Battery Management in *V2G*-based Aggregations

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***Abstract* — Concerns about climate change and energy costs are key drivers in the growth of *Battery Vehicle* (*BV*) utilization. In the Vehicle-to-Grid (*V2G*) paradigm, an aggregation of *BV*s is used for the provision of energy and capacity services, including ancillary services to the grid. Participation in the *V2G* framework may entail additional charge and discharge of the *BV* batteries, leading to reduced life. In this paper, we discuss the formulation of an effective strategy for the aggregator, whose role in the effective implementation of the *V2G* framework is pivotal, to manage the aggregated vehicles, so as to maximize the total lifetimes of all the batteries in the aggregated *BV*s.**

The proposed management strategy makes use of both the *state of charge* (*s.o.c.*) and the *state of health* (*s.o.h.*) as key variables in the allocation of the service request to the *BV* batteries. Each service request is considered in terms of its impacts on both the individual and the entire *BV* aggregation battery health, so to allocate the service provision in the configuration that determines the least decrement in battery life. We explicitly assume the aggregator is responsible for the acquisition and maintenance of the batteries of the aggregated *BV*s and so the maximization of the aggregation battery life is simply the preservation of the value of the aggregator's assets. We illustrate the effectiveness of the approach with simulation results that indicate the success in battery life preservation, with notable improvement over the cases based solely on the use of *s.o.c.* as the key variable.

Keywords — battery vehicle aggregations; battery management; V2G aggregator; battery life maximization; battery health index.

I. Introduction

In recent years, *Battery Vehicles* (*BV*s) have been the object of consistent research and business efforts. Technology improvements have led the cost for a *BV* to drop and the all-electric range of vehicles to increase: *BV*s now represent a viable alternative mean of transportation, offering to customers the opportunity to operate a vehicle with lower fuel costs and lower environmental impact. Costs of *BV*s are expected to decline by nearly 50% by the end of this decade and, combined with incentives provided by some US state governments, the number of *BV*s on the roads is destined to raise: market projections account *BV*s for a share of the car sales market comprised between 5% and 13% by 2020. As an example, California has a goal of having 1.5 million *BV*s on its roads by 2025.

Absent a *V2G* framework, we may view *BV*s as pure loads: if not charged only during off-peak periods, they are capable of a significant impact on the distribution grid. The *V2G* framework was developed so that the *BV*s can be used for grid support services such as frequency up/down regulation, without hindering their functionality as vehicles [1]. In fact, the majority of vehicles are used mainly for commuting, spending in idle state around 22 hours per day: connecting a *BV* to the grid, it can be exploited during this time as a Distributed Energy Resource (DER).

Pivotal to the *V2G* implementation is the role of the aggregator: the impact that the energy stored into a single vehicle can have on the grid is, by all means, negligible; therefore, to have a tangible impact, aggregations of thousands of vehicles, which operate on the grid as a single entity, must be considered. In this paper, we assume the presence of an aggregator for managing one or more fleets of *BV*s: it manages the charge of vehicles, as well as the provision of ancillary services to the grid. Moreover, in our framework, the aggregator is also responsible for the acquisition and maintenance of the batteries: the adopted business model involves the lease of the aggregator-owned batteries to vehicle owners at discounted rates, should they choose to participate in the provision of ancillary services.

Independently of the usage of a *BV* in a *V2G* setting, due to the electrochemical reactions involved in the conversion of energy from chemical to electrical and vice versa, the charge and discharge actions result in a reduction of battery capacity. However, *V2G* service provision may entail additional battery charge and discharge activities: therefore, usage of *BV*s as distributed energy storage supporting the grid, involving an energy throughput to and from the battery higher than the one characterizing the usage of a *BV* only as a vehicle, determines a shorter life span for the batteries involved.

In this paper, we propose a *BV* battery management strategy for a *BV* aggregation in the *V2G* framework that maximizes the total lifetimes of all the batteries. By explicitly taking into account the health of a battery, and the impact that every energy transfer determines in terms of battery lifetime, the proposed strategy allocates each regulation service request to the *BV* batteries so as to minimize the overall detriment to the health of the aggregated batteries. In this way, the aggregator preserves the value of its assets, thereby providing its services to the grid at least cost. Such a strategy represents an effective and economically efficient implementation of the *V2G* concept for both aggregators and *BV* owners. The proposed strategy relies on the estimate of the health of a battery from the measurements by a microcontroller device embedded on each battery. In addition, both operational and environmental factors, which impact battery life, are taken into account in the management of the allocation of service provision to the *BV*s.

The paper is organized as follows. In Section II, we discuss the state of charge and the state of health variables and describe

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their use to provide appropriate information for the battery management in *BV* aggregations in a *V2G* setting. Our discussion includes a description of the various factors that influence battery life degradation and that need to be explicitly considered in the battery management strategy. We include the mathematical formulation needed for the battery management strategy specification. In Section III, we discuss the strategy in the context of the aggregator role and its key implications. The details of the strategy implementation are presented with the specification of the reference management strategy used for comparison purposes. In Section IV, we provide illustrative simulation results obtained with the proposed strategy and compare them with the reference strategy. We indicate the gains obtained over the reference strategy that uses only the state of charge as a determinant variable. In Section V, we summarize our key findings and conclusions and discuss directions for future work.

II. Consideration of Battery Health in the Management Scheme

The battery management strategies for *BV* aggregations in a *V2G* framework available in literature generally make use of the *state of charge* (*s.o.c.*), which represents the amount of charge stored in the battery as a percentage of the total storable charge, as the reference state variable to allocate the services. The *s.o.c.* may be used to evaluate the capability of a vehicle to provide the requested service or to determine the functioning of the *BV* battery (as demand-side or supply-side resource). The main objective for the realization of such management schemes is the maximization of the revenue determined by the provision of the ancillary services or the minimization of air pollutants emissions [2],[3].

We propose a different approach in the management of *BV* aggregations. The focus is on the maximization of the sum of the lifetimes of all the aggregated batteries. To this aim, the *s.o.c.* alone does not capture all the information needed for the management scheme. For this reason, we resort to a metric called *state of health* (*s.o.h.*): it ranges from 1 to 0 and represents an approximation of the normalized capacity of a battery. This metric is used as a key variable in the management strategy, together with the *s.o.c.*: each service request for a *BV* is evaluated in terms of the degradation that it will cause on the battery of the vehicle, given the amount of energy to be transferred and the *s.o.h.* of the battery. In this way, we are able to allocate for the provision of support services to the power grid the subset of the aggregated vehicles that is the least detrimental for the sum of the lifetimes of the batteries in the aggregation. In addition, we include in the evaluation all the environmental and operational factors, such as current, temperature and depth of discharge, that influence battery degradation. In this paper we refer to the limits suggested by USABC, according to which a battery whose battery capacity has decreased to 80% of the original value is at the end of its life; therefore, 0.8 represent the inferior limit for the *s.o.h.*

The *s.o.c.* is the other reference state variable: it defines the energy capability of a battery, therefore is essential to describe how much energy the battery is able to provide, or how much energy it is able to store. Moreover, as detailed later on, low *s.o.c.* levels are more harmful to the health of a battery. On this account, the *s.o.c.* provides significant information for the managing scheme: i.e., considering two batteries with same *s.o.h* but different *s.o.c.* discharging them of the same amount of energy will determine a more relevant deterioration in the battery with the lowest *s.o.c.*

In our implementation, we refer to Li-Ion batteries, which represent the reference battery technology for *BV*s [4],[5].

A. Battery aging and influencing factors

Batteries are complex systems, composed by one or more electrochemical cells. Energy is stored in chemical form while charging, and is converted into electricity during the discharge phase. Battery life involves two different concepts: 1) calendar life and 2) cycle life. The first one, also referred to as shelf life, represents the maximum survival time of a battery without the occurrence of electrochemical reactions. It is strongly dependent on the specific battery chemistry. For our purposes, however, far more important is the cycle life. As described in [6], the electrochemical reactions, related to energy conversion, that take place inside the single cell tend to lower the battery capacity. The cycle life is strongly dependent on environmental and operational factors.

The temperature at which the battery is operated determines a faster decay if outside a nominal operating range, whose values depend on the specific battery chemistry. In fact, higher temperatures speed up the electrochemical reactions and lower the battery internal resistance as seen from the external circuit; on the contrary, lower temperatures, slow down the reactions and increase internal resistance. The influence of the temperature on battery life is particularly strong for Li-Ion batteries; however, the dependence of battery aging on the operating temperature is common to all chemistries [7].

Charge and discharge current also has a relevant impact on battery cycle life: experimental tests show that high currents accelerate capacity decay. Moreover, the current extracted from a battery influences also the apparent capacity of a battery: the higher the current, lower will appear the quantity of charge that is possible to extract from the battery (Peukert's effect) [8].

A second operational factor influential in the capacity decay of a battery is the *depth of discharge* (*d.o.d.*): over the single cycle, intended as a sequence of a complete charge/complete discharge, the *d.o.d.* corresponds to the percentage of energy extracted from the battery in that cycle with respect to the total energy storable. Depending on the specific battery chemistry, deep cycles may impact differently battery life: for our purposes, we must take into account that Li-Ion batteries are more sensitive than other technologies to deep cycles [9]. Moreover, to prevent damaging the battery, during its operation the *s.o.c.*, which is the inverse of the depth of discharge and represents the percentage of energy still stored in the battery with respect to the total storable energy, must be kept between 90% and 10%.

In addition to the operational and environmental factors, also the type of vehicle determines different usage modes for the battery and thus, different impact on battery life. In fact, battery usage in all electric vehicles involves a series of full charge/full discharge and is more predictable, being closer to the conditions the batteries are tested in. On the other hand, Plug-in Hybrid Electric Vehicles can use the electrical motor and the relative energy storage system in different combinations with the internal combustion engine: this variability makes battery usage, and therefore the impact on battery life, less predictable.

B. Mathematical statement

For the application of the proposed management scheme, a device embedded on the battery with the ability to compute the *s.o.h.* metric is needed. Such a device, of which already exist some commercially available solutions (such as those marketed by Delphi and Texas Instruments), is essentially a simple microcontroller and therefore represents an inexpensive addition to the battery system. However, it must be considered that each *BV* has already embedded a metering system to measure the *s.o.c.*, which in any case is needed to manage the charge of the *BV* battery. Thus, the same system may be used to provide the required data to compute the battery health. We adopt the system developed in our previous work, which relies on a previous experimental characterization of the batteries to be employed on the *BV*s of the aggregation [10],[11].

In the following, the *s.o.c.* will be referred to as χ, while the *s.o.h.* metric is referred to as ξ. Starting from the experimental data regarding Li-Ion cells capacity decay in [12], a double exponential function that fits the samples can be obtained:

$$\xi_{fit} = a_0 + a_1 e^{-\left(\frac{n}{\alpha_1}\right)^{\beta_1}} + a_2 e^{-\left(\frac{n}{\alpha_2}\right)^{\beta_2}} \tag{1}$$

where n represents the number of cycles and $a_0, a_1, a_2, \beta_1, \beta_2, \alpha_1, \alpha_2$ are the coefficients to be identified while fitting the data. A single exponential can locally approximate such function:

$$\xi_{fit} = a e^{-\beta n} \tag{2}$$

Indicating with k the index of the individual sample, starting from the two previous values of the function $\xi_{fit}(k-1)$ and $\xi_{fit}(k)$, it is possible to compute the value at $\xi_{fit}(k+1)$ according to Eq. (2), which represent a computation of the *s.o.h.* under the same operational and environmental conditions adopted during the battery testing. Starting from the ξ_{fit} approximation for the *s.o.h.*, we then take into account all the environmental and operational parameters that have an influence on battery life through modification of a and β by means of a fuzzy algorithm.

For an effective deployment of the described system for its utilization in a *V2G* management scheme, we must consider that the charge/discharge actions required for the provision of ancillary services to the power grid generally do not involve full battery cycles. Therefore, the computation of the *s.o.h.* needs to be modified in a way meaningful for the *V2G* utilization. The battery capacity decay data used as experimental reference were obtained under known testing conditions: in particular, batteries were subjected to a series of full charge/full discharge. Therefore, it is possible to relate the cell degradation to the energy throughput it is subjected to. In particular, indicating with V_{nom} the cell nominal voltage and with c_0 the nominal capacity, each cycle the amount of energy transferred to/from the cell is:

$$\delta E = 2\, V_{nom}\, c_0\, \xi \tag{3}$$

Therefore, the cumulative energy throughput for n cycles is expressed as:

$$\delta E_{TOT}(n) = \sum_{i=1}^{n} 2\, V_{nom}\, c_0\, \xi(i) \tag{4}$$

Moving from the number of cycles to the energy throughput, we are able to relate battery degradation to an arbitrary amount of energy transformed by the cell. We explicitly note that, in doing so, the ability to identify a single cycle is lost: in fact, the relation expressed in Eq. (3)-(4) is one-way, and originates by the knowledge of the detailed conditions the original data were obtained in. Even though the notion of *cycle* is lost, for our purposes of considering the degradation of a battery the only relevant information is the amount of energy throughput: the electrochemical reactions that determine the capacity decay depend on the amount of energy converted in the cell, independently of being caused by a discharge or charge phase.

III. Battery Management

A. The role of the aggregator

Any practical implementation of a V2G framework depends heavily on the effective functioning of an aggregator. In fact, the contribution that the energy stored in each *BV* can provide to the grid is negligible in itself. Therefore, to be able to affect the power grid, the vehicles need to be grouped in sizable aggregations - from thousands to hundreds of thousands- that act as single entities, both as loads and as generation/storage devices.

Acting as a load, the aggregation of *BV*s represents the total capacity of the batteries: its significant size allows it to benefit from the buying power typical of a large commercial/industrial customer. The aggregator can then negotiate better prices and make purchases of energy, batteries or other services at rates lower than the ones accessible by the individual *BV* owner [1].

In the same manner, acting as a relevant-size *Distributed Energy Resource* (*DER*), the aggregation can supply both capacity and energy services to the power grid. It can provide both up and down regulation services, which are paid for the capacity it offers, independently of the actual provision of the energy service: in case the vehicles also provide energy to the grid, they receive additional payment. Also in this case the higher negotiating power empowers it to strike better deals, with some of the savings passed on to vehicles' owners.

The aggregator is also in charge of selecting the *BV*s that need to provide energy to the grid, or that can be charged during each time interval: for our purposes, the considered minimal time interval is 5 minutes long. This choice allows a prompt response of the aggregation to requests to raise/lower capacity the DER provides to the grid, while at the same time allowing for better distributing the burden of providing services to the grid among the largest part of vehicles in the aggregation.

We assume everywhere that the aggregator is the owner of the batteries used in every *BV* in the aggregation. The aggregator is responsible for the battery acquisition and maintenance and leases them to the *BV* owners with attractive incentives to those who participate in the provision of *V2G* services [1]. Indeed, under this assumption, the aggregator strives to ensure that the provision of services by the *BV*s under its management utilize their batteries in a way that maximizes the lifetime of those batteries. In the allocation of the service provision among the aggregated *BV*s, the aggregator deploys a management strategy that maximizes the value of its assets. In this aspect, our paper differs from past work in the literature whose focus is the optimization of the individual battery life [13].

B. Management scheme

In the following, we will focus on *BV*s used for daily commuting purposes. Recent studies have shown that the average commuting time is around 52 minutes, with the vehicles in idle state for around 22 hours per day. Our framework is based on the assumption that a commuting vehicle, once reached the destination, is connected to the grid [1]. We assume that the vehicles are parked into parking lots during the day, when the aggregated fleet of vehicles provides ancillary services to the grid, and at home during the night. In particular, considering the average commuter reaching his workplace and leaving his vehicle in a parking lot during office hours, the period for the provision of services to the grid spans from the from 8 a.m. to 6 p.m. Since the fleet related to the same aggregator can be in non-contiguous parking lots, we assume each vehicle is univocally identified through SIM card technology tied to the individual battery.

The assumption that each vehicle embeds a device that can measure the *s.o.c.* and compute the battery *s.o.h.* implies that upon connection to charging station – be it in the parking lot or at home – the vehicle identifies itself and communicates its *s.o.c.* and *s.o.h.* to the aggregator. In addition, some additional information is assumed to be always available and is shared upon connection: this includes data related to operational and environmental conditions, such as ambient temperature, or user-defined settings, such as desired time of departure and required *s.o.c.* for that time. As the measurement device onboard the *BV* battery and the management strategy rely on the past experimental characterization of the *BV* batteries, without any loss of generality, we assume in the following that all the vehicles in the aggregation have identical batteries. Specifically, the batteries considered are based on Tenergy 18650 2200mAh cells, for which an extensive experimental characterization is available [12].

For the simulations, we considered the battery of the vehicle composed of 600 Tenergy 18650 cells, arranged in 10 stripes of 60 cells. The battery parameters are obtaining by scaling the parameters of the single cell. The nominal voltage V_{nom}^{batt} is obtained multiplying the nominal voltage of the single cell for the number of cell in series that compose the battery. As for the battery nominal capacity c_0^{batt}, we obtain it multiplying the maximum energy storable into each cell for the total number of cells, and then dividing by the battery voltage.

C. Strategy implementation

For the implementation of the system on the aggregator side, we obtain simpler decay curves by computing a piecewise linear approximation of the decay curve as a function of the energy throughput. Thus, a decay coefficient may be obtained for each section. The number of sections considered for each curve is three. In our case, such characterization is carried out on three curves with different *d.o.d.*: specifically, the values considered for the *d.o.d.* are 55%, 75% and 85%. Since the *d.o.d.* is the opposite of the *s.o.c.*, the procedure just described allows us to have a decay coefficient for each couple (χ, ξ): in fact, each curve gives us three coefficients, one for each interval of values of the *s.o.h.*; in addition, for each *s.o.h.* interval, we have the coefficient referred to three different *d.o.d.*, thus *s.o.c.*, conditions (see Fig. 1).

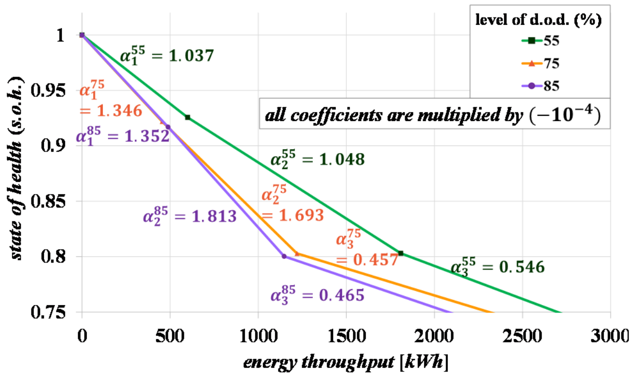

Figure 1. Piecewise approximation of *s.o.h.* and decay coefficients for a single cell

Given a specified amount of energy ΔE provided to, or extracted from, the battery, the variation in *s.o.h.* for the k-*th* vehicle is expressed as:

$$\Delta\xi_k(\xi_k, \chi_k, T_k, i_k) = w(T_k, i_k)\, \alpha(\chi_k, \xi_k)\, \Delta E_k \tag{5}$$

The different coefficients have been organized as a look-up table, accessed with the function $\alpha(\chi, \xi)$. The curves from which the coefficients have been extracted were measured under specific testing conditions: the ambient temperature T was maintained constant at 25° C and the discharge of the batteries was performed at a fixed current rate I_n of 4 A. Therefore, in Eq. (5), we included the function $w(T, i)$, which acts as a weight and takes into account the effect on battery *s.o.h.* of the variations of temperature and current with respect to the testing conditions the experimental curves were obtained in. The weighting function is reported in Eq. (6)

$$w(T_k, i_k) = \gamma_T (T_k - 25)^2 + \gamma_C \left(\frac{i_k}{I_n}\right)^{0.05} \tag{6}$$

where γ_T and γ_C are coefficients to adjust the impact on the *s.o.h.* of the temperature and current weighting terms. The current term is modeled similarly to the expression of Peukert's law, so that a higher current will have a bigger impact, with a current equal to I_n weighting as 1.

In the simulations, the current in/out the battery during the provision of *V2G* services was considered having a fixed value of 10 A. Given that the length of each time interval and the nominal battery voltage are fixed, the amount of energy transferred in/out of each vehicle selected for the grid support services each time interval is a pre-determined constant value.

In designing the simulations, whose results are presented in Section IV, two randomly generated arrays containing *s.o.c.* and *s.o.h.* of the vehicles of the managed fleet are considered as inputs for the management system, together with the ambient temperature. Without loss of generality, we assume that at the end of the 120 time intervals (twelve 5-min long time intervals for each of the ten hours from 8 a.m. to 6 p.m.) the vehicles that participate in the service provision to the grid are recharged exactly the same amount of energy as they were discharged. In this way, all *BV*s are considered for service provision for the same amount of time and each vehicle's energy storage level at 6 p.m. will be identical to that at the time of connection to the grid.

An additional input is represented by the raise/lower capacity signal. Positive values represent the request to increase the capacity, therefore represent request for energy to be provided from the vehicles to the grid; negative values represent requests to lower capacity, therefore constitute energy flows used to charge back the vehicles instead. In the simulations the energy profile was obtained considering a zero-average arbitrary profile, scaled by the minimum number of vehicles to be involved in service provision each time interval (referred to as *base unit*). To avoid the chance of experiencing systematic effects, the array containing the energy request samples is randomly ordered at every run of the simulation. Fig. 2 shows one energy profile referred to the case of a number N of vehicles equal to 11520, with a base unit of $N/40$ vehicles.

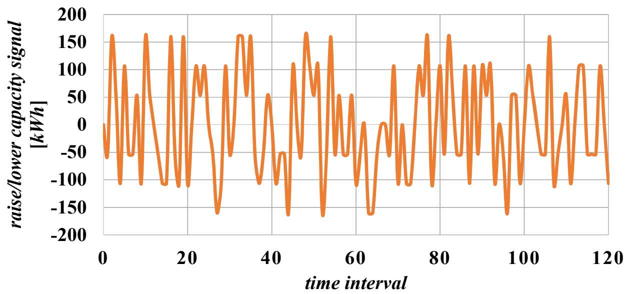

Figure 2. Example of energy profile considered as input for the management system

D. Case studies

We conducted simulations for two different cases. In the first case, only the *s.o.c.* is considered as key variable in the management strategy. The allocation of vehicles depends on their order of arrival (from the implementation point of view, we consider that the array containing the *s.o.c.* of the vehicles is populated according to their order of arrival) according to the principle *first arrived-first served*. For each vehicle selected, the *s.o.c.* is compared with the energy request (towards or from the grid): only in case it is able to satisfy the request, the vehicle is actively allocated in provision of the service. We used this *s.o.c.* based strategy as reference, against which compare the performance of our strategy.

The method we propose adopts a fundamental principle: since the decay of a battery capacity (and thus, of *s.o.h.*) is higher, for the same energy throughput, when the battery already exhibits a low *s.o.h.*, then prioritizing the vehicles whose battery has high *s.o.h.* minimizes the total capacity, and therefore total lifetime, losses. To avoid an unequal exploitation of only the vehicles with healthier batteries and not to have too deep cycles, for every time interval a vehicle cannot be discharged more than once unless all the vehicles have been discharged at least one time, or no other vehicle can support grid services in that time interval. Fig. 3 shows the block diagram relative to the implemented management strategy.

IV. Simulation Tests Results

The implemented strategy has been simulated using MATLAB. The tests have been executed for different number of vehicles and for different base units. In addition, we generated the random *s.o.c.* and *s.o.h.* samples for the input vector using both a Gaussian distribution and a uniform one. Specifically, the

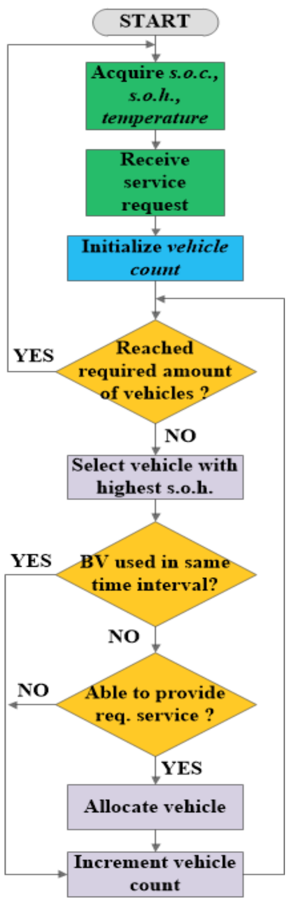

Figure 3. Block diagram of the implemented strategy

Gaussian distribution considered for the *s.o.h.* is centered at 0.9, with standard deviation equal to 0.033, so that the 99.7% of values still don't exceed 1 or be lower than 0.8; as for the uniform distribution, 0.8 and 1 have been considered as minimum and maximum values respectively.

TABLE I. Specifications of the simulated configurations

Name	*Configuration*		
	No. of vehicles (N)	***base unit***	**distribution**
28800-80g	N= 28800	N/80	Gaussian
28800-80u	N= 28800	N/80	Uniform
19200-80g	N= 19200	N/80	Gaussian
19200-80u	N= 19200	N/80	Uniform
19200-40g	N= 19200	N/40	Gaussian
19200-40u	N= 19200	N/40	Uniform
11520-80g	N= 11520	N/80	Gaussian
11520-80u	N= 11520	N/80	Uniform
11520-40g	N= 11520	N/40	Gaussian
11520-40u	N= 11520	N/40	Uniform
960-80g	N= 960	N/80	Gaussian
960-80u	N= 960	N/80	Uniform
480-80g	N= 480	N/80	Gaussian
480-80u	N= 480	N/80	Uniform

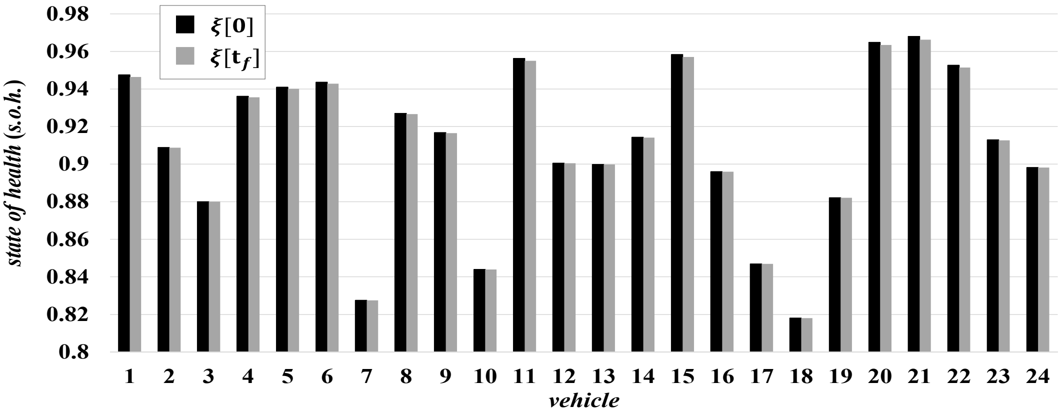

Figure 4. Sample of computed *s.o.h.* values for a subset of vehicles – simulation in configuration 11520-40g

As for the number of the vehicles considered in the simulations, and the relative base unit, different configuration have been tested and are reported in Table I.

Fig. 4 gives a picture of the impact on the *s.o.h.* of the *V2G*-related continuous charge and discharge during 120 time intervals, which correspond to 10 hours of provision of services to the grid in response to a signal as the one showed in Fig. 2. In particular, the results are obtained with the proposed management strategy, in the *11520-40g* configuration. As to be expected, the decrease in *s.o.h.* is of limited value, given the relatively small energy throughput each battery sustains if allocated for service provision. In addition, the decrease in the *s.o.h.* is mainly related to the batteries with a better initial state of health: in fact, our management strategy gives higher priority to them.

For a more thorough characterization, we executed for each configuration a series of 100 simulation runs of the implemented strategy. Since the generation of the input values of s.o.c and *s.o.h.* is random, the results regarding the variation of the *s.o.h.* will be different. We considered the percentage variation of the results of our strategy compared to the reference case as a measure to evaluate the performance of the system. In particular, positive values indicate an increment of performance, represented by a slower battery aging, therefore longer battery life, compared to the reference case. Representative test results are reported in Fig. 5 and show average improvements between 3% and 8%. The improvement over the reference case tends to be higher when initial values are generated according to a uniform distribution. As highlighted also by the extended results relative to configurations 11520-40g and 11520-40u reported in Fig. 6 and Fig. 7, our strategy is more effective if the initial *s.o.h.* of the batteries is uniformly distributed. This phenomenon is directly determined by the fact that values close to the boundaries of the *s.o.h.* input range are more frequently generated than in the Gaussian case. This accounts also for a generally higher dispersion of the results. In addition, the greatest benefits of our strategy occur with a higher *base unit*: also in this case the results are not unexpected, since raising the energy request, with the same number of vehicles in the fleet, means that the stress for the individual battery is higher, which is the condition where an advanced management strategy is more beneficial.

To explain the benefits of a strategy oriented to preserve the lifetime of batteries and of the results obtained with the proposed strategy, a practical example can be considered. If, by means of the *V2G* management strategy, we achieve a decrease in battery health slower by 5% compared to the case assumed as reference (where the *s.o.c.* is the only key variable used for the management), on average the batteries will have a lifetime longer by 5%. The USABC recommendations indicate at least three thousands EV cycles as a requirement for *BV* batteries. Considering a worst case scenario of two full charge/full

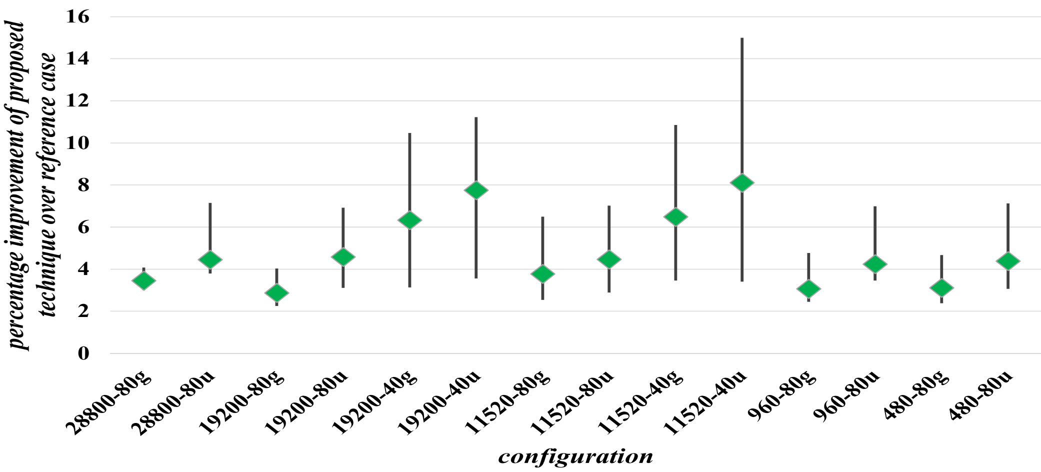

Figure 5. Average percentage improvement and min-max interval as result of 100 simulation runs for each configuration

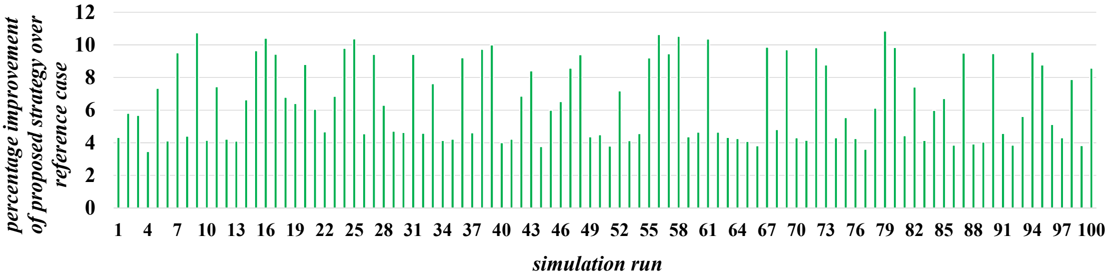

Figure 6. Percentage performance improvement over reference case for 100 simulation runs - configuration 11520-40g

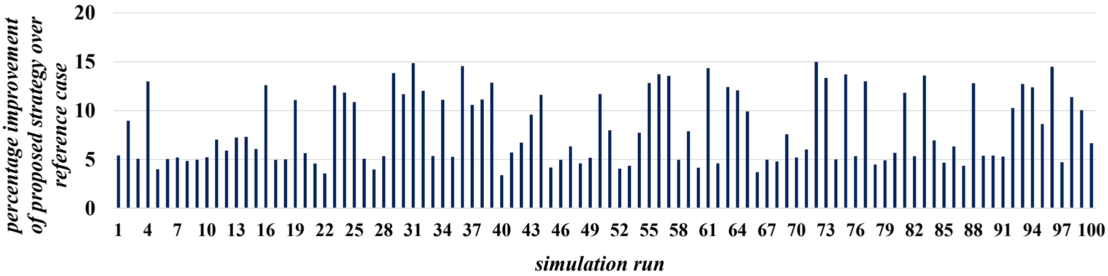

Figure 7. Percentage performance improvement over reference case for 100 simulation runs - configuration 11520-40u

discharge cycles per day (when the vehicle is used in a *V2G* framework), the battery will operate for 1500 days. Therefore, an increase of 5% in lifetime will determine 150 additional cycles, which means 75 additional days of operation.

V. Concluding Remarks

In a *V2G* paradigm, the continuous charge and discharge is detrimental to the life of a battery, determining a shorter battery lifetime. Assuming that the aggregator of the *BV* fleet is responsible for the acquisition and maintenance of the batteries, it has overall responsibility for their management.

The paper proposes an innovative management strategy for aggregation of *BV* providing services to the power grid in a *V2G* framework. We introduce a practical and easily computable metric that provides and appropriate measure of battery health and make detailed use of this metric in the construction of a management scheme for batteries of an aggregation of *BV*s. A salient characteristic of this scheme is to ensure that the provision of *V2G* services results in minimal degradation of the aggregated *BV*s' battery lives. Relying on both the state of charge and state of health metric, the developed strategy allocates the inbound or outbound energy transfers so that their impact on the health of batteries is reduced.

Testing conducted for different numbers of *BV*s, different initial conditions and different levels of energy request show that our strategy determines an increase in battery lifetime of the order of 3% to 8% compared to the reference case, where only the state of charge is used in the allocation of services to the aggregated batteries. Moreover, the additional cost for the implementation of the proposed strategy might lie only on the microcontroller, embedded on each battery, needed to compute the state of health metric. However, to this aim the metering system already required for the measurement of the state of charge can be used.

Future developments will include an optimization scheme, which would ensure a greater flexibility in taking into account individual user preferences. In addition, battery prices and cycle life data, as well as payment for the services provided can be included to optimize aggregator's assets acquisition and management from an economic point of view.

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