Increasing Device Lifetime in Backbone Networks with Sleep Modes

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***Abstract*—We study the impact of sleep modes capabilities on the lifetime of backbone devices. We first define a model that integrates sleep modes in the device lifetime. We then derive a model for the network topology to compute the average network lifetime. Finally, we consider a realistic case study driven by operator feedback. Results indicate that the application of sleep modes can increase the average network lifetime. However, frequent power state transitions of network devices can deteriorate the network lifetime. Thus, we argue that the design and the management of energy-aware networks need to take into account the device lifetime.**

I. Introduction

Power consumption in telecommunication networks has been constantly increasing in recent years [1]. Several works in the literature have tackled the power efficient design and management of telecommunication networks (see [2] for an overview). In particular, one of the most promising approach is the application of sleep modes to network devices. Sleep mode is a low power state, which typically lasts for minutes or hours, during which the device does not perform any (or very limited) computation operations. When a device is in sleep mode, the other devices in the network that are still powered on need to guarantee Quality of Service constraints [3]. This imposes to solve a complex problem, since the traffic is shifted from the devices that are going to be put in sleep mode to the powered on devices.

Sleep mode effectiveness have been deeply investigated in the context of backbone networks [2]. However, the application of sleep modes in operational networks is at the early stage. In particular, manufacturers have not yet provided equipments with sleep mode capabilities, and operators have different constraints (e.g. protection) that prevent devices to be put in sleep mode. Thus, energy-efficiency may not be the only reason to apply sleep modes in backbone network, and finding valid motivations to apply sleep modes seems a mandatory step. To this end, this paper is focused on the study of the interaction of sleep modes and the device lifetime. In particular, we argue that sleep modes can increase the lifetime of network devices. This fact can further stimulates the adoption of sleep modes in current network devices, since network devices can save power but also increase their operational life.

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Traditionally, network devices have been designed so far to be always powered on. In this situation, a device may experience a failure due to variety of causes [4], including optical layer faults, hardware and/or software failures. The lifetime of the device is the period of time before a failure occurs. Recent measurements have shown that only 20% of failures happen during a period of scheduled maintenance activities [4]. Thus, when a network device fails, a non-scheduled maintenance operation needs to be performed, and in the worst case the device has to be replaced with a new one. During this phase, the other devices in the network need to sustain the traffic which was flowing on the failed device, and Quality of Service degradation may be experienced by users. Thus, reducing the frequency of failures events, and consequently increasing the device lifetime, is of crucial importance for telecom operators.

In this context, little attention has been posed so far to the interaction of sleep modes and the device lifetime. In particular, several questions arise. Are sleep modes impacting the lifetime of network devices? How to evaluate this impact? How to build a lifetime model that integrate sleep modes? The answer to these questions is the goal of this paper. We focus on backbone networks, by first formulating a model for the device lifetime which is suitable for the linecards of current routers. We then build a model for the average network lifetime considering generalized graph topologies. Finally, we consider a case study driven by operator feedback. Our preliminary results indicate that the application of sleep modes can increase the device lifetime. However, our results indicate that the application of sleep modes need to be carefully managed, since frequent power state transitions may deteriorate the device lifetime.

To the best of our knowledge, this is the first work investigating the impact of sleep modes on the lifetime of backbone devices. Even though our results have been obtained on a simple model that need further investigation, we think that this work is a first step towards a more comprehensive approach explicitly targeting the device lifetime during the network design and the network management phases.

The paper is organized as follows. The lifetime model is presented in Sec. II. The network model is detailed in Sec. III.

The model results are detailed in Sec IV. Simulation results are presented in Sec. V. Finally, conclusions are drawn in Sec. VI.

II. Modeling the Device Lifetime

We start defining the model to express the lifetime for a single device. We assume that sleep modes are applied to the linecards of a backbone network, which we generically refer to as “links” from now on. We define the lifetime D_{jk} of link from node j to node k as

$$D_{jk} = \frac{1}{\gamma_{jk}} \tag{1}$$

where γ_{jk} is the failure rate defined as the inverse of the Mean Time To Failure (MTTF).

We then evaluate what happens when sleep mode is applied to a link. During this phase, most of the electronic equipment of the device is put in a low-power state. This induces a variation in the temperature of the components which affects the lifetime of the device. In the following, we consider the main parameters related to the temperature that affect the failure rate.

A. Impact of Temperature Decrease

The failure rate of semiconductor and electronic parts tends to decrease when the operating temperature is reduced. In the literature, a fist-order model describing this relation is the Arrhenius law [5]:

$$\gamma^{\mathcal{T}} = \gamma^0 e^{-\frac{E_a}{K\mathcal{T}}} \tag{2}$$

where γ^0 is the failure rate estimated assuming infinite temperature, E_a is the activation energy, K is the Boltzmann constant, $\mathcal{T}$ is the temperature of the device and $\gamma^{\mathcal{T}}$ is the resulting failure rate. The Arrhenius law predicts the failure rate variation with the temperature, and a common assumption is that the failure rate fluctuates twice when temperature changes by $10\,^{\circ}\mathrm{C}$ [6]. However, measurements on real devices [7] have highlighted that this model is just a first order approximation, and the failure rate can be predicted by models fitted to the specific type of devices [7]. In order to take into account the impact of the operating temperature on the failure rate of a device, the Acceleration Factor (AF) [8] is generally defined as a simple metric which measures the increase of the failure rate with respect to a reference temperature:

$$AF^{\mathcal{T}_1} = \frac{\gamma^{\mathcal{T}_1}}{\gamma^{\mathcal{T}_r}} = e^{-\frac{E_a}{K}(\frac{1}{\mathcal{T}_1} - \frac{1}{\mathcal{T}_r})} \tag{3}$$

where $\gamma^{\mathcal{T}_1}$ and $\gamma^{\mathcal{T}_r}$ are the failure rate at the operating and reference temperatures, respectively.

B. Impact of Thermal Cycling

Additionally, also the variation of the temperature has an impact on the failure rate. This phenomenon is called thermal cycling: intuitively, a variation in the temperature of the device induces an increase in the failure rate. This effect is modeled by the Coffin-Mason equation [8], [9]:

$$N^f = C_0(\Delta_{\mathcal{T}} - \Delta_{\mathcal{T}_0})^{-q} \tag{4}$$

where $\Delta_{\mathcal{T}}$ is the variation of temperature, $\Delta_{\mathcal{T}_0}$ is the maximum variation of temperature supported by the device without a variation in the failure rate, C_0 is a material dependent constant, q is the Coffin-Mason exponent, and N^f is defined as the number of cycles to failure. According to (4), the failure rate due to thermal cycling can be defined as:

$$\gamma^{\Delta_{\mathcal{T}}} = \frac{f^{TC}}{N^f} \tag{5}$$

where f^{TC} is the frequency of thermal cycling and $\gamma_{\Delta_{\mathcal{T}}}$ is the estimated failure rate.

C. The Proposed Model

In our context, when a device is in low-power state we assume that its temperature is decreased. Thus, according to (3), this induces a decrease in the failure rate with respect to the full-power state. However, the transition between full and low-power (and vice-versa) induces a variation of temperature, and according to (4) and (5) this induces an increase in the failure rate. More formally, let us define γ_{jk}^{on} and γ_{jk}^{off} as the failure rate of the link at full and low-power modes, respectively. Moreover, according to (5), we define γ_{jk}^{tr} as the failure rate due to the thermal cycling effect induced by power state transitions:

$$\gamma_{jk}^{tr} = f_{jk}^{tr}/2N_{jk}^{f} \tag{6}$$

wherein, f_{jk}^{tr} is the power state transition frequency whilst the factor 2 at the denominator of the fraction in (6) takes into account that each cycle is made up of two transitions.

Given the previous definitions, we then express the overall failure rate of the device as follows.

$$\gamma_{jk} = \left[(1 - \tau_{jk}^{off})\gamma_{jk}^{on} + \tau_{jk}^{off}\gamma_{jk}^{off}\right] + \gamma_{jk}^{tr} \tag{7}$$

The term inside square bracket of (7) is related to the temperature, where τ_{jk}^{off} is the fraction of time that the device spends in low-power state. A weighed mean over time τ_{jk}^{off} is adopted to model this term, resulting in the average failure rate due to temperature. Moreover, (7) includes the term γ_{jk}^{tr} which is due to the thermal cycling effect. The additive model of [9] is adopted to put together all the terms. In particular, the total failure rate is the sum of the individual failure mechanisms, which are commonly assumed to be statistically independent from each other [10].

Since we are interested in evaluating whether the implementation of sleep modes can increase the device lifetime or not, we define the acceleration factor as the ratio between the failure rates experienced in normal condition (i.e., always in full-power state) and with sleep modes:

$$AF_{jk} = \frac{\gamma_{jk}}{\gamma_{jk}^{on}} = 1 - (1 - AF_{jk}^{off})\tau_{jk}^{off} + \chi_{jk} f_{jk}^{tr} \tag{8}$$

$$AF_{jk}^{off} = \frac{\gamma_{jk}^{off}}{\gamma_{jk}^{on}} \tag{9}$$

$$\chi_{jk} = \frac{1}{2\gamma_{jk}^{on} N_{jk}^{f}} \tag{10}$$

In (8), AF_{jk}^{off} is the acceleration factor due to low-power state which, according to (3), is lower than one due to the lower operating temperature when the device is in low-power state. In this model, the failure rates γ_{jk}^{on}, γ_{jk}^{off} and the parameter χ_{jk} are fixed parameters, which depends on the characteristics of the hardware (HW) adopted to build the device. χ_{jk} is the inverse of the number of cycles to failures, weighed by γ_{jk}^{on}. On the contrary, τ_{jk}^{off} and f_{jk}^{tr} are variable parameters and depend on the practical realization of the sleep mode capability. In particular, the variable parameters are determined by the following constraints: i) the network topology, which imposes constraints on the routing of the traffic demands, ii) the traffic variation over time, which limits the maximum amount of resources that can be put in sleep mode, and iii) the time constraints required to put in sleep mode and recover again to full-power a single device.

Now, let us consider the entire network. We define its average lifetime E as:

$$E = \frac{\sum_{jk} D_{jk}}{I} \tag{11}$$

where I is the number of links in the network. Then, we define the network acceleration factor AF as:

$$AF = \frac{E}{E^{on}} = \frac{\sum_{jk} AF_{jk}}{I} \tag{12}$$

where E^{on} is the average network lifetime in normal condition, i.e., by only considering γ_{jk}^{on}.

In the following section, we will consider a model to compute τ_{jk}^{off} and f_{jk}^{tr} on random graph topologies, a traffic variation over time and different time constraints.

III. Network Model

We start with a network described by an Erdös and Rényi (ER) random graph [11] with N nodes and I links. The average node degree is $K = \frac{2I}{N}$. We assume that when sleep modes are applied a fraction of pI links is removed, being $p \in (0, 1)$. In particular, assuming that the links to be powered off are randomly chosen, the new degree of the graph becomes $K' = K(1 - p)$ [12].

The fraction of links p that can be powered off is influenced by the traffic and the Quality of Service (QoS) constraints. In particular, following the assumptions in our previous work [13], we consider the fraction p that jointly satisfy the following conditions:

- *Network Connectivity*. We assume that to ensure a minimum network connectivity each node needs to be connected to at least other two nodes in the network. This is equivalent to imposing the following constraint:
$$p \leq 1 - \frac{2}{K} \tag{13}$$
- *Average Link Utilization*. We then introduce the constraint to limit the average link utilization. In particular, we assume that links can be utilized up to a threshold $\delta \in (0, 1]$. $\delta = 1$ means that the link is utilized up to 100% of its capacity, which is denoted as C. We then compute the maximum p that can be sustained by the network when all links are utilized up to δ. More in depth, we introduce the total amount of traffic R which is injected in the network and the average path length l. We then denote as l' the average path length when the links are put in sleep mode. Given the previous notations, we then impose the maximum p as:
$$p \leq 1 - \frac{Rl'}{N \frac{K}{2} C \delta} \tag{14}$$
We refer the reader to [13] for the explanations on how l and l' are computed. In brief, both of them depends on the specific graph model adopted, and depend on N, K, and p.
- *Maximum Increase in the Shortest path*. Finally, an Internet Service Provider might be interested in limiting the shortest path length when sleep modes are applied. We define the increase in the shortest path length as $\frac{l'-l}{l}$, and we introduce a threshold $\phi \in [0, 1]$ to limit such increase, i.e., $\frac{l'-l}{l} \leq \phi$. In our case, the maximum p for the shortest path constraint of an ER graph is expressed as:
$$p \leq 1 - \frac{e^{\frac{logK}{\phi+1}}}{K} \tag{15}$$

Now supposing that traffic R varies over time on a period T, we compute the maximum fraction of links $p(t)$ that jointly satisfies (13), (14) and (15) according to the traffic $R(t)$ at time t, with $t \in (0, T)$.

The next step is to integrate $p(t)$ in our model. Let us assume first that the same hardware is deployed for all devices in the network. Therefore, the failure rates are the same for each device, i.e., $\forall\, j, k\ \gamma_{jk}^{on} = \gamma^{on}$, $\gamma_{jk}^{off} = \gamma^{off}$, $N_{jk}^{f} = N^{f}$, and consequently $AF_{jk}^{off} = AF^{off}$ and $\chi_{jk} = \chi$. Moreover, it holds that:

$$\frac{\sum_j \sum_k \tau_{jk}^{off}}{I} = \frac{1}{T} \int_0^T p(t)\,\mathrm{d}t \tag{16}$$

Additionally, let us introduce $\bar{f}^{tr}$ as the average power-state transition frequency experienced within the network, i.e., $\bar{f}^{tr} = \frac{\sum_{jk} f_{jk}^{tr}}{I}$. Then, we can express the average network AF as:

$$AF = 1 - \frac{1 - AF^{off}}{T} \int_0^T p(t)\,\mathrm{d}t + \chi \bar{f}^{tr} \tag{17}$$

In this way, we are able to compute the network failure acceleration factor given the graph model, the traffic variation over time and the HW parameters (i.e., AF^{off} and χ).

Now assuming $\chi = 0$ (i.e., $N^f = \infty$) and considering that $p(t) \leq \left(1 - \frac{2}{K}\right)$, we obtain the following lower bound for

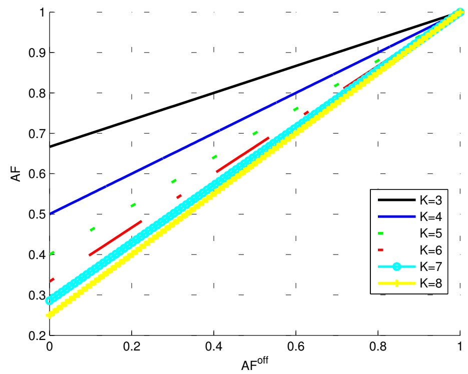

Fig. 1. Lower bound variation of AF vs. AF^{off} and K.

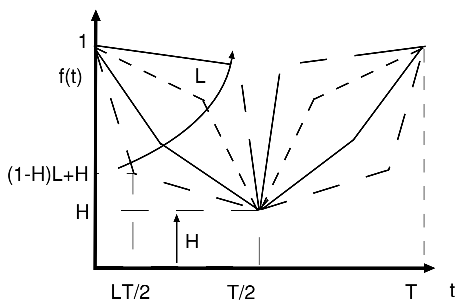

Fig. 2. Traffic Profile Model.

AF:

$$AF \geq \frac{2}{K} + \left(1 - \frac{2}{K}\right) AF^{off} \tag{18}$$

Note that, for sleep mode to be effective in increasing the network lifetime, it must result in $AF < 1$.

IV. Model Results

Unless otherwise specified, we adopt the following set of parameters: number of nodes $N = 10000$, average degree $K = 6$, average link utilization $\delta = 50\%$ [3], link capacity $C = 10$ Gbps [3], and maximum increase of the shortest path $\phi = 1$.

We start considering $\chi = 0$ to estimate the maximum benefit achievable by introducing sleep modes.[1] Fig. 1 reports the acceleration factor AF versus the acceleration factor in low power state AF^{off}. The figure reports the lower bound of (18) for different values of K. As expected, AF is always lower or equal than 1, meaning that the introduction of sleep modes always increases the network lifetime. Interestingly, AF tends to decrease as K increases. In particular, AF passes from 0.73 to 0.4 when $AF^{off} = 0.2$. This is due to the fact that, as the network becomes more connected, a higher percentage of links can be safely powered off, and therefore AF tends to be equal to AF^{off}.

In the following, we introduce the traffic variation over time. We consider a family of symmetric profiles of period

[1] This means that we assume N^f equal to ∞, hence neglecting the contribution of the thermal cycling effect.

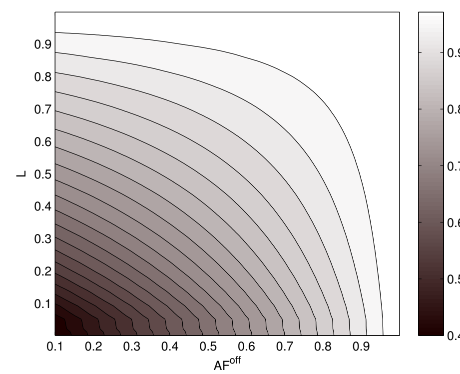

Fig. 3. AF variation vs. AF^{off} and L.

T, defined as follows:

$$R(t) = \begin{cases} \frac{(L-1)(1-H)}{L-H}\frac{2t}{T} + 1 & 0 \leq t < \frac{T}{2}\frac{L-H}{1-H} \\ \frac{(L-H)(1-H)}{L-1}(\frac{2t}{T} - 1) + H & \frac{T}{2}\frac{L-H}{1-H} \leq t \leq \frac{T}{2} \end{cases} \tag{19}$$

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. 2 reports a graphical representation of traffic profiles. In our experiments, the traffic profile is sampled over 200 points, which is equivalent to have one traffic matrix every 7 minutes.

Fig. 3 reports the acceleration factor AF considering the variation of AF^{off} and L and assuming H equal to 0. In this experiment, we set a value of traffic which saturates the links for the peak traffic, i.e., the average link utilization is equal to δ for $t = 0$. In this way, all the links have to be powered on during the peak traffic. As L decreases the amplitude of the off peak zone is increased. Thus, it is possible to put in sleep mode more devices, and consequently AF tends to decrease as L decreases. However, the variation is consistent only when AF^{off} is sufficiently low, i.e., less than 0.5.

We then extend our findings considering also the variation of H, as reported in Fig.4. In this case we keep $L = 0.4$. As H is decreased, the ratio between peak zone and off peak zone is increased, and therefore AF is decreased since more devices can be put in sleep mode. Thus, we can conclude that the variation of traffic strongly influences the acceleration factor.

We then consider the impact of the failure rate due to power state transitions by considering $\chi \geq 0$. To compute $\bar{f}^{tr}$, we define $\mathcal{F}(t)$ as the average number of power state transitions experienced by each link in the interval $(0, t)$, so that it results in:

$$\bar{f}^{tr} = \frac{\mathcal{F}(T)}{T} \tag{20}$$

Then, we assume the following expression for $\mathcal{F}(t)$:

$$\mathcal{F}(t) = (1 + \Gamma) \int_0^t |p'(t)| \, \mathrm{d}t \tag{21}$$

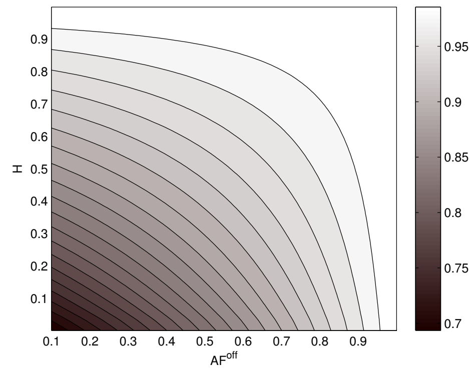

Fig. 4. AF variation vs. AF^{off} and H.

According to (21) the percentage of links which changes its state in an interval (t_a, t_b) in which $p(t)$ is monotone, is proportional to $|p(t_a) - p(t_b)|$. The case of $\Gamma = 0$ corresponds to an optimistic scenario in which if $p(t)$ increases in the interval (t_a, t_b), then the set of devices in sleep mode at time $t_2 > t_1$, with $t_1, t_2 \in (t_a, t_b)$, contains the set of devices in sleep mode at time t_1, and vice-versa if $p(t)$ decreases. On the contrary, by assuming $\Gamma > 0$, we can consider more pessimistic scenarios in which more power state transitions are experienced when passing from a network configuration to another one. According to (20) and (21), and considering the assumed traffic scenario described in (19), it results in:

$$\bar{f}^{tr} = (1 + \Gamma)\frac{2(p(T/2) - p(0))}{T} \tag{22}$$

Fig. 5 reports the variation of AF versus AF^{off} and χ considering a traffic profile with $H = 0$ and $L = 0.4$. Γ is set to 0 in this experiment, which thus represents an optimistic scenario. The red line corresponds to the level curve $AF = 1$. The region on the left of the line is lower than 1, meaning that the values of AF^{off} and χ inside this region decrease AF, and therefore increase the network lifetime. The region on the right is instead the zone where the application of sleep mode does not improve the network lifetime. From the figure, we can see that there is clearly a tradeoff between the values of χ and the values of AF^{off}, meaning that the technological parameters play a crucial role in determining the effectiveness of sleep modes on AF. Intuitively, low values of AF^{off} improve the network lifetime, while high values of χ tend to deteriorate it.

In this regard, although a careful evaluation of the HW parameters influencing the failure rate is out of the scope of the present paper, it is worth providing the reader with a general indication about the range of values that the parameter χ introduced in our model could assume in practice. Concerning the device lifetime in normal condition (i.e., $\frac{1}{\gamma^{on}}$), it is generally assumed between 5–7 years [9]. Instead, concerning the number of cycles to failure N^f, this is influenced by several factors, the most important being the temperature variation $\Delta_{\mathcal{T}}$. The work in [14] provides some experimental results for N^f conducted on CBGA 625 packages as well as projections based on models. According to the graph reported in Fig. 6 in [14], and considering that the expected $\Delta_{\mathcal{T}}$ related to sleep mode should be around 40° C (see for instance the operating temperature for Cisco linecards reported in [15]), we would have $N^f \in [5 \times 10^3, 10 \times 10^3]$ cycles depending on the projection model. Thus, considering the definition in (10), it results in $\chi \in [2.2, 6.1]$ h/cycle.

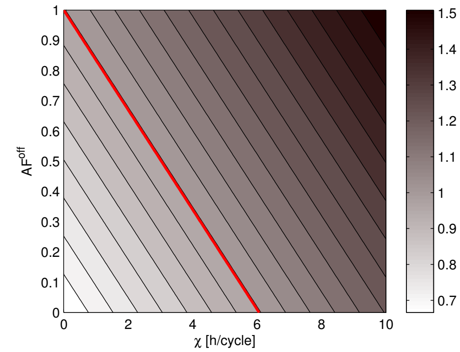

Fig. 5. AF variation vs. AF^{off} and χ $(\Gamma = 0)$.

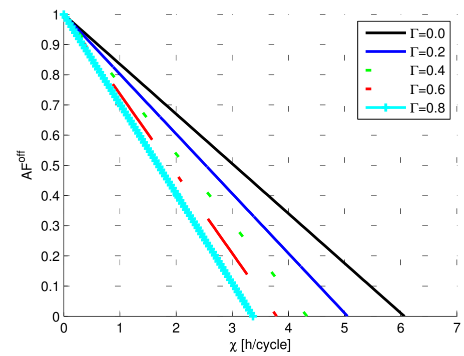

Fig. 6. $AF = 1$ level curves considering the variation of AF^{off}, χ and γ.

In the following, we consider the variation of Γ. As Γ increases, we are considering more pessimistic scenarios in which more devices are activated/deactivated. Fig. 6 reports the level curves corresponding to $AF = 1$ for different values of Γ. As expected, as Γ increases, the level curves tend to be shifted on the left, meaning that the values of χ which make sleep mode not convenient are lower. Thus, as more devices are activated/deactivated, the network lifetime tends to decrease.

V. Simulation Results

In the last part of our work we consider a realistic scenario provided by France Telecom (FT). In particular, we consider a backbone topology composed of $N = 38$ nodes and $I = 144$ links. For this scenario, routing weights, link capacities, and traffic matrices are provided. We refer the reader to [16] for a detailed description of these input parameters. Fig. 7 reports the variation of traffic over time $R(t)$. The traffic is sampled over 5 minutes, resulting in a frequent variability and a clear day-night trend. Given the network scenario, we run the DAISIES algorithm [17] to simulate a practical sleep mode strategy within the network. DAISIES is a distributed on-line adaptive routing technique which works in IP/MPLS

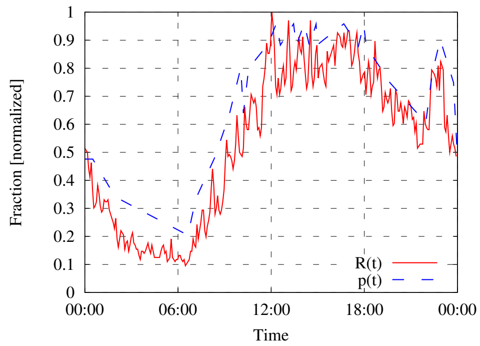

Fig. 7. FT scenario: variation of $R(t)$ and $p(t)$ over time.

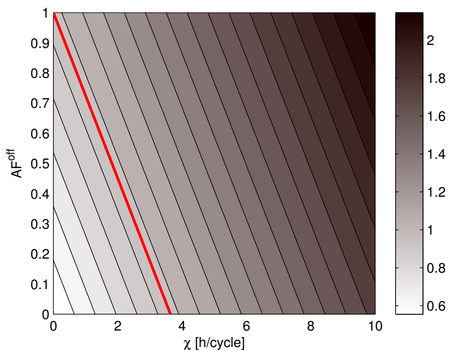

Fig. 8. AF variation vs. AF^{off} and χ for the FT scenario.

networks. By running DAISIES we obtain the fraction of links in sleep mode $p(t)$ according to the considered traffic profile $R(t)$. Moreover, we also compute the power state transition frequency f^{tr}.

Fig. 7 reports the variation of $p(t)$ over time. Interestingly, $p(t)$ tends to vary throughout the day to follow the traffic variation. This results in an average number of transitions equal to 3.2 per day for each link in this time period. The higher value of f^{tr} obtained here with respect to what shown in [17] is due to the higher traffic variability with respect to the sinusoidal traffic profile considered in [17].

Fig. 8 reports the variation of AF versus AF^{off} and χ for the FT scenario with DAISIES. Compared to the optimistic scenario of the theoretical model (Fig.5) the level curve of the simulated scenario is shifted on the left. In particular, the value of χ which makes $AF = 1$ (with $AF^{off} = 0$) is around 6 for the theoretical model and less than 4 for the simulated scenario. This is due to the fact that $R(t)$, and consequently $p(t)$, frequently varies in the simulated scenario, resulting in a higher number of power state transitions. Thus, when traffic frequently varies, it is very important to limit the number of power state transitions and to deploy devices that are less affected by the thermal cycling effect.

VI. Conclusions and Future Work

We have studied the impact of sleep modes on the device lifetime in backbone networks. After formulating a model for the device lifetime, we have evaluated the average network lifetime considering a network model based on random graphs and a simulation scenario driven by operator feedback. Our results indicate different aspects. First, the topology has an important impact, since highly connected topologies tend to increase the network lifetime. Second, traffic has a strong influence, since traffic variations with wide and deep off peak zone tend to increase the lifetime. Finally, we have proven that frequent power state transition may deteriorate the network lifetime compared to the always on solution.

As next step, we plan to study a more comprehensive approach in which the device lifetime is integrated in the design and the management of the network. Moreover, we plan to evaluate the effectiveness of the proposed model on a real case study. Finally, we will extend the proposed model to different types of devices and different segments of the network (access, metro, etc.).

References

[1] S. Lambert, W. Van Heddeghem, W. Vereecken, B. Lannoo, D. Colle, M. Pickavet, and J. Ferry, "Worldwide electricity consumption of communication networks," *Optics express*, vol. 20, no. 26, pp. B513–B524, 2012.

[2] R. Bolla, R. Bruschi, F. Davoli, and F. Cucchietti, "Energy efficiency in the future internet: a survey of existing approaches and trends in energy-aware fixed network infrastructures," *Communications Surveys & Tutorials, IEEE*, no. 99, pp. 1–22, 2010.

[3] L. Chiaraviglio, M. Mellia, and F. Neri, "Minimizing isp network energy cost: Formulation and solutions," *IEEE/ACM Transactions on Networking (TON)*, vol. 20, no. 2, pp. 463–476, 2012.

[4] A. Markopoulou, G. Iannaccone, S. Bhattacharyya, C.-N. Chuah, Y. Ganjali, and C. Diot, "Characterization of failures in an operational IP backbone network," *IEEE/ACM Transactions on Networking (TON)*, vol. 16, no. 4, pp. 749–762, 2008.

[5] K. J. Laidler, *Chemical Kinetics, 3/E.* Pearson Education India, 1987.

[6] "Alpiste Panel Cooling Units Technical Information," *http://www.apiste-global.com/enc/technology enc/detail/id=1262*.

[7] B. De Salvo, G. Ghibaudo, G. Pananakakis, G. Reimbold, F. Mondond, B. Guillaumot, and P. Candelier, "Experimental and theoretical investigation of nonvolatile memory data-retention," *Electron Devices, IEEE Transactions on*, vol. 46, no. 7, pp. 1518–1524, 1999.

[8] J. S. S. T. Association *et al.*, "Failure mechanisms and models for semiconductor devices," *JEDEC Publication JEP122-B*, 2003.

[9] A. K. Coskun, R. Strong, D. M. Tullsen, and T. Simunic Rosing, "Evaluating the impact of job scheduling and power management on processor lifetime for chip multiprocessors," in *Proceedings of the eleventh international joint conference on Measurement and modeling of computer systems*, pp. 169–180, ACM, 2009.

[10] R. Blish and N. Durrant, "Semiconductor device reliability failure models," *Int. Sematech. Technol. Transfer*, 2000.

[11] P. Erdős and A. Rényi, "On random graphs," *Publicationes Mathematicae Debrecen*, vol. 6, pp. 290–297, 1959.

[12] R. Albert and A. Barabási, "Statistical mechanics of complex networks," *Reviews of Modern Physics*, vol. 74, no. 1, p. 47, 2002.

[13] L. Chiaraviglio and A. Cianfrani, "On the effectiveness of sleep modes in backbone networks with limited configurations," in *Software, Telecommunications and Computer Networks (SoftCOM), 2012 20th International Conference on*, pp. 1–6, IEEE, 2012.

[14] R. Ghaffarian, "Accelerated thermal cycling and failure mechanisms for BGA and CSP assemblies," *Transactions-American Society of Mechanical Engineers Journal of Electronic Packaging*, vol. 122, no. 4, pp. 335–340, 2000.

[15] "Cisco CRS Modular Services Card," *http://www.cisco.com*.

[16] F. Idzikowski, "TREND D3.3 Final report for the IRA Energy-efficient use of network core resources, available on line at: http://www.fp7-trend.eu/system/files/private/71-wp3/d33-final-report-ira.pdf," June 2012.

[17] A. Coiro, M. Listanti, A. Valenti, and F. Matera, "Energy-Aware Traffic Engineering: A Routing-Based Distributed Solution for Connection-Oriented IP Networks," *Computer Networks*, 2013.