Energy Management Through Optimized Routing and Device Powering for Greener Communication Networks

Bernardetta Addis, Antonio Capone, *Senior Member, IEEE*, Giuliana Carello, Luca G. Gianoli, and Brunilde Sansò, *Member, IEEE*

I. Introduction

WE ARE currently entering an era of increasing concern for the environment in which the Internet plays an important role both as a replacement for traveling and as a medium to convey environmental information.

However, the Internet itself and its related information and communication technologies (ICT) are starting to have an impact on global warming. ICT contributes with 2% (0.8 Gt CO_2) of global greenhouse gas (GHG) emissions annually [1]–[3], which is a value that exceeds the GHG emission of the aviation sector [4]. As ICTs become more widely available, these percentages are likely to grow to around 1.4 Gt of CO_2, or approximately 2.8% of global emissions, by 2020 [5]. Also, ICT alone is responsible for a percentage between 2% and 10% of the world power consumption [6]. Estimated consumption of the network equipment (excluding servers in data centers) in 2007 was 22 GW. According to a predicted annual growth rate of 12%, it will reach 95 GW in 2020 [5].

The networking community response has been to develop technologies as well as to model approaches to reduce energy consumption. In [7], different types of green networking proposals are discussed and classified in three different groups: 1) those that deal with the partitioning of existing resources among different users, networks, or applications; 2) those that deal with power management and redesign of networking features; and 3) those that are exclusively related to the improvement of hardware efficiency. This paper deals with the second approach, i.e., network elements energy management.

Networks are designed and dimensioned to serve the estimated peak traffic demand. During network operation, traffic requests usually vary remarkably over time, and even during peak hours, they are typically well below the network capacity. Moreover, protection techniques adopted during the design phase to increase network resilience increase capacity and reduce link average utilization. Unfortunately, the power consumption of current network device architectures and transmission technologies is almost traffic-load-independent. As a result, networks consume energy as if they were always fully loaded [8], [9].

A way to improve network energy performance would be to optimize the individual network elements consumption so that it is kept as close as possible of the traffic load [10]. The ideal networking device would be energy-proportional, that is, presenting zero consumption at zero load and increasing linearly up to maximum power with full load. Unfortunately, this is far from the behavior of current devices, even those with the most advanced hardware technologies. This is due to the minimum power required, for instance, to keep active the circuitry of the main board and the routing line cards. Therefore, to achieve a consumption proportional to traffic, we need to manage the whole network energy consumption in a coordinated way by dynamically switching off and on links and nodes according to traffic variations.

In order to switch off part of the network, we need to guarantee that the remaining part has enough capacity to serve traffic load and to reroute flows through active routers. Thus,

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B. Addis is with the Dipartimento di Informatica, Università degli Studi di Torino, Turin 10149, Italy.
A. Capone and G. Carello are with the Dipartimento di Elettronica, Infor-mazione e Bioingegneria, Politecnico di Milano, Milan 20133, Italy (e-mail: antonio.capone@polimi.it).
L. G. Gianoli and B. Sansò are with the Département de génie électrique of the École Polytechnique de Montréal, Montréal, QC H3C 3A7, Canada.

the routing protocol plays an important role and may impose limitations to the energy management strategy. Multi-Protocol Label Switching (MPLS) is largely the most popular technology used in the backbones of Internet service providers (ISPs). MPLS is quite flexible since it allows to route individual flows along a single path from source to destination. However, depending on the signaling approach adopted, switching a flow from one path to another requires time and overhead. Therefore, in general, an energy management mechanism should avoid rerouting flows too often.

In this paper, we consider the problem of optimizing communication networks energy management, assuming that traffic varies according to a given set of time period scenarios and that routing is handled per flow over a single path (unsplittable flow).[1] The model is an operational planning one that takes as entry the expected demands for each time period and proposes an energy-aware traffic engineering solution. From that model, we also extract a heuristic to recreate online operation. When compared to the state of the art presented in Section II, the modeling and optimization approach provides the following novel contributions.

- We explicitly model a set of traffic scenarios corresponding to different time periods and jointly optimize energy consumption over all scenarios in order to capture network management dynamics.
- We consider a per-flow routing mechanism over a single path (unsplittable flows).
- We model two routing strategies (fixed and variable) and compare them in terms of consumption and quality-of-service requirements.
- We use a quite detailed model of router considering it composed of a chassis (that includes the main processing module) and a set of line cards (where transmission links are connected). Based on that model, we use the energy consumption figures of real routers to obtain numerical results.
- We provide a problem formulation based on integer linear programming (ILP) and solve it to the optimum.
- We provide a heuristic close to the online implementation and assess the differences with the offline energy optimization scheme.

The remainder of this paper is organized as follows. In Section II, we review previous papers on green networking and point out the novelties of our work. In Section III, we present the energy management strategy proposed and the system modeling assumption. In Section IV, the mathematical formulation is described in detail, and two versions of the problem are presented. A set of numerical results obtained on different network instances and with different values of the model parameters are shown and discussed in Sections V, VI-A, and VII. Finally, concluding remarks follow in Section VIII.

II. Related Work

The problem of energy consumption of the Internet and the main technical challenges to reduce it have been presented in the seminal work by Gupta and Singh [13]. In the last years, several approaches have been proposed to cope with the problem considering both wireless [4], [14]–[16] and wired networks. In this section, we focus on wired networks only.

Recently, some papers have provided a complete survey of the research on the topic by proposing different taxonomies for the classification of the various green techniques [7], [17]–[19]. In particular, different types of energy-saving approaches have been divided into three categories in [7]: 1) techniques for resource virtualization in end-systems; 2) methodologies for power management and network design; and 3) advanced technologies and architectures for networking devices. Our work falls in the second group. In [17], an interesting classification of the work in this area is proposed based on: 1) target: the element analyzed to obtain the power consumption reduction (communication mediums, network devices, and paths); 2) technique: the technology adopted to reduce energy consumption (new materials and fabrication techniques, switching off techniques, integration of physical components); 3) metric: specific goal of the energy-saving policies. In this paper, the target is the set of paths over which traffic flows are routed, the technique is the switching off of devices and their parts, and the metric is the total energy consumption of the network.

One of the key elements in the study of energy-saving techniques for communication is the definition of energy consumption models. In [20], a consumption model of optical IP networks is presented. In [21], a network-based model for the measurements of Internet power consumption is exposed, where networks are divided into access, metro, and core. Our energy management strategy applies mainly to core and metro networks.

ISPs networks are dimensioned to satisfy estimated peak traffic conditions. However, the traffic level follows a daily periodic behavior [22], while energy consumption is almost constant [8], [9]. The idea of applying sleeping strategies to the different network devices during low traffic periods is the main one discussed in the Gupta and Singh's paper [13].

More recently, other articles have defined strategies to manage individual network devices' low consumption states. In [23], the bursty behavior of Internet traffic is exploited by a sleeping procedure based on a prediction algorithm for the length of the idle periods. The characterization of the Internet traffic generated by personal computers is also exploited in [24] to define a proxying strategy for network access devices.

Instead of switching off the whole device, another approach is to try to make its energy consumption proportional to traffic load. In [10], an analytical framework is proposed to explore the optimal frequency operation of individual hardware equipment such as switches and routers so that power consumption is minimized. Considering Layer-2 switches, Adaptive Link Layer (ALR) is a proposal to change the capacity of the Ethernet links so that lower loads are treated with lower levels of capacity, which induces a lower consumption [25]–[27]. Energy Efficient Ethernet (EEE) is the standardization framework of the IEEE 802.3 az engineering task force concerning Ethernet power reduction, where also shutting down Ethernet links when there is no load present is considered [28]. The energy management strategies just described focus on individual devices. In our work, we apply the energy-saving procedures at the network level and manage network traffic in a coordinated way in order to power on only a subset of the available devices and links.

[1]Preliminary results have been presented in [11] and [12].

In [8], a network design model that considers the consumption of different configurations of chassis and line cards is presented. The target is to minimize the network consumption, guaranteeing robustness and good congestion performance. Reference [29] presents a procedure that aims at saving energy by exploiting dynamic topology. In [30], the characteristics of the electric market in the US is analyzed, and a cost-aware routing policy for service requests that selects the location with the cheapest electric price is presented.

Previous papers closer to our work deal with the energy-aware management of the network as a whole [31]–[38]. Reference [31] discusses advantages of sleep mode and rate adaptation based on power profile of network equipments. The other work on energy-aware network management can be classified according to the routing scheme considered.

The per-flow routing considered here is also adopted in [33] and [35]. The approach to offline energy management proposed in [33] makes use of an optimization framework that aims at minimizing the global network energy consumption by switching off nodes and interfaces. The mathematical formulation is based on the classical capacitated network design (CMCF) problem with splittable flows, while a single set of traffic demands is considered. On the other hand, we model a set of traffic scenarios corresponding to different time periods and jointly optimize energy management in all scenarios. We assume a single path routing (unsplittable flows) that can be applied to MPLS-based networks and consider limitations to routing changes and state variations of devices. Some online energy-aware traffic engineering (EATe) techniques for optimizing links and routers power consumption are instead proposed in [35]; these online procedures exploit a local search scheme and are based on the assumption that the energy profiles of network devices are strongly dependent on the utilization.

Networks operated with shortest-path routing protocols (e.g., OSPF) are instead treated in [32], [34], and [37], but none of those papers considers either multiperiod optimization or interperiod constraints like we do. In [37], some efficient heuristic algorithms are presented. They are able to lexicographically optimize network energy consumption (by switching off both links and nodes) and network congestion by efficiently configuring the link weights. Also, [34] aims at minimizing network energy consumption by operating on the link weights, but differently from [37], no congestion optimization is considered, and only links can be switched off. The Energy Aware Routing (EAR) algorithm presented in [32] proposes the switching off of network elements by exploiting a modified version of the OSPF protocol where only a subset of routers can compute the shortest-path trees. This energy management approach focuses only on the routing protocol and does not directly consider traffic demands and network capacity limitations.

Finally, [36] and [38] are based on less common routing schemes. In [38], a hybrid routing is proposed where both shortest-path and per-flow routing is performed; they aim at switching off the network links while guaranteeing QoS constraints (maximum utilization and maximum path length constraints). The approach is based on a mixed integer programming (MIP) formulation where the traffic demands are routed through a set of precalculated k-shortest paths. Reference [36] proposes, instead, a new mixed ILP (MILP)-based approach to jointly optimize energy consumptions and network congestion in networks operated with carrier-grade Ethernet.

Lastly, part of the literature is also focused into studying and analyzing the potential impact and the effective applicability of the different strategies for energy-aware network management [39]–[42].

To the best of our knowledge, no other work concerning a multiperiod energy-aware optimization with interperiod constraints for IP networks have been presented before.

III. Energy Management Strategy

The problem we now present is the management of network devices in order to save energy, exploiting the possibility of switching off the network resources, namely routers and links, when they are not necessary. Even if, in this work, we do not address implementation issues, we assume that the energy management strategy can be integrated in the commonly adopted network management platforms. Such platforms allow the centralized and remote control of all devices and the change of their configuration (change of routing settings, switch between active/sleep modes) with relatively slow dynamics (hours) [43]. Moreover, we assume the availability of daily traffic profiles for the network that consider traffic variations over different time intervals. These are predictions based on traffic measurements collected by the network monitoring agents commonly used by network operators to gather statistics on key parameters and check network proper operation. In normal conditions, traffic profiles can be predicted with good accuracy and allow planning network resources allocation in advance with limited uncertainty margins [44]. However, in some cases, traffic statistics may change unexpectedly due to external events. For this reason, in the last part of this paper, we also consider the case where resources are managed over a shorter time period in a more dynamic way. In its basic version, the considered optimization problem has the general goal of minimizing the overall energy consumption, given an estimated traffic demand. It is easy to see that such version of the problem is equivalent to classical network design problems [45]: Objective function costs are related to device energy consumption instead of to deployment costs, and the network topology is fixed to the actual one. Such equivalence has been exploited in [33] to define energy-efficient network management approaches.

However, the key element that allows intelligent energy management is the traffic variation over a given time horizon, for instance a day. We divide the considered time horizon into time intervals. During the time horizon, the demand patterns, which we call traffic scenarios, will vary both geographically and in intensity. However, in each time interval, the demands are assumed to be constant. The time horizon and the demand profile are cyclically repeated. Thus, the optimization strategy can be applied over a long-term period. We argue that the energy consumption cannot be optimized considering different traffic scenarios separately, but they need to be jointly considered to take into account the constraints on routing, the signaling overhead for network reconfiguration, the impact on powering the equipment on and off, and the possible quality degradation due to route changes.

The estimation of traffic demand is usually not an easy task for network designers. However, as the network is already in operation, it is reasonable to assume that rather accurate estimations can be obtained by observing the previous intervals using the network monitoring agents commonly available in the management platform.

We consider a router model that reflects the most common architecture adopted by manufacturers. The device includes a chassis, which provides computation and switching functionalities, and a set of line cards, which provides communication interfaces and usually additional network processing capabilities.

In our model, router elements can be switched on and off by the management platform, and there is an energy consumption associated to each of them. The chassis can be powered off only when all its line cards are off. Depending on the considered router type, there may be some additional energy consuming elements, such as cooling fans, not taken into account in the model. However, their energy consumption can be easily included in those of other elements, for example in the chassis one, if they have a fixed speed, and divided among chassis and line cards, if their speed is controlled. Since this model closely reflects the architecture of devices available on the market, it is relatively easy to apply using real consumption values. In our numerical analysis, we use public information provided for a set of router types by a device manufacturer, namely Juniper.

We also assume that an energy consumption is associated to the chassis change of state from *off* to *on*. This corresponds to the energy spent during the powering on phase that, for big and complex devices, can last several minutes. Furthermore, we can use this model parameter to give a penalty to state transitions. This allows to limit the configuration changes in the network and their negative effects on signaling overhead and service quality experienced by traffic flows. We also explicitly consider the possibility of setting a hard limit on the number of state changes of each card element. Note that these are the first elements in our model that link traffic scenarios together, thus requiring a joint optimization.

Another important issue that connects the network configurations in the different time intervals is the routing. We study two variants of the problem. In the first one, the routing is fixed. In the second one, the routing can vary according to the different network equipment and demand conditions. In both cases, we select a single path per flow: In the first case, it remains the same for all intervals, while in the second one it can vary. This routing model is well suited for ISP networks adopting MPLS.

The objective of the problem is to minimize the overall energy consumption during the given time horizon while satisfying the demands in every interval. In Section IV, we provide more details of the problem and describe the mathematical formulation.

IV. Mathematical Formulation

A. Description

A router is composed of a chassis and a set of line cards that allow it to connect to other devices. We assume that links connecting different routers are full-duplex with equal capacity in both directions. Multiple cards of the same type can be used on the same link. We represent the considered network structure with a symmetric directed graph $G(N, A)$, where the set of graph nodes N represents the routers, and the set of arcs A represents the connection between routers, given by links and cards. Since the cards associated with an arc can be switched on and off independently, the arc has multiple states of operation depending on the number of active cards. Note that in the remainder of this paper, we will refer to the connection between two nodes i and j by interchangeably using the two terms arc and link.

The capacity available on a given arc depends on the number of active line cards: Given an arc (i, j), we use an integer variable w_{ij} to represent the number of line cards that have to be powered on in order to provide enough capacity to meet the traffic routed from node i to node j As the network links provide equal capacity in both directions, we must set $w_{ij} = w_{ji}$. In most of our numerical results, we use two cards per link, therefore $w_{ij} \in \{0, 1, 2\}$. We use a parameter μ to denote the maximum fraction of link capacity that can be used. This allows to take into account quality-of-service constraints in network dimensioning and to evaluate the tradeoff between quality and energy consumption.

With respect to the chassis, we assume that it can be either on or off. Clearly, if the chassis is off, all cards, and therefore the links associated with them, will be powered down as well. Thus, to have an idea of the number of states involved in the management, let us assume that each router can connect to four other devices through eight cards, then the number of possible states for each node is $3^4 + 1$.[2]

Another important modeling aspect is the temporal nature of the problem. In fact, the demand varies during the day, and an effective management scheme should take this fact into account to be able to reduce the power consumption. Therefore, we consider that there is a set of scenarios S associated with different hours of the day.

We now have all the elements to define the following sets of parameters and decision variables to proceed to our mathematical modeling.

Parameters

n_{ij}	Number of cards available on link (i, j).
γ	Per-card capacity. The total link capacity is $n_{ij}\gamma$.
μ	A fractional parameter, representing the maximal fraction of the arc capacity that can be used to deal with traffic demand. This parameter is used to ensure congestion control.
π_{ij}	The power consumption of a card associated to arc (i, j) when it is on.
η	Maximum number of switch-on allowed for each card for all traffic scenarios.
Γ	The chassis maximum capacity.
$\bar{\pi}$	The chassis power consumption when on.
D	The set of origin–destination (O/D) demands in the network.
o_d	The origin of O/D demand $d \in D$.
t_d	The destination of O/D demand $d \in D$.
$q_{d\sigma}$	The value of demand $d \in D$ in scenario $\sigma \in \mathcal{S}$.

[2]The additional 1 is because we consider that powering down the chassis is different than powering down all the cards

h_σ The duration of scenario $\sigma \in \mathcal{S}$.

δ Fractional value, representing the chassis energy consumption when switched on from an off state, normalized with respect to hourly chassis consumption.

VARIABLES

x_{ij}^d Routing variable equal to 1 if the demand d is routed on link (i, j), and 0 otherwise.

y_j^σ Chassis status variable equal to 1 if a chassis j is on in scenario σ, and 0 otherwise.

w_{ij}^σ Status variable of link (i, j). It is an integer between 0 and n_{ij}, indicating the number of active cards on link (i, j) in scenario σ.

u_{ijk}^σ Auxiliary variable that is equal to 1 if the kth card linking nodes i and j is switched on in scenario σ.

z_j^σ Energy consumption variable for switching the chassis on from off; it is equal to $\delta\bar{\pi}$ if the chassis j is switched on in scenario σ, and 0 otherwise.

B. Power-Aware Fixed Routing Problem (PAFRP)

In this first problem, the routing is fixed over all scenarios $\sigma \in S$. The objective is to minimize the energy consumption (expressed in watts) subject to routing, system, and operational constraints. We now present in detail each term of the formulation.

1) Objective Function:

$$\min \sum_{\sigma \in S} h_\sigma \sum_{j \in N} \bar{\pi} y_j^\sigma + \sum_{\sigma \in S} h_\sigma \sum_{(i,j) \in A} \pi_{ij} w_{ij}^\sigma + \sum_{\sigma \in S} \sum_{j \in N} z_j^\sigma. \tag{1}$$

The objective is composed of three terms. The first corresponds to the energy consumption due to switched on chassis. The second is the energy consumed by the link cards when they are powered. The final term represents the chassis consumption when they are switched on from an off state.

2) Flow Conservation Constraints:

$$\sum_{\substack{j \in N: \\ (i,j) \in A}} x_{ij}^d - \sum_{\substack{j \in N: \\ (j,i) \in A}} x_{ji}^d = \begin{cases} 1, & \text{if } i = o_d \\ -1, & \text{if } i = t_d \\ 0, & \text{otherwise} \end{cases} \quad \forall i \in N, \forall d \in D. \tag{2}$$

The constraints guarantee that each demand is transported from its origin to its destination.

3) Chassis Capacity Constraints:

$$\sum_{\substack{i \in N: \\ (i,j) \in A}} \sum_{d \in D} q_{d\sigma} x_{ij}^d + \sum_{\substack{i \in N: \\ (j,i) \in A}} \sum_{d \in D} q_{d\sigma} x_{ji}^d \le \Gamma y_j^\sigma \quad \forall j \in N, \forall \sigma \in S. \tag{3}$$

The constraints impose that the total capacity incident to a node must be lower than the maximum capacity allocated to the chassis. They also force the chassis to be switched on where there is at least one demand incident to it.

4) Power Switching Constraints:

$$z_j^\sigma \ge \delta\bar{\pi}\left(y_j^\sigma - y_j^{\sigma-1}\right) \qquad \forall j \in N, \quad \forall \sigma \in S. \tag{4}$$

These constraints force the value of variable z_j^σ to be equal to $\delta\bar{\pi}$ when the chassis j switches from an off state to an on state.

5) Arc Capacity Constraints:

$$\sum_{d \in D} q_{d\sigma} x_{ij}^d \le \mu\gamma w_{ij}^\sigma \qquad \forall (i,j) \in A, \quad \forall \sigma \in S. \tag{5}$$

These constraints state that the capacity available on each arc depends on the state of the corresponding cards.

6) Link-State Constraints:

$$w_{ij}^\sigma = w_{ji}^\sigma \qquad \forall \sigma \in S, \quad \forall (i,j) \in A : i < j \tag{6}$$

$$\sum_{k=1}^{n_{ij}} u_{ijk}^\sigma \ge w_{ij}^\sigma - w_{ij}^{\sigma-1} \qquad \forall (i,j) \in A, \quad \forall \sigma \in S. \tag{7}$$

The first set of constraints (6) forces the state of arc (i, j) to be the same as the state of arc (j, i), and therefore forces the state of a pair of cards connecting two routers to be the same. The second sets of constraints (7) insures that auxiliary variables u assume the appropriate values as a function of the state of the corresponding links. When m cards of a link (i, j) are switched on ($w_{ij}^\sigma - w_{ij}^{\sigma-1}$ is strictly positive and equal to m), then m of the u variables, associated to link (i, j), must be equal to 1.

7) Card Reliability Restriction Constraints:

$$\sum_{\sigma \in S} u_{ijk}^\sigma \le \eta \qquad \forall (i,j) \in A, \quad \forall k. \tag{8}$$

The constraints above are related to the reliability of the hardware. In fact, it is well known that switching hardware on and off may reduce the lifetime of it and can cause, eventually, its dysfunction. For that purpose, we have added these constraints that, unless specified otherwise, limit to one the number of times a card can be switched on in the given time interval.

8) Decision Variable Domains:

$$x_{ij}^d \in \{0,1\} \qquad \forall d \in D, \quad \forall (i,j) \in A \tag{9}$$

$$y_j^\sigma \in \{0,1\} \qquad \forall \sigma \in S, \quad \forall j \in N \tag{10}$$

$$z_j^\sigma \ge 0 \qquad \forall \sigma \in S, \quad \forall j \in N \tag{11}$$

$$w_{ij}^\sigma \in \{0,\ldots,n_{ij}\} \qquad \forall \sigma \in S, \quad \forall (i,j) \in A \tag{12}$$

$$u_{ijk}^\sigma \in \{0,1\} \qquad \forall \sigma \in S, \forall (i,j) \in A, \forall k \in \{1,\ldots,n_{ij}\}. \tag{13}$$

C. Power-Aware Variable Routing Problem

To represent the possibility of adapting the routing to the changing demand over time, variable x_{ij}^d is replaced by $x_{ij}^{d\sigma}$.

The resulting variable power-aware routing problem is similar to the fixed routing model, and for the sake of brevity, we report here only the changes in the model.

The objective function is the same (1). Flow conservation constraints are now given by

$$\sum_{\substack{j \in N: \\ (i,j) \in A}} x_{ij}^{d\sigma} - \sum_{\substack{j \in N: \\ (j,i) \in A}} x_{ji}^{d\sigma} = \begin{cases} 1, & \text{if } i = o_d \\ -1, & \text{if } i = t_d \\ 0, & \text{otherwise} \end{cases} \quad \forall i \in N, \quad \forall d \in D, \quad \forall \sigma \in S \tag{14}$$

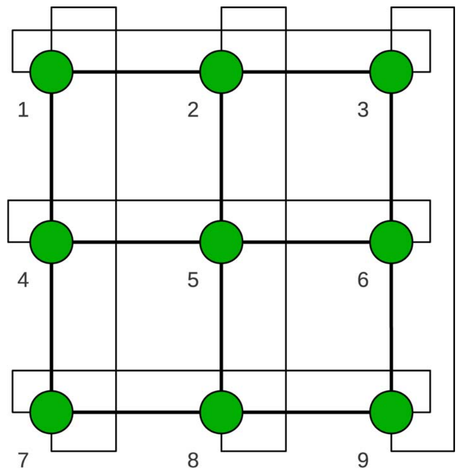

Fig. 1. Network with 9 nodes.

while chassis capacity constraints are modified as

$$\sum_{\substack{i\in N:\\(i,j)\in A}} \sum_{d\in D} q_{d\sigma} x_{ij}^{d\sigma} + \sum_{\substack{i\in N:\\(j,i)\in A}} \sum_{d\in D} q_{d\sigma} x_{ji}^{d\sigma} \le \Gamma y_j^\sigma \qquad \forall j \in N, \quad \forall \sigma \in S. \quad (15)$$

Power switching constraints are the same as in (4), while arc capacity constraints are given by

$$\sum_{d\in D} q_{d\sigma} x_{ij}^{d\sigma} \le \mu\gamma w_{ij}^\sigma \qquad \forall (i,j) \in A, \quad \forall \sigma \in S. \quad (16)$$

Link-state constraints remain unchanged [(6) and (7)], as well as card reliability restriction constraints (8).

Decision variable domains are obviously unchanged except for new variables $x_{ij}^{d\sigma}$, which are now

$$x_{ij}^{d\sigma} \in \{0,1\} \qquad \forall d \in D, \quad \forall \sigma \in S, \quad \forall (i,j) \in A. \quad (17)$$

V. Computational Results

A. Description of the Instances

1) Network Topologies: Three different network topologies were chosen, respectively with 9 (see Fig. 1), 25, and 28 nodes. The two larger topologies belong to the largely used SND-Library [46] (see [47] for the figures of the two SNDLib networks). The 9-node simple network topology will be used for a thorough understanding of the results, while the other topologies confirm the findings for larger and more realistic networks.

2) Network Capacity: Three network capacity cases, called A, B, and C, are considered. For each case, all the routers are assumed to be the same, composed by a single chassis and a given type of cards. Their capacity and consumption are provided in Table I.

3) Network Demand: The network demand evaluation is divided into two problems: how to set a nominal demand for the network and how to characterize the different traffic scenarios.

a) Nominal Demand: All the traffic scenarios considered are generated defining them as a fraction of a nominal demand value that has been set for each of the networks.

TABLE I
Router Chassis and Cards

Chassis features			
case	device	capacity	hourly power cons.
all	Chassis Juniper M10i	16Gbps	86.4 W
Cards features			
case	device	capacity	hourly power cons.
A	FE 4 ports	400 Mbps	6.8 W
B	OC-3c 1 port	155 Mbps	18.6 W
C	GE 1 port	1 Gbps	7.3 W

To make a fair evaluation of the possible energy savings achievable through the proposed energy management strategy, we set the nominal value according to a procedure aiming at finding the highest feasible traffic level according to link capacities. Obviously, we expect that in real networks that have been well dimensioned, the traffic load will be well below that nominal even at peak hour. However, this allows a clear reference point in our analysis.

The used procedure can be explained as follows.

Nominal Demand Algorithm:

1) The set of origin-destination demands is split into two subsets, chosen beforehand deterministically: The demands of one subset have a traffic amount that is greater than the demand of the other subset (twice, in particular).
2) All demands are assigned an intensity equal to a fraction of the card capacity (and twice such value for some pairs). The starting fraction is 1/4.
3) Demands are routed in the network through an ILP model. In particular, we use the feasibility version of the FPARP model using a single scenario and demands to their nominal values [i.e., (2), (3), (5), (6)].
4) If a feasible routing is found, the intensity is increased by the starting fraction, and the demands are routed again; otherwise, the nominal value is the greatest one for which a feasible routing can be found.
5) The resulting fraction multiplied by the card capacity for all origin destination demands results in what we call *the network nominal traffic demand*.

b) Traffic scenarios: The modeling approach presented in Section IV is based on *time scenarios*, that is, a partition of the considered time horizon—a day in this study. We assume that the traffic demands vary during the day and, therefore, different traffic values must be generated in a systematic manner. Obviously, the model is general and can be used with arbitrary traffic profiles. Numerical results are obtained using realistic traffic patterns commonly measured by network operators with a peak during mornings and a second lower peak during afternoons. We consider six traffic scenarios corresponding to the following time intervals: 1) 8–11 a.m.; 2) 11 a.m.–1 p.m.; 3) 1–2.30 p.m.; 4) 2.30–6.30 p.m.; 5) 6.30–10.30 p.m.; 6) 10.30 p.m.–8 a.m. For each scenario and topology, each origin–destination demand intensity is randomly generated using a uniform distribution [values are sampled in $(Av-0.2, Av+0.2)$, with average values Av for each scenario as shown in Fig. 2]. The obtained random values are multiplied by the nominal demand.

In what follows, three different stochastic draws will be considered, based on three different random seeds. The realizations are named a, b, and c, respectively.

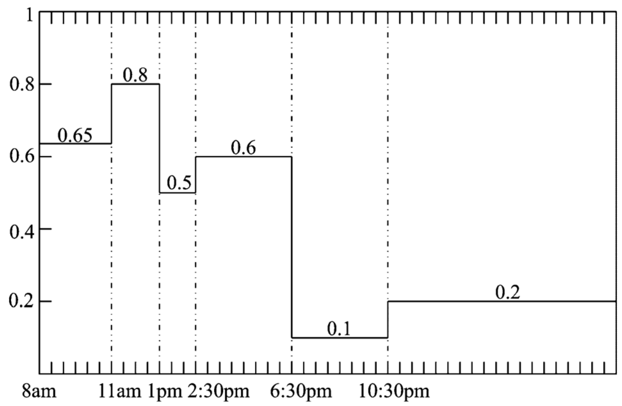

Fig. 2. Traffic scenarios: Average fraction (y-axis) of the nominal value used in given scenario.

B. Results for Small Instances

The tests have been carried out on Intel i7 processors with 4-core and multithread 8x, equipped with 8 GB of RAM. To clearly grasp the impact of the optimization procedure, we present detailed results for the (C, c, 9-nodes) case (device C, random draw c, 9-nodes network topology). We consider that at most one switch-on per device is allowed in the considered time horizon and that the value of δ is equal to 0.5. The value of μ is set to 0.5. CPLEX solves to optimality all the instances within few seconds.

1) Switching Patterns: In Tables II and III, we provide details on the number of active cards and chassis. In particular, Table II gives the number of active cards per link and per scenario, both for fixed and variable routing. Table III gives the chassis statuses (1 if it is on) for the fixed routing; variable routing values are reported only when they differ from the fixed routing ones.

TABLE II
CARD STATUS DETAILS FOR THE 9-NODE NETWORK

	Fixed Routing						Variable Routing					
Card	8 11	11 1	1 2.30	2.30 6.30	6.30 10.30	10.30 8	8 11	11 1	1 2.30	2.30 6.30	6.30 10.30	10.30 8
2-5	0	0	0	0	0	0	0	0	0	0	0	0
4-5	0	0	0	0	0	0	0	0	0	0	0	0
5-6	0	0	0	0	0	0	0	0	0	0	0	0
5-8	0	0	0	0	0	0	0	0	0	0	0	0
1-2	0	0	0	0	0	0	0	2	0	0	0	0
2-3	0	0	0	0	0	0	0	2	0	0	0	0
2-8	0	0	0	0	0	0	0	2	0	0	0	0
7-8	0	0	0	0	0	0	0	2	0	0	0	0
8-9	0	0	0	0	0	0	0	2	0	0	0	0
1-4	2	2	1	2	1	1	0	0	0	1	0	0
6-9	2	2	1	2	1	1	2	2	1	2	1	1
4-7	2	2	2	2	1	1	0	0	0	1	0	0
1-7	2	2	2	2	1	1	2	2	2	2	0	1
1-3	2	2	2	2	1	1	2	2	2	2	1	1
3-6	2	2	2	2	1	1	2	2	2	2	1	1
3-9	2	2	2	2	1	1	2	2	2	2	1	1
4-6	2	2	2	2	1	1	2	2	2	2	1	1
7-9	2	2	2	2	1	1	2	2	2	2	1	1
sum	18	18	16	18	9	9	14	26	13	16	6	7

TABLE III
CHASSIS STATUS DETAILS FOR THE 9-NODE NETWORK

Chassis	8a.m. 11a.m.	11a.m. 1p.m.	1p.m. 2.30p.m.	2.30p.m. 6.30p.m.	6.30p.m. 10.30p.m.	10.30p.m. 8a.m.
5	0	0	0	0	0	0
2	0	0/**1**	0	0	0	0
8	0	0/**1**	0	0	0	0
1	1	1	1	1	1	1
3	1	1	1	1	1	1
4	1	1	1	1	1	1
6	1	1	1	1	1	1
7	1	1	1	1	1	1
9	1	1	1	1	1	1

Considering the fixed routing case, we obtain only three switching patterns for the six scenarios. In the first one, 18 cards are active, and it corresponds to three scenarios (8–11 a.m.), (11 a.m.–1 p.m.), and (2.30–6.30 p.m.). In the second one, 16 cards are active, and it corresponds to scenario (1–2.30 p.m.), while in the third one, only 9 cards are active, and it corresponds to scenarios (6.30–10.30 p.m.) and (10.30 p.m.–8 a.m.). It is worth noticing that the first and second switching patterns are quite similar, as they differ only on two card statuses.

We observe that the strong constraint of using a fixed routing for all traffic scenarios greatly limits the ability of the energy management mechanism to follow traffic variations, changing the activation status of routers and line cards. Nevertheless, the optimization procedure allows to reduce the energy consumption, switching off several routers and lines cards. Moreover, since a large fraction of the energy consumption of a router is due to the chassis (59.7% in the case considered), the optimal energy management strategy privileges solutions where whole routers are powered off.

When variable routing is considered, we get six different switching patterns, one for each scenario (Table II).

As expected, in the case of variable routing, the energy management follows closer the traffic variations changing the network configuration, even if we limit to one the number of switch-ons per network element. Moreover, the patterns are rather different from one another, ranging from the case of scenario (11 a.m.–1 p.m.), where 26 cards are powered on, to scenario (6.30–10.30 p.m.), where only 6 cards are powered on. It is worth noticing that, in the variable routing case, scenario (11 a.m.–1 p.m.) presents two more chassis powered on when compared to the fixed routing case. This allows more flexibility in the switching on and off of cards and, as a consequence, in the changing of the routing (see Table IV).

2) Power and Energy Savings: The behavior observed with the switching patterns is confirmed by the numerical results on energy consumption. In Fig. 3, we present the differences in hourly power consumption between the reference case where all devices are switched on and the optimized cases with variable and fixed routing. It can be appreciated that the flexibility of the variable routing allows to obtain an energy consumption profile that is almost proportional to traffic load (it can be compared to the traffic profile shown in Fig. 2). Moreover, we observe that variable routing produces a power profile that is always lower than that of the fixed routing.

In terms of energy saving, Fig. 4 presents the overall energy savings achieved in the different time intervals. Both in the case of fixed and variable routing, optimal energy management allows to save more during the interval with the smallest traffic amount, namely the night. In fact, as can be expected, keeping all the devices switched on during nighttime causes a great energy waste. As expected, the highest saving is achieved for variable routing.

TABLE IV
ROUTING DETAILS FOR THE 9-NODE NETWORK

Demand		Fixed Routing	Variable Routing					
O-D	Nominal value		8-11a.m.	11a.m.-1p.m.	1-2.30p.m.	2.30-6.30p.m.	6.30-10:30p.m.	10.30p.m.-8a.m.
(1,3)	0.5	1-3	1-3	1-2-3	1-3	1-3	1-3	1-3
(1,9)	1.0	1-4-6-9	1-3-9	1-3-9	1-3-9	1-3-9	1-3-9	1-3-9
(1,7)	0.5	1-7	1-7	1-2-8-7	1-7	1-4-7	1-3-9-7	1-7
(3,9)	0.5	3-9	3-9	3-2-8-9	3-9	3-9	3-9	3-1-7-9
(3,7)	1.0	3-6-4-7	3-1-7	3-1-7	3-1-7	3-1-7	3-9-7	3-1-7
(9,7)	0.5	9-3-1-7	9-7	9-8-7	9-7	9-7	9-7	9-7
(3,1)	0.5	3-1	3-1	3-2-1	3-1	3-1	3-1	3-1
(9,1)	1.0	9-7-1	9-7-1	9-7-1	9-7-1	9-7-1	9-3-1	9-3-1
(7,1)	0.5	7-4-1	7-1	7-8-2-1	7-1	7-1	7-9-3-1	7-1
(9,3)	0.5	9-3	9-3	9-8-2-3	9-3	9-3	9-3	9-3
(7,3)	1.0	7-9-6-3	7-9-3	7-9-3	7-9-3	7-9-3	7-9-3	7-1-3
(7,9)	0.5	7-4-1-3-9	7-9	7-8-9	7-9	7-9	7-9	7-9

TABLE V
COMPARATIVE NORMALIZED CONSUMPTION PER HOUR (WITH RESPECT TO THE REFERENCE CASE) AND CONGESTION: FIXED/VARIABLE ROUTING CASE

Instance		Normalized Consumption							Congestion
		Daily	8	11	1	2.30	6.30	10.30	(ms/Mb)
dev.	μ	cons.	11	1	2.30	6.30	10.30	8	
A	0.5	0.54/**0.38**	0.60/**0.50**	**0.60**/**0.60**	0.57/**0.36**	0.60/**0.46**	0.51/**0.30**	0.51/**0.31**	**5.33**/4.70
A	0.6	0.51/**0.35**	0.54/**0.36**	**0.56**/0.59	0.52/**0.35**	0.55/**0.36**	0.49/**0.30**	0.49/**0.30**	**5.63**/5.25
A	0.7	0.36/**0.32**	0.39/**0.35**	**0.39**/0.40	0.39/**0.34**	0.39/**0.35**	0.35/**0.30**	0.35/**0.30**	4.41/**6.46**
B	0.5	0.47/**0.31**	0.55/**0.42**	**0.55**/**0.55**	0.50/**0.30**	0.55/**0.38**	0.40/**0.22**	0.40/**0.23**	**13.73**/12.14
B	0.6	0.42/**0.27**	0.46/**0.30**	**0.49**/0.51	0.43/**0.29**	0.48/**0.30**	0.38/**0.22**	0.38/**0.22**	**14.52**/13.34
B	0.7	0.28/**0.25**	0.32/**0.29**	**0.33**/**0.33**	0.32/**0.27**	0.32/**0.28**	0.26/**0.22**	0.26/**0.22**	11.38/**16.50**
C	0.5	0.54/**0.38**	0.60/**0.49**	**0.60**/**0.60**	0.56/**0.35**	0.60/**0.45**	0.50/**0.30**	0.50/**0.31**	**2.13**/1.87
C	0.6	0.51/**0.34**	0.53/**0.35**	**0.55**/0.59	0.51/**0.34**	0.54/**0.35**	0.49/**0.30**	0.49/**0.30**	**2.25**/2.11
C	0.7	0.36/**0.32**	0.38/**0.34**	**0.38**/0.39	0.38/**0.33**	0.38/**0.34**	0.34/**0.30**	0.34/**0.30**	1.76/**2.55**

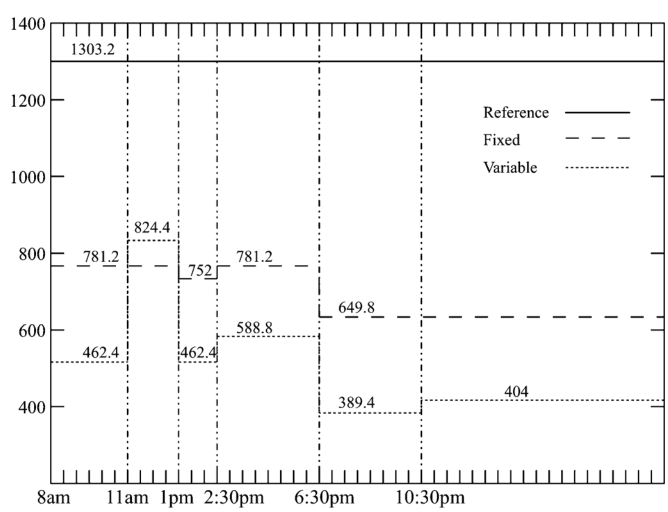

Fig. 3. Hourly power consumption (in W): reference (all devices switched on), fixed routing, and variable routing.

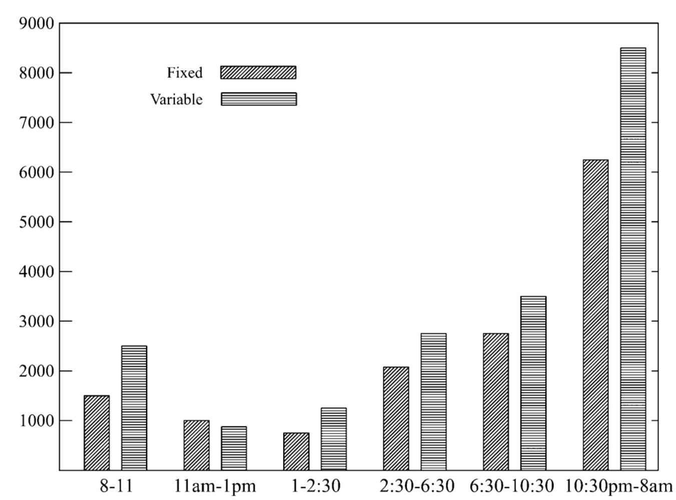

Fig. 4. Overall energy savings (in watthours, Wh) with respect to the reference case: fixed and variable routing.

3) Power and Congestion Comparative Results: Table V presents comparative results between the fixed and variable routing with respect to power consumption and congestion obtained under the following conditions: 1) at most one switch (card); 2) $\delta = 0.5$ (chassis switch consumption); 3) averaged out on three different realizations (a, b, c).

The consumption values are normalized with respect to the power consumption of the reference case. The lowest consumption for each instance is presented in bold. The reader can appreciate that, in the overwhelming majority of the cases, the average consumption is significantly lower for the variable routing case. The last column shows the average arc congestion (see Appendix) for the fixed and the variable routing case, the highest congestion given in bold. Interestingly, congestion is higher in just two cases of variable routing, even though consumption is lower, suggesting that the flexibility of the variable routing is beneficial for both congestion and consumption.

4) Effect of the Card Reliability Restriction Constraint: We have performed several tests for different δ comparing the constrained and the relaxed problem (no limitation on the number of allowed switching on). The results in consumption are very

TABLE VI

TOTAL AND AVERAGE NUMBER OF CARDS HAVING BEEN SWITCHED UP DURING THE STUDY PERIOD FOR DIFFERENT VALUES OF δ, COMPARISON FIXED AND VARIABLE ROUTING

# switch-ups	$\delta = 0.5$ nomax	$\delta = 0.25$ nomax	$\delta = 0.0$ nomax	$\delta = 0.5$ max1	$\delta = 0.25$ max1	$\delta = 0.0$ max1
Total number of cards switched up						
0	1602/1318	1602/1326	1602/1304	1500/1262	1500/1260	1500/1250
1	240/536	240/516	240/548	444/682	444/684	444/694
2	102/90	102/102	102/88	-	-	-
3	0/0	0/0	0/4	-	-	-
Average number of cards switched up						
0	59.33/48.81	59.33/49.11	59.33/48.30	55.56/46.74	55.56/46.67	55.56/46.3
1	8.89/19.85	8.89/19.11	8.89/20.30	16.44/25.26	16.44/25.33	16.44/25.7
2	3.78/3.33	3.78/3.78	3.78/3.26	-	-	-
3	0.00/0.00	0.00/0.00	0.00/0.15	-	-	-

TABLE VII

NORMALIZED CONSUMPTION (WITH RESPECT TO THE REFERENCE CASE) AND NUMBER OF DAILY CARD SWITCHING UP

Instance			VAR, $\delta = 0.25$, $n_{ij} = 2$				VAR, $\delta = 0.25$, $n_{ij} = 1$				FIX, $\delta = 0.25$, $n_{ij} = 2$			
			Energy		Num switch-up		Energy		Num switch-up		Energy		Num switch-up	
ID	dev	rp	max1	nomax	max1	nomax	max1	nomax	max1	nomax	max1	nomax	max1	nomax
france network														
1	A	a	0.57	0.57	76	78	0.60	0.59	36	48	0.63	0.63	44	46
2	A	b	0.58	0.57	80	82	0.60	0.60	40	46	0.66	0.66	48	46
3	A	c	0.57	0.57	72	76	0.59	0.59	34	50	0.63	0.63	44	44
4	B	a	0.47	0.47	74	78	0.54	0.54	38	50	0.54	0.54	44	44
5	B	b	0.47	0.47	80	82	0.54	0.55	36	44	0.56	0.56	46	48
6	B	c	0.46	0.46	72	80	0.53	0.53	32	48	0.54	0.54	44	44
7	C	a	0.56	0.56	72	80	0.59	0.59	38	52	0.63	0.63	44	44
8	C	b	0.57	0.57	80	76	0.60	0.60	42	50	0.70	0.70	44	48
9	C	c	0.56	0.56	72	80	0.59	0.59	40	52	0.63	0.63	44	44
nobel-eu network														
10	A	a	0.59	0.59	56	50	0.66	0.66	30	32	0.67	0.67	40	32
11	A	b	0.59	0.59	54	58	0.66	0.66	26	30	0.67	0.67	32	38
12	A	c	0.59	0.59	60	64	0.66	0.66	32	24	0.67	0.67	36	34
13	B	a	0.49	0.49	58	54	0.62	0.61	22	32	0.57	0.56	26	34
14	B	b	0.49	0.49	64	62	0.61	0.61	40	32	0.56	0.56	38	34
15	B	c	0.49	0.49	64	56	0.61	0.61	44	32	0.56	0.56	34	36
16	C	a	0.59	0.59	50	54	0.66	0.65	20	30	0.66	0.66	32	40
17	C	b	0.58	0.58	54	60	0.65	0.65	32	40	0.66	0.66	36	40
18	C	c	0.58	0.58	62	62	0.66	0.65	40	30	0.66	0.66	30	38

similar and have been omitted for space considerations. However, given such results, as the constraint does not seem to induce many changes, one may wonder if the relaxed problem can provide solutions that naturally restrict the number of switches. We can see in Table VI that this is not the case.

The table presents three cases with $\delta = 0$, $\delta = 0.25$, and $\delta = 0.5$ with and without the switching up constraint. The top part of Table VI presents the total number of cards that have been switched up zero to three times for the fixed and variable routing instances, whereas the bottom presents the average per time scenario.

We can see that even though a large percentage of the cards is switched up one time, regardless of the constraint, when the switching constraint is relaxed, there is still a large percentage of cards that are switched up two or three times.

C. Results for Larger Network Topologies

This section is devoted to the results obtained on the larger instances, based on the *nobel-eu* and on the *france* topologies. Results on such instances show that the conclusions derived from the small instances are still valid for the larger ones. Nine instances are derived for each topology, combining the three different types of devices and three randomly generated demand patterns. All the demands have the same nominal value, computed as described for the smaller instances, and the value of μ is equal to 0.5 for all the instances. The number of nodes which are origin and destination of the traffic demands are 13 for the *france* network and 14 for the *eu-nobel*. The model is solved with CPLEX, with a 6-h time limit.

In Table VII, results are reported. The first and second block of rows are devoted to the *france* and *eu-nobel* networks, respectively. In the first block of columns, the features of the instance are given: ID, types of devices, random realization of the demand pattern—the random profile rp. The second block presents the results obtained with variable routing, $\delta = 0.25$, and $n_{ij} = 2$. The third block shows the results obtained with variable routing, $\delta = 0.25$, and $n_{ij} = 1$. The forth block shows the results obtained with fixed routing, $\delta = 0.25$, and $n_{ij} = 2$. For each instance, the normalized energy consumption is reported as well as the total number of daily switching-up for two cases: 1) the maximum number of allowed switching on for each

TABLE VIII
PERFORMANCE COMPARISON BETWEEN ONLINE AND OFFLINE PROCEDURES: NORMALIZED CONSUMPTION (WITH RESPECT TO THE REFERENCE CASE), NUMBER OF DAILY CARD SWITCHING UP, AND TOTAL NUMBER OF CARDS POWERED ON

Instance			VAR, $\delta = 0.25$, $n_{ij} = 2$, $\mu = 0.5$							
			Offline				Online			
ID	dev	rp	Energy	Gap_{opt}	# Card on	# Switch on	Energy	$Gap_{offline}$	# Card on	# Switch on
france network										
1	A	1	0.570	0.87%	344	76	0.593	4.11%	402	66
2	A	2	0.577	2.54%	342	80	0.603	4.46%	418	72
3	A	3	0.567	0.68%	336	72	0.586	3.42%	386	70
4	B	1	0.469	1.99%	344	74	0.519	10.76%	413	70
5	B	2	0.472	4.21%	344	80	0.508	7.71%	402	66
6	B	3	0.464	1.42%	336	72	0.506	8.97%	394	70
7	C	1	0.563	0.96%	344	72	0.592	5.09%	412	66
8	C	2	0.570	2.26%	340	80	0.593	4.06%	404	70
9	C	3	0.560	0.72%	336	72	0.581	3.64%	386	66
nobel-eu network										
10	A	1	0.569	0.89%	334	56	0.608	2.28%	382	62
11	A	2	0.572	1.54%	326	54	0.602	1.73%	362	56
12	A	3	0.566	0.29%	326	60	0.612	3.34%	372	58
13	B	1	0.468	1.54%	330	58	0.517	4.54%	364	58
14	B	2	0.471	3.08%	324	64	0.510	4.27%	368	56
15	B	3	0.463	0.78%	324	64	0.535	9.21%	378	78
16	C	1	0.563	0.85%	334	50	0.616	4.82%	394	60
17	C	2	0.566	1.48%	324	54	0.621	6.20%	398	66
18	C	3	0.560	0.48%	326	62	0.607	3.55%	372	62

card (η) is set to 1 ($max1$); and 2) the maximum number of allowed switching on for each card (η) is set to 3 ($nomax$).

The results show that variable routing allows to save up to 50% of the daily energy, as was the case for the 9-node instance. The number of cards n_{ij} can influence the performance of the procedure. The energy saving is greater if $n_{ij} = 2$, while the number of cards switching up is reduced if $n_{ij} = 1$. The results confirm that a higher number of cards available on each link achieves a higher energy saving. The fixed routing strongly reduces the total number of switching up, as the cards of the unused links are always off, and at least one card of the used links must remain always on.

Finally it is worth noting that the switching-up constraints do not negatively influence the levels of obtained energy saving.

VI. ONLINE TRAFFIC ENGINEERING APPROACH

As previously mentioned, and given that daily patterns repeat quite regularly, network operators typically have quite reliable estimations of the expected traffic. Thus, a preplanned traffic engineering over a 24-h period is usually possible. However, there may be practical situations where the estimation of a 24-h traffic profile is not possible due to limited information available or to unexpected changes in the traffic demand. In most such cases, it is still possible to make short-term estimations using the traffic measurements provided in real time by the routers. Thus, unexpected traffic variations can be followed in a short time, applying online traffic engineering approaches.

In this section, we show how our model can be exploited to provide an online optimization procedure. The procedure manages energy consumption of one time interval at a time and must be repeated for each time interval. We point out here that the proposed online procedure is not a dynamic algorithm able to follow traffic variations in real time, and it does not make use of stochastic optimization mechanisms. For scenarios with highly varying and unpredictable traffic patterns, the use of dynamic and stochastic methodologies is for sure an interesting option that we leave for further studies.

The energy consumption of one time interval is optimized by solving an ILP model formulated as the one proposed in Section IV, but applied to only one time interval—of course, the demands are assumed to be constant. When the procedure is applied to a new time interval, the impact of chassis switching on and the constraint on the maximum number of cards switching on must be taken into account. Thus, suitable parameters are defined, which represent the energy consumed by chassis switching on in the previously optimized time intervals. Moreover, parameters are defined, which represent the number of switching on of each card in the previously optimized time intervals. Finally, the former status of card and chassis is stored in other parameters. All such parameters are updated any time a new time interval is optimized, according to the derived solution. Such parameters are used in the modified version of constraints (4), (7), and (8).

As we consider demand patterns to be cyclically repeated, to compare online results to offline ones, we assume that the routing and switching pattern is repeated every 24 h. Thus, to guarantee that constraints on card reliability are not violated, if a card has been already switched on η times in the previously optimized time intervals, it is forced to keep its current status (powered on) for the next time intervals. The status can be modified once the cycle corresponding to the considered time horizon is terminated (e.g., after 24 h, all the u^{σ}_{ijk} variables corresponding to the previous optimized scenarios are set to 0).

A. Numerical Results of the Online Procedure

In order to evaluate the performance of the proposed online approach, we apply the online procedure to the instances based on *france* and *eu-nobel* networks. We want to measure the performance degradation due to the limited information available.

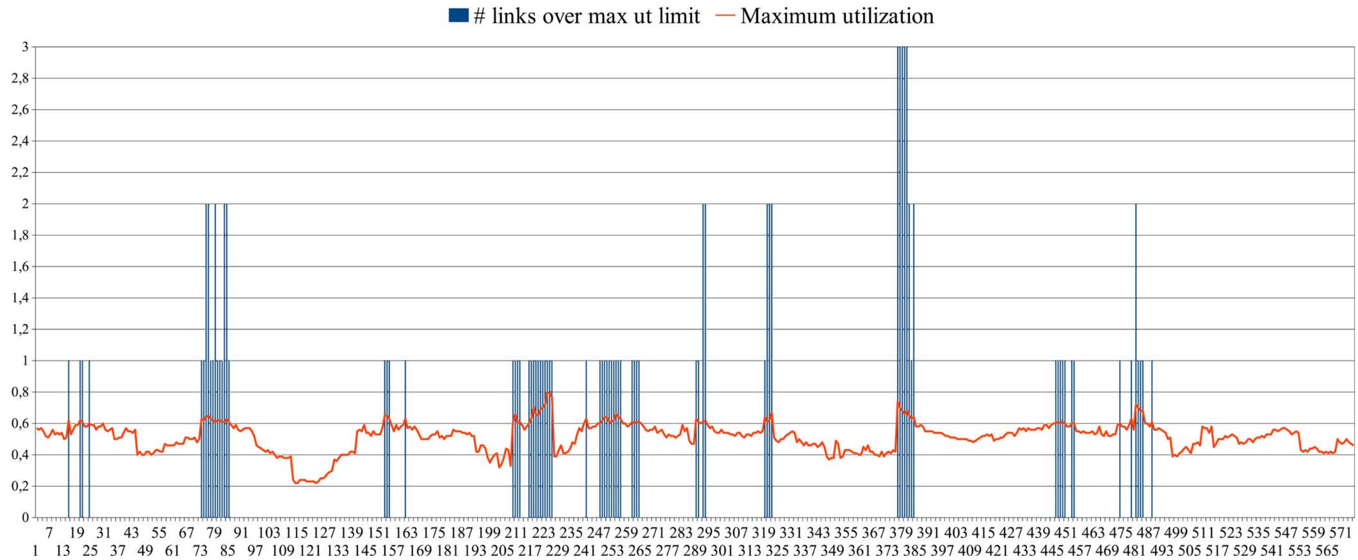

Fig. 5. Maximum utilization values and number of links over the maximum utilization limit during the experimentation with the real traffic matrices.

Starting from a given scenario, we optimized all the scenarios in sequence, solving six optimization problems. All the devices are assumed to be powered on at the beginning. The optimization of a single scenario is stopped after 5 min, as the online procedure is assumed to be applied several times, and therefore it must be fast. As the results on successive scenarios depend on the initial condition—and therefore on the first scenario optimized—we repeat the optimization sequence starting from each scenario, and we report the worst results obtained.

Computational results are shown in Table VIII for the variable routing case where $\delta = 0.25$, $n_{ij} = 2$, and $\mu = 0.5$. The first and second block of rows are devoted to the *france* and *eu-nobel* networks, respectively. For each instance, we report offline model results in the first group of columns and online results in the second group. For each instance, we specify the energy consumption normalized with respect to the case in which all the devices are powered on, the gap percentage w.r.t. the lower bound on the energy consumption, the total number of cards powered on over the whole time horizon, and the total number of cards switching on.

Results show that the online procedure obtains remarkable results in terms of absolute energy saving, with a normalized consumption around 55% for the *france* network and 60% for the *nobel-eu* network. However, as expected, the online procedure provides solutions consuming more energy than those calculated with the offline one. The gap between online and offline solutions is around 5% with a peak of 10% in instances 4 and 15. This is the price to be paid for the limited traffic information used with the online algorithm. Note that the online method generally remains powered on, over the whole time horizon, about 60 cards more than the offline one.

As far as the total number of switching-on is concerned, we observe a different behavior when considering *france* and *nobel-eu* network. In the case of the *france* network, the online procedure switches on a smaller number of cards. This is due to the partial knowledge of the online procedure, which may cause some cards to reach the limit η in the first optimized scenarios. In the case of the *nobel-eu* network, the online method often (see instances 10, 11, and 15–18) switches on more cards than the offline one. However, the number of powered on cards is significantly greater in the online procedure for both sets of instances.

VII. Evaluation With Real Traces

In order to further assess the applicability of our approach, we tested the offline model with variable routing with the *geant* [47] network (23 nodes and 72 links) and a set of real traffic matrices [48]. The set is composed by traffic matrices computed every 15 min for a period of 6 months. Also in this case, we split the single day in six time intervals (4:00–8:30, 8:30–11:00, 11:00–14:00, 14:00–18:00, 18:00–22:00, and 22:00–4:00) according to the traffic profiles of the network. We tested the offline approach for six consecutive days. For each day, we applied the configuration (demand routing and device state) computed w.r.t. the traffic values of the previous day. The value of traffic for a particular demand d in period σ was computed by averaging the traffic values of d among all the real 15-min traffic matrices of the given period. We thus used a very simple traffic forecast based on the average values for each period of the previous day (note that operators can generally have better predictions). Moreover, we set the maximum utilization $\mu = 60\%$, $\delta = 0.25$, $n_{ij} = 1$, and $\eta = 1$. We report in Fig. 5 both the maximum link utilization values and the number of links over the maximum utilization limit registered in each 15-min interval along the entire six days considered for the experimentation. It is important to note that, despite this very simple prediction method, the maximum utilization is generally under the fixed limit, and never over 80%. Moreover, even in the worst case, no more than three links are simultaneously over the limit.

VIII. Conclusion

In this paper, we have tackled the power management problem from two perspectives, the device as well as the network point of view, while specifically exploiting the temporal variations of the demand. From the perspective of the device, we assume that there is the possibility of powering off router cards and even chassis to reduce energy consumption. From the networking standpoint, we take into account the different interactions that relate devices to each other due to the network routing strategy. We presented, to our knowledge, for the first time in the literature, two mathematical models that formulate the optimal router power consumption management, one based on fixed routing, and the other on a more opportunistic type of routing that closely follows the demand variations.

We found that substantial energy savings can be achieved by using our energy management scheme. We also found that variable routing produces a much more efficient power management. Finally, we found that adding the card reliability constraint is important because it does not affect much the savings in terms of consumption, but it restricts the reduction in the lifetime of the equipment that may be caused by switching the cards on and off.

Furthermore, we present an online approach, based on the proposed ILP models, which allows to deal with the energy management problem in case demand previsions are not available or are incomplete. The online approach proves to be quite efficient in providing energy savings. However, due to its incomplete knowledge and to the myopic optimization, the provided savings are worse than those obtained by the offline computed solutions. Thus, even though it is more time-consuming, the offline approach proves to be important to evaluate the best possible savings and should be applied every time a long-term prevision on the demand pattern is available.

APPENDIX

For each scenario $\sigma \in S$, we evaluate the average link congestion as follows. The single link congestion is calculated as

$$\frac{1}{c_{ij} - f_{ij}^{\sigma}} \tag{18}$$

where $f_{ij}^{\sigma} = \sum_{d \in D} q_{d\sigma} x_{ij}^{d\sigma}$ is the flow on card i, j and $c_{ij} = \gamma_{ij} w_{ij}^{\sigma}$ is the capacity of the card i, j. The average congestion is evaluated with respect to active cards only and it is calculated as follows:

$$\frac{1}{\sum_{d \in D} f_d^{\sigma}} \sum_{(i,j) \in A} \frac{f_{ij}^{\sigma}}{(c_{ij} - f_{ij}^{\sigma})} \tag{19}$$

where $f_d^{\sigma} = q_{d\sigma}$ is the flow associated with demand d.

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