

## An energy-aware dynamic RWA framework for next-generation wavelength-routed networks

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### ABSTRACT

Power demand in networking equipment is expected to become a main limiting factor and hence a fundamental challenge to ensure bandwidth scaling in the next generation Internet. Environmental effects of human activities, such as CO<sub>2</sub> emissions and the consequent global warming have risen as one of the major issue for the ICT sector and for the society. Therefore, it is not surprising that telecom operators are devoting much of their efforts to the reduction of energy consumption and of the related CO<sub>2</sub> emissions of their network infrastructures. In this work, we present a novel integrated routing and wavelength assignment framework that, while addressing the traditional network management objectives, introduces energy-awareness in its decision process to contain the power consumption of the underlying network infrastructure and make use of green energy sources wherever possible. This approach results in direct power, cost and CO<sub>2</sub> emissions savings in the short term, as demonstrated by our extensive simulation studies.

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### 1. Introduction

The containment of power consumption and the reduction of the associated green house gases (GHG, mainly CO<sub>2</sub>) emissions are emerging as new challenges for telecommunication operators. In fact, the rising energy costs due to the scarcity of fossil fuels, the increasingly rigid environmental standards and the growing power requirements of modern high-performance networking devices are imposing new constraints, further stressing the requirements towards an energy-aware business model in which the ecological footprint of the network elements (NEs) is explicitly taken into account. In this scenario, governments and society are endorsing the development of “green” renewable energy sources (such as solar panels, wind

turbines, and geothermal plants) for powering NEs. Green energy sources are preferable with respect to the traditional “dirty” ones (e.g. coal, fuel, gas) since they do not emit GHG in the atmosphere while producing electrical energy. Nonetheless, green energy sources (e.g. wind, sun, tide) are not always available at all sites and are variable with time; for this reason, the NEs that are powered by green energy sources are also provided with the legacy, dirty sources. At the occurrence, the smart grid power distribution system switches to the dirty power supply without any energy interruption.

Recent studies [1] confirm that the use of optical technology in high-capacity switches and routers is more energy-efficient than electronic technology and that circuit-switched architectures consume significantly less than their packet-switched counterparts. However, despite the recent efforts in improving the energy-efficiency of the involved technological components [2], the amount of power to be spent worldwide for powering network

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infrastructures can be globally quantified in the order of tens of gigawatts, corresponding to more than 1% of the worldwide electricity consumption [2] (to give an idea, the equivalent of 22 nuclear reactors are needed to generate such a huge power demand). Thus, limiting power consumption in network infrastructures can bring great benefits and reduce their overall ecological footprint, so that the need for a greener, energy-aware Internet is rapidly becoming a fundamental political, social and commercial issue. Furthermore, with the ever increasing demand for bandwidth, connection quality and end-to-end interactivity, computer networks are requiring more and more sophisticated and power-hungry devices, such as high-end routers, signal regenerators, optical amplifiers, reconfigurable add-and-drop multiplexers and very fast (digital signal) processing units. These components tend to increase the energy needs of global communication exponentially so that power consumption is becoming a significant limiting factor for the overall scalability of next-generation high-capacity telecommunication networks. In the next years, large-scale optical transport infrastructures will no longer be constrained mainly by their capacity, but rather by their energy consumption costs and environmental effects [3].

As a consequence, it is necessary to envisage how the next-generation network architectures and protocols can be modified to meet the purpose of energy-efficiency. Unfortunately, the rush for achieving energy-efficiency resulted in the fact that many of the solutions proposed to-date (e.g. [4,5]) tend to minimize *only* the energy consumption of the networks while disregarding the traditional network management goals such as the overall network load-balancing. It is instead mandatory to guarantee that the above modifications will not adversely affect the fundamental operators' optimization objectives of keeping the resource usage fairly balanced, to save on each available link sufficient free capacity for demands that may reasonably emerge in the infrastructure operating lifetime, and minimizing the network usage costs, considered as a static way of expressing operator preference to choose some favorite link resources. In the ideal case, new solutions should not only lower the ecological footprint, but also increase the offered quality-of-service such as the connection blocking probability.

Starting from the above considerations, we introduce [6] energy-awareness into control plane protocols whose goal is to properly condition the route/path selection mechanisms on relatively coarse time scales by privileging the use of green energy sources and energy-efficient links/switching devices, simultaneously taking advantage from the different users' demands across the interested network infrastructures. The selected paths are likely not to be the shortest or best ones, but the resulting power and GHG savings are substantial, and possible losses on the other optimization objectives (i.e. number of blocked connection requests) are taken into account and kept as low as possible. In such a way, the overall power consumption and GHG emissions can be minimized while the traditional optimization objectives (such as load-balancing) are not disrupted. In doing this, we combine all the notable features that a comprehensive energy-aware network model

should have and put them together into a general routing and wavelength assignment (RWA) framework.

The RWA problem is known to be NP-complete [7] and in the dynamic case no optimality is possible since there is no previous knowledge of the connection requests that will be handled by the network. Therefore, we introduce a new heuristic method for efficiently calculating (in polynomial time) the routing information subject to power consumption constraints, taking into account also the specific kind of energy source (dirty or green) used for powering the traversed NEs. In order to evaluate the performance of our approach, we compared our approach with well-known RWA algorithms in the literature. The proposed approach, that in the following will be referred to as *GreenSpark*, introduces energy-awareness into the Spark framework [8], which is a two-stage integrated RWA scheme structured in a pre-selection phase where a number of  $k$  candidate paths satisfying the connection constraints are found and a final selection stage where the optimum path among the candidates determined in the previous phase is chosen according to a properly crafted heuristic. *GreenSpark* is a simple and effective two-stage on-line RWA scheme providing wavelength routing as well as grooming capabilities in the state-of-the-art hybrid electric-optical network infrastructure. In its first stage, this enhanced RWA scheme finds, for each new connection request, a set of feasible lightpaths satisfying both the users' specific end-to-end demands (QoS, bandwidth, etc.) and traditional optimization objectives, while in the second stage it bases its final choice on the aforementioned power and GHG containment requirements. In the end, it finally achieves an optimal trade-off between energy optimization and network/users requirements in an affordable computational time. *GreenSpark* differs from *Spark* for the second stage, which has been here introduced to meet the energy-related criteria. Furthermore, *Spark* used a special parameter ( $kHop$ ) to explicitly limit the length of lightpaths, whilst in *GreenSpark* this is not needed anymore due to the additive nature of the energy consumption function: longer paths will have higher energy consumption and, thus, will have lower probability to be chosen for the routing of the connections.

*GreenSpark* is based on a totally flexible network model supporting heterogeneous equipment, in which the number and type of lambdas can vary on each link or node, together with the associated power consumption, and provides a fully dynamic path selection scheme in which the grooming policy is not predetermined but may vary, along with the evolution of the network traffic. We explicitly consider the influence of traffic on power consumption by using realistic data for traffic demands, network topologies, link costs, and energy requirements of the NEs.

This approach is also based on deeper network engineering considerations that make it behave very differently from the other already existing energy-aware networking approaches, mainly based on the concept of temporarily switching off entire devices or subsystems (the least used ones) in order to minimize energy consumption by rerouting the involved traffic. Such approaches, often referred as sleep mode [9], may be unpractical, especially for large and highly connected switching nodes, since many very

expensive transmission links become unused, hence leaving significant capital investments (CAPEX) unproductive for the entire duration of the sleep interval. Furthermore, sleep mode drastically reduces the overall meshing degree, by limiting the network reliability, and partially negates the possibility of balancing the load on multiple available links/paths [10]. Finally, results in [11] show that sleep mode is achievable just for very few nodes and only at very low loads. Conversely, in our model, energy-aware architectures allow the NEs power consumption to scale with traffic load, as in [10–14]; such architectures are strongly advocated by current efforts from standardization bodies and governmental programs [15] and can be made up using off-the-shelf standard technologies [16,17].

## 2. Related work

"Greening the network" is an active subject of recent research. Several papers have concentrated on the reduction of power consumption. In [13] Gupta and Singh were among the first researchers to envision the idea of energy conservation in Internet-based infrastructures. Shen and Tucker [4] developed mixed integer linear programming (MILP) methods and heuristics to optimize the energy consumption of a IP over WDM transport network. In detail, their objective was minimizing power consumption of the network by switching off router ports, transponders, and optical amplifiers; they proposed two heuristics ("direct bypass" and "multi-hop bypass"). Another approach focusing on a MILP-based formalization of the power-aware routing and wavelength assignment has been also presented by Wu et al. [18]. In their work, energy savings can be achieved by switching off optical cross connects (OXC) and optical amplifiers according to three different algorithms and criteria. In [19,10], ILP mathematical formulations are presented with the double objective of reducing both the energy consumption and the GHG emissions of network infrastructure. Since the ILP solves at the optimum the offline RWA problem, these works give an upper bound for energy and GHG savings. However, using ILP for real-world networks with dynamic traffic is unpractical due to its intractable computational complexity. Energy saving by dynamically switching off idle IP router line cards in low-demand hours was also the approach presented by Idzikowski et al. [5]. They analyzed the effects of reconfiguring routing, at the different layers, by assuming complete wavelength conversion capability in each node. In [20], Chiaraviglio et al. have proposed and evaluated some greedy heuristics based on the ranking of nodes and links with respect to the amount of traffic that they would carry in the context of an energy-agnostic configuration. Silvestri et al. [21] combined traffic grooming and transmission optimization techniques to limit energy consumption in the WDM layer. Traffic grooming shifts traffic from some links to other ones in order to switch empty ones off, and transmission optimization adjusts dispersion management and pulse duration, which decreases the need for using in-line 3R regenerators. The power savings that can be achieved by dynamically adapting the network topology to the traffic volume are investigated in [22],

where a linear programming approach is proposed that is able to identify optimal topologies for given traffic loads and generic network topology. In [23], various power-efficient grooming strategies, combined with lightpath extension and lightpath dropping, are evaluated in WDM networks where nodes have the tap-or-pass capability.

Most of these approaches are characterized by a limited dynamism, and hence are not easily applicable in a fully adaptive online scenario or use power containment techniques based on switching off of inactive elements. In our fully dynamic on-line approach, no switching off is assumed to be feasible (as explained in the previous section) and so, in this, it is completely different and not directly comparable, in term of both performance and effectiveness, with all the previous ones.

## 3. Backgrounds

### 3.1. Wavelength routed networks

A wavelength-routed network, sometime also referred to as an optical circuit switched (OCS) network, is basically composed of several OXC devices and opto-electronic edge routers connected by a set of fiber links. The WDM technology is used to carve up the huge bandwidth available on the optical fibers into lower-capacity wavelengths (optical channels), which may be independently used to carry information across the same physical links. Circuit switched connections, usually with high bandwidth and QoS-on-demand, are typically implemented by dynamically creating and tearing down multi-hop optical channels between client sub-networks according to a specific RWA strategy. The above connections, called lightpaths, "transparently" traverse the fiber network without being converted into an electrical signal. In some cases, they may pass through an optical/electrical/optical (O/E/O) conversion for regeneration, wavelength conversion or add/drop purposes. At the state of the art, there is still a large gap between the available capacity of an optical channel and the much lower bandwidth requirements of a typical connection, but, on the other side, the number of wavelength channels (lambdas) available in most of the networks of practical size is much lower than the number of source-destination connections that need be made. Hence, traffic grooming capability is required on opto-electronic routers operating on the network edge. Accordingly, all the connection requests, which share the same traffic flow characteristics and involve significantly lower capacities than those of the underlying wavelength channels, can be efficiently multiplexed or "groomed" onto the same wavelength/lightpath via simultaneous time and space switching. Similarly, different traffic streams can be demultiplexed from a single lambda-path.

### 3.2. Power requirements in network devices

The fundamental cause of energy consumption in electronic equipment is the effect of loss during the transfer of electric charges, which in turn is caused by imperfect conductors and electrical isolators. Here, the consumption

rate depends on the transition frequency and the number of gates involved, together with fabrication features (such as architecture, degree of parallelism, and operating voltage). In pure transparent optical equipment, the main energy-hungry devices are the lasers, since the optical signal has to reach the other end of the fiber with sufficient “quality” in spite of the signal attenuation, dispersion and non-linear optical phenomena. Besides, the power consumption is also conditioned by sophisticated electronic devices for coping with the technological complexity of the photonic environment. For example, when the involved fiber strands need to cover long distances, several intermediate electrical signal re-generators (3R) or optical amplifiers (OA) are necessary (typically, an OA is needed every 80–100 km and a 3R every 500–1000 km) to ensure that the signal power and quality will be sufficient to reach the other end of the fiber with acceptable optical signal to noise ratio (OSNR). Such OA and 3R have a not negligible energy cost that has to be taken into account when setting up the lightpath requests.

### 3.3. Energy-aware RWA

Introducing energy-awareness in RWA is based on the concept of placing network traffic over a specific set of paths (sequences of nodes and communication links) so that the overall network power demand and/or GHG emissions are minimized, while end-to-end connection requirements are still satisfied. Typical infrastructures are densely meshed, with many redundant interconnections among nodes, so that many available paths can provide multiple reachability options between geographically distant sites. On such a mesh, wavelength routing is used to set-up a logical topology, which is then used at the IP layer for routing. Every time a lightpath is established between any two nodes, the traffic of the lightpath will be handled as a single IP hop by creating the abstraction of a “virtual” network topology on top of the physical one. This “overlay” approach is based on the full separation of the routing functions at each layer, i.e. the connection routing/grooming at the IP layer is independent from the routing of wavelengths at the optical layer. One of the key features of the above model is rearrangeability, i.e. the ability to dynamically optimize the network as a consequence of the independence between the virtual and the physical topology. The above architectural flexibility in building logical topologies, together with physical connection redundancy and over-provisioning, provide fertile grounds for saving energy, since a large number of available traffic routing and device management options can be exploited to optimize energy and carbon footprints network wide. Hence, energy-aware logical network topologies, explicitly conceived to decrease power consumption in the operational phase, can be dynamically built by minimizing the number of energy-hungry devices traversed by the existing lightpaths. In doing this, it is desirable to find a good balance between the competing needs to avoid as many electrically powered hops as possible (to reduce the power consumption at intermediate switching nodes, optical amplifiers and regenerators) and avoid data transmission over excessively long stretches, since moving data is quite

energy-expensive. Energy consumption can be drastically reduced by maximizing the reuse of low-power transmission links and highly connected devices, especially when powered by green sources, instead of obviously spreading the traffic on the available routing/switching devices and communication resources. In other words, since a logical network topology is described by its constituent lightpaths, a logical topology that minimizes the overall energy requirement and the associated carbon footprint is one in which the choice of each individual lightpath, while satisfying the traditional RWA objectives and constraints, is driven by the above energy-efficiency optimization criteria.

In order to support all the above behaviors, energy-related information associated with devices, interfaces and links need to be introduced as additional constraints (together with delay, bandwidth, physical impairments, etc.) in the formulations of dynamic RWA algorithms. Such information must also be handled as new status features in each network element that have to be considered in all the routing and traffic engineering decisions, and conveyed to all the various network devices within the same energy-management domain. This clearly requires modifications to the current routing protocols by properly extending them to include energy-related information in their information exchange messages, such as the power demand associated with a specific end-to-end circuit or the type of energy source currently used by a network element [6]. Analogously, the same information has to be handled by control plane signaling protocols used for the reservation and establishment of paths minimizing the use of dirty power sources, as well as the overall energy consumption, across the network.

## 4. The energy-aware network model

Defining a sustainable and effective network model taking into account power consumption as well as energy source considerations is the essential prerequisite for introducing energy-awareness within the wavelength routing context. A broad variety of NEs contribute to power adsorption in a network: regenerators, amplifiers, optoelectronic and totally optical routers and switches. Each of these devices draws power in a specific way, which depends on their internal components and structures, on the traffic load and on the relationship between the devices. In addition, some nodes may be powered by green energy sources, while others may use traditional dirty energy plants; therefore, a differentiation between energy sources is required. NEs powered by green energy sources will not contribute to the CO<sub>2</sub> emissions but only to increase the overall network energy consumption. In the dynamic RWA problem, the routing of connection requests is done on a local optimality basis, i.e. considering the current information available at the connection setup time. The potential of such an approach should not be underestimated; the conditions that determined such optimality may change, but the RWA strategies keeps its effectiveness as far as it is able to foresee the future network evolutions, both in terms of resources and energy utilization.

The above energy-related information and concepts associated with devices and links must be abstracted and defined in a formal and concise way into a comprehensive model that needs not to delve into unneeded details, but should only describe the essential aspects needed to drive in an energy-conscious way the RWA algorithms and strategies developed upon it. Therefore, we modeled the network from a high-level perspective in an attempt to keep the reference scenario as general as possible focusing on the effectiveness and energy-efficiency of our approach; the issues raised by modulation techniques, spectrum-sliced elastic networks, and other technological breakthroughs, although interesting, fall outside the scope of this paper, which is to provide an energy-aware dynamic RWA schema to route as many connections as possible.

In detail, at the basis of our model we consider a multigraph  $G = (V, E)$  representing the network (Fig. 1), where  $V$  is the set of nodes and  $E$  the set of edges,  $|V| = n$ ,  $|E| = m$ . No specific assumption is made on the number of wavelengths per fiber link and on the number of fibers on each link: any two nodes  $u, v \in V$  may be connected by several edges (thus, *multigraph*). Each fiber link  $(u, v) \in E$  is characterized by its physical length  $l_{u,v}$ , together with the number of available wavelengths  $w_{u,v}$ . There can be more than one fiber connecting the same pair of nodes and, for simplicity sake, we assume that all the fibers are of the same type (e.g. NZ-DSF ITU-T G.655/656), requiring an intermediate amplification or regeneration stage every  $\mathcal{A}$  units of distance. Typically  $\mathcal{A}$  can assume the values  $\mathcal{A}_{OA} = 80$  km for native optical amplification systems and  $\mathcal{A}_{3R} = 500\text{--}1000$  km for 3R electric regeneration devices. On each fiber link  $(u, v)$  there can be multiple wavelength links  $(u, v)_\lambda$ , modeled on the graph  $G$  as an additional “virtual” tagged links, where the tag  $\lambda$  can be any of the wavelengths

available on the physical circuit. Each tagged link  $(u, v)_\lambda$ , is characterized by its static global capacity  $a_{(u,v)_\lambda}$  and dynamic residual capacity  $r_{(u,v)_\lambda}$ . Clearly, for each link  $(u, v)_\lambda$ , its current load is given by  $a_{(u,v)_\lambda} - r_{(u,v)_\lambda}$ . Provided that a single established lightpath or a chain of lightpaths between the source and destination nodes has sufficient available capacity, each connection request can be routed onto that lightpath or chain. Also, a new lightpath may be dynamically established, as the result of grooming decisions.

The nodes of the graph model the routing and switching devices deployed in the network. We consider two types of nodes: LERs (Lambda Edge Routers) and LSRs (Lambda Switching Routers). LER nodes have both the electronic and optical interfaces, and have the capability to insert/extract traditional electronic traffic into/from the network. LSR nodes are OXC or reconfigurable optical add and drop multiplexers (ROADMs) that are capable of switching the traffic at wavelength level (since we model optical circuit switched networks) and may be equipped or not with wavelength converters. Whenever an optical signal is converted into the electronic domain, it is implicitly assumed that it is possible to apply 3R regeneration as well as wavelength conversion and add/drop at sub-wavelength granularity (grooming). Consequently, network traffic may be of two types: electronic time division-multiplexed (TDM) traffic (i.e. traffic that undergoes electronic processing) and pure optical traffic (i.e. WDM traffic entirely managed in the optical domain) with or without optical wavelength conversion. Electronic routers have the ability to add/drop traffic into/from the network, to make electronic WC (Wavelength Conversion) and to regenerate the signal in the electronic domain (3R regeneration). Optical routers support optical traffic with or without all-optical WC. That is, they may deflect wavelengths through an electronic 3R

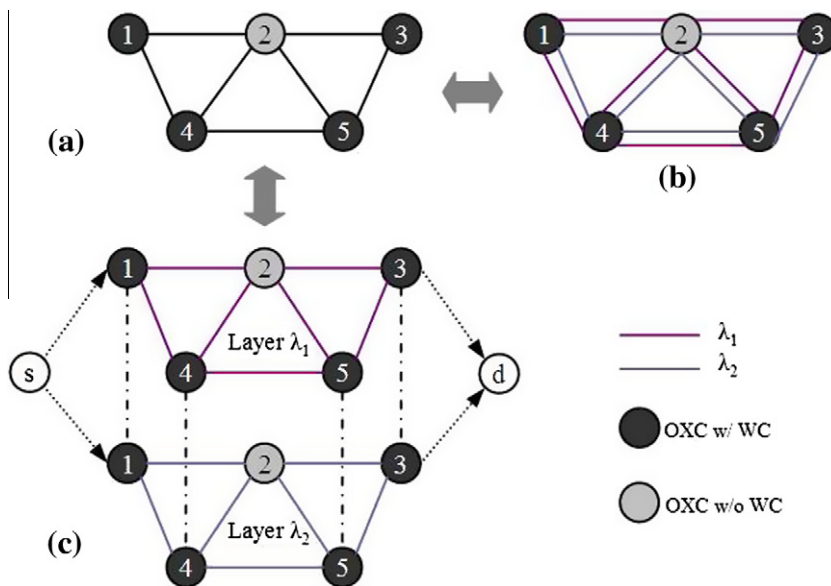


Fig. 1. A network topology with two wavelengths per link (a) and its representations as multigraph (b) and as layered graph (assuming a connection request from node 1 to node 3) (c).

regenerator if the OSNR is too degraded and then switch the wavelength through the corresponding output port [2]. In our network model, connections are bidirectional and unsplitable, i.e. a traffic demand is routed over a single lightpath, and LER nodes can be source or destination of a connection.

As for the energy, we derived a properly crafted per-node, per-link and per-lightpath energy model and power cost function, basing our estimation on the literature [1–3,14,15] and on the manufacturers technical sheets [24,25], with the aim of fitting with the future energy-aware technologies that will adapt their power-consumption with their load [10–14].

We distinguish between green and dirty energy sources, i.e. carbon-emitting and zero-carbon plants. Each node  $n \in V$  has a statically associated attribute  $s_n$  representing the type of energy source (green or dirty) powering the corresponding device, and we assume that green and dirty energy sources are heterogeneously distributed in the network. This attribute has been kept static to avoid unwanted fluctuation in the “green-biased” node selection function due to the temporary unavailability of the specific source (e.g. sun, wind or tide), since the hosting sites are usually equipped with battery systems, ensuring the availability of the accumulated green energy also during the source off-times (e.g. the night hours for solar panels). Anyway, the devices powered by green energy should be always preferred also for cost containment reasons, since the energy costs in the hosting sites/installations are regulated by significantly advantageous contractual conditions. In fact most of the electricity providers and supplying utilities apply some balancing policies for sites producing their own energy from renewable source and placing the energy produced in excess in the “public” electric grid (by reducing the carbon footprint on a more global scale), so that, even in the case in which the required energy would be currently extracted from a dirty source, its cost will be significantly lower when compared with other dirty-only powered sites.

#### 4.1. Per-node power requirements

In order to characterize in a realistic and quantifiable way the energy requirements of a specific network path (needed to accomplish our optimization goals within the RWA context), we need to estimate the power consumption of all the traversed NE (devices on the nodes and transmission links) as a function of the involved traffic type. In doing this, we essentially consider two main traffic types:

1. Electronic traffic, comprising add/drop, electronic WC, 3R regeneration.
2. Optical traffic, with or without optical WC.

The above traffic types are characterized by a considerably different power consumption when traversing a NE: electronic traffic requires more power than optical traffic with

WC and the latter consumes more power than optical traffic without WC, due to the different devices involved [1,2].

Therefore, the power consumption of a specific light-path depends on:

1. The type of devices traversed along its route from source to destination node, e.g. router, switch, signal amplifier/regenerator, etc.
2. The “device class”, in terms of hardware architecture and aggregated switching performance of the network element itself. More precisely, modular switching nodes capable to handle higher throughputs consume less energy per bit than smaller ones [26,27] since they are more optimized and tend to be located in the center of the network where the traffic is more aggregated, and “opaque” nodes equipped with electronic switching matrices are more energy-hungry than their transparent photonic counterparts.
3. The type of traffic that it transports through each network element, i.e. electronic, optical with WC and optical without WC.

The power consumption of real electronic and optical switching nodes with and without WC are reported in [1,2], where it can be observed that the electronic traffic grows quickly with respect to the optical one and that, within the optical traffic context, the WC is the main factor internal to the switching device requiring a not negligible quantity of energy. In [14] it is shown that the base system of an idle network device consumes approximately half of the total power drained by the device, while the other half is consumed when the router is in its maximum configuration, i.e. maximum number of line cards/modules installed and operating at their full load. These power consumptions refer to commercially available devices whose architectures are not energy-aware: their power consumptions only slightly depend (2–3%) on the current traffic load, but strongly depend on the number of line cards installed [14,28]. Next-generation energy-aware routing/switching nodes, designed with energy-efficiency in mind and allowing dynamical adjustment of their power consumption with the variation of the traffic load by selectively putting into sleep or low-power mode some interfaces, line cards, and subsystems, will be characterized by a significantly dominating load-dependent energy consumption component. However, by estimating the power demands used in our model from the available quantitative data gathered from the current devices implicitly forces the model to operate in a worst-case situation making the achieved results more comforting (since they will be greatly improved with the introduction of next generation energy-aware devices). Therefore, even if actual router architectures are not energy-aware, in the sense that they consume the same amount of power regardless of the traffic load, here we consider future energy-aware architectures that scale their power consumption with their current traffic load, thus giving rise to optimization [1,10,27].

Consequently to [14,28], we assume that the power consumption of a network element, modeled by a node or link, can be divided into two equal parts: “fixed” and “variable” power absorption. The fixed power consumption is always present and is needed just for the device to stay “on”, while the variable power consumption depends on the actual traffic load that the device is currently supporting. The case in which the fixed power consumption is significantly greater or lower than the variable part would affect more or less proportionally the optimization gains. In particular, for the current energy-unaware devices, the fixed part is much greater than the variable part (which only represents 2–3% of the total power consumption), leaving almost no space for optimization. In the opposite situation, if the fixed power consumption was much lower than the variable part, the likely outcome would be that the optimization margins will increase a lot; in this sense, our approach of assuming 50% for fixed and 50% for variable power consumption can be considered as conservative.

The previous considerations can be used to build a sufficiently general per-node power consumption model. Starting from the power consumptions of the network routing devices (in Watts) as function of their aggregated bandwidth (in Gbps) [1,2], we obtained the linear power consumption equations [10] reported in Table 1, which we used to calculate the real *maximum* power consumption of any kind of network node given its aggregated bandwidth. In such a linear model, a slope of  $m$  means that for each unit of traffic (Gbps) the router consumes  $m$  units of power (W). For example, an electronic router with an aggregated bandwidth of 10 Tbps is characterized by a maximum power absorption of 30 kW. An optical switch with the same aggregated bandwidth consumes 0.62 kW with WC and 0.2 kW without WC, which totally agree with the values reported in [2,14].

Starting from such maximum power consumption values, we obtain the curves in Fig. 2, in which the minimum power consumption associated with the network device  $n$  in the idle state is given only by the fixed power consumption  $\phi_n$  of its base. The maximum power consumption  $2\phi_n$  is achieved when the node is fully loaded, i.e. when the current load  $x$  is equal to the maximum aggregated bandwidth  $B_n$  of the node  $n$ . How the power consumption scales between these two values has been studied carefully in [10]. In this work we observed that the power consumption associated with electronic traffic is higher than the one associated with optical traffic (Fig. 3a – optical node power consumption not in scale; see the peak power consumption of optical nodes in Fig. 3b for in-scale values). Furthermore, we also observed that the power consumption of smaller nodes follows a worse trend with respect

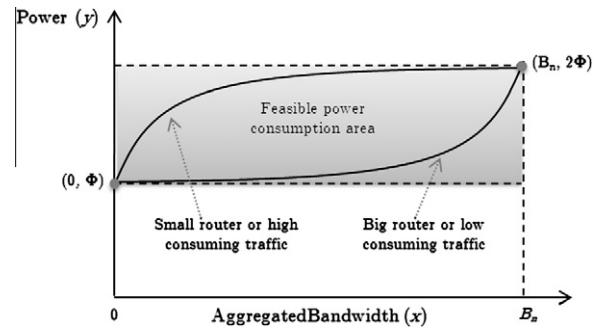


Fig. 2. Minimum and maximum power consumption of a network node.

to bigger ones, in which the per bit energy consumption is lower (Fig. 3b). Therefore, we can delineate two extremes: big nodes transporting optical traffic as the least power consumers, and small nodes transporting electronic traffic as the most power hungry devices. To this end, we studied different power consumption functions, both present in literature and analytically conceived, to describe and carefully balance the power consumption of all the possible combinations between these two extremes.

In more formal terms, we define for all the routing and switching nodes, a power consumption function  $\Psi_n(x)$  expressing the power requirements of a node  $n$  characterized by device-specific static consumption  $\phi_n$  and performance class (aggregated bandwidth)  $B_n$ , variably conditioned by a traversing traffic load  $x$ . The function  $\Psi_n(x)$  can be viewed as a linear combination of the logarithmic function  $\theta_n(x)$  and the line function  $\vartheta_n(x)$  weighted by the parameter  $\alpha_n(x)$ :

$$\Psi_n(x) = \alpha_n(x) \cdot \theta_n(x) + (1 - \alpha_n(x)) \cdot \vartheta_n(x) \quad (1)$$

where

$$\begin{aligned} \theta_n(x) &= \underbrace{\left[ \phi_n - \ln \left( \frac{e^{\phi_n}}{B_n} \cdot (B_n - x) + \frac{x}{B_n} \right) \right]}_{\text{variable power consumption}} + \underbrace{\phi_n}_{\text{fixed power consumption}} \\ &= 2\phi_n - \ln \left( \frac{e^{\phi_n}}{B_n} \cdot (B_n - x) + \frac{x}{B_n} \right), \end{aligned} \quad (2)$$

is the equation of the logarithmic function passing through the points  $(0, \phi)$  and  $(B_n, 2\phi)$ , modeling the best per-bit energy consumption (i.e. optical traffic w/o WC in Fig. 3a) and:

Table 1

Power consumption (in Watts) dependency laws on aggregated bandwidth and load (in Gbps) for different types of nodes (linear case).

| Node type      | Power consumption (y) as function of the aggregated bandwidth (x) | Power consumption (y) as function of the load (x) assuming half fixed ( $\phi$ ) and half variable ( $m \cdot x$ ) |
|----------------|---|--|
| Electronic     | $y = 3x$  | $y = 1.5x + \phi$  |
| Optical w/ WC  | $y = 0.062x$  | $y = 0.031x + \phi$  |
| Optical w/o WC | $y = 0.02x$   | $y = 0.01x + \phi$   |

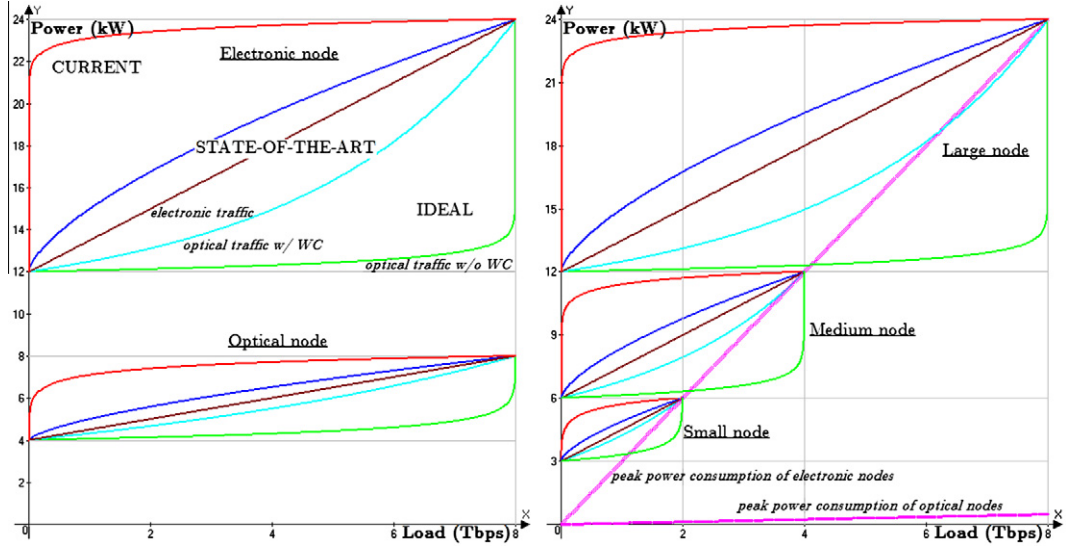


Fig. 3. Power consumption functions of current, ideal and state-of-the-art for electronic and optical nodes (a) and for different sizes of nodes (b).

$$\vartheta_n(x) = \underbrace{\frac{\phi_n}{B_n} x}_{\text{variable power consumption}} + \underbrace{\phi_n}_{\text{fixed power consumption}}, \quad (3)$$

is the equation of the line function passing through the points  $(0, \phi)$  and  $(B_n, 2\phi)$ , modeling the worst per-bit energy consumption (i.e. electronic traffic in Fig. 3a).

$B_n$  is the capacity (aggregated bandwidth) of the router  $n$  (its performance class), and  $\alpha_n(x)$  is the weighting parameter between  $\theta_n(x)$  and  $\vartheta_n(x)$  depending on the class/performance of the router  $n$  and on the parameter  $\beta(x)$  which accounts for the specific type of traffic associated with the load  $x$  that is actually passing through the node  $n$ :

$$\alpha_n(x) = \frac{B_n}{\max\{B_n, \forall n \in V\}} \cdot \beta(x), \quad 0 \leq \alpha \leq 1, \quad (4)$$

$$\beta(x) = \begin{cases} 1 & \text{if the traffic } x \text{ is optical w/o WC} \\ 0.323 & \text{if the traffic } x \text{ is optical w/WC} \\ 0.00\bar{6} & \text{if the traffic } x \text{ is electronic} \end{cases} \quad (5)$$

$0 \leq \beta \in \{1, 0.323, 0.00\bar{6}\} \leq 1.$

Note that:

1. The values of  $\beta(x)$  have been obtained using the values of real routers from Table 1, taken in such a way to penalize the more power consuming devices and traffic types; e.g. for the electronic traffic,  $\beta(x) = \frac{m_{\text{optic w/o wc}}}{m_{\text{electronic}}} = \frac{0.01}{1.5} = 0.00\bar{6}$ .
2.  $\alpha_n(x)$  weights one Eq. (2) or the other Eq. (3) function according to the device class and traffic characteristics of the involved NE.

Table 2  
Notation used in the energy model.

| Parameter                   | Energy model  |
|-----------------------------|---|
| $\phi_n$                    | Fixed power consumption of node $n$   |
| $\Psi_n(x)$                 | Overall power consumption (fixed + variable) of node $n$ with traffic load $x$  |
| $\theta_n(x)$               | Logarithmic function  |
| $\vartheta_n(x)$            | Line function   |
| $\alpha_n(x)$               | Linear combination weighting function   |
| $e$                         | Euler's number (base of the natural logarithms)   |
| $B_n$                       | Performance class of node $n$ (aggregated bandwidth of all interfaces)  |
| $\beta(x)$                  | Weighting function on the type of traffic   |
| $m$                         | Slope of the power consumption functions (linear case)  |
| $w_{u,v}$                   | Number of wavelengths/channels crossing fiber $(u, v)$  |
| $\Psi_{(u,v),\lambda}(x)$   | Power consumption of the link $(u, v)$ on the wavelength $\lambda$ with traffic load $x$  |
| $l_{u,v}$                   | Length of the fiber $(u, v)$ (km)   |
| $\eta_{(u,v),\lambda}^u(x)$ | Power consumption of the interface on the node $u$ associated with the wavelength $\lambda$ on the fiber $(u, v)$ supporting the traffic load $x$ |
| $Q_{u,v}$                   | Power consumption associated with the individual amplification device on link $(u, v)$  |
| $A_{OA}$                    | Maximum allowed length of a link without need of optical amplification (km)   |
| $A_{3R}$                    | Maximum allowed length of a link without need of 3R regeneration (km)   |
| $R(x)$                      | Power consumption associated with the individual 3R regeneration of the traffic load $x$ (one for each wavelength)                                |
| $\Psi_\pi(x)$               | Power consumption of lightpath $\pi$ with traffic load $x$  |
| $l_\pi$                     | Cumulative length of path $\pi$ (km)  |



3. The fixed power consumptions  $\phi_n$  of nodes are obtained from [1,2,14].

For an explanation of the symbols used in the notation refer to Table 2.

#### 4.2. Per-link power requirements

End-to-end transmission links are characterized by a power consumption depending not only on the specific demand associated with the hardware interfaces located in both the endpoints, but also on the impact introduced by the optical amplification and regeneration devices needed by the signal to reach the endpoints with an acceptable quality, and thus, on the length of the traversed fiber strands.

Accordingly, the power absorption of a transmission link realized on the wavelength  $\lambda$  between the nodes  $u$  and  $v$  can be entirely described by the specific power demand characterizing the involved end-to-end interfaces plus the power required for powering all the possible intermediate regenerators or optical amplifiers, if any. If the fiber between  $u$  and  $v$  is currently crossed by  $w_{u,v}$  wavelengths, we consider that the power requirements due to the intermediate devices will be shared between the  $w_{u,v}$  channels simultaneously; typically, as for the OA, the entire frequency band (e.g. C-band) is amplified as a whole, without per wavelength granularity, whilst as for 3R regeneration, per wavelength 3R is required. Thus the power consumption  $\Psi_{(u,v)_\lambda}(x)$ , associated with a link on the wavelength  $\lambda$  with load  $x$  traversing the fiber  $(u,v)$ , whose length is  $l_{u,v}$ , can be described as:

$$\Psi_{(u,v)_\lambda}(x) = \eta_{(u,v)_\lambda}^u(x) + \eta_{(u,v)_\lambda}^v(x) + \left[ \frac{l_{u,v}}{A_{OA}} \right] \cdot \frac{Q_{u,v}}{w_{u,v}} + \left[ \frac{l_{u,v}}{A_{3R}} \right] \cdot R(x), \quad (6)$$

where

1.  $\eta_{(u,v)_\lambda}^u(x)$  is the power consumption of the interface on the node  $u$  associated with the wavelength  $\lambda$  on the fiber  $(u,v)$  when operating at the minimum speed allowing to support a traffic load  $x$  without any loss or delay increase. Here we do not take into account the variable effect on power consumption of the dynamic traffic traversing the interface, whose impact is already considered in the per-node consumption, and only model the specific per-interface power demand according to its specific static hardware features (type of laser, its power, etc.) and to a multiple threshold scale characterizing its consumption depending on current operating speed (implicitly dependent from the load  $x$ ). The above  $\eta_{(u,v)_\lambda}^u(x)$  function can be modeled as in [27].
2.  $Q_{u,v}$  is the power consumption associated with the individual amplification device on link  $(u,v)$  (between 3 and 15 W) operating throughout the fiber link (one for the entire frequency band); for simplicity, we assume that all the amplification devices operating on the same link have the same power consumption.
3.  $R(x)$ , defined in the same way as  $\vartheta_n(x)$  (i.e. electronic traffic in a node), is the power consumption associated with the individual 3R regeneration device of the traffic load  $x$

(one for each wavelength), when present; for simplicity, we assume that all the regeneration devices operating on the same link have the same power consumption.

#### 4.3. Per-lightpath power requirements

Given a lightpath  $\pi$  as a sequence of nodes and tagged links  $(u,v)_\lambda$  with a traffic demand  $x$ , the power consumption  $\Psi_\pi(x)$  of  $\pi$  is given by the sum of the individual power absorption of all the traversed nodes and links plus the required regenerations:

$$\Psi_\pi(x) = \sum_{n \in \pi} \Psi_n(x) + \sum_{(u,v)_\lambda \in \pi} \Psi_{(u,v)_\lambda}(x) + \left\lfloor \frac{l_\pi}{A_{3R}} \right\rfloor \cdot R(x), \quad (7)$$

where  $l_\pi$  is the cumulative path length. The third component in the Eq. (7) sum is needed to cope with fully transparent lightpaths whose length exceeds the maximum length  $A_{3R}$  that a signal can travel without need of 3R regeneration. In this case, since all the intermediate devices do not convert the signal back and forth into electrical/optical form and only introduce impairments, a 3R regeneration stage is required in correspondence with at least  $\left\lfloor \frac{l_\pi}{A_{3R}} \right\rfloor$  intermediate nodes. If the lightpath  $\pi$  is fully transparent (without wavelength conversion), the tag  $\lambda$  is the same on all the wavelength links.

### 5. The two-stage RWA scheme

The proposed energy-aware RWA scheme operates on-line, running at each request of a dedicated connection with specific service requirements (typically QoS on the bandwidth capacity) between two network nodes. In such a dynamic scenario, connection requests have to be served as soon as possible when they arrive; thus, we designed GreenSpark with simplicity in mind, which was considered as a necessary requisite when developing the dynamic RWA scheme to keep as low as possible the computational complexity. According to the typical assumptions in OCS networks, each connection is considered to be bidirectional and consists of a specific set of traffic flows that cannot be split between multiple paths. A connection can be routed on one or more (possibly chained) existing lightpaths between the source and the destination nodes with sufficient available capacity or on a new lightpath dynamically built on the network upon the existing optical links. Connection routing and grooming decisions are taken instantaneously reflecting an highly adaptive strategy that dynamically tries to fulfill the network resource utilization and connection serviceability objectives together with minimizing the overall power consumption by privileging cheaper (in terms of power demands) chains of nodes/links and, between them, trying to maximize the usage of devices powered by green energy sources.

Without loss of generality, we route connection requests with only a constraint on the required bandwidth, and rely on the incorporation of other policies within the bandwidth-routing framework to perform routing based on several QoS and impairment metrics such as limited latency, error rate, hop-count, delay, and losses. Such con-

straints can be incorporated into SLAs by converting these requirements into a bandwidth requirement as shown in [29]. Impairments are accounted for by modeling 3R regeneration into the framework, supported by the study in [30] in which impairment-awareness is included into the regeneration placement for WDM networks, and optoelectronic signal regeneration is employed to address the signal quality of lightpaths that are found to be impaired without compromising the signal quality of any of the lightpaths.

The apparently conflicting goals of minimizing cost and length of designed paths while keeping the network resource usage fairly balanced, and optimizing the overall power consumption by reusing, as possible, energy-efficient paths across the network, give origin to a multi-variate and multi-objective optimization problem that can be solved according to a *divide-et-impera* strategy, set up of two-stages in which each stage separately handles a specific objective by using properly crafted heuristics. Specifically, in the first stage (pre-selection phase), the goal is to determine an ordered list (whose length is defined by a parametric value  $k$ ) of feasible minimum cost paths that fully satisfy the connection demands, trying to leave on each link of these paths sufficient room to satisfy further requests as much as possible. Such strategy clearly implies balancing the load on all the available network resources. In the second stage (energy-aware decision phase), the proposed scheme analyzes, for each path found in the stage one, its power requirement as given by the aforementioned energy model, and then selects the best available solution according to several heuristic criteria based on finding a good compromise between the traditional carrier's objectives and the new green requirements (i.e. limiting power consumption or using green energy sources to reduce GHG emissions).

Towards this goal, we explicitly defined and studied two different green optimization objectives: the first one, aiming at reducing the power consumption throughout the network, and hence its operating expenditures; the second one, oriented to minimize the network carbon footprint on the environment by minimizing the GHG emissions.

### 5.1. Prerequisite control plane facilities

The proposed scheme also requires several forms of cooperation between the nodes concurring to the RWA problem solution. This implies that every node needs to run distributed control-plane services (such as those provided by the GMPLS framework) keeping up-to-date information about the complete network topology, resource usage and power demand attributes, as well as taking care of resource reservation, allocation, and release.

More precisely, a periodic link-state advertisement (LSA) scheme must convey all the link and node state information (including energy related ones) to every node in the network, ensuring the complete synchronization between all the nodes' network status views. Since the amount of per-link state information is very small, any appropriate enhanced link state scheme like those employed by OSPF can be adequate for this purpose, like the one developed in [6].

The Dijkstra-based path selection scheme of stage one should meet certain conditions:

1. A link may not reserve more traffic than it has capacity for.
2. Shorter paths should be preferred when they consume fewer network and energy resources.
3. Critical resources, e.g. residual bandwidth in bottleneck links, should be preserved for future demands.

The last two conditions reflect that what we really seek is to keep the connection blocking probability (or, in other words, the rejection ratio) as low as possible, or equivalently to increase as much as possible the network utilization.

In addition, an extended signaling/reservation protocol, such as RSVP-TE, can be used to setup and release paths and lightpaths and handle all the bandwidth, fiber or wavelength resources reservation and allocation/deallocation operations required during such activities. In detail, as a new request arrives, the control plane on each node, starting from the originating one, runs our source-based localized RWA algorithm, calculates the new overlay network topology and triggers the proper path setup actions by sending a reservation request toward the destination and provisionally reserving bandwidth resources. The RWA scheme, operating according to a two-layer model (i.e. an underlying pure optical wavelength routed network core and an opto-electronic time division multiplexed layer built over it) should determine if the request can be routed on one of the already available lightpaths, by time-division multiplexing it together with other already established connections, or a new lightpath is needed on the optical transport core to join the terminating (edge) nodes. In presence of multiple options between new feasible and already established lightpaths, the link weighting and path selection functions of the two stages, applied on the existing lightpaths and to the wavelength links that can be used to set up new lightpaths, together with the energy costs, dynamically determine the best compromise (between network and energy costs) routing solution for the request, starting from the current network status. For example, if two lightpaths between source and destination exist, both with sufficient available capacity, if the difference in network cost between them falls below a specific acceptability threshold, the tie is resolved in favor of the greener lightpath. Such policy guarantees maximum lightpath utilization and automatically achieves, as long as possible, effective dynamic grooming and power usage, assuming that the topology (link state) database is properly updated.

The signaling scheme for triggering the new lightpath set-up and reserving the required bandwidth, fiber or wavelength resources along the path is very similar to the RSVP-TE protocol used by GMPLS. To make a reservation request, the source node needs the path and the bandwidth that it is trying to reserve. The request is sent by the source along with path information. At every hop, the node determines if adequate bandwidth is available in the onward link. If the available bandwidth is inadequate, the node rejects the requests and sends a response back to

the source. If the bandwidth is available, it is provisionally reserved, and the request packet is forwarded onto the next hop in the path. If the request packet successfully reaches the destination, the destination acknowledges it by sending a reservation packet back along the same path. As each node in the path sees the reservation packet, it confirms the provisional reservation of bandwidth. In addition, it also performs the required configuration needed to support the incoming traffic such as setting up labels in a GMPLS label switching node, or reconfiguring the lambda switching internal devices (such as MEMS) in a transparent optical wavelength switching system.

### 5.2. The first stage: selecting the candidate paths

The first stage of the GreenSpark RWA schema computes a list of  $k$  feasible cycle-free paths, in increasing order of cost, between the source and the destination nodes of the connection to be routed, constrained by its QoS requirements. Here  $k$  is a configurable parameter that can be used to limit the number of feasible paths that should be considered in the following step, thus controlling the depth and granularity of the analysis process according to a performance/precision compromise. The K-SPF ( $k$ -shortest paths first) algorithm used has been explicitly modified to meet the specified bandwidth requirements of each new request and to enforce the wavelength continuity constraint so that, when traversing converter nodes, we are totally free in selecting any outgoing link of the multigraph (i.e. any wavelength), whereas with all the other nodes we can only select an outgoing link corresponding to the same wavelength associated with the incoming one. The above pre-selection process is driven by a link weighting function  $\omega((u, v)_\lambda)$  taking into account, for each link  $(u, v)_\lambda$ , the (static) global capacity  $a_{(u, v)_\lambda}$  and the current (dynamic) residual capacity  $r_{(u, v)_\lambda}$  still available on the link. Intuitively, a *good* weighting function should be inversely proportional to both the residual and the maximum capacities, but the contribution of these two factors need not be the same. Following the analysis in [8], the link weighting function is defined as:

$$\omega : E \rightarrow \mathfrak{R}, \omega((u, v)_\lambda) = (r_{(u, v)_\lambda} \cdot \log_{a_{(u, v)_\lambda}})^{-1} \quad (8)$$

Such a function exhibits the desirable property of leading to a good load-balancing over the network, since it tries to avoid bottleneck link by assigning higher costs to smaller (low global capacity  $a_{(u, v)_\lambda}$ ) and more congested (low residual capacity  $r_{(u, v)_\lambda}$ ) links. Note that every two links with the same residual/maximum capacity ratio but different residual or maximum capacity values will have different associated weights. This avoids assigning the same weight to two links with the same saturation ratio but with different residual or global capacity. Therefore, we choose the weighting function (8), which satisfies all the desired properties discussed before. Note also that the first stage is exclusively based on load-balancing criteria, and no energy consideration is present at all; this guarantees that the  $k$  paths selected in this stage are the best balanced ones, thus giving priority to the traditional network optimization criteria of minimizing the connections blocking

ratio. Energy-awareness is introduced only in the second stage, where the greenest path among the  $k$  best-balanced candidate paths is finally selected.

### 5.3. Second stage: choosing the best path

The  $k$  minimum cost paths found by the K-SPF algorithm in the first stage are the  $k$  best paths as for network's blocking probability (the percentage of rejected connection requests), since the weighting function  $\omega((u, v)_\lambda)$  tends to balance as much as possible the use of the network resources. Among these  $k$  best-balanced paths, we now have to choose the *optimal* path among them according to our energy-aware selection criteria, aiming at minimizing the power consumption or the carbon footprint. For this purpose we need to introduce a properly crafted heuristic working as a path scoring function, to differentiate among the available preselected paths and choose the most energy-efficient one. The scoring function  $f_S$  is defined on the set of all the possible paths  $\Pi$  and will evaluate the power consumption and carbon footprint of the  $k$  paths  $K = \{\pi_i, i = 1, 2, \dots, k\}$  obtained from the first step:

$$f_S(\pi) : \Pi \rightarrow \mathfrak{R}. \quad (9)$$

The (total) power consumption  $\Psi_\pi(x)$  of a path  $\pi$  defined in eq. (7) can be decomposed as the sum of the power consumption of the traversed devices that are powered by green  $\Psi_\pi^G(x)$  and dirty  $\Psi_\pi^D(x)$  energy sources:

$$\Psi_\pi(x) = \Psi_\pi^G(x) + \Psi_\pi^D(x). \quad (10)$$

Note that the carbon footprint of a lightpath is only given by the power consumption of the involved NEs that are powered by dirty energy sources, as the NEs powered by green energy sources do not contribute to GHG emissions.

Therefore, if our primary objective is to minimize the GHG emissions (GreenSpark MinGas), we have to choose the path  $\pi$  which has the lowest carbon footprint  $\Psi_\pi^D(x)$  (primary objective) and, among paths with the same minimum carbon footprint (if any), we choose the path that minimizes the total power consumption  $\Psi_\pi(x)$  (secondary objective):

$$f_S(\pi) = \Psi_\pi^D(x) + \log \Psi_\pi(x). \quad (11)$$

Analogously, if our main goal is reducing the overall power consumption and, thus, the network operating energy costs (GreenSpark MinPower), we need to use an objective function privileging the paths with minimal total power consumption  $\Psi_\pi(x)$  and, among them, choosing the one with the minimum carbon footprint  $\Psi_\pi^D(x)$ :

$$f_S(\pi) = \Psi_\pi(x) + \log \Psi_\pi^D(x). \quad (12)$$

The computation of the scoring function is done for each of the  $k$  minimum cost paths, and the path  $\pi^*$  eventually chosen is the one with the lowest  $f_S(\pi)$  value:

$$\pi^* = \arg \min \{f_S(\pi) | \pi \in K\}. \quad (13)$$

If more than one such lightpaths exist (i.e. with the lowest  $f_S(\pi)$  value), the one with the minimum  $i$  index in the set of lightpaths  $K$  is selected (to maximize load-balancing).

The path  $\pi^*$  is the “best” path between the best load-balanced paths that minimizes the carbon footprint or overall power consumption according to the proposed energy model, and it will be used to route the connection request.

Note that the first stage cost function is defined over the set of edges (8), whereas the energy-aware scoring function is defined over paths (9) to reflect our intent of achieving an acceptable compromise between the traditional network optimization objectives, typically based only on specific link properties, and the energy-related ones that need to take into account more complex considerations to be done on the higher layer concepts of lightpath/channel, interface and node role and wavelength processing practice such as optical amplification and 3R regeneration. That is why we structure the decision process into two independent phases and select among the  $k$  candidate paths the one with the minimum carbon footprint or power consumption according respectively to the functions (11) and (12), instead of simply selecting the minimum cost path based only on the traditional cost function (8).

The generic GreenSpark algorithm is sketched in Fig. 4. The algorithm takes as input the current network state  $G$ , the connection request  $\rho = (s, d, b)$  between node  $s$  and  $d$  with QoS bandwidth requirement  $b$ , the  $k$  parameter of the K-SPF and the objective function  $f_S$ . In the first stage (lines 1–2), the K-SPF algorithm finds the  $k$  minimum cost paths with sufficient free bandwidth connecting the source and destination nodes. The  $k$  paths are the best ones according to the load-balancing cost function  $\omega((u, v)_\lambda)$  of Eq. (8). In the second stage (lines 3–7), the chosen objective function  $f_S$  is evaluated for the  $k$  minimum cost paths and the best path  $\pi^*$  is eventually chosen to route the connection request  $\rho$ . Finally, the new  $\omega((u, v)_\lambda)$  costs are updated only for the edges of the path  $\pi^*$ , and the chosen path and new network state are returned.

## 6. Time and space complexity analysis

In the first stage, the computing of the K-SPF for finding the  $k$  feasible paths for a specified source–destination pair requires in the worst case a time complexity of  $O(k \cdot (m + n \cdot \log n))$  [31]. The second stage computes the objective function  $f_S$  for each of the  $k$  paths found. The function calculation requires the computation of the power consumption or GHG emissions for each network element in the path. The maximum length of a cycle-free path in a graph with  $n$  nodes is  $n - 1$ , thus the second stage requires  $O(k \cdot n)$ . Hence, since the K-SPF complexity is the dominating factor between the two stages, the worst case runtime is given by the polynomial time complexity  $O(k \cdot (m + n \cdot \log n))$ . Therefore, GreenSpark belongs to the same polynomial complexity class of the fastest SPF improved by using a priority queue with a Fibonacci heap in the implementation,  $O(m + n \cdot \log n)$  [32]. GreenSpark complexity is also lower than the quadratic complexity of the original SPF algorithm,  $O(n^2)$ , and significantly lower than the cubic complexity of naïve MIRA  $O(n^3 m \cdot \log(n^2/m))$  optimized with the Goldberg max-flow algorithm [33].

As for space complexity, our multigraph network representation requires less space with respect to the layered graph approach conventionally used in dynamic RWA algorithms (Fig. 1). Using up to  $\lambda$  wavelengths on each edge, the layered representation with  $C$  converter nodes will require  $\lambda n + 2$  nodes ( $\lambda$  layers, each dedicated to an individual wavelength, plus two additional nodes to serve as ingress and egress) and  $\lambda m + 2\lambda + C \cdot (\lambda - 1)$  edges (converters can be modeled by cross-layer edges that connect each layer to the  $\lambda$  adjacent layer – a wavelength conversion spanning multiple frequencies will thus entail many such edges in sequence), whilst the equivalent multigraph representation will require only  $n$  nodes and  $\lambda m$  edges, thus notably reducing the space complexity. Besides, in the layered graph, the ingress and egress nodes as well as the edges

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### Algorithm 1 GreenSpark( $G, \rho, k, f_S$ )

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#### Input:

$G$ : current network state

$\rho = (s, d, b)$ : connection request;  $s, d$ : source, destination nodes;  $b$ : required bandwidth

$k$ : parameter of K-SPF

$f_S$ : objective function (MinPower / MinGas)

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#### Output:

$G^*$ : new network state

$\pi^*$ : selected route and wavelength assignment

- 1: Label network edges with cost function  $\omega((u, v)_\lambda)$
  - 2:  $K \leftarrow$  K-SPF( $G, \rho, k$ )
  - 3: **for** each path  $\pi \in K$  **do**
  - 4:   evaluate  $f_S(\pi)$
  - 5: **end for**
  - 6:  $\pi^* = \arg \min \{f_S(\pi) | \pi \in K\}$
  - 7:  $G^* \leftarrow$  Update the  $\omega((u, v)_\lambda)$  costs of network edges  $(u, v)_\lambda$  along the chosen path  $\pi^*$
  - 8: **return** ( $\pi^*, G^*$ )
- 

Fig. 4. The GreenSpark algorithm.

connecting them to the network have to be built each time a new connection arrives, whilst in the multigraph approach this preprocessing phase is not necessary thanks to its compact representation. Note that, even in absence of wavelength conversion, all the layers of the layered graph have to be explored, since the (first) wavelength of the lightpath may be any, which compensates the additional check needed in the multigraph approach to enforce the wavelength continuity constraint. Furthermore, the higher number of nodes and edges required by the layered graph with respect to the multigraph approach increases the time complexity which strictly depends on the  $n$  and  $m$  parameters.

The low computational and space complexity required by the GreenSpark algorithm with the multigraph network representation helps lightening the computational burden of path computing elements and serving the connections with lower delay with respect to more complex approaches.

## 7. Performance evaluation and results analysis

In order to evaluate the effectiveness of the GreenSpark energy-aware RWA framework and its impact on the power consumption and carbon footprint of telecommunication networks, we conducted an extensive simulation

study on the network topology modeled as undirected graphs in which each link has a non-negative capacity and a specific power demand depending on both its physical and technological features. All the nodes in the graph are characterized, apart from the traditional network-level capabilities such as wavelength conversion and add-and-drop capability, by their power absorption and type of energy source (i.e. green or dirty), as defined in the energy model of Section 4.

To improve the significance of the obtained results and make them more easily comparable with the other experiences available in literature, we spent a significant effort on the use of realistic data in all our experiments (network topology, traffic demands, costs, and power consumption models). Accordingly, we used in our simulations the well-known network topology Geant2 [34] of Fig. 5 with the bandwidths for the links ranging from OC-1 to OC-768 bandwidth units. Here, traffic demands have been modeled by using different randomly generated or static predefined [35,36] traffic matrices. In the latter case, the traffic volumes have been scaled proportionally to the reported traffic distributions. The energy model has been fed with the realistic power consumption values associated with nodes and links taken from [2,10,37]. Recall that, since no per-node sleep mode is assumed to be possible, the network elements are always powered on and therefore the GreenSpark algorithm bases its decisions exclusively

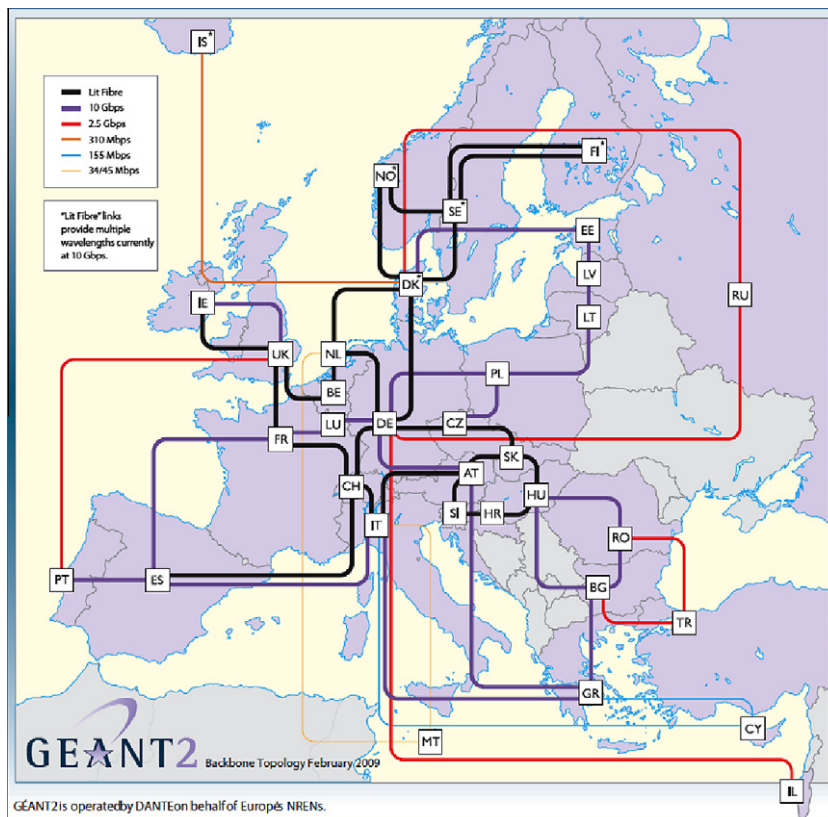


Fig. 5. Geant2: real network topology used in simulations.

on the variable power consumption part, which is the only one that can vary and thus be optimized. Power consumption results refer thus only to the variable power consumption.

Each connection request was characterized by a bandwidth demand ranging from OC-1 to OC-192 units (i.e. from 50 Mbps up to 10 Gbps). As the network load grows, that is, the number of busy connection resources increases more and more with respect to the free/released ones, we continuously monitored the overall network power demand, the percentage of green energy used compared to the maximum available, and the network efficiency expressed by the rejection ratio/blocking factor. All the simulation experience has been conducted in a properly crafted optical network simulation environment [38] that allows the creation of network topologies along with the specification of simulation parameters and configuration files. All the results have been determined with a 95% confidence interval not exceeding 6% of the indicated values, estimated by using the batch means method with at least 25 batches. All the runs have been performed on an Intel® Core™ i7-950 CPU @ 3.07 GHz with 16 GB RAM and 64 bit operating system server running Sun® Java® Runtime Environment v.1.6. In all the experiments, we used a dynamic traffic model in which connection requests, defined by a Poisson process, arrive with a parametric rate of  $\gamma$  requests/s and the session-holding time is exponentially distributed. The connections are distributed on the available network nodes according to the above random-generated or predefined traffic matrices, as summarized in Table 3.

In our lambda-switched optical framework, the resources occupied by the routed connections are counted as the sum of the ratio between the free and the busy bandwidths along the edges. Resources are thus represented as the sum of the bandwidths on all the network edges, while the traffic volume is represented by the quantity of the utilized bandwidth in a certain time.

In all the experiments, GreenSpark has not been compared with other analogous power-containment solutions known in literature because, at the state-of-the-art, almost all the available schemes achieve their savings by powering off interfaces or entire nodes (practice avoided in real network as already mentioned in the introduction), so that the comparison would be misleading since shutting down an entire device would cancel its fixed power consumption which, in our always-on approach, is present all the time. Conversely, the use of provably efficient and publicly available algorithms such as min hop algorithm (MHA) [39] and

minimum interference routing algorithm (MIRA) [40], already implemented in several commercial solutions, gives us a real portrait of the power and GHG savings that will be consequent to the introduction of the proposed schema within real world infrastructures, and, at the same time, demonstrates the absence of significant performance burdens in traditional network management objectives (increasing blocking probability, reduced load-balancing, etc.) due to the new energy optimization goals.

The behavior of the algorithm varying the  $k$  parameter has been extensively studied (Section 7.2) and, for the considered network topology, an optimal value of  $k = 3$  was chosen as the best compromise between the different optimization objectives of the two stages (load-balancing and greenness) and time performance (recall from Section 6 that the complexity depends on  $k$ ). However, for clearness sake, we first show the results of the comparative simulations with the other RWA algorithms (Section 7.1) and, then, show how the biasing of the  $k$  parameter affects the performance (in terms of the two stage objective) and the time complexity of GreenSpark for the given network topology.

### 7.1. Comparative simulation study

In the first set of simulation shows, we report the comparison of the GreenSpark framework with other well-known RWA algorithms. In these tests, the  $k$  parameter of GreenSpark has been tuned to an optimal value ( $k = 3$ ) for the considered network topology, as a result of the extensive simulation study reported in Section 7.2.

In Fig. 6 we plotted the connection blocking probability versus the generated connection requests. We can observe how MHA exhibits the highest blocking probability, essentially due to the congestion of the communication links associated with the shortest paths. MIRA [40] improves the performance of MHA, and achieves lower blocking probability. However, starting from 500 connection requests, its blocking probability grows at quite a fast pace. All the algorithms belonging to the Spark family (Spark, GreenSpark MinPower and GreenSparkMinGas) perform sensibly better than the other ones, and all their versions achieve similar and very satisfactory results in terms of the connection blocking probability.

In Fig. 7 we compared the total power consumption (green and dirty) obtained by the different algorithms versus the connection requests. MIRA reveals to be the highest power consumer, followed by MHA which, in contrast with

**Table 3**  
Parameters used in the simulations.

| Simulation parameters       | Dante Geant2 network   |
|-----------------------------|--|
| Number of connections       | Varying from 0 to 3000 with different resolutions                                |
| Random generated bandwidths | {1, 3, 12, 24, 48, 192} OC-units with different distribution probability         |
| GreenSpark $k$              | 1, 3, 5  |
| Spark $k$ , $kHop$          | 3, 20  |
| $A_{OA}$ , $A_{3R}$         | 80 km, 1000 km   |
| Source, destination         | Varying according to a Poisson process, duration times exponentially distributed |
| RWA algorithms              | MHA, MIRA, Spark, GreenSpark MinPower, GreenSpark MinGas                         |
| Measurements                | Blocked connections, power consumptions, green energy percentages                |

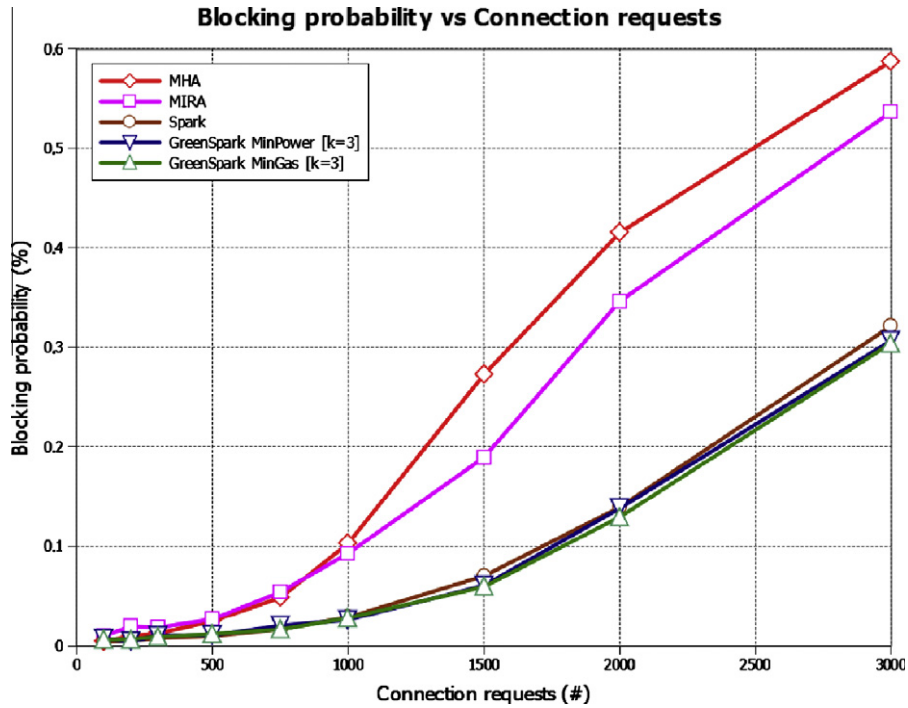


Fig. 6. Connection blocking probability versus connection requests.

the previous graph, performs better than MIRA. This is due to the longer paths chosen by MIRA with respect to MHA that, in turn, always chooses the shortest paths to route

the connections (and, thus, statistically introduces less power consumption). In this graphic, we can also observe the first big difference inside the Spark family: the

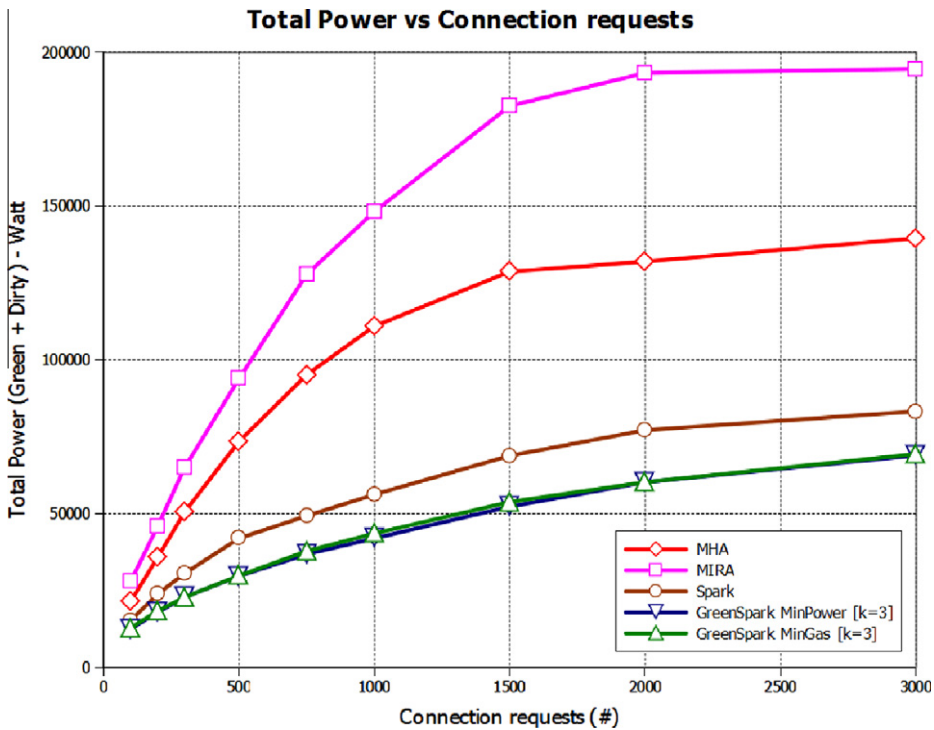


Fig. 7. Total power versus connection requests.

GreenSpark algorithms have lower total power consumption with respect to the energy-unaware Spark. Besides, we note that the two GreenSpark algorithms, MinPower

and MinGas, perform almost the same as for the total power consumption, with MinPower doing slightly better, as expected. Anyway, the fact that the two GreenSpark

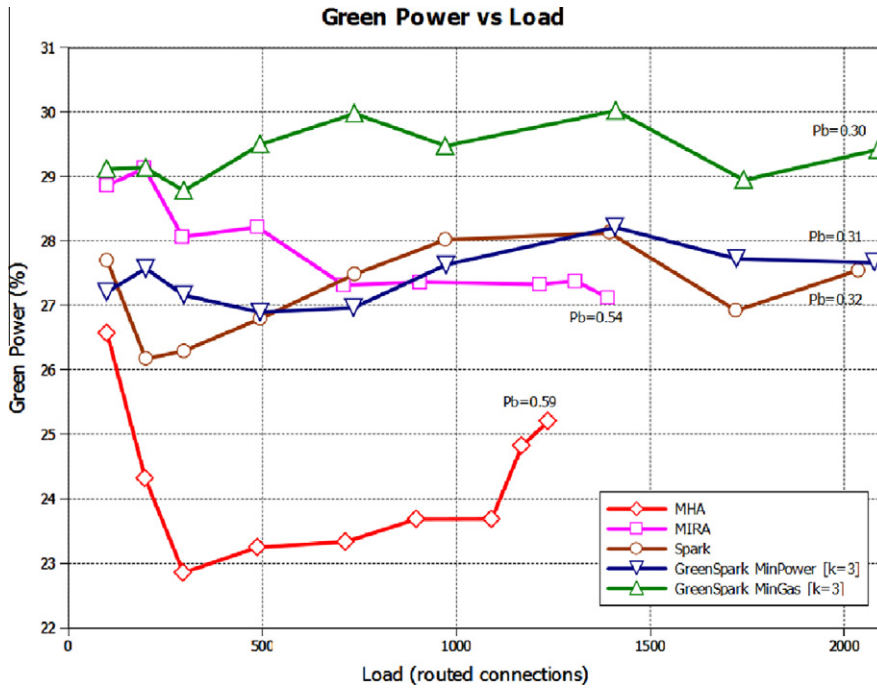


Fig. 8. Green power (percentage) versus load (routed connections).

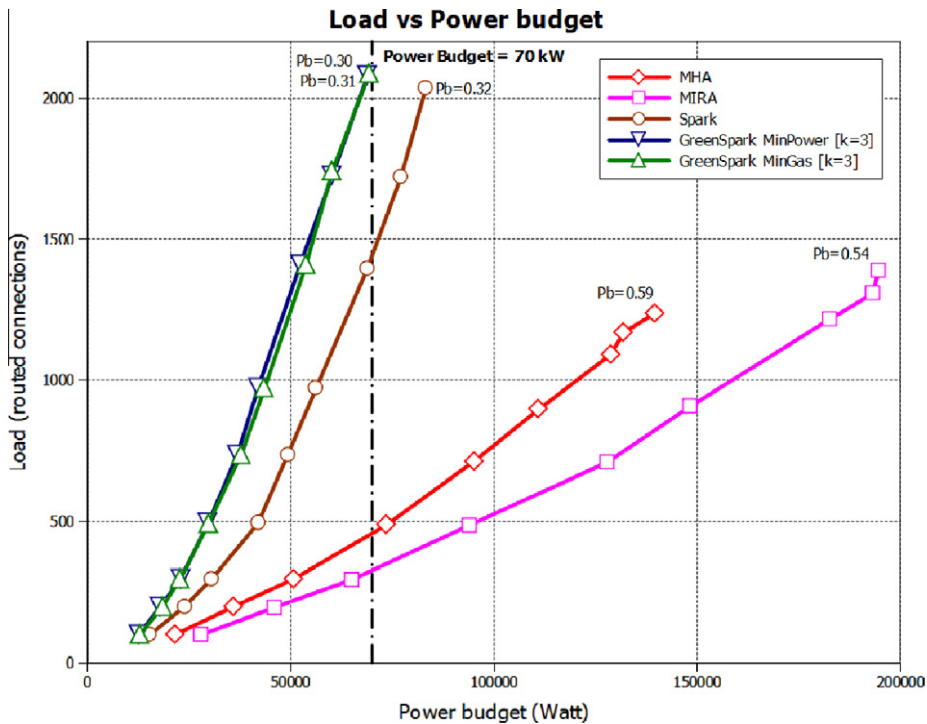


Fig. 9. Load (routed connections) versus power budget.



algorithms have almost the same total power consumption does not mean that their carbon footprint is the same. This leads us to the next graphic of Fig. 8, in which the green component of the power consumption has been reported.

The results, highlight that there is big difference in the use of green energy depending on the chosen GreenSpark optimization goal, as well as for the other algorithms. GreenSpark MinGas exhibits the topmost green power usage percentage, i.e. it prefers lightpaths passing through green-powered NEs and avoids sites powered by dirty sources as much as possible. More than 29% of the total power used by GreenSpark MinGas comes from green energy sources, thus saving considerable quantity of CO<sub>2</sub> from being emitted by the network during its operations. The other two algorithms of the Spark family are characterized by a lower green power usage, as expected, while keeping the blocking probability unaffected. Although being energy-unaware, MIRA performed quite well in our tests in terms of green power usage percentage, basically due to its minimum interference driving criteria which tends to balance the usage of network resources (whose energy is equally distributed among green and dirty energy sources), even if it exhibits a very high connection blocking probability, reaching values of 54% starting from a load of just 1450 connections. MHA exhibits the worst performance both for the green power usage and for the connection blocking probability, showing its limitations in complex network scenarios where a number of constraints, comprising the energy-efficiency ones, have to be taken into account. A particularly interesting issue comes from

the observation of the pseudo-sinusoidal trend in the use of the green resources characterizing all the algorithms of the Spark family. This behavior is due to the specific cost and scoring functions associated with this family, in which less costly/greener paths will be chosen first, making the green energy percentage rise. As the usage of green paths raises, however, also the dynamic cost assigned to such paths increases as a consequence of their increased load (according to the load-balancing criteria of Eq. (8)), until alternative non-green paths will be cheaper than the green ones and thus will be preferred for connections routing. This will make the green energy percentage decrease, but, at the same time, increase the cost of these alternative paths, until it will be again more convenient to route the incoming connections on green paths, and so on. Therefore, the pseudo-sinusoidal trend of the Spark family is somehow a visual proof of the efficiency of the two phase selection scheme which, at first, tries to balance the network load and, then, to minimize the specific scoring function, such as the total power (GreenSpark MinPower), the total GHG emissions (GreenSpark MinGas) or the total cost (Spark).

Starting from the consideration that it is a common practice that network operators contract a fixed power budget with their energy supplier and then strive to remain within that budget since surpassing the threshold will result in high penalty rates on the overall energy costs, in Fig. 9 we plotted the load versus the power budget required to route the connections. The energy-aware GreenSpark algorithms exhibit an almost optimal growth trend,

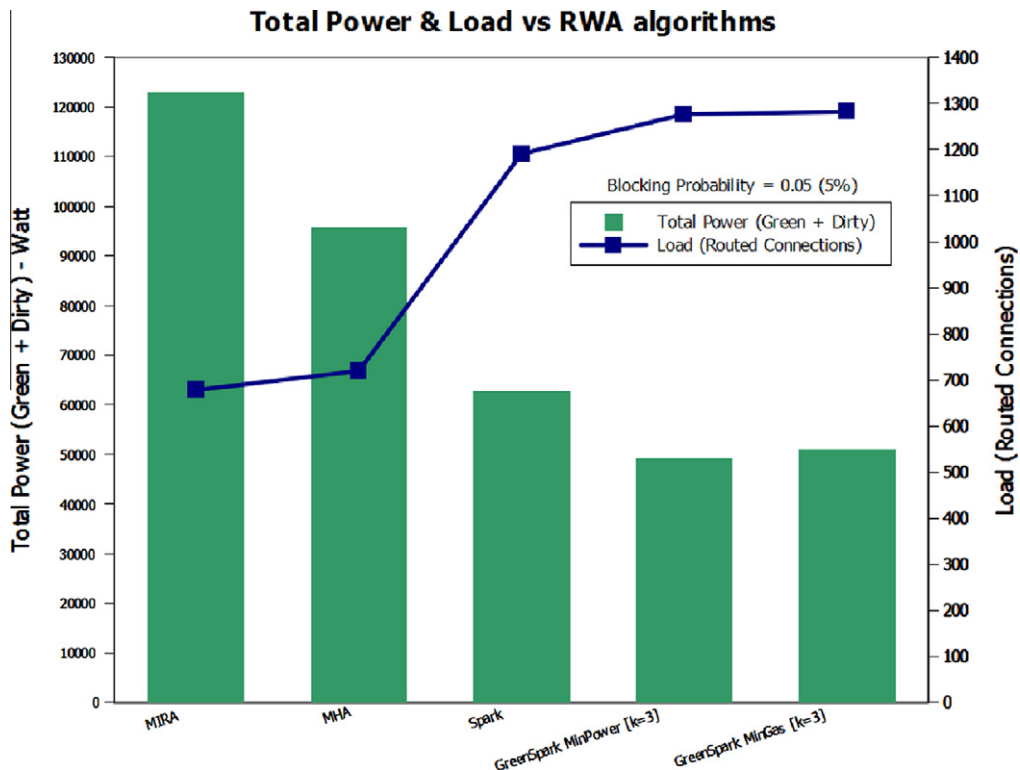


Fig. 10. Total power (green + dirty) and load (routed connections) versus different algorithms at a load causing a blocking probability of 0.05 (5%).

showing the highest increase in the load against a fixed increase in the power budget with respect to the other algorithms. We can observe that the entire set of connections can be routed in the network keeping its power

budget below the 70 kW threshold (and the blocking probability at the lowest observed values). From this point of view, Spark performs notably well, considering that it is energy-unaware: its power budget is only 83 kW. It is

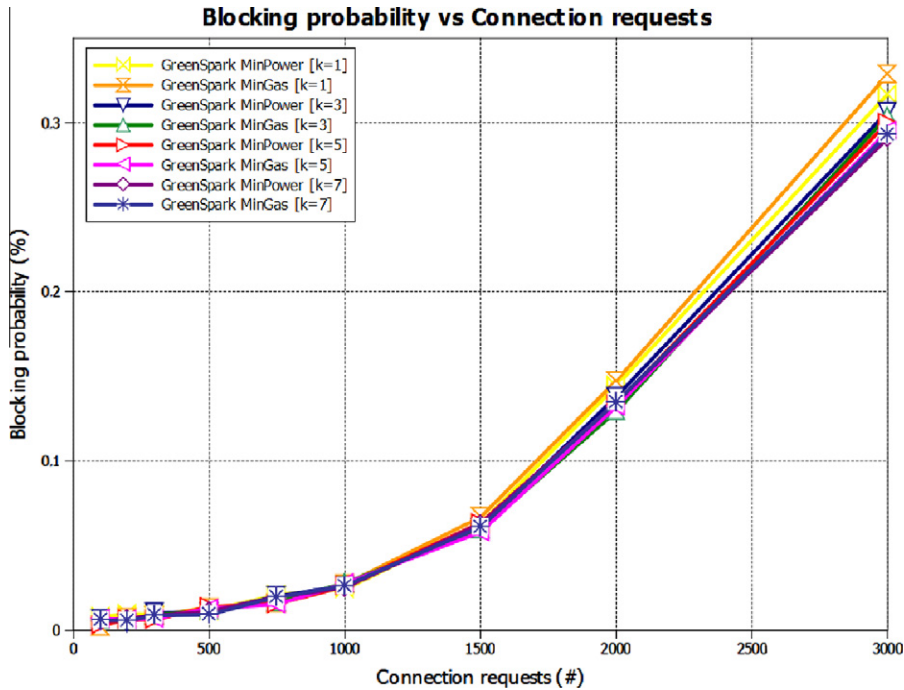


Fig. 11. Connection blocking probability versus connection requests.

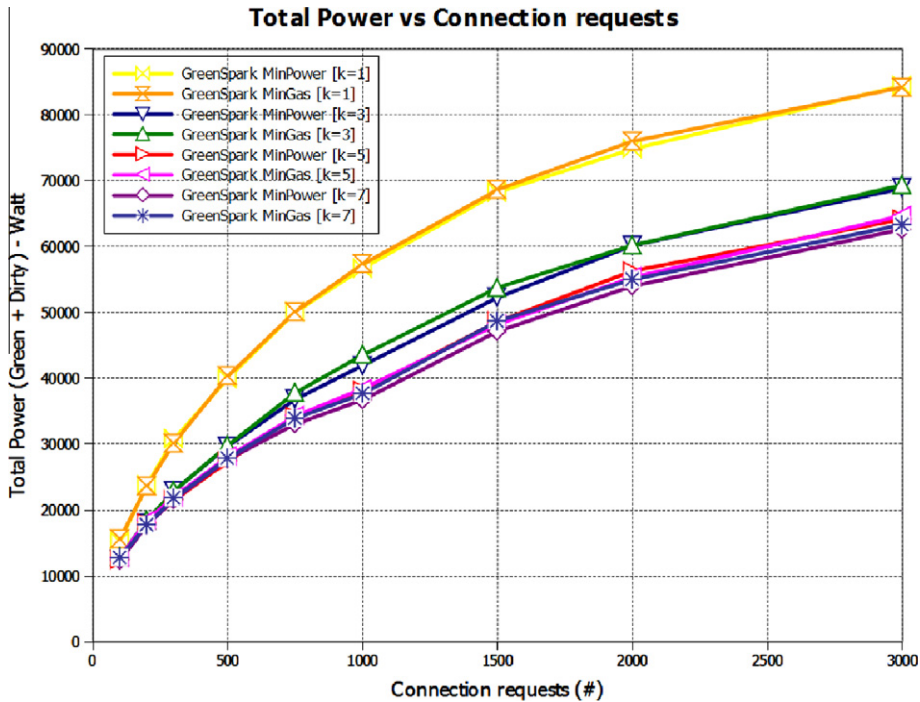


Fig. 12. Total power versus connection requests.

worthwhile to note that inside the power budget of the Spark algorithms, there are much many connections (more

than 2000) with respect to the MHA and MIRA algorithms, which only route between 1200 and 1400 connections.

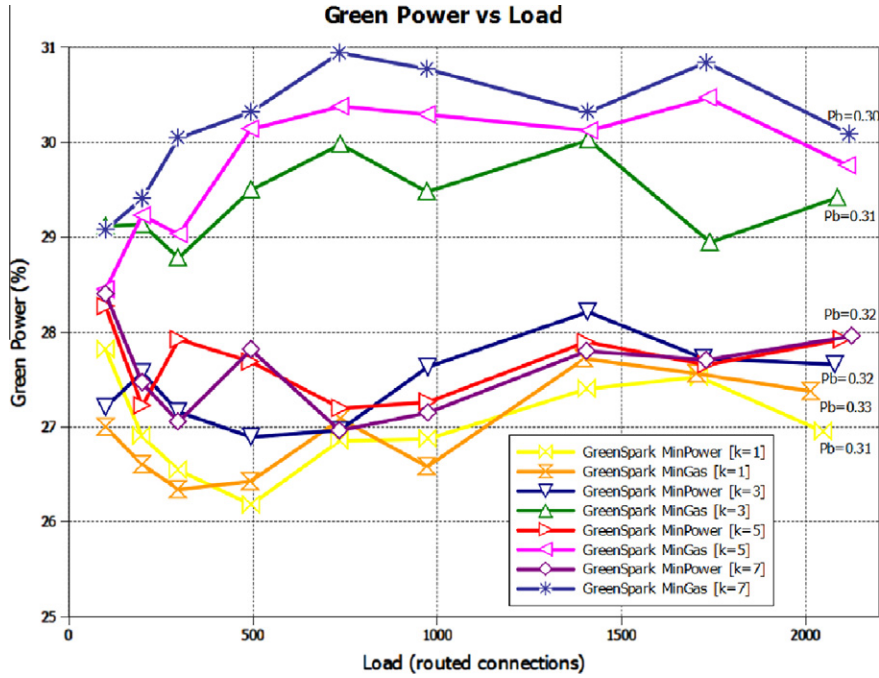


Fig. 13. Green power (percentage) versus load (routed connections).

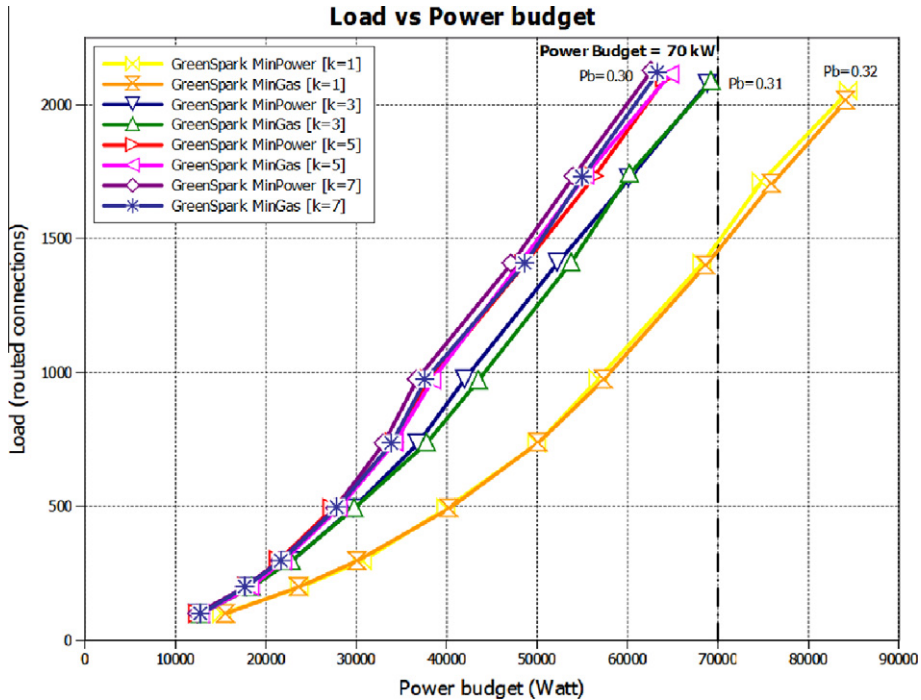


Fig. 14. Load (routed connections) versus power budget.

Furthermore, their power budgets are sensibly higher, being 140 kW and 195 kW respectively, between two and three times more than GreenSpark.

The last test of this series was conducted by keeping the QoS on the blocking probability at the constant value of 5%. We measured both the total required power and the load offered by the algorithms. The graphic in Fig. 10 clearly shows the great improvements introduced by the Spark family both for the power consumption and the routed connections. In particular, we observe that the GreenSpark algorithms need as low as half of the power required by MIRA and MHA and route double the number of their connections, making them very attractive also for QoS constrained networks with strict requirements on the connection blocking probability.

As a conclusion, we observe that there is a generation gap between the Spark family and the traditional MIRA and MHA algorithms, both in terms of power consumption and blocking probability. In particular, Spark performances are quite satisfactory, but GreenSpark algorithms, thanks to the two stages load-balancing and green objectives balanced by the  $k$  parameter, perform much better in terms of power and GHG, with MinGas even superior than MinPower, since it considerably lowers the GHG emissions while keeping almost the same total power requirements than MinPower. Results showed that GreenSpark algorithms not only significantly lower the required power and GHG emissions but also increase the connections acceptance

ratio, showing that properly crafted RWA algorithms can enable greener networks with even better performance than before.

### 7.2. Tuning the GreenSpark $k$ parameter

The  $k$  parameter value biases the load-balancing criteria of stage one (Eq. (8)) and the greenness criteria of stage two (Eq. (11) and Eq. (12)). Stage one restricts the set of possible paths to the best balanced  $k$  paths between ingress and egress nodes according to its cost function  $\omega((u, v)_i)$ ; stage two selects, among such paths, the greenest one according to its scoring function (MinGas or MinPower). At the extreme cases, a  $k$  value of 1 would restrict the stage one to always select the minimum cost path (thus, the best load-balanced path according to Eq. (8)) and the stage two to always select the only path available from stage one, making the algorithm totally energy-unaware, and therefore reducing it to a “simple” Dijkstra-based weighted shortest path (that is a minimum cost one); from the other side, a large enough  $k$  value (greater than the maximum number of possible paths between any two nodes) would make the algorithm totally “green”, completely discarding the load-balancing effect of stage one. Therefore, smaller values of the  $k$  parameter bias the solution by privileging well balanced paths, while larger values of the  $k$  parameter privilege energy related objectives rather than the traditional network

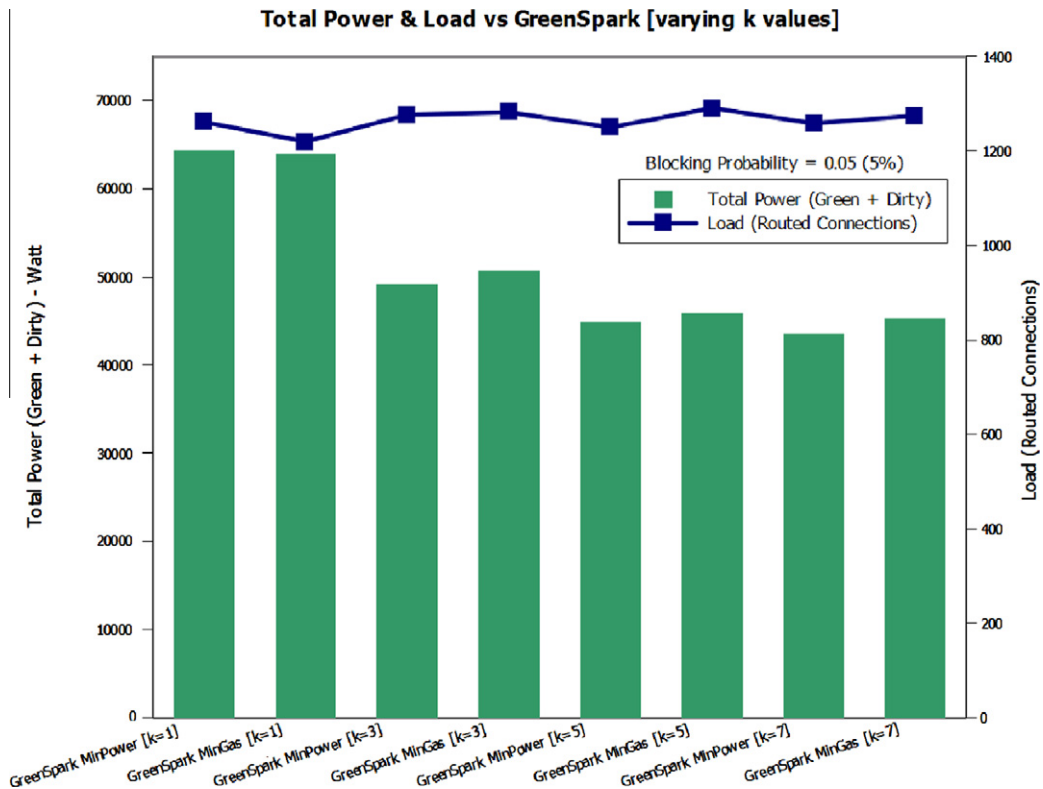


Fig. 15. Total power (green + dirty) & Load (routed connections) versus GreenSpark with varying  $k$  values at a load causing a blocking probability of 0.05 (5%).

management ones. A in depth study of the  $k$  parameter is therefore interesting and it is reported here for the Geant2 network topology.

In Fig. 11 we show the blocking probability of GreenSpark with varying values of the  $k$  parameter versus the connection requests. As expected, the  $k$  value affects very little the blocking ratio since the actual load-balancing is done in the first stage, whose output are always the  $k$  best balanced paths; in this sense, load-balancing is assured by stage one.

On the contrary, if we look at the total (green + dirty) power consumption versus the connection requests reported in Fig. 12, we observe that the higher the  $k$  value, the lower the total power consumption, as expected. In fact, with higher  $k$  values, the second stage will have the possibility to choose among a greater number of alternative paths to minimize ecological footprint of the network, both for MinPower and MinGas, which indeed perform very similar; in this sense, the green aspect is committed to stage two.

However, if we take a look inside the total power consumption at the green power percentage versus the load reported in Fig. 13, we see that there is a notable difference in the use of green energy sources at high  $k$  values. With  $k = 5$  and  $k = 7$ , the green power percentage of GreenSpark MinGas markedly increases (whilst the MinPower is in the average as expected being GHG-unaware), showing that there is still room for green optimization at the expense of additional computational complexity due to the calculation of the higher number of alternative paths in the stage one. This result suggested the basis of a future work of ours, in which we will try to reach such greener paths through a one-stage algorithm with an omni-comprehensive energy-aware/load-balancing cost function employed to directly achieve such paths. We also note that the green power percentage for  $k = 1$  is quite high, showing that the load-balancing may have positive effects on the GHG emissions when the energy sources are heterogeneously distributed in the network.

In Fig. 14 we plotted the load versus the required power budget for different  $k$  values. As seen in Fig. 12, with the same  $k$  value, MinPower and MinGas perform quite similarly in terms of total power consumption, but GreenSpark will require different power budgets depending on the  $k$  value. The higher the  $k$ , the lower the power budget but also the higher the computational complexity required for the path calculation at each connection request set-up time. Anyway, it is worthwhile to note that there is great improvement between  $k = 1$  and  $k = 3$ , and only limited gain for greater values, meaning that already with  $k = 3$  alternative paths the GreenSpark framework is able to sensibly reduce the power budget in an optimal balance between greenness and performance.

Finally, the results of the test on the QoS on the blocking probability at the constant value of 5% is shown in Fig. 15. The total power required decreases with the increase of the  $k$  parameter value but again, while from  $k = 1$  to  $k = 3$  there is a great reduction of the total power, when passing from  $k = 3$  to  $k = 5$  and  $k = 7$  there is no such a great benefit. Note also that, at such low load (5% of blocking probability), there is no great difference in varying the  $k$  values as for

the number routed connections since most of the connections will have sufficient resources to be routed, even if a slightly better performance is observed in correspondence of the  $k = 3$ , i.e. when both the load-balancing and the greenness objectives are fairly weighted.

## 8. Conclusions and future work

In this work, we focused our research effort on GreenSpark, a novel heuristic-driven dynamic RWA framework aiming at the minimization of power consumption and GHG emissions in wavelength routed backbone networks. GreenSpark operates by progressively routing the dynamically incoming connections on a two-stage basis; in the first stage, a set of  $k$  feasible paths is found according to traditional load-balancing objective. Then, in the second stage, the greenness of the  $k$  paths is evaluated both in terms of power consumption (MinPower) and GHG emissions (MinGas), and the greenest path is finally selected to route the connection. Even with low  $k$  values (i.e.  $k = 3$ ), and despite its very low computational complexity, GreenSpark achieves significant power savings and carbon footprint reduction together with an increment of the load-balance, resulting in lower blocking probability as compared with several widely used routing algorithms, as verified by the extensive simulation study.

Apart from defining an energy consumption model for the IP over WDM network, one of the most significant added values of the framework is the incorporation of both physical layer issues, such as power demand of each component, and virtual topology-based energy management with integrated traffic grooming, adversely conditioning the usage of energy hungry links and devices. Moreover, since the above model also takes into account the type of power supply associated with each device, by privileging green sources, the proposed scheme can also be useful for equalizing the carbon footprint of entire areas within a real network scenario in which each device location may be characterized by a differentiated (green or dirty) energy source. Here, multi-objective optimization may help us in finding the appropriate trade-off according to the relative importance of network performance and environmental friendliness.

As future work, we are studying an omni-comprehensive energy-aware/load-balancing cost function to directly find green paths in a single stage with even lower computational complexity. In addition, we are investigating new energy-aware traffic engineering strategies and network re-optimization methods, aiming at dynamically reducing power demand, GHG emissions and costs on a time basis, by moving data wherever electricity costs are lowest at a particular time.

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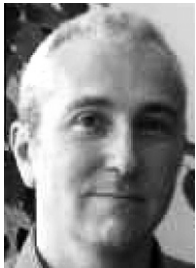
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