On the Effectiveness of Sleep Modes in Backbone Networks with Limited Configurations

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***Abstract*—We study the problem of putting in sleep mode devices of a backbone network, while limiting the number of times each device changes its power state (full power mode or sleep mode). Our aim is to limit the number of network configurations, i.e., the change of the current set of network devices at full power. We develop a model, based on random graph theory, to compute the energy saving given a traffic variation, QoS constraints, and the number of allowed network configurations. Results show that the energy savings with few configurations (two or three per day) are close to the maximum one, in which a new configuration is applied for each traffic matrix. Thus, we can conclude that a practical implementation of sleep mode strategies for network operators is to define, on the basis of typical traffic trend, few configurations to be activated in specific time instants.**

I. Introduction

The continuous growth of Internet traffic represents a challenge for the network infrastructures of Internet Service Providers (ISPs). One of the consequences to be considered is the energy consumption increase of network devices [1], since this effect could represent a bottleneck for ISP networks in the near future [2]. Starting from the seminal work [3] different solutions have been proposed to increase the energy efficiency of wired networks (see [4] for an overview). The presented solutions rely on two main approaches [5]: dynamic power scaling and smart standby. In particular, network devices exploiting dynamic power scaling adapt their working rate according to the actual utilization. On the contrary, with the smart stand-by devices are put in a low-power state when not strictly needed.

In this work we focus on the smart standby approach in backbone networks. Hereafter, we call sleep mode the period of time (which may last for minutes or hours) during which a device is in a low-power state. When some devices are in sleep mode, the other devices that remain powered on have to meet Quality of Service (QoS) constraints, which require the knowledge of the traffic exchanged in the network. We denote as configuration the set of devices in sleep mode at a given time not violating any QoS constraint. Since traffic varies over time, most of works in the literature (see for example [6], [7], [8]) assume to compute and apply a new configuration for each traffic matrix, resulting in a large number of applied configurations per day (one for each traffic matrix).

However, applying a large number of configurations has several drawbacks in operational networks. First, frequent transitions between full power and sleep mode result in an increase of the Mean Time Between Failures, since network devices are designed to be always powered on. Second, routing protocol convergence at the IP layer is negatively affected: this is due to the fact that topology changes have to be propagated in the network (even in the presence of a central controller), and current routing protocols may show a slow convergence when many devices change continuously their power state. Third, deciding when applying each configuration without violating any QoS constraint is not trivial, since traffic frequently changes. For all these reasons, the number of network configurations has to be limited.

In this work, we present a model based on random graph theory to quantify the energy saving of a network under QoS constraints and a maximum number of admissible configurations. The model lets us introduce an important insight: the energy saving with a limited number of configurations (two or three per day) is already close to the maximum one (a new configuration applied at each traffic variation). To the best of our knowledge, none of the related works in the field of energy-efficient backbone networks have conducted a similar analysis.

The closest papers to this work are [9], [10]. In [9] the problem of choosing a time interval to apply an energy saving network configuration is evaluated. In particular an heuristic is defined so that to determine a reduced network topology and the window size of its duration. The main difference with respect to our work is that in [9] a single energy saving configuration is considered and a comparison with the maximum energy saving is not performed. In [10] a model to evaluate sleep mode gains with random graphs is proposed. The main differences of this work with respect to [10] are the following. First, the scope of our previous work is to evaluate the power saving of sleep modes under different power models (for current and future devices), while in this work we evaluate the energy saving given a power model, a traffic profile and a maximum number of configurations.

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Second, while in [10] the configuration is assumed to be given by an oracle, here we compute the *best* configuration which fulfills different QoS constraints. Third, in our previous work we did not consider the variation of traffic and the maximum number of configurations, while here we explicitly take them into account.

The paper is organized as follows. In Section II a detailed description of the network model is proposed; In Section III we evaluate the energy saving when a limited number of network configurations is available while in Section IV the numerical results are shown; finally in Section V conclusions are drawn.

II. Network Model

The aim of the network model is to relate the number of links to put in standby to the network topology, the traffic matrix and the QoS constraints. The model is based on the following assumptions: i) we focus on links only,[1] ii) we consider average link power consumption and average number of links per node, iii) we assume a random policy to select which devices to be powered off for a given configuration, iv) we consider traffic uniformly exchanged among all nodes, v) we assume that during peak hour all links have to be powered on. All these assumptions represent a conservative scenario, and the actual savings of operational networks may be even larger than the ones shown in this paper: for instance a smart selection of standby links by means of a power aware routing strategy could highly increase energy saving. However, the indications provided by our analysis(i.e. the fact that few configurations are able to save an amount of power comparable to the maximum one) are still valid and general.

In the following, we detail how the model is built. In particular, we start from a graph with N nodes and L undirected links. The average node degree is $K = \frac{2L}{N}$. This means that each node is connected to other K nodes on average. Moreover, the average power consumption of a link is $\mathcal{P}_L$.

The power consumption of the network when all links are powered on is:

$$P_{TOT} = N\frac{K}{2}\mathcal{P}_L \tag{1}$$

We then consider a fraction of $p \in [0, 1]$ links put in sleep mode. When a link is put in sleep mode, we assume that its power consumption is negligible. The total power of the network then becomes:

$$P'_{TOT} = N\frac{K'}{2}\mathcal{P}_L \tag{2}$$

where K' is the average node degree when sleep mode is applied. We assume the set of links powered off is randomly chosen. Under such hypothesis, the graph composed by the links powered on maintains the same properties of the initial graph, and the new degree can be computed as $K' = K(1-p)$ [11].

[1] Our model can be extended to the case in which nodes are put into sleep mode. However, we leave this feature as future work.

A. QoS Constraints

We then introduce the QoS constraints which limit the fraction of links p that are put in sleep mode.

1) Network Connectivity: The minimum network connectivity is guaranteed when p is lower than the fragmentation threshold [11]:

$$p < 1 - \frac{1}{\frac{E[(K')^2]}{K'} - 1} \tag{3}$$

where $E[(K')^2]$ is the second moment of the degree distribution when sleep mode is applied. If p is larger than the fragmentation threshold, then connectivity is not guaranteed among all node pairs, and clusters of nodes not connected together appear.

However, recent measurements studies have proven that normally K ranges between 4 and 8 for telecommunication networks [12]. Thus, each node is connected from 4 to 8 other nodes in the network on average. In our study, we assume that a node is connected to other two nodes on average when sleep mode is applied, i.e., $K' \geq 2$. Intuitively, this correspond to the condition in which each node acts as "transport" device by moving traffic from a source node and then sending it to a destination node. Thus, we impose the minimum degree constraint as:

$$p \leq 1 - \frac{2}{K} \tag{4}$$

Lemma 1 If the degree constraint (4) holds, then also the fragmentation constraint (3) is satisfied.

Proof: We prove this condition by contradiction, assuming that

$$1 - \frac{1}{\frac{E[(K')^2]}{K'} - 1} > 1 - \frac{2}{K} \tag{5}$$

From [11] it holds that: $E[(K')^2]$=$E[K^2](1-p)^2 + p(1-p)K$. Moreover, we express $E[K^2] = K^2 + \sigma_K^2$, where σ_K^2 is the degree variance. By substituting $E[(K')^2]$ we find that condition (5) is never satisfied. ■

2) Average link utilization: Let us define the average link load $\rho \in (0, 1)$ when all devices are powered on. The link load is normally kept below a maximum utilization threshold δ to avoid congestion, i.e. $\rho \leq \delta$. Then, we express the average link load as:

$$\rho = \frac{D_{max} l}{N\frac{K}{2}C} \tag{6}$$

where D_{max} is the maximum amount of traffic in the network, l is the average shortest path length, and C is the average link capacity. By imposing the load threshold, we compute D_{max} as:

$$D_{max} = \frac{\delta N \frac{K}{2} C}{l} \tag{7}$$

In our model we consider D_{max} as the peak traffic matrix. Note that this is a conservative assumption, since we consider a peak traffic matrix that "saturates" all network links i.e., the utilization of every link is equal to δ.

We then consider the load when devices are in sleep mode. The sleep mode can be enabled only when traffic decreases, so

TABLE I
NETWORK AVERAGE SHORTEST PATH LENGTH

Model	l	l'
ER	$\frac{log(N)}{log(K)}$	$\frac{log(N)}{log(K(1-p))}$
PL	$1+\frac{\log\left(\frac{N}{K}\right)}{\log[(E[K^2]-K)/K]}$	$1+\frac{\log\left(\frac{N}{K(1-p)}\right)}{\log\left[\left(\frac{E[K^2]-K}{K}\right)(1-p)\right]}$

we assume an amount of traffic $D < D_{max}$. The new average load ρ' can be expressed as:

$$\rho' = \frac{Dl'}{N\frac{K}{2}(1-p)C} \tag{8}$$

where l' is the average shortest path length when sleep mode is applied. Clearly, the new load must be lower than the maximum utilization threshold, i.e. $\rho' \leq \delta$. Thus, we can bound the maximum p as:

$$p \leq 1 - \frac{Dl'}{N\frac{K}{2}C\delta} \tag{9}$$

To compute ρ and ρ', we need to define the shortest path length l and l', which depend on the graph model considered. In the literature, different graph models have been proposed (see [13] for an overview). However, deciding which model fits better current Internet topologies is an open issue. Therefore, in this work we adopt two different graph models: the Erdös and Rényi (ER) model and the Power Law (PL) model. In the ER model [14] nodes are connected by links according to a given probability, and the resulting degree distribution follows a Poisson distribution. On the contrary, in the Power Law (PL) model [11] the distribution $P_K(k)$ of the node degree K follows a power-law distribution, i.e., $P_K(k) \sim k^{-\gamma}$. The intuition is that some nodes behave like *hubs*, and have many more connections than others. Tab. I reports the shortest path length l and l'. We refer the reader to [10] for details on how these expressions are obtained.

3) Increase of the Shortest Paths: Finally, an Internet Service Provider might be interested in limiting the shortest path length when sleep mode is applied. We define the increase in the shortest path length as $\frac{l'-l}{l}$, and we introduce a threshold $\phi \in (0,1)$, i.e. $\frac{l'-l}{l} \leq \phi$. For an ER model, the maximum p for the shortest path constraint is expressed as:

$$p \leq 1 - \frac{e^{\frac{logK}{\phi+1}}}{K} \tag{10}$$

Similarly, it is possible to define an equivalent constraint also for the PL model:

$$p \leq 1 - e^{\frac{\log\left(\frac{(E[K^2]-K)}{K}\right)+\log\left(\frac{N}{K}\right)[1-(\phi+1)l]}{2-(\phi+1)l}} \tag{11}$$

with l defined in Tab. I for the PL model.

4) Putting things together: Given the network model (ER or PL), the QoS thresholds (δ and ϕ), and the traffic matrix D, we are able to compute the maximum p which jointly satisfies connectivity (4), maximum link utilization (9) and increase of the shortest path (10) or (11). In this way, we can derive the total power consumption P'_{TOT} and estimate the power saving. In the next section, we will show how to compute the energy savings from the variation of D over time and a limited number of configurations.

III. TRAFFIC VARIATION AND NUMBER OF CONFIGURATIONS

In this section we consider the traffic variation to evaluate the relationship among the energy saving and the number of network configurations. A network configuration i is a network state with a non empty set of links in sleep mode and satisfying QoS constraints. The overall set of network configurations to be applied during a day is denoted with Δ_i, where i is the index of a network configuration, and it is bounded by the maximum number of configurations G. For example $G = 1$ means that one configuration is applied over the day (e.g. during night when traffic is low) to save energy. In particular when $G = 1$ the network has two states: the peak hours state, when all links are powered on, and the off-peak state, when configuration $i = 1$ is applied and a subset of network links is in sleep mode.

Each configuration is able to satisfy a maximum amount of traffic and so the set of configurations Δ_i depends on the traffic behavior. In this work we consider a traffic profile $D(t)$, symmetric around $T/2$,[2] being T the traffic period; we focus our attention on the decreasing traffic phase i.e., $[0, T/2]$, but a similar analysis can be derived for the traffic increase phase. Let us define as $[\tau_i, \tau_{i+1}]$ the time interval during which the configuration i is applied. Since the traffic is decreasing, the number of links that configuration i is able to put in sleep mode depends on the traffic at time τ_i i.e., the maximum traffic in the considered time interval. As a consequence we define as $p(\tau_i)$ the fraction of links put in sleep mode when configuration i is applied; $p(\tau_i)$ satisfies the conditions (4), (9) and (10) for ER model or (11) for PL model considering traffic $D(\tau_i)$.

The energy consumption of the network E'_{TOT} when G configurations are applied can be expressed as:

$$E'_{TOT}(G) = N\frac{K}{2}\mathcal{P}_L\sum_{i=0}^{G}(\tau_{i+1}-\tau_i)(1-p(\tau_i)) \tag{12}$$

with $\tau_0 = 0$, $p(\tau_0) = 0$ and $\tau_{G+1} = T/2$. Let us define the energy saving S when G configurations are applied as:

$$S(G) = 1 - \frac{E'_{TOT}(G)}{E_{TOT}} \tag{13}$$

where E_{TOT} is the energy consumption of the network with all links powered on, which can be expressed as: $E_{TOT} = N\frac{K}{2}\mathcal{P}_L\frac{T}{2}$.

Given the number of configuration G, our aim is to maximize the saving (13). Thus, we need to find the time instants (τ_1^*, τ_2^*, .. τ_G^*) that maximize $S(G)$. Fig. 1 reports an example of linear traffic variation and corresponding power consumption variation for $G = 1, 2, 3$. The intuition is that,

[2] We leave as future work the extension for the asymmetric case.

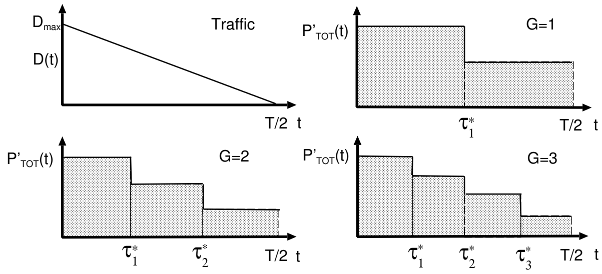


Fig. 1. An example of traffic variation and power consumption variation for $G = 1$, $G = 2$ and $G = 3$.

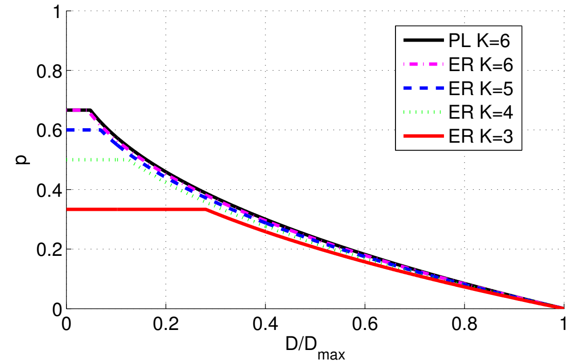


Fig. 2. Variation of p vs traffic for ER and PL models.

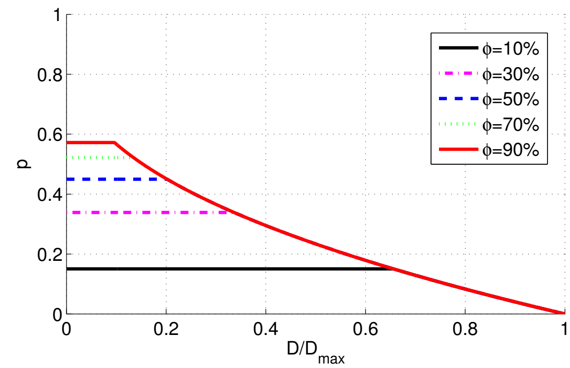


Fig. 3. Variation of p vs traffic for different Δ_l values.

in order to maximize the saving, the values of (τ_1^*, τ_2^*, .. τ_G^*) are chosen in order to minimize the shaded area of the figure, which corresponds to (12).

For example, $G = 1$ corresponds to the case in which we select a single set of powered off links that maximizes the energy saving $S(1)$, which can be expressed as:

$$S(1) = \left(1 - \frac{\tau_1}{\frac{T}{2}}\right) p(\tau_1) \tag{14}$$

Since the traffic is decreasing, the saving is maximized for the value τ_1^* solving the equation $\frac{dS(1)}{d\tau_1} = 0$. Similarly, we can extend this process to generic G configurations.

Finally, it is possible to define an upper bound on savings, by computing a new configuration for each variation of traffic:

$$S(U) = \frac{2}{T} \int_0^{\frac{T}{2}} p(\tau) d\tau \tag{15}$$

By comparing $S(G)$ with $S(U)$ we are able to evaluate the effectiveness of sleep modes when G is limited.

IV. Results

We first investigate how much p is affected by the traffic and the connectivity constraint. Unless otherwise specified, we adopt the following set of parameters: $N = 1000$, $\delta = 50\%$ [15], $C = 10$ Gbps [15], $\mathcal{P}_L = 500$ W [16]. We initially vary D continuously between D_{max} and zero. For each D, we compute the maximum p not violating the constraints. Fig. 2 reports the variation of p versus the normalized traffic D/D_{max}. The figure reports the results for the PL and ER graph models. For the PL model, we adopt a Pareto distribution (see [10] for details). With high traffic, p is low, since many devices has to be powered on to satisfy the traffic demands. Note that at the peak $D/D_{max} = 1$ p is zero since the network is exactly dimensioned to carry the peak amount of traffic, and it is not possible to put in sleep mode any device. However, as traffic decreases, p steadily increases. Interestingly, for low traffic, p is constant, due to the fact that the connectivity constraint has been reached. Focussing then on the model, both PL and ER presents a similar trend, showing that the network model performs similarly for both these graph families. Finally, the figure reports also the variation of the degree K. Interestingly, p decreases with K. This is due to the fact that, since K is lower, the network is composed by less links. Consequently, the connectivity constraint becomes tighter than the maximum load constraint, and so it is possible to put in sleep mode less devices. On the contrary, for highly connected networks (i.e, high values of K), the connectivity constraint is reached for extremely low values of traffic, i.e. $D/D_{max} = 0.1$ for $K = 6$. Note that the degree of current networks ranges between 4 and 8, thus we are more likely in the situation in which p mainly depends on traffic rather than the connectivity constraint.

We then consider also the constraint on the increase of the shortest path length ϕ. Fig. 3 reports the variation of p versus D/D_{max} for the ER graph model with $K = 6$. When $\phi = 10\%$ p is below 20%, meaning that the fraction of links that are put in sleep mode is rather limited. However, as ϕ increases, p steadily increases, being the maximum p equal to 58% for $\phi = 90\%$. Thus, we can conclude that the setting of ϕ strongly influences the quantity of links that can be put in sleep mode. In particular, an operator should carefully choose the value of ϕ which trades between QoS and power saving, e.g. $\phi = 50\%$ is a good tradeoff in our model.

In the following, we vary D over time and we consider the impact of applying a limited number of configurations. Rather than focussing on a single profile, we consider a family of

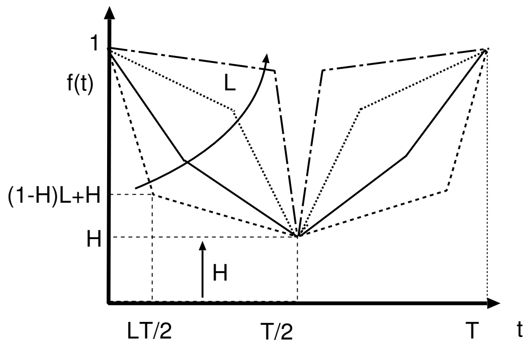


Fig. 4. Traffic Profile Model.

symmetric profiles of period T, defined as follows:

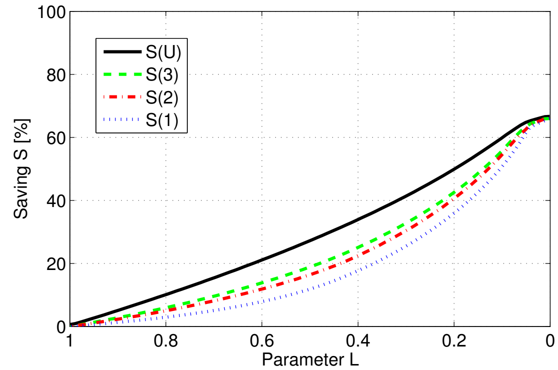
$$D(t) = \begin{cases} \frac{(L-1)(1-H)}{L-H}\frac{2t}{T} + 1 & 0 \le t < \frac{T}{2}\frac{L-H}{1-H} \\ \frac{(L-H)(1-H)}{L-1}(\frac{2t}{T} - 1) + H & \frac{T}{2}\frac{L-H}{1-H} \le t \le \frac{T}{2} \end{cases} \quad (16)$$

In particular, parameter $L \in (0, 1)$ varies the width of the off-peak zone, while $H \in (0, 1)$ varies the difference between peak traffic and off peak traffic. In this way, we are able to capture different traffic behaviors and to generalize as much as possible our results. Fig. 4 reports a graphical representation of traffic profiles.

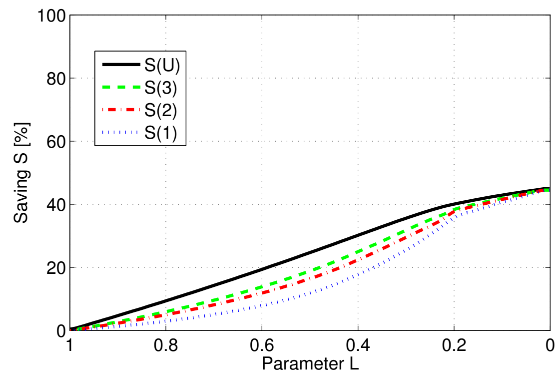
We consider initially the variation of L, while we keep $H = 0$. This case is representative of traffic profiles with a peak during the day and a deep off-peak during the night. Fig. 5(a) reports the saving for different configurations and an ER graph model with $K = 6$. Moreover, the figure reports also the upper bound $S(U)$. Savings are low when $L \approx 1$, since the width of the off-peak zone is reduced. Conversely, the saving steadily increases when L decreases. The saving with one configuration is below $S(U)$ (as expected). The gap between $S(U)$ and $S(1)$ is maximum for $L \approx 0.5$, which corresponds roughly to the case in which the traffic profile is a straight line (as reported in Fig. 1). In this case, a single switch off is far for the upper bound. However, the savings steadily increase with G. For example, the saving $S(3)$ is only 10% lower than the upper bound. Thus, a limited number of configurations are able to save an amount of energy comparable with the upper bound.

We then repeat the variation by imposing a maximum increase of the shortest path length $\phi = 50\%$. Fig. 5(b) reports the savings obtained with different configurations. Differently from the previous case, the savings are lower, since this constraint strongly influences the fraction of links that can be put in sleep mode. However, the gap between the upper bound and the fixed configurations is even reduced, being also the saving $S(2)$ close to the upper bound. This is due to the fact that, as the constraint ϕ becomes tight, p is less dependent on the variation of traffic. Thus, few configurations are enough to achieve a saving close to the maximum one.

Finally, we investigate the impact of H, which controls the difference between peak and off peak traffic. We consider again an ER model with $K = 6$. Fig. 6 reports the variation



(a) Without maximum increase of the shortest path length



(b) With maximum increase of the shortest path length ($\phi = 50\%$)

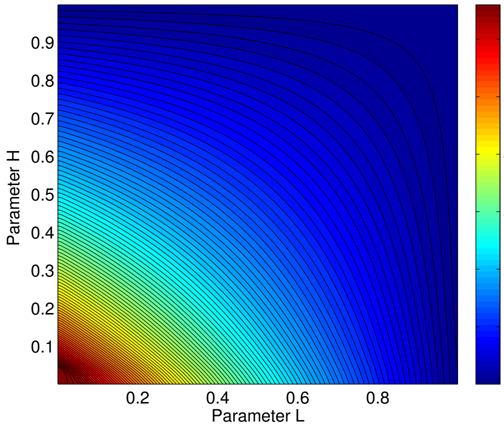
Fig. 5. Saving vs parameter L for ER model with $K = 6$.

of H for $G = 1, 2, 3$ and the upper bound U. With $H \approx 1$ the saving decreases, since the difference between off-peak and peak traffic is low. On the contrary, when $H \approx 0$ the saving increases. Note that nowadays, we are in the bottom of the figures, i.e. the difference between the peak and the off-peak traffic is high). For $L < 0.1$ and $H < 0.1$ the savings $S(1)$, $S(2)$ and $S(3)$ are close to the upper bound $S(U)$, i.e., typically larger than 50%. Considering then the full range of values, $S(1)$ and $S(2)$ save less energy than $S(U)$. However, saving $S(3)$ is close to the upper bound $S(U)$. This fact further corroborates our intuition that few configurations are able to obtain energy savings comparable to the maximum one.

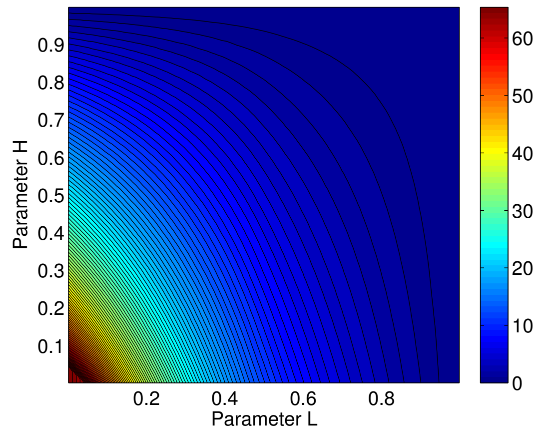
V. CONCLUSIONS

We have evaluated the effectiveness of sleep modes in backbone networks with a limited number of configurations. Results show that the saving obtained with few configurations (at most three) is only 10% far from the maximum saving. We think that this is an important indication for operators, since few configurations require a simplified sleep mode management as well as a marginal impact on the QoS perceived by users.

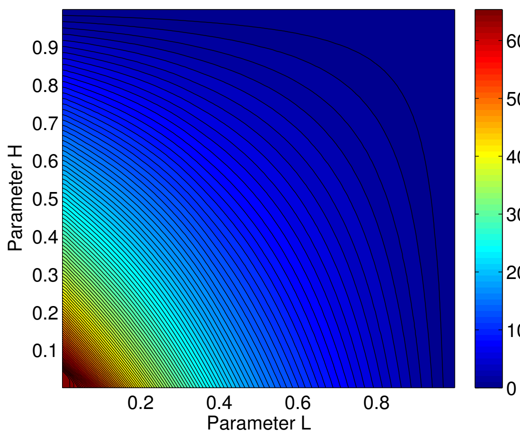
As next steps, we will consider the case in which also nodes can be put into sleep mode. Moreover, we will extend our findings on a real topology with measured power consumption figures and measured traffic profiles.



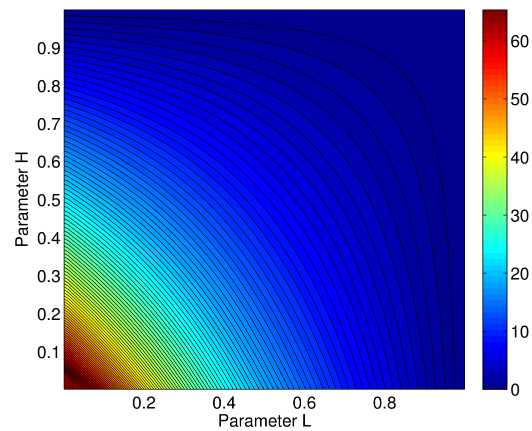
(a) $S(U)$



(b) $S(1)$



(c) $S(2)$



(d) $S(3)$

Fig. 6. Saving vs parameters L and H for ER model with $K = 6$.

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