for the EE and throughput maximization are presented. In the case of EE maximization, the energy efficiency increases with the available transmission power and remains constant after reaching the maximum. For higher available transmission power value, it is not fully exploited. In contrast, the throughput maximization causes the energy efficiency to drop as a result of increasing data rate and fully utilized maximal transmit power.

The minimum data rate constraint provides the end-user's data rate higher or equal to the assumed threshold and has been considered, e.g., in [34] and [35]. On the right side of Fig. 13 the energy efficiency versus the minimum required throughput for EE maximization and transmission power minimization are plotted. It can be observed that with increasing the data rate requirement the energy efficiency decreases

in both schemes above some point. However, for relatively low throughput requirements and the EE maximization, the energy efficiency takes constant value because the throughput resulting from optimization is higher than the data rate requirement.

D. OPTIMIZATION OF EE IN AN OFDM SINGLE LINK
The complexity of the energy-efficient resource allocation algorithm depends on the degrees of freedom of the considered system and on the utilized model of the data rate and power consumption as well as the system limitations/requirements. In the literature, two sets of the optimization variables are considered in the context of a single-link scenario: (i) the transmit powers allocated on the resource unit or related to them data rates achieved on the resource unit, (ii) the transmit powers/data rates on the resource unit and applied modulation and coding scheme. It means that in the first approach the data rate is estimated by the Shannon formula, thus only transmission power can be determined and the modulation and coding schemes are not selected. In contrast, in the second approach the data rate is esteemed by different methods where the transmit power and the modulation and coding scheme have be to determined. The first set of the optimization variables has been considered in [36], [37], and [58]. In [58] the authors have optimized the energy efficiency by selecting optimal transmission power using Dinkelbach method with superlinear convergence. Due to the rate-dependent circuit power consumption model, in [36] and [37] the energy efficiency has been maximized by obtaining the optimal value of the data rate achieved on each subcarrier. Moreover, in [58] the Charnes-Cooper and Dinkelbach methods have been used to solve the energy-efficient resource allocation optimization problem. The authors have shown that both methods give the same optimal result. In [34] and [35] the energy efficiency is optimized for an uncoded M-QAM modulated OFDM link. The modulation order is expressed as the function of the data rate, thus, in fact, the data rate achieved per subcarrier is optimized. The authors has proven that the defined optimization problem is quasiconcave, thus if a local maximum exists, it is also globally optimal. In order to find the optimal data rate for the single subchannel transmission Gradient Assisted Binary Search (GABS) method has been proposed which then is used in the Binary Search Assisted Ascent (BSAA) algorithm to find the optimal solution in the multi-subchannel scenario.

The second set of optimization variables is considered in [22]. The transmit power and modulation and coding scheme are determined per each subcarrier in order to maximize the energy efficiency. In the first step of proposed algorithm the Dinkelbach method has been used to transform the objective function. Next, the transmit power for each MCS has been obtained. Finally, based on the cost-benefit function the modulation and coding scheme is selected per subcarrier.

In Table 5 the summary of the energy-efficient resource allocation methods in a single-link scenario is presented.

TABLE 5. Summary of the energy-efficient resource allocation methods in a single-link scenario.

| Scenario	Optimization variables	Methods	Convergence	References
the data rate estimated by the Shannon formula, the linearly rate-dependent circuit power consumption model	transmit power allocated on subcarriers	Charnes-Cooper method	constant	[36]
the data rate estimated by the Shannon formula, the linearly rate-dependent circuit power consumption model	transmit power allocated on subcarriers	Dinkelbach method	superlinear	[37]
the data rate estimated by the Shannon formula, the constant value of the circuit power consumption	transmit power allocated on subcarriers	Dinkelbach method and Charnes-Cooper method	constant (Charnes-Cooper method), superlinear (Dinkelbach method)	[58]
the data rate estimated by the Shannon formula with the scaling factors, the linearly rate-dependent circuit power consumption model, adaptive OFDM system	transmit power allocated on subcarriers, modulation and coding scheme per SC selection	Dinkelbach method	superlinear	[22]
the data rate estimated by the Shannon formula with the scaling factors, the constant value of the circuit power consumption, uncoded M-QAM	transmit power allocated on subchannel	solve the quasiconcave problem by GABS and BSAA algorithms	linear	[34], [35]
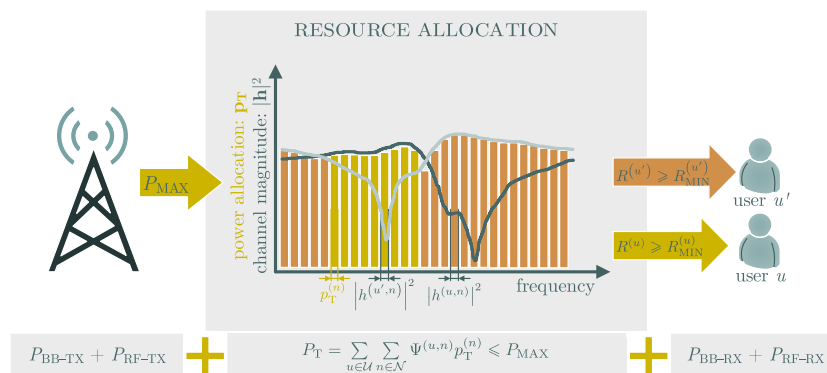
FIGURE 14. The multi-cell OFDMA downlink network, where $p_{\mathrm{T}}^{(n)}$ determines the power allocated on SC n, $\Psi^{(u,n)}$ the binary variable determining if the subcarrier n is assigned to user u or not while the channel coefficients in the link between BS and users u and u' are defined by $h^{(u,n)}$ and $h^{(u',n)}$, respectively. The data rate achived by user u and u' are denoted as $R^{(u)}$ and $R^{(u')}$ respectively. The variables related to the system constraints are denoted as P_{MAX}, $R_{\mathrm{MIN}}^{(u)}$ and $R_{\mathrm{MIN}}^{(u')}$ which define the maximum transmit power and the minimum data rate achieved by user u and u', respectively.

V. MULTI-USER OFDMA NETWORK

Let us consider the multi-user OFDMA network where one base station serves some number of users which share the bandwidth divided into subcarriers. In this case the energy efficiency metric can be associated with the whole network or individual users, thus can be defined in different ways. In the literature, three main approaches to maximizing the energy efficiency metric can be distinguished [61]:

(i) maximizing the energy efficiency of the whole network,
(ii) maximizing the sum of the users energy efficiency,
(iii) maximizing the minimum user's energy efficiency.

In the first approach, the energy efficiency is defined as the ratio of total throughput (the sum of users data rate) to the total consumed power in the network. It means that the channel coefficients of all users have to be available in one unit. Therefore such an approach is mostly applied in the downlink scenario wherein the base station allocates the resources. The energy efficiency for the second and third approach is defined

by the sum of the ratio of data rate achieved by each user to the power consumed by it. Thus the energy efficiency is maximized individually for each user and the channel coefficient of other users are not required. Therefore these definitions are usually considered in the uplink transmission. Moreover, it is obvious that depending on the definition the resource allocation and resulting from it the value of energy efficiency can be different.

In Figure 14 and 15 the example of the downlink and uplink transmissions in the multi-user OFDMA network is presented, respectively. It can be observed that (in the contrast to the single link scenario) the available bandwidth is shared among many users in the network. It means that not only transmit power but the subcarrier assignment has to be determined as well. Moreover, for some systems, the modulation and coding schemes have to be determined for each user. Thus, more degrees of freedom can be distinguished compared to the single link scenario.
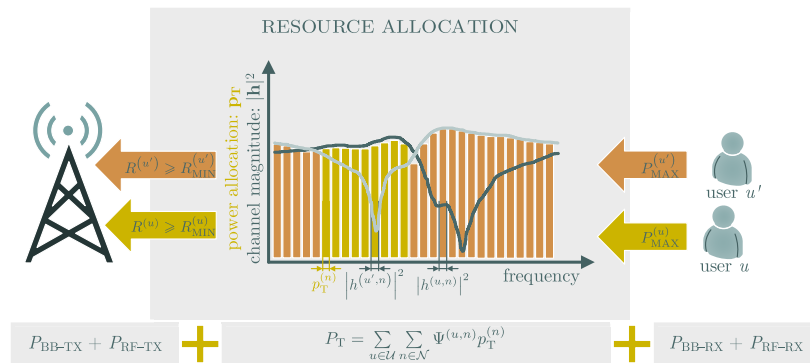
FIGURE 15. The multi-cell OFDMA uplink network, where $p_{\mathrm{T}}^{(n)}$ determines the power allocated on SC $n \in \mathcal{N}$, $\Psi^{(u,n)}$ the binary variable determining if the subcarrier n is assigned to user u or not while the channel coefficients in the link between BS and users u and u' are defined by $h^{(u,n)}$ and $h^{(u',n)}$, respectively. The data rate achived by user u and u' are denoted as $R^{(u)}$ and $R^{(u')}$ respectively. The variables related to the system constraints are denoted as $P_{\mathrm{MAX}}^{(u)}$, $P_{\mathrm{MAX}}^{(u')}$, $R_{\mathrm{MIN}}^{(u)}$ and $R_{\mathrm{MIN}}^{(u')}$ which define the maximum transmit power and the minimum data rate for u and u', respectively.

A. TRANSMISSION RATE ESTIMATION IN A MULTI-USER OFDMA NETWORK

In the case of the multi-user OFDMA network, the total throughput is the sum of the throughput for each user. The user's data rate is determined by the sum of data rate achieved on each subcarrier assigned to it. In the literature, all three approaches of the data rate estimation presented in Section III-A can be found:

(i) based on the Shannon formula considered among others in [62], [63], [64], [65], [66], [67], [68], and [69]. In [61], [62], [63], [64], [65], [66], [67], and [70] the subcarriers are considered independently (are not grouped into RBs), thus the resource allocation is determined per subcarrier. Whereas in [68] and [69] the subcarriers are grouped into resource blocks as in some practical wireless communication systems, e.g., LTE.

(ii) estimated by the Shannon formula with scaling factors considered in [71] and [72]. In [71] the Shannon formula is scaled by the factor dependent on a target bit error rate for an uncoded M-QAM modulation. In [72] the scaling factor is used to model the imperfect channel state information.

(iii) based on the error-rate function and the spectral efficiency of the applied MCS considered in [29] where the subcarriers are grouped into resource blocks and all RBs assigned to the same user must use the same modulation and coding scheme. In this case, the throughput results from the spectral efficiency of the applied MCS, effective SINR and the block-error rate which has been estimated by the complementary error function with two fitting parameters for each MCS. The values of the fitting parameters for the MCS used in the LTE standard have been provided in [29].

When grouping subcarriers into resource blocks, each RB includes multiple subcarriers subject to different channel gains, thus, an effective SNR mapping method should be applied to collect, and represent the channel state information. In [26] and [27] one can find methods of channel-quality representation for the user's RBs. In [69] and [73] the effective SINR over one RB has been obtained using the mean instantaneous capacity method which is based on the Shannon formula.

B. ESTIMATION OF THE POWER CONSUMPTION IN A MULTI-USER OFDMA NETWORK

In the multi-user OFDMA network the total power consumption power (similar to the single link scenario) consists of the transmit power and the power consumption of BB and RF processing at the transmitter and receiver. The total transmit power is equal to the sum of the users' transmission power. The users' transmission power is usually determined as the sum of the transmit power allocated on the resources assigned to them. This definition works both for uplink and downlink scenario. As shown in the Figures 14 and 15 the transmit power can be potentially allocated per subcarrier. While this is an additional degree of freedom, able to increase achivable data rate, it comes at a cost. The receiver has to know the power allocated on each subcarrier to enable channel estimation and decoding, thus the signalling overhead is much bigger than in a more practical scenario, e.g., in LTE where the transmit power is the same among all resource blocks assigned to the user [29]. In the case of the BB and RF processing the power consumption model can be determined for each user differently that can result, e.g., from different end-user devices. Thus, the receiver circuit power is the sum of power consumed by the BB and RF processing at the end-users in the downlink scenario. For example in [64], the power of the circuit is divided into the power consumed at the base station and the user equipment which is scaled with the number of subcarriers assigned in the base station to

TABLE 6. The values of the power consumption parameters.

Papers	Scenario	Circuit power [W]	Power amplifier efficiency	$\beta \left[\frac{\text{W}}{\text{Mbit/s}} \right]$
Xing *et al.* [70]	downlink	0	100%	–
Wang *et al.* [72]	downlink	0.01	38%	–
Xiong *et al.* [62]	uplink, downlink	$\{0.05, 10\}$	38%	–
Ye *et al.* [67]	uplink	0.1	38%	–
Bossy *et al.* [29]	downlink	0.1	100%	–
Ren *et al.* [66]	downlink	0.2	38%	–
Tham *et al.* [71]	downlink	1.0	38%	0.1
Sboui *et al.* [61]	downlink	1	100%	–
Wang *et al.* [65]	downlink	10	40%	0.1
D.W.K Ng *et al.* [74]	downlink	10	100%	0.1
Yang *et al.* [68]	downlink	$\{10, 30\}$	38%	$\{1, 2\}$
Xiong *et al.* [63]	downlink	$\{15, 30\}$	38%	0.2
D.W.K Ng *et al.* [75]	multicell downlink	10	20%	–
Qi *et al.* [76]	downlink	10	33%	2

users. In the rest of the cited papers the power consumed by circuits remains constant or is modeled as the linear function of achieved data rate. Therefore, in Table 6 the values of the total fixed circuit power, power amplifier efficiency parameter and/or β parameter from a set of well established papers are provided.

It can be observed that the power amplifier efficiency parameter in most cited paper hovers around 38% while the circuit power and β parameter oscillate much more. Moreover, in all cited paper all parameters: the circuit power, the power amplifier inefficiency and parameter β is the same for all users in the network.

C. CONSTRAINTS IN A MULTI-USER OFDMA NETWORK

It is obvious that each constraint of the system can cause a reduction in maximal energy efficiency. Nevertheless, let us remember that the maximization of the energy efficiency does not ensure the network fulfils users QoS requirements. For example, Figure 16 shows the data rates and transmit powers of three users in the network. Two of them are located close to the base station while the third is located at the edge of the cell. The resources (transmit power and subcarriers) have been allocated to maximize the energy efficiency of the whole network. It can be observed that none resources are allocated to the user at the edge of the cell. Thus, despite maximum energy efficiency is achieved, not all users are served. Therefore, in this case the minimum data rate constraints are required. In the literature, the following constraints for the energy efficiency optimization of the multi-user OFDMA network have been considered:

- the maximum transmission power constraint which has been considered in [61], [62], [63], [64], [65], [66], [67], [70], [71], [72], [74], [75], and [76]. In the case of the downlink transmission this constraint ensures that the sum of transmission powers allocated in the base station is less than or equal to the maximum allowed value. Whereas, for the uplink transmission [62], [67] the maximum transmission power constraint concerns each user

in the network. It means that the sum of transmit powers allocated on subcarriers for a given user has to be less than or equal to the maximum transmit power of its device. It is obvious that the maximum transmit power can vary among users as shown in Figures 14 and 15. Moreover, in [61] the authors constrain the maximal transmit power per subcarrier in order to avoid inter-cell interference.

- the minimum data rate constraint considered in [61], [62], [63], [64], [65], [67], [72], [74], [75], and [76]. In both (downlink and uplink) scenario it means that the data rate of a given user has to be not smaller than assumed value. In [61], the authors constrain the transmit rate achieved on each subcarrier. It needs to be above a minimum rate threshold. Moreover, this value can be different for each user as shown in Figures 14 and 15.

- the subcarrier/resource block allocation constraint examined in [61], [62], [63], [64], [65], [66], [67], [69], [70], [72], [73], [74], and [76]. This constraint guarantees that a given subcarrier/resource block can be assigned to maximally one user, in order to avoid the inter-user interference. It is usually realized by introducing the auxiliary variables which take binary values making the optimization problem a *Mixed-Integer Nonlinear Fractional Programming* (MINFP) problem for which the techniques described in Section III-D are not sufficient. Therefore, in Section V-D the methods dealing with MINLP in the context of energy efficiency optimization are reviewed.

- the instantaneous proportional rate fairness constraint contemplated in [62], [66], and [71] which ensures that each user would obtain a predetermined proportion of the system throughput in each resource-allocation determination [77].

- constraints resulting from system model considered in [29], [69], and [73]. Such constraints usually are not described by the equation in the optimization problem because results from the considered system model, directly. For example in [29], [69], and [73] the
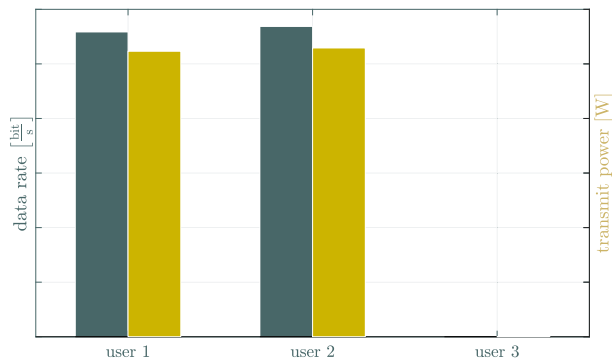
FIGURE 16. The data rates and transmit powers of three users in the network where two of them are located close to the base station while the third is located at the edge of the cell. Case with EE maximization without additional constraints.

subcarriers are grouped into resource blocks and for each user, the same MCS over all its allocated RBs has to be used. Moreover, in [29] the transmit power is constant per RB for all RBs assigned to a given user.

D. EE OPTIMIZATION IN A MULTI-USER OFDMA SYSTEM

Let us note that in the context of the multi-user OFDMA network not only the transmit power but also the subcarrier/resource blocks assignment has to be determined. The subcarrier/resource blocks assignment is usually realized by the binary variables so that the optimization problems can be classified as *Mixed binary Integer NonLinear Fractional Programming* (MINLFP) problems which are very difficult to solve by standard optimization techniques. Therefore, in this section the optimization techniques used to solve a MINLFP problem in the context of the energy efficient multi-user OFDMA network are presented.

In most of the cited papers, the optimization procedure consists of at least two stages out of all presented below:

(i) transmission power allocation,
(ii) subcarriers/resource blocks assignment and/or
(iii) modulation and coding scheme selection.

The values of the optimization variables of the particular stage are usually determined while setting the values of the optimization variables for other stages as fixed. Such approach can be realized by the primal decomposition technique which reformulates the problem into many maximization problems. For example, in the first stage the values of the transmission power allocated at the subcarrier which maximize the energy efficiency are determined. In the second stage, based on these powers, the optimization is carried by changing subcarriers assignment and modulation and coding schemes. For continuous transmit power values, standard optimization techniques can be used as long as the problem is concave/convex. The more complex task is to determine the binary decision variables. Various methods can be used to solve MINLP problems [78], e.g., branch-and-bound [69], [73], outer approximation or generalized Bender's decomposition method. The drawbacks of these

methods are their poor scalability, i.e., these are efficient only for small size problems. For example, in branch-and-bound method the complexity increases exponentially as the problem size increases. Therefore, the suboptimal solutions which give the near-optimal results have been proposed in the literature. In this paper, we focus on the most common method which can be applied to different system models. In this method, applied in [29], [64], [65], and [74], the binary decision variables have been relaxed to be real numbers within interval [0, 1] and then the Dinkelbach [57], dual decomposition method and KKT conditions [79] have been applied to determine the power and subcarrier allocation. Due to the Dinkelbach method, the primal decomposition technique and taking the derivatives with respect to transmission power and then with respect to binary variables the cost-benefit metric can be determined. It means that for each subcarrier/resource blocks the cost-benefit metric equal to the achieved throughput minus the transmit power multiplied by the parameter resulting from the Dinkelbach method can be obtained. Thus, if this value is positive a given subcarrier should be allocated to the user but if it is negative the assignment of this subcarrier to the user is unprofitable from the EE point of view. It is obvious that if for a given subcarrier/resource blocks more than one user has a positive value of the cost-benefit metric this subcarrier should be allocated to the user with the highest one. Then, the authors have rounded the relaxed variables to 0 or 1 to get an integer-valued solution. The presented suboptimal solution gives the near-optimal results with superlinear convergence.

While in minority, there are also other solution methods used in the literature. For example, in [69], [73] the branch-and-bound method has been applied to find optimal RB allocation. In [69] and [73] the brute force search has been applied to find optimal subcarrier assignment, but due to extremely high complexity near-optimal and suboptimal solution have been proposed as well. The suboptimal methods which are based on the energy efficiency transmit power estimation and subcarrier assignment resulting from spectral-efficient maximization have been designed in [66] and [67]. Another suboptimal methods have been proposed in [61], [63], [64], and [72]. A suboptimal method based on deep learning is proposed in [70]. Nevertheless, the review of all proposed methods is not the goal of this paper because these depend on the system model and do not have universal nature.

VI. MULTI-USER OFDMA RELAY NETWORK

The use of relay nodes in the network is a promising technique for increasing the energy efficiency of the system. In the literature, different scenarios of transmission with help of relay nodes can be distinguished. Figure 17 illustrates four transmission modes in the multi-user OFDMA relay network which can be found in the literature:

(i) direct transmission [80], [81], [82], [83],
(ii) relayed transmission [80], [81], [82], [83], [84], [85],
(iii) relayed transmission with direct link [86], [87], [88],
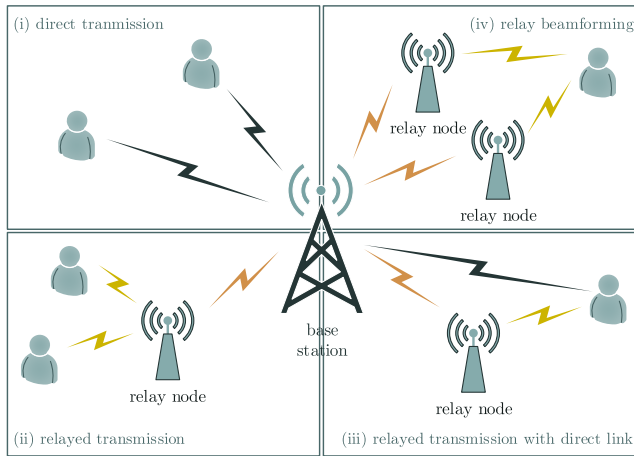(iv) relay beamforming [89].

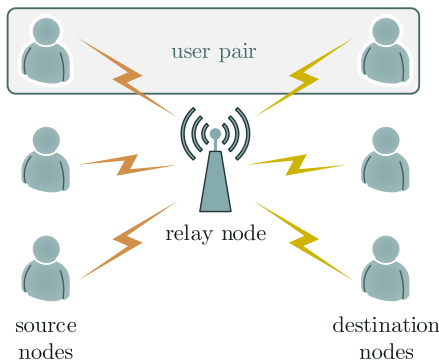**FIGURE 17.** The transmission modes in the multi-user OFDMA relay network.

FIGURE 18. The scenario where three user pairs communicate in parallel via the relay node.

TABLE 7. The factors increasing or decreasing the energy efficiency of relayed and direct transmission.

	Increasing EE	Decreasing EE
relayed transmission	• the distance to end-user is divided into two or more shorter parts with lower channel attenuation • reducing the transmit power while providing the same throughput or increasing the throughput for the same power allocation • less complex signal processing may be used • possibility of regenerating the signal in the relay nodes	• two time slots are required to deliver data to end-user • the relay nodes consume the power related to receiving, processing and transmitting data • more (than in the direct transmission) optimization variables which can cause more complex resource allocation algorithm
direct transmission	• one time slot is required to deliver data to end-user • less circuit power consumption than in the multi-user OFDMA relay transmission • less (than in the relayed transmission) optimization variables can reduce the complexity of resource allocation algorithm	• high transmit power for the long links • complex signal processing may be required for the long links

Depending on the system model, the transmission mode is selected related to network conditions from the considered set of modes. The set of transmission modes can contain all transmission modes, several or one of them, e.g., direct transmission and relayed transmission. Another scenario commonly considered in the literature, is when the user pairs communicate with each other via the relay node as shown in Figure 18.

Nevertheless, irrespective of the scenario, in the case of the multi-user OFDMA relay network, the transmission is typically analyzed in two time slots. One use case is relayed transmission with direct link. In the first time slot, a transmitter sends data to be received by the relay and by the end-users. In the second time slot, the relay forwards the received data to their destination. The relayed transmission is considered as the promising technique for increasing the energy efficiency because the distance to end-user is divided into two or more shorter parts with lower channel attenuation. It allows reducing the transmit power while providing the same throughput or increasing the throughput for the same power allocation. Moreover, the smaller distances (better channel conditions) can result in less signal processing to be required, e.g., less

complex data encoding and decoding. On the other hand, the cooperative transmission required two time slots to deliver data to end-user whereas the direct transmission only one. Moreover, similar to the base stations and end-user devices the relay nodes consume the power related to receiving, processing and transmitting data, as well. Thus, there are a few aspects which can increase as well as decrease the energy efficiency in the case of relay networks. These are summarized in Table 7 in contrast to the direct transmission. Therefore, adaptive resource allocation methods are required to maximize the energy efficiency metric.

As one may have guessed, in the context of the multi-user OFDMA relay network more degrees of freedom than for multi-user OFDMA network can be distinguished. In the literature the following degrees of freedom can be found:

- the transmission mode selection - if more than one of modes presented in Figure 17 are considered in the system, the transmission mode can be selected. Usually, in the system models from the literature, the direct transmission and the transmission with the help of the relay node are selectable. Moreover, two options of adaptability are possible. In the first the users are divided into groups, each with a pre-determined transmission mode [80], [81], [82]. In the second option the transmission modes are adaptively selected for every user related to the current channel conditions [83], [86], [89].
- the relay nodes selection - in the literature, two approaches are considered in the context of relay nodes selection. In the first approach the users are assigned to the relay nodes permanently [80], [81]. In the second
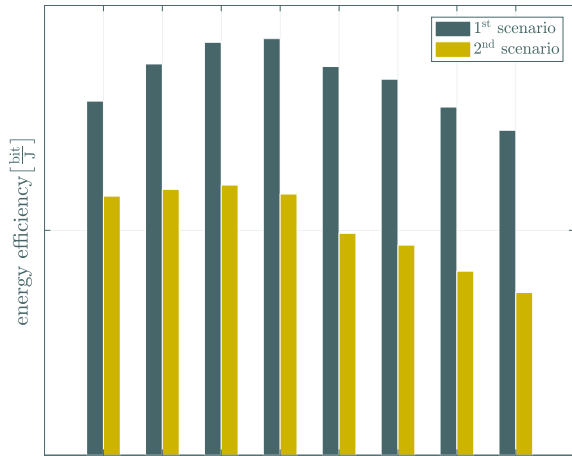
FIGURE 19. The energy efficiency against the number of the relay nodes.

FIGURE 20. The energy efficiency against the distance form the base station to the relay node.

FIGURE 21. The trade-offs observed in the multi-user OFDMA relay network.

approach the relay nodes are selected adaptively [82], [83], [86], [87]. The complexity of the first approach is lower than of the second one but the achieved energy efficiency can be lower. It results from the fact that in the adaptive relay selection more ways to transmit signal is possible. Finally, in the case of relay beamforming the relay nodes selection is extended to the set of relay nodes selection [89]. It means that more than one relay node can transmit data to one user.

- the subcarrier/resource block pairing - relies on matching subcarriers in the first and second time slots, which maximize the energy efficiency. The subcarrier pairing is realized in two way: the same [80], [81], [87], [90] or different [82], [83], [84], [85], [86], [89], [91], [92], [93] subcarriers are used in the first and second time slots. The first approach can be less efficient in terms of energy efficiency but less computationally complex than the second approach which reallocates resources in the second time slot. Nevertheless, the resource reallocating requires downconversion of the signal to baseband which may consume additional power.

- the localization and the number of relay nodes - these aspects are not usually determined during the optimization procedure but have a significant impact on the achieved energy efficiency. Let us remember that each relay node consumes power when it is turned on. Thus, if the number of relay nodes is too high the power consumption can dominate over the potential profit resulting from applying the cooperative transmission. In Figure 19 the energy efficiency against the number of relay nodes for a sample scenarios is plotted [83], [86]. It can be observed that in both scenarios exist some number of the relay nodes in the network which maximize the energy efficiency. Below this value, the potential of the relayed transmission is not fully used while above this value the circuit powers dominate over the achieved profit. Moreover, if the relays are misplaced in the network, the benefit of using them may be negligible. An extreme
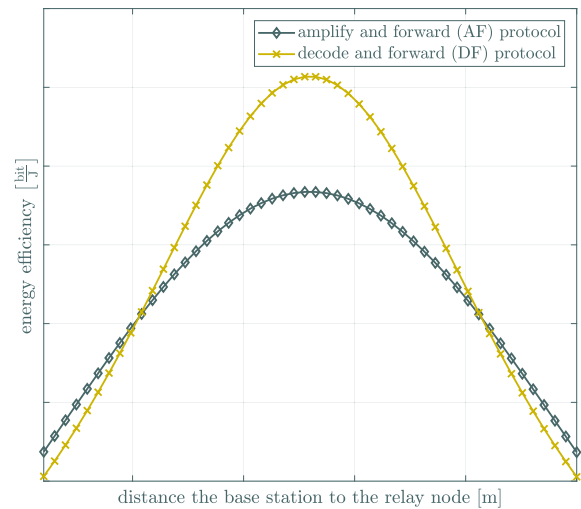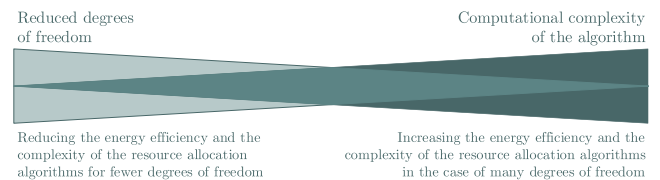
case is when the relay node is located very close to the base station or the end-user. In such cases, the distance to the end-user is divided into a very short and long path with a length comparable to that of the direct link. Figure 20 illustrates the energy efficiency versus distance to the relay node from the base station for the Amplify and Forward (AF) and the Decode and Forward (DF) relaying protocols which are elaborated in the next subsection. The relay is placed in between source and destination nodes of fixed positions. It can be observed that for both relaying protocols the highest energy efficiency is achieved when the relay divides the distance between the base station and end-user in half.

- the transmit power and subcarrier/resource block allocation - in this case, the transmission powers allocated on subcarriers and subcarriers assignment to the users are determined (similar to the multi-user OFDMA network or the single link).

Finally, in Figure 21 the trade-offs observed in the multi-user OFDMA relay network are presented. Let us observe that if the number of degrees of freedom increases the computational complexity of the resource allocation algorithms increases. On the other hand fewer number of degrees of freedom reduces the computational complexity of the algorithms at the cost of potentially decreased energy efficiency.

A. DATA RATE ESTIMATION IN A RELAY NETWORK

All the papers considered in this article, investigating a multi-user OFDMA relay network use the Shannon formula
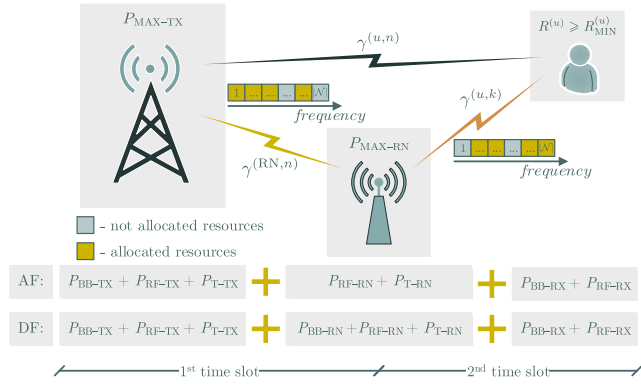
FIGURE 22. The transmission with the help of the relay node and the power consumption related to the amplify and forward and decode and forward relaying protocols, where $\gamma^{(x,y)}$ determines the SNR value at the receiver x observed on subcarrier y.

for the data rate estimation. This is in the contrast to the OFDM single link and multi-user OFDMA network, where other solutions were used as well. However, the specific usage of Shannon formula depends on the considered relaying protocol. Figure 22 illustrates the transmission with help of the relay node and the power consumption related to the amplify and forward and decode and forward relaying protocols. Let us note that if the direct link is not considered (e.g., it is in a deep fade), the SNR at the end-user device on subcarrier n aims to zero: $\gamma^{(u,n)} \to 0$. Such an assumption is commonly applied mainly due to the increase in the complexity of the optimization problem. Nevertheless, if the direct link is taken into account, it can cause the increase in the energy efficiency without any additional cost because the signal received by the end-user from the relay node, in the second time slot, is combined with the signal received from the base station in the first time slot, using e.g. the maximum-ratio combining (MRC) method, thus the SNR in the receiver increases, as well. In the context of the energy efficient resource allocation the link data rate is described differently for each relaying protocol:

- the amplify and forward protocol wherein the signal received in the first time slot by a relay node is amplified and transmitted to the end-user in the second time slot. Thus, it can be observed that no time-consuming and energy-intensive signal processing is carried out. On the other hand, let us remember that the relay amplifies not only desired signal but all other received signals as well. The data rate of user u while using subcarrier pair (n, k), i.e., subcarrier n for transmission from BS and subcarrier k for transmission from the relay, and MRC reception can be estimated by [94], [95]:

$$r^{(u,n,k)} = \frac{W}{2} \log_2 \left(1 + \frac{\gamma^{(\mathrm{RN},n)} \gamma^{(u,k)}}{1 + \gamma^{(\mathrm{RN},n)} + \gamma^{(u,k)}} + \gamma^{(u,n)} \right), \tag{11}$$

where $\gamma^{(x,y)}$ determines the SNR value at the receiver x, where u denoted UE and RN denotes the relay node, observed on subcarrier y as shown in Figure 22. Because of two-slot transmission the factor $\frac{1}{2}$ scales Shannon formula. Moreover, in some papers, e.g., [80], [81], [82],

TABLE 8. Pros and cons of the relaying protocols.

	Pros	Cons
Amplify and Forward (AF)	• no time-consuming and energy-intensive BB signal processing is carried out • two time slots are enough to deliver the data • the simple structure of the relay node	• the increase in the total power consumption resulting from RF signal processing in the relay node • the relay node amplifies not only desired signal but also other received signals (the potential errors can be propagated to the end-user) • the resource reallocation is limited and may require additional signal processing that increases the power consumption
Decode and Forward (DF)	• the potential errors can be eliminated in the relay node (are not propagated to the end-user) • the possibility to resource reallocation during the BB signal processing	• the increase in the total power consumption resulting from the BB and RF signal processing in the relay node • the time-consuming signal processing may require more than two time slots to deliver the data to end-user • the complex structure of the relay node

the authors have applied the approximation for high receiver's SNR values. Moreover, in [84], [90], and [96] the data rate estimation of the AF relaying protocol in the interference networks can be found.

- the decode and forward protocol wherein the received by relay node data (in the first time slot) are decoded and then coded again and forwarded to end-user (in the second time slot). This approach can increase the total power consumption but the potential errors can be eliminated in the relay node and thus they are not propagated to the end-user. For DF relaying protocol the data rate of user u using subcarrier pair (n, k) may be expressed as [83], [85], [88], [94], [97], [98]:

$$r^{(u,n,k)} = \frac{W}{2} \min \left\{ \begin{array}{l} \log_2 \left(1 + \gamma^{(\mathrm{RN},n)} + \gamma^{(u,n)} \right) \\ \log_2 \left(1 + \gamma^{(u,k)} \right) \end{array} \right\}. \tag{12}$$

The factor of $\frac{1}{2}$ in (12), similarly as in (11), accounts for the fact that two time slots are required. Moreover, in [91], [92], and [93] the data rate estimation of the DF relaying protocol in the interference networks can be found.

Sometimes, the authors have consider AF relaying protocol instead of DF protocol because they think that DF relaying protocol requires more than two time slots due to the time-consuming signal processing. Finally, in Table 8 the pros and cons of the described relaying protocols are summarized.

It can be observed that the equations (11) and (12) describe the data rate achieved by user u using a given subcarrier pair. Thus, in general, the total throughput in the multi-user OFDMA relay network within two time slots is equal to the sum of the data rate for all users links using subcarriers

assigned to them, in one of the selected transmission modes or relaying protocols if they can be adaptively selected according to channel conditions. It means that the total throughput can contain the throughput of relayed transmission as well as the throughput of direct transmission. In order to avoid inter-user interference, typically it is assumed that the subcarriers pair can be assigned to the maximum one user among all transmission modes. Nevertheless, there are some paper where the same subcarrier can be used by more users [83], [86], [97], [99]. It may result in interference among signals transmitted to different users but if the channel attenuation values in the interfering links are relatively high, the interference may be small enough that the transmission will result in higher EE.

B. TOTAL CONSUMED POWER ESTIMATION IN A RELAY NETWORK

Similar to the data rate estimation, the total consumed power depends on the relaying protocol:

- in the case of the AF relying protocol the signal received by relay node does not have to be downconverted to baseband, thus the total power consumption equals:

$$P = \underbrace{P_{\text{T-TX}} + P_{\text{T-RN}}}_{P_{\text{T}}} + \underbrace{P_{\text{BB-TX}} + P_{\text{BB-RX}}}_{P_{\text{BB}}} + \underbrace{P_{\text{RF-TX}} + P_{\text{RF-RN}} + P_{\text{RF-RX}}}_{P_{\text{RF}}}, \quad (13)$$

as shown in Figure 22. It can be observed that the transmit power is the sum of transmission power allocated in the transmitter and relay node keeping in mind that these transmissions happen typically in two consecutive time slots. Moreover, the power consumption by the RF signal processing in the relay node $P_{\text{RF-RN}}$ can be divided into receiving and transmitting part but in the literature, it is usually assumed to be one value.

- in the DF relaying protocol, the received signal is downconverted, decoded, coded and modulated, causing increased power consumption. Thus, the power consumption model contains in addition the power consumed by the BB processing in the relay node $P_{\text{BB-RN}}$ resulting in the total power consumption:

$$P = \underbrace{P_{\text{T-TX}} + P_{\text{T-RN}}}_{P_{\text{T}}} + \underbrace{P_{\text{BB-TX}} + P_{\text{BB-RN}} + P_{\text{BB-RX}}}_{P_{\text{BB}}} + \underbrace{P_{\text{RF-TX}} + P_{\text{RF-RN}} + P_{\text{RF-RX}}}_{P_{\text{RF}}}. \quad (14)$$

Similarly to the power consumption by the RF signal processing in the relay node, the power consumed by the BB processing $P_{\text{BB-RN}}$ can be divided into transmitting and receiving part but it is usually assumed to be one value. Moreover, $P_{\text{BB-RN}}$ may depend on the complexity of the signal processing.

Depending on the considered past work, some elements of the models presented above are taken into account and some

are omitted. Therefore, similarly as in the previous section in the case of multi-user OFDMA network, the values of the power consumption parameters used by various authors are collected in Table 9. It is obvious that due to the diversity of the relay nodes and end-user devices in the network the circuit power consumption can be different. Nevertheless, in all cited papers it is assumed that the circuit power consumption is the same among the end-user devices and relay nodes. Moreover, in some papers [87], [89] the circuit power has not been divided into power consumed by BS, relay node and end-user but has been summed in one value. Furthermore, it can be observed that in Table 9 the direction of transmission (downlink or uplink) is not specified for some papers. These authors consider transmission between pairs of users with help of the relay node as shown in Figure 18. If some value in Table 9 is not specified, it means that such an parameter has not been considered. If there is more than one value provided, it means that the authors have analyzed different scenarios.

C. CONSTRAINTS IN A MULTI-USER OFDMA RELAY NETWORK

There is high number of potential degrees of freedom in the multi-user OFDMA relay network. Below we summarize the constraints considered in the related papers:

- the maximum transmit power constraint considered in [80], [81], [82], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [96], and [98]. In the context of practical wireless communication systems, the transmit power should be limited in each transmitter. Nevertheless, the common approach in the literature is to ensure that the sum of the power allocated in all transmitters does not exceed the maximum power budget of the whole system. In the contrast to the common approach in [100] the power allocated on a given SC is limited.

- the minimum data rate constraint which has been taken into account in [82], [84], [86], [88], [90], and [98]. Due to two time slots that are required to deliver the data to the end-user in the relayed transmission mode, two approaches are considered in the context of the data rate constraints. In the first approach, the data rate is considered over two time slots. It means that in the direct transmission the data rate achieved by the user is summed over two time slots [86], [98] or scaled by factor $\frac{1}{2}$ [82]. If the sum of the data rate achieved in the direct transmission mode is not scaled the factor $\frac{1}{2}$ is neglected for relayed transmission. Whereas, in the second approach the minimum data rate constraint ensures that the data rate achieved in the one time slot has to gather or equal to the assumed threshold, thus for the relayed transmission the data rate is scaled by the factor $\frac{1}{2}$ [84], [90], [96].

- the subcarrier assignment constraints which restrict each subcarrier to be used at most once in each time slot in order to avoid interference. In the contrast to the multi-user OFDMA network this constraint has two meanings in the context of relay network. On the one

TABLE 9. The values of the power consumption parameters in the multi-user OFDMA relay networks.

Papers	Scenario	TX circuit power [W]	RN circuit power [W]	RX circuit power [W]	TX PA efficiency	RN PA efficiency	$\beta \left[\frac{W}{Mbit/s}\right]$
Cheung et al. [80], [81]	AF downlink	60	20	–	38%	20%	–
Loodaricheh et al. [82]	AF downlink	100	0.1	0.1	38%	100%	–
Lu et al. [87]	DF with DL downlink	$\{0.05, 0.1, 0.2\}$	–	–	50%	50%	0.38
Xiong et al. [89]	DF with DL downlink	0.2	–	–	38%	38%	0.01
Bossy et al. [83]	DF downlink	40	4	0.1	100%	100%	–
Basturk et al. [98]	DF downlink	3.16	0	0.1	40%	100%	–
Xu et al. [100]	DF uplink	–	–	–	100%	100%	–
Najjar et al. [95]	AF multicell downlink	0.1	0	0	100%	100%	–
Bossy et al. [86]	DF downlink	40	4	0.1	100%	100%	0.01
Zappone et al. [97]	DF	–	–	0.01	100%	100%	–
Xiong et al. [101]	AF	0.025	–	0.025	40%	40%	–
Singh et al. [84], [90]	AF	0.2	0.1	0.2	100%	100%	–
Singh et al. [91]	DF	–	0.025	0.025	100%	100%	–
Singh et al. [96]	AF	0.025	0.025	0.025	100%	100%	–
Singh et al. [92]	DF	0.01	–	0.01	100%	100%	–
Singh et al. [93]	DF	0.025	0.05	0.025	100%	100%	–
Zheng et al. [88]	DF	1.66	1.66	1.66	50%	50%	1

hand, it ensures that a single transmission mode, usually direct or relayed, is chosen for each user-subcarrier pair while on the other hand guarantees that each subcarrier is only allocated to at most one end-user. In this form, the subcarrier assignment constraints have been considered in [80], [81], [82], [88], [89], [98], and [100]. Nevertheless, in the literature exist papers [83], [86], [90] where the subcarrier can be utilized in the direct and relayed transmission mode simultaneously, but within one transmission mode, it can be utilized by one user. Such an approach can cause interference, however, the properly designed resource allocation algorithm can increase the energy efficiency compared to the network without inter-user interference. Moreover, in the scenario wherein the user pairs communicate with each other via relay node [84], [85], [87], [91], [92], [93] (Figure 18) or only the relayed transmission mode is considered [87], the subcarrier assignment constraints comes to guaranteeing that subcarrier or subcarrier pair is utilized by only one user.

- the proportional rate fairness constraint considered in [87], [89], and [101]. It is defined in the same way as in the multi-user OFDMA network. Thus, each user would obtain a predetermined proportion of the system throughput in each resource-allocation determination.
- the maximum outage probability constraint considered in [95], [100], and [102] ensures that the outage probability of the link is lower than the given threshold value.

D. EE OPTIMIZATION IN A MULTI-USER OFDMA RELAY NETWORK

In this section the most popular techniques used in the context of the energy efficient optimization in the multi-user OFDMA relay network are reviewed. As we presented in Figure 21 the complexity of the resource allocation algorithm
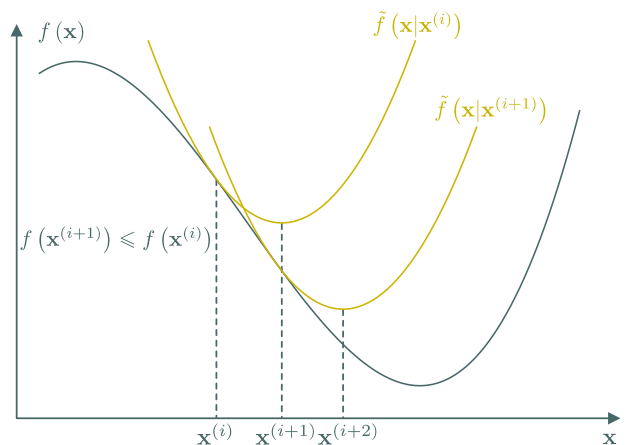

FIGURE 23. The illustration of the Successive Concave/convex Approximation (SCA) method.

increases with the number of the degree of freedom. Moreover, usually the originally defined optimization problem can not be solve by the standard optimization techniques and some transformations may be required. Thus, let us review the techniques/methods applied to solve the energy efficiency optimization problem in the multi-user OFDMA relay network:

- the Dinkelbach method known from the previous sections allows to transform the objective fractional function into a new parameterized concave function. Let us remember that the Dinkelbach method can be applied if the numerator of the objective function is concave while the denominator is convex or if the numerator is affine, the denominator does not have to be restricted in sign. The transformation of the objective function into the parameterized concave function has been applied in [80], [81], [82], [83], [84], [85], [86], [89], [90], [91], [92], [93], [96], [97], [98], and [101], thus in 15 out of

16 cited in this section papers, even when the numerator is non-concave. In this case other methods (described below) can be applied to transform the non-concave objective function into the series of concave functions.

- the epigraph method which is usually applied in the context of the decode and forward relaying protocol and the linearly rate-dependent circuit power consumption model. It can be observed that in equation (12) the $\min \{\cdot\}$ function is used to calculate the data rate for DF relaying protocol. From the optimization point of view it causes that the optimization problem belongs to the class of the max-min programming problem [83], [85], [91], [92], [93], [94], [97]. Therefore, by applying the epigraph method the auxiliary variable is introduced replacing the $\min \{\cdot\}$ function. It requires two additional constraints to be created because the auxiliary variable has to be lower than or equal to the arguments of $\min \{\cdot\}$ function but on the other hand the standard optimization techniques can be applied after this transformation. In the case of the linearly, rate-dependent circuit power consumption the auxiliary variable is introduced making the denominator convex or affine [86].

- the Successive Convex/concave Approximation (SCA) method transforms the non-convex/non-concave function into the series of convex/concave ones. The main idea of SCA method in the context of non-concave function is presented in Figure 23. The non-concave function $f(x)$ is locally approximated in i-th iteration by a concave function $\tilde{f}\left(x|x^{(i)}\right)$ that is equal to the approximated function for $x = x^{(i)}$ and not smaller in the rest of its range. The approximation is used to find new solution $x^{(i+1)}$. This procedure is repeated until the stop criteria are met. Because the approximation of the originally optimization problem is solved in each iteration, it is not guaranteed to obtain the global optimum. Nevertheless, due to convexity/concavity the convergence of the method is guaranteed. The SCA method is usually applied in the context of the system with inter-user interference wherein the function describing the users data rate is the source of the non-concavity [83], [84], [86], [90], [91], [92], [93], [96], [97], [101]. In the literature two approaches to determine the approximation function can be found. In the first approach, the concrete approximation function together with replacing the optimization variables by equivalent ones is used. It means that the non-concave/non-convex function has to have a specific form that allows for approximation. This is commonly applied in the relayed transmission with the assumption that the direct link is not used [84], [90], [91], [92], [93], [96].

The more universal method, based on the Difference of Concave/Convex (DC) programming, is considered in the second approach. This requires the approximated non-concave/non-convex function to be a difference of concave/convex functions. Then, the subtrahend is

approximated using the first order Taylor series at a given point achieving the difference of a concave/convex function and a linear function. This solution is typically used when the first one is not possible.

- the Hungarian algorithm that solves the assignment problem in polynomial time and is usually used in the context of the subcarrier pairing. It means that the Hungarian algorithm determines which subcarriers will be utilized as a pair in the first and second time slot, respectively. The input of the Hungarian algorithm is the $|\mathcal{N}| \times |\mathcal{N}|$ matrix with each element containing the cost of utilizing a given subcarrier pair in the first and second time slot. From the energy efficiency optimization point of view, it means that for each subcarrier pair, the user and relay node which maximize the energy efficiency have to be determined. Thus, actually, all possible combinations of the user-relay node pair for a given subcarriers pair should be checked. Hence the complexity of the resource allocation algorithm in the approach where the users are assigned to the pre-defined relay nodes is lower than in the approach with the adaptive assignment because fewer combinations have to be checked. The cost of utilizing a given subcarrier pair used by the user-relay node pair can be obtained by the cost-benefit metric in an analogical way as in the multi-user OFDMA network. In the context of computational complexity, the time complexity of the original algorithm is $\mathcal{O}\left(|\mathcal{N}|^4\right)$ [103] but it can be modified to achieve an $\mathcal{O}\left(|\mathcal{N}|^3\right)$ [104] running time. Thus, it can be observed that the subcarrier pairing together with adaptive relay selection causes the high computational complexity of the energy efficiency resource allocation algorithm.

Finally, Table 10 presents the optimization methods used depending on the scenario. It can be seen that with the increasing complexity of system model and the increase in the number of degrees of freedom, the number of optimization methods that have to be used grows. At the same time the computational complexity of the resource allocation algorithm rises.

VII. REPRESENTATIVE USE-CASES FOR ENERGY-EFFICIENT OFDM NETWORKS
A. ENERGY-EFFICIENT OFDM LINK WITH COMPUTATIONAL AWARENESS

As an example of a single OFDM link, a setup shown in [22] can be considered. The solution proposed in that paper maximizes EE being the ratio of the data rate calculated using Shannon formula scaled appropriately for each of considered MCSs (21 pairs of modulation and coding schemes with various coding rates, see [22]), and power consumed by an OFDM link. This power is composed of fixed analog circuits power and variable transmit- and BB processing power. The system operates with constraint transmit power over all 256 considered subcarriers under multipath fading and additive white Gaussian noise. The achievable EE as

TABLE 10. The optimization methods used depending on the system model.

	System model							Optimization methods					
	Amplify and Forward (AF)	Decode and Forward (DF)	pre-defined relay assignment	adaptive relay selection	subcarrier pairing	linearly rate-dependent power consumption model	inter-user interference	Dinkelbach method	epigraph method	SCA method	Hungarian algorithm	cost-benefit metric	other
Cheung *et. all* [80], [81]	×		×					×				×	
Loodaricheh *et. all* [82]	×			×	×			×			×	×	
Xiong *et. all* [89]		×		×		×							×
Bossy *et. all* [83]		×		×	×		×	×	×	×	×	×	
Bossy *et. all* [86]		×		×	×	×	×	×	×	×	×	×	
Lu *et. all* [87]		×		×		×							×
Singh *et. all* [90]	×		×				×	×	×				
Singh *et. all* [85]		×	×		×			×	×		×		
Singh *et. all* [84], [96]	×		×		×		×	×	×	×		×	
Singh *et. all* [91]–[93]		×	×		×		×	×	×	×	×	×	
Xiong *et. all* [101]	×		×				×						×
Zheng *et al.* [88]		×						×					×
Basturk *et al.* [98]		×	×	×	×			×					×
Xu *et al.* [100]		×		×	×			×			×	×	

a function of transmission power and distance between the transmitter and the receiver is shown in Fig. 24. The reference method is a rate-maximizing algorithm that first distributes the power among subcarriers using water-filling approach. This is followed by MCS selection that maximizes rate for each subcarrier. It is visible that for both distances the proposed EE-maximizing algorithm outperforms the reference method. There is an optimal transmission power, maximizing EE, that increases with distance.

B. ENERGY-EFFICIENT MULTI-USER OFDMA NETWORK WITH COMPUTATIONAL AWARENESS

Representative results of the EE maximization for a multi-user scenario are shown in [29]. The downlink transmission system is LTE-like allocating orthogonal resource blocks to multiple users. For each user each of the assigned RBs uses equal power and a single MCS. There are 15 different MCS considered in [29] with rate estimation based on effective SNR calculation and SNR to BLER mapping. The power consumption model consists of fixed component, modeling analog components and baseband processing (as assumed, fixed for given MCS, the same for whole RB), and variable component of transmit power. The achievable EE as a function of number of users for 100 RBs and as a function of the number of resources blocks for 10 or 15 users is shown in Fig. 25 and Fig. 26, respectively.

The proposed solution, maximizing the EE of the system is compared against two reference algorithms. First, *Max-throughput* algorithm uses the same transmit power as the proposed solution. Each RB is allocated to the user with the highest channel gain. Next, water-filling is performed to
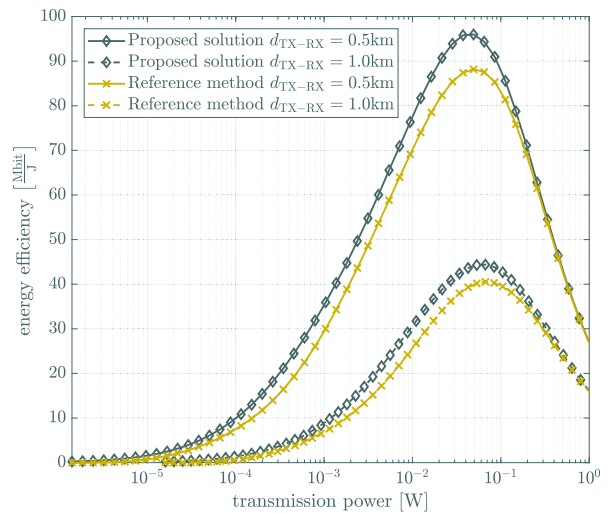

FIGURE 24. The energy efficiency versus the transmission power for a single link OFDM transmission.

distribute known transmit power among subcarriers. Finally, a single MCS is selected for each allocated UE in order to maximize rate. The second reference algorithm, called *Shannon EE*, maximizes EE but considering Shannon formula as an estimator of data rate.

It is visible that for both considered cell radiuses (0.75 km and 3 km) the proposed solution outperforms the reference solutions in terms of EE. The difference is the higher the higher number of users, as visible in Fig. 25, and the higher the number of available resource blocks, as visible in Fig. 26. The most important outcome is significantly improved EE of the proposed method against *Shannon EE* method, showing that simplified, Shannon-based rate estimation is not accurate
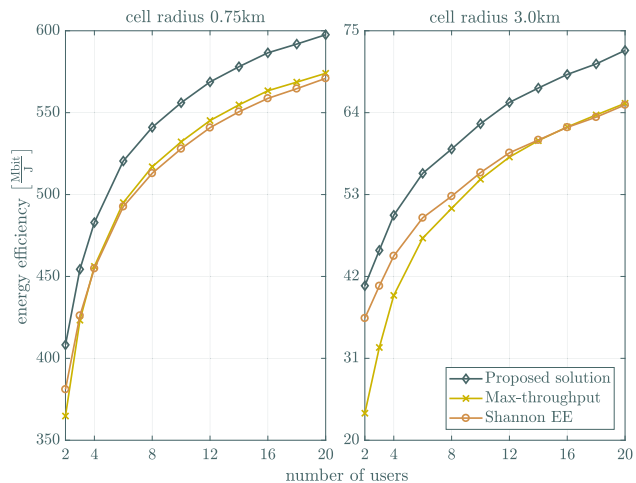
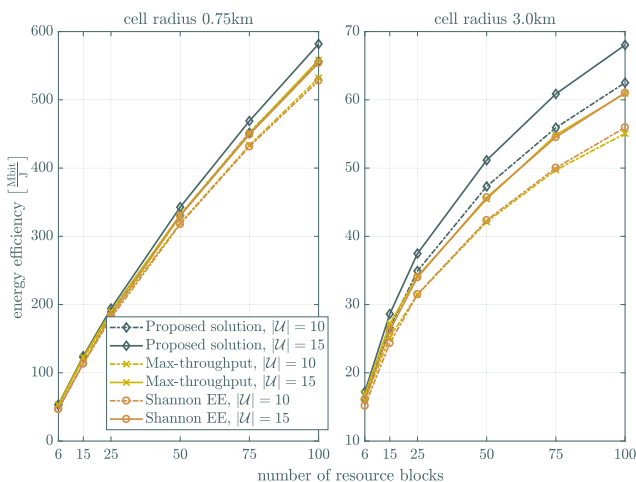**FIGURE 25.** The energy efficiency versus the number of users for different cell radius. Multi-user scenario.

FIGURE 26. The energy efficiency versus the number of available RBs for different cell radius. Multi-user scenario.

FIGURE 27. The energy efficiency and throughput versus the number of users for the multi-relay network.

without parallel transmission, 3) without relay, with parallel transmission, 4) without relay, without parallel transmission. While the proposed solution is able to leverage all these possibilities, the *Reference method* considers only options without parallel transmission, i.e., without intra-cell interference. Fig. 27 shows that for an OFDM system of 16 subcarriers with 8 relays located in a cell both considered algorithms have increasing EE and data rate with number of users. The gap between both solutions is the greater the more users are in the cell. For higher number of users the proposed algorithm can easier find a pair of them with such a channel gain relations that allows the parallel transmission to be scheduled as more efficient.

VIII. IMPACT OF PRACTICAL RF FRONT-END ON OFDM ENERGY-EFFICIENCY

An important topic that is typically overlooked while optimizing resources allocation for OFDM-based networks is the nonlinearity of OFDM transceivers. All above mentioned works consider OFDM transceivers as linear systems resulting in, e.g., linear increase of the consumed power with the allocated power and no influence of power allocation on interference power for this link. However, while this model can be used for high-throughput systems it cannot be used when the transceiver is optimized for low energy consumption. This is mainly caused by nonlinear characteristic of any practical power amplifier [105]. The operating point of a power amplifier, called "back-off" is the difference between the PA clipping power and the mean transmit power (in logarithmic scale). When high back-off is used the nonlinear distortion can be negligible at the cost of low power amplifier efficiency. When trying to maximize the PA efficiency, thus, emitting the maximal part of the PA input power as a useful waveform, low back-off has to be used and high nonlinear distortion is expected. Note that the power amplifier efficiency is not a fixed value [47]. It depends not only on the power back-off but also on the amplifier architecture (defined

enough to model the LTE-like system. However, both for the proposed solution and the reference solutions, the achievable EE rises with the number of RBs or users, showing positive influence of the enlarged solution space.

C. ENERGY-EFFICIENT MULTI-USER OFDM RELAY NETWORK WITH COMPUTATIONAL AWARENESS

A representative example of multi-user optimization supported by relays in a cell is shown in [86]. The considered downlink transmission is structured both in frequency, using subcarriers, and in time, using time slots. As the transmission from the relay to the end user can be performed using the same time-frequency resources as the transmission from the BS to another user, interference can be expected. Here, the data rate is calculated using Shannon formula. The power consumption is composed of fixed power, transmission power and BB processing power proportionally depending on the data rate. In total, four transmission modes are considered: 1) with relay, with parallel transmission (i.e., with the subcarriers reuse in the second time slot corresponding to relying, what creates interference with direct links), 2) with relay,
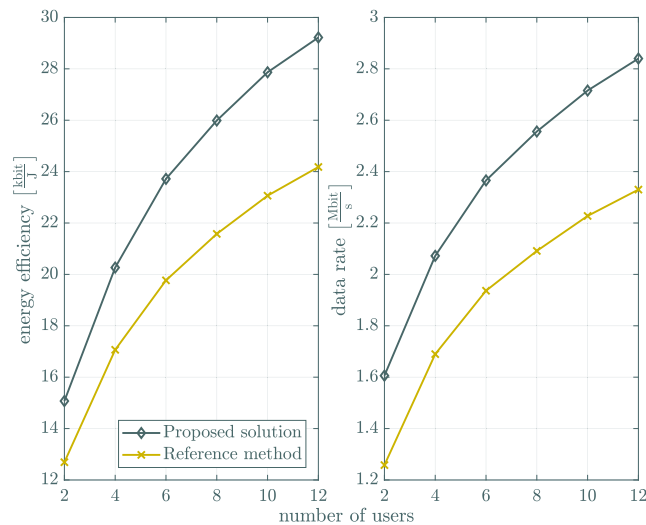
by its class) [106] or even on the methods of powering it. One of the heavily investigated scheme that can allow for the amplifier increased energy efficiency is envelope tracking, whose aim is to adjust PA supply voltage according to the envelope of the transmitted signal [107]. Even if the PA energy consumption is reliably modeled, the nonlinearity of the supply voltage should be considered while powering a transceiver from batteries. The battery capacity decreases nonlinearly with the energy consumption of PA [108].

The nonlinear PA input-output (AM/AM and AM/PM) characteristic has even stronger influence on the transmitted OFDM signal and its distortion. As a result of nonlinear processing, all utilized OFDM subcarriers, undergo inter-modulation. New power components appear in the PA output signal spectrum at frequencies being linear combination of the input signal subcarrier frequencies. This is also visible as a Gaussian noise-like distortion at the occupied subcarriers [109]. The effect depends not only on the chosen PA back-off but also on the PA characterstics or on the properties of the OFDM signal being amplified. There are tens of different models of nonlinear PA ranging from some complicated Volterra-series, through polynomial representation with or without memory, to a simple clipper having linear AM/AM characteristic in a given range of input power and saturation above this range [110]. It has been shown in [111] that a PA of clipper-like characteristic guarantees the highest Signal to Noise and Distortion power Ratio (SNDR). Even if the PA characteristic is not like this, it is common to utilize Digital Pre-Distortion (DPD) (being a nonlinear signal processing unit applied before OFDM signal enters PA) [112], so that the effective joint characteristic of DPD and PA is clipper-like.

While DPD minimizes the nonlinear distortion power, there is also an input OFDM waveform feature that plays an important role. Note that minimum distortion power at the PA output is obtained for a signal of constant envelope, e.g., Minimum Shift Keying signal. In the case of an OFDM signal, a sample for each time instance is a sum o many subcarriers modulated by typically uncorrelated complex data symbols. As there may be tens or hundreds of subcarriers, central limit theorem applies, resulting in OFDM signal samples being approximated by the complex Gaussian distribution [113]. This causes the instantaneous signal envelope to fluctuate significantly. This is typically measured for an OFDM symbol using Peak to Average Power Ratio (PAPR) metric that is the ratio of peak sample power to mean sample power. Observe that while both PAPR and PA back-off are defined in relation to the mean signal power, PAPR higher than the back-off for clipper PA means that some OFDM signal samples are clipped. As typical PAPR for OFDM symbol is greater than 6 dB, it means that PA can output signal of mean power up to 25% of its maximal rated power not to observe distortions. Such a scheme would be highly ineffective in terms of EE. For this reason, a number of signal processing algorithms have been elaborated that reduce PAPR of an OFDM signal [20] or even directly the induced distortion being aware of the PA characteristics [114], [115]. On the other hand, recent

investigations have shown that the nonlinear ''distortion'' can be used to improve reception quality [116]. Last but not least, the above described Gaussian signal approximation is valid for the appropriately high number of subcarriers of possibly equal power. It has been shown that the PAPR distribution changes if the utilized subcarriers do not constitute a single block in frequency [117], or have varying power [118]. The ultimate example is an OFDM transmitter modulating a single subcarrier resulting in PAPR of 0 dB.

All these models and signal processing blocks should be considered at the stage of resources allocation for OFDM links or networks. However, even for simplified OFDM transceiver nonlinearity modeling, there is a limited number of papers that consider it in resources allocation algorithms. In [119], power allocation in an OFDM-based cognitive radio is considered, in order to maximize secondary user rate. The in-band and out-of-band distortion is calculated for the 3rd order polynomial nonlinearity. However, the model does not consider variation in allocated power among subcarriers, neither frequency-specific character of nonlinear distortion. Similar model and optimization is used in [120] for Generalized Frequency Division Multiplexing. As such, the same limitation of the results validity is observed. A clipper nonlinerity model is considered for optimization of power allocation in an OFDM-based link with relay. However, again there is no frequency-selectivity of the utilized distortion model, neither the number of utilized subcarriers influences the results. The optimization variable is the total allocated power, and equal power is allocated to each subcarrier.

The above discussion shows that there are still unsolved problems in resources allocation for energy efficient OFDM-based transmission. One of these is the front-end nonlinearity aware optimization.

IX. PRACTICAL OFDM SYSTEM DESIGN TRADE-OFFS AND RECOMMENDATIONS FOR ENERGY EFFICIENCY

As discussed in the previous sections, the role of computational awareness in OFDM/OFDMA resource allocation optimization for the expected energy-efficiency of future radio communication systems cannot be overestimated, and has been emphasized in a number of recent papers. However, there are some limitations of the wireless systems or costs related to EE maximization, that can prevent the optimal solution to be achieved or makes it not profitable.

Let us now summarize these design trade-offs which are graphically presented in Figure 28 and provide recommendations.

A. EE MAXIMIZATION VS. OPTIMIZATION COMPLEXITY

Power consumption associated with the implementation of the optimization algorithms to achieve maximal energy efficiency can be significant. The definition of optimization problem and its constraints are becoming more and more complex in order to reflect complex relation between different factors, e.g., influence of coding/decoding schemes on the transceiver power consumption. At the same time, the more
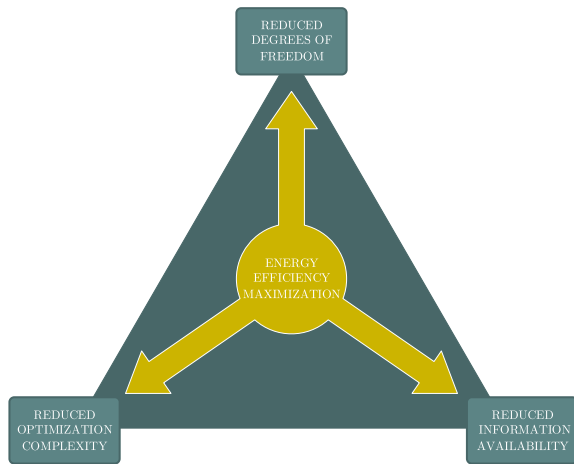
FIGURE 28. Trade-offs in achieving EE.

complex problem results typically in more advanced optimization methods that need to be applied to find the global optimum. The resource allocation optimization methods, e.g., a combination of Dinkelbach method, SCA, Hungarian method, etc., can be significantly computationally complex, requiring many iterations to be employed. Moreover, these problems do not scale well with increasing problem size, e.g., number of considered users or subcarriers. As such, obtaining of a global EE maximum might be impossible in full-size networks in real time. Even if possible, this can bring so much energy consumption for computation of a solution, that it becomes impractical. Algorithms complexity and required computational resources (the cost) must be balanced with the performance improvement (the profit) that comes with exploiting the optimization algorithms. A suboptimal solution may achieve the EE performance close to the optimal at significantly lower computational time or energy. It can be achieved by utilizing a natural property of the SCA, Dinkelbach etc. algorithms, being iterativeness. The algorithms can be terminated after fewer iterations, reducing computational complexity proportionally to the savings in number of iterations. Another option, related to the numerical optimization methods, is proper definition of a starting point. By setting it close to the final solution, e.g., by using some simplified models or historical knowledge, fast convergence can be achieved. Nevertheless, it is well known that wireless communication systems operate in real-time and thus low complexity solutions are required for resource allocation. Therefore, based on the results resulting from the high complexity optimization methods near-optimal solutions can be proposed with lower computation complexity. For example, in the case of relay network [86], instead of checking all possible user-relay node pair combinations, based on the results users can be assigned to the ready node a prior. Another approach is to applied *look-up-table* (LUT). Based on the simulation results, it is possible to determine the relationship between system parameters, e.g. transmit power values may be assigned for a given channel gains, or relay nodes may be selected for given locations. Then, by placing this information in the LUT, resource allocation may be accomplished by

reading the corresponding row of the table. Moreover, the process of reading from the table can be improved by applying the hashing or a different data structure e.g. a binary tree.

B. EE MAXIMIZATION VS. INFORMATION AVAILABILITY AND SIGNALING OVERHEAD

Even if the EE optimization algorithm results in globally optimal solution, it is optimal only for the considered system model, being inherently imperfect. The most common source will be delayed or quantized channel- and network-state information required by the optimization algorithm. Finding the proper balance between EE maximization and provisioning of accurate input knowledge is one of the main trade-offs for the deployment of EE OFDM networks. First, this information can be inaccurate or outdated at source since it is based on (inevitably imperfect) estimation of the channel coefficients in the presence of noise using, typically, pilot signals from past symbol periods. Moreover, this information is typically quantized in order to reduce the required throughput of the control channel, e.g., to send it periodically from a UE performing channel estimation to a BS allocating resources. Last but not least, it may not be available in full at all network nodes, i.e., transmission of all channel coefficients of a given link to all other network nodes or to a central resource management unit, in order to coordinate inter-BS interference, would be associated with impractically high signalling overhead and potentially significant delay. Even if the optimal solution is calculated on time in the central resource management unit, the decision should be distributed among all controlled BSs within very tight latency budget.

Therefore, an optimization using reduced (but representative) information of links qualities should be considered, accepting reduced EE. The second option is to use hierarchical or distributed optimization, that performs delay and control link-demanding optimization locally at a single base station. This allows for prompt reaction to mobile radio channel changes, limiting control messages between BSs. The hierarchical optimization means that local decisions are supported by global, but slowly-varying coordination among BSs.

C. EE MAXIMIZATION VS. AVAILABLE DEGREES OF FREEDOM

A limitation in achieving high energy-efficiency may be a particular radio communication standard or a radio architecture with a limited number of degrees of freedom. For example, only one MCS might be available (allowed by system recommendations) for a given OFDM symbol or resource block (as in LTE or 5G system standard) or a fixed power per RB will be emitted. Moreover, the power-consumption of the wireless transceiver may be invariant of the resources allocation, e.g., the power consumed by a class A power amplifier may be independent of the transmitted signal or base-band power consumption may not scale linearly with the transmission rate. In such cases the potential EE gain by optimization can be limited, making the total signaling and

computing overhead not justified. In the practical design of energy-efficient OFDM-based communication networks one has to assess (by simulations or measurements) whether the energy-efficiency improvement achieved by the EE optimization algorithms is high enough and worth the computational and signaling costs.

This problem cannot be solved differently than by enabling additional degrees of freedom by redesigning transceivers or adding amendments to standards.

X. FUTURE WORKS AND CHALLENGES

The focus of this paper is the energy efficient resource allocation in the systems based on OFDM/OFDMA techniques. The reason for this is that the OFDM/OFDMA techniques are used in most of the current wireless communication systems and are intended to be used in the future. However, the presented discussion can extended to another modern OFDM/OFDMA-based technologies.

One example can be Mobile Edge Computing (MEC). The main goal of the MEC is to offload intensive mobile computations to computing nodes located at the edges of cellular networks [121]. Therefore, the energy efficient computations offloading requires both energy efficient wireless transmission which, e.g., in 5G systems is realized with the use of OFDM/OFDMA techniques and energy efficient tasks computation. One of main challenges in this context is reliable estimation of the power consumption in the processing nodes. For example, in [122], [123], and [124] this power depends on the CPU clock frequency, the total CPU cycles required for computing tasks and the effective switched capacitance depending on the chip architecture. Although it is a widely used and high-level energy consumption model, it is still highly architecture dependent. Thus, it can be observed that also in MEC systems the power consumption models can be of different complexity and accuracy. The second crucial issue in designing energy-efficient MEC systems is the adaptive selection of the processing node because tasks can be computed locally or in one of many cloud nodes. In the case of local computing, the energy consuming transmission to a cloud node is not required but task computation itself may consume more energy. On the other hand, the task offloading requires the transmission to the cloud node which consumes the power and radio resources but the processing unit can be more efficient. The selection of the processing node causes the optimization problem to be classified as the MINLP problem which, in the context of EE maximization, is also a fractional programming problem. Thus, it can be observed that the optimization techniques described in this paper can be applied to the discussed MEC system.

Another technique to consider is Non-Orthogonal Multiple Access (NOMA) [125], [126], [127], [128] which can achieve higher spectral efficiency than OMA (Orthogonal Multiple Access). However, it should be remembered that higher spectral efficiency does not always result in higher energy efficiency. In the case of Non-Orthogonal Multiple Access more than one user uses the same frequency resource causing interference to each other. Therefore, NOMA requires an advanced interference cancellation algorithm. From the energy efficiency point of view, the additional power consumed by the interference cancellation algorithm has to be estimated and may be dominant over the gain resulting from increased spectral efficiency. Moreover, interference between users causes the energy efficiency optimization problem to be non-concave and can not be solved by standard optimization techniques as we have shown in Section VI-D. Nevertheless, the optimization techniques described in this paper can be applied in such case. Finally, it can be observed that Non-Orthogonal Multiple Access can be a promising technique for increasing the spectral as well as energy efficiency but all its aspects have to be taken into account in designing energy efficient resource allocation algorithm. Nonetheless, our analysis can be the baseline to investigate the energy efficient resource allocation in NOMA systems.

Another interesting problem is the concept of Age of Information (AoI) which was introduced in 2011 by [129] to quantify the freshness of the knowledge we have about the status of a remote system. More specifically, AoI is the time elapsed since the generation of the last successfully received message containing update information about its source system. In practice, it describes how often the data are updated, so it is completely different from the delay or latency. The frequent updating of information ensures its high timeless and accuracy but also consumes a lot of energy which is undesirable in the case of battery powered IoT devices. In the literature, the AoI concept has been investigated for many different aspects. In [130], [131], and [132] the age of information has been considered in the packet management point of view e.g. in [132] the authors presented the age improvements by having smaller buffer sizes and introducing packet deadlines, in which a packet deletes itself after the expiration of its deadline. In the context of wireless communication the AoI has been considered in [133], [134], [135], [136], [137], and [138]. In [133] the authors has dealt with the age of information for a sensor network with wireless power transfer capabilities. The considered sensor node harvests energy from radio frequency signals, generates an update when its capacitor/battery becomes fully charged and transmits by using all the available energy without further energy management. The average AoI performance of the considered greedy policy is derived in closed form and is a function of the size of the capacitor. The optimal value of the capacitor that maximizes the freshness of the information, corresponds to a simple optimization problem requiring a 1-D search. The AoI minimization problem for a network with general interference constraints, and time varying channels have been considered in [135]. The authors have proposed two methods which demonstrates significant improvement in age due to the availability of channel state information. Similar optimization problem has been investigated in [137] but with minimum throughput constraints. They have developed four low-complexity transmission scheduling policies that minimize AoI and evaluate their performance against the

optimal policy. The simulation results show that two proposed methods outperform the other policies, both in terms of AoI and throughput, in every network configuration simulated, and achieve near-optimal performance. The wireless sensors networks (WSN) in the context of the information freshness has been considered in [133] and [139], but only in the second paper the energy efficiency aspect has been taken into account. In [140] the upload scheduling scheme which minimize the update energy consumption subject to information freshness constraints has been proposed. Nevertheless, in both paper and others viewed by authors of this project papers the edge computing concept has not been considered.

Thus, it can be observed that the information freshness in the context of the cellular IoT edge computing network is relatively poorly studied while it could be a crucial factor in designing the cellular IoT network. In particular in the system where the data timeless is a priority e.g. emergency systems, dynamic spectrum access systems, vehicle/airplane networks or the stock exchange systems.

XI. CONCLUSION

In this paper, we review the energy-efficient resource allocation methods in the single OFDM link, the multi-user OFDMA network, and the multi-user OFDMA relay network with computational awareness. The definitions and general aspects of the energy-efficiency resource allocation in wireless communications are provided, e.g., the transmission rate estimation, the estimation of the power consumption, the system limitations and requirements as well as optimization methods. Many solutions proposed by various authors are discussed and compared. As the optimization problems for EE maximization with constraints are relatively complex, the mathematical apparatus required is quite advanced as well. Though, the gain in EE can be quite significant making the whole effort profitable. The two main issues to be addressed in the future are presented in Section VIII and Section IX. First, the nonlinear transceivers' characteristics should be considered in the optimization. By making the system model more realistic other degrees of freedom can be revealed at the cost of optimization complexity. Secondly, the achievable EE depends on many factors, mostly available computational resources, control channels, and available degrees of freedom. While the multicarrier schemes are plausible to be used in the communication systems beyond 5G, the designers of these systems will have to face these problems finding a trade-off between all these factors. In Section X the future works and challenges in the context of energy efficiency resource allocation for other techniques based on OFDM/OFDMA are provided. It can be observed that other techniques used in the modern wireless communication system are based on or use OFDM/OFDMA techniques. Thus, the energy efficient OFDM/OFDMA resource allocation is the part of them. Moreover, we have shown that many aspects of designing energy efficient OFDM/OFDMA resource allocation can be found in other techniques. Therefore, our paper can be treated as the baseline for future works.

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BARTOSZ BOSSY received the M.Sc. and Ph.D. degrees (Hons.) in telecommunications from PUT, in 2015 and 2022, respectively. He is currently a Research Assistant with the Institute of Radio-communications. He was involved in a number of national and international projects. His research interests include green communications, energy-efficient resource allocation, and fog networks and optimization.

PAWEŁ KRYSZKIEWICZ (Senior Member, IEEE) received the M.Sc. and Ph.D. degrees (Hons.) in telecommunications from the Poznan University of Technology (PUT), Poland, in 2010 and 2015, respectively. He is currently an Assistant Professor with the Institute of Radiocommunciations, PUT. Moreover, he is the Co-Founder and the Technical Director of RIMEDO Labs, the spin-off from PUT. He is also a Fulbright Alumnus of the Worcester Polytechnic Institute, MA, USA. He has been involved in a number of national and international (including EU-funded) research projects. He is the author of over 100 research papers, two book chapters, and one book. His main research interests include problems concerning the physical layer of multicarrier and multiantenna systems, green communications, and dynamic spectrum access.

HANNA BOGUCKA (Senior Member, IEEE) received the Ph.D. and Doctor Habilitus degrees in telecommunications from the Poznan University of Technology (PUT), Poznań, Poland, in 1995 and 2006, respectively. Currently, she is a Full Professor and the Director of the Institute of Radiocommunications, PUT. Moreover, she is the Co-Founder and the Head of Cooperation of RIMEDO Labs, the spin-off from PUT. She is involved in the research activities in the area of wireless communications: radio resource management, cognitive radio, and green-communication. She has been involved in multiple European 5th–7th Framework Program and Horizon 2020 Projects, National Science Centre Projects, and industry cooperation. She is the author of 200 research papers, three handbooks in the area of radio communications, and three scientific monographs on flexible and cognitive radio. She is a member of the Polish Academy of Sciences. She has been appointed as the IEEE Communications Society Director of the EMEA Region (Europe, Africa, and Middle East) and elected as the IEEE Radio Communications Committee Chair (2015–2016). Currently, she is the IEEE ComSoc Fog/Edge Industry Community Regional Chair in Europe.

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