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A Statistical Approach for Modeling the Aging Effects in Li-Ion Energy Storage Systems

MARIO MUREDDU[1], ANGELO FACCHINI[2,3], AND ALFONSO DAMIANO[1], (Member, IEEE)

[1]Department of Electrical and Electronic Engineering, University of Cagliari, 09123 Cagliari, Italy

[2]IMT School for Advanced Studies Lucca, 55100 Lucca, Italy

[3]Italian National Research Council, Institute for Complex Systems, 00185 Roma, Italy

Corresponding author: Alfonso Damiano (alfio@diee.unica.it)

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ABSTRACT This paper presents a novel approach for the technical and economic assessment of Li-ion battery energy storage systems (BESS) in smart grids supported by renewable energy sources. The approach is based on the definition of a statistical battery degradation cost model (SBDCM), able to estimate the expected costs related to BESS aging, according to the statistical properties of its expected cycling patterns. This new approach can improve the assessment of the economical sustainability of BESSs in this kind of applications, helping in this way the planning processes in electricity infrastructures in presence of high penetration of intermittent renewable energy sources. The SBDCM proposed in this paper is a statistical generalization of a battery degradation model presented in the literature. The proposed approach has been validated numerically comparing the results with those of the deterministic model considering for the BESS a stochastic dataset of input signals. In order to test the usefulness of the proposed model in a real world application, the proposed SBDCM has been applied to the evaluation of the economic benefit associated to the development of distributed energy storage system scenarios in the Italian power system, aimed to provide ancillary services for supporting electricity market.

INDEX TERMS Energy storage systems, energy storage management, statistical battery degradation model, renewable energy sources, ancillary services markets.

I. INTRODUCTION

The increasing amount of Renewable Energy Sources (RESs) installed worldwide is introducing novel challenges in planning and management of power systems. In particular, the fluctuating output of RESs sums up with the uncertainty of load consumption, increasing the electricity market balancing volumes and costs [1]. In this context, the Energy Storage Systems (ESSs) are foreseen as a possible solution in order to reduce the workload of backup systems and improve the overall stability of power systems [2], [3].

Despite of the results already obtained, nowadays the cost and the efficiency of ESSs are still an open debate, since most of the approach proposed for economic evaluations are based on a general lifetime estimation, and does not include a more precise aging evaluation for these type of systems. This is particularly true for Battery-based ESSs (BESSs), which aging properties can sensibly vary with the application, and are known to show a highly non-linear aging behavior. Nevertheless, some authors proposed different methods to include a more accurate analysis of aging effects into the cost function used for optimization usage of ESS, and particularly BESSs, in power systems.

Among them, [4] highlighted this issue, proposing the use of a cycling based calculation of aging, finding how the BESS profitability strongly depends on both the type of service for which the BESS is used for and the control method used for its management. Recently, a more advanced aging modeling of Li-ion BESSs has been proposed under the form of a Battery Degradation Model (BDM) [5]. This model is able to estimate the battery aging in a closed form considering both the calendar aging, mainly due to the passage of time, and the cycling aging, due to the effective usage of the BESS. As an implementation of the proposed BDM, the implementation of Distributed Energy Storage Systems (DESSs) for supporting the Ancillary Services Markets (ASM) in power systems has been considered and analyzed [5]. It points out how DESSs can effectively improve the reliability of power grids, reducing, at the same time, load curtailment. However, it also underlines how different usage of BESSs due to different size, power to capacity ratio or control rules highly impacts on the battery aging, which can in turn influence the economic profitability of the process.

This is due to the complexity of the estimation of the aging costs of the installed ESSs, which can significantly impact on the cumulative costs of energy services and depend in turn on the sequences of cycling and usage of the ESSs. Furthermore, the complexity of this task increases in case of an high randomness of the charging/discharging cycles at which the BESS is subject to. In this case, the deterministic analysis of the battery aging is impossible to achieve, since its degradation is highly dependent on the incoming random signal. In order to overcome this critical issue a novel Statistical Battery Degradation Model (SBDM) is proposed, aiming to evaluate the BESSs aging in highly stochastic environments, such as the ones involving an high RES penetration. The proposed SBDM is therefore a statistical generalization of the Battery Degradation Model (BDM) proposed in [5].

The proposed SBDM relies on the assumption that, on a long run, stochastic signals with the same time properties (such as autocorrelation, expected value and amplitude) produce a similar aging effect on the same type of BESSs. This assumption has been tested numerically for Gaussian white noise and colored noise [6], [7]. In order to apply the SBDM in a real world application, an estimation of the economic impact of the implementation of a publicly owned Distributed BESS (DESS) in the Italian Ancillary Service Markets (ASM) has been performed. For this purpose, a Statistical Battery Degradation Cost Model (SBDCM) has been proposed, and further included in a more large Probabilistic Power Flow (PPF) framework. This approach allowed for the statistical evaluation of the BESS aging in such a complex environment. Furthermore, the aging effects have been described in terms of systemic costs by applying the calculations proposed in subsec. IV-A. This finally allowed for the evaluation of the global market costs in presence of a DESS, which include a detailed assessment of the expected DESS aging costs.

The results confirm, in a more precise and cost effective way, the results shown in [4] and [5], which clearly state that the usage of BESS in ASM is economically advantageous only under certain usage circumstances. Moreover, a sensitivity analysis shown the high dependence of the economic result on the overnight costs and cumulative size of the DESS.

The paper is organized as follows: the proposed methodology and the novel SBDM is firstly described in section II. Section III reports the procedure implemented for validating the SBDM. In Section IV the results of the application of the proposed model to the Italian ASM are presented and discussed. Finally, the conclusions are reported in section V.

II. THE STATISTICAL BATTERY DEGRADATION COST MODEL

The estimation of the aging costs of BESSs is hard to achieve for applications including power inputs of stochastic nature. This is due to the difficult estimation of the aging properties of batteries for both non-periodic usage schemes and random fluctuations. In order to overcome the first issue, [5] recently proposed a BDM able to estimate the aging of Li-ion BESSs in non-regular cycling use cases. Starting from this model, here is proposed a SBDM, based on the assumption that random signals with defined stochastic properties impact the BESSs aging in a similar way. The SBDM is based on the definition of the concept of average cycle, obtained as the integral mean of the BDM proposed in [5], weighted with the statistical distributions of the cycle properties.

These concepts are described in detail in the following subsections. In particular, subsection II-A briefly introduces the BDM proposed by *Xu et al.* [5], which will serve as a starting point for the following considerations. Then, subsection II-B describes the here proposed SBDM, and defines an approach for linking the statistic aging with a realistic cost estimation of the process.

A. DETERMINISTIC BATTERY DEGRADATION MODEL

The deterministic BDM methodology defined in [5] is based on (1), which relates the battery cycle life L with the battery degradation function f_d. The cycle life L is directly linked with the quantity D, the remaining capacity of the degraded BESS. In turn, f_d depends on both cycle and calendar aging, which are the effects related to the battery cycling and the passage of time, respectively. It also includes the effect of the initial Solid Electrolyte Inter-phase (SEI) film formation by means of parameters α_{sei} and β_{sei}.

$$L = 1 - \alpha_{sei} e^{-\beta_{sei} f_d} - (1 - \alpha_{sei}) e^{-f_d} \tag{1}$$

The dependence of f_d from the calendar aging function f_t with the cycle aging one f_c can be found in (2), where N is the number of performed cycles.

$$f_d(t, \delta, \sigma, T_C) = f_t(t_{use}, \overline{\sigma}, \overline{T_c}) + \sum_{n}^{N} f_c(\delta, \sigma, T_c) \tag{2}$$

More in detail, calendar aging function $f_t(t_{use}, \overline{\sigma}, \overline{T_c})$ is modeled as dependent from average State Of Charge (SOC) $\overline{\sigma}$ and temperature $\overline{T_c}$ during usage, and from usage time t_{use}. The dependence from these parameters is reported in (3). In turn, the expression of S_t, S_σ and S_{T_C} are described in (4), (5) and (6). The parameters k_t, k_σ, k_T, σ_{ref} and T_{ref} have been selected from [5].

$$f_t(t, \sigma, T_C) = S_t(t) \cdot S_\sigma(\sigma) \cdot S_{T_C}(T_C) \tag{3}$$

$$S_t(t) = k_t t \tag{4}$$

$$S_\sigma(\sigma) = e^{k_\sigma(\sigma - \sigma_{ref})} \tag{5}$$

$$S_{T_C}(T_C) = e^{-k_T(T_C - T_ref)\frac{T_c}{T_{ref}}} \tag{6}$$

Moreover, cycle aging function $f_c(\delta, \sigma, T_c)$ depends on the cycle Depth of Discharge (DoD) δ, the average SOC over the cycle σ and the average temperature over the cycle T_c. The expression of $f_c(\delta, \sigma, T_c)$ is given in (7). The expressions of

S_δ, S_σ and S_{T_C} are given by (8), (5) and (6). The parameters $k_{\delta 1}$, $k_{\delta 2}$ and $k_{\delta 3}$ are obtained from [5].

$$f_c(\delta, \sigma, T_C) = S_\delta(\delta) \cdot S_\sigma(\sigma) \cdot S_{T_C}(T_C) \tag{7}$$

$$S_\delta(\delta) = (k_{\delta 1}\delta^{k_{\delta 2}} + k_{\delta 3})^{-1} \tag{8}$$

B. STATISTICAL GENERALIZATION OF THE BDM

The estimation of the degradation of BESSs in highly stochastic environments requires a statistical description of the battery usage patterns, which does not fit with a deterministic formulation of the BDM proposed in [5]. This is due to the randomness of the signal in these cases. In fact, when the usage patterns of the BESS are stochastic, it is impossible to know in advance its exact cycling. However, if the random signal shows specific statistical properties and is replicated for a long enough period, it is acceptable to assume that, on average, the cycling patterns will converge to a well defined statistical distribution.

For this reason, the definition of the SBDM assumes a statistical description of the charge-discharge process. This description assumes that it is possible do estimate the cycling statistics of the BESS in terms of $\chi(t_{cyc}, \sigma, \delta, T_c)$, which is the multivariate Probability Density Function of experiencing a cycle with a certain combination of t_{cyc}, σ, δ and T_c. This distribution χ depends on the particular application for which the BESS is used for. Once this quantity is known, it is possible to estimate $\overline{f_d}^{cyc}$, which describes the degradation function for a statistically representative cycle, which can be obtained by (9).

$$\overline{f_d}^{cyc} = \int\int\int\int \chi(t_{cyc}, \sigma, \delta, T_c) \cdot f_d(t_{cyc}, \sigma, \delta, T_c) \cdot d\sigma d\delta dT_c dt_{cyc} \tag{9}$$

Once the quantity $\overline{f_d}^{cyc}$ has been calculated, the expected aging during a certain period T can be calculated by means of (10) as a function of $\overline{f_d}^{cyc}$ and N_{cyc}, which is the number of statistical representatives cycles observed in a time interval T.

$$f_d^{stat}(T) = N_{cyc} \cdot \overline{f_d}^{cyc} \tag{10}$$

Combining equations (1), (9) and (10), the battery life cycle can be obtained from the proposed PPF cycles and described in terms of $L(N)$, where N is the number of statistically representative cycles performed by each ESS. Given the average cycle length $\overline{\Delta t}_{cyc}$, the quantity $L(N)$ assumes the form of a time dependent function $L_t(t)$ as reported in (11).

$$L_t(t) = L(\overline{\Delta t}_{cyc} \cdot N) \tag{11}$$

Starting from this formulation, it is possible to identify the aging parameters of BESSs. It is common practice to consider an ESS as degraded when it reaches 80% of the original capacity $\mathcal{C}$ ($L = 0.2$). Using this information, and assuming the quantity $\overline{\Delta t}_{cyc}$ negligible with respect of the full battery life time, the function $L_t(t)$ can be considered continuous. In this way, the expected degradation time τ can be obtained from (12).

$$\tau = L_t^{-1}(0.2) \tag{12}$$

This quantity is related with DESS depreciation costs by (13), where C^{inst} are the total installation cost of the DESS, with $C^{inst} = c^{inst} \cdot D_0$. Here D_0 is the size of the installed BESS and c^{inst} are its overnight costs per unity of capacity. Therefore, the average depreciation costs A_D, during a given time interval Δt, are obtained by performing (13).

$$A_D = \frac{C^{inst}}{\tau_D} \cdot \Delta t \tag{13}$$

Moreover, the maintenance cost M have been assumed to be proportional to the installation costs. This is achieved introducing z which relates maintenance costs to the installation costs, as reported in (14).

$$M = z \cdot A \tag{14}$$

III. NUMERICAL VALIDATION OF THE SBDM

This section aims to validate the assumptions behind the proposed SBDM, as defined in subsec. II-B. The first assumption A_1 states that statistically equivalent BESS input signals, eventually filtered with a well defined transfer function, cause statistically significant aging on equivalent BESS, provided that the signal is applied for a long enough time interval. The second assumption A_2 assumes that it is possible to statistically define a "mean BESS cycle", which aging properties are representative of the ones caused by the (eventually filtered) input signal.

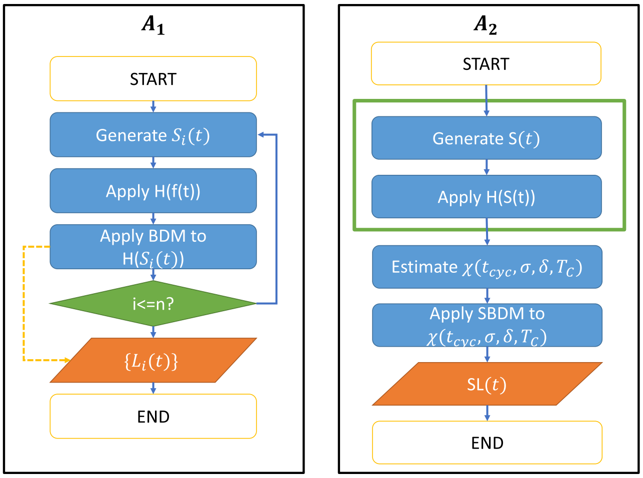

FIGURE 1. Validation process of the assumptions A_1 and A_2.

In order to validate the first assumption A_1, consider the simulation environment depicted in Fig. 1, left side. The process starts with the generation of n independent and identically distributed random time series $S_i(t)$, $0 < t < T$ obtained from a certain statistical distribution Ψ, and with well defined autocorrelation properties Ξ. Considering each of these series $S_i(t)$ as the input profile of the same class of Li-ion BESS, eventually filtered with a transfer function $H(f(t))$, it is possible to estimate the aging of the BESS at time T by applying (15), where $B(g)$ represents the whole BDM process described in II-A. If the set $\{DD_i(T)\}$ (standing

TABLE 1. Means and standard deviations for the validation of A_1 assumption for WGN and AS signals.

Signal type	$\overline{DD(T)}$	$std(DD(T))$
WGN	0.7295	0.0006
AS	0.725	0.001

for deterministic degradation) of the obtained aging outcomes shows a small enough statistical variability, the assumption can be considered valid. Here, the term small enough is dependent on the context and should be evaluated accordingly to the needs of the application.

$$DD_i(T) = B(H(S_i(t))), \quad 0 < t < T \tag{15}$$

In the following, the validity of this assumption is tested for two different sets of input signals, filtered with a transfer function $H(f(t))$ corresponding with the so-called "dumb control", described in the following. The considered input signals are defined by different Ψ and Ξ properties: a White Gaussian Noise (WGN), and an Autocorrelated Signal (AS) typical of medium sized power grids with high penetration of RES [6], [7]. The WGN is a non-correlated Gaussian noise, obtained by independently generating random numbers from a Gaussian distribution [8]. On the other hand, in order to test the assumption A_1 with input signals representing a realistic application of a BESS, a set of AS series has been generated by using an ARMA model [7]. The choice of the ARMA model for the sampling of power system output series has been widely studied in literature [7], [9], and this model has been shown to produce very good representation of this type of signals. The ARMA parameters have been obtained by fitting a one-year long power time series, which is the output (at PCC) of the IEEE-69 nodes prototypical grid described in [10] and [11]. The transfer function H, often called *dumb charging*, is defined in (16). In the equation, $P_{avail}(t)$ is the available BESS power output, as defined in (17) and (18), where $E_{ESS}(t)$ is the energy stored in the BESS at time t, P_{min} and P_{max} are the minimum and maximum power output of the BESS.

$$P_{in}(t) = \begin{cases} P_{avail}(t), & \text{if } P_{avail}(t) \leq S_i(t) \\ S_i(t) & \text{otherwise} \end{cases} \tag{16}$$

$$0.1 \cdot D \leq E_{ESS}(t) \leq 0.9 \cdot D \tag{17}$$

$$P_{min} \leq P_{avail}(t) \leq P_{max} \tag{18}$$

The numerical sampling of $\{DD_i(T)\}$ has been carried out for both WGN and AS signal types with an average value $\mu = 0$ and standard deviation $\sigma = 1$, for a value of $n = 500$ and a value of $T = 10yr$ (520 weeks). The signals have been applied to a BESS of capacity $C = 1$ and a power to capacity ratio of 1. All values are given in p.u. Results are shown in table 1, where $\overline{DD(T)}$ and std(DD(T)) are the experimental mean and standard deviation of the sample [6]. Also, the latter measure is considered as the sampling error. The outcome shows a relative error of approximately 10^{-3}, with the error associated to the AS signal being around the double of the WGN one. This values can be considered acceptable for the main applications associated to this type of BESSs.

The assumption A_2, states that the statistical description of the cycling patterns which arises from the function $H(S(t))$ in terms of $\chi(t_{cyc}, \sigma, \delta, T_c)$ can be used for the definition of a statistically representative cycle for the aging process. The application of the SBDM in the form of (9) and (1) to this representative cycle can then be used for the estimation of the aging of the BESS. This represents a great advantage in terms of assessment of the BESS life, since the definition of $\chi(t_{cyc}, \sigma, \delta, T_c)$ becomes the only necessary input of the model, which can be easily measured experimentally or estimated numerically. The flowchart of the validation process is shown in Fig. 1, right part. The outcome of the process is the value SL(t), representing the statistical aging curve of the BESS. In order to validate the results of this process, the resulting SL(t) has been calculated for both the WGN and the AS signals. In order to obtain a statistically representative $\chi(t_{cyc}, \sigma, \delta, T_c)$, the cycling patterns have been evaluated numerically for a simulated time period of one year. Subsequently, the SL(t) curves have been compared with the results of the validation for the assumption A_1. This comparison in shown in Fig. 2. The result show that the results of the SBDM fits with the variability of the numerical experimental sampling in the case of the AS signal, whereas it tend to underestimate the battery aging by 0.1% in ten years in the case of the WGN signal. Anyway, this deviation is still acceptable for the majority of the applications of this method.

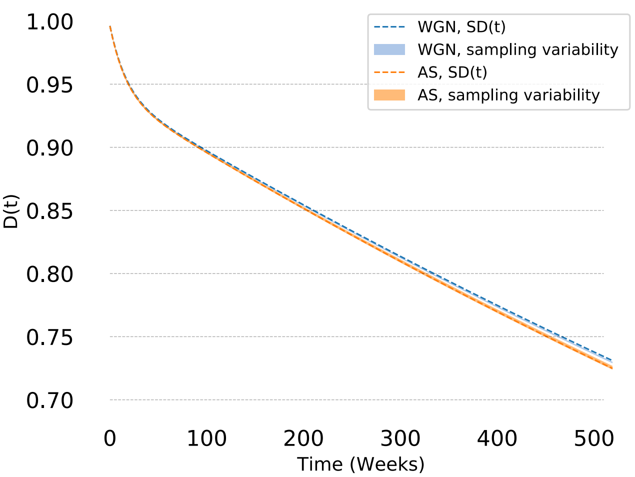

FIGURE 2. The comparison between the statistical aging SL(t) and the numerical sampling of aging for statistically equivalent signals. The plot shows the time evolution of the expected remaining capacity *D*(*t*) of the BESS in both cases, for both WGN and AS signals. Results show how the statistical aging method provides a precise estimation of aging during the entire time frame, for both of tested signals.

IV. STATISTICAL COST EVALUATION OF THE IMPACT OF DESS IN THE ITALIAN ASM

In order to test the application of the newly proposed SBDM and SBDCM methods, it has been carried out an analysis of the economic sustainability of the usage of DESS in the

Italian ASM. The usage of DESSs in ASM is of particular interest because of the complex stochastic nature of the power signals involved in these types of markets, especially in case of high penetration of intermittent RES. For this reason, the installation of a public owned DESS oriented to the filtering of RES and loads induced fluctuations can be useful for the reduction of ASM prices, especially for what concerns the network balancing procedures. In order to model this stochastic behavior of the network, the full balancing market procedure has been simulated numerically by means of a PPF procedure coupled with the proposed SBDCM for the estimation of the cumulative market costs, by following the process described in IV-A. Since it is difficult to include BESS temperature factors in this type of analysis, the temperature of the considered BESS have been considered as constant at $t_{ref} = 25°$. The case study and simulation results concerning the application of the proposed approach are reported in the following. Particularly, subsec. IV-A quickly introduces the balancing market simulation model proposed in [12]. This model has been used in combination with the proposed SBDCM for the estimation of the economic impact of Distributed ESSs in the balancing market of the Italian power system. The Subsec. IV-B introduces the Italian power system, its related electricity market, and the DESS scenarios considered in the planning analysis. Subsequently, Subsec. IV-C reports the statistical results of the proposed methodology regarding the DESS usage and the DESS cycle life assessment. Finally, the results of the economic analysis are presented, discussed and compared with the canonical lifetime estimation methods in Subsec. IV-D.

A. APPLICATION OF THE SBDM TO THE ASSESSMENT OF ESS COSTS IN MARKET APPLICATIONS

Different approaches have been proposed in technical literature for the planning, the sizing and management of ESSs in power systems [3], [13]–[20]. In particular, the coupling between electricity markets and storage systems, making use of different techniques for mimicking the market, has been investigated. This includes game theory-based approaches, time series reconstruction and risk-based algorithms willing to simulate the impact of ESSs on electricity markets. In recent years, the estimation of market volatility and costs in systems with high penetration of RES has been addressed with Probabilistic Power Flow (PPF) procedures [21]–[24]. The use of PPF procedures is necessary, since the randomness of RES power production cannot be modeled with a deterministic approach. As expected, the results of these approaches show how, in general, an increase in the RES penetration leads to an increased volatility in markets [24]. The use of ESS for the provision of ancillary services in power systems is seen as a viable path to reduce the volatility of the associated markets [10], [25], [26]. However, the lack of statistical models for the assessment of battery degradation makes a correct estimation of the Battery amortization costs difficult to achieve, possibly leading to an incorrect estimation of the global cost of the process.

In order to test a real world application of the proposed SBDM, it has been performed an investigation of the economic sustainability of a DESS for the provision of ancillary services in power systems. This has been achieved by integrating the SBDM with a Probabilistic Power Flow (PPF) procedure. Results have been used to identify the best DESS configurations under different price scenarios. Finally, the best solutions for each scenario have been analyzed to understand the economic sustainability of DESSs by considering different overnight costs.

The overall procedure consists in the evaluation of the results of a PPF performed on the system under varying conditions, given by different combinations of DESS sizes D and overnight costs c^{inst}. A schematic summary of the procedure is given in Fig. 3.

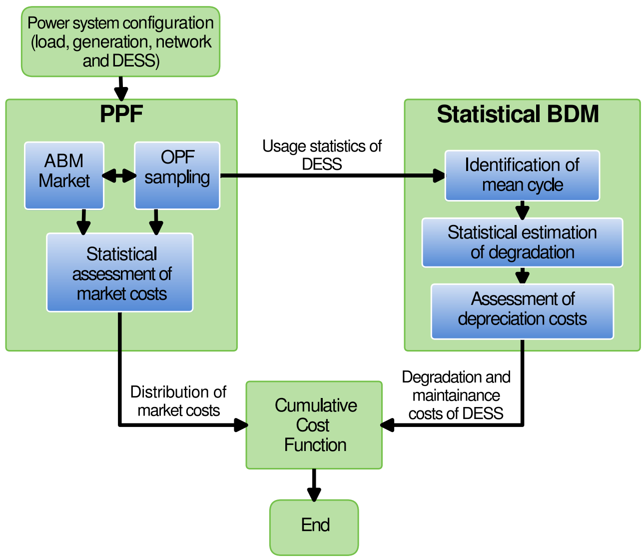

FIGURE 3. The flowchart of the proposed methodology.

The PPF procedure is necessary since the balancing process in power systems is intrinsically random, due to the intermittent nature of power demand and RES generation. In this paper, the proposed PPF procedure resorts to the stochastic sampling procedure proposed in [12]. This procedure consisted in the sampling of R possible market configurations per each combination of D and C^{inst}. Each sample obtained by the procedure is in fact the merit-order based OPF of the specific realization, obtained by stochastically perturbing the initial condition. As outcome of each of the samplings, it has been possible to obtain both a series of total market costs and a series of time evolutions of the SOC of the ESSs composing the DESS, which allowed in turn the calculation of the aging costs associated to the usage of DESSs in the considered scenario. All these costs have then been aggregated with the DESS maintenance costs, allowing for the estimation of the global system costs in all the simulated scenarios.

The market costs of DESSs are described by means of a statistical distribution representing the market cumulative cost CC_D. This cumulative cost is related to: the daily market costs C_D; the depreciation costs of the entire DESS $A_D(c^{inst})$; its maintenance costs $M_D(c^{inst})$; and the costs of its associated losses I_D. In turn, all these quantities depend on D, the planned DESS capacity, and are evaluated considering the time period Δt according to (13). In particular, the distribution CC_D can be calculated as reported in (19).

$$CC_D = C_D + A_D + M_D + I_D \tag{19}$$

In general, C_D, A_D, M_D and I_D depend on the DESS configuration. Particularly, C_D and I_D are obtained directly from the PPF procedure, and generally vary for varying DESS capacities. The estimation of A_D and M_D can be determined by means of the proposed SBDCM.

The estimation of CC_D allows for the identification of other important key performance indexes of the proposed scenario: the DESS Total Repay Time (TRT) τ^D_{TRT} and the Total Repay Ratio (TRR) τ^D_{TRR}. In particular, since the expected effect of DESS is the reduction of the balancing market costs, the economic improvement of G_D can be determined by means of (20), where K_{ref} are the market costs in a certain reference market configuration.

$$G_D = K_{ref} - C_D - I_D \tag{20}$$

Given the overnight costs C^{inst}, the system's TRT and TRR are calculated by means of (21) and (22) respectively.

$$\tau^D_{TRT} = \frac{(1+z)C^{inst}(D, c^{inst})}{G_D} \tag{21}$$

$$\tau^D_{TRR} = \frac{\tau^D_{TRT}}{\tau_D} \tag{22}$$

B. CASE STUDY: APPLICATION TO THE ITALIAN POWER SYSTEM

The proposed methodology has been applied referring to the balancing phase of the ASM of the Italian power system. The tested DESS have been spatially distributed considering as planning criteria the expected power variability induced by RES and load of each node. The system configuration has been obtained from two main datasets. The first one, is extracted from the public documentation provided by the Italian Transmission System Operator (TSO) TERNA on its website which gives the characteristics of the power system. It includes the location of each 220 and 380 kV substations and the distribution of transmission lines with their electrical characteristics. The location of conventional generators with both their power rates and ramp limits is also detailed. Moreover, it includes a description of the system market zones. The second dataset is provided by the Italian market supervisor (GME) on its website. It reports the detailed time evolution of production and consumption for each 15 minutes of reference days. The RES production has been estimated referring to the procedure described in [12], using the original datasets regarding the wind and photovoltaic local production published on its website by the Italian authority for RES, the GSE. The resulting structure of the Italian power system is reported in Fig.4. The red circles are the generation nodes where the balancing market transaction are allowed, while blue edges are the transmission lines. In this paper, the methodology for the economic assessment described in IV-A has been applied considering different planning scenarios characterized by DESS cumulative capacities of $D = 1, 2, \ldots, 10$ GWh respectively. The PPF procedure consisted in the sequential sampling of 1000 full reference days. In turn, each day consisted in evaluating the time evolution of 96 time intervals, representing the system progression in 15 minutes steps.

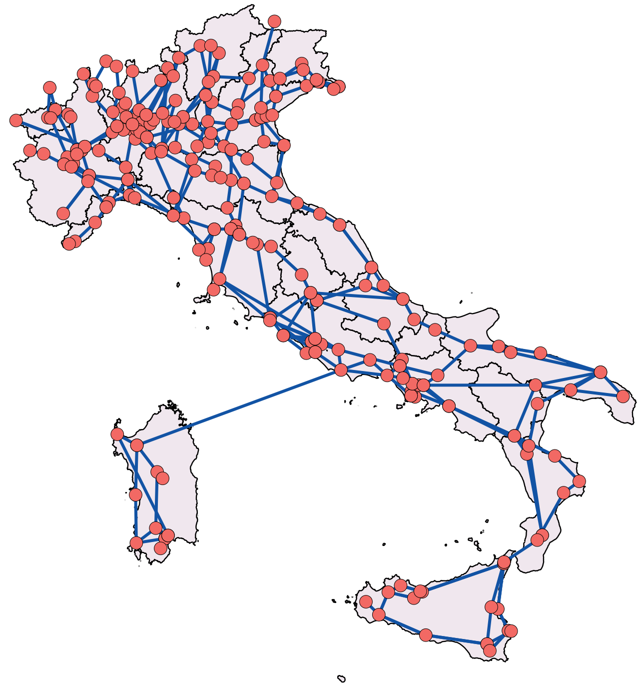

FIGURE 4. Geographical representation of the Italian power system employed as case of study. The red circles are the generation nodes where the balancing market transaction are allowed, while blue edges are the transmission lines.

C. BATTERY USAGE AND DEGRADATION RESULTS

The simulation results are presented in Figs. 5, 6, 7 and 8. In particular, 5 shows a representation of the bivariate distribution $\chi(\delta, \sigma)$, for a value of $D = 1$ GWh. Fig. 6 shows the statistical distribution of cycles time length $\chi_{t_{cyc}}(t_{cyc})$ per each tested value of D. Furthermore, Fig 7 shows the cycle life curve $D = 1 - L_t(t)$ of the DESS, where the red dotted line refers to a remaining cumulative capacity ratio of 80%, at which the batteries of DESS can be considered degraded. Finally, Fig. 8 reports the statistical distribution of DoDs $\chi_\delta(\delta)$, for all the tested values of the DESS capacities D.

Fig. 5 shows the obtained distribution χ in terms of δ and σ, which show an high probability to experience cycles with $\delta \approx 0.1$, being them at low or high average σ. The results of Fig. 6 highlight how the ESS cycling periods are narrowly distributed around an average value $\bar{t}_{cyc}$ characterized by a value of 45 minutes which is not affected by the variation of the

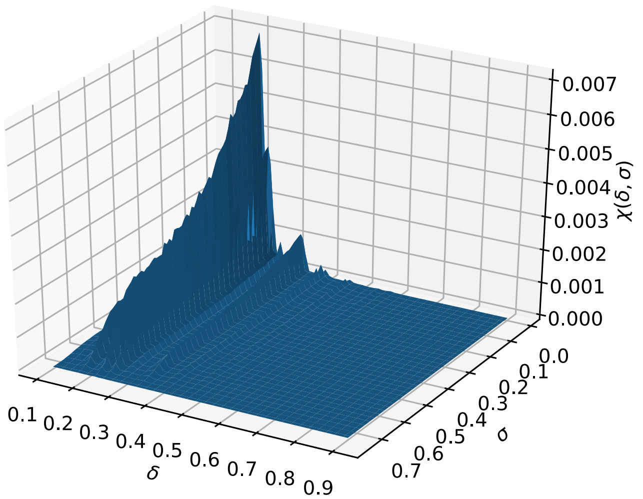

FIGURE 5. The numerically obtained multivariate Probability Density Function of $\chi(\delta, \sigma)$, for a value of $D = 1$ GWh. In general, the $\chi(\delta, \sigma)$ shows a decreasing trend for increasing δ and σ, showing the presence of an high number of low DoD cycles.

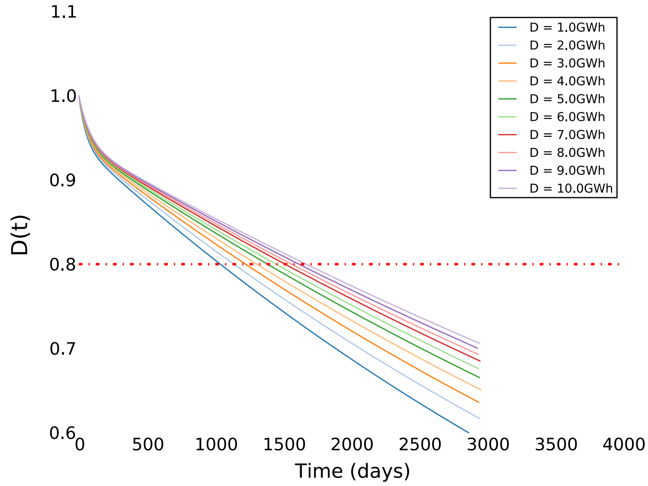

FIGURE 7. Degradation curves per different values of D (cumulative capacity). Each curve shows the time evolution of $D(t)$, the remaining capacity after time t. In general, battery expected lifetime increases with increasing installed capacity, ranging between 3 and 5.5 yrs.

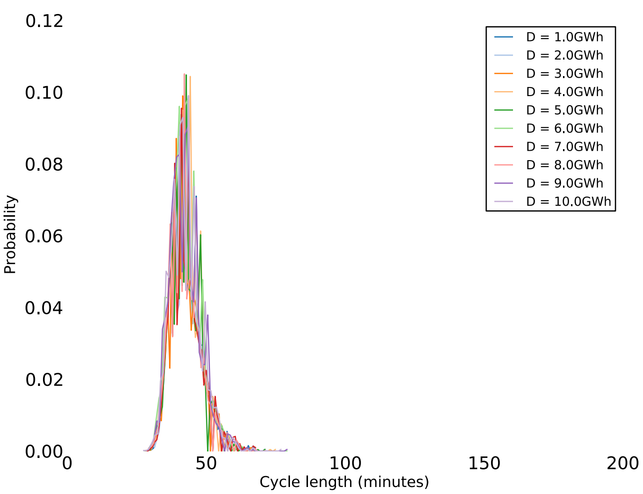

FIGURE 6. Statistical distribution of the time length of cycles, per different values of D (cumulative capacity). Though very noisy, the most expected time length is around 45 minutes for every considered value of D.

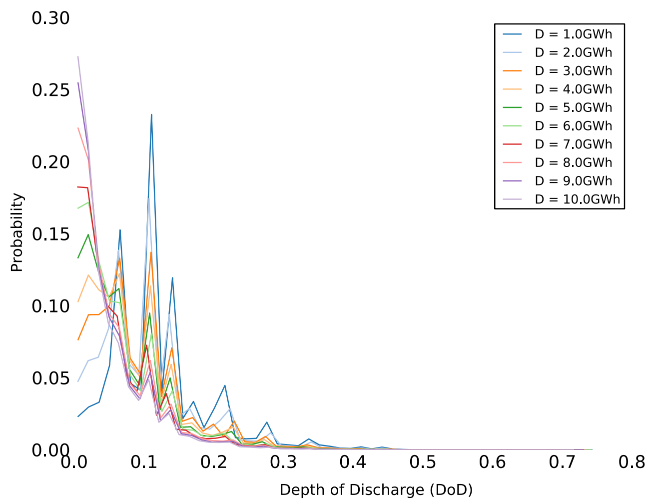

FIGURE 8. Estimated statistical distribution of the cycling Depth of Discharge δ per different values of D (cumulative capacity).

cumulative capacity D of DESS. Figs. 5 and 6, together, provide a graphical representation of $\chi(t_{cyc}, \sigma, \delta, T_c)$ used in (9) for the calculation of the aging of the statistical representative cycle $\overline{f_d}^{cyc}$ (since T_c is considered constant during the entire process). By applying (1), (9) and (10) to the obtained $\chi(t_{cyc}, \sigma, \delta, T_c)$ it has been possible to assess the DESS life cycle for the case of study considering different values of cumulative capacities D. These findings are reported in Fig. 7, and show how bigger DESS sizes are related to higher battery life. This is mainly due to the different cycling patterns of the tested DESS, as shown in the $\chi_\delta(\delta)$ distribution reported in Fig. 8, for all the tested values of D. Looking at this Figure, it is clear how the higher is D, the smaller is the average cycling DoD performed by the DESS, increasing in this way the expected DESS life cycle.

The previously given findings allow the identification of τ^D, which increases monotonically with D ranging between 1050 and 2000 days, i.e. 3 and 5.5 years. Considering the value of $\bar{t}_{cyc} = 45$ mins, the number of statistically representative cycles, before degradation of ESSs occur, correspond to values ranging between 35000 and 60000. Such relevant number is explained by the frequent cycling characterized by small DoD, which is related to the intermittence of the ancillary service in the balancing market at which the ESSs are devoted to. The larger τ^D for increasing values of D is mainly due to the different shapes of the $\chi_\delta(\delta, D)$. As reported in Fig. 8, high values of D show an increased probability of performing low DoD cycles, which in turn impact less on the battery degradation. Furthermore, in Fig. 9 the p distribution for the analyzed case study, which reports the delivered power ratio for different values of D, is presented.

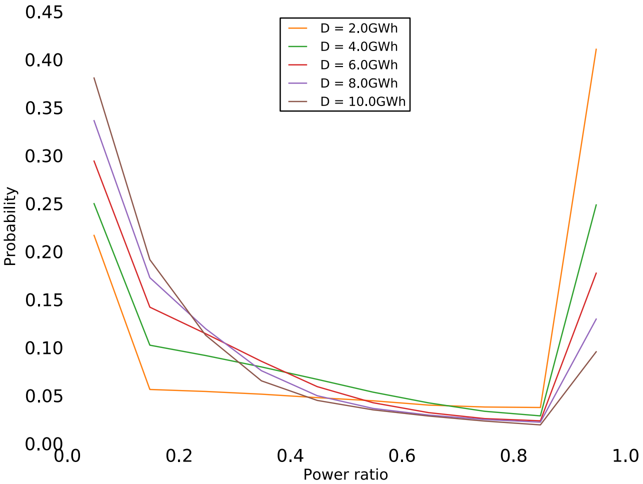

FIGURE 9. **Simulation results of the proposed methodology achieved for the Italian power system oriented to the stochastic analysis of the usage patterns of the DESS. Probability to provide a power ratio *p*, for each ESS of the system. Results are shown for DESS cumulative capacities of $D = 2, 4, 6, 8$ and 10 GWh respectively.**

It refers to DESSs cumulative capacities of $D = 2, 4, 6, 8$ and 10 GWh respectively. Results show how these distributions are bimodal, revealing one peak around low values of p and one peak around 100% of the available power. The probability of observing $p = 100\%$ strongly depends on the DESS capacity D. In particular, a DESS with $D = 10$ GWh works at full power with a probability of 10%. This value increases for decreasing installed capacity, and for $D = 4$ GWh the DESS works at power rate higher than $> 50\%$ of rating power for more than 50% of the time. The reduced power usage of the DESS in the balancing phase can translate in free resources, which can be used for providing further ancillary services to the system.

D. COSTS ESTIMATION

The information regarding the battery life cycle obtained by the PPF+SBDCM methodology in the Italian power system has been used to identify the average daily market cumulative costs CC_D for different cumulative capacities D. These values represent the combined cost of the balancing market of the system, summed with the battery depreciation and operative costs. In order to compare these results with the current configuration, the results include the CC_{ref}, which are the balancing market costs for a cumulative capacity of DESS D equal to zero. If the decrease in daily market costs due to the presence of the DESS is larger than its daily depreciation and operative costs, then $CC_D < CC_{ref}$. In this case, the installation of DESS is economically advantageous with respect to the current configuration. Since the depreciation costs A_D of the DESS depends on its overnight costs per unit of capacity, the CC_D has been evaluated for the different values of c^{inst} ranging between 200 and 800 Euros/kWh. The obtained results for this case study are shown in Fig. 10.

Particularly, the cumulative costs curves show a non-monotonic behavior, with a global minimum dependent

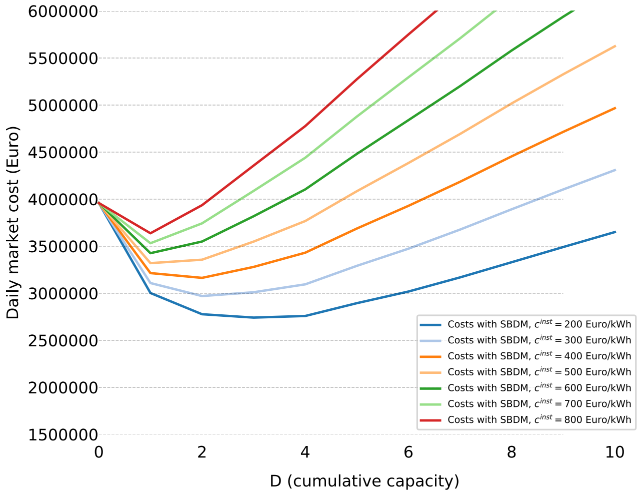

FIGURE 10. **Simulation results regarding the daily cumulative balancing market cost of the analyzed case study versus the cumulative capacity of DESS for different values of specific cost of battery capacity c^{inst}.**

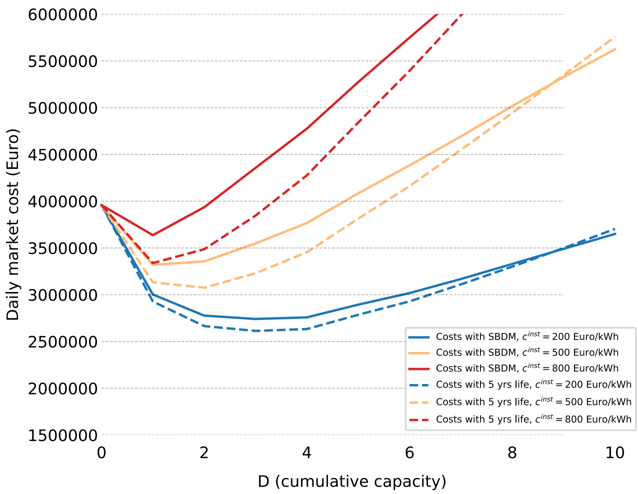

FIGURE 11. **Comparison between the cumulative market costs calculated with aging costs obtained with both SBDM (continuous line) and a fixed 5 yr lifetime (dashed line) for different values of specific cost of battery capacity c^{inst}.**

on c^{inst}. This minimum has been found to be smaller than CC_{ref} for every value of c^{inst} in the considered case study. The relative decrease in cumulative costs ranges from about 10% for $c^{inst} = 800$ Euro/kWh, to a value of 30% for a $c^{inst} = 200$ Euro/kWh. Moreover, the proposed methodology allows for the identification of the storage capacity D minimizing the daily cumulative cost of the balancing market for different values of c^{inst}. As expected, the outcome of the analysis sensibly varies with c^{inst}. In particular, the analysis with $c^{inst} = 800$ Euro/kWh shows a minimum cost region around of a cumulative capacity of 1 GWh, whereas a value of $c^{inst} = 200$ Euro/kWh shows an range of cumulative capacity between between 2 and 5 GWh. This result highlights how the installation of a DESS for balancing purposes is economically profitable in the case study. Finally, Table 3 shows the values of τ^D_{TRT} and τ^D_{TRR} for different combinations of D and c^{inst} in the case of study. These quantities represent, respectively,

TABLE 2. Values of τ_{TRT}^{D} and τ_{TRR}^{D} for different combinations of D and c^{inst} in the analyzed case of study. The green cells highlight the economically sustainable results, the red cells highlight the non-economically sustainable ones.

c^{inst}(Euro/KWh)	200		300		400		500		600		700		800	
D(GWh)	τ_{TRT}^{D}	τ_{TRR}^{D}	τ_{TRT}^{D}	τ_{TRR}^{D}	τ_{TRT}^{D}	τ_{TRR}^{D}	τ_{TRT}^{D}	τ_{TRR}^{D}	τ_{TRT}^{D}	τ_{TRR}^{D}	τ_{TRT}^{D}	τ_{TRR}^{D}	τ_{TRT}^{D}	τ_{TRR}^{D}
1	184	0.177	276	0.266	369	0.355	461	0.443	553	0.532	645	0.621	737	0.709
2	276	0.242	414	0.364	552	0.485	690	0.606	828	0.727	966	0.848	1104	0.97
3	370	0.302	556	0.453	741	0.605	926	0.756	1111	0.907	1296	1.058	1482	1.209
4	463	0.354	695	0.531	927	0.709	1159	0.886	1390	1.063	1622	1.24	1854	1.417
5	584	0.421	876	0.632	1168	0.842	1460	1.053	1752	1.264	2044	1.474	2337	1.685
6	703	0.485	1055	0.728	1407	0.97	1758	1.213	2110	1.456	2461	1.698	2813	1.941
7	841	0.555	1261	0.832	1681	1.109	2101	1.387	2522	1.664	2942	1.941	3362	2.218
8	989	0.632	1483	0.948	1978	1.264	2472	1.58	2967	1.896	3461	2.212	3956	2.529
9	1153	0.713	1730	1.069	2306	1.426	2883	1.782	3459	2.138	4036	2.495	4612	2.851
10	1333	0.798	1999	1.196	2665	1.595	3332	1.994	3998	2.393	4664	2.791	5331	3.19

TABLE 3. List of acronyms used in the paper.

BESS	Battery Energy Storage Systems
RES	Renewable Energy Sources
SBDM	Statistical Battery Degradation Model
SBDCM	Statistical Battery Degradation Cost Model
DESS	Distributed Energy Storage system
ESS	Energy Storage systems
BDM	Battery Degradation Model
ASM	Ancillary Services Markets
PPF	Probabilistic Power Flow
SEI	Solid Electrolyte Interphase
DoD	Depth of Discharge
SOC	State Of Charge
PDF	Probability Density Function
WGN	White Gaussian Noise
AS	Autocorrelated Signal
TRT	Total Repay Time
TRT	Total Repay Ratio
TSO	Transmission System Operator

the payback time of the DESS for different values of D, and the ratio between the payback time and the DESS degradation time. The DESS can be fully payed back only if $\tau_{TRR}^{D} < 1$. As expected, τ_{TRT}^{D} and τ_{TRR}^{D} clearly increase with growing D and c^{inst}. Results confirm how each value of c^{inst} has a range of installed storage D which makes DESSs economically sustainable, just by providing ancillary services to balancing markets. The analysis of the results represents the expected feedback in the planning process of DESS. Moreover, as highlighted by Fig.9 for this particular case study, the application of DESS in the balancing market leaves a significant probability to experience free DESS power capacity, useful to provide further ancillary services.

Finally, the obtained results have been compared with an estimation of the market cumulative costs in which the DESS amortization costs have been assessed by considering a fixed lifetime estimation of 5 yrs. The comparison shows how this results tends to underestimate the global costs for small DESS sizes, and to overestimate them for big DESS sizes. This is due to the fact that smaller BESSs tend to perform more high DoD cycles, which reduces their expected lifetime. If this effect is not correctly characterized, their amortization costs are underestimated, leading to a non correct estimation of the global costs of the process. This in turn can lead to a non correct planning procedure.

V. CONCLUSION

The introduction of a statistical-based assessment of the Li-Ion BESS degradation allows for the estimation of the amortization costs of this type of batteries for use cases in highly stochastic operating conditions. The model, once validated on two toy-model test cases, has been applied for the assessment of the electric and economic impacts of different DESS planning scenarios on the Italian market-based power system, by also including the battery aging effects. In particular, the results of the case study put in evidence the existence of an economically sustainable configuration of DESS, with optimal size dependent on its overnight costs and ranging between 1 and 5 GWh. Moreover, the power usage statistics of the DESS during the provision of ancillary services in balancing markets show a significant availability of spare resources, allowing the provision of further ancillary service in the balancing market. The obtained results make the proposed methodology suitable for further investigation related to economic evaluation of additional services that can be provided by Li-ion ESS, especially for use cases involving the random usage of this devices.

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MARIO MUREDDU received the Ph.D. degree in physics from the University of Cagliari in 2015. From 2015 to 2016, he held a post-doctoral position for two years at Jacobs University Bremen. He has been holding a post-doctoral position at the University of Cagliari since 2017. His research interests span the application of complex systems, artificial intelligence, and blockchain to sustainable energy applications. In particular, he focused on modeling the role of energy storage systems and energy markets during the renewable energy transition, and in the modeling and planning of electric mobility on local and regional scale.

ANGELO FACCHINI received the degree in telecommunications engineering and the Ph.D. degree in physical chemistry. From 2003 to 2009, he visited as a Guest Scientist at the Max Planck Institute for the Physics of Complex Systems, Dresden. He is currently an Assistant Professor with the IMT School for Advanced Studies Lucca and an Associate Scientist with the Italian National Research Council, Institute for Complex Systems. His research interests are in the field of data science, complex systems, and sustainability science. In the field of complex systems, his research focuses on nonlinear dynamics, stochastic processes, statistical physics, and complex networks. In the field of sustainability science, he develops his research on urban development, urban metabolism, megacities, and in general on the relation between energy, water, and urbanization, including energy and water infrastructures. On the above-mentioned topics, he has published over 40 papers in international journals, among these PNAS, *Nature Energy*, *Scientific Reports*, *Physical Review E*, *Applied Energy*, and *Energy*.

ALFONSO DAMIANO (M'12) was born in Cagliari, Italy, in 1966. He received the Graduation degree in electrical engineering from the University of Cagliari, Cagliari, in 1992.

In 1994, he joined the Department of Electrical and Electronic Engineering, University of Cagliari, as an Assistant Professor. Since 2001, he has been an Associate Professor of electrical energy management and electrical machines. Since 2012, he has been a Visiting Professor with the Institute for Advanced Studies of Lucca, Lucca, Italy. He is a Scientific Coordinator of the Sardinian Regional Renewable Energy Laboratory, Cagliari. In 2013, he was a main Scientific Advisor of Project Smart City, A Labeled Municipalities. Since 2013, he has been involved, as a main Scientific Advisor in the development and implementation of two experimental microgrids based on novel energy storage management systems, the project is supported by the European Community. He has authored 140 papers published in international conference proceedings and journals. His current research interests include electrical drives, energy management, and energy storage systems, especially regarding electric vehicle and renewable energy system applications.

Prof. Damiano is a member of the Industrial Application Society, Industrial Electronic Society, the Vehicular Technology Society, and the Power Engineering Society. He received the Sustainable Energy Europe and Managenergy Award from the European Commission in 2014. He also received the Second Prize Paper Award from the Power Electronics Technical Committee of the IEEE Industrial Electronics Society at the 39th Annual Conference of the IEEE Industrial Electronics Society.