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A spatial HMM approach for green networking

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ABSTRACT

Green networking becomes more and more important, especially with the rapid development of data centers in recent years. In this paper, in order to minimize the energy consumption of a network, we present a novel energy saving approach, called Predictive Green Networking Approach (PGNA), based on a spatial Hidden Markov Model (sHMM). The sHMM is proposed to describe both the topology and the traffic distribution of the network. Loads of links in the network can be predicted based on the sHMM, and the links that most likely become near idle can be put into sleep mode to save energy. A *deep-sleep* method is proposed to maximize the energy saving while the network satisfies the connectivity and the maximum utilization constraints. We test the performance of PGNA with two real ISP backbone topologies and real traffic demands. The results show that our approach is effective and works better than related approaches.

1. Introduction

The emission of greenhouse gases (such as CO_2) is increasing faster than originally predicted, and the information and communications technology (ICT) sector is one of major contributors. As we all know, over the last two decades, the ICT equipment is widely used across all industries, including industrial and residential sectors. In the past, ICT equipment is designed aiming at high performance and low cost, regardless of energy consumption and adverse impact on the environment [1]. ICT products and services yielded about 3.9% of total worldwide electricity consumption in 2007, and the number has increased to 4.6% in 2012 [2]. Furthermore, the report in [3] shows that the ICT sector yielded 0.53 billion tones carbon dioxide equivalent in 2002, and the number was expected to 1.43 billion in 2020. Moreover, the equipment in ICT is responsible for 80% of ICT carbon emissions. Thus it is imperative to reduce the energy consumption of ICT, especially for the ICT equipment.

It is well known that the Internet traffic fits the daily pattern, and the network equipment is typically designed for network loads in the peak time in order to guarantee the network performance and traffic growth in the future. Therefore, networking systems are designed traditionally with two flaws: over-provisioning and redundancy [4]. Obviously it is an enormous waste of resources especially when the network is in off-peak time. Hence, it's necessary and also feasible to save energy for the Internet by improving the efficiency and putting spare resources into sleep mode.

Traditional solutions for green networking can be classified into *single element oriented* and *whole network oriented* based on the research objects. The single element oriented solutions focus on reducing energy consumption of a single element (e.g. a line card [5] or a router [6]). In this work, we focus on saving energy for a whole network.

Our aim in this paper is to shut off (i.e., put into sleep mode in this paper) redundant links in the network under the connectivity and the maximum link utilization constraints. We propose a spatial Hidden Markov Model (sHMM) and a sHMM-based solution, called the Predictive Green Networking Approach (PGNA). The sHMM models both the network topology and the traffic distribution over the network. Data of the network topology and traffic matrices of the network collected in the current period are used to train/update the model parameters. Then, the model parameters are applied to predict loads of all links in the next period. The links that most likely become near idle in the next period will be tried to shut off.

A method called *deep-sleep* is proposed to make sure that the number of links to be shut off is maximized and the network satisfies some constraints. The constraints are to keep full connectivity of the network and its maximum link utilization from being increased or beyond over a given limit. Based on this method, if the links to be shut off do not affect already existed "hot" links or cause new "hot" ones, they can be shut off. Therefore, it is expected to shut off more links compared with related works that do not allow existing of any hot link. Because the method can put

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more links into sleep mode, the network seems “sleeping deeper”, without significant degradation of network performance due to the constraints.

To the best of our knowledge, it is the first time to apply a sHMM and the *deep-sleep* method to the energy saving problem. It is also the first time in the wired network to use prediction but present network traffic loads to choose the closable links.

The rest of the paper is organized as follows. Section 2 overviews the related work. Section 3 introduces a sHMM. Then the *deep-sleep* method is proposed in Section 4. Section 5 describes PGNA in details. Section 6 presents a performance analysis for PGNA. Section 7 presents a discussion about the implementation of PGNA. Finally, conclusions are drawn in Section 8.

2. Related work

The green networking in wired networks has been introduced since several years ago. Most of them focused on individual elements (e.g., a line card, a router, or a switch) [5–8]. Most recently, some works began to focus on a whole network instead of a single or few elements. The pioneering work [9] on this subject exploited the impact of network protocols on reducing energy consumption of the Internet, and showed that sleeping is a feasible strategy to save the Internet’s energy consumption. Solutions in [10–14] focused on exploring network topology to save energy without utilizing any knowledge of traffic loads. Among them, [10,11] modified the link-state routing protocol (i.e., OSPF), and [12–14] exploited algebraic connectivity of the topology to detect a set of network links for powering down. The topology oriented solutions work only when the network is in off-peak periods. However, without the knowledge of traffic loads, they cannot guarantee the network performance (e.g., network congestion and packet loss).

In traffic aware solutions, the green networking problem typically uses both the traffic routing and the topology of the network as input, and an Integer Linear Programming (ILP) or a Mixed-Integer Linear Programming (MILP) formulation is applied to solve it. However, the problem turns out to be NP-complete, and therefore heuristic approaches are needed to reduce the computation and make the solution practically. Among those solutions, [15–17] used an ILP to formulate the problem to reduce the energy consumption in an Internet service provider (ISP) backbone network, and proposed corresponding heuristic solutions [18–21]. Similarly, formulated the energy saving problem as an/a ILP/MILP formulation and proposed heuristic algorithms for exploiting bundled links in backbone networks. Andrews et al. [22] tried to reduce energy consumption via *speed scaling* by studying a min-cost integer routing problem, and [23] focused on the energy down model by considering that each network element either works in zero-rate mode or full rate mode. In [24], an energy-aware traffic engineering mechanism was proposed by formulating as a MILP problem, and a heuristic solution was proposed to reduce the computation time by adding a bound on maximum link utilization (e.g. 50%) and reducing the candidate paths to k-shortest paths instead of searching for all paths. Lee et al. [25] took the energy saving problem as a link weight assignment problem for OSPF protocol and also proposed a heuristic approach.

In particular, the solution in [26] tries to minimize energy consumption for Internet service provider (ISP) networks. The energy saving problem is formulated as an ILP formulation, and a heuristic algorithm (we call it Heuristic Energy Saving Algorithm (HESA)) is proposed to solve it. HESA tries to shut off the links iteratively in the order of utilization from small to large. For every try to shut off a link, HESA checks the network’s connectivity and then checks if all links’ new utilizations are below a given bound by rerouting all the traffic data after the shut-off. Both HESA and PGNA are to try to shut off links heuristically while the network satisfies some given networking constraints. However, unlike HESA, PGNA tries to shut off the link based on the knowledge of prediction via sHMM. Moreover, a *deep-sleep* method is proposed to make PGNA shut off much more links. The networking constraints in PGNA are more optimized than HESA.

In addition, Heller et al. [27] focused on saving energy for data center and proposed ElasticTree which included an ILP method, a greedy heuristic method and a topology-aware heuristic method. In [28], the authors presented a solution in which an OpenFlow controller that can create an energy-efficient spanning tree overlay. Wang et al. [29] and Markiewicz et al. [30] applied green approaches to the controller for global power management in SDN, by rerouting traffic in a dynamic manner and powering down the idle switches/routers and links. The solution in [31], from another perspective, focused on energy saving on data center network with SDN by scheduling flows with exclusive routing. The solution in [32] minimized the network energy consumption by exploiting the idea of eliminating redundant data traffic so that the network links’ capacity increases virtually.

3. A spatial HMM

Hidden Markov Model (HMM) is a statistical Markov model for modeling a wide range of time series data, in which the Markov states are unobserved or hidden [33,34]. We define a spatial hidden Markov model (sHMM) to model an arbitrary packet transmits through a series of nodes over the network.

Suppose a network consists of N nodes (i.e., routers and switches). We treat all the hosts and other networks that are connected to the network as a virtual node, which is denoted as the $N+1$th node of the network. Then the virtual node is treated as both the source and the sink of all packets. In an equilibrium state of the network, the total number of packets entering the network is expected to be equal to the ones flowing out (note that the packet loss is not considered here). Thus the packets arriving at the virtual node are assumed to depart it eventually.

There are a massive number of packets transmitted in the network. If we randomly select one of the packets for consideration, its path over the network is a random series of nodes. We do not trace every packet. Our observations are arriving rates of packets through every one of the links. In considering that we cannot know which series of nodes a packet passed through just from the observed arriving rates of packets, each node in the network is thus assumed as a hidden state, and the links as the transitions between states. Therefore, the network topology represents the state transition graph. It can be equivalently expressed using a trellis diagram, as shown in Fig. 1, where each series of states represents a probable path that a packet may take.

The spatial HMM is represented as a quintuple, i.e. $\lambda = (N+1, M, A, B, \pi)$ where

1. $N+1$ is the number of states (i.e., nodes in the network plus a virtual node) as aforementioned;

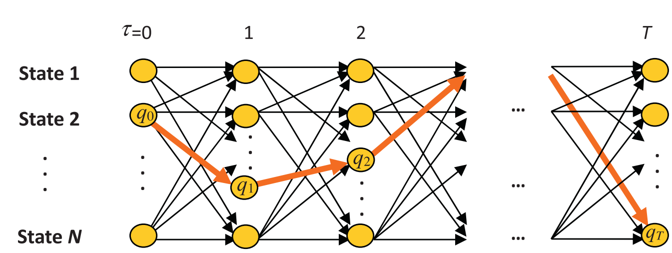

Fig. 1. A trellis diagram of spatial states transition graph with a transmission path $q_1, q_2, \ldots, q_T$.

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2. M is the number of distinct observable values (i.e., discrete arriving rate of packets over a link);
3. $\mathbf{A} = \{a_{ij}\}$ is a matrix of state transition probabilities, where a_{ij} is the state transition probability from state i to j, and

$$a_{ij} = P[q_t = j | q_{t-1} = i], \ 1 \le i, j \le N+1, \tag{1}$$

where q_t is denoted as a state at time t;
4. $\mathbf{B} = \{b_{ij}(v)\}$ is a matrix of observation probability distribution, where $b_{ij}(v)$ is the probability that v is observed while transiting from state i to state j, and

$$b_{ij}(v) = P[o_t^{i,j} = v | q_{t-1} = i, q_t = j], 1 \le i, j \le N+1 \tag{2}$$

where $o_t^{i,j}$ is the observation on the arriving rate of packets passed through link $E(i, j)$ at time t;
5. $\pi = \{\pi_i\}$ is the initial state distribution, where

$$\pi_i = P[q_0 = i], \ 1 \le i \le N+1. \tag{3}$$

We assume that a packet in the network is located in node q_t at time t. The packet's transmission route is $q_0, q_1, \ldots, q_t, \ldots, q_T$ as shown in Fig. 1, where T is the length of the path. The corresponding sequence of observations is $o_1^{q_0 q_1}, \ldots, o_T^{q_{T-1} q_T}$. Then the probability that a packet routed through this path is

$$P\left(q_0, q_1 \ldots, q_T, o_1^{q_0,q_1}, o_2^{q_1,q_2}, \ldots, o_T^{q_{T-1},q_T}\right) = P[q_0] \prod_{\tau=1}^{T} P[q_\tau | q_{\tau-1}] P[o_\tau^{q_{\tau-1},q_\tau} | q_{\tau-1}, q_\tau], \tag{4}$$

where q_0 is the initial node in which we assume the packet is located initially. When all possible paths are taken into account, the likelihood function of the observations is

$$P[\mathbf{o}_1 \mathbf{o}_2 \ldots \mathbf{o}_t] = \sum_{q_0 q_1 \ldots q_t} P\left(q_0, q_1 \cdots, q_t, o_1^{q_0,q_1}, o_2^{q_1,q_2}, \ldots, o_t^{q_{t-1},q_t}\right), \tag{5}$$

where $\mathbf{o_t}$ is the snapshot of the network traffic distribution at time t with element $o_t^{i,j}$ denoting the rate of packets passed through link $E(i, j)$ at time t, and $\mathbf{o}_1, \mathbf{o}_2, \ldots, \mathbf{o}_t$ (or $\mathbf{o}_{1 \to T}$ for short) denote all observations while taking into account all possible paths of length t. To compute Eq. (5), we define a forward variable $\alpha_t(i)$ $(1 \le i \le N+1)$ by

$$\begin{aligned}\alpha_t(i) &= P[\mathbf{o}_{1\to t}, q_t = i] \\ &= \sum_{q_0 q_1 \ldots q_{t-1}} P[q_0] \prod_{\tau=1}^{t-1} P[q_\tau | q_{\tau-1}] P[o_\tau^{q_{\tau-1},q_\tau} | q_{\tau-1}, q_\tau] \\ &\quad \cdot P[q_t = i | q_{t-1}] P[o_t^{q_{t-1},i} | q_{t-1}, q_t = i].\end{aligned} \tag{6}$$

It yields the forward algorithm

$$\begin{aligned}\alpha_{t+1}(i) &= \sum_{q_t} \alpha_t(q_t) a_{q_t,i} P[o_{t+1}^{q_t,i} | q_t, q_{t+1} = i] \\ &= \sum_{q_t} \alpha_t(q_t) a_{q_t,i} b_{q_t i}(o_{t+1}^{q_t,i}).\end{aligned} \tag{7}$$

The likelihood of the observations given by (5) is thus

$$P[\mathbf{o}_{1\to t}] = \sum_i \alpha_t(i). \tag{8}$$

Therefore, $\frac{\alpha_t(i)}{P[\mathbf{o}_{1\to t}]} = P[q_t = i | \mathbf{o}_{1\to t}]$ represents the probability that a packet is located in node i at time t, given the observation sequence $\mathbf{o}_{1 \to t}$. In other words, since $\sum_i \frac{\alpha_t(i)}{P[\mathbf{o}_{1\to t}]} = 1$, $\frac{\alpha_t(i)}{P[\mathbf{o}_{1\to t}]}$ represents the normalized load (i.e., ratio of total packets in the network) that node i processes at time t.

With the sHMM, we can compute each link's Predicted Transition Probability (PTP).

Let the forward variable at future time $T+k$ $(k = 1, 2, \ldots)$ be $\alpha_{T+k}(i)$. We have

$$\begin{aligned}\alpha_{T+k}(j) = P[\mathbf{o}_{1\to T}, q_{T+k} = j] &= \sum_{q_T} P[\mathbf{o}_{1\to T}, q_T, q_{T+k} = j] \\ &= \sum_{q_T} \alpha_T(q_T) P[q_{T+k} = j | q_T] \\ &= \sum_{q_T} \alpha_T(q_T) \sum_i P[q_{T+k-1} = i, q_{T+k} = j | q_T] \\ &= \sum_i \alpha_{T+k-1}(i) a_{ij}.\end{aligned} \tag{9}$$

Denote $\vec{\alpha}_{T+k}$ as the vector of $\alpha_{T+k}(i)$ for all $1 \le i \le N+1$, or

$$\vec{\alpha}_{T+k} = \left[\alpha_{T+k}(1), \quad \alpha_{T+k}(2), \quad \ldots, \quad \alpha_{T+k}(N+1)\right]. \tag{10}$$

Then from Eq. (9), we can compute $\vec{\alpha}_{T+k}$ for $\forall i, 1 \le i \le N+1$ by

$$\vec{\alpha}_{T+k} = \vec{\alpha}_{T+k-1}\mathbf{A} = \vec{\alpha}_T \mathbf{A}^k, \quad k \in \mathbb{N}. \tag{11}$$

Therefore, the ratio of packets through link $E(i, j)$ in the next kth time interval is

$$\mu_{T+k}^{ij} = P(q_{T+k-1} = i, q_{T+k} = j | \mathbf{o}_{1\to T}) = \frac{\alpha_{T+k-1}(i) a_{ij}}{\sum_l \alpha_T(l)}. \tag{12}$$

The average ratio of packets through link $E(i, j)$ during the next period $[T+1, T+K]$, denoted as $\overline{\mu_K^{ij}}$, is

$$\overline{\mu_K^{ij}} = \frac{\sum_{k=1}^{K} \alpha_{T+k-1}(i) a_{ij}}{K \sum_l \alpha_T(l)}, 1 \le i, j \le N+1. \tag{13}$$

Because packets that will pass through $E(i^*, j^*)$ in the next period will be routed to other links if $E(i^*, j^*)$ is shut off. Therefore, the state transition probability matrix $\mathbf{A}$ must be changed when link $E(i^*, j^*)$ is shut off. Denote S as the set of links that are sleeping, $\mathbf{A}(S)$ is the state transition probability matrix with elements $a_{i^*,j^*} = 0$ if $E(i^*, j^*) \in S$. Let $\mathbf{A}(S)$ be normalized so that $\mathbf{A}(S)\vec{e} = \vec{e}$, where $\vec{e}$ is a vector with all unity elements. Accordingly, let $\overline{\mu_K^{ij}}(S)$ denote the average ratio of packets that will pass through link $E(i, j)$ in the next period when the links in S are shut off. In the case that all output links of node i^* are shut off, $a_{i^*,i^*} = 1$ and node i^* becomes an absorbing state/node.

Suppose $S \ne \phi$ and the state transition probability matrix is $\mathbf{A}(S)$. Using Eqs. (11) to (13), we get $\overline{\mu_K^{ij}}(S)$ $(\forall i, j)$. Let

$$E(i^*, j^*) = \arg \min_{\forall E(i,j) \notin S} \left\{\overline{\mu_K^{ij}}(S)\right\}.$$

Then $E(i^*, j^*)$ is the link that will have the smallest traffic load in the next period and can be shut off if $\overline{\mu_K^{ij}}(S \cup E(i^*, j^*))$ $(\forall i, j)$ satisfies some constraints, where $\overline{\mu_K^{ij}}(S \cup E(i^*, j^*))$ is computed using Eqs. (11) to (13). Because $\overline{\mu_K^{ij}}(S)$ and $\overline{\mu_K^{ij}}(S \cup E(i^*, j^*))$ are predictions of the future traffic loads, the current traffic load $\vec{\alpha}_T$ does not change while computing them using Eqs. (11) to (13).

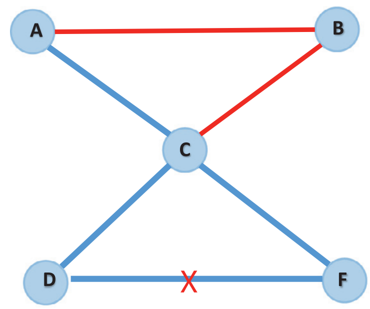
Note that the complexity of training the sHMM is $O(N^2 T)$, and the complexity of computing $\overline{\mu_K^{ij}}$ is $O(N^2 K)$.

4. The deep-sleep method

We propose the *deep-sleep* method to make sure that the number of shut-off links are maximized, while the network can satisfy the constraints. There are two networking constraints:

1. the network connectivity constraint;
2. the maximum utilization constraint.

The network connectivity constraint is to make sure that the network is always connected after the selected links are shut off.



Q3 **Fig. 2.** An example for the *deep-sleep* method. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

To achieve this, we leverage on the theory of Laplacian matrix to check the connectivity of a network [14,35]. First, we take a network as a graph, and then denote the adjacency matrix of the graph as $\mathbf{\Theta}$ and the degree matrix of the graph as $\mathbf{D}$. Then the Laplacian matrix, denoted as $\mathbf{L}$, will be

$$\mathbf{L} = \mathbf{D} - \mathbf{\Theta}. \tag{14}$$

The N (the number of nodes in the network) eigenvalues of $\mathbf{L}$ can be computed. We sort the eigenvalues in ascending order: $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_N$. The second eigenvalue, i.e., ε_2, is called the *algebraic connectivity* which is the indicator of the network's connectivity. The network is connected if $\varepsilon_2 \neq 0$, otherwise the network is disconnected.

The second networking constraint, i.e., the maximum utilization constraint, is to make sure that after the selected links are shut off, the following two conditions are satisfied:

1. there will not exist any link whose utilization becomes exceeding the given threshold (denoted as σ_{max}) after shutting off the selected links. In other words, the cardinality of the set
$$\mathbb{E} = \{E(i, j) | ut(i, j) > \sigma_{max}\} \tag{15}$$
will not increase, where $\mathbb{E}$ is called the exceeding set and $ut(i, j)$ is denoted as the utilization of $E(i, j)$.
2. and for the links whose utilizations are already exceeding σ_{max} before the shut-off, their utilizations must not increase after the shut-off. In other words, for any $E(i, j) \in \mathbb{E}$, $ut(i, j)$ will not be increased by shutting off the selected links.

In this regard, there is no any link that will become congested if it is not congested yet, or more congested if it is already congested. Compared with existing approaches which usually stop shutting off links in the case of $\mathbb{E} \neq \emptyset$, our approach can shut off more links. To explain this, we depict a simple example in Fig. 2. The utilizations of red link AB and BC exceed σ_{max}, and the utilizations of blue links are below σ_{max}. If the link DF is shut off, the traffic from DF will be rerouted through the link DC and CF. In this regard, both $ut(A, B)$ and $ut(B, C)$ do not increase at all. Hence, the link DF can be shut off. In other words, when $\mathbb{E} \neq \emptyset$, it is still reasonable to try to shut off more links that do not affect the network performance.

Suppose the total load is $L = \sum_{i,j} o_T^{i,j}$. Then the utilization of link $E(i, j)$ in the next period will be $\overline{\mu_K^{ij}}(\mathbb{S})L/C_{i,j}$, where $\mathbb{S}$ is the set of links to be shut off in the next period, and $C_{i,j}$ is the capacity of link $E(i, j)$. Let $E(i^*, j^*)$ be the link to be checked if it can be shut off in the next period. Suppose the shutting off satisfies the connectivity constraint. Now we check whether it satisfies the maximum utilization constraint:

if for all $E(i, j) \neq E(i^*, j^*)$,

$$\overline{\mu_K^{ij}}(\mathbb{S} \cup E(i^*, j^*))L/C_{i,j} \leq \max\left\{\overline{\mu_K^{ij}}(\mathbb{S})L/C_{i,j}, \sigma_{\max}\right\}, \tag{16}$$

then the maximum utilization constraint is satisfied and link $E(i^*, j^*)$ can be shut off in the next period. Then let $\mathbb{S} = \mathbb{S} \cup E(i^*, j^*)$ and repeat the procedure to add more links into the set.

5. PGNA approach

In the current period, PGNA collects the sequence of observations $\mathbf{o}_1, \ldots, \mathbf{o}_T$, and uses $\mathbf{o}_1, \ldots, \mathbf{o}_T$ to train the sHMM. Then in the end of the current period, it uses the trained sHMM to compute $\vec{\alpha}_T$, $\overline{\mu_K^{ij}}(S_0)$ and $\overline{\mu_K^{ij}}(S_0)L/C_{i,j}$ for all $E(i, j) \notin S_0$, where S_0 is the set of links that are currently in sleep mode.

The procedure to determine the set of links that will be shut off in the next period is as follows.

1. Let $S' = S_0$.
2. Let $E(i^*, j^*) = \arg\min_{E(i,j)\notin S'}\{\overline{\mu_K^{ij}}(S')\}$ be the link that will have the smallest APTP in the next period.
3. Check whether it can be shut off:
if the connectivity constraint is satisfied and for all $E(i, j) \notin S' \cup E(i^*, j^*)$,
$$\overline{\mu_K^{ij}}\big(S' \cup E(i^*, j^*)\big)L/C_{i,j} \leq \max\left\{\overline{\mu_K^{ij}}(S')L/C_{i,j}, \sigma_{\max}\right\},$$
then let $S' = S' \cup E(i^*, j^*)$; otherwise, let $E(i^*, j^*)$ be the link that will have the next smallest load; go back to Step 3;
4. Go back to Step 2, and repeat the procedure until no more links can be added into S'.

After the set S' is determined, in the beginning of the next period, the links of S' are shut off. Then start a new period to collect a new sequence of observations.

The complexity of PGNA includes the training of sHMM and computation of checking the network's connectivity and the maximum utilization constraints. The complexity of the algebraic connectivity computation is equal to $O(N^2)$. Checking the utilization constraint has the complexity of $O(N^2)$. Therefore, the algorithms complexity is equal to $O(N^2T)$ (if $T > logN$) or $O(N^2 logN$) (if $T \leq logN$).

6. Performance analysis

In this section, we present simulations to test the performance of PGNA, and make a comparison with another energy saving solution. Since the solutions in [15–17,24,26], which are most relevant to PNGA, are similar to each other, and HESA [26] is the typical one of them, we therefore selected HESA as the most appropriate approach to be compared with.

Two real ISP topologies will be used, and two case are considered:

1. A test case with generated traffic matrices;
2. A test case with real traffic data.

6.1. Topology description

The two topologies we used in this paper are real ISP topologies:

1. GERMANY50, with 50 nodes and 88 links, as shown in Fig. 3(a);
2. ABOVENET, with 138 nodes and 372 links, as shown in Fig. 3(b).

The topology GERMANY50 which is a German research network, is from the library: Survivable fixed telecommunication Network Design library (SNDlib) [36]. The SNDlib also provides one day's actual traffic demands of networks. But since it does not provide the information of link capacities, we have to set capacities for all links: we use Dijkstra's algorithm to route all traffic demands to

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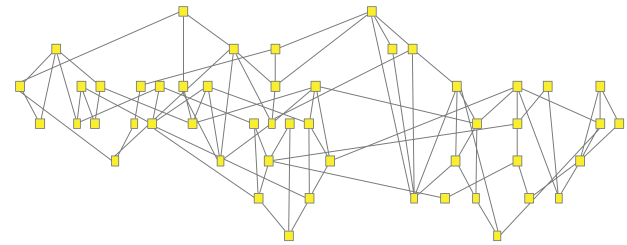
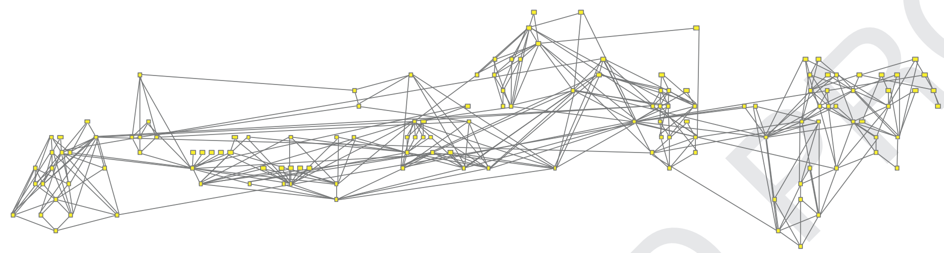


(a) GERMANY50 with 50 nodes and 88 links



(b) ABOVENET with 138 nodes and 372 links

Fig. 3. Two real ISP topologies.

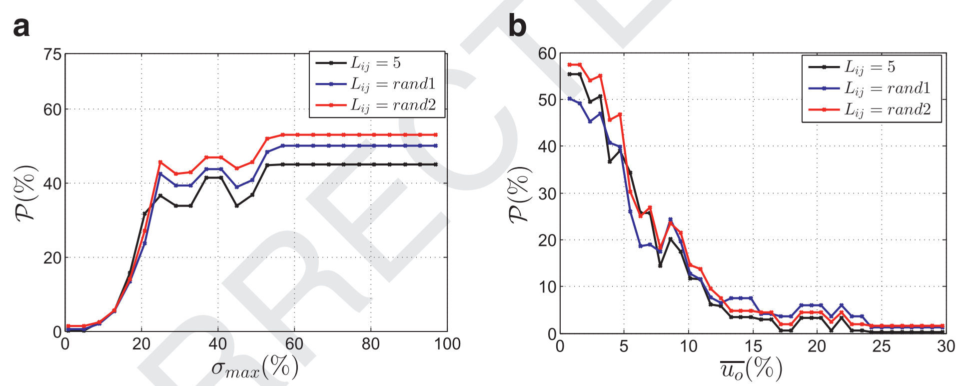


Fig. 4. The comparative results under different assignments of L_{ij}.

the network, and find out the maximal link traffic load denoted as L_{max}; then each link is assigned a capacity with the granularity of $\frac{L_{max}}{30\%}$, $\frac{L_{max}}{30\%\times 10}$, $\frac{L_{max}}{30\%\times 100}$, denoted as $100c_0$, $10c_0$, c_0, while make sure that the utilizations of all links are below 30%. Note that the capacity granularity (i.e., $100c_0$, $10c_0$, c_0) is the unit to form a link capacity. This is because, in real networks, a link typically consists of several channels to achieve the link capacity.

The second topology ABOVENET is from the project Rocketfuel [37] which is an ISP topology mapping engine. For sake of simplicity, we assign all links with the same capacity for this topology.

For energy consumption of each link, we do not consider the energy-consuming factor of air conditioning of the device. The energy consumption model of link $E(i, j)$ presented in [26] is given by

$$\mathcal{P}_{ij} = \left(\mathcal{P}^{g}_{ij} + \mathcal{P}^{l}\right)\frac{C_{ij}}{\bar{c}_0}, \tag{17}$$

where $\mathcal{P}_{ij}$ is the energy consumption of link $E(i, j)$; $\mathcal{P}^{g}_{ij}$ is the energy consumption of link (optical) regenerators which depends on the link length; $\mathcal{P}^{l}$ is the energy consumption of a single line card; $\bar{c}_0$ is granularity channel capacity to achieve a link capacity; $C_{ij}/\bar{c}_0$ is the number of granularity channels. As we can see from Eq. (17), if we assume the length of all links are almost the same (i.e., let $L_{ij} = \bar{L}$, $\forall i, j$; L_{ij} is the length of link $E(i, j)$, and $\bar{L}$ is the average length of links), then $\mathcal{P}_{ij} \propto C_{ij}/\bar{c}_0$. We have done simulations to show the assumption is reasonable:

We have simulated in three cases. In case one, $L_{ij} = 5$ ($\forall i, j$); in case two and three: L_{ij} is assigned from 1 to 10 randomly for all i, j. Note that $\mathcal{P}^{g}_{ij}$ is assumed being proportional to L_{ij}. The results are shown in Fig. 4.

Fig. 4(a) shows the results as a function of threshold σ_{max} (note that $\overline{u_o}$ is fixed to 3.91% in this case). Fig. 4(b) shows the results as a function of $\overline{u_o}$ (note that σ_{max} is fixed to 50% in this case). Note that $\overline{u_o}$ is denoted as the mean link utilization of the original network in which all links are active.

As we can see in Fig. 4, the three results show similar trend under different assignments of L_{ij}. In other words, the assumption (i.e., $L_{ij} = \bar{L}$) is reasonable. In this regard, we therefore simplify the energy consumption model in which the energy consumption of each link proportional to its capacity for simplicity, i.e.,

$$\mathcal{P}_{ij} = \delta C_{ij}, \quad 1 \le i, j \le N, \tag{18}$$

where δ is a constant.

Besides the real traffic demands from the SNDlib, we generate two sets of traffic matrices with ascending and descending curve, respectively. PGNA needs T traffic matrices to train the sHMM and uses the $T+1$th traffic matrices to verify the result. Then the generated traffic formulations for each pair of access nodes are

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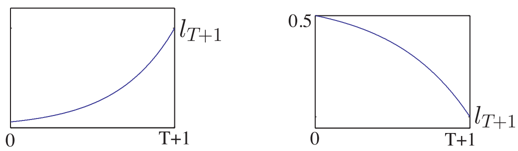

(a) AEC (b) DEC

Fig. 5. Generated traffic.

1. Ascending Exponential Curve (AEC) as shown in Fig. 5(a), and the generating formulation is

$$f(t) = \frac{l_{T+1}}{e^3} \exp\left(\frac{3\,t}{T+1}\right), \quad 0 < t \leq T+1, \tag{19}$$

where l_{T+1} is a constant and equal to $f(T+1)$.

2. Descending Exponential Curve (DEC) as shown in Fig. 5(b), and the generating formulation is

$$f(t) = 0.5 - \frac{0.5 - l_{T+1}}{e^2 - 1}\left[\exp\left(\frac{2(t-1)}{T}\right) - 1\right], \quad 0 < l_{T+1} < 0.5, \; 0 < t \leq T+1. \tag{20}$$

Therefore, for each pair of access nodes, the generated traffic series are $f(1), f(2), \dots, f(T+1)$. In particular, since $l_{T+1} = f(T+1)$, we can test the performance of PGNA by setting different values of l_{T+1} to generated different slope of line: ascending and descending curve, respectively. Moreover, the smaller l_{T+1} is, the more gently the traffic curve is, and vice versa. Note that l_{T+1} is proportional to $\overline{u_o}$.

6.2. Performance metrics

We use the following parameters to test the performance of PGNA:

1. λ, the shut-off ratio (SOR), denoted as the ratio of links that are put into sleep mode, and is computed by

$$\lambda = \frac{|\mathcal{S}|}{|E|}, \tag{21}$$

where $\mathcal{S}$ is the set of links that are shut off, and E is the set of all links in the network;

2. $\mathcal{P}$, the Energy-Saving Ratio (ESR), and

$$\mathcal{P} = 1 - \frac{\sum_{E(i,j) \text{ is on}} \mathcal{P}_{ij}}{\sum_{i,j} \mathcal{P}_{ij}}, \tag{22}$$

3. $\overline{u}$, the Mean Utilization (MU) of the network, computing by,

$$\overline{u} = \frac{\sum\limits_{\forall i,j} u_{ij}}{|E|}, \tag{23}$$

where u_{ij} is the utilization of the link $E(i, j)$.

4. $\mathcal{H}$, the Average Hop Increase (AHI) of all routes after links are shut off, computed by

$$\mathcal{H} = \frac{\sum \mathcal{H}'_{ij} - \sum \mathcal{H}_{ij}}{\sum \mathcal{H}_{ij}} \tag{24}$$

where $\sum \mathcal{H}_{ij}$ is the sum of hops of all paths, while $\sum \mathcal{H}'_{ij}$ is the sum of hops of all paths after the selective links are shut off.

In general, the change of MU and AHI can reflect the change of network performance. Specifically, both network congestion and packet loss increase when MU increases; the packet latency increases when AHI increases after links are shut off. In other words, the network performance degrades when MU or AHI increases.

6.3. Results analysis

In the following simulation, we will test the performances under different thresholds and traffic loads by setting different values of l_{T+1}. where in particular we set

$$l_{T+1} = l \cdot c_0, \quad l \geq 0, \tag{25}$$

where l is a factor that determines the value of l_{T+1}.

6.3.1. Results with different thresholds

In this section, we randomly choose 20 nodes to be access nodes for the topology GERMANY50 and 50 access nodes for the topology ABOVENET. We start by exploring the impact on performance under different σ_{max}.

For topology GERMANY50, we fix $l = 0.05$ and generate the two sets of traffic matrices, namely AEC and DEC. Therefore, the MU of the original network (i.e., $\overline{u_o}$) is fixed too and $\overline{u_o} = 3.91\%$. The results are shown in Fig. 6 as a function of the σ_{max} varying from 0 to 100%.

Fig. 6 (a) and (b) show the effectiveness of PGNA to save the energy for the network GERMANY50. We can see that both λ and $\mathcal{P}$ increase as the threshold σ_{max} increases, and they grow fast until the inflection point, namely $\sigma_{max} = 20\%$. When $\sigma_{max} \geq 65\%$, PGNA's performance reaches its limit ($\lambda = 36.4\%$ and $\mathcal{P} = 45.1\%$), and no more energy can be saved even if σ_{max} grows. As Fig. 6(c) and (d) shows, when σ_{max} grows, $\overline{u}$ and $\mathcal{H}$ grow too as a price of the increase of $\mathcal{P}$. When $\sigma_{max} \geq 65\%$, $\overline{u}$ and $\mathcal{H}$ reach the maximum which are $\overline{u} = 31.5\%$ and $\mathcal{H} = 1.08$. Therefore the larger σ_{max} is, the more energy PGNA can save while the larger MU and AHI are which means the resulting network congestion as a tradeoff.

For topology ABOVENET, we fix $l = 0.05$ and $\overline{u_o} = 4.40\%$. The results are shown in Fig. 7. Since the capacity of all links in ABOVENET is the same, the energy consumption of each link is the same due to Eq. (18), and therefore the result of λ is the same with $\mathcal{P}$. We can see that the results in ABOVENET show a trend similar to the results in GERMANY50, however SOR in ABOVENET is less than GERMANY50 because there are less ratio of redundant links in ABOVENET than in GERMANY50. The maximal λ is 9.4%, however the maximal $\overline{u}$ and $\mathcal{H}$ are small, namely 4.9% and 0.049, respectively.

6.3.2. Results with comparison

In this section, we randomly choose 20 nodes to be access nodes for the topology GERMANY50 and 50 access nodes for the topology ABOVENET. We explore the performance of PGNA comparing with HESA under different peaks of the traffic. We fix the threshold $\sigma_{max} = 50\%$ and test the PGNA with AEC and DEC under different values of $\overline{u_o}$ by setting different values of l.

Results in GERMANY50. We start by evaluating the performance in topology GERMANY50 with AEC and DEC. Since the comparative results in DEC show a trend similar to the results in AEC, we just focus on the results of AEC as shown in Fig. 8.

We start by focusing on the results of PGNA. As we can see in the Fig. 8(a) and (b), both λ and $\mathcal{P}$ decrease in general with the increase of $\overline{u_o}$. That is, the smaller $\overline{u_o}$ is, the more spare network links exist, and the more energy that can be saved. As shown in Fig. 8(c) , with the increase of the $\overline{u_o}$, the PGNA curve gets closer to $\overline{u_o}$'s curve until they overlap. In other words, as the SOR decreases, the increment of MU decreases. In particular, for $\overline{u_o} \leq 1.56\%$, up to 43.18% of links are shut off, and up to 55.35% of energy consumption is saved, while as a tradeoff, the MU rises to 8.65% and the AHI is up to 1.10.

As pointed out in [38], the MU in the Internet backbone networks is less than 5% during the idle time, and is less than 30% during the peak time. Therefore we can analyze the performance

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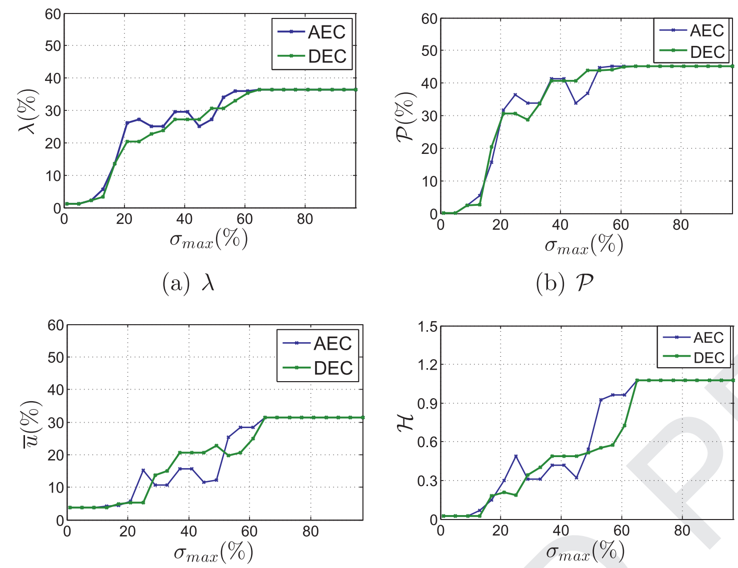
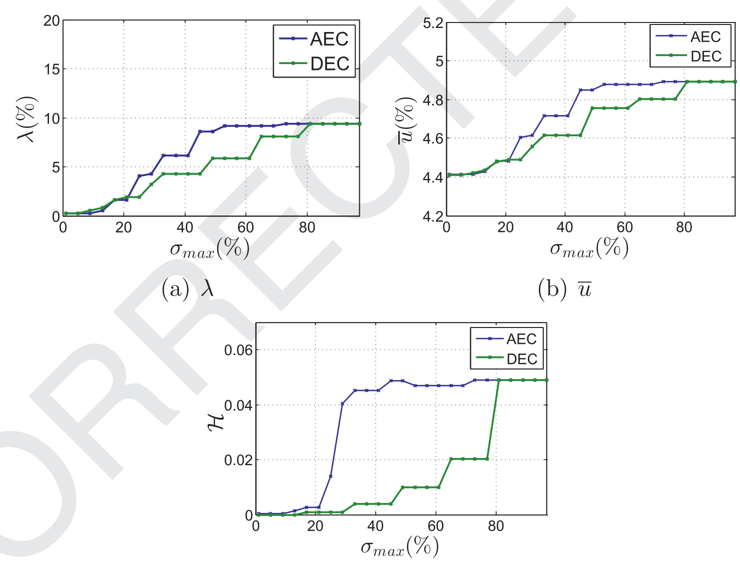


(a) λ (b) $\mathcal{P}$ (c) $\overline{u}$ (d) $\mathcal{H}$

Fig. 6. The comparative results of PGNA as a function of σ_{max} in topology GERMANY50.



(a) λ (b) $\overline{u}$ (c) $\mathcal{H}$

Fig. 7. The comparative results of PGNA with different σ_{max} in topology ABOVENET.

for the network during the idle time by approximatively considering the scenario where $\overline{u_o} \leq 5\%$, and compute the average performance by approximatively considering the scenario where $\overline{u_o} \leq 30\%$. In other words, when the network is idle, the average SOR is computed by

$$\overline{\lambda_{5\%}} = \frac{1}{|x|} \sum_{x \leq 5\%} \lambda(x), \tag{26}$$

where x is the value of $\overline{u_o}$, $\lambda(x)$ is denoted as the value of λ at $\overline{u_o} = x$, and $|x|$ is the length of x with $x \leq 5\%$. Similarly we can compute the average ESR denoted as $\overline{\mathcal{P}_{5\%}}$, the average MU denoted as $\overline{u_{5\%}}$ and the average AHI denoted as $\mathcal{H}_{5\%}$. Another parameter is the increase of the MU after the shut-off, denoted as $\Delta\bar{u}_{5\%}$ and computed by

$$\Delta\bar{u}_{5\%} = \frac{1}{|x|} \sum_{x \leq 5\%} (\overline{u}(x) - x), \tag{27}$$

Table 1
The performance of the idle network in topology GERMANY50 with AEC.

Parameter	PGNA	HESA
$\overline{\lambda_{5\%}}$	35.23%	23.11%
$\overline{\mathcal{P}_{5\%}}$	47.77%	24.97%
$\overline{u_{5\%}}$	9.89%	6.06%
$\Delta\bar{u}_{5\%}\%$	7.15%	3.33%
$\mathcal{H}_{5\%}$	0.83	0.57

where $\overline{u}(x)$ is the MU after the shut-off at $\overline{u_o} = x$. The results are shown in Table 1.

As we can see in the Table 1, when the network is in idle time (e.g. the network during late at night and early in the morning), more than one-third of links in the network can be put into sleep mode, and nearly half of energy consumption can be saved

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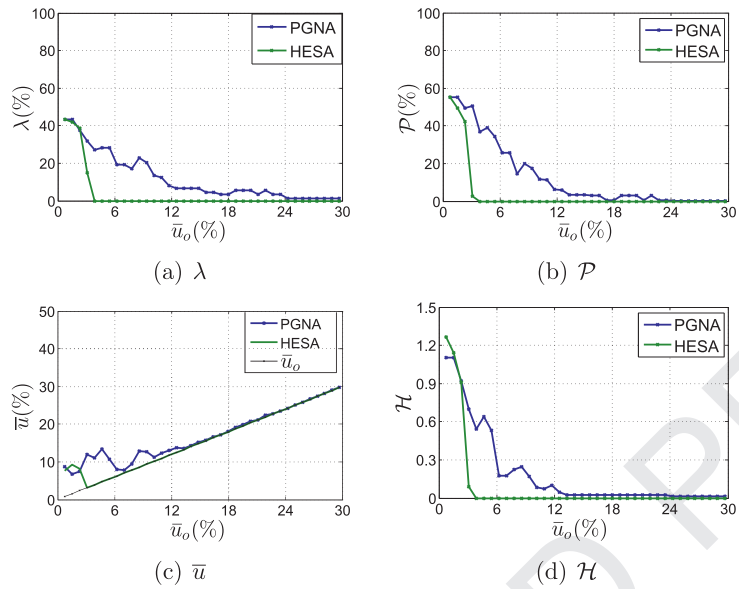

Fig. 8. The comparative results as a function of $\overline{u_o}$ with the AEC in topology GERMANY50.

Table 2
The average performance in topology GERMANY50 with the AEC.

Parameter	PGNA	HESA
$\overline{\lambda_{30\%}}$	12.05%	3.65%
$\overline{\mathcal{P}_{30\%}}$	12.98%	3.94%
$\overline{u_{30\%}}$	17.05%	15.77%
$\Delta\bar{u}_{30\%}$	1.08%	0.53%
$\mathcal{H}_{30\%}$	0.19	0.09

Table 3
The performance of the idle network in ABOVENET with AEC.

Parameter	PGNA	HESA
$\overline{\lambda_{5\%}}$%	16.8%	11.4%
$\overline{u_{5\%}}$%	3.8%	3.7%
$\Delta\bar{u}_{5\%}$%	0.83%	0.81%
$\mathcal{H}_{5\%}$	0.60	0.09

by PGNA. As a tradeoff, the network's MU increases to 9.89%, and AHI rises to 0.83.

Furthermore, we approximatively compute the average performance of the network by considering the scenario where $\overline{u_o} \leq 30\%$. Like the way we compute the parameters for the network in idle time, we compute $\overline{\lambda_{30\%}}\%$, $\overline{\mathcal{P}_{30\%}}\%$, $\overline{u_{30\%}}\%$ and $\Delta\bar{u}_{30\%}\%$ in a similar way, and the results are shown in Table 2. Therefore we can see that on average PGNA can shut off about 12% of links and about 12% of energy consumption can be saved. As a tradeoff, the MU and AHI increase, namely $\Delta\bar{u}_{30\%} = 1.08\%$ and $\mathcal{H}_{30\%} = 0.19$.

Now, we focus on the comparison between the performance of the PGNA and the HESA. As shown in Fig. 8, we can see that the results of PGNA and HESA are the same at the beginning, but with the increase of $\overline{u_o}$, both λ and $\mathcal{P}$ of HESA drop much more rapidly than PGNA's until they become zero. As we can see in Tables 1 and 2, PGNA can shut off much more links than HESA. In the idle network, PGNA can shut off about 12% more links and the energy saved by PGNA is about twice as much as that saved by HESA. As a tradeoff, the MU and AHI in PGNA is larger but are only 3.83% and 0.25 more than HESA , respectively. For the average of the performance of the network, the links PGNA shuts off are more than threefold of those HESA does, and the energy PGNA saves is also about threefold of that HESA does, while the MU and AHI in PGNA are 1.28% and 0.10 more than HESA, respectively.

Notice that, another big difference as we can see in Fig 8 is that HESA stops working when $\overline{u_o} \geq 3.91\%$, while PGNA still works well until $\overline{u_o} \geq 24.23\%$. This thanks to the deep-sleep method we use in PGNA.

Results in ABOVENET. We test our solution with the AEC and DEC in topology ABOVENET comparing with HESA. Since, the comparative results in DEC show a trend similar to the results in AEC, we just focus on the results of AEC as shown in Fig. 9.

The result of λ is the same with $\mathcal{P}$ because the energy consumption of all links in ABOVENET is the same. As shown in Fig. 9, the largest SOR is about 30% less than 43% in GERMANY50. Table 3 shows the comparative results of the network in idle ($\overline{u_o} \leq 5\%$), and we can see that PGNA can shut off about 5.4% more links than HESA, while the MU is maintained below a low level (namely 3.8%) which is only 0.1% more than HESA's MU and AHI is only 0.60. As Fig. 9(a) shows, when $\overline{u_o} > 3\%$, HESA cannot shut off any link while PGNA still works well which benefits from the deep-sleep method in PGNA, and $\bar{u}$ and $\mathcal{H}$ is small as shown in Fig. 9(b) and (c).

6.3.3. Results with real traffic

The real traffic demands of topology GERMANY50 is from the SNDlib [36]. The SNDlib sampled the network' traffic demands for every 5 minutes while anonymized some privacies (e.g. the absolute time information) and lasted for one day (i.e., from 00: 00 to 23: 55). In this simulation, we use one hours' traffic matrices for training and predicting the next 15 min link traffic, In other words, we set $T = 12$ and $K = 3$, and the given threshold is fixed as $\sigma_{max} = 50\%$. We assume PGNA can turn on or shut off the network links every 15 min. The results are shown in Fig. 10.

As we can see in Fig. 10(c), the average utilization of the original topology (namely $\overline{u_o}$) fits the day-night pattern. Since the first hour's data are used for training, the results are started at 01: 00. As shown in Fig. 10(a) and (b), both λ and $\mathcal{P}$ reach the top in the morning while $\overline{u_o}$ reaches the bottom because the network is in off-peak time. We denote $\bar{\lambda}$ as one day's average SOR computing

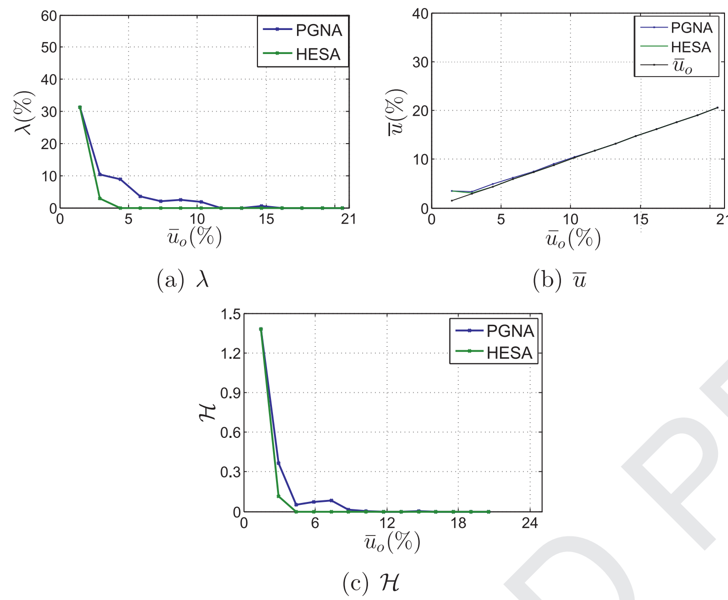

Fig. 9. The comparative results as a function of $\overline{u_o}$ with the AEC in topology ABOVENET.

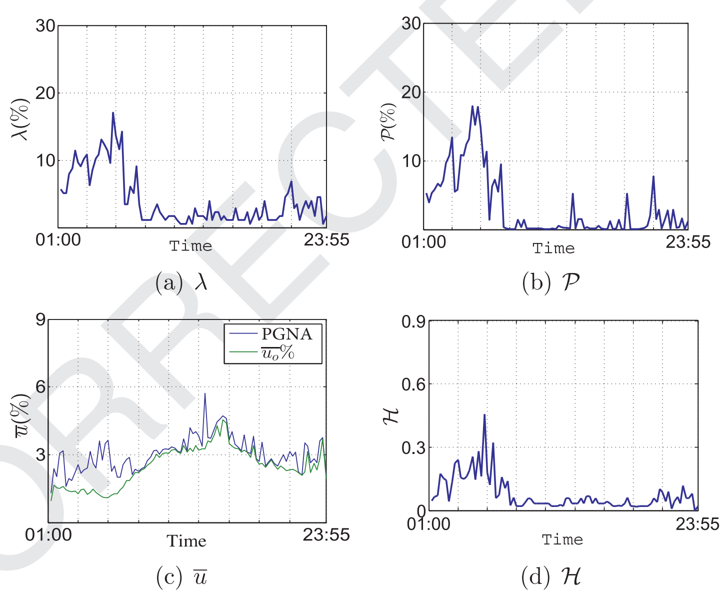

Fig. 10. The results of PGNA in topology GERMANY50 with real traffic demands.

by

$$\overline{\lambda} = \frac{1}{|\mathcal{N}_{T'}|}\sum_t \lambda(t), \tag{28}$$

where $|\mathcal{N}_{T'}|$ is the length of data in period T' (e.g., the morning or the whole day), and $\lambda(t)$ is the SOR of PGNA at time t ($t \in T'$). In a similar way we compute $\overline{\mathcal{P}}$ as one day's average ESR and $\overline{\mathcal{H}}$ as one day's average AHI. We denote $\Delta\bar{u}$ as the average increase of $\overline{u}$ after the shut-off computed by

$$\Delta\bar{u} = \frac{1}{|\mathcal{N}_{T'}|}\sum_t (\overline{u}(t) - \overline{u_o}(t)), \tag{29}$$

where $\overline{u}(t)$ is the MU of PGNA at time t and $\overline{u_o}(t)$ is the MU of original topology at time t. Table 4 shows the average performance for both morning (from 01:00 to 07:00) and whole day. From Table 4 we can see that PGNA can shut off about one fifth of links and save about one fifth of energy consumption in the early morning while the network is in idle state. Meanwhile, the MU increases only 2% after the shut-off and the AHI is only 0.176, which means PGNA can save much energy with a light impact on network performance. For the results of the whole day, the average SOR can reach about 8% and the average ESR reaches about 7% while the MU and the AHI are both maintained at a small value.

Table 4
The average performance of GERMANY50 with real traffic.

Parameter	Morning	Whole day
$\overline{\lambda}$	20.2%	8.3%
$\overline{\mathcal{P}}$	20.0%	6.5%
$\overline{\mathcal{H}}$	0.176%	0.076%
$\Delta\overline{u}$	2.0%	1.0%

7. Implementation discussion

To approximate the optimal solution, we have to determine the least set of links which need to be active, and the idle links can

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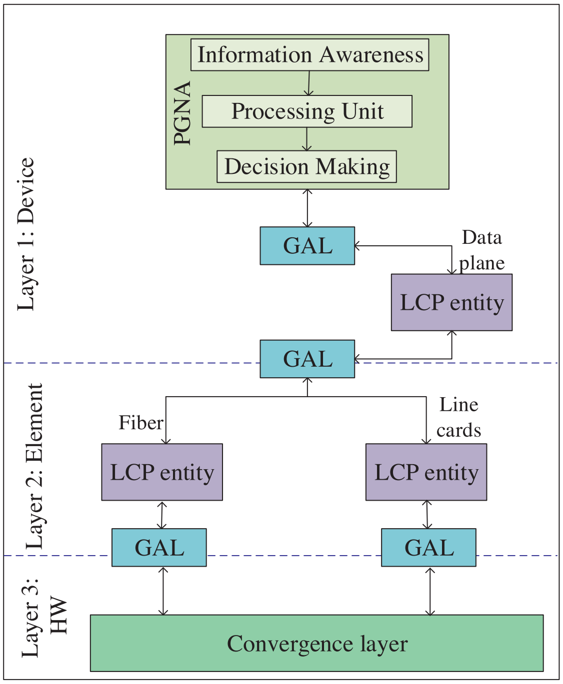

Fig. 11. The hierarchical architecture of the PGNA.

be shut off while the network performance is perfectly guaranteed in the present and the near future. Due to the computation of the least set is a NP-complete problem, our approach PGNA computes the least set heuristically based on predicted traffic, with two network constraints to guarantee the network performance. With sHMM, the computation for the least set is reduced, and the traffic prediction reaches the maximum likelihood probability. The simulation results show that there is a great opportunity to deploy PGNA in a real network. PGNA can be deployed in any centralized control network. In this section, we take Software-Defined Networking (SDN) as an illustration.

SDN becomes a hot issue in recent years, which is an innovative clean-slate networking architecture [39]. SDN is a centralized-control networking architecture and consists of control plane which makes decisions where the traffic should be sent, and data plane which is focusing on routing traffic data to the selected destination. The control plane in SDN has the situation awareness of the whole network, including network topology and historical traffic demands.

We can make use of an existing power management mechanism in SDN, namely the GAL (Green Abstraction Layer) [40] which has been standardized in ETSI. GAL uses hierarchical organization to provide multiple local and network-wide energy control policies. With GAL in SDN, the architecture of PGNA consists of three layers, shown in Fig. 11. A LCP, namely Local Control Policy, is a control algorithm of an individual device or element. As we can see in Fig. 11, PGNA's architecture is organized as a tree of devices. The lowest layer, namely the HardWare (HW) component layer, consists of power management primitives with which LCP can control the hardware's power state. The second layer is the element layer, in which GAL can control the power state of all devices' elements, e.g., the line card, optical fiber and CPU. The top layer is the device layer, which is the root of the tree.

PGNA can provide network-wide energy-management policies to green the network, and consists of three processes:

1. Information awareness, in which PGNA collects the information of the whole network every t time (e.g. 5 min), including topology information and traffic demands;
2. Processing unit, in which PGNA trains the sHMM model and computes the prediction for the network;
3. Decision making, in which PGNA decides which links to be put into sleep mode every t' time (e.g. every 30 min).

When an energy-management decision is made every t' time, PGNA sends power commands to all affected device's LCP. Then the device's LCP sends commands to its affected elements' LCP (e.g. line card and the physical link) in the element layers. Finally, the affected elements' LCPs turn on or shut off the elements according to the commands.

It is worth noting that in some networks (e.g. a backbone network) there exists some links that cannot be shut off because of carrying backup paths for fault-tolerant. Therefore PGNA should allow some links to be denoted as no-shutoff.

8. Conclusion

In this paper, we solve the energy-consumption problem by proposing PGNA to predict the network traffic and then try to shut off the links as long as the network constraints are satisfied. In PGNA, a sHMM is used to model the network, and a *deep-sleep* method is proposed to shut off the near idle links as many as possible.

In order to evaluate the performance of our solution, we used two real ISP topology from the SNDlib and the Rocketfuel, respectively. Two typical sets of traffic matrices were generated and real traffic demands from SNDlib were used to test the PGNA. The results show that our solution are effective for energy saving, especially when the network is during off-peak time. Comparing to anther energy-saving approach, namely HESA, PGNA works much better in both topology. For instance, when the network is in idle time, the energy PGNA saves is about twice as much as HESA in GERMANY50.

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