Modeling the Impact of Power State Transitions on the Lifetime of Cellular Networks

Luca Chiaraviglio[1], Marco Listanti[1], Josip Lorincz[2], Edoardo Manzia[1], Martina Santucci[1]
[1]DIET Department, University of Rome Sapienza, Rome, Italy, email {name.surname}@uniroma1.it
[2]FESB-Split, University of Split, Split, Croatia, email josip.lerinc@fesb.hr

***Abstract*—We consider the effect of power state transitions on the lifetime of Base Stations (BSs) in a cellular network. In particular, we take into account the impact of putting in sleep mode the BS, and also the change of the radiated power. When the BS reduces its power consumption, its lifetime tends to increase, as a consequence of the temperature reduction. However, the change in the power state triggers a negative effect which instead tends to reduce the BS lifetime. We therefore propose a model to evaluate the BS lifetime considering the two aforementioned effects, triggered either by the application of a sleep mode state or a change in the radiated power. Our results, obtained over a representative case study, indicate that the BS lifetime may be negatively affected when power state transitions take place. Therefore, we argue that the lifetime should be considered in the process of deciding how and when to change from a power state to another one.**

I. Introduction

Cellular networks are intensely deployed in the whole world. The downlink power of a single Base Station (BS) depends on the number of terminals connected to it, their signal to interference plus noise ratio, as well as the amount of received power for each terminal. In the literature, different solutions have been proposed so far in order to adjust the power radiated by the BS (see for example [1]) in order to serve its associated users, and also to reduce the overall interference with the neighboring BSs.

At the same time, power consumption consumed by a single BS is far to be negligible [2]. Moreover, the radiated transmit power influences the total BS power consumption [3]. These facts, coupled also with the high cardinality of BSs in an operator network, have stimulated researches towards the reduction of power in cellular networks. Among the different proposed solutions, one of the most promising approaches to reduce energy is the application of a sleep mode (SM) state to the BS. More in depth, the BS is completely powered off during low traffic hours (e.g. at night), still guaranteeing coverage and traffic requirements by the remaining BSs that remain powered on. The efficacy and efficiency of BS SMs have been extensively studied in previous work (see for example the survey [4]).

A power state transition may therefore occur either when the BS passes from full power to SM (and vice-versa), or when the radiated power is varied. The change in the power state may trigger a change on the temperature of some of the BS components. However, some natural questions arise: How do SM and radiated power impact the BS lifetime? Is it possible to build a model to predict the lifetime increase/decrease of a BS as a consequence of its power state change? The answer to these questions is the goal of this paper. In particular, we first consider the main effects triggered by the temperature change on the BS. Then, we build a simple model to compute the lifetime increase/decrease of the BS. Finally, we evaluate the proposed model on a realistic case-study. Our results indicate that the lifetime of the single BSs may be negatively affected when power state transitions take place. This reduction of lifetime will deteriorate the reliability of the network (due to the fact that BSs increase their failure rate), as well as bringing to an increase in the reparation and mainteinance costs of BSs. Therefore, we argue that the lifetime should be considered in the process of deciding how and when to change from a power state to another one.

The closest paper to our work is [5], which proposes a simple model to compute the lifetime increase/decrease of a an entire cellular network as a consequence of a SM approach. In this paper, we go three steps further by: i) proposing a model that consider different power state transitions (e.g., due to SM and/or radiated power scaling), ii) evaluating the lifetime on the whole network and also on the single BSs, iii) evaluating the lifetime evolution over time. More in depth, when the BS consumes less power or it is put in SM, the lifetime tends to increase, since the temperature of its components is reduced. However, the power state change (either from power on to SM or for different values of radiated power) triggers a negative effect which tends to decrease the BS lifetime. The combination of these two effects then lead to the variation of the total lifetime experienced by the BS.

The rest of the paper is organized as follows. The main effects related to temperature impacting the BS lifetime are summarized in Sec. II. Sec. III then presents our model for estimating the BS lifetime. Results, obtained from a realistic case study, are reported in Sec. IV. Finally, Sec. V concludes our work.

II. Impact of Temperature on the BS Lifetime

A first order model to compute the failure rate $\gamma^{\mathcal{T}}$ of a device given its temperature $\mathcal{T}$ is the Arrhenius law [6]:

$$\gamma^{\mathcal{T}} = \gamma^0 e^{-\frac{E_a}{\mathcal{K}\mathcal{T}}} \text{ [1/h]} \quad (1)$$

where γ^0 is the failure rate estimated assuming a very high temperature, E_a is the activation energy (i.e. the minimum energy needed to activate the failure variation) and $\mathcal{K}$ is the Boltzmann constant. Interestingly, when the temperature is decreased, the failure rate is decreased too. Although more detailed models have been proposed in the literature (see for example [7]) all of them predict a decrease in the failure rate when the temperature is reduced. This means that, if the reduction of the temperature would be the only effect taken under consideration, keeping the BS in low-power states for the longest amount of time would be of benefit for its lifetime.

However, a device may suffer strain and fatigue when temperature conditions change, in particular when this happens in a cyclic way (i.e. from one temperature to another one). The Coffin-Manson model [8] describes the effects of material fatigue caused by cyclic thermal stress. The predicted failure rate due $\gamma^{\Delta_\mathcal{T}}$ to the thermal cycling effect is then expressed as:

$$\gamma^{\Delta_\mathcal{T}} = \frac{f^{TC}}{N^f} \text{ [1/h]} \tag{2}$$

where f^{TC} is the frequency of thermal cycling and $\gamma^{\Delta_\mathcal{T}}$ is the estimated failure rate. The term N^f is the number of cycles to failure, and it is commonly denoted as:

$$N^f = C_0(\Delta_\mathcal{T} - \Delta_{\mathcal{T}_0})^{-q} \tag{3}$$

where $\Delta_\mathcal{T}$ is the temperature variation of the cycle, $\Delta_{\mathcal{T}_0}$ is the maximum admissible temperature variation without a variation in the failure rate, C_0 is a constant material dependent, q is the Coffin-Manson exponent. From this model, we can clearly see that the more often the BS experiences a temperature variation, the higher will be also its failure rate. In the following, we therefore build a model to capture this effect and also to consider the impact of temperature reduction reported in Eq. 1.

III. BS Lifetime Model

We first derive the model to compute the lifetime increase/decrease of a single BS, and then we extend this model to the whole network. We start from the assumption that each BS in the network set up a discrete set of power state values. The total BS power is composed by two terms [2]: the static power, that has to be counted if the BS is not in SM, and the dynamic power, which instead depends on the radiated power. In particular, we assume a set of $\mathcal{P}$ power states whose cardinality is $K = |\mathcal{P}|$. Let us denote with P_1,P_2,...,$P_{K-1} \in \mathcal{P}$ the power consumed by the BS for dynamic power with indexes 1,2,...,$(K-1)$, respectively. Moreover, $P_{off} \in \mathcal{P}$ is the power consumed when the BS is in SM state. The power states are ordered in increasing order, i.e., $P_{off} < P_1 < P_2 < P_{K-1}$.

For each power state, we denote as τ_{off}, τ_1,τ_2,...,τ_{K-1} the time spent by the BS at power state P_{off},P_1,P_2,...,P_{K-1}, respectively. The total amount of time under consideration is denoted with T. Moreover, we associate a temperature value of the BS for each power state. Given the fact that we have different temperatures, according to Eq. 1 we can associate a failure rate for each power state: γ_{off},γ_1,γ_2,...,γ_{K-1}.

The total failure rate of BS γ_s considering only the impact of different power states is then defined as:

$$\gamma_s = \gamma_{off}\frac{\tau_{off}}{T} + \sum_{i=1}^{K-1} \gamma_i \frac{\tau_i}{T} \text{ [1/h]} \tag{4}$$

which is the sum of the different failure rates, weighed by the normalized amount of time spent in each power state.

In the following, we consider the impact on the failure rate of the thermal cycling effect, which is triggered by the power state transitions. In particular, we denote with δ_{i-j} the failure rate triggered when passing between power state i and power state j. Similarly, we denote as δ_{off-j} the failure rate when passing between a SM state and power state j. By assuming that the amount of time when passing from one power state to another one does not influence the failure rate, we express the total failure rate δ_t due to power state transitions as:

$$\delta_t = \sum_{j}^{K-1} \delta_{off-j} + \sum_{i}^{K-1}\sum_{j>i}^{K-1} \delta_{i-j} \text{ [1/h]} \tag{5}$$

The total failure rate of BS γ_{tot} is then the sum of the failure rates considering the different power states and the failure rates due to power state transitions:

$$\gamma_{tot} = \gamma_s + \delta_t \text{ [1/h]} \tag{6}$$

γ_{tot} is the sum of failure rates as we have assumed that the failure rates due to the different effects are statistically independent from each other [9].

In the literature, it is common to evaluate the increase/decrease of the current failure rate γ_{tot} with respect to a reference failure rate γ_{tot}^{ref}. This metric is called acceleration factor [8], which we denote as:

$$AF = \frac{\gamma_{tot}}{\gamma_{tot}^{ref}} \tag{7}$$

In particular, if the current failure rate is lower than the reference failure rate, the AF is lower than one, and therefore the lifetime is increased. On the contrary, if the AF is greater than one, the lifetime is decreased. Ideally, the AF should be always kept below one. By moving γ_{tot}^{ref} inside Eq. (6) we can express AF as:

$$AF = AF_s + AF_t \tag{8}$$

where $AF_s = \gamma_s/\gamma_{tot}^{ref}$ is the acceleration factor due to the time spent in different power states, while $AF_t = \delta_t/\gamma_{tot}^{ref}$ is the acceleration factor due to power state transitions.

We can express the AF_s term as:

$$AF_s = \underbrace{AF_{off}\frac{\tau_{off}}{T}}_{\text{SM}} + \underbrace{\sum_{i=1}^{K-1}[AF_i\frac{\tau_i}{T}]}_{\text{radiated power}} \tag{9}$$

where $AF_{off} = \gamma_{off}/\gamma_{tot}^{ref}$ is the acceleration factor in SM, which is always lower than one since we have assumed that the temperature of the SM state is lower compared to the reference temperature. Similarly, $AF_i = \gamma_i/\gamma_{tot}^{ref}$ is the acceleration factor in power state i, which is again lower or equal than than one since the temperature at power state k is always lower or equal than the reference temperature. Moreover, since the temperature at power state i is lower than the temperature at state $i-1$, it holds that: $AF_{off} < AF_1 < AF_2 < ... < AF_{K-1} \leq 1$.

We then consider the second term AF_t of Eq. 8. According to Eq. 2, the failure rate due to power transitions between state i and state j can be defined as $\delta_{i-j} = \frac{f_{i-j}}{N_{i-j}^f}$, where f_{i-j} is the frequency of power switching between the states and N_{i-j}^f is the maximum number of cycles between state i and state j before a failure occurs. Intuitively, when f_{i-j} is larger than

N_{i-j}^{f}, a failure occurs on the device. The ratio between δ_{i-j} and γ_{tot}^{ref} is then defined as:

$$\frac{\delta_{i-j}}{\gamma_{tot}^{ref}} = \chi_{i-j}^{ref} f_{i-j} \tag{10}$$

where $\chi_{i-j} = \frac{1}{N_{i-j}^{f}\gamma_{tot}^{ref}}$ is a weigh parameter of the power state frequency f_{i-j}. The acceleration factor due to power state transitions is then defined as:

$$AF_t = \underbrace{\sum_{j=1}^{K-1} \chi_{off-j}^{ref} f_{off-j}}_{\text{SM}} + \underbrace{\sum_{i=1}^{K-1} \sum_{j>i}^{K-1} [\chi_{i-j}^{ref} f_{i-j}]}_{\text{radiated power}} \tag{11}$$

AF_t can take values even larger than one, since both f_{off-j} and f_{i-j} may be larger than one (especially when different power state transitions occur during the time period T). As a consequence, this term tends to increase the total acceleration factor and therefore to decrease the BS lifetime.

We now consider the different parameters included in the AF metric. In particular, the weights χ_{off-j}^{ref} and χ_{i-j}^{ref} are HW parameters, i.e., they are fixed given the failure rate at the reference temperature and the number of cycles to failures. Similarly, also the terms AF_{off} and AF_i may be known by measuring the failure rate at a given power value. On the contrary, the terms τ_{off} and f_{off-j} depends on the implementation of the SM approach. In practice, these terms need to be carefully planned by taking into account the current BS and the neighboring ones, i.e., to avoid a coverage hole or an overloading of the neighboring BSs. Similarly, the terms τ_i and f_{i-j} depends instead on the policy to allocate power to users, which may depend on the number of active terminals and their signal to interference ratio.

Since both SMs and power allocation states are varied considering a set of BSs as a whole, an operator might be interested to observe the acceleration factor over the BS set $\mathcal{Z}$. In particular, we can define an average AF as:

$$AF^{tot} = \frac{\sum AF^i}{|\mathcal{Z}|} \tag{12}$$

where AF^i is the acceleration factor of BS i computed with Eq. 8. Intuitively, if $AF^{tot} < 1$, the BSs in the network fails less often compared to the reference failure rate, and therefore the average lifetime tends to increase. On the contrary, when $AF^{tot} > 1$ the lifetime tends to decrease. Similarly, the operator might be interested to observe the worst case acceleration factor, i.e., $AF^{max} = \max_i AF^i$.

IV. Model Evaluation

We first detail the algorithm and the scenario used to compute the input parameters for our model, then we discuss how we have set the model parameters, and finally we show the main results obtained.

A. Power-aware Algorithm and Scenario

We consider an energy-aware algorithm and a realistic cellular deployment scenario, both obtained from [10]. Due to the lack of space, we refer the reader to [10] for a comprehensive description. In brief, we consider a scenario with 33 Universal Mobile Telecommunication System (UMTS) macro BSs and a service area of 9.2×9.2 km^2. Each macro BS consumes a fixed amount of power, that has to be counted if the BS is powered on, and a dynamic one which depends on the radiated power (that can take values equal to 10W, 20W, 30W or 40W). Inside the SA, we assume more than 3000 user terminals (UTs) requesting voice and data services. Unless otherwise specified, we assume the maximum data rate for each UT is equal to 384 kbps. Moreover, we assume a day-night traffic variation with a deterministic profile over the 24h, with a minimum traffic granularity equal to one hour. Over such scenario, we solve the optimization problem of minimizing the energy consumption of active BSs while guaranteeing the required coverage and capacity demand for all the UTs which are active in each time period. For each BS, we collect the frequency and duration of each power state obtained from the solution of the optimization problem.

TABLE I. AF_i VALUES FOR EACH POWER STATE

Power State	P_1 (10 W)	P_2 (20 W)	P_3 (30 W)	P_4 (40 W)
AF_i	$\frac{1-(1-AF_{off})}{2}$	$\frac{1-(1-AF_{off})}{3}$	$\frac{1-(1-AF_{off})}{6}$	1

TABLE II. FREQUENCY NOTATION AND FREQUENCY WEIGHT FOR EACH POWER VARIATION

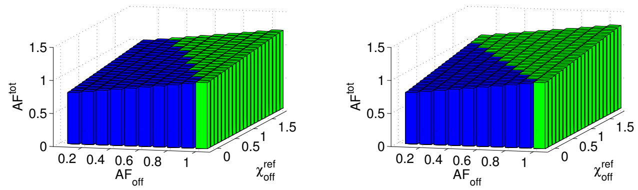
Power Variation	off	10 W	20 W	30 W
Frequency Notation	F_{off}	F_1	F_2	F_3
Frequency Weight	χ_{ref}^{off}	$W\chi_{ref}^{off}$	$2W\chi_{ref}^{off}$	$3W\chi_{ref}^{off}$

B. Parameters Setting

We first assume that the reference failure rate γ_{ref}^{tot} is the one obtained when the BS transmits at maximum power, i.e., 40W. γ_{ref}^{tot} is normalized to 1 for simplicity. Then, our goal is to compute the BS AF over the whole day under consideration. To this extent, we need to sum the acceleration factor due to the time spent in different power states (AF_s of Eq. 9) and the one due to power state transitions (AF_t of Eq. 11).

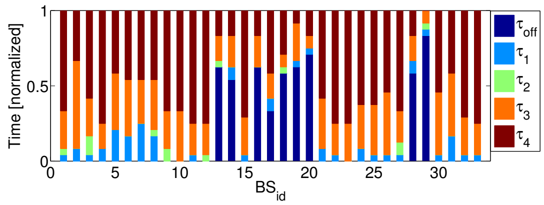
Focusing on AF_s, we report in Tab. I the AF_i parameter for each active power state. In particular, we assume that the values of AF_i are linearly selected between $\frac{1-(1-AF_{off})}{2}$ (which corresponds to the AF experienced when the BS transmits at 10W) and 1 (which corresponds to the maximum transmission power). The AF_i are always much larger than AF_{off}, since we expect that even with radiated power equal to 10W a large amount of components has to be powered on, leading to a much higher temperature w.r.t. the SM case.

As next step, we consider the AF due to power state transitions (AF_t). Since setting all the frequency weights χ in Eq. 11 would be very challenging in practice, we assume that: i) the same weight χ_{ref}^{off} is paid when passing from each of the active power states to SM (and vice-versa), ii) the same weight is paid when the same difference in terms of radiated power occurs (e.g., from 10 W to 20 W, or from 20 W to 30 W), iii) the weight paid when the radiated power is changed is much lower compared to χ_{ref}^{off}. Tab. II reports the adopted frequency weights, together with the corresponding notation for denoting the frequency (e.g., F_1 accounts for all the transitions involving a change in the radiated power equal

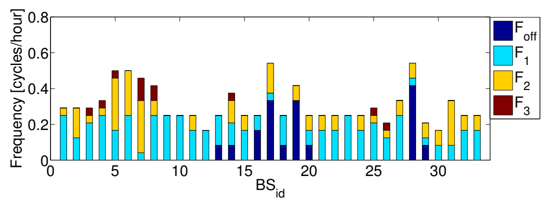


(a) $W = 0.1$ (b) $W = 0.2$

Fig. 1. AF^{tot} in the network vs. different values of parameter W (Blue bars: $AF^{tot} < 1$, green bars:$AF^{tot} \geq 1$).



(a) Normalized time spent in each power state



(b) Frequency of power transitions

Fig. 2. Normalized time spent in each power state and frequency of power transitions.

to 10 W). As such, the term AF_t is computed as follows: $AF_t = W\chi_{ref}^{off}\sum_{k=1}^{3} kF_k + \chi_{ref}^{off}F_{off}$, being W a small value ($W << 1$). The reasons for choosing these settings are the following ones. First, we assume that BS components are optimized to limit the thermal cycling effect triggered by radiated power variations, therefore we have set the frequency weights in such a way that they are always much smaller than χ_{ref}^{off} (by setting the W parameter). Moreover, we expect that the highest temperature change is triggered when the BS enters/leaves a SM state, which justifies the same weight paid when passing from an active power state to SM. Finally, as reported in Eq. (2)-(3) the most important factor impacting the thermal cycling effect is the difference in temperature between two power states and not their absolute temperature values. This fact motivates the adoption of a frequency weight based on the difference in temperature (i.e., off, 10 W, 20 W or 30 W).

Summarizing, we are now able to compute the AF for a single BS, leaving AF_{off}, χ_{ref}^{off} and W as HW input parameters. Additionally, we assume that all the BSs in the considered scenarios have the same HW characteristics, i.e, AF_{off} and χ_{ref}^{off} are the same for all the BSs.

C. Case-study Results

We compute the total AF in the network AF^{tot} as defined in Eq. (12), considering a period of time T equal to 24 hours. Fig. 2 reports the AF computed considering the variation of AF_{off}, χ_{ref}^{off} and W. We can clearly see that as AF_{off} is reduced, AF^{tot} tends to decrease. Ideally, AF_{off} may be equal to zero, meaning that the BS lifetime is increased to infinity when a SM state is set. However, even in this case, the network AF^{tot} is strictly larger than zero since a subset of the BSs in the scenario have to be powered on to meet user coverage and capacity constraints. On the contrary, AF^{tot} tends to increase when χ_{ref}^{off} is increased. Interestingly, two distinct regions are present: one with $AF^{tot} < 1$ (i.e. increase of lifetime), and one with $AF^{tot} \geq 1$ (i.e. equal or decrease of lifetime). Thus, power state transitions may even decrease the BS lifetime compared to a case in which the BS always transmits at maximum power. Finally, when W is increased (left to right subplot), the region in which $AF^{tot} < 1$ is promptly reduced. Since in all cases power state transitions have an impact on the lifetime, we argue that they should be carefully planned, i.e., either to maximize the BS lifetime or to limit the lifetime decrease.

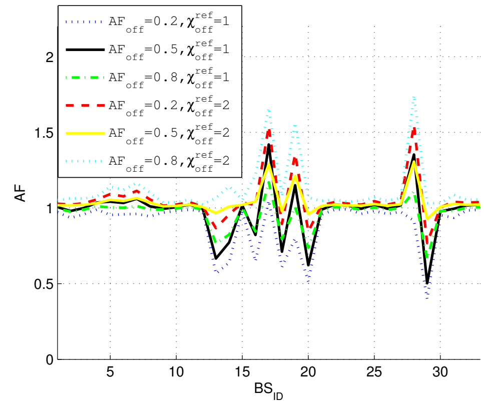


Fig. 3. AF for the single BSs in the network.

In the following, we consider the impact of our model on the single BSs. To this extent, Fig. 2(a) reports the normalized time spent in each power state. Interestingly, all the BSs tend to use the entire set of active power states (corresponding to a normalized time spent in τ_1, τ_2, τ_3 and τ_4), suggesting that the radiated power tends to follow the dynamics of traffic (i.e., maximum during peak hours and then lower during off peak hours). Moreover, the SM state τ_{off} is reached by a subset of the BSs, since it is not possible to put in SM all the BSs. To give more insight, Fig. 2(b) reports the frequency of each transition. In this case, most of transitions involve difference of power equal to 10W and 20W, while seldomly a variation of 30W. Moreover, for the BSs having frequency from/to SM larger than zero, we can see that, even for BSs for which the normalized time in SM state is more than 50% (e.g. BS 28 and BS 19), the frequency is around 0.4 cycles/hour, suggesting that these BSs are put in SM and then to active power several times during a day. Additionally, Fig. 3 reports the AF for each BS in the network for different values of AF_{off}, χ_{ref}^{off}. Unless otherwise specified, W is set to 0.1. Interestingly, we can see that the impact of AF is not the same for all BS in the network, with some BSs that tend to steadily increase their AF (e.g., the BS 28 has a maximum AF equal to 1.7, which means a lifetime reduction of 70%), and others which instead are able to decrease the AF. Thus, we argue the need of a wise strategy in selecting the power state transitions considering the single BSs lifetime.

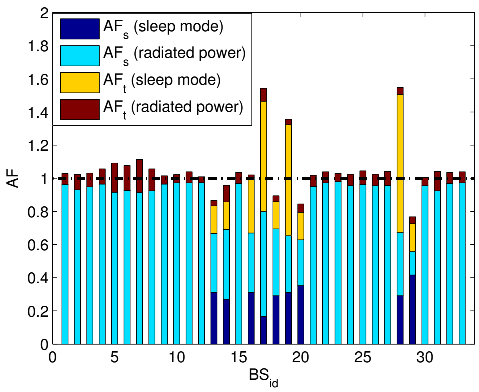


Fig. 4. AF components in the network with $\gamma_{off} = 0.5$ and $\chi_off = 2$ [h/cycle].

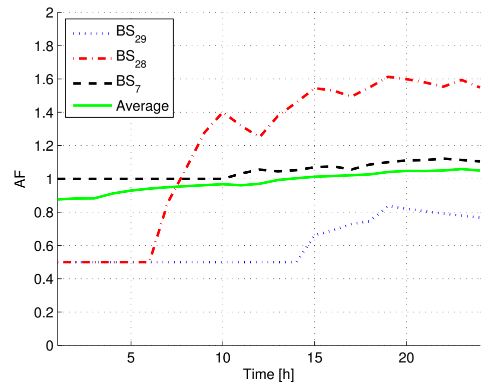


Fig. 5. AF evolution vs. time with $\gamma_{off} = 0.5$, $\chi_off = 2$ [h/cycle] and $W = 0.10$.

In the following, we consider the acceleration factor due to the time spent in different power states (AF_s) and the one due to power state transitions (AF_t). In this case, we consider $AF_{off} = 0.5$, $\chi_{ref}^{off} = 2$ [h/cycle] and $W = 0.1$. Fig. 4 reports the values of AF_s and AF_d, by differentiating also between the amount due to radiated power and the one due to SM. Interestingly, we can see that the BSs presenting the highest total AF are also the ones having the highest AF_t in SM, which accounts for the frequency at which BSs enter/leave SM, as well as the HW parameter χ_{ref}^{off}. The values of AF_s on the contrary are always lower than one, due to the fact that AF_{off}, AF_i, τ_{off}/T and τ_i/T, are always lower than one. Moreover, we can see that the radiated power has a small impact on AF_t. However, for some BSs, the term AF_t due to the radiated power tends to bring the overall AF larger than 1, which means a decrease in the lifetime.

In the last part of our work, we have considered how the AF evolves over time. In particular, we have computed the AF for each hour in the network, i.e., starting from 00:00 and computing the AF in the current hour considering the power state variations occurred from 00:00 to the current hour. Fig. 5 reports the AF evolution considering $\gamma_{off} = 0.5$, $\chi_off = 2$ [h/cycle] and $W = 0.10$. The figure reports two BSs exploiting SMs (BS_{29},BS_{28}) and one which is always powered on (BS_7). Interestingly, we can see that the network AF is initially lower than one, then at 11 a.m. it becomes higher than one. This suggests that the energy-aware algorithm has initially decreased power of BSs as a consequence of periods of low traffic. However, since user traffic increases during the following morning hours, different BSs have to change their power state. As a result, the lifetime in the network is even decreased at the end of the day. Moreover, the single BSs present very different trends, being for example BS_{28} experiencing different power states during the day which negatively impact its lifetime. Thus, we can conclude that the management of power state transitions should not only take into account the short-term objective of reducing current energy (i.e., in each hour) but also the long term objective of increasing the lifetime in the network.

V. Conclusions and Future Work

We have proposed a model to predict the lifetime in a cellular network as a consequence of a change in the power states (either from/to SMs or a change in the radiated power). Our results show that the lifetime may be negatively impacted if the effects of power state variations are not properly taken into account. This may lead to a decrease of lifetime for the single BSs, or even for the whole network under consideration. Moreover, since the lifetime is a long-term objective, i.e., it has to consider sufficiently long time periods, short term-objectives like energy minimization may clash with it. As future work, we plan to propose algorithms that integrate lifetime, energy consumption and user constraints in order to decide when and how to change the power state for each BS in the network. Moreover, we plan to measure the temperature of a BS to estimate more precisely the HW input parameters.

References

[1] D. I. Kim, E. Hossain, and V. K. Bhargava, "Downlink joint rate and power allocation in cellular multirate wcdma systems," *IEEE Transactions on Wireless Communications*, vol. 2, no. 1, pp. 69–80, 2003.

[2] G. Auer, V. Giannini, I. Gódor, P. Skillermark, M. Olsson, M. A. Imran, D. Sabella, M. J. Gonzalez, C. Desset, and O. Blume, "Cellular energy efficiency evaluation framework," in *Proc. of IEEE VTC Spring, Budapest, Hungary*, pp. 1–6, May 2011.

[3] J. Lorincz, T. Matijevic, and G. Petrovic, "On interdependence among transmit and consumed power of macro base station technologies," *Computer Communications*, vol. 50, pp. 10–28, 2014.

[4] J. Wu, Y. Zhang, M. Zukerman, and E. Yung, "Energy-efficient base stations sleep mode techniques in green cellular networks: A survey," *IEEE Communications Surveys and Tutorials*, 2015.

[5] L. Chiaraviglio and J. Lorincz, "The impact of sleep modes on the lifetime of cellular networks," in *Proc. of the SoftCOM, Split, Croatia*, 2014.

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

[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," *IEEE Transactions on Electron Devices*, vol. 46, no. 7, pp. 1518–1524, 1999.

[8] JEDEC Solid State Technology Association *et al.*, "Failure mechanisms and models for semiconductor devices," *JEDEC Publication JEP122-C*, March 2006.

[9] R. Blish and N. Durrant, "Semiconductor device reliability failure models," *International Sematech Technology Transfer #00053955A-XFR*, May 2000.

[10] J. Lorincz, A. Capone, and D. Begusic, "Impact of service rates and base station switching granularity on energy consumption of cellular networks," *EURASIP Journal on Wireless Communications and Networking*, vol. 2012(342), no. 1, pp. 1–24, 2012.