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Traffic-aware Advanced Sleep Modes management in 5G networks

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Abstract—Advanced Sleep Modes (ASMs) are defined as a progressive shutdown of the Base Station (BS) depending on the activation and the deactivation times of the different components. This transition duration defines different levels of sleep modes that can be implemented in future 5G networks. We propose in this paper a management strategy based on Q-learning approach which will enable to find the best combination and durations of ASM levels depending on the traffic load and the network operator’s policy regarding energy reduction versus latency. Our results show that even in delay-sensitive scenarios, high energy gains can be achieved in low and moderate traffic loads, respectively 55% and 10%, without inducing an extra latency. Starting from a certain traffic load (approximately 30%), ASM should not be implemented in case of stringent latency constraint.

Index Terms—Advanced Sleep Modes, 5G networks, Q-learning, traffic load, latency.

I. INTRODUCTION

The multiplicity of mobile devices and the upsurge of new services have led to an exponential growth of traffic demand. This has induced a huge increase in the energy consumed by the network operators [1] which has an impact on both the operator’s Operational Expenditures (OPEX) and the environment due to the increasing CO₂ emissions [2]. To cope with these problems, considerable efforts have been invested to reduce the energy consumption of mobile networks and more precisely of the Base Stations (BSs) as they are the most energy consumers (around 80% of the overall mobile energy consumption) [3]. Several techniques and technological levers have been investigated in this area such as Massive Multiple Input Multiple Output (MIMO) systems [4], cell zooming [5] and sleep modes [6].

We focus in this work on the feature of Advanced Sleep Modes (ASMs) which corresponds to a progressive deactivation of the BS’s components [7]. Different levels are considered in ASM according to the time needed for the activation and the deactivation (transition time) of each component. Going from one level to another, more components are deactivated which reduces the BS’s power consumption, but this is at the expense of a longer delay as more time is needed to reactivate the BS again.

The sleep modes are already present in LTE systems under the name of μ DTX ($\approx 71 \mu$ s) [3]. With the lean carrier design in 5G networks permitting to have less control signals,

deeper sleep modes can be implemented. It has been shown in previous works [8] that ASMs can reduce up to 90% of the energy consumption in very low load. However, the delay increase may be up to 5ms which is critical for some 5G use cases like Ultra-Reliable Low Latency Communications (URLLC) where the maximum acceptable latency is around 1ms [9]. For this reason, a delay-sensitive orchestration of the different ASM levels is needed in order to know how much each of them is allowed to be used depending on the length of the idle periods of a BS and according to the network operator’s needs with respect to latency. A first study was presented in [10] where a Q-learning based implementation strategy has been applied for the case of very low loads. Hence, a more comprehensive investigation is needed in order to derive the optimal policies for higher loads values.

We present in this paper a traffic-aware implementation strategy which enables to have a codebook mapping the traffic load to the possible actions to be performed in the Q-learning algorithm. According to the constraint of the network operator imposed on the latency and to the traffic conditions, especially regarding the average inter-arrival times, several policies can be deduced.

The remainder of this paper is as follows: Section II-A describes the concept of ASMs, the 5G new radio opportunities that can be exploited to have deeper sleep modes, the buffering strategy and the proposed solution for ASM implementation. Section III develops our ASM management solution based on Q-learning approach. Section IV presents the simulation results and Section V concludes the paper and gives some perspectives for future works.

II. SYSTEM DESCRIPTION

A. Advanced Sleep Modes description

The different components and sub-components of a BS can be classified into four categories according to the time needed by each of them to deactivate and then wake up again (transition time) as presented in [7]. These categories define the different possible levels of sleep modes that a BS can enter, and are denoted as “Advanced Sleep Modes”:

- SM₁: represents the shortest sleep mode which needs a transition time of 71μ s (OFDM symbol). The power amplifier and some components of the digital baseband and the analog front-end (both in Rx and Tx) are deactivated.

- SM₂: corresponds to a longer sleep mode which needs 1ms as a transition time (1 sub-frame or TTI) and in which more components of the analog front-end are disabled compared to the first level.
- SM₃: the power amplifier, all the components of the digital baseband and almost all the parts of the analog front-end (except the clock generator) are switched off. This subset of components needs 10 ms (a frame) to deactivate then wake up again.
- SM₄: corresponds to the standby mode in which the BS retains its wake-up functionalities but almost all its components are deactivated. It groups the components that need more than 1s for the transition latency (deep sleep mode).

The ASMs are defined only based on the transition times of the BS's components. However, the sleep length of each of them has not been defined. We assume that the minimal sleep duration in each sleep level is in the same time scale of the transition time corresponding to that level, and that both the activation and deactivation delays are half of this transition time. This is summarized in Table I.

TABLE I: Advanced Sleep Modes characteristics

Sleep level	Deactivation duration	Minimum sleep duration	Activation duration
SM ₁	35.5 μ s	71 μ s	35.5 μ s
SM ₂	0.5 ms	1 ms	0.5 ms
SM ₃	5 ms	10 ms	5 ms
SM ₄	0.5 s	1 s	0.5 s

B. Signaling in 5G new radio

In LTE systems, the BS sends periodically control signals such as Cell-specific Reference Signals (CRS) broadcasted during 4 OFDM symbols out of 14, Primary and Secondary Synchronization Signals (PSS and SSS) transmitted every 5ms and Physical Broadcast CHannel (PBCH) which is transmitted in the first sub-frame of the LTE radio frame. With such frequent signaling, only the first level of sleep modes (SM1) is applicable.

With the lean carrier design of 5G new radio, synchronization signals are grouped in blocks and are sent periodically with a configurable periodicity among this set [5, 10, 20, 40, 80, 160 ms] as agreed in 3GPP [11]. This allows to enter deeper sleep mode levels i.e., SM2 and SM3. For this reason, we consider in this work the first three ASM levels.

C. Buffering strategy

We consider in this work only users in connected mode and ignore users' initial access. When a user arrives during a sleep mode, his arrival triggers the activation of the BS. In the meantime, the user request is kept in a buffer until the BS wakes up and serves him. The buffering delay depends on the depth of the sleep mode and on its phase, i.e., whether the

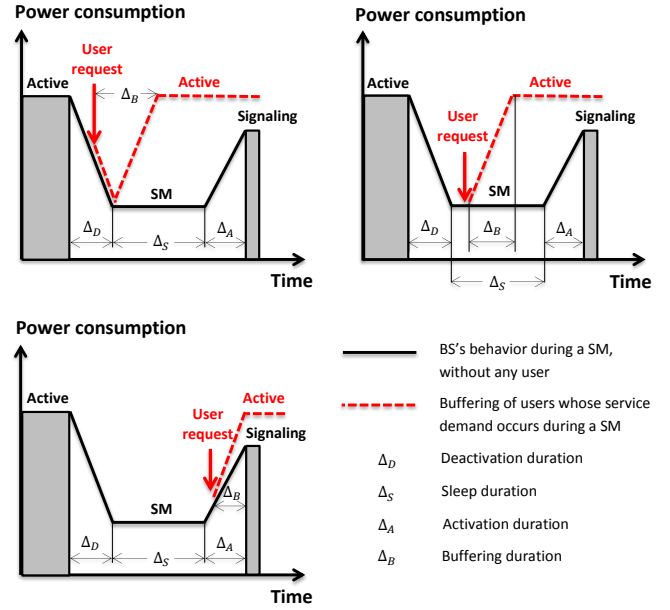


Fig. 1: Buffering delays in ASMs

BS is deactivating, activating or it is in the sleep mode itself. This is illustrated in Figure 1.

The deeper the sleep mode, the more power reduction we can have as we deactivate more hardware. This hampers the responsiveness of the BS due to the buffering time for the users arriving during the sleep mode. This may be a problem in some scenarios where there is a high constraint imposed on the delay such as URLLC type of service. Hence, a delay-sensitive implementation strategy is needed in order to be able to profit from the ASM without inducing any impact on the latency.

D. Delay-sensitive implementation strategy

We proposed in [10] an implementation strategy for ASM which consists of putting the BS in different levels of sleep modes as follows: each time the BS is idle, we start with the deepest level (SM3), then we wake up the BS gradually: we put it into SM2 and then SM1 then in the idle mode as shown in Figure 2. Each sleep level can be repeated many times before going to the next one. The target is to determine the duration of each sleep mode.

The idea is to have different possibilities of sleep durations in each sleep mode level according to the policy of the network operator. If this policy consists of prioritizing the energy consumption reduction, then the best strategy is to remain in the deepest sleep level until the arrival of the next user which will trigger the activation of the BS. However, if the network operator decides to prioritize the users' latency, then the best strategy to follow is to anticipate the arrival of a user by taking more conservative actions (lower durations of sleep modes) so that whenever a user arrives, he finds the BS ready to serve him. In the case where both energy reduction and latency are to be considered, we make use of a utility function which is

equal to the weighted sum of both criteria. We try to maximize it following the same strategy i.e., deepest sleep level first. We make so based on a Q-learning algorithm that depends on the traffic load, as shown next.

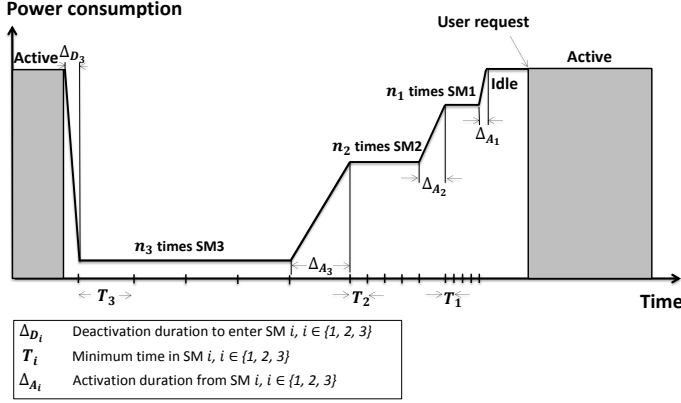


Fig. 2: Delay-sensitive implementation strategy of ASMs

III. ASM MANAGEMENT BASED ON Q-LEARNING APPROACH

As in [10], we consider the Q-learning approach [12] in order to find the optimal duration for each sleep mode level. The advantage of this method is that it is model-free which makes it well adapted for the ASM problem.

A. Q-learning algorithm

The Q-learning approach is based on the estimation of a state-value function denoted by Q which links the state s to the action a and is updated in each iteration.

Table II presents the pseudo-code summarizing the Q-learning algorithm:

Q-learning algorithm
Initialize $Q(s, a)$ arbitrarily Repeat (for each episode): Initialize s Repeat (for each step of episode): Choose a from s using policy derived from Q (e.g., ϵ -greedy) Take action a , observe R, s' $Q(s, a) \leftarrow Q(s, a) + \alpha [R + \gamma \max_{a'} Q(s', a') - Q(s, a)]$ until s is terminal

TABLE II: Q-learning algorithm

where :

- an episode is defined according to the users' dynamics. The departure of a user corresponds to the beginning of an episode, if there is any other user being served.
- s denotes the current state of the system and s' the following state after performing action a .
- R is the reward achieved by choosing action a .
- α is the learning rate.

- γ is the discount factor describing the weight given to future rewards.
- The ϵ -greedy algorithm operates in such a way to test random actions with probability ϵ (exploration) and to take the actions which maximize the Q value with a probability $1 - \epsilon$ (exploitation).

B. Q-learning characteristics

1) *State space*: It corresponds to the different states of the BS. It can be either active (serving a user), idle (not transmitting anything but it is still activated) or in sleep mode (SM₁, SM₂ or SM₃).

$$S = \{\text{active, idle, SM}_1, \text{SM}_2, \text{SM}_3\}.$$

2) *Decision epochs*: The decision points are defined at the end of each state: if the BS was in the active state, the departure of a user marks the end of this state and an action should be performed. This is the start of an episode. After performing that action, the BS will be in the next state, first in SM₃ if applicable, or else SM₂, or else SM₁. Once the time allowed for the corresponding sleep level elapses, another decision should be taken, it consists of going to a higher SM level. This is repeated until the arrival of a user which will end the current episode and impose the activation of the BS or after having entered all the possible sleep mode levels then activated the BS.

3) *Action space*: The action space corresponds to the decisions that can be taken at each decision point. An action consists of finding n_i the number of times the BS can repeat the following sleep mode level i . Let N_i be the set of possible values that n_i can take, for $i \in \{1, 2, 3\}$.

So, the action space is:

$$A_s = \{N_3 \times N_2 \times N_1\}.$$

The objective is to find the optimal triplet (n_3, n_2, n_1) which maximize a reward function R .

4) *Reward function*: The reward R for a given episode can be defined as the weighted sum of the energy gain E_{gain} and the added delay D , that are achieved following the sleep strategy during that episode.

Hence, R can be written as follows:

$$R = -\epsilon D + (1 - \epsilon) E_{gain} \quad (1)$$

where ϵ is a normalized weight ($\epsilon \in [0, 1]$) that denotes the importance given to the two factors D and E_{gain} . A small ϵ means that the energy reduction is prioritized over the delay and vice versa.

C. Traffic-aware action space

The ASMs are intended to be used during the idle periods of the BS. They are most profitable when the traffic load is very low as we have enough time between the users to put the BS in deep sleep mode for large periods. It has been shown that in almost zero-load condition, we can achieve up

to 90% of energy reduction [8]. When the load increases, the users' inter-arrival time decreases which will restrict the use of sleep modes. The action space denoting the number of times to repeat each sleep mode level is a finite set of some possible values that should be well adapted to the traffic load.

An action n_i can be written as follows:

$$n_i = \lfloor x_i n \rfloor \quad (2)$$

where:

- x_i is the number of times to repeat the sleep mode i in order to cover all the idle period only by this level. It can be defined as $x_i = \frac{I}{T_i}$ with I is the average inter-arrival time of users and T_i the duration of sleep mode i .
- n is a multiplicative factor taken in such a way to have different possibilities of sleep duration for each sleep mode level while being around the optimal value x_i . We consider $n \in [0, 0.1, 0.2, 0.5, 1, 2, 5, 7, 10]$ in our numerical experiments shown next.

IV. NUMERICAL RESULTS

A. Simulator description

We consider a 2x2 MIMO BS with a single sector and we simulate an FTP service where the users request to download a file of exponential size and once the download is complete they quit the network. The simulator is event-based where an event corresponds to the dynamics of users and sleep modes (activation, deactivation, change of sleep level). The different characteristics of the simulator are given in Table III.

TABLE III: Simulator characteristics

Network parameters	
Antenna height	30 m
Bandwidth	20MHz
Scheduling type	Round Robin
Channel characteristics	
Thermal noise	-174 dBm/Hz
Path loss (d in km)	$128.1 + 37.6 \log_{10}(d)$ dB
Shadowing	Log-normal (6dB)
Traffic characteristics	
Users' arrivals	Log-normal with mean λ and variance $v = \frac{\lambda}{10}$
Service type	FTP
Average file size	4 Mbits
Q-learning parameters	
Learning rate	$\alpha = \frac{1}{N_{s,a}}$ where $N_{s,a}$ is the number of visits to the action-state pair (s, a) .
Discount factor	$\gamma = 0.1$
Exploration factor	$\epsilon_{exp} = 0.1$

In order to quantify the outcome of the proposed solution, we focus on two performance metrics: energy consumption and latency.

The energy consumption can be defined as follows:

$$EC = \sum_{i=1}^{N_e} \tau_{i-1,i} P_{i-1,i} \quad (3)$$

where:

- N_e is the number of events.
- $\tau_{i-1,i}$ is the duration between two events $i-1$ and i .
- $P_{i-1,i}$ is the power consumed by the BS during $\tau_{i-1,i}$ and is computed using IMEC power model tool [13]. This power value depends on the state of the BS during that period as mentioned in Table IV.

TABLE IV: Power consumption of 2x2 MIMO BS (1 sector) in different states.

Radiated Power: 46 dBm, Bandwidth: 20 MHz

Active	Idle	SM ₁	SM ₂	SM ₃
250 W	109 W	52.3 W	14.3 W	9.51 W

The latency of a user can be computed as follows:

$$\Delta_{Latency} = T_{serve} - T_{req} \quad (4)$$

where T_{serve} is the time when the BS starts serving the user and T_{req} is the time when the request occurs. We focus here on the latency induced by the sleep modes due to the buffering approach.

We consider different values of arrival rates $\lambda \in \{1, 3, 6, 10, 20, 35\}$ (users/s/Km²) which are translated into loads of 1%, 4%, 9%, 15%, 30% and 55%, respectively. The load is defined as the fraction of time during which the BS was active:

$$\rho = \frac{1}{T} \sum_{i=1}^{N_e} \tau_{i-1,i} \mathbb{1}_{\{x_e(\tau_{i-1,i})=1\}} \quad (5)$$

where :

- $T = \sum_{i=1}^{N_e} \tau_{i-1,i}$, is the total observation time.
- $x_e(\tau_{i-1,i}) = \begin{cases} 1 & \text{if the BS was active during } \tau_{i-1,i}. \\ 0 & \text{otherwise.} \end{cases}$

B. Convergence analysis

The convergence criteria is based on the computation of the maximum variation of the quality-value $Q(s, a)$ in each iteration for all the state-action pairs (s, a) . Figure 3 shows the convergence behaviour in a low load scenario (1%) with $\epsilon = 0.75$ during the learning phase. The maximum variation tends to zero for a sufficiently high number of iterations (in the order of 10^4).

C. Performances results

We consider five different values of ϵ : 0.001, 0.25, 0.5, 0.75 and 0.999. For $\epsilon \approx 0$, the energy consumption reduction is prioritized, whereas when $\epsilon \approx 1$, it is the delay that counts the most. In the cases in between, different weights are given to the two factors.

1) Output policies:

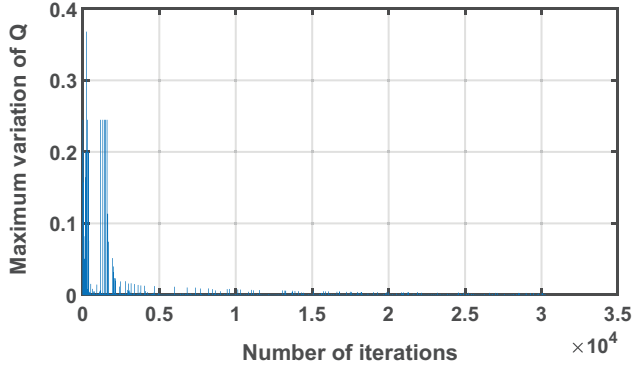


Fig. 3: Convergence evolution

Table V presents the different policies, i.e., the triplet (n_3, n_2, n_1) , that are deduced depending on the value of ϵ for the different considered arrival rates. The more we increase ϵ the more we reduce the time spent in SM_3 giving more opportunities for the next levels.

2) Energy consumption reduction with ASM:

Figure 4 shows the energy consumption reduction achieved for different loads and different values of ϵ . The highest energy gain (90%) is achieved in low load with the lowest ϵ . The more we increase the load, the more we reduce the energy gain as we use less sleep modes between the users' arrivals. For a given value of load, the energy gains decrease with ϵ , as when we increase ϵ , we give more weight to the delay so that we use the sleep modes for shorter periods to prevent the arrival of users during the sleep state. Even with this constraint, we can achieve up to 55% of energy reduction in low loads. For average loads, the energy gain is also significant (10% of reduction for 10% of load). Starting from 30% of the load, the best policy to take in order to satisfy the delay constraint is to not use any sleep mode level.

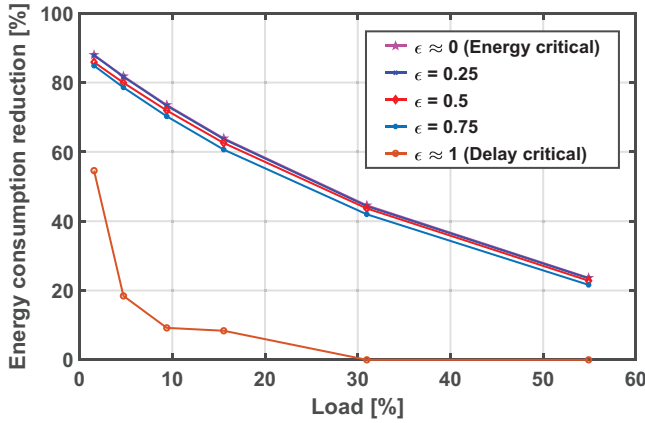


Fig. 4: Energy consumption reduction

3) Influence on users' latency:

Figure 5 shows the variation of the added delay caused by the sleep strategy for different values of load and ϵ . We observe that if we increase ϵ , we can reduce this impact on latency until

TABLE V: Policies

Arrival rate (users/s/Km ²)		$\epsilon \approx 0$	$\epsilon = 0.25$	$\epsilon = 0.5$	$\epsilon = 0.75$	$\epsilon \approx 1$
$\lambda_1 = 1$	n_3	6944	1389	694	694	694
	n_2	69444	69444	13889	6944	0
	n_1	1369327	391236	978091 1369327 1956182	391236 978091 1369327 1956182	39124
$\lambda_2 = 3$	n_3	4630	463	231	231	46
	n_2	9259 23148 32407 46296	46296	4630	2315	0
	n_1	130412 326030 456442 652061	652061	130412 326030 456442 652061	326030	13041
$\lambda_3 = 6$	n_3	1157	139	116	116	0
	n_2	4630 11574	13889	4630 16204	1157	0
	n_1	65206 163015 228221 326030	136933	163015 228221 326030	65206	6521
$\lambda_4 = 10$	n_3	1389	69	69	69	0
	n_2	13889	6944	2778	694	0
	n_1	195618	68466 97809	97809 136933 195618	136933 195618	3912
$\lambda_5 = 20$	n_3	694	40	35	14	0
	n_2	6944	1984	3472	694	0
	n_1	97809	39124 55891	68466 97809	97809	0
$\lambda_6 = 35$	n_3	397	40	8	4	0
	n_2	3968	1984	1984	394	0
	n_1	55891	39124 55891	39124	55891	0

having no (or very little) influence (lowest curve).

V. CONCLUSION

We presented in this paper a traffic-aware, energy and delay-sensitive implementation strategy for ASM in 5G networks. It takes into account the traffic variation and the constraint that may be imposed by the network operator on energy and latency in order to derive the policy that captures the projected trade-off between them. Different policies can be achieved based on different traffic loads as well as the network operator's policy regarding delay and energy reduction. Our results show that significant energy gains can be achieved by the ASM, especially in low load scenarios and when there is no constraint imposed on the delay: up to 90% of energy reduction. Even with a high constraint on the delay,

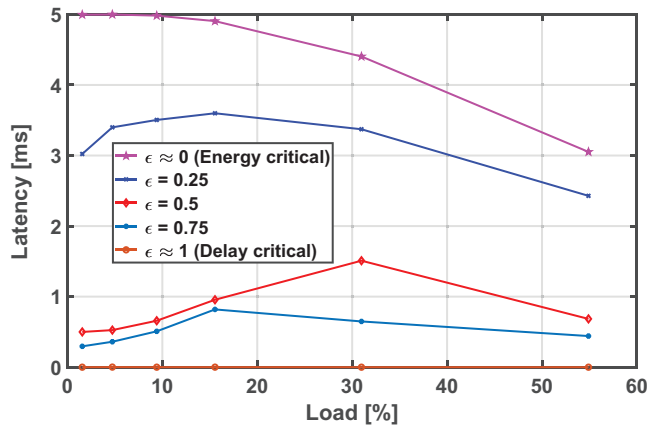


Fig. 5: Impact on latency

the energy reduction can still achieve high values: up to 55 % in low load and 10% in moderate load. Starting from a certain load threshold (approximately 30%), the ASM cannot be used anymore if the delay is prioritized over the energy reduction.

This study was performed without considering the control signals. As an extension of this work, we aim to add the periodic signaling and find out the possible changes in the policies that we can deduce according to the traffic conditions. It is also interesting to extend the work to a network with multiple BSs and consider cooperation between them in order to have the highest possible energy gains with the minimal impact on the delays. A centralized orchestration of the different BS sleeping cycles is thus needed.

REFERENCES

- [1] J. G. Andrews et al., "What Will 5G Be?," in *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1065-1082, June 2014.
- [2] A. Fehske et al., "The global footprint of mobile communications: The ecological and economic perspective," *IEEE Communications Magazine*, vol. 49, no. 8, pp. 5562, August 2011.
- [3] P. Frenger et al., "Reducing Energy Consumption in LTE with Cell DTX," 2011 IEEE 73rd Vehicular Technology Conference (VTC Spring), Yokohama, 2011, pp. 1-5.
- [4] F. E. Salem, A. Tall, Z. Altman and A. Gati, "Energy consumption optimization in 5G networks using multilevel beamforming and large scale antenna systems," 2016 IEEE Wireless Communications and Networking Conference, Doha, 2016, pp. 1-6.
- [5] Z. Niu, Y. Wu, J. Gong and Z. Yang, "Cell zooming for cost-efficient green cellular networks," in *IEEE Communications Magazine*, vol. 48, no. 11, pp. 74-79, November 2010.
- [6] J. Wu et al., "Energy-Efficient Base-Station Sleep-Mode Techniques in Green Cellular Networks: A Survey," in *IEEE Communications Surveys & Tutorials*, vol. 17, no. 2, pp. 803-826, Secondquarter 2015.
- [7] B. Debaillie et al., "A Flexible and Future-Proof Power Model for Cellular Base Stations," 2015 IEEE 81st Vehicular Technology Conference (VTC Spring), Glasgow, 2015, pp. 1-7.
- [8] F. E. Salem et al., "Advanced Sleep Modes and Their Impact on Flow-Level Performance of 5G Networks," 2017 IEEE 86th Vehicular Technology Conference (VTC-Fall), Toronto, ON, 2017, pp. 1-7.
- [9] NGMN Alliance, 5G White Paper, 2015, <https://www.ngmn.org/5g-white-paper/5g-white-paper.html>
- [10] F. E. Salem et al., "Reinforcement learning approach for Advanced Sleep Modes management in 5G networks," 2018 IEEE 87th Vehicular Technology Conference (VTC-Fall), Chicago, 2018, pp. 1-5.
- [11] 3GPP TS 38.331, "Radio Resource Control (RRC) protocol specification (Release 15)," V15.1.0, 2018-03.

- [12] C. J. Watkins and D. Peter, "Q-learning," *Machine Learning*, vol. 8, no. 3-4, pp. 279-292, 1992.
- [13] IMEC Power Model Tool, <https://www.imec-int.com/powermodel>