Dimensioning Renewable Energy Systems to Power Mobile Networks

Original
Dimensioning Renewable Energy Systems to Power Mobile Networks / Renga, D.; Meo, M.. - In: IEEE TRANSACTIONS ON GREEN COMMUNICATIONS AND NETWORKING. - ISSN 2473-2400. - 3:2(2019), pp. 366-380. [10.1109/TGCN.2019.2892200]

Availability:
This version is available at: 11583/2853823 since: 2021-01-21T10:49:42Z

Publisher:
Institute of Electrical and Electronics Engineers Inc.

Published
DOI:10.1109/TGCN.2019.2892200

Dimensioning renewable energy systems to power Mobile Networks

Daniela Renga, *Member, IEEE,* and Michela Meo, *Member, IEEE*

***Abstract*—To face the huge increase in the mobile traffic demand, denser cellular access networks are extensively deployed by Mobile Operators, entailing high cost for energy supply. Hence, Renewable Energy (RE) sources are often adopted to power base stations (BSs), in order to make them more self-sufficient and reduce the energy bill. Nevertheless, sizing a RE generation system is a critical task, and the dimensioning methods available in the literature are based on simulation or optimization approaches, hence resulting time consuming or computationally complex. This paper proposes and validates a simple still effective analytical method that, based on the location dependent mean value and variance of RE production, allows to find feasible combinations of photovoltaic (PV) panel and battery sizes, suitable to power a BS and decrease the storage depletion probability below a target threshold. Furthermore, the application of this method highlights the role of RE production variance. Higher values of the variance require larger PV panels, almost doubled with respect to locations with low variance. However, only locations with higher variance benefit from increasing the battery size and relaxing the constraint on energy self-sufficiency, with the scope of reducing the required PV panel capacity and the capital expenditures.**

NOWADAYS, Mobile Network Operators are enforced to deploy denser mobile access networks, due to the staggering increase of the mobile traffic observed in the recent years, and that is bound to further grow at remarkable pace in the next future. According to 2017 Cisco forecast [1], by 2021 there will be nearly 4.6 billion Internet users worldwide, accounting for almost 60% of the global population, 27 billion of networked devices and connections are expected by the same year, with up to 13 connected devices per capita in North America and Western Europe. By 2021 smartphone traffic will exceed PC traffic, showing a seven-fold increase in the period 2016-2021, with mobile data traffic growing twice as fast as fixed IP traffic This substantial raise in the cellular traffic entails the need to deploy properly dimensioned cellular networks, allowing to make Internet access available everywhere and providing the high bandwidth capacity required for the increasing number of mobile users and for the introduction of applications that result more and more demanding in terms of bandwidth requirements. More than 4 billion base station installations could be counted worldwide back in 2012, and this number is bound to remarkably increase due to the aforementioned reasons [2]. Considering that the access segment is responsible of up to 80% of the total network consumption, it appears evident how the energy demand to operate cellular networks is rapidly growing and Mobile Operators are facing huge operational costs due to power supply [3]. Hence, several research efforts are devoted to the deployment of effective solutions to make mobile networks more energy efficient, with the twofold objective of reducing costs and improving sustainability. The integration of renewable energy (RE) sources in mobile networks to power Base Stations (BSs) is becoming an attractive solution to reduce the Mobile Operator energy bill and, also, a promising approach to make them more independent from the electric grid. The installation of a local generator to produce solar energy for the cellular network operation is a solution widely deployed in real implementations. Indeed, according to estimates from [4], almost 43,000 solar powered BSs could be counted worldwide in 2014, and more than 390,000 renewable powered BSs are expected to be newly installed in the period 2012-2020, at a rate that will grow up to 84,000 per year in 2020, 6 times higher with respect to 2012 [2]. This approach is typically adopted in some remote regions or emerging countries in order to guarantee the mobile service continuity, with the main driver being the provisioning of energy supply where the traditional power grid is unreliable, due for instance to frequent power outages, or it is not available at all. Furthermore, this solution may provide economical benefits in some rural areas where the connection of the BSs to the electric grid may result more expensive than the installation of a local RE generator.

A relevant issue to be tackled in case of solar energy powering is represented by the intermittent nature of the renewable energy generation, leading to erratic and rather unpredictable production patterns. Hence, some kind of storage must be envisioned in order to harvest any extra amount of renewable energy that is not immediately used, and to make it available for future usage when no renewable energy is currently produced. This may lead to higher initial investment for providing the required infrastructure, i.e., photovoltaic (PV) panels and a storage system to harvest extra amounts of produced renewable energy. Nonetheless, the capital expenditure (CAPEX) can actually be compensated on the medium term by lower operational expenditure (OPEX), thanks to the decrease in the amount of energy bought from the grid [5]. The increasing relevance of renewable energy sources in mobile communication networks motivated several research groups to investigate the topic, focusing on the potentiality of RE as power supply in a setup

D. Renga and M. Meo are with the Dipartimento di Elettronica e Telecomunicazioni, Politecnico di Torino, Turin, Italy e-mail: {name.lastname}@polito.it.

Manuscript received ?? ??, ????.

where the [6]–[9]. However, one of the most critical tasks to cope with when designing a green mobile network is the dimensioning of the PV panels and the storage, a process that entails a trading off between energy self-sufficiency, service continuity and feasibility constraints. The process of dimensioning a RE generation system suitable for mobile networks is not deeply investigated in the literature, and the available methods for sizing a RE system are based either on simulation or optimization approaches. This study aims at providing an analytical tool to dimension the RE generation system, balancing between the need for satisfying the network energy demand and the target degree of network independence from the power grid. The advantage of the analytical tool with respect to the other approaches is that it allows us to study the relationship among the fundamental parameters of the system and it facilitates, by being extremely fast to compute, the derivation of feasibility regions that relate these parameters. The main contributions of our work are the following:

- Further validation of the stochastic model of the RE production proposed in our previous paper [10], which is based on a random variable, characterized by a mean value and a variance, that represents the daily RE production. The model is validated by considering various additional types of probability distributions of the daily RE generation (Gamma, Beta and Weibull distribution), besides the Normal and Uniform distribution. Results are compared with respect to those obtained under the empirical distribution of RE production, as derived from real profiles of solar energy production in the city of Turin.
- Design of a 3-state Markovian model to represent the level of battery charge at the beginning of the day in a scenario where a BS is powered by PV panels and by the grid, and where some energy storage is envisioned to harvest extra amounts of energy that are not immediately used. This model basically aims at evaluating the probability of battery depletion.
- Based on the proposed 3-state Markovian model, derivation of an easy-to-use analytical formula to dimension the RE power supply system. Given a location with a specific mean value and variance of the daily RE production, and given a target value of the maximum battery depletion probability, this formula allows to define feasibility regions that include all the possible combinations of PV panel and battery capacity that respect the desired constraint on the BS self-sufficiency.

The proposed tool keeps into account the local pattern of the RE generation at the specific latitude and the impact that the variability of the solar energy production may have in the system sizing. Finally, some considerations about investment costs and feasibility issues are introduced to refine the application of this method in order to find the proper system dimensioning capable to balance the desired performance targets and the feasibility and cost constraints. The rest of the paper is organized as follows. Sec. I presents the related work and highlights the contribution of our work. Sec. II describes the scenario of the green mobile access network considered in this work, while Sec. III details how the RE generation has been modeled. The Markovian model deployed to investigate the operation of the renewable powered mobile network is introduced in Sec. IV and validated in Sec. V. The analytical formula derived from this model to dimension the RE generation system is presented in Sec. VI, whereas Sec. VII investigates the feasibility regions for system dimensioning, based on the application of the proposed formula. Sec. VIII provides some considerations about cost and feasibility issues related to the system sizing process. Finally, Sec. IX concludes the paper.

I. Related work

The dimensioning of a renewable energy system to power mobile networks is a challenging process, since several factors should be taken into account and traded off in order to achieve a proper sizing. The identification of adequate capacity values for the photovoltaic panels and for the storage must deal with the renewable energy production intermittence, the traffic variability, the desired level of self-sufficiency with respect to the traditional power grid, the physical feasibility constraints, while satisfying the need to guarantee a continuous service availability.

A. Characterizing the renewable energy generation

A proper RE system dimensioning strictly relies upon an adequate characterization of RE production. The profiles of solar energy production from PV panels show huge variability not only over seasons, but even from day to day and within the same day, also depending on the location and the varying weather conditions. Various approaches can be found in the literature to represent the solar energy generation. Some of them are simulation models based on data-sets of the real solar radiation in a given location, that are exploited to perform simulation studies allowing to dimension a RE generation system based on the energy demand either of a single BS [11]–[13] or of a portion of a mobile access network [5]. However, the simulation approach is typically time consuming, and it necessarily requires the availability of huge data-sets to accurately represent the solar energy production. Stochastic models typically are more efficient than simulation based methods, although they may result in a high computational complexity. The solar energy production profile from PV panels is sometimes modeled by using Markov chains. In [14] a two-state Markov model is proposed to determine the proper storage size of a photovoltaic system allowing to reduce the number of insufficient supply days to an acceptable level. Authors in [15] design a Markov model for the solar radiation and deploy various techniques to define the best sizing of the storage. Some models take into account finer time scale variations of RE production within the day. The analytical model for solar power shaping proposed in [16] characterizes both the short-term (of the order of few minutes) and long-term (of the order of minutes-hours) scale variations in daily solar power, besides the diurnal variations due to the succession of the daylight period and the nighttime. Authors in [17] build a theoretical framework based on stochastic power network calculus for analyzing the performance of power networks with RE generators and storage. Explicit formulas are derived to compute performance metrics for investigating the power system reliability and for the dimensioning process. Nevertheless, these approaches do not provide tools of easy application for dimensioning a RE generation system based on the network energy demand, due to the high computational complexity that may be entailed by similar models, also in view of the fine granularity of the considered time scales. In this work we propose a simple stochastic model for characterizing the daily RE production, aiming at trading off accuracy and complexity when dimensioning a RE system to power mobile base stations in a given location.

B. Renewable energy system dimensioning in mobile networks

Various studies in the literature investigate algorithms aiming at efficiently managing the locally produced renewable energy and at properly exploiting the energy storage or the application of Resource on Demand techniques, in order to make the green mobile network more independent from the electric grid and to improve the capability of facing possible power outages, sometimes providing cost analysis [5], [18]–[23].

In some paper studying the application of energy management strategies in green mobile networks connected to the Smart Grid, performance evaluations are conducted under variable combinations of PV panels and battery sizing [24]. Authors in [25] propose a stochastic model to represent the photovoltaic energy produced to power BSs. The model is applied considering different locations and solar panel sizes. In [26] a green mobile network is powered by locally produced RE, that can be shared among the BSs. The paper proposes a method to jointly optimize the BS operation and the power distribution, in order to minimize the network on-grid power consumption. Nevertheless, only few studies explicitly focus on the system dimensioning issue and thoroughly evaluate the impact of variable system sizing on the renewable powered network performance, in order to derive a proper system dimensioning [5], [12], [13], [27]–[32]. Authors in [27] aim at achieving a feasible system dimensioning by proposing an algorithm to dynamically adapt the mobile service of a renewable powered base station, based on the current energy available at the storage, the weather forecast and the historical pattern of base station consumption. [12] and [28] analyze, via simulation, the problem of properly sizing a PV generator and the energy storage in order to provide adequate power supply for a single BS, providing cost analysis and battery lifetime evaluation. Authors in [13] deploy a model to derive the optimal combination of PV panel and storage size for powering a BS, subject to the predefined constraint on the worst month outage probability. [29] adopts a multi-state Markov model representing the hourly harvested solar energy to find the optimal system dimension allowing to minimize cost, given the limit on the maximum allowed battery depletion probability at a solar powered BS. The analytic model proposed in [30] is applied to evaluate the outage probability of a renewable powered BS, and a discrete time Markov process is adopted to represent the battery charge level. In [31] a green energy provisioning method is proposed, in order to address the system sizing issue when deploying a green energy system to power base stations. The presented solution applies a traffic load balancing algorithm with the aim of minimizing the CAPEX, still satisfying the constraints on the Quality of Service. In [5] a renewable powered mobile network is studied via simulation under different combinations of PV panel and system sizes, with possible application of Resource on Demand (RoD) strategies, and trading off the battery depletion probability, the feasibility constraints and the capital expenditures. [32] investigates the introduction of RoD and WiFi offloading techniques to improve the interaction of a green mobile network with the Smart Grid, in a Demand Response context. The impact of the system dimensioning on the capability of responding to the Smart Grid requests of increasing or decreasing the energy consumption is evaluated via simulation. [33] proposes a methodology for sizing the capacity of a RE generator system to power stand-alone base stations. Unlike most studies that usually base the prediction of RE production on the irradiation data observed during the Typical Meteorological Year (TMY), [33] employs series-of-worst-months (SWM) meteorological data, making the technique more accurate in obtaining a proper dimensioning.

The papers available in the literature typically address the dimensioning issue proposing simulation or optimization methods. However, the process of dimensioning a renewable generation system to power BSs by means of simulations or optimization models may be computationally complex and require long computational time. The study presented in our paper rather aims at providing a simple analytical method for properly sizing a renewable system in a green mobile network, based on the local RE production profile. To the best of our knowledge, this is the first work proposing an analytical formula allowing to determine the capacity of PV panels and batteries required to power BSs in a given location, in order to guarantee the satisfaction of a given constraint on the maximum allowed storage depletion probability.

II. The renewable powered mobile network

As depicted in Fig. 1, the scenario analyzed in this study consists of a single LTE BS that is powered by locally produced RE and by the electric grid. In order to tackle the typical intermittent nature and unpredictable pattern of RE generation, the BS is equipped with a storage system in which any extra amount of RE that is currently produced but not immediately used for the BS operation is stored. The previously stored RE can be drained from the battery to power the BSs in those periods in which the RE cannot be generated or its production level is not enough to fully satisfy the network need. A constant power demand of 1 kW is assumed, given the limited variability observed with traffic load [34]. The energy management

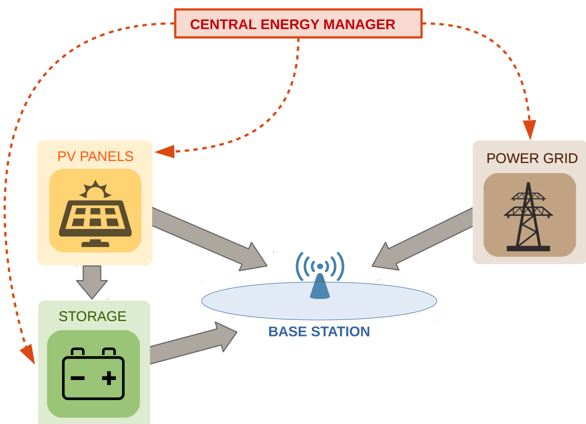


Fig. 1: Scenario where a base station is powered by renewable energy and the traditional power grid.

strategy works as follows. The energy required for normal network operation is first satisfied by the current production of RE. As an alternative, if the current generation is not sufficient or no RE is being produced at all at the moment, the required energy is drawn from the storage system, as long as it is not discharged. Finally, if neither of these options is viable or a residual need still remains to be satisfied, the amount of required energy is supplied by the electric grid.

The purpose of this strategy is to improve the independence of the mobile network from the power grid, hence reducing the operational cost. Whereas a full energy self-sufficiency is hard to be achieved without a very huge initial investment for the RE generator system and the storage, a rather slight relaxation on the network energy independence constraint allows to attain feasible system dimensions [5]. To achieve this objective, a proper system dimensioning should be performed and this, in its turn, should be obtained keeping into account the location dependent RE production level and its variability over time.

III. Modeling the RE generation

The variability of RE production entails considerable issues in terms of system dimensioning: due to the intermittent provisioning of RE, the PV panel should be over-sized with respect to the average network power need, in order to feature sufficient capacity to guarantee high RE production level, hence satisfying the current operation need, and producing extra amounts of RE large enough to accomplish future power demand during period of null production. In addition, also the storage capacity should be properly sized to harvest extra amounts of energy required for operating the network. The approaches currently available in the literature do not provide easy-to-use tools to properly dimension a RE generation system capable to satisfy the mobile network energy demand. This work proposes a simple stochastic model for characterizing the daily RE production, that is represented by a random variable, as often observed in the literature [20], [35]–[37]. According to the model proposed in our study, it is sufficient to know the average value of daily solar energy production registered in the considered location along with its variance to characterize the local RE production. Based on this pair of parameters, it is then possible to dimension the RE generation system so as to respect predefined constraints on the target level of the BS self-sustainability and on the system feasibility, as it will be detailed in Sec. IV. Hereafter, the PV system powering the BSs is first described, whereas the stochastic model adopted to model the RE generation is detailed afterwards.

A. The PV system

In this work we assume that a single BS is equipped with a set of PV panels, made up by multiple modules, that enable the sun radiation conversion into electricity, with an efficiency that depends on the technology adopted. The efficiency of currently available commercial modules, built with traditional technologies (crystalline silicon), typically ranges between 15-20%. Emerging technologies, like Concentrating Photovoltaics (CPV), allow to more than double these values (up to 38.9% in laboratory tests), but they are not yet available for commercial products [38]–[40]. The nominal capacity of a PV module is the maximum DC output power obtained by the PV device under standardized environmental conditions, including a light intensity of 1000 W/m^2 and a temperature of 25 °C, and it is measured in peak Watt [Wp]. The nominal capacity is commonly used to express the size of the PV panel, hence of the PV modules composing it, regardless the adopted PV technology.

The feasibility of the PV system should be kept into account when implementing a RE powered system, both in terms of required deployment area and in terms of cost. Considering some among the most efficient PV modules currently available on the market and built with crystalline silicon technologies, an efficiency as high as 20% [38] can be assumed and an area of 1.63 m^2 is observed for PV modules with a nominal capacity of 0.333 kWp [12]. This results in a PV panel surface of about 4.9 m^2 per each kWp of PV panel capacity. In relation to cost, the capital expenditures (CAPEX) amount to 750 €/kWp, with a typical lifetime duration of about 25 years [5], [12].

B. The RE production model

In this study the daily production of RE in a given location is considered. The profiles of RE generation are derived from real location based data, obtained from the tool PVWatts [41]. These profiles take into account the intra-day variability of renewable energy production due to the daily variations of solar radiation, the temperature variations, the presence of clouds, and the settings of both Tilt and Azimuth angles. In our case, a Tilt angle of 20 °and an Azimuth angle of 180 °were assumed. The RE production profiles considered in this work refer to the city of Torino. In order to perform our study in the worst case conditions, the RE production during the cold months only (November, December and January) is modeled. Indeed, these months feature the lowest levels of average daily RE production, along with the shortest duration of daily RE generation, due to the typically shorter daylight length.

Based on the stochastic model proposed in our previous work [10], we denote as RE_d the random variable representing the amount of RE generated in a day assuming a PV panel with capacity 1 kW_p. RE_d is characterized by a mean value and a variance, which depend on the location, and features a uniform probability distribution. Of course, the actual total amount of energy that is produced per day during the daylight period, denoted as RE_D, depends on the actual PV panel capacity, denoted as S_{PV}. It can hence be derived as:

$$RE_D = RE_d \cdot S_{PV} \tag{1}$$

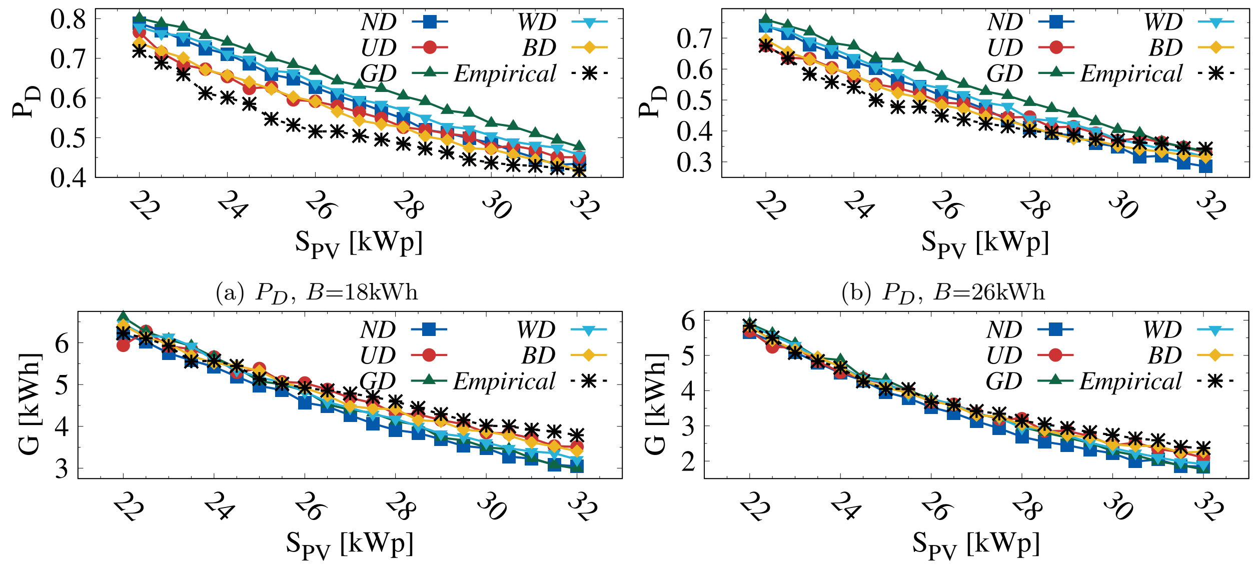
According to [10], the use of the uniform distribution to represent the RE_d can model the real system operation better than the normal distribution. In order to further validate the application of a uniform probability distribution to represent the random variable RE_d, additional types of probability distributions have been tested with respect to [10], where only the normal (ND) and uniform (UD) distributions were studied. The RE generation level is strictly dependent on the solar irradiance. In the literature, the solar irradiance is commonly modeled as a random variable, and different types of functions can be adopted to represent its probability distribution [35]–[37], [42], [43]. Besides Normal and Uniform distributions, other common distribution types adopted to characterize the solar irradiance are represented by the Weibull, Gamma, and Beta distribution [35]–[37]. Fewer studies are available modeling solar irradiance with Exponential, Geometric, Logistic, Lognormal and Loglogistic distributions [35], [37]. In our work, among the various distributions that are typically adopted in the literature to model the solar irradiance, the Gamma (GD), Beta (BD) and Weibull (WD) distributions have been selected to characterize the RE generation. The model performance obtained under these distributions has hence been compared against the Empirical distribution (ED), that is considered as a reference, and against the results derived in [10] under ND and UD. The ED of RE_d allows to test the system behavior in a realistic setting, since it is derived from real data of RE production in Torino in the worst-case 3-month period. For all the distribution types that have been tested, the same mean value (E[RE_d]) and variance (v_R) of RE_d obtained from the empirical data have been applied: E[RE_d]=1.005 kWh, v_R = 439.15^2 Wh^2, with coefficient of variation CV = 43.7%. The average probability of storage depletion, denoted as P_D, and the average amount of daily on-grid energy demand, denoted as G, have been analyzed. Fig. 2 reports the values of P_D and G under the various types of RE_d distribution, compared against the ED, for increasing PV panel sizes, S_{PV}, and two different battery capacities (18 kWh and 26 kWh), denoted as B. The results derived using a real location-based distribution of RE_d are consistent with results derived from the model using a more general RE_d distribution. In general, P_D and G tend to decrease as S_{PV} becomes larger. For PV panel capacity higher than 26 kW_p, ND, GD and WD tend to slightly underestimate the daily energy demand from the grid G with respect to ED, whereas the depletion probability P_D is overestimated under these distributions for any PV panel size. Under UD and BD, the estimation of P_D is very close to the real values for any PV panel size and the obtained values of G are mostly completely overlapping with those derived under ED. These results confirm that other types of distributions typically used to model the RE generation, like GD and WD, do not outperform the UD in modeling the operation of the RE powered Radio Access Network. Furthermore, the Beta distribution shows a behavior similar to the uniform distribution in predicting the real system performance. Hence, the selection of the UD is further confirmed as appropriate to model the daily RE production by these results. Moreover, although the system behavior under UD and BD is rather similar, the first distribution is preferred to the latter due to the lower computational complexity required during the analysis process.

IV. Markovian model for the storage

As previously mentioned, the BSs are equipped with a storage system to harvest the extra amount of unused RE for future usage. Markovian models are often adopted to analyze the operation of green mobile networks [24], [29], [30], [44]–[46]. Hence, based on the model of the location dependent RE production deployed in Sec. III, we design a 3-state Discrete Time Markov Chain model to represent the charge level of the battery that is employed to harvest the extra RE produced by a PV panel powering a base station. From this Markovian model, we thus derive a simple analytical formula from which, based on the mean value and variance of the RE generation and on the maximum allowed probability of battery depletion, the proper dimensioning of the capacity of the PV panel and the storage can easily be obtained. The storage system is now detailed and, afterwards, the Markovian model proposed in this work to characterize the mobile network storage system is presented.

A. Harvesting RE

The extra RE that is produced but not immediately used to power the BS can be harvested into a storage for future utilization. In our scenario, the storage consists of a set of lead-acid batteries, which represent a technology commonly adopted for harvesting purposes in RE systems



(a) P_D, B=18kWh

(b) P_D, B=26kWh

(c) G, B=18kWh

(d) G, B=26kWh

Fig. 2: Depletion probability (P_D) and grid demand (G) normal (ND), uniform (UD), Gamma (GD), Weibull (WD), Beta (BD) distribution of RE_d, compared against empirical distribution (ED), with B=18kWh and B=26kWh.

[47]. Each storage element features a voltage of 12 V with capacity 200 Ah. Although each storage unit can theoretically store an amount of energy as high as 2.4 kWh, the available battery capacity that can actually be exploited is lower. Indeed, a maximum Depth of Discharge (DOD) $\leq$50-70% should be assumed in order to assure a battery lifetime duration of up to 1000 cycles [48], [49], since values of DOD as high as 80% would halve the service time [50]. Irregular charging and discharging patterns, typically observed in renewable powered systems, also affect the battery efficiency, which results variable over time and highly dependent on the battery State of Charge (SOC) [51]. The best performance in terms of charge efficiency is obtained for SOC around 60%, whereas for SOC>80%, that may represent a typical operating regime in RE systems for batteries with DOD=50%, the efficiency decreases below 60% [52], [53]. Hence, although operating at high SOC level contributes to slow down the battery aging and the capacity loss processes [47], [54], the related drop in efficiency results in storage losses that may account for a significant energy waste, with a deep impact on the battery and PV panel dimensioning [53]. An overall average charge efficiency of 85% is commonly assumed for lead-acid batteries [53]. When considering also the discharging process, the total energy efficiency is estimated to be 75% [48], meaning that for each energy unit (1 kWh) drawn from the storage and actually available to power the BS, around 1.33 kWh of RE must have been produced.

In order to maximize the lifetime duration and optimize the battery energy output, a charge control system should be envisioned to take care of limiting the maximum DOD and avoiding other events that may damage the battery, like for example overcharge and over-discharge conditions [55]–[57]. Factors such as DOD and charge rate have an impact on battery charge efficiency [56], whereas battery age shows a limited effect on reducing the efficiency over time [58]. In our scenario the storage consists of N_B battery units, each with capacity 2.4 kWh. We denote with B the total capacity of the entire battery set. The actual available capacity, denoted as C_B, is derived as $C_B = B \cdot DOD$.

As the RE is produced, it is utilized to power the BS, assuming that the solar energy is first used to power the BS, whereas only the extra amounts of RE that are not immediately used for powering the BS are harvested into the storage afterwards, as long as there is still enough space. This behavior follows a principle that is similar to the *Harvest-Use-Store* (HUS) paradigm that is adopted in wireless networks [59], [60]. Following this principle, charging/discharging losses can be minimized with respect to the case in which the battery is first charged and then the energy is drawn from the storage to satisfy the BS demand. When no RE is currently being generated or if its production is not sufficient to satisfy the BS demand, energy can be drawn from the storage. Only in case the battery results empty, the energy required is taken from the power grid.

B. The 3-state Markovian model for the storage

We consider C_B as the actual capacity of the storage to be modeled. A 3-state Markov chain is defined, where each state, denoted as S, corresponds to a possible battery charge level that is observed at the beginning of the day, i.e. at the beginning of the daytime period, when RE starts being produced. The battery charge level is hence observed at the most critical time of the day, in terms of BS self-sufficiency, since during the night RE is not produced and the BS has drawn the needed energy from the battery, that might hence result depleted. The Markov chain model is represented in Fig. 3 and the 3 states are here defined:

- *state E (Empty)*: no energy is available in the battery and the storage charge is null ($E = 0 \quad kWh$).
- *state L (maximum Level at the beginning of the day)*: this state represents the maximum charge level that might be observed at the beginning of the day after a night of normal BS operation, assuming that, at the beginning of the previous night period (i.e. after the last hour of RE generation on the day before), the battery was at full charge (i.e. the battery charge was equal to C_B). Let us denote as D_n the BS energy demand during the night hours. Considering that during the night-time no RE is produced, L is defined as follows: $L = C_B - D_n \quad kWh$.
- *state M (Intermediate)*: the battery charge is at an intermediate level, defined as $M = \frac{L}{2} \quad kWh$.

The transition from current state S_i to state S_j occurs with a time step of 24 hour. To define how transition probabilities have been computed, let us denote by D_d the BS energy demand during the daytime, whereas D_n represents the nightly demand. Since the BS energy demand is very little load proportional, with rather high power consumption also in those periods during which the traffic is very low, BS consumption is assumed to be constant. The variable H denotes the amount of energy that can be harvested daily in the battery, in case the BS daily consumption is lower than the total RE produced:

$$H = RE_D - D_d - D_n \tag{2}$$

Finally, assuming that the current state S_i may be E, M or L, the transition probability from state S_i to state S_j, denoted as $p_{i,j}$, can be computed as follows:

1) *Case* $S_j = E$: $\quad p_{i,j} = pS_i + H \leq 0$
2) *Case* $S_j = I$: $\quad p_{i,j} = p0 < S_i + H \leq L$
3) *Case* $S_j = L$: $\quad p_{i,j} = pS_i + H \geq L$

In the computation of transition probabilities, charging and discharging losses are kept into account, and the constraint on the maximum charging/discharging rate has been respected.

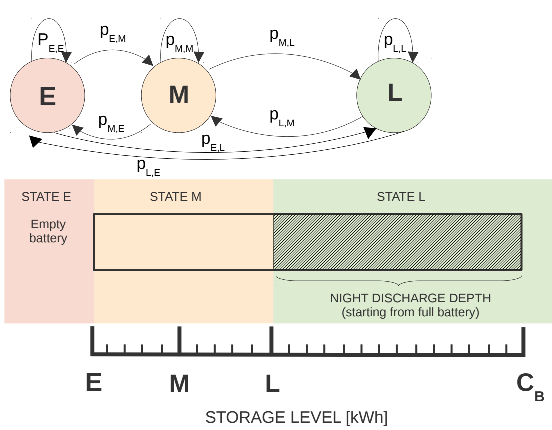


Fig. 3: Markovian 3-state model for the storage.

V. Storage model validation

The Markovian model proposed to analyze the RE generation for powering a mobile system has been validated by comparing the performance results obtained under the model against the results derived by investigating the same scenario via simulation. Furthermore, the model has been tested under different traffic profiles and BS power consumption configurations.

A. Comparing the model performance against simulation results

The simulations have been performed assuming the city of Turin as location for the renewable powered BS. A software tool deployed in our research group is used to simulate the charging level of the battery of a renewable powered BS at the beginning of each day. Simulations last for a period of three months. In the trace-driven simulation, the values of the daily RE production during the three coldest months of the Typical Meteorological Year are derived from the tool PVWatts, considering the city of Torino. In the model, the daily RE generation per kW$_p$, RE$_d$, has a uniform distribution, with mean value E[RE_d]=1.005 kWh, variance v_R = 439.15^2 Wh^2, and coefficient of variation CV = 43.7%, as derived from the empirical distribution of RE production in the same location. Since the system is analyzed during the coldest months, the average light-time duration is 9 hours, hence the daytime energy demand, D_d, corresponds to $9{\cdot}D_h$. RE_D represents the average daily renewable energy that can be obtained in a given location where a PV system of size S_{PV} is present. The local solar radiation determines the mean value of RE_d, i.e. the daily energy production per unitary PV panel capacity, whereas the PV system size S_{PV} is a factor that scales up the renewable power generation to its actual value RE_D.

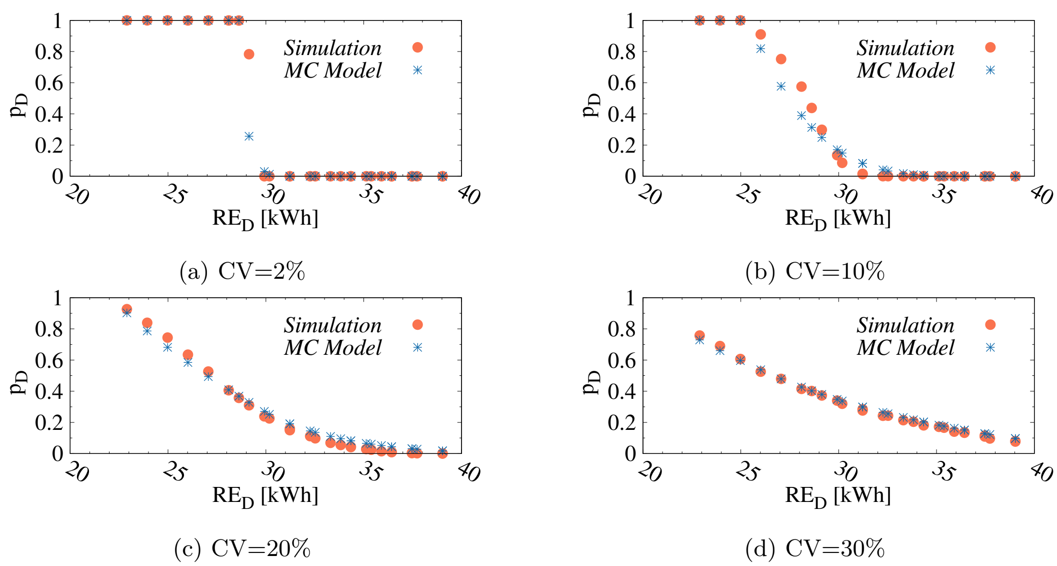
The BS power consumption is assumed to be constant, with an hourly energy demand, denoted as D_h, of 1 kWh. The model has been validated under several combinations of system sizing (S_{PV},C_B). At the initial conditions, the battery is assumed to be fully charged. Losses due to PV panel efficiency and environmental conditions are considered. Charging and discharging losses are kept into account as well. The main parameter settings of the simulation are summarized in Table I.

Let us denote as p_D the battery depletion probability at the beginning of the daytime. $p_{D_{Sim}}$ represents the value of p_D obtained by simulation, assuming a time step granularity of 24 hours. $p_{D_{Mod}}$ is the estimated value of $p_{D_{Sim}}$, predicted by the Markovian model, assuming the same time step granularity. $p_{D_{Mod}}$ actually corresponds to the steady state probability π_0 for the three-state Markov chain. Fig. 4 reports the values of $p_{D_{Sim}}$ and $p_{D_{Mod}}$ for increasing levels of average daily RE production and under different values of CV. A fixed value of C_B is assumed (26 kWh). The values of p_D obtained by simulation or under the model tend to decrease sharply for RE_D around 26-30 kWh in case of lower values of CV (2-10%). Conversely,

TABLE I: Simulation settings.

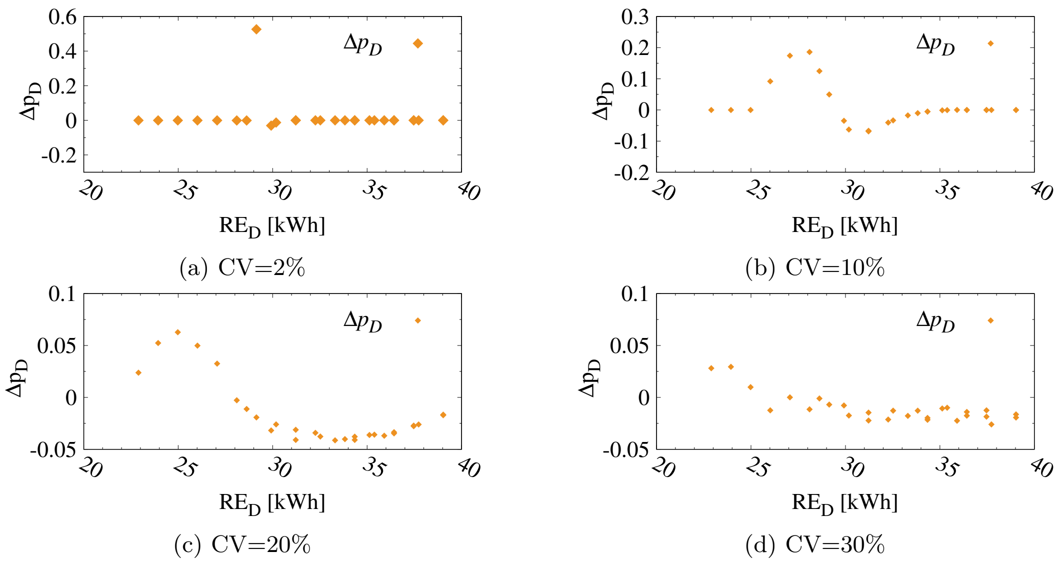
Location	Turin*
ERE_d	1.005 kWh
CV of RE_d	42.7%
RE_D range	23-29 kWh
B	18, 22, 26 kWh
D_h	1 kWh
Simulation period	3 months
Simulation time step	1 day

*The empirical distribution of the RE daily production is obtained based on real profiles derived from PVWatts, considering data of 3 months during the cold season and assuming a uniform probability distribution.



(a) CV=2%
(b) CV=10%
(c) CV=20%
(d) CV=30%

Fig. 4: Battery depletion probability, p_D, obtained via simulation and from the Markovian model.



(a) CV=2%
(b) CV=10%
(c) CV=20%
(d) CV=30%

Fig. 5: Difference between $p_{D_{Sim}}$ and $p_{D_{Mod}}$ (Δp_D) versus RE production level.

when the variance is higher, p_D is below 1 even for very low RE_D and it decreases gradually as the RE generation increases. The curve representing $p_{D_{Mod}}$ is almost overlapping with the pattern of the depletion probability derived from the simulation for any S_{PV}, given a fixed location or, alternatively, for any value of RE_d, given a fixed S_{PV}. Indeed, the difference between the depletion probability obtained from the simulation and its model predicted value, denoted as $\Delta p_D = |p_{D_{Sim}} - p_{D_{Mod}}|$, is always negligible and it is almost null under most sets of values of mean RE production and CV, as shown in Fig. 5. Higher differences between the simulated and predicted values of p_D can be found in the range of RE_D values that correspond to the window during which the switch between two operating regimes occurs: the regime of insufficient production and the regime of production sufficient for BS operation. The width of this window is larger as the CV becomes higher, but the maximum difference between simulated and predicted value is much lower than in case of smaller CV. Δ_{p_D} is often negligible, anyhow resulting $\leq$0.05 in almost all cases.

Fig. 6 shows the values of $p_{D_{Sim}}$ and $p_{D_{Mod}}$ for increasing values of RE_D, considering a location where the CV of RE_d is 20%. For small RE generation, there is a larger Δp_D in case of larger battery size, whereas a small battery allows to limit this difference. Nevertheless, Δp_D is always below 0.05 and, for $RE_D > 9\ kWh$, it is negligible. When RE_D is lower, the model results to be very accurate in predicting the simulated value of p_D, since the battery is so small with respect to the average RE generation level that it will result empty most of the time at the beginning of the day both in the simulation and under the model, with no significant effect on the average battery level due to RE generation variability. When the size of the battery is larger, the model results just slightly less accurate within the RE_D window of transition between the two regimes of operation, due to lower estimation accuracy registered when the daily RE production is smaller with respect to the daily BS demand.

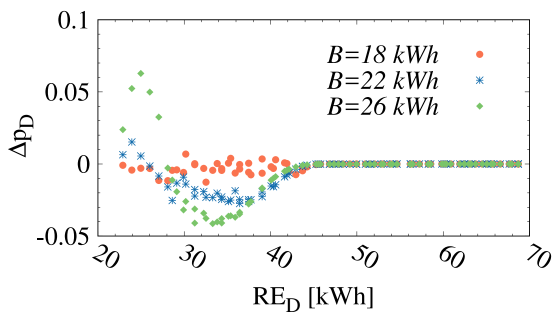


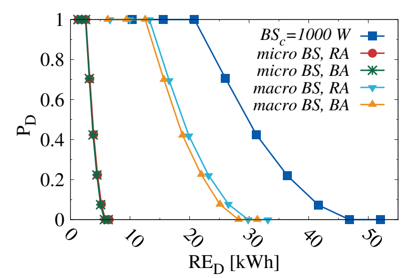
Fig. 6: Difference between $p_{D_{Sim}}$ and $p_{D_{Mod}}$ (Δp_D) under different values of battery capacity.

The model can be easily extended and applied to other locations featuring different RE generation profiles, by simply considering the corresponding mean value of RE_d and its variability. The value of CV is adopted instead of the variance, since it allows to immediately compare the variability degree of RE_d between different locations, regardless the actual mean value.

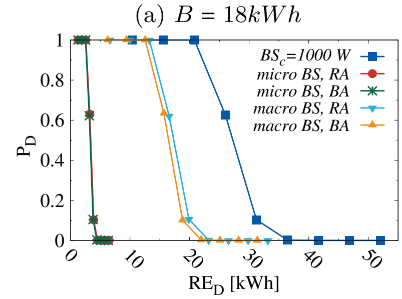
B. Testing different BS consumption and traffic profiles

In order to further validate the proposed model, we test additional scenarios considering the power consumption models of a micro and a macro BS, and two different mobile traffic profiles, from a residential area (RA) and a business area (BA). The computation of the consumption depends on some real traces provided by an Italian mobile operator, both in a business and in a residential area [5]. We consider a macro LTE BS with Radio Remote Head (RRH) technology, that consumes 840 W at full load, and a micro BS that consumes 145 W at full load.

Fig. 7 reports the depletion probability, P_D, for increasing values of daily RE production, for a micro and a macro BS, both in a RA and in a BA, compared against the case in which a constant power consumption of 1 kW is assumed for the BS. The battery capacity is either 18 kWh (Fig. 7a) or 30 kWh (Fig. 7b). The value of P_D decreases as the RE production increases, with a sharper descent for the micro BS. A larger battery allows to obtain a higher reduction of P_D for the same value of RE production. In the case of the macro BS, a higher RE production is required to reduce the value of P_D to the same extent. Furthermore, the curves representing the depletion probability in a RA and in a BA do not result overlapped like in the case of the micro BS. However, the difference is limited and it is due to the slightly different consumption patterns derived from the different traffic profiles.



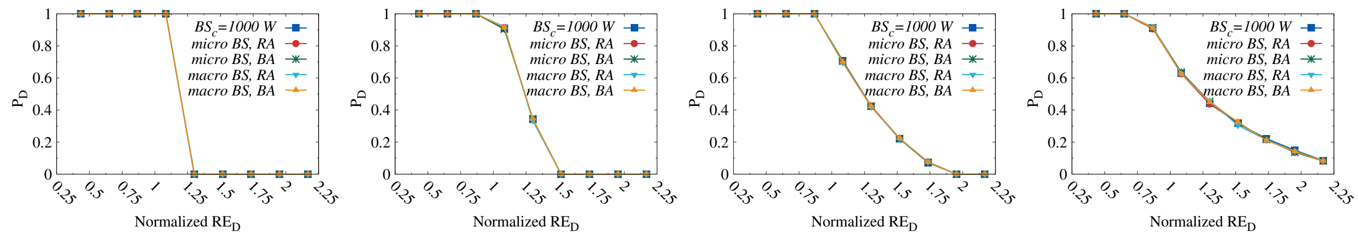
(a) $B = 18kWh$



(b) $B = 30kWh$

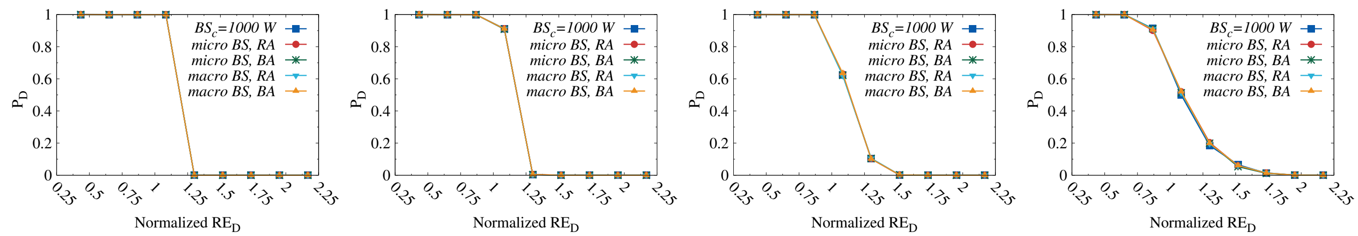
Fig. 7: Depletion probability for daily RE production in various scenarios, assuming CV=20% and a battery capacity of 18 kWh and 30 kWh.

Figs. 8-9 show the values of P_D under the same scenarios considered in Fig. 7, for increasing values of the daily RE production normalized with respect to the daily BS consumption (which is almost 3 kWh for the micro BS, about 15 kWh for the macro BS and 24 kWh for the baseline case). Various CV values are considered and the battery capacity is either 0.75 (Fig. 8) or 1.25 (Fig. 9) the daily BS consumption. As the CV increases, larger levels of daily RE production are required to achieve very low values of P_D. This is even more evident when the battery is smaller. Interestingly, in all the scenarios, the curves result overlapped. This means that, although the depletion probability is clearly affected by the CV of the daily RE production, it does not depend on the



(a) CV=2% (b) CV=10% (c) CV=20% (d) CV=30%

Fig. 8: Depletion probability for normalized daily RE production, assuming a battery capacity that is 0.75 the BS consumption.



(a) CV=2% (b) CV=10% (c) CV=20% (d) CV=30%

Fig. 9: Depletion probability for normalized daily RE production, assuming a battery capacity that is 1.25 the BS consumption.

traffic profile or on the considered BS consumption model, but rather on the ratio between the daily RE production or the battery capacity and the daily BS consumption. Hence, the proposed Markovian model can be easily generalized and applied to represent different scenarios both in terms of mobile traffic profiles and mobile technology adopted for the BS.

VI. Dimensioning of the RE generation-storage system

We now describe how the proposed Markovian model representing the energy storage level of a renewable powered BS can be applied to dimension the system. Furthermore, based on the 3-state Markovian model, an analytical formula is derived to provide a simple tool to properly dimension the total required RE system capacity, in terms of S_{PV} and C_B, based on the location and on the target level of energy self-sufficiency with respect to the electric grid.

A. Estimating depletion probability p_D

Given a location with specific average and variance of daily RE production RE_d, different combinations of system dimensioning pairs (S_{PV}, C_B) lead to different values of battery depletion probability, p_D. For a fixed combination of (S_{PV}, C_B), the expected value of storage depletion probability can be estimated by applying the Markovian model proposed, a fast method that provides reliable results, showing sufficient accuracy with respect to those derived via simulation. Fig. 10 reports the values of p_D obtained from the Markovian model, $p_{D_{Mod}}$,

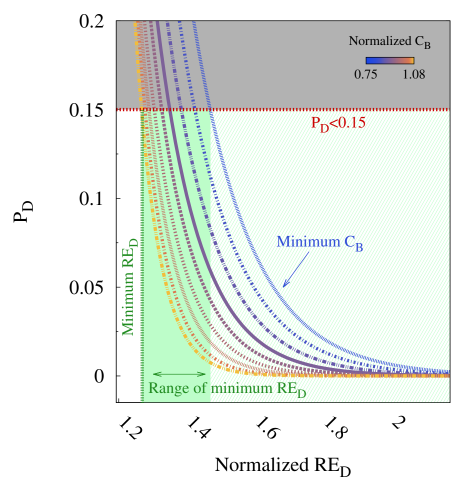


Fig. 10: Example of system dimensioning based on simulation, for CV = 16%.

for increasing values of daily RE production RE_D, in a location with CV of RE_d 16%. The average level of RE_D is normalized on the x axis with respect to the daily BS demand, $C_{BS} \cdot 24$, i.e. 24 kWh. Each curve in the plot represents a different size of the storage. Similarly to the RE production levels, the values of the battery capacity C_B are normalized with respect to the daily BS demand. The results can hence be easily extended to BSs showing a different power consumption, scaling them up by a factor corresponding to the daily BS consumption. The curves plotted in the graph are exponential functions obtained by interpolation of the points obtained from the model, with a coefficient of determination $R^2 \geq 0.95$ in all cases. The storage depletion probability sharply decreases as the RE_D grows larger, becoming null for high RE production. As the storage capacity becomes larger, the curves tends to shift left, meaning that smaller PV panels are sufficient to provide the same value of storage depletion probability. Let us assume a location with mean RE_d of about 2 kWh and CV=16%. To proper dimension the RE system for the considered location, we set the constraint on the maximum value of P_D as 0.15, that defines an upper-bound limit on p_D (red horizontal line in Fig. 10). According to this constraint, we can move on any battery curve, as long as we move on the curve portion below the upper limit of p_D. Furthermore, the battery size must be larger than the minimum battery capacity required to guarantee the energy supply needed during the night (i.e., Minimum C_B, blue curve in Fig. 10). Keeping into account the duration of the night-time (15 hours) and the charging losses, the battery should allow to store an amount of energy corresponding at least to 75% the daily BS consumption. In our scenario, a battery with capacity C_B=18 kWh must hence be selected. To respect the constraint on the maximum p_D, the minimum admitted value of RE_D depends on the selected storage size (the range of possible values is highlighted by the green vertical rectangle). Assuming C_B=26kWh (8% higher than the daily BS energy demand) in order to minimize the panel size, the normalized RE_D must be at least 1.27 fold the daily demand (green vertical line). This means that the PV panel size must be at least:

$$S_{PV} \geq \frac{1.27 \cdot C_{BS} \cdot 24}{ERE_d}$$

Assuming an average RE_d =2 kWh, for example, we need at least S_{PV}=15.24 kWp, corresponding to an area of about 76 m^2, which may result to be feasible in absence of strict physical constraints. Given fixed battery, we can further reduce p_D by using larger PV panels. If a smaller PV panel size is required due to feasibility and cost constraints, a larger C_B can be considered, in order to achieve a better trade-off between the storage size and the PV panel capacity. When feasibility issues force the use of rather small PV panels, slightly larger batteries allow to highly reduce the storage depletion probability. However, when larger PV panel capacities are adopted, increasing the battery size does not have a relevant impact on decreasing the p_D.

This method allows not only to derive the storage depletion probability for specific combinations of PV panel and storage sizes in a given location, but, most importantly, it theoretically allows to dimension the RE generation system in a specific location providing the average value of RE_d and its CV, in order to guarantee a target maximum depletion probability. Nevertheless, the method is time consuming due to the high number of combinations of pair (S_{PV},C_B) that must be tested in order to increase the accuracy and several interpolation operations that must be performed afterwards. Furthermore, this process must be repeated for any location showing a different variability of RE generation, or for evaluating the dimensioning that is required depending on the considered season. Hence, as it will be better described in the next subsection, this paper aims at deploying an analytical formula allowing to provide a proper system dimensioning to reduce the probability of storage depletion p_D below a target threshold, based on the RE production level (mean value and variance) in a given location. Finally, a slightly modified version of the same analytical formula can be easily adopted to define feasibility regions that take into account not only the battery depletion probability, but also other feasibility constraints, like those on the maximum area occupancy (for the PV panels) and the maximum capital expenditures based on the available budget.

B. Deriving an analytical formula for system sizing

An analytical formula is here proposed, based on the Markovian model, to dimension the RE generation system in order to obtain a value of the probability of storage depletion p_D lower than a target threshold. Given a location with mean value and CV of the RE generation and the constraint on the maximum p_D, this formula allows to easily identify a set of feasible combinations of values for the PV panel size and the storage capacity. Within this feasibility region of possible solutions, the decision of adopting a specific combination of values can then be taken based on additional parameters, like costs, for example, considering either the capital expenditures and the system operation.

Let us consider a generic location with mean value of renewable energy generation ERE_d and coefficient of variation CV, and denoting as p_D* the constraint set on the maximum allowed storage depletion probability. The PV panel size S_{PV} and the storage capacity C_B represents the unknown parameters whose (sets of) feasible values must be found to properly dimension the system. Based on the Markovian model, the relations between the transition probabilities and the steady state probabilities (denoted as π_i for each state i) can be expressed in a closed form from the transition matrix $\mathbf{P}$, where $p_{i,j}$ represents the transition probability from state $i \in \{0, M, L\}$ to state $j \in \{0, M, L\}$.

The relations between the parameters provided as inputs (i.e., mean value and CV of the RE generation, the constraint on the maximum depletion probability allowed p_D*) and the system size parameters, searched as output, can hence be derived as reported hereafter. Let us denote as $U_{RE_D}x$ the probability density function of the random variable RE_D having a uniform distribution, such that $U_{RE_D}x = U_{RE_d}x \cdot S_{PV}$. Remember that $U_{RE_d}x = \frac{1}{2\sigma\sqrt{3}}$ $for\ RE_{min} \leq x \leq RE_{max}$, where σ is the standard deviation of RE_d, whereas RE_{min} and RE_{max} are the extremes of the support of $U_{RE_d}x$.

$$\pi_0 = \pi_0 \cdot {}_{a_1}^{a_2} U_{RE_D}x + \pi_M \cdot {}_{b_1}^{b_2} U_{RE_D}x + \pi_L \cdot {}_{c_1}^{c_2} U_{RE_D}x \quad (3)$$

where:

$$
\begin{aligned}
&a_1 = b_1 = c_1 = RE_{min} \cdot S_{PV} \\
&a_2 = D_d + D_n \\
&b_2 = -\frac{M}{1-l_f} + D_d + D_n = -\frac{L}{2 \cdot 1 - l_f} + D_d + D_n \\
&c_2 = -\frac{L}{1-l_f} + D_d + D_n \\
&RE_{min} = ERE_d - 2\sigma\sqrt{3} = ERE_d \cdot 1 - 2\sqrt{3} \cdot CV \\
&L = C_B - D_n
\end{aligned}
$$

l_f denotes the *loss factor* due to energy losses occurring during the charging or discharging process, and corresponds to 15%, whereas RE_{min} represents the minimum possible value of daily RE production per 1 kWp PV panel capacity. ERE_d is the mean value of RE_d.

$$\pi_L = \pi_0 \cdot {}^{d_2}_{d1} U_{RE_D} x + \pi_M \cdot {}^{e_2}_{e_1} U_{RE_D} x + \pi_L \cdot {}^{f_2}_{f_1} U_{RE_D} x \quad (4)$$

where:

$$
\begin{aligned}
&d_1 = D_d + D_n + \frac{L}{1-l_f} \\
&e_1 = D_d + D_n + \frac{M}{1-l_f} = D_d + D_n + \frac{L}{2 \cdot 1 - l_f} \\
&f_1 = D_d + D_n \\
&d_2 = e_2 = f_2 = RE_{max} \cdot S_{PV} \\
&RE_{max} = ERE_d + 2\sigma\sqrt{3} = ERE_d \cdot 1 + 2\sqrt{3} \cdot CV
\end{aligned}
$$

RE_{max} represents the maximum possible value of daily RE production per 1 kWp PV panel capacity.

$$
\begin{aligned}
\pi_M = \pi_0 \cdot &\left[1 - {}^{a_2}_{a_1} U_{RE_D} x - {}^{d_2}_{d_1} U_{RE_D} x\right] \\
+\pi_M \cdot &\left[1 - {}^{b_2}_{b_1} U_{RE_D} x - {}^{e_2}_{e_1} U_{RE_D} x\right] \\
+\pi_L \cdot &\left[1 - {}^{c_2}_{c_1} U_{RE_D} x - {}^{f_2}_{f_1} U_{RE_D} x\right]
\end{aligned} \quad (5)
$$

Based on these algebraic relations, the PV panel size S_{PV} and the battery size C_B can be expressed by means of analytical formulas as functions of the mean value of RE_d, its CV and π_0. These formulas can then be used to dimension the system, deriving the set of feasible values of the unknown variables S_{PV} and C_B allowing to provide $\pi_0 \leq p_D*$, given the mean value and CV of RE_d in the considered location. No additional constraints are set on the values of π_M and π_L, except $\pi_0 + \pi_M + \pi_L = 1$. Note that the variable C_B represents the portion of the storage corresponding to the maximum DOD of the whole battery, B. The real size of the battery should therefore be derived by increasing C_B by a fraction such that $B = \frac{C_B}{DOD}$.

VII. Analytical tool application

The analytical formulas introduced in the previous section have been applied for dimensioning the system, in order to identify the feasibility regions for the PV panel and the storage sizes, based on the local RE production and the objective storage depletion probability. Furthermore, the impact of the RE generation variance on the system dimensioning has been investigated.

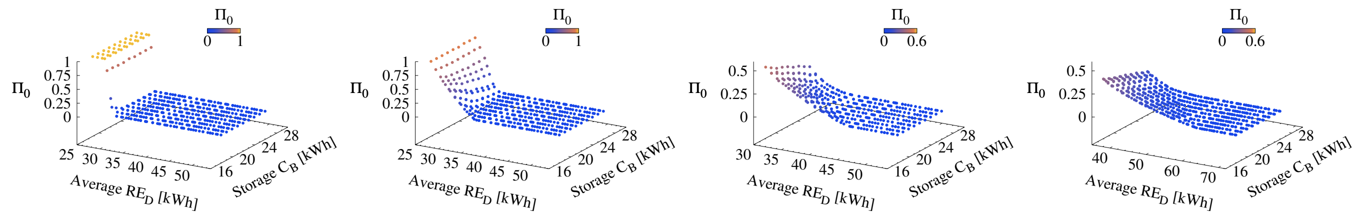
A. Feasibility regions for system dimensioning

The proper combinations of PV panel and battery sizes allowing to reduce the storage depletion probability below a target threshold can be identified by deriving the formulations of the steady state probabilities from the transition matrix M, that can be solved to find the values of S_{PV} and C_B, subject to the constraints:

$$
\begin{aligned}
&\pi_0 + \pi_M + \pi_L = 1 \\
&\pi_0 \leq p_D*
\end{aligned}
$$

Fig. 11 reports the values of the target battery depletion probability at the steady state, π_0, in relation to the combination of battery capacity and RE generation levels that, according to the Markovian model, allow to achieve the desired value of π_0, for different values of CV. In each plot, the first horizontal axis represent the average daily amount of produced RE, denoted as ERE_D; the latter horizontal axis corresponds to the storage capacity C_B; the vertical axis reports the value of the depletion probability at the steady state, π_0. In general, for any CV, π_0 tends to be higher for combinations with low values of C_B and S_{PV}, whereas for very large values of storage and PV panel capacity π_0 becomes null. However, the shape of the transition between these two extremes varies a lot depending on the variance of RE production. For locations where the RE production is rather constant over time (CV=2%), π_0 is equal to 1 if the PV panel and the storage are low, but it rapidly decrease by slightly increasing the size of both the PV panel and the storage. As the variance of the RE production increases, the maximum values of depletion probability becomes lower, up to less than 0.4 in case of CV=30% even with the smallest system size. Furthermore, the transition from size combinations providing high depletion probability to combinations assuring $\pi_0 = 0$ becomes more gradual as the variance in the RE production becomes larger. This means that in those locations where the variance, hence the CV, is low, small system sizes are sufficient to obtain a null depletion probability. However, even a slightly underdimensioned system may give raise to a steep increase of the depletion probability. For larger variances, small to intermediate system sizes are sufficient to obtain depletion probability values lower than 0.25, but larger system sizes are required for improving the system performance in terms of depletion probability, up to values below 0.05. When the CV is high, increasing the PV panel size alone is not sufficient to deeply decrease π_0 if the battery is very small, but combining a larger PV panel and a battery with higher capacity may highly decrease the battery depletion probability.

Let us consider a location where the average daily RE production per kWp, ERE_d, is equal to n kWh and CV=30% (Fig. 11c). Setting a target threshold p_D* for the depletion probability on the z axis, the feasible combinations of PV panel and storage sizes can easily been derived from the set of pairs ERE_D, C_B on the x and y axes, respectively, corresponding to values of $\pi_0 \leq p_D*$. Considering that $ERE_D = ERE_d \cdot S_{PV}$, the required PV panel size for the



(a) CV=2% (b) CV=10% (c) CV=20% (d) CV=30%

Fig. 11: Battery depletion probability at the steady state, π_0, for multiple combinations of RE generation levels and battery size, under increasing values of CV.

considered location is obtained as $S_{PV} = \frac{RE_D}{n}$. Finally, the total required capacity for the battery is derived as $B = \frac{C_B}{DOD}$.

B. Impact of RE generation variance

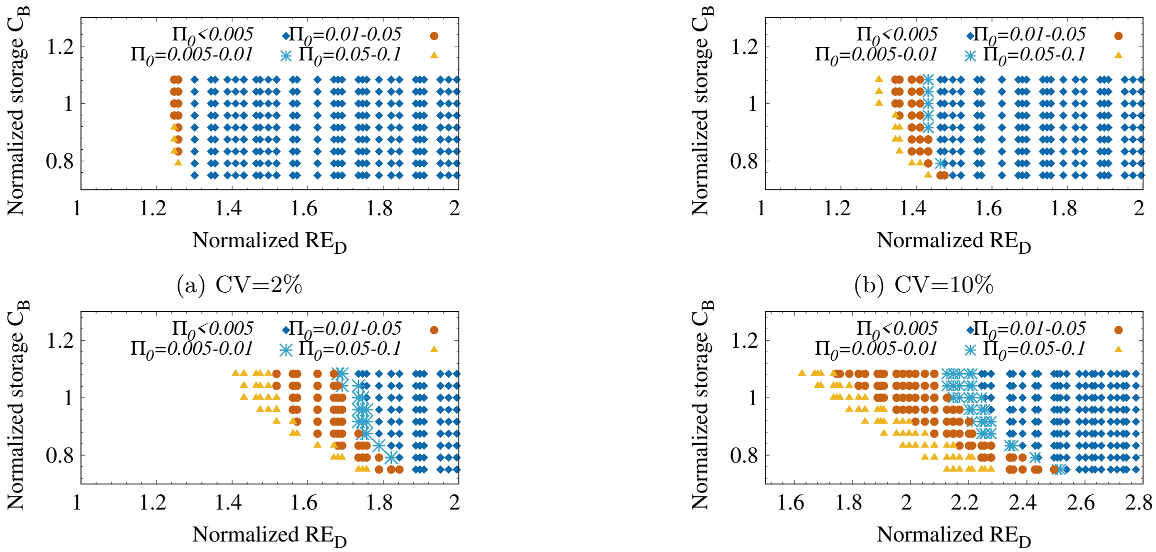
Fig. 12 shows the feasibility regions in terms of combinations of battery size C_B and average daily RE production RE_D for various values of CV, both normalized with respect to the average daily consumption of a macro BS, assumed to be 24 kWh. Since the average daily RE generation RE_D is proportional to the PV panel size S_{PV}, for a given average daily RE generation per kWp, RE_d, observed in the considered location, the various regions correspond to different sets of combinations of PV panel size S_{PV} and storage capacity C_B allowing to achieve different target depletion probabilities, hence π_0: $\pi_0 < 0.005$ (blue squares); $0.005 \leq \pi_0 < 0.01$ (light blue asterisks); $0.01 \leq \pi_0 < 0.05$ (orange circles); $0.05 \leq \pi_0 < 0.1$ (yellow triangles). Furthermore, the graphs highlight the impact of the variance of RE generation on the distribution of the feasibility regions.

The minimum sizing required to achieve values of π_0 as low as 0.005 or less highly depend on the CV. For fix RE_d, a PV panel size capable to provide 1.3 the BS daily consumption may be sufficient if the variance of the RE production is low; moreover, the battery size shows no significant impact, hence a small storage with capacity of less than 4 fold the BS daily need is enough to guarantee very low depletion probabilities. Conversely, when the CV is higher, the minimum PV panel size assuring $\pi_0 < 0.005$ must be capable of providing a RE_D that is up to more than 2.5 the BS daily need. However, when the CV is higher, the impact of the battery size is higher. For example, in case CV=30%, increasing C_B by up to 40% allow to reduce S_{PV} by up to 11.8%, still maintaining the same target on the battery depletion probability. This aspect is relevant when feasibility issues are considered, since PV panels with lower capacity require a smaller physical area to be installed, besides having lower capital costs.

When the variance of RE_D is high, although the system size is generally larger, a slight relaxation on the constraint on the target depletion probability -for example by moving to the feasibility region where π_0 is between 0.005% and 0.01%- allows to reduce the system dimensioning. This becomes more evident by shifting to the next feasibility region, where $\pi_0 = 0.01 - 0.05\%$. Furthermore, an increase in the battery capacity from 0.75 up to 1.05 the daily BS need leads to a reduction of the PV panel size of almost 30%. Conversely, in case the variance is low, it is not convenient to relax the constraint on the target depletion probability, since the gain in terms of PV panel and battery size reduction would be negligible and there would be the risk of sharply shifting to a region with very high battery depletion probability.

VIII. Considerations on cost and feasibility

In the process of system dimensioning based on the definition of a target battery depletion probability in a given location, costs may play a relevant role. In particular, capital expenditures can be taken into account in order to refine the identification of the proper system size, hence selecting the best combination of PV panel size and storage capacity within the feasibility region identified by applying the proposed analytical method. A cost of 750 €/kWp can be assumed for the panels, whereas the cost per kWh of battery capacity can be as high as 58.33 € [5]. Considering the range of sizes for PV panels and storage observed within the feasibility regions in our results, the cost of the PV panel is definitely dominant with respect to the cost of the battery. This means that, in locations with high variability of the RE generation a small increase in the battery size will allow to decrease the battery depletion probability at the price of a small raise in the cost; furthermore, it will be possible to decrease the PV panel size, still maintaining the same target depletion probability, and significantly reduce cost. For instance, let us assume a location where the average daily RE generation RE_d is 2 kWh, its CV is 30% and the target battery depletion probability is between 0.001 and 0.05. A system with $C_B = 17\ kWh$ (hence $B = 34\ kWh$, assuming a DOD=50%) and $S_{PV} = 28.2$ kWp is capable to meet the target constraint on the battery depletion probability. Nevertheless, by increasing the battery size by 40%, the PV panel size S_{PV} can be reduced by 30%, leading to a cost reduction of about 26.5%. Conversely, in those locations showing low variability in the RE generation, an increase in the battery size does not have a relevant impact on the PV panel capacity reduction. Hence, once the minimum PV panel size allowing to meet the constraint on p_D is identified, it is advisable to rather select a smaller



(a) CV=2%

(b) CV=10%

(c) CV=20%

(d) CV=30%

Fig. 12: Feasibility regions in terms of target of battery depletion probability at the steady state, π_0, for multiple combinations of RE generation levels and battery size, under increasing values of CV.

battery, although the total CAPEX will result only slightly decreased with respect to the case of a larger storage. On the one hand, the selection of a larger battery may reduce the PV panel size, hence CAPEX, in locations where the variability of RE production is higher. On the other hand, this results also in an improvement of the system feasibility, since the area of the surface required to install the PV panel is reduced as well. Assuming an efficiency of the PV panel of around 19%, an area of about 5 m^2 is needed per each kWp of PV panel capacity [5]. In the aforementioned case (location with ERE_d =2 kWh, CV=30%, p_D between 0.001 and 0.05) the PV panel size S_{PV} is reduced by 30%, and the area needed for the installation shrinks from more than 140 m^2 to less than 99 m^2.

Further studies should be performed to deploy an analytical tool for system dimensioning that embeds also constraints on CAPEX and area required for installation. Moreover, as future work, OPEX should be taken into account, by including in the method a parameter to evaluate the impact of the battery charging/discharging process on the storage lifetime duration, that in turn affects the frequency of battery replacement.

IX. Conclusion

Due to the staggering increase in mobile traffic, Mobile Operators are enforced to deploy denser mobile access network, with consequent huge cost for power supply. Renewable energy represents a promising solution to power BSs, in order to reduce the energy bill and increasing sustainability. Nevertheless, due to the intermittence of RE production and its variability observed over time and at different latitudes, a proper dimensioning of RE systems to power mobile network is crucial to make the network more self-sustainable and guarantee the mobile service continuity. In this work we propose a simple analytical tool to dimension the RE system to power a BS, that trades off accuracy and computational complexity.

Based on a 3-state Markovian model representing the storage charging level of a renewable powered BS, an analytical formulation is derived to dimension the photovoltaic panel and battery capacity in order to reduce the probability of storage depletion, p_D, below a target threshold. The RE generation is represented as a random variable with uniform distribution. For a given location, the analytical tool receives as input the mean value and variance of the location dependent RE production, and it allows to easily identify a feasibility region of possible combinations of values for the PV panel size and the storage capacity. Within this set of possible solutions, the proper combination can then be selected based on additional parameters, like costs or area of the required installation surface.

Our results show that the uniform distribution is as much or even more accurate in representing the distribution of daily RE production than other types of distributions adopted in the literature, and it can hence be preferred due to the lower computational complexity entailed. Simulation results prove that the Markovian model, despite being simple, is very reliable in representing the RE powered BS operation and predicting the battery depletion probability, with an estimation error that results negligible in most cases. The proposed analytical tool is very effective in dimensioning the PV panel and battery size, based on the target threshold defined for the battery depletion probability p_D. In addition, our results demonstrate that whereas a PV panel size capable of providing 1.3 fold the BS daily energy need is sufficient to reduce p_D below 0.005 in locations where the variance of RE production is low, an almost doubled PV panel capacity is required in case of higher RE production variability. Nevertheless, while an increased battery size does not improve the performance where the RE production variability is low, in locations showing high variance of the RE production it is convenient to increase the battery size to reduce the PV panel size, still obtaining the same depletion probability. Although a 40% larger battery allows to reduce the PV panel size by just 12%, this provides a twofold benefit, both in terms of smaller PV panel surface occupancy and of CAPEX reduction, since the costs for PV panel capacity dominates on the storage costs. Finally, locations with high variability of RE production may benefit from a slight relaxation on the depletion probability constraint, that can be conveniently applied to significantly reduce the system dimensioning.

Future work is required to deploy an analytical tool for system dimensioning that embeds also constraints on CAPEX, area of the physical surface required for installation and frequency of battery replacement.

References

[1] Cisco, in *Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2016-2021 White Paper*, February 2017. [Online]. Available: http://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/mobile-white-paper-c11-520862.html

[2] "Off-grid power for mobile base stations - Renewable and alternative energy sources for remote mobile telecommunications: Global market analysis and forecasts," *Pike Research*, 2013.

[3] G. Auer, O. Blume, V. Giannini, I. Godor, M. A. Imran, Y. Jading, E. Katranaras, M. Olsson, D. Sabella, P. Skillermark, and W. Wajda, "Energy efficiency analysis of the reference systems, areas of improvements and target breakdown energy aware radio and network technologies (earth) project," M. A. Imran and E. K. (UNIS), Eds., 2012 (2010).

[4] H. Smertnik, "Green power for mobile bi-annual report, GSM Association," Aug 2014.

[5] M. Dalmasso, M. Meo, and D. Renga, "Radio resource management for improving energy self-sufficiency of green mobile networks," in *Performance Evaluation Review*, vol. 44, no. 2, Sept 2016, pp. 82–87.

[6] V. Chamola and B. Sikdar, "Solar powered cellular base stations: current scenario, issues and proposed solutions," *IEEE Communications Magazine*, vol. 54, no. 5, pp. 108–114, 2016.

[7] M. Meo, Y. Zhang, R. Gerboni, and M. A. Marsan, "Dimensioning the power supply of a LTE macro BS connected to a PV panel and the power grid," in *2015 IEEE International Conference on Communications, ICC 2015, London, United Kingdom, June 8-12, 2015*, pp. 178–184.

[8] M. H. Alsharif, J. Kim, and J. H. Kim, "Green and sustainable cellular base stations: An overview and future research directions," *Energies*, vol. 10, no. 5, 2017.

[9] A. M. Aris and B. Shabani, "Sustainable power supply solutions for off-grid base stations," *Energies*, vol. 8, no. 10, pp. 10 904–10 941, 2015.

[10] D. Renga and M. Meo, "Modeling renewable energy production for base stations power supply," in *2016 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Nov 2016, pp. 716–722.

[11] M. Meo, Y. Zhang, R. Gerboni, and M. Ajmone Marsan, "Dimensioning the power supply of a LTE macro BS connected to a PV panel and the power grid," in *Communications (ICC), 2015 IEEE International Conference on*, June 2015, pp. 178–184.

[12] M. Ajmone Marsan, G. Bucalo, A. D. Caro, M. Meo, and Y. Zhang, "Towards zero grid electricity networking: Powering BSs with renewable energy sources," in *Communications Workshops (ICC), 2013 IEEE International Conference on*, June 2013, pp. 596–601.

[13] V. Chamola and B. Sikdar, "Resource provisioning and dimensioning for solar powered cellular base stations," in *Global Communications Conference (GLOBECOM), 2014 IEEE*, Dec 2014, pp. 2498–2503.

[14] N. Kakimoto, S. Matsumura, K. Kobayashi, and M. Shoji, "Two-state markov model of solar radiation and consideration on storage size," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 1, pp. 171–181, Jan 2014.

[15] H. Abdellatif and I. El-Amin, "Markov modeling of solar radiation and storage sizing," in *2015 IEEE 8th GCC Conference Exhibition*, Feb 2015, pp. 1–6.

[16] Y. Ghiassi-Farrokhfal, S. Keshav, C. Rosenberg, and F. Ciucu, "Solar power shaping: An analytical approach," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 1, pp. 162–170, Jan 2015.

[17] K. Wang, F. Ciucu, C. Lin, and S. H. Low, "A stochastic power network calculus for integrating renewable energy sources into the power grid," *IEEE Journal on Selected Areas in Communications*, vol. 30, no. 6, pp. 1037–1048, July 2012.

[18] M. Deruyck, D. Renga, M. Meo, L. Martens, and W. Joseph, "Accounting for the varying supply of solar energy when designing wireless access networks," *IEEE Transactions on Green Communications and Networking*, vol. 2, no. 1, pp. 275–290, March 2018.

[19] M. J. Farooq, H. Ghazzai, A. Kadri, H. ElSawy, and M. S. Alouini, "A hybrid energy sharing framework for green cellular networks," *IEEE Transactions on Communications*, vol. 65, no. 2, pp. 918–934, Feb 2017.

[20] N. B. Rached, H. Ghazzai, A. Kadri, and M.-S. Alouini, "Energy management optimization for cellular networks under renewable energy generation uncertainty," *TGCN*, vol. 1, no. 2, pp. 158–166, 2017.

[21] D. Renga, H. A. H. Hassan, M. Meo, and L. Nuaymi, "Energy management and base station on/off switching in green mobile networks for offering ancillary services," *IEEE Transactions on Green Communications and Networking*, pp. 1–1, 2018.

[22] H. Ghazzai, M. J. Farooq, A. Alsharoa, E. Yaacoub, A. Kadri, and M. S. Alouini, "Green networking in cellular hetnets: A unified radio resource management framework with base station on/off switching," *IEEE Transactions on Vehicular Technology*, vol. PP, no. 99, pp. 1–1, 2016.

[23] M. Miozzo, L. Giupponi, M. Rossi, and P. Dini, "Switch-on/off policies for energy harvesting small cells through distributed q-learning," in *2017 IEEE Wireless Communications and Networking Conference Workshops (WCNCW)*, March 2017, pp. 1–6.

[24] D. Renga, H. A. H. Hassan, M. Meo, and L. Nuaymi, "Improving the interaction of a green mobile network with the smart grid," in *2017 IEEE International Conference on Communications (ICC)*, May 2017, pp. 1–7.

[25] M. Miozzo, D. Zordan, P. Dini, and M. Rossi, "Solarstat: Modeling photovoltaic sources through stochastic markov processes," in *2014 IEEE International Energy Conference (ENERGYCON)*, May 2014, pp. 688–695.

[26] X. Huang, T. Han, and N. Ansari, "Smart grid enabled mobile networks: Jointly optimizing bs operation and power distribution," *IEEE/ACM Transactions on Networking*, vol. 25, no. 3, pp. 1832–1845, June 2017.

[27] D. Valerdi, Q. Zhu, K. Exadaktylos, S. Xia, M. Arranz, R. Liu, and D. Xu, "Intelligent energy managed service for green base stations," in *2010 IEEE Globecom Workshops*, Dec 2010, pp. 1453–1457.

[28] M. Meo, Y. Zhang, R. Gerboni, and M. Marsan, "Dimensioning the power supply of a LTE macro BS connected to a PV panel and the power grid," in *Communications (ICC), 2015 IEEE International Conference on*, June 2015, pp. 178–184.

[29] V. Chamola and B. Sikdar, "A multistate markov model for dimensioning solar powered cellular base stations," *IEEE Transactions on Sustainable Energy*, vol. 6, no. 4, pp. 1650–1652, Oct 2015.

[30] ——, "Outage estimation for solar powered cellular base stations," in *Communications (ICC), 2015 IEEE International Conference on*, June 2015, pp. 172–177.

[31] T. Han and N. Ansari, "Provisioning green energy for base stations in heterogeneous networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 7, pp. 5439–5448, July 2016.

[32] M. Ali, M. Meo, and D. Renga, “Wifi offloading for enhanced interaction with the smart grid in green mobile networks,” in *2017 IEEE 14th International Conference on Networking, Sensing and Control (ICNSC)*, May 2017, pp. 233–238.

[33] V. Chamola and B. Sikdar, “Dimensioning stand-alone cellular base station using series-of-worst-months meteorological data,” in *Communication Systems (ICCS), 2014 IEEE International Conference on*, Nov 2014, pp. 339–343.

[34] M. Imran, E. Katranaras, G. Auer, O. Blume, V. Giannini, I. Godor, Y. Jading, M. Olsson, D. Sabella, P. Skillermark *et al.*, “Energy efficiency analysis of the reference systems, areas of improvements and target breakdown,” Tech. Rep. ICT-EARTH deliverable, Tech. Rep., 2011.

[35] T. P. Chang *et al.*, “Investigation on frequency distribution of global radiation using different probability density functions,” *International Journal of Applied Science and Engineering 8 (2)*, pp. 99–107, 2010.

[36] F. Y. Ettoumi, A. Mefti, A. Adane, and M. Bouroubi, “Statistical analysis of solar measurements in Algeria using beta distributions,” *Renewable Energy*, vol. 26, no. 1, pp. 47–67, 2002.

[37] Y. D. Arthur, K. B. Gyamfi, and S. Appiah, “Probability distributional analysis of hourly solar irradiation in Kumasi-Ghana,” *International Journal of Business and Social Research*, vol. 3, no. 3, pp. 63–75, 2013.

[38] A. F. Morgera and V. Lughi, “Frontiers of photovoltaic technology: A review,” in *Clean Electrical Power (ICCEP), 2015 International Conference on*, June 2015, pp. 115–121.

[39] “Fraunhofer ISE: Photovoltaics Report,” https://www.ise.fraunhofer.de/en/downloads-englisch/pdf-files-englisch/photovoltaics-report-slides.pdf, 2015-11-17.

[40] IEA-ETSAP and IRENA, “Solar photovoltaics: Technology brief,” *Energy Technology Systems Analysis Programme and International Renewable Energy Agency, Tech. Rep.*, January 2013.

[41] A. P. Dobos, *PVWatts Version 5 Manual*, Sep 2014. [Online]. Available: http://www.osti.gov/scitech/servlets/purl/1158421

[42] M. Jurado, J. Caridad, and V. Ruiz, “Statistical distribution of the clearness index with radiation data integrated over five minute intervals,” *Solar Energy*, vol. 55, no. 6, pp. 469–473, 1995.

[43] J. Tovar, F. Olmo, and L. Alados-Arboledas, “One-minute global irradiance probability density distributions conditioned to the optical air mass,” *Solar energy*, vol. 62, no. 6, pp. 387–393, 1998.

[44] S. Suman and S. De, “Solar-enabled green base stations: Cost versus utility,” in *2017 IEEE 18th International Symposium on A World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, June 2017, pp. 1–8.

[45] G. Leonardi, M. Meo, and M. A. Marsan, “Markovian models of solar power supply for a lte macro bs,” in *2016 IEEE International Conference on Communications (ICC)*, May 2016, pp. 1–7.

[46] A. P. C. da Silva, D. Renga, M. Meo, and M. A. Marsan, “The impact of quantization on the design of solar power systems for cellular base stations,” *IEEE Transactions on Green Communications and Networking*, vol. PP, no. 99, pp. 1–1, 2017.

[47] S. Hua, Q. Zhou, D. Kong, and J. Ma, “Application of valve-regulated lead-acid batteries for storage of solar electricity in stand-alone photovoltaic systems in the northwest areas of China,” *Journal of Power Sources*, vol. 158, no. 2, pp. 1178 – 1185, 2006.

[48] H. Gharavi and R. Ghafurian, “IEEE recommended practice for sizing lead-acid batteries for stand-alone photovoltaic (PV) systems IEEE std 1013-2007,” in *Proc. IEEE*, vol. 99, no. 6, 2011, p. 917 – 921.

[49] M. Jafari, G. Platt, Z. Malekjamshidi, and J. G. Zhu, “Technical issues of sizing Lead-Acid batteries for application in residential renewable energy systems,” in *Electric Power and Energy Conversion Systems (EPECS), 2015 4th International Conference on*, Nov 2015, pp. 1–6.

[50] C. Mi, M. A. Masrur, and D. W. Gao, in *Hybrid Electric Vehicles: Principles and Applications with Practical Perspectives*. John Wiley and Sons, Ltd, Chichester, UK, 2011.

[51] “Lead-acid battery guide for stand-alone photovoltaic systems,” in *IEA Task III, Report IEA-PVPS 3-06:1999*, December 1999.

[52] Y. Parvini and A. Vahidi, “Maximizing charging efficiency of lithium-ion and lead-acid batteries using optimal control theory,” in *American Control Conference (ACC), 2015*, July 2015, pp. 317–322.

[53] J. W. Stevens and G. P. Corey, “A study of lead-acid battery efficiency near top-of-charge and the impact on PV system design,” in *Photovoltaic Specialists Conference, 1996., Conference Record of the Twenty Fifth IEEE*, May 1996, pp. 1485–1488.

[54] H. Al-Sheikh and N. Moubayed, “Health status and diagnosis of batteries in renewable energy systems: An overview,” in *Electrical and Power Engineering (EPE), 2012 International Conference and Exposition on*, Oct 2012, pp. 922–927.

[55] B. Huang, P. Hsu, M. Wu, and P. Ho, “System dynamic model and charging control of lead-acid battery for stand-alone solar PV system,” *Solar Energy*, vol. 84, no. 5, pp. 822 – 830, 2010.

[56] “Ieee guide for selecting, charging, testing, and evaluating lead-acid batteries used in stand-alone photovoltaic (PV) systems,” *IEEE Std 1361-2014 (Revision of IEEE Std 1361-2003)*, pp. 1–39, June 2014.

[57] “IEEE recommended practice for sizing lead-acid batteries for stand-alone photovoltaic (PV) systems - redline,” *IEEE Std 1013-2007 (Revision of IEEE Std 1013-2000) - Redline*, pp. 1–58, July 2007.

[58] Y. Ghiassi-Farrokhfal, S. Keshav, and C. Rosenberg, “Toward a realistic performance analysis of storage systems in smart grids,” *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 402–410, Jan 2015.

[59] M. Ku, W. Li, Y. Chen, and K. J. R. Liu, “Advances in energy harvesting communications: Past, present, and future challenges,” *IEEE Communications Surveys Tutorials*, vol. 18, no. 2, pp. 1384–1412, Secondquarter 2016.

[60] J. W. Kimball, B. T. Kuhn, and R. S. Balog, “A system design approach for unattended solar energy harvesting supply,” *IEEE Transactions on Power Electronics*, vol. 24, no. 4, pp. 952–962, April 2009.

Daniela Renga received the Ph.D. in Electrical, Electronics and Communications Engineering in 2018, and the Master degree in Computer and Communication Networks Engineering in 2014, both from the Politecnico di Torino, Italy. In 2004 she received a Laurea degree in Medicine from the Università degli Studi di Torino, Italy. She is currently a post-doc researcher at the Department of Electronics and Telecommunications of the Politecnico di Torino. Her research interests are in the fields of energy efficient wireless networks, resource management, network modeling, smart grids and renewable energy sources for sustainable mobile networks.

Michela Meo received the Laurea degree in Electronic Engineering in 1993, and the Ph.D. degree in Electronic and Telecommunications Engineering in 1997, both from the Politecnico di Torino, Italy. Since November 2006, she is professor at the Politecnico di Torino. She co-authored about 200 papers and edited a book with Wiley and special issues of international journals, including ACM Monet, Performance Evaluation, and Computer Networks. She chairs the Steering Committee of IEEE OnlineGreenComm and the International Advisory Council of ITC. She is associate editor of IEEE Communications Surveys & Tutorials, area editor of IEEE Transactions on Green Communications and Networking, and was associate editor of IEEE Transactions of Networking. She was program co-chair of several conferences among which ACM MSWiM, IEEE Online GreenComm, IEEE ISCC, IEEE Infocom Miniconference, ITC. Her research interests include performance evaluation and modeling, green networking and traffic classification and characterization.