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A Novel Energy Model for Renewable Energy-Enabled Cellular Networks Providing Ancillary Services to the Smart Grid

Hussein Al Haj Hassan, Daniela Renga, Michela Meo and Loutfi Nuaymi

Abstract

In this paper, we consider cellular networks powered by the Smart Grid (SG) and by local renewable energy (RE) sources. While this configuration promises energy savings, usage of cleaner energy and cost reduction, it has some intrinsic complexity due to the interaction between the network operators and the SG. Motivated by the significant advancement in the SG, we consider the case where cellular networks provide the SG with ancillary services by replying to the grid's explicit requests to increase or decrease their consumption. We propose a new approach for configuring and operating base stations (BSs) to provide ancillary services. Based on real data, we model the energy state of a BS as a Markov chain taking into account the proposed energy management policy, randomness of SG requests and RE generation. We use the model to evaluate the performance of the system, and to decide proper settings of its parameters in order to minimize the energy operational cost. The performance of our proposal is then compared against those of other approaches. Results show that important cost savings, with negligible degradation in quality of service, are possible when RE generation, SG patterns and storage sizes are properly taken into account.

Index Terms

Future Cellular Networks, Markov Chains, Renewable Energy, Smart Grid, Energy Model

I. Introduction

In the last decades, energy performance has become one of the key research and innovation topics in any industrial field. Among the fast growing industries a relevant role is played by the Information and Communications Technology (ICT). From one perspective, ICT has substantially contributed in the advancement of existing industries and development of new concepts. From another perspective, ICT industry is responsible for significant percentage of the green house gas emissions (GHGE). According to [1], the relative contribution of ICT's GHGE could grow

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from roughly 1.6% in 2007 to exceed 14% of the 2016-level worldwide GHGE by 2040, which is equivalent for more than half of the current relative contribution of transportation sector.

Furthermore, the ICT industry is experiencing significant growing in its energy consumption which is about 7% growth rate per year [2]. Fueled by the exponential increase in mobile traffic, the strongest growth is being observed in communication networks for about 10% per year. This number is expected to further increase due to the continuous increase in the users' traffic. For example, it is forecast that the global mobile data traffic will witness an increase of seven-fold between 2016 and 2021 [3]. To satisfy users' demand, the fifth generation (5G) wireless system is under intensive development of base stations (BSs) [4]. This increase in the number of BSs imposes serious concerns about the sustainability of the networks in the future and the growth of the energy cost that can reach more than 32% of the operational expenditure [5]. This observation prompted the creation of a new direction in the domain of cellular network energy research: the use of renewable energy (RE) to power BSs [6]. In contrast to off-grid BSs, in which RE is used to sustain and provide service continuity, the use of RE to power on-grid BSs targets to several objectives, among which reducing grid energy consumption, reducing Carbon emissions, and reducing the electric bill [6].

Meanwhile, significant efforts are put in the evolution of the power grid into a smarter one - the Smart Grid (SG) [7]. The recent development in the SG allows customers to make more informed decisions in their energy management [8], which is translated into reduction of the customers' energy cost and Carbon emissions. There exist several ways for the grid customers to interact with the SG. This depends on the size of the customer's energy consumption as well as the chosen program (e.g. real time pricing or providing ancillary services). In this work, we consider cellular networks that are willing to provide the grid with ancillary services. Every day, the SG Transmission System Operator predicts the total energy demand of the next day based on weather forecast, historical data and demand of high consumers (e.g., those that consume more than 1 MW) [9]. Then, it organizes an auction between the providers and retailers to fix the electricity price for each hour of the next day. Consumers can buy energy at lower price, with respect to traditional dynamic tariff programs, as a reward for the information about their expected energy demand. Next day (focus of this paper), additional trades are done to compensate the errors of the energy demand prediction done in the previous day. Among these trades, some are made in advance, just 15 to 30 minutes before the tariff applies. These trades are known as *Ancillary Services* [10]. The SG explicitly requests customers (willing to provide ancillary services) to adapt their consumption to the grid's conditions. Customers (BS in our case) reply to the grid requests and provide ancillary services by increasing the energy consumption if the request is of type *up* and decreasing their energy consumption if the request is of type *down*.

For a mobile operator, the deployment of on-site renewable energy sources (RESs) and energy storage units co-located with the BSs promotes the operator to be a suitable candidate to provide ancillary services. However, new challenges rise due to the dynamism of the SG and the intermittent generation of RE [6]. In this paper, we consider a mobile operator willing to provide the SG with ancillary services through its access network. BSs are powered by the SG and equipped with local RE sources and energy storage units. The harvested RE and energy storage are used by the mobile operator to reply to the SG requests by adjusting the grid energy consumption of the network, and thus provide the SG with ancillary services. Although a BS has relatively small energy demand, the aggregated energy demand of a mobile network can be significant due to the large number of BSs. However, each BS may experience different conditions such as different RE generation and availability. The amount and profile of RE generation change depending on the weather and location of the BS. Moreover, the same BS can experience different conditions from day to day. In our previous work, [11], [12] we considered the case in which the operator, in order to further respond to the SG requests, can switch on and off the BSs. In this paper, instead, we focus on a scenario in which, in order to further adjust the mobile network energy consumption, Radio Resource Management (RRM) techniques are used at the individual BSs. While BS management can be quite effective, in several scenarios switching off the BSs is not possible due to the risk of coverage holes. In these cases, RRM can be used at the BSs to respond to the SG requests. We model the energy state of the BS as a multi-dimensional Markov chain, for which its transition probabilities are calculated based on the stochastic models of RE production and SG request patterns as well as the adopted energy management policy. Then, the model is numerically solved to choose proper settings of the parameters and thresholds of the energy policy with the objective of minimizing the net operational cost. The large number of states and possible transitions from one state to another, which is also affected by the large number of possible thresholds, increases the complexity of finding a closed form solution and studying it analytically.

The rest of the paper is structured as follows. Section II presents the related work. We describe the model of the renewable powered BS operation in Section III. The modeling of the SG operation and the energy management strategy implemented by the green BS to react to the SG requests are detailed in Section IV. The Markovian model deployed to represent the entire system operation is presented in Section V, whereas the performance indicators are defined in Section VI. Section VII presents the obtained results before concluding in Section VIII.

II. Related work and contribution

Cellular networks have succeeded in responding to the demand of various types of users; spectrum efficiency as well as quality of service have been well optimized to meet the requirements of users. However, the increase of the traffic was accompanied by an increase in the energy demand. The latter challenges the operators to reduce their energy consumption. Consequently, several techniques were proposed to increase the energy efficiency of cellular networks, such as radio resource management (RRM), cell layout adaptation, heterogeneous deployment, cognitive radio, etc. [13]. In addition, network operators started to explicitly consider the use of RE sources in powering their BSs [6]. The two approaches are complementary as it is easier to power BSs with RE if they have lower energy footprint.

There exist many studies that tackles the problem of energy efficiency in cellular network including the use of RE, see [6], [14], [15]. However, the evolution of the power grid into a smarter one, the Smart Grid [7], imposes new research problems in the domain of "energy efficient cellular network" from economic and environmental perspectives. In this context, each of the existing approach considers the SG from a different perspective.

For example, several studies consider the SG as the main energy provider that informs the cellular networks with the energy price and its variation, i.e. dynamic tariff of electricity. In this context, the authors of [16] study adaptive power management for wireless BSs powered by local RE sources and the SG. The aim is to minimize the cost of energy by managing the energy resources in a variable energy price environment. Similarly, the study done in [17] considers the problem of minimizing the electricity bill for a cellular BS powered by the SG and locally harvested RE with hourly-varying electricity prices known a day ahead. The study in [18] considers the problem of minimizing the on-grid energy cost of a heterogeneous cellular network with BSs powered by RE and the SG, while considering real-time pricing of grid energy. The problem of minimizing the on-grid energy cost is studied for a single BS equipped with RES under variable electricity price in [19]. Delaying data as well as battery management are used to reduce the energy demand when the price of electricity is high. In [20], the authors study the minimization of cost in space-time varying electricity price. In contrast to previously mentioned studies, the authors consider a centralized RE farm to power the BS in a geographic area. A micro-grid of BSs, RES and energy storage is considered in [21]. BS ON/OFF switching and energy management are used to reduce the energy cost considering variable traffic load and price of grid energy.

Another perspective is using the SG for energy sharing between base stations. For example, the authors investigate energy sharing in the context of Smart Grid-enabled mobile networks, where RE is generated at each BS and can be shared with other BSs in [22]. By jointly optimizing the operation of BSs and distribution of power, the network achieves about 18% on-grid power savings. In [23], the authors use energy sharing and load shifting to minimize the grid energy expenditure of cellular networks powered by both grid and RE. The authors proposed a three-phase distributed control policy, where base stations and mobile users adjust their strategies independently only with their local information. In [24], the authors proposed a hybrid energy sharing framework for cellular network where physical power lines and energy trading with other BSs using SG are used. The energy management framework determines the quantities of electricity and RE to be procured and exchanged among BSs, respectively, while considering battery capacities and real-time energy pricing.

Furthermore, some studies consider the SG as a platform for interaction with several energy retailers. In [25], the authors aim at maximizing the profit of LTE cellular operators while minimizing the CO_2 emissions. The study uses BSs switch ON/OFF and optimizes the amount of energy procured from different retailers. In [26], BS switching on/off mechanism and an energy management policy are employed. The study investigates the interactions between multiple mobile operators and energy retailers with a number of renewable sources. The goal is to maximize the profits of collaborative mobile operators, achieving environmental goals and introducing more fairness among mobile operators in the procurement decision.

These approaches succeed in reducing the energy cost and/or Carbon footprint of cellular networks. However, they mainly consider the interests of the cellular network operators. In the context of SG, there exist another forms of energy trading with the SG. For example, some are made in advance, just 15 to 30 minutes before the tariff applies. These trades are known as *Ancillary Services* [10]. In short, ancillary services are trades of energy that are performed by the customers by increasing or decreasing their grid energy consumption to answer explicit requests of the SG. Ancillary services aim at reducing the short term imbalance between the SG demand and supply, and special incentives are provided for those who participate in providing them.

A. Contributions

Providing ancillary services have been widely investigated in the case of industrial, household, Heating, Ventilation and Air Conditioning (HVAC) loads and with electric vehicles in Vehicular-to-Grid (V2G) scenarios [27], [28]. On the contrary, in the telecommunications field, this context has been studied mainly in Data Centers [29], [30], whereas its application is rarely considered in mobile access networks. To the best of our knowledge, our study in [31] was the first to consider the problem of a base station that adapts its energy consumption to reply to the SG requests and provides ancillary services. In that work, RE sources and energy storage are used to provide the SG with ancillary services. On the one hand, BSs use RE and the storage to reply to the SG requests and help the grid in matching the energy demand-supply. On the other hand, the SG pays in return for these services, which will minimize the energy cost of the network. The proposed approach is limited to a heuristic algorithm. Moreover, the proposed algorithm uses fixed parameters. In [12], we consider the case of a mobile network that provides the SG with ancillary services. A Markovian model is proposed to model the energy state of the network. The network uses energy storage, RE as well as base station switching ON/OFF to reply to the SG's requests and provide ancillary services. In [32], [33], stochastic models are proposed to analyze the impact of parameter quantization on the model performance. Moreover, WiFi offloading are used to enhance the interaction with the SG.

In this paper, we investigate a renewable energy-powered base station that is actively interacting with the SG and that implements an energy management policy to react to the SG periodical requests of increasing or decreasing its grid energy consumption. To this aim, the base station can exploit the locally produced RE and the energy storage. Furthermore, radio resources can be deactivated to decrease the base station consumption when requested by the SG. In addition, the effect of weather condition variability on the SG request patterns is taken into account in the system model. The main contributions of the paper are:

- We study the performance of a renewable-powered base station that is providing ancillary services to the SG. An energy management policy is proposed to answer the SG requests and reduce the network's operational cost. Moreover, the BS energy state is modeled as a Markov Chain considering the proposed energy policy and randomness of RE generation and SG requests.

- We consider real data for both RE and SG requests. In contrast to previous work such as [12], [32], [33], since the daily weather conditions may affect not only the variability of the RE production but also the SG request patterns, we investigate the correlation between historical data of SG requests and the meteorological data, by analyzing the temperature variation throughout a year. We find that the SG requests (Up, Down, Null) can be categorized as 5 patterns that identify various daytypes, corresponding to different SG request probability distributions, depending on weather conditions.
- The proposed approach works at the level of a BS, which allows to take into account the specificity of each base station in terms of RE sources size, storage capacity, weather condition and allow obtaining different operational parameters for each base station.
- In contrast to [12], that uses switching off base stations, this paper considers radio resource management algorithm by deactivating some of the resource blocks. This is motivated by the fact that switching off base station may lead to coverage holes and may not be scalable considering large networks.
- The proposed Markovian model allows to compute several performance indicators such as RE utilization, energy storage state, percentage of replying to the SG, amount of energy used in providing ancillary service, Quality of Service (QoS) degradation and net operational cost. The proposed model also allows to choose the proper settings of the energy policy used to operate the BS.
- The proposed model can be used to choose the proper size of RE generators as well as the storage while considering the operation of the BS providing ancillary services to the SG. Although this paper does not focus on the sizing procedure, results presented in Section VII are presented for different RE sources and storage sizes.
- The performance of the energy policy operating under proper settings is compared with other algorithms.

Table I presents the notation used in the rest of the paper.

III. Modeling the green base station operation

In this paper, we construct a Markovian model of a base station equipped with RE and storage and providing ancillary service to the SG. In this section, we explain the models of parameters and components of the BS used to construct the Markovian model, which is presented in Section V. We present the power consumption model of the base station. Moreover, we explain the adopted radio resource management (RRM) strategy and the approach used to evaluate the quality of service (QoS) degradation when applying the strategy.

A. *Base station power consumption model*

TABLE I
NOTATIONS.

Time slot duration	T
Number of RE generation levels	N
Discrete random variable representing generated RE in time slot i	G
Probability associated to the value of generated RE G_k	p_k
Step between G_k and G_{k+1}	α
Power demand of BS without RRM algorithm	μ
Power demand of BS with RRM algorithm	μ_D
Storage capacity	S_{max}
Number of storage levels	N_s
Discrete variable representing storage level at a generic time slot i	s
Step between s_j and s_{j+1}	δ_s
Smart Grid request	r
Smart Grid request Up	U
Smart Grid request Down	D
Smart Grid request Null	N
Storage threshold during Smart Grid request Up	th_U
Amount of energy taken from the grid and stored to respond to the grid Up request	A
Storage threshold during Smart Grid request Down	th_D
State of the Markov chain defined as (s,r)	$\overline{x}$
Steady state probability of state $\overline{x}$	$p(\overline{x})$

We consider the well-known EARTH model to compute the base station power demand [34]. The power demand (input power), P_{in}, consists of a static part P_0 and a load dependent part related to the base station transmitted power P_T. The input power also depends on the number of active resource blocks,

$$P_{in} = N_{trx} \cdot (P_0 + \frac{n}{n_{max}} \cdot \Delta P \cdot P_T), \tag{1}$$

where N_{trx} is the number of transceiver chains of BS, n is the number of active resource blocks, n_{max} is the maximum number of available resource blocks and ΔP is the slope of the load dependent power part.

B. RRM strategy and QoS

In this work, we use activating/deactivating radio resources as the radio resource management strategy. We consider that the base station is responsible of serving several types of users having different QoS constraints as in our previous work [35]. We use the unified sigmoid function, proposed in [36], as the utility function to estimate the user satisfaction as function of the achieved bit rate. This utility is suitable for studying users' satisfaction with different QoS requirements. The Sigmoid function is expressed as:

$$u(r) = \frac{1}{\alpha + \beta e^{-\lambda(r-R_0)}} + \gamma, \tag{2}$$

where r represents the allocated resources, corresponding in our study to the achieved user bit rate. R_0 is the resource requirement (required bitrate) of the user and represents the point of inflexion. α, β, λ and γ are pre-determined parameters to determine the shape of the utility function depending on the type of traffic. Figure 1 presents an example of utility functions for different types of traffic. As seen in the figure, the increase in the resource (bitrate

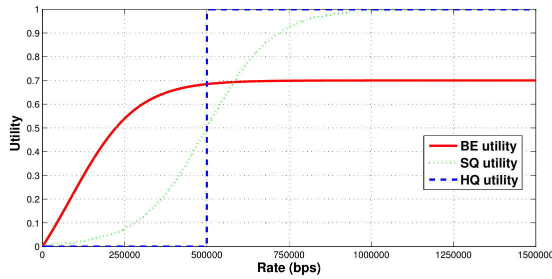


Fig. 1. Example of utility functions for different type of traffics, where BE, SQ and HQ stand for best effort, soft-quality and hard-quality. (λ_{BE} = 0.00001, β = 2.333, λ_{HQ} = 0.01, λ_{SQ} = 0.00001, R_0 = 500000bit/sec).

in our case) has different impact on the user's utility depending on the type of the user (BE: best effort, SQ: soft quality, HQ: Hard quality). For example, HQ user, such as Voice, needs a specified amount of resources to maintain their requirements. Allocating more resources for SQ traffic increases its utility until certain limit. BE traffic does not have specified amount of needed resources ($R_0 = 0$).

The defined utility is in terms of the user rate. We calculate the bit rate of a user based on 3GPP TR 36.942 [37]. The rate is calculated as follows. The received signal power, P_r, to a user from a base station with transmitting power, P_t, is:

$$P_r = 10log_{10}(P_t \cdot 1000) - (Lo - G_T - G_R) \quad [dBm], \tag{3}$$

where Lo is the path loss computed using Cost 231 extended Hata model as in [37], G_T and G_R are respectively the gain of the transmitter and receiver. The detected signal-to-noise (SNR) ratio is computed as:

$$SNR = P_r - N \quad [dB], \tag{4}$$

where N is the thermal noise power expressed by:

$$N = 10log_{10}(1000 \cdot KT_0 \cdot BW) + NF \quad [dBm], \tag{5}$$

where KT_0 is the thermal density noise, BW is the user's allocated bandwidth, and NF is the noise figure. Using the calculated SNR and the number of allocated resource blocks, the user rate is calculated based on [37].

We consider that the BS is transmitting at a fixed power. This will eliminate the possibility of coverage holes in the network. Thus, the number of activated radio resource blocks determines the level of satisfaction of users. The number of activated resource blocks is a tradeoff between the user satisfactions and power demand of the BS. In [35], we studied this tradeoff as a weighted sum of user satisfaction (based on the utility function) and power demand of the BS. In this work, we use a heuristic algorithm that determines the number of active radio resource blocks n_{act} when RRM is applied by the energy strategy presented in Section IV-B; under no RRM policy, all the resources will be activated. The number of active resource blocks when RRM is applied is computed as follows:

$$n_{act} = \left\lceil n_{max} \cdot \frac{TI}{TI_{max}} \right\rceil, \tag{6}$$

where $\lceil a \rceil$ is the smallest integer larger or equal to a and TI represents the traffic intensity with a maximum of TI_{max}. The QoS degradation of a user is calculated as the ratio of user's utility when RRM is applied, U_{RRM}, to the utility when no RRM is applied, U_{ref}. The QoS degradation is calculated following: $QoS_{deg} = \frac{U_{RRM}}{U_{ref}}$.

C. Modeling renewable energy generation and energy storage

The RE generation varies depending on the type of generator and on several factors such as the weather, location and period of year. Our model describes the evolution of the system in discrete-time, the time step has duration T. The amount of RE that is generated in a time slot i is represented by a discrete random variable G whose probability mass function is drawn according to the harvesting profile. A similar model is considered in [38].

Although the energy harvesting process has time-varying statistics, for simplicity we assume that the amounts of generated energy in different time slots are independent. The generated energy is discretized in N levels. In a time slot, an amount of energy G_k [Wh] is generated with probability p_k, with $k = 1, \cdots, N$ and $\sum_{k=1}^{N} p_k = 1$. Levels are in ascendant order, so that $G_k < G_j$ if $k < j$. The maximum amount of energy generated in a time slot is denoted by G_{max}. N is computed by $N = \lceil \frac{G_{max}}{\alpha} \rceil$, where α represents the chosen step between G_k and G_{k+1}. Clearly, increasing N leads to a more accurate, yet more complex, model. When RE sources are not available at the BS site, the generated energy is 0, so $G_0 = 0$.

In RE powered systems, the use of energy storage is important due to the intermittent energy generation of renewable sources. Energy storage is typically employed to store excess RE and compensate its unavailability that is quite frequent such as during nights in case of solar energy. In addition, we use the energy storage to help the BS to reply to the SG and provide ancillary services. During request of type Down, the previously stored energy can be used to reduce the energy demand from the grid and thus to reply to the SG request. During request of type Up, the energy storage is used to harvest excess grid energy (higer than BS demand) to reply to the grid request, which can be also used later during requests of type Down. Moreover, generated RE is stored in case of Up request to avoid wastage of RE, since RE cannot be used; otherwise, the grid energy consumed by the base station would decrease, thus leading to penalty due to violation of the grid request.

The maximum amount of energy that can be stored, that is the storage capacity, is denoted by S_{max}. To represent the amount of stored energy, we discretize the energy storage into identical levels. The number of levels N_s depends on S_{max} and on the difference between two consecutive levels, δ_s. Hence, $N_s = \frac{S_{max}}{\delta_s} + 1$. The choice of δ_s is a trade-off between the model complexity and accuracy. On the one hand, a large δ_s leads to a small number of storage levels but higher discretization errors. On the other hand, choosing a small value of δ_s leads to a large number of storage levels but a higher accuracy in modeling the system. The storage level in a given time slot is denoted by s. Note that charging and discharging losses are not considered in this work.

IV. Modeling the interaction with the Smart Grid

We now present how we model the operation of the SG performing its Demand Response policy. Moreover, we describe the energy management strategy implemented by the BS to interact with the SG.

A. Modeling the Smart Grid operation

In the SG, if excess energy is available, the grid requests to its customers (willing to provide ancillary services), and hence to the BSs, to increase their grid energy consumption; the SG issues a request indicated by Up. If the demand is higher than the generated energy, the grid requests to decrease the grid energy consumption, the request is of type Down. Otherwise, the grid does not request any change in the energy consumption, and this is denoted by a Null request. Ancillary services are provided by customers (BSs in our case) to reply to the grid request. This is done by increasing the grid energy consumption when the request is Up and decreasing the grid energy consumption when the request is Down. The ancillary services markets are country-dependent and a review of these markets designs is available in [39]. The terms request Up and request Down, that we use in the paper, correspond to regulation Down and regulation Up, respectively, in the SG nomenclature.

To study the statistics of the SG requests and represent them with a stochastic model, we analyze real data (an SG request every time step of 30 min) provided by the RTE [40], which owns the main French energy transmission network. Based on the data, the SG request may change from any state to another or stay in the same state for more than one time step. Figure 2 shows the average monthly percentage of each state of the SG. Being the production and consumption very dynamic, the state Null represents a small percentage of the cases: its average does not exceed 10%. There are some seasonal variations: the state of Down is more than 70% of the requests in November and December, while it is less than 40% in April, when the highest percentage of state is Up (58%). Taking an overall average, the state Down is the most frequent one, with 53% of occurrences, while Up occurs 42% of the times.

Energy Consumption of SG customers is strongly related to weather (e.g., due to the need for heating and cooling). However, the SG request (UP or Down) is related to the error of energy demand prediction verified the next day. Knowing that weather and historical data are among the most used parameters in predicting energy consumption [42], we study the relation between SG requests and weather (temperature) by investigating real data for one year of SG requests, corresponding weather (for the same dates of SG requests data) and historical weather. Figure 3 presents the average daily temperature for the studied year in France.

From the analysis of the SG data provided by RTE and the weather history, we define the *general weather*, which corresponds to the average temperature of a day calculated from historical meteorological data. We consider the

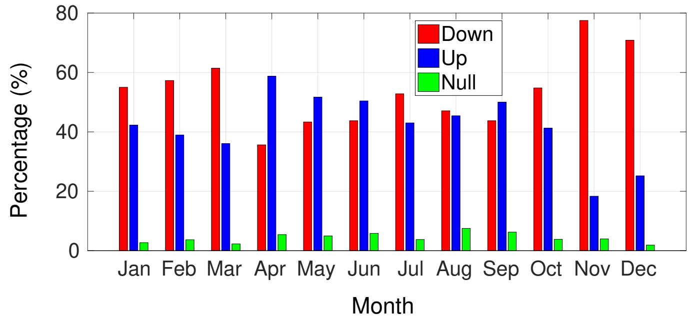


Fig. 2. Average monthly percentage of each state of the SG.

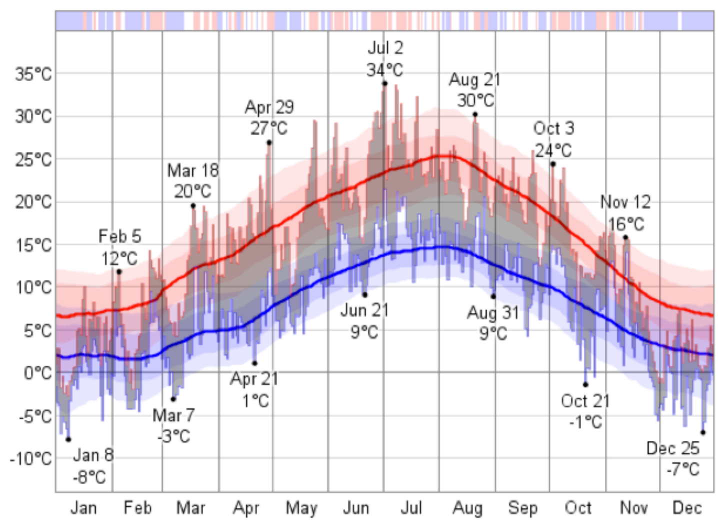


Fig. 3. Temperature variation throughout the year in France [41].
Legends: The daily low (blue) and high (red) temperature with the area between them shaded gray and superimposed over the corresponding averages (thick lines), and with percentile bands (inner band from 25th to 75th percentile, outer band from 10th to 90th percentile).

general weather as cold, average or hot if the average temperature is respectively below $10°C$, between $10°C$ and $15°C$, and more than $15°C$. For each day, we also define the *relative weather*, which is determined by comparing the actual weather of the day (average temperature) to the general weather. For example, if we consider April 29, see Figure 3, the temperature is very high with respect to the average temperature, calculated by using historical data. Thus, the relative weather is very hot. For each of the three categories of general weather, we consider 5 types of relative weather, depending on the temperature gap between the actual daily average temperature and the average temperature defined by the general weather: very hot, hot, average, cold and very cold. By combining the general weather with the relative weather conditions we have 15 combinations of possible meteorological conditions. Table II presents the relation between relative weather, general weather and patterns of SG request. Each pattern corresponds to a different probability distribution of the requests (Up, Down and NULL) for a day. By analyzing data provided by [40], we identify 5 patterns; in pattern 1 and 5 the occurrence of either Down or Up through a day is extremely high (more than 70%), in pattern 2 and 4 the occurrence of either Down or Up during a day is

TABLE II
RELATION BETWEEN GENERAL WEATHER, RELATIVE WEATHER AND SG STATES.

General weather / Relative weather	Cold	Average	Hot
Very cold	Pattern 1	Pattern 2	Pattern 5
Cold	Pattern 2	Pattern 1	Pattern 5
Average	Pattern 3	Pattern 3	Pattern 3
Hot	Pattern 5	Pattern 4	Pattern 2
Very hot	Pattern 5	Pattern 4	Pattern 1

TABLE III
THE OCCURRENCE PROBABILITY OF EACH STATE FOR DIFFERENT SG PATTERNS.

Smart Grid	State Down	State Up	state Null
Pattern 1	0.8	0.15	0.05
Pattern 2	0.62	0.3	0.08
Pattern 3	0.42	0.42	0.16
Pattern 4	0.3	0.6	0.1
Pattern 5	0.2	0.77	0.03

between 60% and 70%, in pattern 3 there is no dominant request, i.e., Up and Down occur roughly with the same probability. Table III presents the occurrence probability of each state in a day based on the SG pattern. Indeed, it is possible to have larger number of patterns with more precise values. However, this would complicate the prediction of the correct pattern on the day ahead. In our proposed approach (see Section V-A), the predicted pattern of the SG is used to properly choose the parameter settings of the energy policy. For each pattern, the probability of switching from a state (request) to another is calculated from data belonging to all the days that follow the corresponding pattern. We denote the probability of switching from SG state to another as the SG transition probability.

For a day with given weather conditions, we may expect the type of SG pattern, based on Table II, and thus the occurrence of each type of request as well as the corresponding SG transition probability. It should be noted that these patterns are identified for France. Nevertheless, the results presented in Section VII can be generalized considering that the patterns are represented as occurrence probabilities of the SG request states. However, If another country/dataset is considered, a study of the new dataset to extract the patterns is required as step in building up the model presented in Section V.

B. *Energy management policy*

The energy management policy determines how the base station replies to the SG request. The BS can use generated RE, energy storage and/or RRM to reply to the grid request. In this work, we do not aim at proposing an optimal policy due to the huge complexity caused by the large number of varying parameters involved in the problem. Our work rather aims at deploying an empirical energy management strategy to improve the interaction with the SG. Thus, we propose a greedy energy policy that takes actions based on the state of the energy storage and the request of the SG.

The energy management strategy, summarized in Algorithm 1, works as follows. If the SG request is Down, the BS uses RE and the storage to decrease its grid energy consumption as much as possible. When the storage is below a threshold th_D, stored energy is not used to decrease the energy drained from the SG, so as to avoid the risk of a complete storage discharge. Thus, The BS threshold th_D should satisfy the constraint: $th_D > (\mu_{max} \cdot T - G_{min})$, where G_{min} is the minimum generated RE, $\mu_{max} \cdot T$ is the maximum energy demand of the BS. To reply to the SG when the request is down and storage is below th_D, RE is used. In case of unavailable or insufficient RE generation, the RRM presented in Section III-B is applied. In Algorithm 1, μ_d and μ represent the energy demand of the base station with and without RRM respectively. Note that choosing small values for th_D leads to higher ancillary service but, also, to lower amounts of stored energy.

If the SG request is Up, the BS satisfies its energy demand from the power grid and, in addition, an amount of energy A is taken from the grid and stored. In order to reduce possible energy wastage, if the storage is above a threshold th_U, the BS acquires from the SG only the amount of energy that the BS needs to operate, and, in this case, only RE is stored. The threshold th_U should satisfy $th_U < S_{max} - (G_N + A)$, where G_N is the maximum amount of generated RE. The setting of th_U is critical to avoid excessive storing of grid energy and wastage of RE. Moreover, a good choice of th_U is important to respond to Up requests and to ensure the possibility to use stored energy to reduce the energy consumption from the grid when the request is Down. In the case of Null request, the SG has no preference and thus the BS keeps the same energy consumption from the grid as announced the day ahead.

In general, setting the parameters th_D, th_U, and A is critical and not straightforward, since the effect of the parameters on the performance depends on many factors including the RE generation, SG request variation, storage size, grid energy price, and price of providing ancillary services. In the next section, we construct a Markovian model of a renewable powered BS providing ancillary services to the SG. The transition probabilities of the model depend on the decisions taken by the energy policy and on the setting of the thresholds th_U and th_D as well as the value of A. In the proposed approach (Section V-A), we evaluate the model for different values of the thresholds and A to obtain a proper parameter setting, with the objective of minimizing the net operational cost. On the one hand, this allows a significant, although not necessarily optimal, cost reduction, and a remarkable improvement of the capability of providing ancillary services to the SG.

V. Markovian model of the green system operation

In this section, we describe the procedure of constructing the proposed Markov chain that represents a base station equipped with RE and storage and provides the SG with ancillary services. As shown in Figure 4, the state of the BS is represented as a multi-dimensional discrete Markov chain that reflects both the level of the energy storage

Algorithm 1 Energy management algorithm

switch *grid request* **do**
  case UP
    draw $\mu \cdot T$ from the grid;
    if $s \leq th_U$ **then**
      draw A from the grid and store it into battery;
    end if
  case $DOWN$
    if $s \geq th_D$ **then**
      derive $E = \min(\mu \cdot T, G_i)$ from G_i;
      if needed, derive $\mu \cdot T - G_i$ from the battery;
    else (case $s < th_D$)
      if $\mu \cdot T \leq G_i$ **then**
        derive $E = \mu \cdot T$ from G_i;
      else
        Apply the RRM algorithm: Set the number of activated resource blocks to n_{act}
        if $\mu_D \cdot T > G_i$ **then**
          use $E = G_i$;
          draw $\mu_D \cdot T - G_i$ from the grid;
        else
          derive $E = \mu_D \cdot T$ from G_i;
        end if
      end if
    end if
  case $NULL$
    draw $\mu \cdot T$ from the grid;
Harvest residual RE into battery, waste the extra amount;

and the SG request state, also depending on the daily pattern of the SG requests, that we denote P_i . Time evolves according to time slots of duration T. The state of the Markov chain is given by $\overline{x} = (s, r)$, where s represents the storage level with number of levels N_s; $r \in \{U, D, N\}$ represents the type of SG request Up, Down or Null. For each daytype with a given pattern of SG requests, P_i, the number of states in the Markov chain state space is $3 \cdot N_s$, where N_s is the number of energy storage levels. Thus, decreasing the value of δ_s leads to a higher number of states and a more accurate model, yet a more complex one.

The possible transitions between the Markov model states depend on the generated RE (modeled in Section III-C), SG operation (modeled in Section IV-A) and the proposed energy management policy (proposed in Section IV-B). The probability that after an SG request of type r, a requests of type r' follows is denoted by $P(r, r')$ and it is derived from the statistics of the requests described in Section IV-A. For each pattern of the SG variation presented in Table III, we use the pattern statistics to calculate $P(r, r')$. The amount of RE generation is represented by a discrete random variable, G, whose probability mass function is determined based on real data as described in Section III-C. In addition to RE and SG requests, the possible transitions and their corresponding probabilities depends on the actions taken by the energy management policy and on the threshold setting. For simplicity, we assume that the SG request switching and the RE generation are independent, although both RE generation and SG request state are related to the weather. However, the SG request state is mainly affected by the relative weather and several additional parameters that do not affect the RE generation, such as energy market, type of day, social

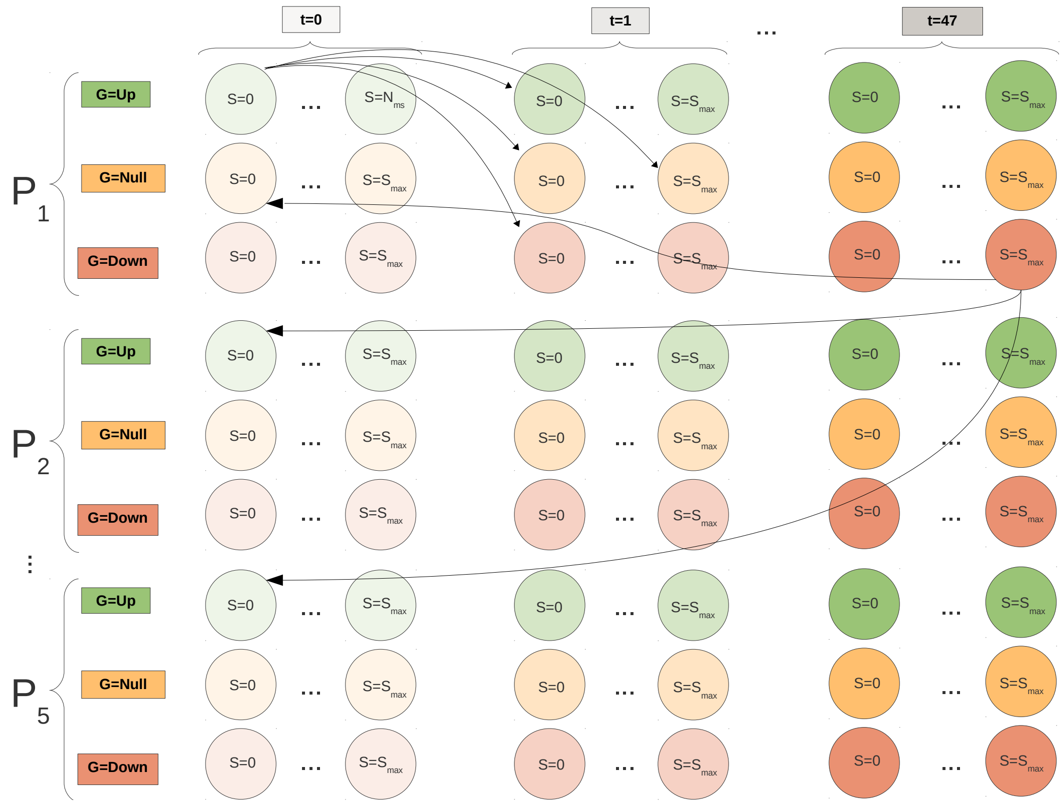


Fig. 4. Markovian model of the green system operation. Only some sample transitions, among all those possible, are reported.

behavior, special events and low energy consumers/providers. Following such parameters at the level of the 30-minute time step is overwhelming, if possible, and leads to significant independence of the SG requests from the RE generation. Moreover, this leads to the randomness of the SG request state at the time step level (each time the SG sends a request).

In addition, the probability of transition of energy level depends on the energy policy. Table IV presents the transition probability from state $\overline{x} = (s, r)$ to state $\overline{x}' = (s', r')$ used to construct the Markov chain representing the energy state of the BS. Note that the model is designed for BSs powered with local RE sources. However, several BSs would not be powered by RE sources. Moreover, some of the RE sources do not provide energy in certain periods of the day, such as solar panels where they do not generate energy during night. In this case, the transition probabilities of the model presented in Table IV model are still valid with $p(G_k = 0) = 1$.

A. Approach

In this section, we explain the proposed approach that utilizes the models presented in the previous sections. The approach consists of two stages, see Figure 5. The first stage, which is done off-line, decides the operating parameters of the system as follows: 1) Model the patterns of SG requests (Section IV-A). 2) Model the RE generation depending on the weather (Section III-C). 3) Use the energy policy to reply to the SG requests (Section

TABLE IV
MARKOV CHAIN TRANSITION PROBABILITY FROM FROM $\overline{x} = (s, r)$ TO $\overline{x}' = (s', r')$.

Condition on $\overline{x}$		Probability	Condition on $\overline{x}'$
$r = D$	$s \leq th_D$ and $G_K \geq \mu \cdot T$	$P(D, r') \cdot p_k$	$s' = \min(\max(s, s + G_k - \mu \cdot T), S_{max})$
	$s \leq th_D$ and $G_K < \mu \cdot T$	$P(D, r') \cdot p_k$	$s' = \min(\max(s, s + G_k - \mu_D \cdot T), S_{max})$
	$s > th_D$	$P(D, r') \cdot p_k$	$s' = \min(s + G_k - \mu \cdot T, S_{max})$
$r = U$	$s < th_U$	$P(U, r') \cdot p_k$	$s' = s + G_k + A$
	$s \geq th_U$	$P(U, r') \cdot p_k$	$s' = \min(s + G_k, S_{max})$
$r = N$		$P(N, r') \cdot p_k$	$s' = \min(s + G_k, S_{max})$

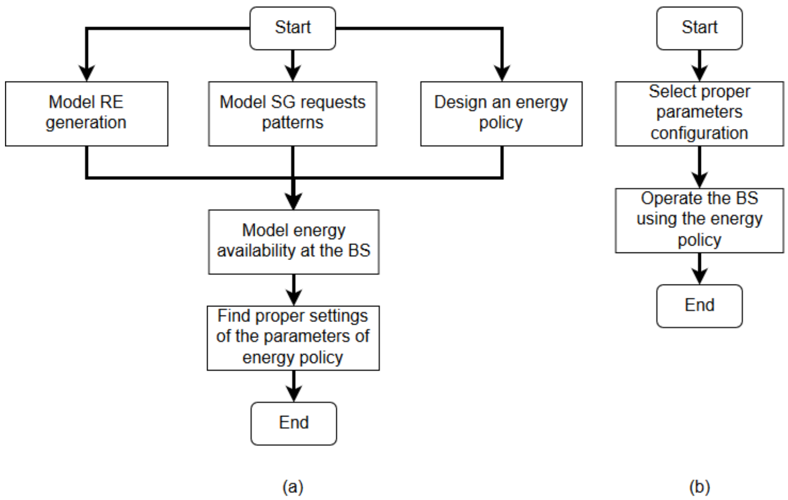


Fig. 5. Proposed approach: (a) first stage (offline), (b) Second stage (online).

IV-B). 4) Model the energy availability at the BS, taking into account RE generation, the SG patterns model, the energy consumption and the proposed energy management policy (Section V). 5) Use the model to find proper setting of the parameters of the energy management policy. In step 5, the parameters are chosen based on the objective of the operator, which is pursued by maximizing or minimizing the corresponding performance indicator(s). The performance indicators that can be calculated using the model are presented in Section VI. In this paper, we consider the objective of minimizing the energy operation cost.

The second stage of the proposed approach is performed on-line by using the parameters obtained in the first stage to operate the base station. Note that the proper parameters configuration for the energy management policy is selected each day to minimize the cost based on the daily weather forecast and the SG request pattern expected in the considered day-type.

VI. Performance Indicators

Several indicators can be derived from the model in order to evaluate the behavior of the system. In the following we present the main indicators.

A. Renewable energy utilization and waste

We define the RE utilization as the ratio of consumed RE over the generated RE. The utilization of renewable energy (URE) is calculated as $URE = 1 - WRE$, where WRE is the ratio of wasted RE normalized over the generated RE. The wasted RE is due to the unavailability of the storage, and it is computed as the sum of wasted energy during the cases of Down, Up and Null. RE waste occurs in case of Down when $G_k - \mu \cdot T > S_{max} - s_j$, where G_k is the amount of generated RE (it has probability p_k), s_j is the current state of the storage and μ is the power demand of the BS. In case RRM is applied, μ must be replaced by μ_D. The probability of wasting energy in case of Down is:

$$P_w^D = \sum_{R_D} \sum_{Z_D} p_k \cdot p(\overline{x}), \tag{7}$$

where R_D is the subset of states in the Markov chain in which the grid request is Down and Z_D includes all the possible values of generated RE such that there is not enough space in the battery to store all the extra amount of RE not used by the BS:

$$R_D = \left\{\overline{x} = (s, r) \ s.t. \ r = D\right\}, \qquad Z_D = \left\{k \ s.t. \ G_k - \mu \cdot T > S_{max} - s\right\}.$$

When the SG request is Up, RE is wasted when $s_j > th_U$ and the generated RE is more than the available storage capacity. The probability of wasting RE during state Up is:

$$P_w^U = \sum_{R_U} \sum_{Z_U} p_k \cdot p(\overline{x}), \tag{8}$$

where R_U is the subset of states in the Markov chain in which the grid request is Up and the battery level is higher than th_U, while Z_U includes all the possible values of generated RE for which there is not enough space in the battery to store all the generated RE:

$$R_U = \left\{\overline{x} = (s, r) \ s.t. \ s > th_U, \ r = U\right\}, \qquad Z_U = \left\{k \ s.t. \ G_k > S_{max} - s\right\}.$$

When the SG request is Null, the probability of wasting RE is:

$$P_w^N = \sum_{R_N} \sum_{Z_N} p_k \cdot p(\overline{x}), \tag{9}$$

where R_N is the subset of states in the Markov chain in which the grid request is Null and Z_N includes all the possible values of generated RE for which there is not enough available capacity in the battery to store the generated RE:

$$R_N = \left\{\overline{x} = (s, r) \ s.t. \ r = N\right\}, \qquad Z_N = \left\{k \ s.t. \ G_k > S_{max} - s\right\}.$$

The average amount of wasted RE in all states is $E_w = E_w^D + E_w^U + E_w^N$, where E_w^D, E_w^U and E_w^N are calculated as follows:

$$
\begin{aligned}
E_w^D &= \sum_{R_D}\sum_{Z_D} p_k \cdot p(\overline{x}) \cdot (G_k - \mu \cdot T - S_{max} + s), \\
E_w^U &= \sum_{R_U}\sum_{Z_U} p_k \cdot p(\overline{x}) \cdot (G_k - S_{max} + s), \\
E_w^N &= \sum_{R_N}\sum_{Z_N} p_k \cdot p(\overline{x}) \cdot (G_k - S_{max} + s).
\end{aligned}
$$

B. Energy storage

Another interesting indicators are the average stored energy and the probability of having low storage. We consider that the storage is low when it is not enough to power the BS without additional sources. The probability of having low storage, denoted as P_{ls} is $P_{ls} = \sum_L p(\overline{x})$, where L is the subset of states in the Markov chain in which the storage level is too low to satisfy the BS power demand:

$$L = \left\{\overline{x} = (s, r) \ s.t. \ s < \mu_{max} \cdot T\right\},$$

where μ_{max} is the maximum power demand of the BS. The average state of the storage is calculated as $S_{av} = \sum_J p(\overline{x}) \cdot s$, where J is the whole Markov chain state space.

C. Ancillary services

The amount of energy used when providing ancillary services depends on the storage state as well as RE generation and the chosen thresholds. We are interested in the average amount of energy used during state Down and state Up. In state Down, the average amount of energy used for providing ancillary services is computed as follows:

$$E_{anc}^D = \frac{\sum_{Pr}\sum_E p(\overline{x}) \cdot p_k \cdot min(\mu \cdot T, (\mu - \mu_D) \cdot T + G_k) + \sum_{Fr} p(\overline{x}) \cdot \mu \cdot T}{\sum_{R_D} p(\overline{x})}, \tag{10}$$

where Pr is the subset of states in the Markov chain in which the grid request is Down and the storage level is below the threshold th_D: the SG request may not always be fulfilled (*Partial response*), since grid energy consumption can be reduced using generated RE and by applying the RRM; E is the set of all the possible values of RE that can be generated, up to G_{max}: Fr is the subset of states in the Markov chain in which the request is Down and the grid request can be always satisfied (*Full response*) even if RE is not available, since the storage level is high enough to satisfy the BS energy demand; R_D includes all the possible states in the Markov chain in which the grid request is Down:

$$
\begin{aligned}
Pr &= \left\{\overline{x} = (s, r) \ s.t. \ s < th_D, r = D\right\}, \\
E &= \left\{k \ s.t. \ G_k \leq G_{max}\right\},
\end{aligned}
$$

$$Fr = \left\{ \overline{x} = (s, r) \ s.t. \ th_D \leq s, r = D \right\},$$

$$R_D = \left\{ \overline{x} = (s, r) \ s.t. \ r = D \right\}.$$

During state Up, ancillary services are provided for states below th_U, and in this case the additional energy drained from the grid is equal to A. Thus, the amount energy used in providing ancillary services during state Up is:

$$E_{anc}^{U} = A \cdot \frac{\sum_{Ir} p(\overline{x})}{\sum_{I} p(\overline{x})}, \tag{11}$$

where Ir is the subset of states in the Markov chain in which the grid demand is Up and the request of increasing the energy consumption from the grid can be satisfied (*Increase response*), since there is still enough space in the battery to store the extra amount of energy taken from the grid; I is the set of all the states in the Markov chain in which the grid request is Up:

$$Ir = \left\{ \overline{x} = (s, r) \ s.t. \ s \leq th_U, r = U \right\},$$

$$I = \left\{ \overline{x} = (s, r) \ s.t. \ r = U \right\}.$$

Although, this metric does not differentiate between the amount of grid energy decreased/increased during the states Up and Down, it aims at estimating how much the BS is capable of providing ancillary services in each state. To differentiate between the two states, the indicator net operational cost gives different weight (via price) of energy used in providing ancillary service in each state (higher price in case of Down request and lower price in case of Up request), as shown in Section VI-E.

D. QoS degradation

An important metric in evaluating the proposed approach in replying to the SG requests is studying its effect on the quality of service of mobile users. The proposed model allows us to calculate the probability of degradation of quality of users, which is the probability of being in a state where request is Down, energy level is below th_D and generated RE is less than the energy demand of the BS. In this state, RRM strategy is used to reply to the SG request. The probability of QoS degradation is:

$$P_{deg} = \sum_{Pd} \cdot p(\overline{x}), \tag{12}$$

$$Pd = \left\{ \overline{x} = (s, r) \ s.t. \ s < th_D, r = D, G_k < \mu \cdot T \right\}.$$

The average QoS degradation is calculated by:

$$D = D_{avg} \cdot P_{deg}, \tag{13}$$

where D_{avg} is calculated by averaging the QoS degradation for large number of simulations or measurements when the radio resource management is applied. For a radio resource management algorithm, the exact value of the quality of service degradation depends on the traffic intensity, network resources (active resource blocks of the base station) and demand and condition of each user.

E. Net operation cost

The net operation cost is the difference between the operational cost due to buying on-grid energy and the gain due to providing ancillary services. The net operational cost C is expressed as follows:

$$C = [(P^g \cdot Price) - (P_D^{anc} \cdot Price_D^{anc}) \cdot x - (P_U^{anc} \cdot Price_U^{anc}) \cdot y + (P^{viol} \cdot Penalty^{viol}) \cdot z] \cdot T,$$

where P^g is the average power taken from the grid. $Price$ is the average price of grid energy, P_D^{anc} and P_U^{anc} are the average adjustment powers in case of request Down and Up respectively. $Price_D^{anc}$ and $Price_U^{anc}$ are the gain due to participating in providing the services in case of request Down and Up respectively, P^{viol} is the power difference when opposing the request direction (violating the request). $Penalty^{viol}$ is the penalty of opposing the request direction.

x is set to 1 if the BS participates in providing ancillary services during a Down request. If the request is Down, and the BS did not participate in ancillary services or violated the request, then x is set to 0. x is also set to 0 when the request is Up or Null. y is set to 1 if the BS participates in providing ancillary services during an Up request. If the request is Up, and the BS did not participate in ancillary services or violated the request, then y is set to 0. y is also set to 0 if the request is Down or Null. In case of violation of Up or Down requests z is set to 1. In the proposed policy, x is always 1 when the request is Down and the BS can always fulfill this request by using RE, stored energy and/or RRM. y can be 0 or 1 when the request is Up, since the policy may not participate in ancillary services if the storage is above th_U. z is always set to 0 in the proposed policy, since the BS may not participate in providing ancillary services but it would not violate the request in any case.

F. Choice of thresholds

Our aim is to find a proper setting of the thresholds of the energy policy, where it is possible to choose any of the performance indicators to formulate the problem. We focus on the net energy cost due to the MNOs priority in reducing the energy cost of the BSs. In this case, the choice of thresholds is done to minimize the net energy operational cost C: $\underset{thi,thd,A}{\text{minimize}} \quad C$. The results of the proposed energy policy presented in the following section are obtained under proper threshold values, that are tuned by calculating the steady state probabilities of the Markov model for all the possible thresholds and choosing the best thresholds by performing an exhaustive search considering the objective of minimizing the net operational cost.

VII. Results

In this section, we evaluate the performance of the proposed energy management policy for different patterns of SG requests, RE generation and storage size. Furthermore, setting the parameters used in the energy management algorithm is investigated. Based on the data provided by [40], the SG sends a request every period T = 30 min. Using these data, we model the green mobile system operation by designing a Markov chain for each of the SG request patterns identified in Section IV-A. We evaluate the system performance under several combinations of RE generation levels, provided by [43], and storage sizes. RE generation is expressed as a percentage of the BS energy demand, that is assumed to be equal to 1200 Wh. This allows to generalize the results for different locations, since the location of the base station significantly affects the amount of generated RE. To represent battery charge levels in the Markovian model, stored energy is quantized into steps of 100 Wh.

The average price of on-grid energy and average gain of providing ancillary services are calculated from data provided by [40] as follows: average on-grid energy cost: 37 €/MWh, average gain of ancillary service in case of Down: 60 €/MWh, average gain of ancillary service in case of Up: 24 €/MWh. In France, there are more than 90000 BSs [44]. If we consider that a network operator has 20000 LTE BSs, the annual energy cost of these BSs is about 8 M€. The reward for providing ancillary services in case of Down is higher than the price of grid energy. Thus, the BS gains a positive revenue in case of a Down SG request, if it succeeds in providing ancillary services. In case of an Up request, the gain of providing ancillary service is lower than the on-grid energy price; hence, providing the service is equivalent to buying grid energy at lower price.

First, we present the first stage entailing the off-line proper setting of thresholds that are adopted for the energy management algorithm. The proper settings of the thresholds are calculated using exhaustive search within a predefined set, with the objective of minimizing the operational cost of the BS. Note that the results derived next, except in Section VII-B2, are derived by solving the Markov chain numerically. Afterwards, we discuss results related to the second stage of our approach, that are derived under the proper parameter configuration obtained in the first stage. We study the impact of RE system dimensioning on the capability of providing ancillary services. Furthermore, the effect of different patterns of SG requests on the system performance is analyzed in terms of operational cost, under various RE system sizing. In addition, the effects on cost of the application of RRM technique are examined. Finally, the proposed energy management policy is compared with respect to other approaches from the literature.

A. First stage: off-line threshold setting

The analysis of the proper threshold setting allowing to minimize cost is important to understand the performance of the proposed energy management policy. For all considered cases, the threshold th_D (used in the Down state) is the same and corresponds to the maximum energy demand of the BS. This result is predictable since the gain of providing ancillary services in Down is high, and the BS will try to respond to the grid request as much as possible in this case. The thresholds th_U and A do not follow the same trend, their optimal values change in the various scenarios. Table V presents the threshold values allowing to minimize cost in the case of pattern 3. For a fixed RE

TABLE V
OPTIMIZED THRESHOLDS FOR PATTERN 3.

Storage size (Wh)	RE (%)	th_U (Wh)	A (Wh)
2000	22	600	300
2000	44	600	300
2000	66	500	100
4000	22	1900	600
4000	44	1300	600
4000	66	400	200
6000	22	4000	600
6000	44	1600	600
6000	66	400	200

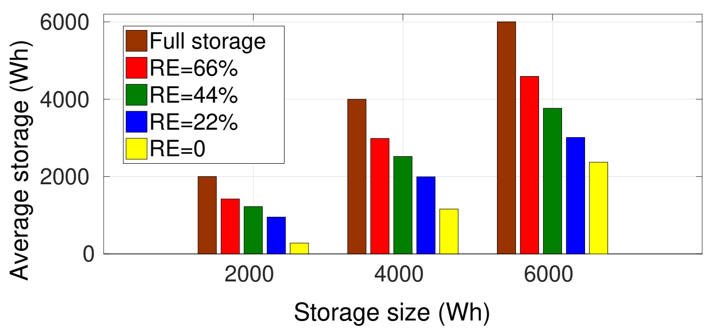


Fig. 6. Average storage state for different RE generation and storage sizes.

generation, the values of th_U and A increase with the storage size. Given the storage size, the proper values of th_U and A decrease with increases of RE generation, so as to avoid wastage RE. This is true for other patterns also. For fixed RE generation and storage size, the suitable values of th_U and A, for patterns with high probability of Down state (low probability of Up state), are higher than those for a pattern with lower probability of the Down state (higher probability of Up state). This is justified by the fact that the BS will try to ensure available energy in the storage, by storing energy from the grid in Up state, to reply to the grid request in Down state and increase its gain.

B. Second stage: performance analysis under optimal parameter setting

In our approach, the energy storage is one of the main components that enables BSs to provide the SG with ancillary services. Figure 6 presents the average stored energy for different RE generations and storage sizes (averaged for all patterns). As expected, the average amount of stored energy increases with the increase of RE generation. We notice that the average stored energy is very low when RE in unavailable, RE=0. We focus now on RE utilization that was introduced in Section VI-A. The results are presented in Figure 7 for different RE generations and storage sizes (results are the averaged for all patterns). The energy management policy achieves high utilization of RE. RE utilization decreases when increasing the RE generation, and slightly increases when increasing the storage. Figure 8 (a) shows the ratio of average energy used for providing ancillary services, for all patterns, to the BS energy demand in the Down state for different amounts of RE generation and values of the

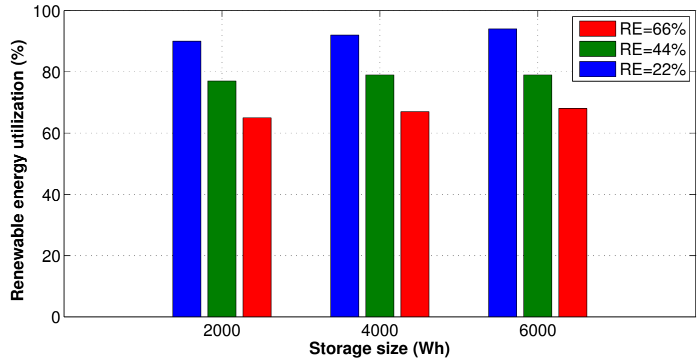
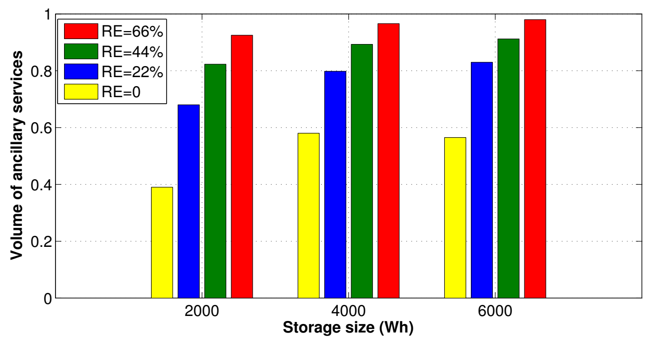
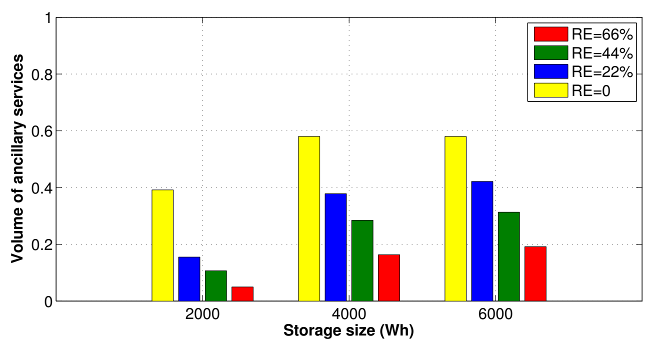


Fig. 7. RE utilization for different RE generation and storage sizes.



(a)



(b)

Fig. 8. Ratio of average energy used for providing ancillary services to the BS demand in case of state Down (a) and state Up (b).

storage size. Clearly, the energy used for providing ancillary services in Down increases with the RE and storage size. Notice that the ratio of ancillary services is almost 1 when RES and storage size are large, which justifies the limit achieved in the gain in terms of operational cost (presented later). Providing ancillary services in Down state reduces the net cost. However, providing ancillary services in case of Up is equivalent to buying energy with cheaper price. Figure 8 (b) presents the amount of energy used for providing ancillary services in Up state normalized by the BS energy demand. The increase of RE leads to lower amount of services, since the BS prefers to use RE (free energy) than to buy energy to be used later even at cheap price. This also justifies the choice of the thresholds of

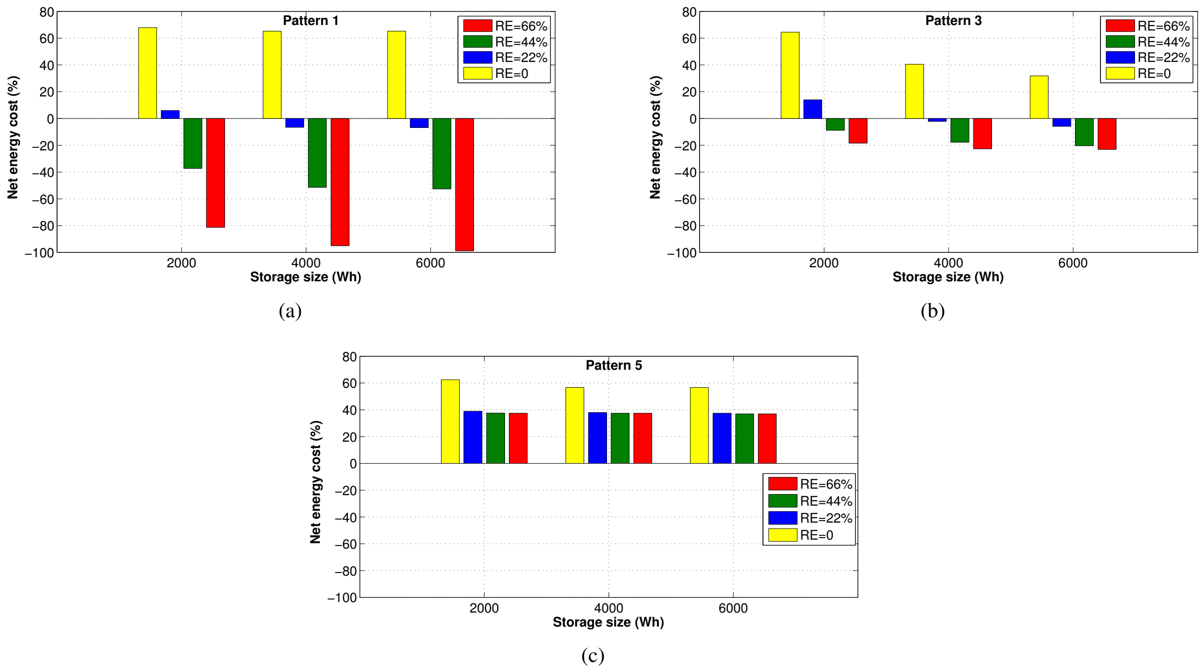


Fig. 9. Normalized energy operation net cost for different RE average generation, storage sizes and SG request patterns (a: pattern 1; b: pattern 3; c: pattern 5).

the energy management policy presented before, where increasing the RE leads to lower th_U and A.

Our results show that a larger size of the battery allows to raise the volume of ancillary services, with a more evident effect in case no PV panels are installed. However, in our scenario a battery storage with capacity larger than 4 kWh does not provide further significant improvement to this extent.

The net energy operational cost depends on many parameters including the generated RE, storage size and SG pattern. In general, the net cost decreases when RE generation increases since the base station can rely more on RE. Moreover, increasing the size of the storage allows more storing of excess RE, which can be used later to further decrease the net cost. Figure 9 presents the normalized net cost of energy using our proposed approach (RRM is not considered in this case) for different values of the amount of generated RE, storage size and SG patterns (Patterns 1,3 and 5 are presented). The normalized net energy cost (NNEC) is calculated following: $NNEC = \frac{C}{C_{ref}}$, where C is the net operational cost calculated in VI-E and C_{ref} is the energy cost calculated assuming that the BS relies only on on-grid energy, without applying our proposed approach; $C_{ref} = E_{BS} * Price$ where E_{BS} is the BS energy demand without applying RRM and $Price$ is the unitary price of on-grid energy.

From Figure 9, we see that the effect of RE variations and storage size is different in each pattern. For example, the impact of increasing the RE generation or storage size is obvious in pattern 1, where this increase leads to relatively high reduction in terms of the energy net cost. On the contrary, increasing RE generation or/and storage size is almost negligible in pattern 5. Indeed, pattern 5 is dominated by Up requests, which means that the BS should increase its consumption, and thus the BS should store energy from the grid. Nevertheless, the proposed energy policy succeeds to significantly reduce the energy operation cost even with small amount of RE for all the patterns. When RE is available ($RE \neq 0$), the range of energy cost reduction is between 61.1% (pattern 5, RE=22%, 2000 Wh storage) and 198.88% (pattern 1, RE=66%, 6000 Wh storage). In the latter case, the SG pays for the cellular operator approximately the same value that is usually paid by the operator to run the BS. It should be noted that negative net cost is achieved when the gain due to providing ancillary services exceeds the cost of grid energy.

Regarding the cost saving, the impact of the battery size is limited when no RE is locally produced and only in some cases higher cost saving can be achieved with larger battery size, depending on the sequence of SG requests. When a local RE generator is present, a larger battery size allows to obtain an additional, still limited, reduction in cost. Nevertheless, under some patterns of SG requests, increasing the battery size makes no difference at all in terms of cost saving (pattern 5). A more relevant role to this extent is played by the PV panel size. In general, the storage of a renewable powered BS should not be too small with respect to the BS energy demand, in order to guarantee sufficient energy supply when RE is not produced and the SG asks for a decrease in the consumption from the grid. Furthermore, the storage should be large enough to harvest the extra amounts of energy drawn from the grid to accomplish the SG requests of type Up.

1) Performance under Radio Resource Management: We study the effectiveness of the proposed approach in utilizing local RE generation and using radio resource management for reducing the operational costs and replying to the SG requests. Figure 10 shows the average net cost that is obtained by averaging the results obtained in the patterns and taking into account the probability of each pattern. The results are shown for the cases with and without RRM. When RE sources are not available (RE=0), the network operator can achieve some reduction in the cost using the storage only. Significant reduction in net cost is achieved when using RRM up to 42 percentage points (storage size 2000 Wh). Increasing the storage size will increase the reduction until some limit where no further reduction is achieved. In case of available RE, increasing the RE generation and the storage size can lead to important gain in cost, where negative energy cost can be achieved. These results also show that the benefits in terms of average cost reduction obtained under RE generation when a larger battery is installed are more evident during the actual system operation, with respect to the case of Figure 9. In that case, the focus was on cost saving achieved for single daytypes, each featuring a given pattern of SG requests. Under some patterns, it might seem not convenient to increase the battery capacity to very high levels, since the benefits that could be obtained would be limited. Hence, in order obtain further cost reduction, increasing the PV panel size would result more effective. Conversely, in this case the battery capacity has a more relevant impact on cost reduction, likely due to the combination of different patterns of SG requests occurring with different probabilities during the actual system operation.

In addition, RRM can further decreases the net cost. It can be easily noticed that the effect of RRM algorithm decreases with the increase of RE generation and storage size, where the base station can rely more on RE to reply the SG requests. Finally, it should be noted that there is a certain limit that can be achieved even with the increase

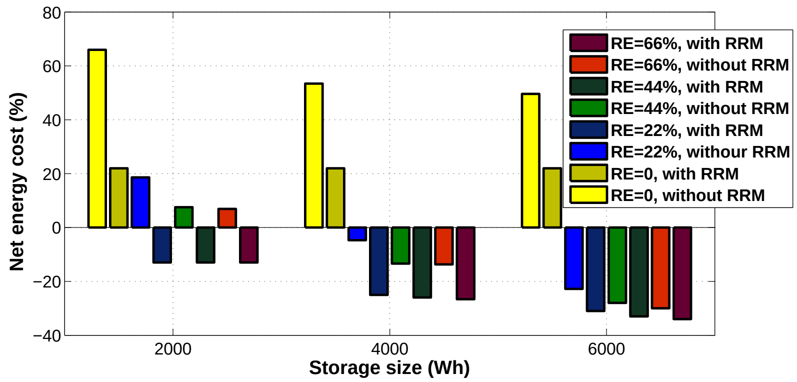


Fig. 10. Average energy operation net cost for different RE average generation and storage sizes.

TABLE VI
PARAMETERS' VALUES AND ASSUMPTIONS.

Parameters	Values and assumptions
Number of sectors in a BS	3
Carrier frequency	$2GHz$
Bandwidth	10 MHz, FDD
Cell radius	500 m
User distribution	Uniform
Maximum number of users	27
Number of resource blocks	50
Resource block bandwidth	180kHz
Path loss	Cost 231 extended Hata model
G_T	15 dBi
G_R	0
Schedulers	Round Robin
Noise figure	9 dB
BS power model	EARTH [34]

of RE generation and the storage. This result can help mobile operators in choosing the size of their RE sources and energy storage and to avoid over-sizing and paying unnecessary capital investment.

2) Comparison with other policies: In order to validate the model, we simulate the performance of a BS considering SG requests for 365 consecutive days provided by [40]. The data used for simulations is not the same used for deriving the proper threshold configuration of each pattern. The simulated scenario considers a BS and uniformly distributed users with different QoS demand. Table VI summarizes the parameters used in the simulations. Traffic intensity variates based on [45] with a maximum of 27 users, where the users are divided equally into HQ, SQ and BE users. The user's QoS is evaluated based on calculating the utility function in terms of achieved bit rate and user's demand as illustrated in Section III-B.

We consider that the BS is equipped with solar panels and a 6 kWh energy storage. We assume that, based on weather predictions, the BS knows the SG request pattern for the next day, and uses the proper threshold settings for that pattern, storage size and RE generation. For the night, we consider the threshold configuration allowing to minimize cost for the case of RE=0.

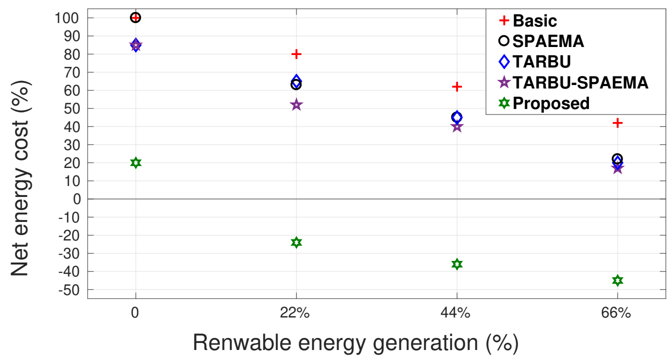


Fig. 11. Net energy cost for simulated algorithms with respect to RE generation.

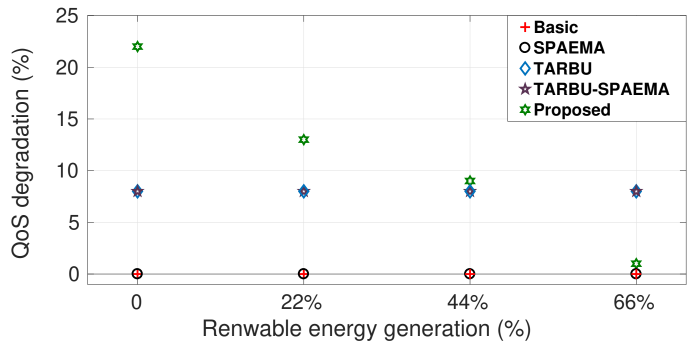


Fig. 12. Quality of service (QoS) degradation for simulated algorithms with respect to RE generation.

We compare the results of the proposed scheme with four other algorithms: Basic greedy, SPAEMA [46], traffic-aware resource block utilization (TARBU) [47] and TARBU combined with SPAEMA. Basic algorithm uses RE when it is available, stores excess generated energy, and uses the stored energy in case of unavailable RE. In contrast to the approach considered in this paper, where the aim is to provide the grid with ancillary services, SPAEMA is designed for deciding the usage of RE based on dynamic tariff of grid energy (real-time price of grid energy) [46]. TARBU determines the number of active resource blocks based on the intensity of the traffic, where RE usage follows basic algorithm. TARBU-SPAEMA utilizes RE based on grid energy price and storage state while activating and deactivating resource blocks based on traffic intensity.

Figure 11 presents the net energy cost normalized to the reference cost, which is the energy cost of the BS when consuming only grid energy without using any energy efficiency technique. One of the advantages of the proposed approach is that it allows to reduce the cost even without the deployment of RE sources, where operators can exploit on-site energy storage and RRM algorithms. However, this comes with a relatively high degradation of QoS (22%) as illustrated in Figure 12. From Figure 11, we see that the proposed approach overcomes other approaches in term of energy cost. Unlike the other approaches, which only reduce the on-on-grid energy cost, the proposed approach leads to negative energy cost, i.e. the SG pays to the operator. Basic approach has the worst performance in terms of cost reduction. SPAEMA and TARBU have almost the same energy cost for different RE generation, but TARBU leads to a small QoS degradation. When using TARBU-SPAEMA, the cost reduction is further increase preserving the same QoS degradation.

Considering the proposed approach, the cost reduction increases with RE generation. Moreover, the QoS degradation decreases with RE generation, where more RE means lower probability of low storage and thus radio resource management algorithm is hardly used. When RE generation is 66%, the proposed approach achieves -46% net energy cost with negligible degradation in QoS, and this emphasizes the efficiency of this approach when RE sources and storage size are well chosen.

VIII. Conclusion

With the growing of cellular communication industry, network operators are challenged to decrease their Carbon footprint as well as their energy costs to sustain environmental and profitable business. Thus, cellular operators are deploying on-site RE sources and managing their energy resources. At the same time, energy distributors are deploying Smart Grid environments in which energy generation and consumption are jointly considered, and consumers can become active in optimizing the energy usage.

In this paper, we propose a novel energy model for cellular networks in SG and RE environments, in which BSs use the harvested energy and energy storage and adjust their radio resources to provide the SG with ancillary services. We provide a Markovian characterization of the BS based on the analysis of historical meteorological data and real data of an SG operator. We also propose a simple energy management policy for BSs equipped with RE sources and energy storage to answer the SG requests. Moreover, radio resource management is used to reply to the SG request when RE and the storage are not sufficient. From the solution of the Markovian model, we can choose the parameters of the energy management policy in order to minimize cost. Results show that the proposed approach can achieve *negative* operational cost up to 98.88% of the initial electric bill, and support the grid by providing ancillary services. Finally, we test our approach by simulating a BS using the energy policy with proper threshold configurations for 365 consecutive days. Results confirm the effectiveness of the proposed approach where up to -46% net energy cost is achieved with negligible degradation of quality of service.

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