

WDM/OCDM Energy-Efficient Networks Based on Heuristic Ant Colony Optimization

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Abstract—The ant colony optimization for continuous domains (ACO_R) approach is deployed in order to solve two resource allocation (RA) optimization problems associated to the signal-to-noise plus interference ratio metric with quality-of-service constraints in the context of hybrid wavelength-division multiplexing/optical code-division multiplexing networks. The ACO_R-based RA optimization strategy allows optimally regulating the transmitted optical powers, as well as maximizing the overall energy efficiency (sum EE) of the optical network. In this context, a suitable model for heuristic optimization approach is developed, with emphasis on the network performance under optimized ACO_R input parameters. Extensive simulation results for both power allocation and EE optimization problems are discussed taking into account realistic networks operation scenarios. Computational complexity analysis is performed in order to obtain a suitable, yet sturdy, algorithm regarding the robustness *versus* complexity tradeoff. The performance and complexity of the proposed heuristic approach are compared with a disciplined convex optimization approach based on CvX tools.

Index Terms—Ant colony optimization (ACO), convex optimization (CvX) tools, energy-efficient design (EED), nonconvex optimization, power rate allocation, resource allocation, wavelength-division multiplexing/optical code-division multiplexing (WDM/OCDM) systems.

I. INTRODUCTION

THE evolution of optical networks is toward the all-optical networks (AONs), which eliminate the optical-to-electrical-to-optical conversion while allowing for unprecedented transmissions rates. The AONs are able to implement ultra-high-speed transmitting and provide flexible bandwidth allocation, routing, and switching of data in the optical domain, presenting the transparency to data formats and protocols, which increases network flexibility [1]. The future trends of optical technologies network encompass wavelength-division multiplexing (WDM), orthogonal frequency-division multiplexing, and optical code-division multiplexing (OCDM).

New solutions based on the mix of these technologies can potentially meet the cited characteristics.

OCDM-based technology has attracted a lot of interests, and it was considered as a promising technique in optical core networks to increase bandwidth utilization by providing subwavelength granularity and to resolve contention problem in optical circuit, burst, and packet switching networks [2]. This technology presents various advantages, including asynchronous operation, high network flexibility, protocol transparency, simplified network control, and potentially enhanced security [3].

In hybrid WDM/OCDM networks, data signals in routing network configuration are carried on optical code path (OCP) from a source node to a destination node passing through nodes where the signals are optically routed and switched [4]. In these networks, each different code defines a virtual channel transmitted in a common channel, and the interference that may arise between different OCPs is known as multiple-access interference (MAI) [3], [4]. Furthermore, the establishment of OCP with higher optical signal-to-noise plus interference ratio (SNIR) allows reducing the number of retransmissions by higher layers, thus increasing network throughput.

For a dynamic traffic scenario, the objective is to reduce the blocking probability of the connections by routing, assigning channels, and to maintain an acceptable level of optical power and appropriate SNIR all over the network [5]. Furthermore, different channels can travel via different optical paths and have different levels of quality of service (QoS) requirements. The QoS depends on SNIR, dispersion, and nonlinear effects. Therefore, it is desirable to adjust network parameters in an optimal way, based on online decentralized iterative algorithms to accomplish such adjustment [6]. Accordingly, the dynamic optimization allows an increased network flexibility and capacity. The SNIR optimization problem appears to be a huge challenge, since the MAI introduces the near-far problem [7]. Furthermore, if the distances between the nodes are quite different, like in real optical networks even with equalization procedures, the signal power received from various nodes will be significantly distinct. Then, an efficient power control is needed to cope with this problem and enhance the performance and throughput of the network; this could be achieved through the SNIR optimization [8], [9]. In this case, which is analogous to the Code-division multiple-access (CDMA) cellular system, the power control (centralized or distributed) is one of the most important issues, because it has a significant impact on both network performance and capacity. It is the most effective way to avoid the near-far problem and to increase the SNIR [8].

The SNIR optimization could be integrated with routing wavelength assignment (RWA), considering the SNIR optimization

Manuscript received April 18, 2014; revised June 23, 2014; accepted July 30, 2014. Date of publication August 28, 2014; date of current version November 22, 2016. This work was supported in part by the National Council for Scientific and Technological Development (CNPq) of Brazil under Grant 202340/2011-2 and Grant 303426/2009-8 and in part by Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (Scholarship) and State University of Londrina-Paraná State Government (UEL).

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Digital Object Identifier 10.1109/JSYST.2014.2345665

procedure implemented after the routing step and the OCP assignment have been established. This approach is conveyed to the generalized multiprotocol label switching signaling protocol in order to allocate the available power resources if and only if the connection meets SNIR constraints [6].

The power control in optical system has been investigated in the context of access networks aiming at solving the near-far problem and establishing the QoS at the physical layer [7]–[9]. Therefore, the optimal selection of the systems parameters such as the transmitted power and the transmission rate would improve their performances. In addition, some works have shown the utilization of resource allocation and optimization algorithms such as local search, simulated annealing, genetic algorithm, particle swarm optimization, and game theory to regulate the transmitted power, bit rate variation, and the number of active users in order to maximize the aggregate throughput of the optical networks [10]–[13]. However, the complexity and unfairness in the strategies presented are aspects to be improved. In the case of the transport WDM/OCDM networks optimization, it is necessary to consider the use of distributed iterative algorithms with high performance–complexity tradeoffs and the imperfections of the physical layer, which constitute a new research area so far [11]. The routed WDM/OCDM networks bring a new combination of challenges with the power control, such as amplified spans, multiple links, accumulation, and self-generation of the optical amplified spontaneous emission (ASE) noise, as well as the MAI generated by the OCPs [5].

The dispersive effects from polarization mode dispersion (PMD) and chromatic dispersion or group velocity dispersion (GVD) introduce pulse broadening and peak power reduction, while significantly affecting the overall performance of optical communication systems. Furthermore, the utilization of compensations techniques is considered in the link design. The effects of chromatic dispersion can be compensated by dispersion management principle based on precompensation schemes, postcompensation techniques, or dispersion-compensating fibers [14]. These schemes can be used isolated or together. Moreover, to compensate the effects of PMD, it is adequate to consider PMD compensation scheme that requires a dynamically controlled birefringent element, which has the same PMD characteristics as the fiber but in the opposite birefringent axis [15].

In two-dimensional (2-D) (time/wavelengths) optical CDMA (OCDMA) codes, in addition to pulse broadening and peak power reduction, the effects of chromatic dispersion and PMD include time skewing [16], [17]. Time skewing is the phenomenon in which temporal spreading of multiwavelength pulses and relative delays occur among chips at different wavelengths. Time skewing results in incorrect decoding and then errors in bit detection. This effect, associated with GVD and PMD, presents dynamic behavior and fluctuations induced by external stress/strain applied to the fiber after installation, as well as by changes in environmental conditions [18], [19]; however, it can be effectively compensated by using tunable compensation schemes, optimum threshold detection, and preskewing/postskewing technique at the encoders/decoders, despite of the additional cost and complexity [16], [19], [20]. The use of encoders/decoders based on fiber Bragg gratings

(FBGs) to compensate both out-band and in-band dispersion is quite attractive [21]. Additionally, the forward error correction techniques are very promising to mitigate the GVD, PMD, and skewing effects [16], [19].

In this context, at the physical transmission level, SNIR is considered as the dominant performance parameter in link optimization layer, with dispersion and nonlinearity being limited by proper link design [22]. In addition, in this work, the fiber compensation schemes and the time skewing compensation techniques have been considered in the link design; moreover, the dominant impairment in the SNIR is given by ASE noise accumulation in chains of optical amplifiers [4]–[6], [11], [22].

Against this background, resource allocation has not been largely investigated considering energy efficiency aspects [23]. This issue has become paramount since energy consumption is dominated by the WDM/OCDM-based networks due to the large amount of passive network elements [4]. Hence, in our work, optimization procedures based on ant colony optimization (ACO) are investigated in details, aiming to efficiently solve the optimal resource allocation for SNIR optimization of OCPs from WDM/OCDM networks under QoS and energy efficiency constraints, considering imperfections on the physical layer. The heuristic optimization method is based on the behavior of ants seeking a path between their colony and a source of food. This method is attractive due to its performance–complexity tradeoff and fairness features with regard to other optimization methods that deploy matrix inversion, purely numerical procedures, or other heuristic approaches [13], [24]. Herein, the adopted SNIR model considers the MAI between the OCP based on 2-D codes (time/wavelength) and ASE at cascaded amplified spans [4], [13].

The main contributions of this paper are twofold. The first contribution is the *proposition of a heuristic ACO scheme for allocation of transmitted power with increasing energy efficiency applicable to optical WDM/OCDM transport networks*. Different from [13], we have utilized a specific fitness function with regard to energy efficiency. The second contribution is *a comprehensive analysis and comparison with an analytical disciplined convex optimization (CvX) approach, taking into account the performance and complexity metrics*.

The rest of this paper is organized as follows. In Section II, the optical transport structure (WDM/OCDM) is described, whereas in Section III, the SNIR optimization metric for the OCPs based on ACO is described in order to solve the resource allocation problem. In the network optimization context, figures of merit are presented, and the ACO is developed in Section IV, with emphasis on its input parameters optimal choice and the network performance. Afterward, in Section V, numerical results are discussed for realistic networks operation scenarios. Finally, the main conclusions are offered in Section VI.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. WDM/OCDM Transport Network

The transport network considered in this work is illustrated in Fig. 1. It is formed by nodes that have optical core routers interconnected by WDM/OCDM links with OCPs defined by

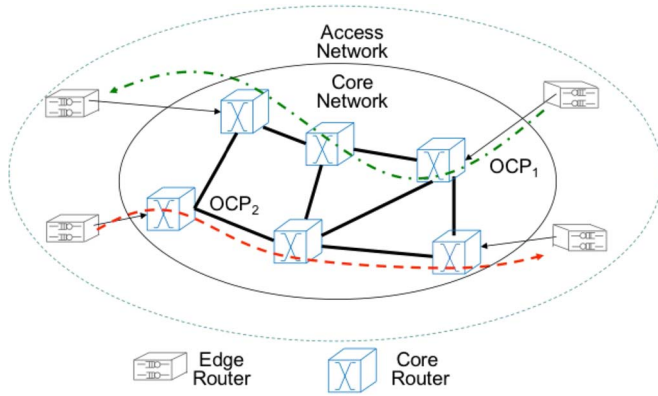


Fig. 1. WDM/OCDM transport network architecture.

patterns of short pulses in wavelengths [4]. The architecture, devices, and equipment of this network were developed in [4], [25], and [26] and previously utilized in others works, for instance, [13] and [27]–[29].

The links are composed of sequences of span, and each span consists of optical fiber and optical amplifier. The transmitting and receiving nodes create a virtual path based on the code; the total link length from source nodes to destination nodes is given by the summation of the length of all traversing hops, i.e., $d_{sd} = \sum d_{(n,m)}$, where s and d are the source and the destination, respectively; and $d_{(n,m)}$ is the length of link n, m in the path between s, d .

The optical core router consists of code converter routers in parallel forming a 2-D router node, and each group of code converters in parallel is preconnected to a specific output performing routing by selecting a specific code from the incoming broadcasting traffic [25], as depicted in Fig. 2. This kind of router does not require light sources or optical-to-electrical-to-optical conversion and can be scaled by adding new modules. Furthermore, the wavelength conversion is not available in the optical code router. The 2-D code is transmitted, and its route in the network is determined by a particular code sequence. For viability characteristics, we consider network equipment, such as code-processing devices (encoders and decoders at the transmitter and receiver) and star coupler; optical routers could be made using robust lightweight technology platforms.

B. OCDM Codes

The 2-D codes can be represented by $N_\lambda \times N_T$ matrices, where N_λ is the number of rows, which is equal to the number of available wavelengths, and N_T is the number of columns, which is equal to the code length. The code length is determined by the bit period T_B , which is subdivided into small units, i.e., chips, each of duration $T_c = T_B/N_T$. In each code, there are w short pulses of different wavelengths, where w is called the weight of the code. An $(N_\lambda \times N_T, w, \lambda_a, \lambda_c)$ code is the collection of binary $N_\lambda \times N_T$ matrices each of code weight w ; the parameters λ_a and λ_c are nonnegative integers and represent the constraints on the 2-D codes autocorrelation and cross correlation, respectively.

The 2-D code design and selection is very important for good system performance and high network scalability with

low bit error rate (BER) [4]. Note that coding in multiple dimensions, such as two dimensions, adds more flexibility while increasing the capacity and performance. The 2-D codes have better performance than 1-D codes and can significantly enhance the number of active and potential users, while holding compatibility with technological maturity of optical networks [3]. It is worth noting that the drawback of 2-D codes is the increase in cost with regard to 1-D codes [30].

The OCDM 2-D encoder creates a combination of two patterns: a wavelength-hopping pattern and a time-spreading pattern. The common technology applied for code encoders/decoders are FBGs. The losses associated with the encoders/decoders are given by $C_{\text{Bragg}}(\text{dB}) = N_\lambda a_{\text{Bragg}} + a_{\text{Circulator}}$, where a_{Bragg} is the FBG loss, and $a_{\text{Circulator}}$ is the circulator loss. The usual values of losses for this equipment are $a_{\text{Bragg}} = 0.5$ dB and $a_{\text{Circulator}} = 3$ dB [13].

III. SNIR OPTIMIZATION PROCEDURES

In the present approach, the SNIR optimization is based on the definition of the minimum power constraint, which is also called sensitivity level, assuring that the optical signal can be detected by all optical devices. In addition, the maximum power constraint aids to minimization of the nonlinear physical impairments, because it makes the aggregate power on a link to be limited to an acceptable value. Hence, the power control in optical networks appears to be an optimization problem.

A. SINR and Optical Power Optimization in OCDMA

Denoting Γ_i the carrier-to-interference ratio (CIR) at the required decoder input, in order to get a certain maximum BER tolerated by the i th optical node and defining the K -dimensional column vector of the transmitted optical power $\mathbf{p} = [p_1, p_2, \dots, p_K]^T$, the optical power control problem consists in finding the optical power vector \mathbf{p} that minimizes the cost function subject to a CIR and a power constraint for each optical node, i.e.,

$$\begin{aligned} \min_{\mathbf{p} \in \mathbb{R}_+^K} \mathbf{1}^T \mathbf{p} &= \min_{p_i \in \mathbb{R}_+} \sum_{i=1}^K p_i \\ \text{s.t. } \Gamma_i &= \frac{G_{ii} p_i G_{\text{amp}}}{G_{\text{amp}} \sum_{j=1, j \neq i}^K G_{ij} p_j + 2N_{\text{sp}}^{\text{eq}}} \geq \Gamma^* \\ P_{\min} &\leq p_i \leq P_{\max} \quad \forall i = 1, \dots, K \\ P_{\min} &\geq 0 \quad P_{\max} > 0 \end{aligned} \quad (1)$$

where $\mathbf{1}^T = [1, \dots, 1]$, and Γ^* is the minimum CIR to achieve a desired QoS; G_{ii} is the attenuation of the OCP signal taking into account the power loss between the nodes, according to network topology, whereas G_{ij} corresponds to the attenuation factor for the interfering OCP signals at the same route; G_{amp} is the total gain at the OCP, $N_{\text{sp}}^{\text{eq}}$ is the spontaneous noise power (ASE) for each polarization at cascaded amplified spans, p_i is the transmitted power for the i th OCP, and p_j is the transmitted power for the interfering OCP. Using matrix notations, the

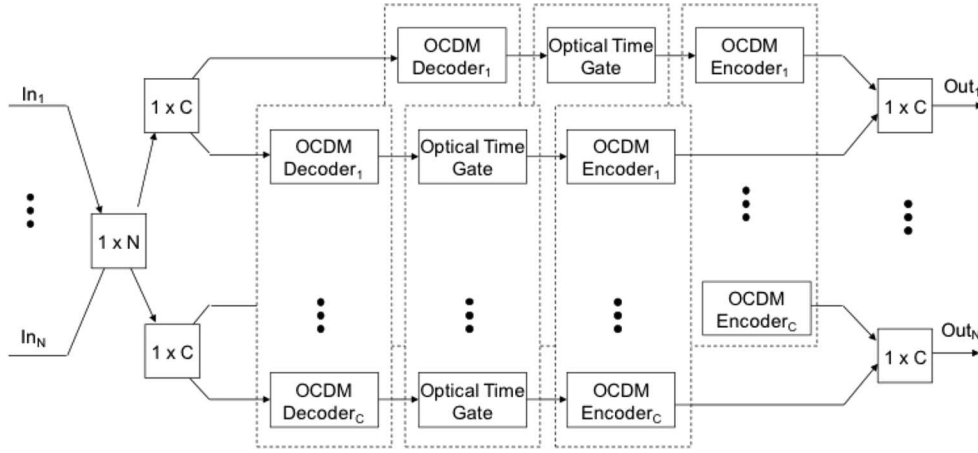


Fig. 2. Optical 2-D core router node.

problem formulated in (1) can be written as $[\mathbf{I} - \mathbf{\Gamma}^* \mathbf{H}] \mathbf{p} \geq \mathbf{u}$, where \mathbf{I} is the identity matrix, \mathbf{H} is the normalized interference matrix, whose elements are evaluated by $H_{ij} = G_{ij}/G_{ii}$ for $i \neq j$ and zero for another case; thus, $u_i = \Gamma^* N_{sp}^{eq}/G_{ii}$, where there is a scaled version of the noise power. Substituting inequality by equality, the optimized power vector solution through the matrix inversion $\mathbf{p}^* = [\mathbf{I} - \mathbf{\Gamma}^* \mathbf{H}]^{-1} \mathbf{u}$ could be obtained. The matrix inversion is equivalent to centralized power control, i.e., the existence of a central node in power control implementation. The central node stores information about all physical network architecture, such as fiber length between nodes, amplifier position and regular update for the OCP establishment, and traffic dynamics. These observations justify the need for online optical SNIR optimization algorithms, which probably have convergence properties for general network configurations.

The SNIR and the CIR in (1) are related by the factor N_T/σ , i.e.,

$$\gamma_i \approx \frac{N_T}{\sigma^2} \cdot \Gamma_i. \quad (2)$$

Hence, the SNIR at each OCP and considering 2-D codes can be rewritten as

$$\gamma_i = \frac{N_T^2 G_{ii} p_i G_{amp}}{\sigma^2 G_{amp} \sum_{j=1, j \neq i}^K G_{ij} p_j + 2N_{sp}^{eq}} \quad (3)$$

where σ^2 is the average variance of the aperiodic cross-correlation amplitude, the noise for the i th amplifier is given by $N_{sp}^i = 2n_{sp} \cdot h \cdot f(G_i - 1)r_C$, which takes into account the two polarization modes found in a single-mode fiber [5], n_{sp} is the spontaneous emission factor, typically around 2–5 range, $h = 6.63 \cdot 10^{-34}$ [J/Hz] is the Planck's constant, f is the carrier frequency, G_i is the erbium-doped fiber amplifier gain, and r_C is the optical bandwidth.

Furthermore, when the Gaussian approximation is adopted, the bit error probability (BER) can be approximated by $P_b(i) = (1/2)\text{erfc}(\sqrt{\gamma_i}/2)$, where $\text{erfc}(\cdot)$ is the complementary error function.

Note that the dominant impairment in SNIR is determined by the ASE noise accumulation in chains of optical amplifiers

for future optical networks [5], [6]. The ASE at the cascaded amplified spans is given by the model presented in [6] and utilized in [13] and [29]. For details, please see these references.

Finally, in our optimal system model, it is assumed the use of laser sources with very short coherent length in order to mitigate the beat-noise effects on the code performance [31]. Thus, our study considers the self-generation of the ASE noise, as well as the MAI generated by the OCPs, as the deleterious effects, which impact the overall SNIR optical network optimization. Since this study focuses on investigating the heuristic ACO resource allocation optimization procedures aiming to maximize energy efficiency in WDM/OCDM networks, we do not include beat noise in the analysis. However, this effect can be straightforward included in our analysis considering the results and modeling described in [31] and [32].

In the following, we formulate and discuss two resource allocation problems that arise in hybrid WDM/OCDM networks under specific QoS constraints: 1) power control under SNIR constraint; and 2) energy-efficient network design.

B. OPT.1: OCP Power Control Design Under SNIR Constraint

The power control optimization problem consists in finding the minimal transmission power for each user that satisfies its QoS requirements, usually a minimum transmission rate. Since user rate is directly related to the user SNIR, one may use it as a QoS measure. Thus, the power allocation problem may be mathematically stated as

$$\begin{aligned} &\text{minimize}_{\mathbf{p} \in \mathcal{P}} && \mathbf{p} = [p_1, p_2, \dots, p_U] \\ &\text{s.t.} && \gamma_i \geq \gamma_i^* \\ &&& 0 \leq p_i \leq p_{\max} \end{aligned} \quad (4)$$

where γ_i is the i th SNIR, γ_i^* is the desired SNIR level, and p_i is the i th user's transmit power. Note that p_i should be bounded (and be nonnegative) for any feasible power allocation policy, with the correspondent power allocation vector described by

$$\mathbf{p} \in \mathcal{P} \stackrel{\text{def}}{=} \left\{ [p_i]_{1 \times U} \mid p_i \geq 0, \sum_{i=1}^U p_i \leq p_{\max} \right\} \quad (5)$$

where p_{\max} represents the maximum total transmit power available at all optical transmitters.

In order to apply the ACO algorithm to solve the power allocation problem, one should express the optimization problem into a mathematical objective or cost function. In [33] and [34], a cost function for power control using genetic algorithms has been proposed. This function was later modified in [35] in order to solve the power control problem under heuristic swarm intelligence approach. Herein, the cost function of [35] is deployed with the ACO algorithm, i.e.,

$$\begin{aligned} \text{maximize} \quad & J_1(\mathbf{p}) = \frac{1}{U} \sum_{i=1}^U \mathbb{F}_i^{\text{th}} \cdot \left(1 - \frac{p_i}{p_{\max}}\right) \\ \text{s.t.} \quad & \text{(C.1)} \quad \gamma_i \geq \gamma_i^* \\ & \text{(C.2)} \quad 0 \leq p_i \leq p_{\max} \\ & \text{(C.3)} \quad r_i = r_{i,\min} \quad \forall i = 1, \dots, U \end{aligned} \quad (6)$$

where the threshold function is defined as

$$\mathbb{F}_i^{\text{th}} = \begin{cases} 1, & \gamma_i \geq \gamma_i^* \\ 0, & \text{otherwise} \end{cases}$$

whereas constraint (C.3) imposes the minimum information rate that guarantees QoS for the i th user.

C. OPT.2: OCP EED

The energy-efficient OCDM design can be formulated as an optimization problem that aims to maximize the ratio between the overall information rate (or, equivalently, the system throughput) \mathcal{S} by the total power consumption, which is given by

$$P_T = \iota \cdot \sum_i^U p_i + P_C \quad (7)$$

including the transmitted power p_i and the power consumption in the optical layer P_C , where the parameter ι is related to power efficiency of the transponder. The power consumption model adopted herein is based on the model described in [36] according to the transmitted bit rate.

The energy-efficient OCDM design can be formulated from the point of view of energy efficiency definition, i.e., $\eta_E = \mathcal{S}/P_T$, as

$$\begin{aligned} \text{maximize}_{\mathbf{p} \in \mathfrak{P}} \quad & J_2(\mathbf{p}) = \frac{\mathcal{S}}{P_T} = \sum_{i=1}^U \frac{\frac{m_i}{m_i} \cdot \log_2(1 + \theta_i \gamma_i)}{\iota \cdot \sum_i^U p_i + P_C} \left[\frac{\text{bit}}{\text{Joule}} \right] \\ \text{s.t.} \quad & \text{(C.1)} \quad 0 \leq p_i \leq p_{\max} \\ & \text{(C.2)} \quad \gamma_i \geq \gamma_i^* \quad \forall i \\ & \text{(C.3)} \quad r_i \geq r_{i,\min}^{\text{serv}} \\ \text{with} \quad & (1 + \theta_i \gamma_i) = 1 + \frac{\theta_i \mathcal{F}_i \cdot p_i |g_{ii}|^2}{\sum_{i \neq j}^U p_j |g_{ij}|^2 + \sigma^2} \end{aligned} \quad (8)$$

where $m_i = \log_2 M_i$ is the modulation order, and θ_i is the inverse of the gap between the theoretical bound and the

real information rate r_i ; in the context of WDM/OCDM, the processing gain \mathcal{F}_i is equal to the code length, i.e., $\mathcal{F}_i = N_T = T_B/T_c$; $w_i = r_c/\mathcal{F}_i$ is the user's nonspreading equivalent signal bandwidth, whereas the available bandwidth for the i th OCDMA user is approximated by $r_c = T_c^{-1}$. Furthermore, θ_i usually is written as [24]

$$\theta_i = -\frac{1.5}{\log(5\text{BER}_i^{\text{MAX}})} \quad (9)$$

where $\text{BER}_i^{\text{MAX}}$ is the maximum tolerable BER for the i th user's service. Finally, the correspondent power allocation vector is described by the set

$$\mathbf{p} \in \mathfrak{P} \stackrel{\text{def}}{=} \{[p_i]_{1 \times U} \mid 0 \leq p_i \leq p_{\max}\}. \quad (10)$$

The EE (η_E) optimization problem consists in finding the appropriate transmitted power for each user belonging to different user's multimedia classes, namely, "serv" = {VOICE, VIDEO, DATA} with different QoS minimum user rates ($r_{i,\min}$) and maximal tolerable BER ($\text{BER}_{\text{serv}}^*$), which is mapped into minimum SINR, in a such way that the overall system energy efficiency is maximized; it means spending the minimum energy consumption to achieve the QoS of each user at different classes. However, this point of operation is not necessarily the point of maximal spectral efficiency, particularly in the case when there exists enough availability of power resource at the transmitter side.

The objective function for the EE optimization in (8) can be classified as a nonlinear fractional program [37], [38]. This objective function is the ratio of two functions that are generally nonconvex (nonconcave) functions. In fact, the numerator of (8) is concave with respect to the variables $p_i, \forall i$, since it is a nonnegative sum of multiple concave functions. In addition, the denominator is affine, i.e., convex as well as concave. It is well known that, for this kind of objective function, the problem is quasi-concave [39].

1) DM: Since concave-convex fractional programs share important properties with concave programs, it is possible to solve concave-convex fractional programs with many standard methods deployed with concave programs; here, we use the Dinkelbach's method (DM) [37], [38] in an inner-outer (loops) iterative method.

Deploying the iterative DM [37], [38], it is possible to solve the quasi-concave energy-efficient design (EED) OPT.2 problem in Section III-C in a *parameterized concave form*. Generally speaking, the original concave-convex fractional program can be expressed as

$$\text{maximize}_{x \in \mathcal{X}} \quad \lambda(x) = \frac{f(x)}{z(x)}$$

where \mathcal{X} is a compact connected set, and $z(x) > 0$ is assumed. The original fractional program above can be associated with the following parametric concave program [37], [39]:

$$\text{maximize}_{x \in \mathcal{X}} \quad f(x) - \lambda z(x)$$

where $\lambda \in \mathbb{R}$ is treated as a parameter. The optimal value of the objective function in the parametric problem, denoted by $F(\lambda)$,

is a convex and continuous function that is strictly decreasing. In addition, without loss of generality, we define the *maximum energy efficiency* λ^* of the considered system as

$$\lambda^* = \frac{\mathcal{C}(\mathbf{p}^*)}{\mathcal{U}(\mathbf{p}^*)} = \underset{\mathbf{p} \in \mathcal{P}}{\text{maximize}} \quad \frac{\mathcal{C}(\mathbf{p})}{\mathcal{U}(\mathbf{p})}$$

$$\text{i.e.,} \quad \begin{cases} F(\lambda) > 0 \Leftrightarrow \lambda < \lambda^* \\ F(\lambda) = 0 \Leftrightarrow \lambda = \lambda^* \\ F(\lambda) < 0 \Leftrightarrow \lambda > \lambda^*. \end{cases} \quad (11)$$

Hence, DM summarized in Algorithm 1 solves the following problem:

$$\underset{\mathbf{p} \in \mathcal{P}}{\text{maximize}} \quad \mathcal{C}(\mathbf{p}) - \lambda \mathcal{U}(\mathbf{p}), \quad (\text{DM}) \quad (12)$$

which is equivalent to finding the root of the nonlinear equation $F(\lambda) = 0$.

Algorithm 1: Dinkelbach's Method

Input: λ_0 satisfying $F(\lambda_0) \geq 0$; tolerance ϵ
Initialize: $n \leftarrow 0$,
repeat
 Solve problem (12) with $\lambda = \lambda_n$ to obtain \mathbf{p}^*
 $\lambda_{n+1} \leftarrow (\mathcal{C}(\mathbf{p}^*)/\mathcal{U}(\mathbf{p}^*))$;
 $n \leftarrow n + 1$
until $|F(\lambda_n)| \leq \epsilon$;
Output: λ_n ; \mathbf{p}_n

DM is in fact the application of Newton's method to a nonlinear fractional program [40]. As a result, the sequence converges to the optimal point with a superlinear convergence rate [38]. In summary, Dinkelbach [37] proposed an iterative method to find increasing values of feasible λ by solving the parameterized problem

$$\max_{\mathbf{p}} F(\lambda_n) = \max_{\mathbf{p}} \{\mathcal{C}(\mathbf{p}) - \lambda_n \mathcal{U}(\mathbf{p})\}, \text{ at } n\text{th iteration.} \quad (13)$$

The iterative process continues until the absolute difference value $|F(\lambda_n)|$ becomes as small as a prespecified ϵ .

In order to demonstrate the DM effectiveness, illustrative EE optimization results for the OPT.2 problem are discussed in Section V-B. The inner loop in Algorithm 1 has been performed first by CVX optimization tool, a package for specifying and solving convex programs [41], [42] and, second, by deploying the ACO_R metaheuristic method, which is reviewed in the following.

IV. ACO_R METAHEURISTIC

ACO_R is a metaheuristic based on the ants behavior when looking for food. It was first proposed for combinatorial optimization problems. In this version, each ant walks through the points of the input set and deposits pheromone on its edges. The next point selection is probabilistically done, considering

the amount of pheromone on each edge, jointly with the heuristic information. Given a set of points next to an ant, the probability of each of this points to be chosen forms a probability mass function (PMF). The main idea of ACO_R is the change of this PMF to a probability density function (pdf); this way, an ant samples a continuous pdf instead of choosing a point next to it. This is due to the fact that the continuous domain has infinite points to be chosen. The pdf used in this work is the Gaussian pdf given its soft capacity of generating random numbers and due to the fact that it has only one maximum point located at the mean of the process. Nevertheless, this last feature is not useful when the search space has more than one feasible regions. To overcome this problem, ACO_R uses a weighted sum of Gaussians with different means to sample each dimension of the problem.

The essential steps in the ACO algorithm implementation and input parameters optimization procedure, including "file size," "pheromone evaporation coefficient," "population size," "diversity parameter," and "volatility coefficient," have been discussed in previous works. Due to space limitations, we recommend the reader interested to consult [24], [43], and [44]. Furthermore, the deployed heuristic ACO_R algorithm parameters for both OPT.1 and OPT.2 problems are discussed in Section V-A1 (see Table II).

A. DM-ACO_R Adaptation

The ACO_R algorithm was adapted in order to fit the DM inner loop. It is well known that the initial guess leads to the quality of solution for every metaheuristic. In addition, in Algorithm 1, a new input \mathbf{p}_{n-1}^* is supplied for the inner-loop algorithm on each outer-loop iteration. Since each input cannot be forgotten, each ACO_R instance must populate its solution file in a way that it does not lose the achievement of the previous outer-loop iterations.

Thus, the volatility coefficient α has been adopted, aiming to control the generation of new instances for the ACO_R solutions. The random generation of a solution file in the n th outer-loop iteration is given by

$$s_l \sim \mathcal{U}[\mathbf{p}_{n-1}^* - \Psi; \mathbf{p}_{n-1}^* + \Psi], \quad l = 1, 2, \dots, Fs \quad (14)$$

where \mathbf{p}_{n-1}^* is the best power vector found in the previous outer-loop iteration, and Ψ is the sample interval limit given by

$$\Psi = e^{-\alpha \cdot n}. \quad (15)$$

Therefore, the solutions generation process is always a perturbation in the previous outer-loop best solution. For instance, if $\mathbf{p}_{n-1}^* = \mathbf{p}_0^*$ in the first iteration of the algorithm, the sample must be done throughout the domain $s_l \sim \mathcal{U}[P_{\min}, P_{\max}]$. Furthermore, the perturbation will be tighter as DM evolves, since the sample interval control Ψ is done by a bivariate negative exponential function of α and n in (15). The procedure to obtain suitable values for α parameter is presented in Section V-A1.

V. NUMERICAL RESULTS

For computational simulation purpose, we have chosen the network global expectation model proposed in [45]. For all destination nodes, the OCPs were generated in each node using a shortest path algorithm [6]. The distances between the nodes vary uniformly within the interval [50; 100] km, considering mean hop count of 3 and a network diameter¹ of 500 km. This parameters choice represents adequate topology dimensions to be deployed with the WDM/OCDM technology, such as those of South of Finland and Germany networks [13], [46]. This approach is independent of the type of routing RWA algorithm used, and it is quite reasonable to evaluate the overall power consumption and energy efficiency of networks [36], [47], [48].

The heuristic $\text{ACO}_{\mathbb{R}}$ algorithm [44] is deployed aiming to solve both OCDM resource allocation problems, as discussed in Section III, i.e., power control under SNIR constraint and energy-efficient network design. The quality of the solution achieved by $\text{ACO}_{\mathbb{R}}$ is evaluated through the average *normalized mean square error* (NMSE) metric, i.e.,

$$\text{NMSE}[n] = \frac{1}{\mathcal{T}} \cdot \sum_{t=1}^{\mathcal{T}} \frac{\|\mathbf{p}_t[n] - \mathbf{p}^*\|^2}{\|\mathbf{p}^*\|^2}, \quad n = 1, \dots, N \quad (16)$$

where $\|\cdot\|^2$ denotes the squared Euclidean distance between vector \mathbf{p}_t and the optimum solution vector \mathbf{p}^* at the t th realization, \mathcal{T} is the number of realizations, and N is the maximum number of iterations. For the EED problem (OPT.2) with iterative DM, at the end of N iterations, there is a new loop of iterations (i.e., inner and outer loops).

Moreover, the algorithm robustness \mathcal{R} can be thought as the ratio between the number of convergence success cS to the total number of process realizations \mathcal{T} after N iterations in each realization, i.e.,

$$\mathcal{R} = \frac{\text{cS}}{\mathcal{T}} \cdot 100[\%], \quad \text{at } N \text{ iterations} \quad (17)$$

and the speed as the average number of iterations needed for the algorithm to achieve convergence in \mathcal{T} trials for a given problem. This figure of merit has been deployed in this work as a measure of quality of convergence for heuristic algorithms.

For all numerical simulations, typical parameter values for the noise power in all optical amplifiers were assumed [5], [11], [14]. The WDM/OCDM resource allocation Monte Carlo simulations were carried out within the MATLAB 7.0 platform context; the main adopted parameters are presented in Table I. Hence, $n_{\text{sp}} = 2$, $h = 6.63 \cdot 10^{-34}$ [J/Hz], $f = 193.1$ [THz], $G = 20$ [dB], and $r_C = 100$ [GHz] were adopted. In addition, an amplifier gain of 20 dB with a minimum spacing between nodes of 80 km has been considered herein. Losses for encoder/decoder based on Bragg gratings were calculated as illustrated in Section II-B, and router losses of 20 dB were included in the power losses model [4], [25]. The adopted OCDM code parameters were code weight of 4 and code length of 101; thus, the code is characterized by $(4 \times 101, 4, 1, 0)$.

¹Longest of all the calculated shortest paths in a network.

TABLE I
MAIN WDM/OCDM SYSTEM AND CHANNEL PARAMETERS

Parameters	Adopted Values	Unit
Min. nodes distance	$d_{(n,m)} = 80$	[km]
Central Frequency	$f = 193.1$	[THz]
Bandwidth per wavelength	$r_c = 100$	[GHz]
2D OCDM codes ($N_\lambda \times N_T, w, \lambda_a, \lambda_c$)	$(4 \times 101, 4, 1, 0)$	
Chip period (OCDM Codes)	$T_c = 9$	[ps]
Number of OCPs	$U \in \{4; 8; 12\}$	
Max. laser power	$P_{\text{max}} = 20$	[dBm]
Min. laser power	$P_{\text{min}} = P_{\text{max}} - 90$	[dBm]
Power circuitry consumption	$P_C = 25 \cdot U$	[W]
Power efficiency (transponder)	$\iota^{-1} = 2/3$	
Noise Power per EDFA span	$P_n = -28$	[dBm]
EDFA Gain	$G = 20$	[dB]
Spontaneous emission factor	$n_{\text{sp}} = 2$	
Router losses	20	[dB]

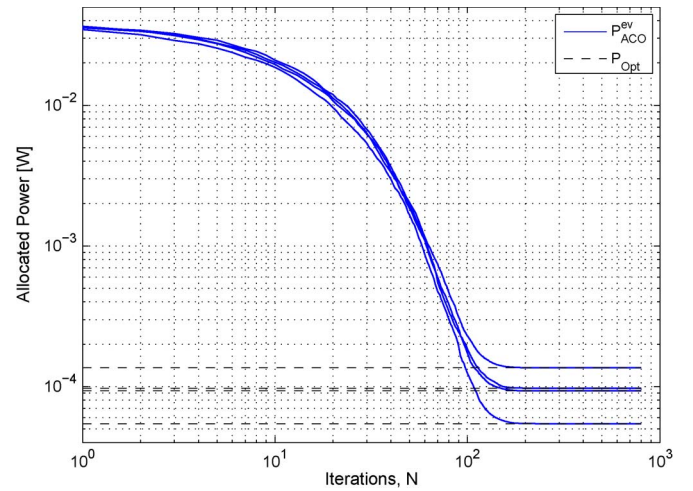


Fig. 3. Individual power levels evolution for the $\text{ACO}_{\mathbb{R}}$ algorithm in a system with $U = 4$ OCPs.

A. OCP MPD

This subsection presents the results achieved for the OPT.1 problem, which, in turn, aims to configure the system in a way that all OCPs transmit through the smallest eligible power levels. This way, Fig. 3 shows the power levels evolution as a function of the iterations of the $\text{ACO}_{\mathbb{R}}$ algorithm, where it can be seen that the reduction in the OCPs transmission power levels is about three orders of magnitude, a quite substantial reduction in the OCP power transmission levels.

The quality of the solutions achieved by the $\text{ACO}_{\mathbb{R}}$ algorithm is evaluated through the NMSE metric, as shown in Fig. 4(a). It is well known that the problem of minimum power allocation is not straightforward, since cost function and constraint functions are not convex. Thus, the nonconvexity of the problem increases the performance loss of the $\text{ACO}_{\mathbb{R}}$ algorithm when system loading increases, due to the higher number of local optima. As shown in Fig. 4(a), the performance loss drastically increases with the system loading, increasing from $\text{NMSE} \approx 10^{-25}$ to $\text{NMSE} \approx 10^{-7}$ after $N = 1000$ iterations, when the number of OCPs grows from $U = 4$ to $U = 12$. It is worth noting that an NMSE of 10^{-3} is still an excellent approximation to the optimal power allocation solution, indicating that $\text{ACO}_{\mathbb{R}}$ is a

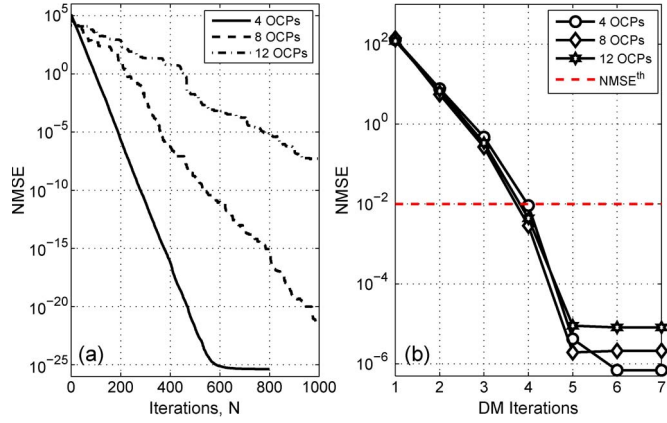


Fig. 4. NMSE evolution of the ACO_R algorithm considering $U = \{4, 8, 12\}$ OCPs; results averaged over \mathcal{T} realizations. (a) Power allocation problem (MPD) with $\mathcal{T} = 1000$. (b) Energy efficiency problem (EED) with $\mathcal{T} = 300$ and $N_{\text{DM}} = 7$ outer loops.

TABLE II
OPTIMIZED ACO_R INPUT PARAMETERS AND RESPECTIVE ROBUSTNESS FOR THE OPT.1 [(6)] AND OPT.2 [(8)] PROBLEMS

U (OCPs)	4	8	12
q (OPT. 1)	0.10	0.10	0.10
q (OPT. 2)	0.30	0.30	0.30
ξ	1.30	1.30	1.30
m	4	8	12
Fs	7	7	7
\mathcal{R} , eq. (17)	100 %	100 %	100 %

robust approach for solving the OPT.1 problem even when the number of OCPs' nodes increases.

1) ACO_R and DM-ACO_R Input Parameters Optimization: In order to accomplish the promising performance for the heuristic optimization approach, the input parameters configuration for the ACO_R algorithm should be optimized.

In the adopted ACO_R input parameter optimization procedure, simulation experiments were carried out in order to determine the suitable values for the DM-ACO_R input parameters, such as file size (Fs), pheromone evaporation coefficient (ξ), population (m), and the diversity parameter (q). In addition, the proposed changes in volatility coefficient (α) have been optimized, too. As a result, Table II summarizes the ACO_R numerical values for the optimized ACO input parameters along with the achieved robustness metric considering different numbers of OCPs. The same ACO_R input parameters have been adopted for both optimization problems, except for the diversity parameter, in which $q = 0.1$ for OPT.1 and $q = 0.3$ for OPT.2 have been adopted.

The input parameters optimization procedure addressed herein is based on [43], where an iterative method for parameters optimization is proposed. In this approach, an initial input parameters configuration achieved with a nonexhaustive search is established. Then, each parameter is tested throughout its domain, whereas the other parameters are kept in their initial values. This step is circularly repeated for each input parameter. For more details, please see [43].

B. WDM/OCDM Energy Efficiency Design (EED)

At first glance, one can guess that the minimum power allocation approach described in Section V-A is able to save a substantial amount of energy since all OCPs are transmitting with the smallest eligible power levels. Although data transmission is performed through packages with predetermined size (in terms of bits), it is easy to see that the best way to save energy is to reduce the transmission cost in terms of energy per bit transmitted averaged over all OCPs and a long period of time. Thus, in the following, the overall energy efficiency maximization problem (OPT.2) is investigated aiming to provide a fast and sturdy approach for optimally allocating energy and information rate in WDM/OCDM networks.

Numerical results here include the following:

- 1) comparison using DM in the outer loop, with inner loop in Algorithm 1 performed by ACO algorithm (DM-ACO) and CvX (DM-CVX), considering OCPs power, rate, and energy efficiency figure of merits;
- 2) EE as a function of total power consumption p_{max} for different numbers of OCPs, where typical EE \times total power consumption includes power circuitry;
- 3) run time analysis for the DM-ACO and DM-CVX approaches in solving the OPT.2 optimization problem.

EED performance with DM-CVX is investigated deploying CvX tools, namely, CVX, a package for specifying and solving convex programs [41], [42]; the purpose herein is to demonstrate the DM effectiveness, as well as compare heuristic and analytical CvX approaches. DM is deployed with the inner loop of Algorithm 1 performed by CVX package tool.

Next, the efficiency of the heuristic approach DM-ACO will be compared in solving the EED OPT.2 problem. The EED is investigated deploying the ACO_R algorithm in the inner loop of DM. The same initial optical power vector and optical channel configuration adopted with the DM-CVX approach are used, aiming to analyze the effectiveness of the metaheuristic for the OPT.2 problem.

Illustrative EE optimization results are depicted in Figs. 5 and 6. Fig. 5(a) and (b) depicts illustrative results for the total energy efficiency ($\sum \text{EE}$) as a function of the transmission power allocation of the first and last OCPs, i.e., p_1 and p_{12} , respectively; whereas the other OCPs individually hold their best power allocation given by DM computed at the end of the optimization process, i.e., $N_{\text{DM}}^{\text{aco}, \text{cvx}} = 7$. For DM-ACO and DM-CVX, it is clear that after three or four iterations, the first and last OCPs achieve their individual near-optimum EE; as a consequence, the maximal overall EE holds. Note that the similar evolution of the power levels for both algorithms (DM-ACO and DM-CVX) in the outer loop of DM is due to the total convergence of the ACO_R algorithm in the inner loop of DM. A detailed analysis of convergence is carried out ahead, as shown in Fig. 8.

Fig. 6 shows the achieved rates relative to the minimum QoS given by $\text{BER}_{i, \text{serv}}^*$ after the respective N_{DM} iterations for both analytical CvX and heuristic ACO_R approaches. Thus, all the $U = 12$ users operate under maximum $\sum \text{EE}$ configuration satisfying their respective QoS; it is found that the problem is feasible with regard to (C.1) and (C.2) constraints in (8). One

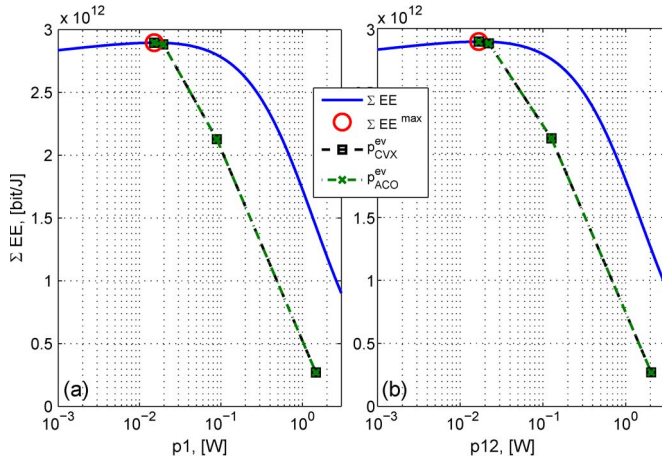


Fig. 5. Sum EE behavior for the optimal power vector \mathbf{p}^* , except to (a) p_1 and (b) p_{12} . $U = 12$ OCPs. Number of iterations in DM: $N_{\text{DM-CVX}} = 7$; $N_{\text{DM-ACO}} = 7$ achieving $\epsilon = 10^{-5}$.

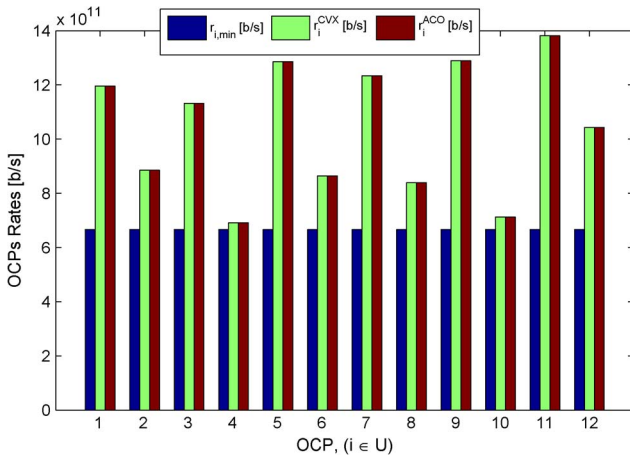


Fig. 6. Minimum and achievable rates after $N_{\text{DM-CVX}} = N_{\text{DM-ACO}} = 7$ iterations.

TABLE III
IDENTICAL PERFORMANCE METRICS FOR THE EE PROBLEM
ACHIEVED WITH BOTH ANALYTICAL (DM-CVX) AND
METAHEURISTIC (DM-ACO) APPROACHES

Metric Σ	$U = 4$	$U = 8$	$U = 12$
EE [bpJ]	$3.4196 \cdot 10^{12}$	$3.3394 \cdot 10^{12}$	$2.8958 \cdot 10^{12}$
Rate [bps]	$2.4024 \cdot 10^{12}$	$1.1574 \cdot 10^{12}$	$6.6839 \cdot 10^{11}$
Power [W]	1.4234	2.8852	4.3325

can conclude that both algorithms achieve the same individual rates, while all OCPs satisfy their respective QoS.

Finally, Table III summarizes the main performance metrics achieved by both DM-CVX and DM-ACO algorithms; both heuristic and analytical approaches have achieved same values for the figures of merit Σ EE, sum rate, and sum power metrics under different system loadings.

Next, the NMSE for the DM-ACO algorithm, taking as reference the analytical optimization approach (DM-CVX), is evaluated in order to check the quality of solution achieved by the metaheuristic for the EED problem. Fig. 4(b) depicts the NMSE evolution as a function of DM outer loop for the DM-ACO algorithm relative to the DM-CVX solution considering $\mathcal{T} = 300$ realizations. As reference, the $\text{NMSE}^{\text{th}} = 10^{-2}$ has

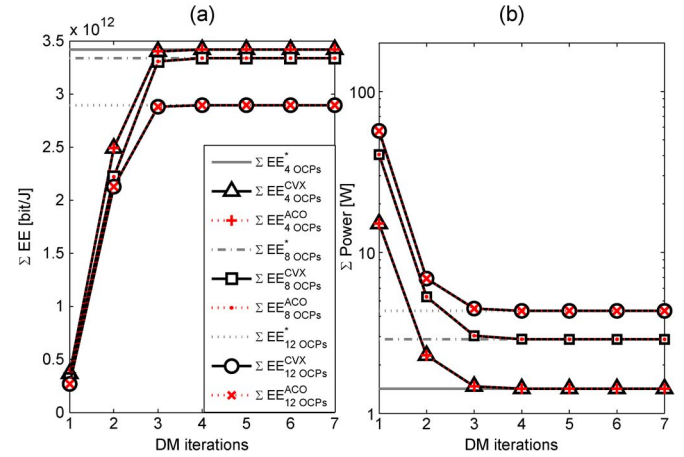


Fig. 7. DM-ACO and DM-CVX performance. (a) Total energy efficiency evolution. (b) Total power evolution as a function of DM iterations for $U \in \{4; 8; 12\}$ OCPs.

been considered as the maximum eligible NMSE for the metaheuristic approach to achieve a 99.999% of Σ EE* obtained via DM-CVX. One can see that, after five outer-loop DM iterations, DM-ACO is able to reach an NMSE smaller than 10^{-2} for all considered system loadings, and in one more iteration, it is able to achieve an $\text{NMSE} \approx 10^{-5}$. In addition, the NMSE keeps improving further to 10^{-5} , showing that the ACO_R algorithm is powerful enough to perform inner loop in EED optimization in conjunction with DM deployed in the outer loop.

Fig. 7(a) and (b) shows the total energy efficiency evolution and the corresponding total power evolution through DM-ACO and DM-CVX outer-loop iterations, respectively. For both algorithms, one can note a similar power and EE evolution behavior, due to the equal initial power vectors and the same static channel assumed, aside from the powerful convergence feature of the ACO_R algorithm. Once DM-ACO deploys the same number of outer iterations as DM-CVX, it is concluded that ACO_R is a powerful heuristic when maximizing the DM parametric function, i.e., (12). An analysis of cost function evolution through the number of inner-loop iterations is discussed ahead in Fig. 8. Despite of the large number of inner-loop iterations required to the ACO_R convergence, it results in smaller run time with regard to CVX while achieving very similar outputs. Run time analysis is explored in the following (see Fig. 10).

In general, heuristic approaches present a nonmonotonic convergence behavior. Despite this, for the WDM/OCODM energy efficiency optimization problem, DM-ACO was able to achieve total power and Σ EE convergence after four to five outer-loop iterations. Indeed, note that the associated total power and the Σ EE evolution depicted in Fig. 7 present the same pattern evolution for both algorithms. In those cases where $U \in [4; 12]$, the Σ EE and total power evolutions for both metaheuristic and CvX algorithms are monotonically nondecreasing (nonincreasing), respectively.

The inner-loop evolution for ACO_R and CvX optimization under 30 OCPs is shown in Fig. 8, where $F(\cdot)$ is the DM's parametric function for the OPT.2 problem, i.e., (13). For the CVX optimization tools [41], the instantaneous values of the internal variables are not available during the optimization

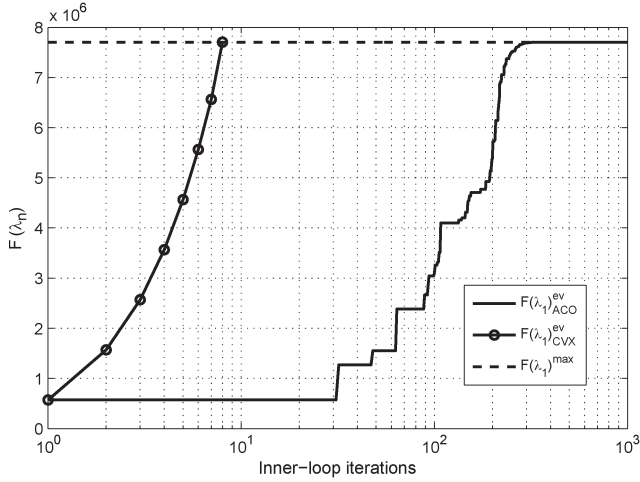


Fig. 8. $\text{ACO}_{\mathbb{R}}$ and CVX inner-loop cost function evolutions during the first DM iteration in Algorithm 1; $U = 30$ OCPs.

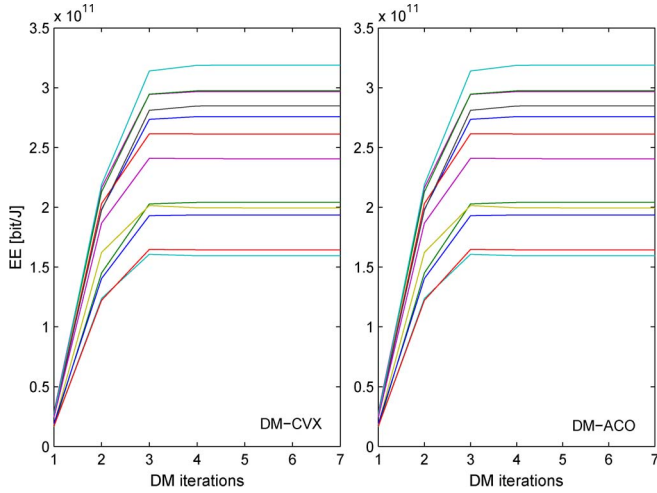


Fig. 9. Individual energy efficiency evolution for both DM-ACO and DM-CVX algorithms. $U = 12$ OCPs.

process. Hence, we have assumed a linear convergence for the internal steps of CVX. Indeed, $\text{ACO}_{\mathbb{R}}$ reaches the maximum cost function value after ≈ 300 inner-loop iterations. From the previous results, it can be easily noticed that outer-loop evolutions for DM-ACO and DM-CVX are very similar under all system loadings evaluated ($U \leq 12$ users). In fact, $\text{ACO}_{\mathbb{R}}$ is able to reach a maximum of $\text{NMSE} < 10^{-5}$ in the inner-loop function with regard to DM-CVX across each DM outer-loop iteration.

Fig. 9 shows the individual EE evolution considering DM-ACO and DM-CVX optimization approaches. Note that the individual EE evolution is not monotonic for any of the algorithms, due to the fact that the aim of the single-objective optimization posed by the OPT.2 problem is to maximize the total energy efficiency of the system. Furthermore, the similarity among the DM-ACO and DM-CVX individual EE (and power evolutions, not shown here) is due to the total convergence achieved by $\text{ACO}_{\mathbb{R}}$ in each inner-loop iteration, as pointed out in Fig. 8. It is worth noting that both DM-ACO and DM-CVX algorithms are able to find suitable steady solutions (individual equilibrium point) in just five outer-loop iterations.

TABLE IV
AVERAGE PERCENTAGE OVER $\mathcal{T} = 1000$ TRIALS FROM DM-ACO RELATED TO THE ANALYTICAL DM-CVX OUTPUT AFTER N_{DM} ITERATIONS OBTAINED FROM FIG. 7 FOR DIFFERENT VALUES OF ϵ_{max}

DM Precision	Metric	$U = 4$	$U = 8$	$U = 12$
ϵ_{max} in the range: $[10^{-5}; 10^{-2}]$	$\sum \text{EE}$	100%	100%	100%
	$\sum \text{Rate}$	100%	100%	100%
	$\sum \text{Power}$	100%	100%	100%
	Robustness	100%	100%	100%

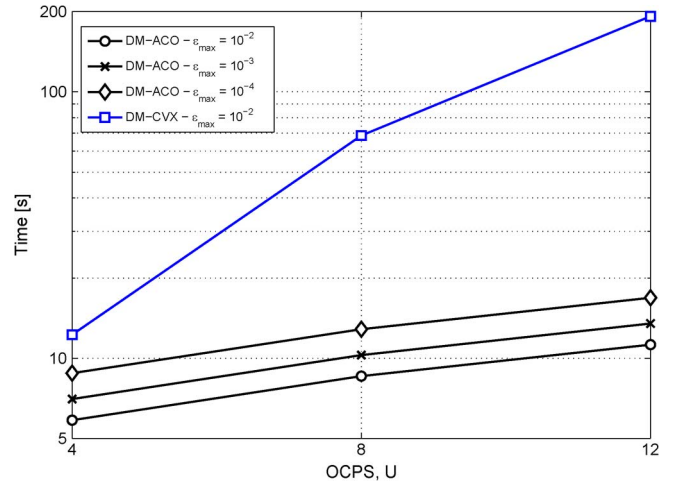


Fig. 10. OPT.2 problem run time for DM-ACO and DM-CVX.

C. Computational Complexity

In order to validate the DM-ACO approach as a powerful tool for solving the EED problem, its computational complexity must be considerably smaller than DM-CVX. Indeed, the numerical results in the following corroborate the robustness and effectiveness of the $\text{ACO}_{\mathbb{R}}$ algorithm deployed in the inner loop of DM for solving the EED problem.

Table IV summarizes the robustness metric from (17) and percentages of $\sum \text{EE}$, $\sum \text{Power}$, and $\sum \text{Rate}$ achieved through the DM-ACO algorithm with regard to DM-CVX in terms of different ϵ_{max} values, where ϵ_{max} is a prespecified maximum tolerance value in solving the DM parametric (13). It can be seen that, for all system loadings considered, the metaheuristic achieves 100% of robustness, which, in turn, ensures the algorithm stability and its capability in solving the $\sum \text{EE}$ maximization problem. Furthermore, the algorithms performance does not deteriorate when a less tight tolerance value in solving the DM equation is adopted, i.e., $\epsilon_{\text{max}} = 10^{-2}$. As a result, we can relieve the run time of the algorithm (by relaxing its precision) without considerable loss in the performance.

Fig. 10 depicts run time as a function of the number of users U for DM-ACO and DM-CVX, through different values of ϵ_{max} . It can be seen that DM-CVX run time is considerably greater than that of DM-ACO in all system loadings, which is expected since DM-ACO is a metaheuristic approach. In addition, the difference in computational complexity between the two approach substantially increases with the number of OCPs. Furthermore, Table IV shows that relaxing the precision of the algorithm does not affect the quality and stability of its solutions. Hence, we can set up DM-ACO with $\epsilon_{\text{max}} = 10^{-2}$ to achieve a fast and powerful approach for the $\sum \text{EE}$ optimization problem.

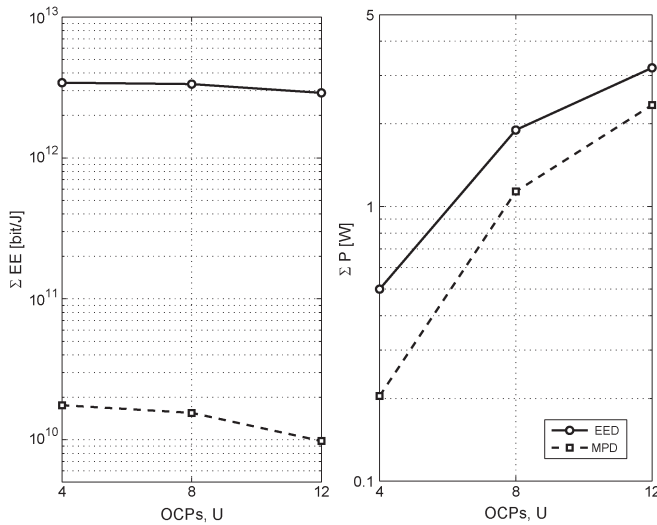


Fig. 11. EED versus MPD approaches in terms of \sum EE and \sum Power metrics.

Thus, DM-ACO proved to be a faster, more promising, and sturdier approach in solving WDM/OCDM EED problems with a smaller run time than the analytical CvX.

D. MPD Versus EED

It has been shown through the last subsections that the ACO_R algorithm is able to efficiently solve the two WDM/OCDM resource allocation problems. Indeed, energy saving is a challenge outlined in green communications, and the EED approach presented in this paper leads to it. In order to evaluate the impact of \sum EE decreasing and the correspondent sum power increasing when the number of OCPs in a WDM/OCDM system grows, Fig. 11 depicts the \sum EE and \sum Power metrics as a function of the number of OCPs, U , for the two approaches discussed in this paper, i.e., OPT.1 versus OPT.2, i.e., minimum power allocation design (MPD) versus EED. Interestingly, one can see that the total power level allocated by MPD is clearly smaller than the total power allocated by the EED optimization approach. On the other hand, the number of bits transmitted per unity of joule under EED criterion is remarkably greater than that under the MPD approach, showing that just setting the OCPs' instantaneous power levels to the minimum eligible values does not lead to energy saving in a best efficient way. Finally, MAI is reduced when a smaller transmission power level is chosen; thus, the MPD approach leads to increasing the maximum number of users supported under optical networks limited by interference.

VI. CONCLUSION

In this paper, the ACO_R algorithm has been successfully applied to solve two resource allocation optimization problems in WDM/OCDM networks under realistic system operation conditions: fixed-rate power control and EED with QoS constraints. In particular, for the OPT.2 problem, the heuristic DM-ACO method has demonstrated to be very competitive

with regard to the analytical DM-CVX approach in terms of quality of solution and computational complexity. More importantly, the developed optimization designs demonstrated to be useful in order to obtain spectral-efficient and energy-efficient systems suitable for WDM/OCDM networks. Indeed, the performance-complexity tradeoff achieved by the DM-ACO method in solving both EED and MPD optimization problems in the context of WDM/OCDM is very promising with regard to the analytical disciplined convex optimization approach.

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