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

Mateus de Paula Marques, Fábio Renan Durand & Tauifik Abrão

Abstract—The ant colony optimization for continuous domains (ACOc) approach is deployed in order to solve two resource allocation (RA) optimization problems associated to the signal-to-noise plus interference ratio (SNIR) metric with quality-of-service (QoS) constraints in the context of hybrid wavelength division multiplexing/optical code division multiplexing (WDM/OCDM) networks. The ACOc-based RA optimization strategy allows regulate optimally the transmitted optical powers, as well as to maximize 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 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 trade-off. The performance and complexity of the proposed heuristic approach are compared with a disciplined convex optimization approach based on CVX tools.

Index Terms—Resource allocation; energy-efficient design; power-rate allocation; non-convex optimization; ant colony optimization (ACO); WDM/OCDM systems; convex optimization tools.

I. INTRODUCTION

The evolution of optical networks is toward the all-optical networks (AON) which eliminate the optical-to-electrical-to-optical (OEO) conversion while allows for unprecedented transmissions rates. The AONs are able to implement ultra-high speed transmitting, 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 (OFDM) and optical code division multiplexing (OCDM). New solutions based on the mixed of these technologies can potentially meet the cited characteristics.

Optical code division multiplexing (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 wavelength division multiplexing/optical code division multiplexing (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 also 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 on-line 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 [8]. Furthermore, the SNIR optimization problem and to increase the SNIR [8]. In this case, which is analogous to the 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 procedure implemented after the routing step and the optical code path assignment have been established. This approach is conveyed to the generalized multiprotocol label switching (GMPLS) 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. Besides, some works have showed the utilization of resource allocation and optimization algorithms such as local search, simulated annealing, genetic algorithm (GA), particle swarm optimization (PSO) and game theory (GT) 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 trade-offs and the imperfections of physical layer, which constitute a new research area so far [11]. The routed WDM/OCDM networks brings a new combination of challenges with the power control, like 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 GVD (group velocity dispersion) introduce pulse broadening and peak power reduction, while affect significantly 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 pre-compensation schemes, pos-compensation 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 2D (time/wavelengths) OCDMA-codes, besides pulse broadening and peak power reduction, the effects of chromatic dispersion and PMD include the time skewing [16], [17]. Time skewing is the phenomenon in which temporal spreading of multi-wavelengths pulses and relative delays occur among chips at different wavelengths. The time skewing results in incorrect decoding and then errors in bit detection. This effect, associated with GVD and PMD, present dynamic behavior and fluctuations induced by external stress/strain applied to the fiber after installation, as well, by changing in environmental conditions [18], [19]; however, it can be effectively compensated by using tunable compensation schemes, optimum threshold detection and pre-skewing/post-skewing 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 to compensate both out-band and in-band dispersion is quite attractive [21]. Additionally, the forward error correction (FEC) 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]. Besides, 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 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 regarding other optimization methods that deploy matrix inversion, purely numerical procedures or another heuristic approaches [13], [24]. Herein, the adopted SNIR model considers the MAI between the OCP based on 2D codes (time/wavelength) and ASE at cascaded amplified spans [4], [13].

The main contributions of this paper are twofold: firstly, the proposition of a heuristic ant colony optimization (ACO) scheme for allocation of transmitted power with increasing energy efficiency applicable to optical WDM/OCDM transport networks. Different of [13], we have utilized a specific fitness function regarding energy efficiency; and secondly, 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 following: in Section II the optical transport structure (WDM/OCDM) is described, while in Section 3 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 optical code paths defined by patterns of short pulses in wavelengths [4]. The architecture, devices and equipment of this network were developed in [4], [25], [26] and previously utilized in others works, for instance [13], [27]–[29].

The links are composed by sequences of span and each span consists of optical fiber and optical amplifier. The transmitting
and receiving nodes create virtual path based on the code; the
total link length from source 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 source and destination,
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 two-dimensional (2D) router node, and each group of code converters in parallel is pre-connected 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-electrical-optical conversion and can be scaled by adding new modules. Furthermore, the wavelength conversion is not available in the optical code router. The 2D 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), star coupler, optical routers could be made using robust, lightweight technology platforms.

### B. OCDM Codes

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

The 2D 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 2D, adds more flexibility while increasing the capacity and performance. The 2D codes have better performance than 1D codes and can significantly enhance the number of active and potential users, while hold compatibility with technological maturity of optical networks [3]. It is worth noting that the drawback of 2D codes is the increase of cost regarding 1D codes [30].

The OCDM 2D 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 fiber Bragg gratings (FBGs). The losses associated with the encoders/decoders are given by $$C_{\text{Bragg}}(\text{dB}) = N_\lambda \alpha_{\text{Bragg}} + \alpha_{\text{Circulator}}$$, where $$\alpha_{\text{Bragg}}$$ is the FBG loss and $$\alpha_{\text{Circulator}}$$ is the circulator loss. The usual value of losses for this equipment are $$\alpha_{\text{Bragg}} = 0.5\ \text{dB}$$ and $$\alpha_{\text{Circulator}} = 3\ \text{dB}$$ [13].

### III. SNIR Optimization Procedures

In the present approach, the SNIR optimization is based on the definition of the minimum power constraint, also called sensitivity level, assuring that the optical signal can be detected by all optical devices. Besides, the maximum power constraint aid 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. SNIR and Optical Power Optimization in OCDMA

Denoting $$\Gamma_1$$ the carrier-to-interference ratio (CIR) at the required decoder input, in order to get a certain maximum bit error rate (BER) tolerated by the i-th optical node, and defining the $$K$$-dimensional column vector of the transmitted optical power $$\mathbf{p} = [p_1, p_2, \ldots, p_K]^T$$, 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 constraints for each optical node:

$$\min_{\mathbf{p} \in \mathbb{R}_+^K} \mathbf{1}^T \mathbf{p} \quad \text{s.t.} \quad \Gamma_1 = \frac{G_{ii} p_i G_{\text{amp}}}{\sum_{j=1, j\neq i}^K G_{ij} p_j + 2N_{\text{eq}}^{\text{sp}}} \geq \Gamma^{*},$$

where $$\mathbf{1}^T = [1, \ldots, 1]$$ and $$\Gamma^*$$ is the minimum CIR to achieve a desired QoS; $$G_{ij}$$ is the attenuation of the OCP signal taking into account the power loss between the nodes, according to network topology, while $$G_{ii}$$ corresponds to the attenuation factor for the interfering OCP signals at the same route, $$G_{\text{amp}}$$ is the total gain at the OCP, $$N_{\text{eq}}^{\text{sp}}$$ is the spontaneous noise power (ASE) for each polarization at cascaded amplified spans, $$p_i$$ is the transmitted power for the i-OCP and $$p_j$$ is the transmitted power for the interfering OCP. Using matrix notations, the problem formulated in (1) can be written as $$\left[\mathbf{I} - \Gamma^* \mathbf{H}\right] \mathbf{p} \geq \mathbf{u}$$, where $$\mathbf{I}$$ is the identity matrix, $$\mathbf{H}$$ is the normalized interference matrix, which elements evaluated by $$H_{ij} = G_{ij}/G_{ii}$$ for $$i \neq j$$ and zero for another case, thus $$u_i = \Gamma^* N_{\text{eq}}^{\text{sp}}/G_{ii}$$, where there is a scaled version of the noise power. Substituting inequality by equality, the optimized power vector solution through the matrix inversion $$\mathbf{p}^* = [\mathbf{I} - \Gamma^* \mathbf{H}]^{-1} \mathbf{u}$$ could be
the bit error probability (BER) can be approximated by $r(EDF A)$ gain, and $G$ range, $h$ 

Hence, the SNIR at each OCP and considering $2D$ codes can be re-written as:

$$\gamma_i = \frac{N_r}{\sigma^2} \cdot \Gamma_i$$

where $\sigma^2$ is the average variance of the aperiodic cross-correlation amplitude, the noise for the $i$-th amplifier is given by $N_{sp}^2 = 2n_{sp} \cdot h \cdot f (G_i - 1) r_c$, which take into account the two polarization mode 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 fibre amplifier (EDFA) gain, and $r_c$ is the optical bandwidth.

Furthermore, when the Gaussian approximation is adopted, the bit error probability (BER) can be approximated by $P_b(i) = \frac{1}{2} \text{erfc}(\sqrt{\gamma_i}/2)$, where $\text{erfc}(\cdot)$ is the complementar 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 [6] [5]. The ASE at the cascaded amplified spans is given by the model presented in [6] and utilized in [29] [13]. 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 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], [32].

In the following, we formulate and discuss two resource allocation problems that arise in hybrid WDM/OCDM networks under specific QoS constraints: a) power control under SNIR constraint; b) 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 direct related to the user SNIR one may use it as a QoS measure. Thus, the power allocation problem may be mathematically stated as:

$$\begin{align*}
\text{minimize} \quad & p \in \mathcal{P} = [p_1, p_2, \ldots, p_U] \\
\text{s.t.} \quad & \gamma_i \geq \gamma_i^* \\
& 0 \leq p_i \leq p_{\text{max}} 
\end{align*}$$

where $\gamma_i$ is the $i\text{th}$ SNIR, $\gamma_i^*$ is the desired SNIR level and $p_i$ is the $i\text{th}$ 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:

$$p \in \mathcal{P} = \left\{ [p_i]_{i=1}^U \mid p_i \geq 0, \sum_{i=1}^U p_i \leq p_{\text{max}} \right\}$$

where $p_{\text{max}}$ 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], [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:

\[
\text{maximize } J_1(p) = \frac{1}{U} \sum_{i=1}^{U} \gamma_i \left( 1 - \frac{p_i}{p_{\text{max}}} \right),
\]

\[\text{s.t. (C.1) } \gamma_i \geq \gamma_i^*, \quad (C.2) \quad 0 \leq p_i \leq p_{\text{max}}, \quad (C.3) \quad r_i = r_{i,\text{min}}, \quad \forall i = 1, \ldots, U\]

where the threshold function is defined as:

\[\gamma_i = \begin{cases} 1, & \gamma_i \geq \gamma_i^* \\ 0, & \text{otherwise} \end{cases}\]

while constraint (C.3) imposes the minimum information rate that guarantees quality of service for the \(i\)th user.

**C. OPT.2 – OCP Energy-Efficient Design (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) \(S\) by the total power consumption, given by

\[P_t = \lambda \cdot \sum_{i=1}^{U} p_i + P_c,\]

including the transmitted power \(p_i\) and the power consumption in the optical layer \(P_c\), where the parameter \(\lambda\) 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, \(\eta_i = \frac{S}{P_t}\), as:

\[
\text{maximize } J_2(p) = \frac{S}{P_t} = \sum_{i=1}^{U} \frac{\log_2(1 + \theta_i \gamma_i)}{m_i} \cdot \left( 1 + \frac{\theta_i F_i \cdot p_i |g_{\text{int}}|^2}{\sum_{i\neq j} F_j |g_{ij}|^2 + \sigma^2} \right) [\text{bit Joule}]
\]

\[\text{s.t. (C.1) } 0 \leq p_i \leq p_{\text{max}}, \quad (C.2) \quad \gamma_i \geq \gamma_i^*, \quad \forall i, \quad (C.3) \quad r_i \geq r_{i,\text{min}}\]

where \(m_i = \log_2 M_i\) is the modulation order, \(\theta_i\) 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 \(F_i\) is equal to code length, \(F_i = N_r = \frac{2}{T_r}\); \(w_i = \frac{1}{T_r}\) is the user’s non-spreading equivalent bandwidth, while the available bandwidth for the \(i\)th OCDMA user is approximated by \(r_c = T_c^{-1}\). Furthermore, \(\theta_i\) usually is written as [24]:

\[
\theta_i = -\frac{1.5}{\log(5 \text{BER}_{\text{MAX}})}
\]

where BER_{MAX} is the maximum tolerable bit error rate for the \(i\)th user’ service. Finally, the correspondent power allocation vector is described by the set:

\[p \in \mathcal{P} \overset{\text{def}}{=} \{ p_i \in \mathbb{R}^U \mid 0 \leq p_i \leq p_{\text{max}} \}\]

The EE \((\eta_i)\) 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 rate \(r_{i,\text{min}}\) and maximal tolerable BER \((\text{BER}_{\text{MAX}})\), which is mapped into minimum SINR, in a such way that the overall system energy efficiency is maximized; it is meaning spend the minimum energy consumption to achieve the QoS of each user at different classes. However, this point of operation not necessary is the point of maximal spectral efficiency (SE), specially in the case when exists enough availability of power resource at the transmitter side.

The objective function for the EE optimization in (8) can be classified as nonlinear fractional program [37], [38]. This objective function is the ratio of two functions that is generally a non-convex (non-concave) function. In fact, the numerator of (8) is concave with respect to \((w.t.)\) the variables \(p_i\), \(\forall i\), since it is a non-negative sum of multiple concave functions. Besides, 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) **Dinkelbach’s Method:** 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 [37], [38] in a inner-loop (loops) iterative method.

Deploying the iterative Dinkelbach’s method [37], [38] it is possible to solve the quasi-concave EED OPT.2 problem of Section III-C in a parameterized concave form. Generally speaking, the original concave-convex fractional program can be expressed as:

\[
\text{maximize } \lambda(x) = \frac{f(x)}{z(x)},
\]

where \(X\) 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]:

\[
\text{maximize } f(x) - \lambda z(x),
\]

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. Besides, without loss of generality, we define the maximum energy efficiency \(\lambda^*\) of the considered system as:

\[
\lambda^* = \frac{C(p^*)}{l(U(p^*))} = \max_{p \in \mathcal{P}} \frac{C(p)}{l(U(p))} \overset{(11)}{=}
\]

i.e.,

\[
\begin{align*}
F(\lambda) &> 0 \iff \lambda < \lambda^* \\
F(\lambda) &= 0 \iff \lambda = \lambda^* \\
F(\lambda) &< 0 \iff \lambda > \lambda^*
\end{align*}
\]

Hence, Dinkelbach’s method summarised in Algorithm 1 solves the following problem:

\[
\text{maximize } C(p) - \lambda U(p),
\]

(D.M.)

which is equivalent to find the root of the nonlinear equation \(F(\lambda) = 0\).
Dinkelbach’s method 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] proposes an iterative method to find increasing values of feasible \( \lambda \) by solving the parameterized problem:

\[
\max_{p} F(\lambda_n) = \max_{p} \{ C(p) - \lambda_n U(p) \}, \text{nth iteration (13)}
\]

The iterative process continues until the absolute difference value \( |F(\lambda_n)| \) becomes as small as a pre-specified \( \epsilon \).

**Algorithm 1 Dinkelbach’s Method**

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

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

IV. ACO\( \_\) Metaheuristic

The ACO\( \_\) 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 done probabilistically, 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 is to control the generation of new instances for the ACO\( \_\) solutions. The random generation of a solution’ file in the \( n \)-th outer-loop iteration is given by:

\[
s_l \sim U \left[ p^*_{n-1} - \Psi; p^*_{n-1} + \Psi \right], \ l = 1, 2, \ldots, F_s \quad (14)
\]

where \( p^*_{n-1} \) is the best power vector found in the previous outer-loop iteration, and \( \Psi \) 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 \( p^*_{n-1} = p^*_0 \) in the first iteration of the algorithm, the sample must be done throughout the domain \( s_l \sim U \left[ P_{\min}, P_{\max} \right] \). Furthermore, the perturbation will be tighter as the DM evolves, since the sample interval control \( \Psi \) is done by a bivariate negative exponential function of \( \alpha \) and \( n \) in eq. (15). The procedure to obtain suitable values for \( \alpha \) 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 varying uniformly within the interval \([50; 100]\) km, considering mean hop count of 3 and a network diameter of 500 km. This parameters choice represents adequate topology dimensions to be deployed with the WDM/OCDM technology, such that 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 ACO\( \_\) algorithm [44] is deployed aiming to solve both OCDM resource allocation problems, as discussed in section III: a) power control under SNIR constraint; b) energy-efficient network design. The quality of the solution achieved by ACO\( \_\) is evaluated through the average normalized mean squared error (NMSE) metric:

\[
\text{NMSE}[n] = \frac{1}{T} \sum_{t=1}^{T} \frac{||P_t[n] - P^*||^2}{||P^*||^2}, \quad n = 1, \ldots, N \quad (16)
\]

\(^1\)Longest of all the calculated shortest paths in a network.
where \( ||\cdot||^2 \) denotes the squared Euclidean distance between vector \( p_t \), the optimum solution vector \( p^* \) at the \( t \)-th realization, \( T \) is the number of realizations and \( N \) is the maximum number of iterations. For the EED problem (Opt.2) with iterative DM method, at the end of \( N \) iterations there is a new loop of iterations (i.e., inner and outer loop).

Moreover, the algorithm robustness \( R \) can be thought as the ratio between the number of convergence success \( \Xi \) to the total number of process realizations \( T \) after a \( N \) iterations in each realization:

\[
R = \frac{\Xi}{T} \cdot 100 \quad \% \quad @N \text{ iterations} \quad (17)
\]

and the speed as the average number of iterations needed to the algorithm achieves convergence in \( T \) 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 is presented in Table I. Hence, it was adopted \( n_{sp} = 2 \), \( h = 6.63 \times 10^{-34} \) [J/Hz], \( f = 193.1 \) [THz], \( G = 20 \) [dB], and \( r_c = 100 \) [GHz]. Besides, 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 at 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 \((4 \times 101, 4, 1, 0)\).

### Table I
**MAIN WDM/OCDM SYSTEM AND CHANNEL PARAMETERS**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Adopted Values</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min. nodes distance</td>
<td>( d_{(n,m)} = 80 )</td>
<td>km</td>
</tr>
<tr>
<td>Central Frequency</td>
<td>( f = 193.1 )</td>
<td>THz</td>
</tr>
<tr>
<td>Bandwidth per wavelength</td>
<td>( r_c = 100 )</td>
<td>GHz</td>
</tr>
<tr>
<td>2D7 ODMC codes</td>
<td>((4 \times 101, 4, 1, 0))</td>
<td></td>
</tr>
<tr>
<td>Chip period (OCDM Codes)</td>
<td>( T_c = 9 )</td>
<td>ps</td>
</tr>
<tr>
<td>Number of OCPs</td>
<td>( U \in {4, 8, 12} )</td>
<td></td>
</tr>
<tr>
<td>Max. laser power</td>
<td>( P_{max} = 20 )</td>
<td>dBm</td>
</tr>
<tr>
<td>Min. laser power</td>
<td>( P_{min} = P_{max} - 90 )</td>
<td>dBm</td>
</tr>
<tr>
<td>Power circuitry consumption</td>
<td>( P_c = 25 - U )</td>
<td>W</td>
</tr>
<tr>
<td>Power efficiency (transponder)</td>
<td>( \epsilon = 2/3 )</td>
<td></td>
</tr>
<tr>
<td>Noise Power per EDF span</td>
<td>( P_n = -28 )</td>
<td>dBm</td>
</tr>
<tr>
<td>EDF A Gain</td>
<td>( G = 20 )</td>
<td></td>
</tr>
<tr>
<td>Spontaneous emission factor</td>
<td>( n_{sp} = 2 )</td>
<td></td>
</tr>
<tr>
<td>Router losses</td>
<td>20</td>
<td>dB</td>
</tr>
</tbody>
</table>

A. **OCM Minimum Power Allocation Design (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 ACO\(_R\) algorithm, where it can be seen that the reduction in the OCPs transmission power levels is about three order of magnitude, a quite substantial reduction in the OCP power transmission levels.

![Figure 3](image-url)  
**Figure 3.** Individual power levels evolution for ACO\(_R\) algorithm in a system with \( U = 4 \) OCPs.

The quality of the solutions achieved by the ACO\(_R\) 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 non-convexity of the problem increases the performance loss of the ACO\(_R\) algorithm when system loading increases, due to the higher number of local optima. As one can see from Fig. 4.a, the performance loss increases drastically 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 a NMSE of \( 10^{-3} \) is still an excellent approximation to the optimal power allocation solution, indicating that ACO\(_R\) is a robust approach for solving OPT.1 problem even when number of OCPs nodes increases.

![Figure 4](image-url)  
**Figure 4.** NMSE evolution of ACO\(_R\) algorithm considering \( U \in \{4, 8, 12\} \) 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 \( N_{out} = 7 \) outer-loops.

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 ACO\(_R\) algorithm should be optimized.

In the adopted ACO\(_R\) input parameter optimization pro-
EDURE, simulation experiments were carried out in order to determine the suitable values for the DM-ACO₂ input parameters, such as file size ($F_s$), pheromone evaporation coefficient ($\xi$), population ($m$) and the diversity parameter ($q$). Besides, the proposed changes in volatility coefficient ($\alpha$) have been optimized too. As a result, Table II summarizes the ACO₂ numerical values for the optimized ACO input parameters along with the achieved robustness metric considering different number of OCPs. The same ACO₂ 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.

<table>
<thead>
<tr>
<th>$U$ (OCPs)</th>
<th>4</th>
<th>8</th>
<th>12</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q$ (OPT. 1)</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>$q$ (OPT. 2)</td>
<td>0.30</td>
<td>0.30</td>
<td>0.30</td>
</tr>
<tr>
<td>$\xi$</td>
<td>1.30</td>
<td>1.30</td>
<td>1.30</td>
</tr>
<tr>
<td>$m$</td>
<td>4</td>
<td>8</td>
<td>12</td>
</tr>
<tr>
<td>$F_s$</td>
<td>7</td>
<td>7</td>
<td>7</td>
</tr>
<tr>
<td>$K_f$, eq. (17)</td>
<td>100 %</td>
<td>100 %</td>
<td>100 %</td>
</tr>
</tbody>
</table>

The input parameters optimization procedure addressed herein is based in [43], where an iterative method for parameters optimization is proposed. In this approach, an initial input parameters configuration achieved with a non exhaustive search is established. Then, each parameter is tested throughout its domain, while the others 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 pre-determined 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 allocate energy and information rate in WDM/OCDM networks. Numerical results in this subsection include:

a) Comparison using Dinkelbach’s method (DM) in the outer-loop, with inner-loop in the Algorithm 1 performed by ACO algorithm (DM-ACO) and CVX (DM-CVX), considering OCPs power, rate and energy efficiency figure of merits;
b) EE as a function of total power consumption $P_{max}$ for different number of OCPs, where typical EE × total power consumption includes power circuitry;
c) Run time analysis for the DM-ACO and DM-CVX approaches in solving OPT.2 optimization problem.

EED performance with DM-CVX is investigated deploying convex optimization tools, namely CVX, a package for specifying and solving convex programs [41], [42]; the purpose herein is to demonstrate the Dinkelbach’s method effectiveness, as well as compare heuristic and analytical convex optimization approaches. DM method 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 ACO₂ algorithm in the inner-loop of the Dinkelbach’s method. The same initial optical power-vector and optical channel configuration adopted with DM-CVX approach are used aiming to analyze the effectiveness of the meta-heuristic for the OPT. 2 problem.

Illustrative EE optimization results are depicted in Figs. 5 and 6. Figs. 5-a and 5-b depict illustrative results for the total energy efficiency ($\sum$ EE) as a function of the transmission power allocation of the first and last OCP, $p_1$ and $p_{12}$, respectively, while the others OCPs hold individually their best power allocation given by DM computed at the end of the optimization process, i.e., $N_{ACO,CVX}^{DM} = 7$. For DM-ACO and DM-CVX it is clear that after 3 or 4 iterations, the first and the last OCPs achieves its 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 method is due to the total convergence of the ACO₂ algorithm in the inner loop of DM. A detailed analysis of convergence is carried out ahead, Fig. 8.

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

Fig. 6 shows the achieved rates relative to the minimum QoS given by $BER_{\text{req CVX}}^*$ after the respective $N_{DM}$ iterations for both analytical CVX and heuristic ACO₂ approaches. Thus, all the $U = 12$ users operate under maximum $\sum$ EE configuration satisfying their respective QoS; it is found that the problem is feasible regarding to C.1 and C.2 constraints of eq. (8). One can conclude that both algorithms achieve the same individual rates, while all OCPs satisfy its 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 $\sum EE$, sum rate and sum power metrics under different system loading.

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

<table>
<thead>
<tr>
<th>Metric $\sum$</th>
<th>$U = 4$</th>
<th>$U = 8$</th>
<th>$U = 12$</th>
</tr>
</thead>
<tbody>
<tr>
<td>EE [b/ps]</td>
<td>$3.4196 \times 10^{-12}$</td>
<td>$3.3939 \times 10^{-12}$</td>
<td>$2.8958 \times 10^{-12}$</td>
</tr>
<tr>
<td>Rate [bps]</td>
<td>$2.4024 \times 10^{-12}$</td>
<td>$1.1574 \times 10^{-12}$</td>
<td>$6.8399 \times 10^{-12}$</td>
</tr>
<tr>
<td>Power [W]</td>
<td>$1.4234$</td>
<td>$2.8892$</td>
<td>$4.3525$</td>
</tr>
</tbody>
</table>

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 meta-heuristic 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 DM-CVX solution considering $T = 300$ realizations. As reference, the NMSE$^{\text{th}} = 10^{-2}$ has been considered as the maximum eligible NMSE for the meta-heuristic approach to achieve a 99.999% of $\sum EE^*$ obtained via DM-CVX. One can see that after five outer-loop DM iterations, the DM-ACO is able to reach a NMSE smaller than $10^{-2}$ for all considered system loadings, and in one more iteration, it is able to achieve a NMSE $\approx 10^{-5}$. Besides, NMSE keeps improving further $10^{-5}$, showing that the ACO$_R$ algorithm is powerful enough to perform inner-loop in EED optimization in conjunction with Dinkelbach’s method deployed in the outer-loop.

Fig. 5a and Fig. 5b show the total energy efficiency evolution and the corresponding total power evolution through DM-ACO and DM-CVX outer-loop iterations. 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 the powerful converge feature of the ACO$_R$ algorithm. Once DM-ACO deploys the same number of outer iterations as DM-CVX, it concludes that ACO$_R$ is a powerful heuristic when maximizing the Dinkelbach’s method parametric function, eq. (12). An analysis of cost function evolution through the number of inner-loop iterations is discussed ahead on Fig. 8. Despite of the large number of inner-loop iterations required to the ACO$_R$ convergence, it results in smaller run time regarding CVX while achieving very similar outputs. Run time analysis is explored in the following (Fig. 10).

In general, heuristic approaches present a non-monotonic convergence behavior. Despite of this, for the WDM/OCDM energy efficiency optimization problem, the DM-ACO was able to achieve total power and $\sum EE$ convergence after four-five outer-loop iterations. Indeed, note that the associated total power and $\sum EE$ evolution depicted in Fig. 7 present the same pattern evolution for both algorithms. In those cases where $U \in \{4; 12\}$, the sum EE and total power evolutions for both meta-heuristic and CVX algorithms are monotonically non-decreasing (non-increasing), 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, eq. (13). For the CVX optimization tools [41], the instantaneous values of the internal variables are not available during the optimization process. So, we have assumed a linear convergence for the internal steps of the CVX. Indeed, the ACO$_R$ reaches the maximum cost function value after $\approx 300$ inner-loop iterations. From the previous results, it can be easily noticed that outer-loop evolution for DM-ACO and DM-CVX are very similar under all system loadings evaluated ($U \leq 12$ users). In fact, the ACO$_R$ is able to reach a maximum of NMSE $< 10^{-5}$ in the inner-loop function regarding DM-CVX across each DM outer-loop iteration.

Figs 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 show here) is due to the total convergence achieved by ACO$_R$ 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
Table IV
AVERAGE PERCENTAGE OVER \( T = 1000 \) TRIALS FROM DM-ACO RELATED TO THE ANALYTICAL DM-CVX OUTPUT AFTER \( N_{\text{MAX}} \) ITERATIONS OBTAINED FROM FIG. 7 FOR DIFFERENT VALUES OF \( \epsilon_{\text{MAX}} \).

<table>
<thead>
<tr>
<th>DM Precision</th>
<th>Metric</th>
<th>( U = 4 )</th>
<th>( U = 8 )</th>
<th>( U = 12 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \epsilon_{\text{MAX}} ) in the range:</td>
<td>( \sum_{\text{EE}} )</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>( 10^{-5}; 10^{-2} )</td>
<td>( \sum_{\text{Rate}} )</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>( \sum_{\text{Power}} )</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td></td>
<td>Robustness</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

C. Computational Complexity

In order to validate the DM-ACO approach as a powerful tool for solving EED problem, its computational complexity must be considerably smaller than DM-CVX. Indeed, the numerical results in following corroborate the robustness and effectiveness of ACO\( _R \) algorithm deployed in the inner-loop of the Dinkelbach’s method for solving the EED problem.

Table IV summarizes the robustness metric from eq. (17) and percentages of \( \sum_{\text{EE}} \), \( \sum_{\text{Rate}} \) and \( \sum_{\text{Power}} \) achieved through DM-ACO algorithm regarding DM-CVX in terms of different \( \epsilon_{\text{MAX}} \) values, where \( \epsilon_{\text{MAX}} \) is a pre-specified maximum tolerance value in solving the DM parametric eq. (13). It can be seen that for all system loadings considered, the meta-heuristic 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.

Figure 10 depicts run time as a function of the number of users \( U \) for DM-ACO and DM-CVX, through different values of \( \epsilon_{\text{MAX}} \). It can be seen that DM-CVX run time is considerably greater than DM-ACO in all system loadings, which is expected since DM-ACO is a meta-heuristic approach. Besides, the difference in computational complexity between the two approach increases substantially 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. So, 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. Thus, DM-ACO proved to be fast, promising and sturdy 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 last sub-sections that the ACO\( _R \) algorithm is able to solve efficiently the two WDM/OCDM resource allocation problems. Indeed, energy saving is a challenge outlined in green communications, and the EED approach presented in this work leads to it. In order to evaluate the impact of \( \sum_{\text{EE}} \) decreasing and the correspondent sum power increasing when the number of OCPs in a WDM/OCDM system grows, Fig. 11 depicts the \( \sum_{\text{EE}} \) and \( \sum_{\text{Power}} \) values, where \( \sum_{\text{Power}} \) is a pre-specified maximum tolerance value in solving the DM...
Power metrics as a function of the number of OCPs, \( U \), for the two approaches discussed in this work: \textit{OPT.1 versus OPT.2}, i.e., minimum allocation design (MPD) \textit{versus} energy-efficient design (EED). Interestingly, one can see that the total power level allocated by MPD is clearly smaller than the total power allocated by EED optimization approach. On the other hand, the number of bits transmitted per unit of joule under EED criterion is remarkably greater than 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 efficiently way. Finally, multiple access interference is reduced when a smaller transmission power level is chosen, thus, MPD approach leads to increase the maximum number of users supported under optical networks limited by interference.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure11.png}
\caption{Energy efficient design (EED) \textit{versus} minimum power allocation design (MPD) approaches in terms of sum EE and sum power metrics.}
\end{figure}

VI. CONCLUSIONS

In this paper the ACO\(_8\) 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 energy-efficient design with QoS constraints. Especially for a problem OPT.2, the heuristic DM-ACO method has demonstrated be very competitive regarding 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 trade-off achieved by the DM-ACO method in solving both EED and MPD optimization problems in the context of WDM/OCDM is very promising regarding the analytical disciplined convex optimization approach.

ACKNOWLEDGEMENT

This work was supported in part by the National Council for Scientific and Technological Development (CNPq) of Brazil under Grants 202340/2011-2, 303426/2009-8 and in part by CAPES (scholarship) and Londrina University - Paraná State Government (UEL).

REFERENCES


