Evaluation of the Energy Storage Systems impact on the Italian Ancillary Market

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***Abstract*— The increasing of Renewable Energy Source (RES) generation requires power systems to become more flexible, in order to manage injections variability and uncertainty at various timeframes. Energy storage systems, such as electrochemical technologies, represent a broadly deployable asset, which could support effectively RES deployment. The present paper describes a Mixed Integer Linear-constrained Programming (MILP) model to simulate battery energy storage systems behavior within the Italian ancillary services market. The main purpose of the tool is to investigate the economic viability of storage technologies in the provision of network services.**

***Index Terms* - Ancillary Services, Battery Energy Storage Systems, Dispatching, Mixed-Integer-Linear-Programming, RES integration.**

NOMENCLATURE

Indices

t: Index for time steps.
b: Index for BESS.
z: Index for market zones.
i: Index for discretized SoC intervals.
k: Index for energy level.
j: Index for discretized discharge efficiencies intervals.

Parameters

$IC(b)$: Investment cost [€/kWh].
$Cdod(b, n_{soc})$: Additional DoD costs [€/kWh].
$Cap_{min}(b)$: Min. capacity [kWh].
$\eta_{ch}(b,n_{eta})$: Charging efficiency.
$\eta_{dis}(b\ n_{eta})$: Battery discharging efficiency.
ε, M: Low, high penalty factors.
n_{soc}: Number of discretized SoC intervals.
n_{pow}: Number of discretized C-rate intervals.
n_{η}: Number of discretized discharge efficiencies intervals.
$Ncyclemax(b)$: BESS max. number of cycles.
$Ncycle(b, n_{pow})$: Number of the battery cycles, function of C-rate.
$Pmax(b)$: BESS nominal power [kW].
$Pmin(b)$: Max. battery charge power [kW].
$Cap_{nom}(b)$: Nominal capacity [kWh].
$P_{min\_SOC}(b,n_{soc})$: Min. deliverable power [p.u. w.r.t. $Pmin$].
$P_{max\_SOC}(b,n_{soc})$: Max. deliverable power [p.u. w.r.t. $Pmax$].
$P_{\max\_dis}(t, b)$: Max. available power, function of actual SoC [kW].
$PowStep_{dis/ch}(n_{soc},t)$: Discretization intervals of the max. power vs. SoC curve.
$PowThs_{\eta}[n_{eta}, b]$: Auxiliary variable used to define the power step thresholds to discretize the efficiency curve.
$PowThs_{E}[n_{pow}, b]$: Auxiliary variable used to define the power step thresholds to make the battery work at different C-rate.
$Res\_sec(b)$: Half-band available for the secondary reserve [kW].
$SoC_{Step}[j, b]$: Ratio between the considered BESS nominal capacity and the number of SoC intervals.

Variables

$SoC(t,b)$: Actual battery SoC [kWh].
$CMax_{residual}(b)$: Actual max. capacity of the BESS [kWh].
$BESS\_cost\ (t,b)$: Penalty factor correlated to BESS lifetime reduction due to high DoD [€/kWh].
$E_{cycle}(b)$: Exchanged energy [kWh].
$E_{level}(t,b, n_{pow})$: Exchanged energy in each n_{pow} level [kWh].
$Ncycles_{eff}(b)$: Number actual cycles.
$P_{up}[t, b]$: Exchanged up power [kW].
$P_{down}[t, b]$: Exchanged down power [kW].
$Pup_{\sec\_res}(t,\ b)$: Increasing secondary reserve contribution [kW].
$Pdw_{\sec\_res}(t,\ b)$: Decreasing secondary reserve contribution [kW].
$Pup_{\text{ter}\_res}(t,\ b)$: Increasing tertiary reserve contribution [kW].
$Pdw_{\text{ter}\_res}(t,\ b)$: Decreasing tertiary reserve contribution [kW].
P_{ratio}: Auxiliary variable defining the ratio between the actual and the nominal power (usually called C-rate).
$u(t,b, n_{soc})$: Binary variable defining the SoC.
$u_{ch}/u_{dis}(t, b)$: Auxiliary variables defining the SoC or discharge.
$u_{\eta}(t, b, n_{\eta})$: Binary variable defining the charge or discharge efficiency.
$u_{ratio_E}(t, b, n_{pow})$: Binary variable defining the actual C-rate interval.
$u_{ratio_\eta}(t, b, n_{\eta})$: Binary variable defining the actual C-rate interval.
$w_{ch}(t,b)$: Binary variable defining the active SoC.

I. INTRODUCTION

Worldwide, in the electricity markets, the needs for balancing services, rapid generation ramping, and energy arbitrage are expected to increase with the rising of wind and solar energy penetration. Consequently, energy storage systems are supposed to play a major role in the future, thanks to their ability to provide different services to the electric grid, from peak shaving, load leveling, spinning reserve, capacity firming, up to frequency regulation [1][4][3]. Energy storage can also provide an economic alternative for relieving transmission congestion in regions where conventional generation and transmission expansion is problematic [5]. Many studies have shown that Battery Energy Storage Systems (BESS) economic viability is possible, e.g. in Germany [6] many existing BESS have proved successful in the ancillary services provision.

Generally speaking, establishing a complete and accurate BESS model is pivotal in order to study the interaction between grid-connected BESS and power system, providing an accurate evaluation of their performance. However, a detailed model generally asks for a high elaboration/simulation time that can affect the computational viability of the model itself.

BESS modelling differs for the degree of details they use to reproduce the battery behavior. Some of them manage the battery like a black-box, others reproduce the electric quantities seen at the battery terminals (i.e. voltage and current), some others go deeply into the chemical representation. Over the years, various models were developed aiming at estimating the operating conditions and predicting aging of a battery. It is possible group them in several categories [32][33][34][35]. *Electrochemical models* consider the chemical reactions taking in place a battery by accounting for mass, energy and momentum balances for each specie, phase and component of the cell. They are able to detail local distribution of concentration, electrical potential, current and temperature inside the cell. Unfortunately, these models need a heavy computation effort and are complex to be set. *Electrical models* adopted an equivalent electric circuit to represent voltage and current transient at the BESS external terminals. Actually, the accuracy of the model is correlated to complexity of the equivalent electric circuit and to the accuracy of the data adopted to set the model itself. Eventually, the complex electrochemical reactions inside a battery are significantly affected by random variables as ambient temperature and usage profiles, consequently mathematical *stochastic models* could be adopted [36][37].

The final goal of this present paper is to properly model BESS economic viability in the Ancillary Services Market (hereafter ASM). In an ASM, unsolved cross-areas congestions are managed and regulating reserves are collected on power plants. Simulating an ASM is a quite complex task, it requires to model many generators, loads and, eventually, BESSs for several market sessions, i.e. the total problem resulted to have a huge number of variables [10]. In the approach proposed, ASM has been modelled thanks to an ancillary market simulator named MODIS (Market Operation and DISpatching) [11]. It performs the optimal operation schedule over the simulated target year, with hourly detail, considering generation technical constraints and costs, transmission capacity limits between regions and operational requirements for system security (operating reserves).

Focusing on BESS representation within an ASM model, in order to limit the computational effort, very simplified models are normally adopted: constant efficiency, ideal/constant power and capacity bound, etc. are the most common assumptions. These approximations, if not managed properly, could cause errors in the evaluation of BESS performances. Unfortunately, Electrochemical or Electrical BESS models, i.e. model capable to provide an adequate accuracy in the BESS' behavior simulation, cannot be directly adopted due to the computational effort required.

In literature many papers focus on BESS contribution to the ancillary services market: [12] investigates the opportunity to control industrial loads and storage for demand response, day-ahead scheduling is the target of the algorithm proposed. [13] evaluates BESS contribution to spinning reserve and frequency control proposing an innovative operational strategy devoted to maximize the regulation effectiveness; a statistical approach is adopted in order to quantify the approach performances. [14] proposed a detailed model of both the energy and the ancillary services market, taking into account traditional power plants and BESSs; a robust approach is proposed in order to properly evaluate uncertainty. [15] approached a quite similar problem exploiting Nash-Cournot equilibrium model to evaluate BESS contribution in supporting renewable generation. Also [16] focuses on BESS participation in day ahead and reserve markets, in particular it is investigated the possibility of an aggregated regulation of several resources distributed in the grid.

Nevertheless, as already introduced, in such works BESSs are evaluated adopting simplified model, i.e. numerical results could be affected by the assumptions adopted to limit the computational effort of the simulation. [17] proposes a preliminary investigation of the point, demonstrating how degradation phenomena (i.e. performances degradation) could strongly affects the BESS economic viability.

The technical focus of this paper is on a new BESS model based on an abstract vision of the electrochemical cell behavior. In the model proposed, experimentally fitted analytical equations are adopted. The target of the approach proposed is to guarantee a viable computational effort but also to provide a proper modelling of BESS efficiency, cycle lifetime, SOC impact on maximum charge/discharge power. Eventually, such a model is adopted in a numerical simulation of the Italian ancillary services market in order to evaluate its economically feasibility.

The paper is structured as follow. In chapter II the new BESS model is presented. In chapter III, the results of some tests aimed at validating the model are reported. Eventually, in chapter IV a test case based on the Italian ASM for the short-medium period (real-size case study with 237 thermal units, 6 equivalent hydro units and 10 market zones) is detailed in order to validate the battery model functionalities. Finally, conclusions are drawn in chapter V.

II. Model Formulation

This paper proposes a new battery model designed to be integrated in the ASM simulator MODIS, a multi-area market simulator, specifically developed for the Italian ASM [11]. The tool is capable to reproduce, for a whole year, with hourly discretization, the balancing actions of the various generating units, by respecting the required security margins. In the model, BESS can provide different services such as balancing, secondary and tertiary reserve, in the same way of the other players in the market (thermal and hydro units). The unit commitment problem under security constraints (SCUC) is solved using a deterministic optimization approach, aiming at minimizing the overall costs associated with the ancillary services provided by the enabled units. Such a problem is formulated as a Mixed Integer Linear Programming (MILP) and it is implemented through a Branch-and-Cut search for finding the optimal solution. The methodology is detailed in [18] and results to be capable of finding the optimal solution requiring significantly less CPU time compared to other solvers such as SBB, DICOPT and CPLEX [19]. Other deterministic methods proposed in literature include priority list [20], integer mathematical programming [21], Branch-and-Bound search [22], dynamic programming [23], Lagrangian relaxation [24] and decomposition techniques [25].

Because of the complexity of the model and the required computational time, MODIS takes advantage of an external library (GUROBI 7.5) that solves the optimization problem through the aforementioned Branch-and-Cut search algorithm. The algorithm requires as input the main characteristic (max. and min. power, fuel cost, efficiency, bidding strategy, max. and min. volume constraints for the hydro power plants) of the modeled power units, their DAM (Day Ahead Market) dispatching program and their bidding prices, the installed renewable energy sources capacity, the unbalance and the required reserves. The main constraints are [26]:

- power balance equation between load and generation;
- secondary and tertiary reserve demand constraints;
- power unit technical constraints, such as minimum start-up and shutdown times, operative costs and min./max. capacity;
- start-up cost, according to Italian ASM pricing rules;
- constraints on transmission capacity;
- network integrity constraints.

All the services requested in a given area and in a given time step could be provided by eligible units and by the available capacity interconnecting each area. Actually, the objective function consists in the minimization of costs associated with all the hydro-thermal balancing production, as shown below:

$$fo = P_{th,t}^{up} \cdot Bid_{th,t}^{up} - P_{th,t}^{down} \cdot Bid_{th,t}^{down} + P_{hyd,t}^{up} \cdot Bid_{hyd,t}^{up} - P_{hyd,t}^{down} \cdot Bid_{hyd,t}^{down}$$

Where $P_{th,t}^{up}$, $P_{th,t}^{down}$, $P_{hyd,t}^{up}$ and $P_{hyd,t}^{down}$ represent the balancing up and down powers of thermal- and hydro-electric plants, whereas $Bid_{th,t}^{up}$, $Bid_{th,t}^{down}$, $Bid_{hyd,t}^{up}$ and $Bid_{hyd,t}^{down}$ are the corresponding bidding offers.

In such a perspective, the BESS model proposed is designed to take into account a set of technical and economic aspects, affecting the performance and profitability of its operation:

- BESS investment costs;
- maximum available charge/discharge power, as a non-linear function of the SoC (State-of-Charge) of the battery;
- Depth of Discharge (DoD) penalty-cost, related to BESS lifetime reduction and to the efficiency decrease affecting BESS operated at extreme DoD conditions;
- Charge (discharge) efficiency as non-linear function of the C-rate;
- C-rate penalty cost, related to BESS cycle life decrease affecting BESS operated at high charge/discharge rates;
- Capacity fade, related to linear reduction of capacity with respect to cycles

To make the problem mathematically tractable, a piecewise linearization of discharge/charge power and efficiency curves is adopted.

In the following diagram block the proposed model is schematized.

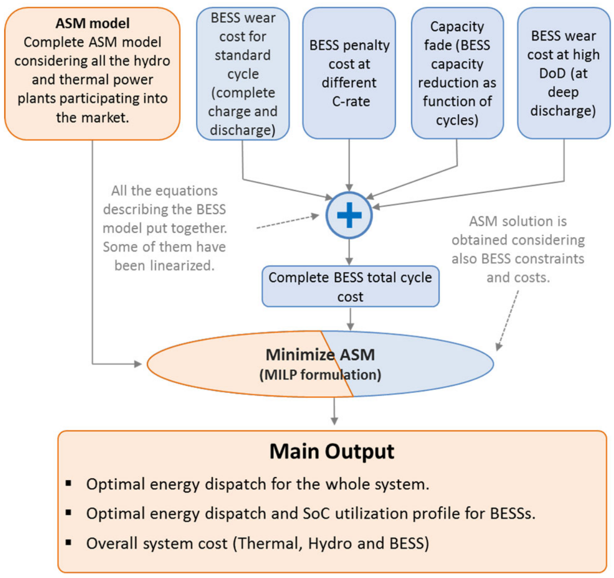

Figure 1: ASM + BESS model diagram block.

The proposed BESS model is formulated as a MILP one in order to fit the current main model formulation and to effectively describe the technical constraints that characterize BESSs behavior.

The overall optimization is carried out in order to minimize the cost of the ASM (cost given by upward and downward moves of thermal and hydro-electric power plants). In such a market BESS could reduce dispatch cost of providing the requested services competing with traditional units. BESS capital and operational costs are directly taken into account in the objective function, i.e. the tool activates BESSs only if dispatch costs of traditional units are greater than BESSs duty cycle costs.

The formulation proposed is useful to investigate BESSs economic performance in the ASM from two different perspectives:

- Transmission System Operator - not directly involved in the investment but concerned in reducing the cost of ancillary services, i.e. owner's gains aren't taken into account.
- Market player investing in BESSs - in this case market operator's gain can be modelled increasing BESS investment cost by a proper quantity, to represent the minimum profit expectation.

BESS economics optimization is performed concurrently with the ASM model through the following formulation:

$\forall t$ in time, $\forall b$ in battery, $\forall k$ in n_{pow}:

$$min \sum_{t,b,k} \left\{ \frac{IC[b]}{Ncyclemax[b,k]} \cdot Cap_{nom}[b] \cdot \frac{E_{level}[t,b,k]}{2 \cdot CapMax_{residual}[b]} + BESS\_cost[t,b] \cdot Cap_{nom}[b] \right\} \tag{1}$$

The first term of the objective function represents the battery ageing cost, function of the utilization factor of the battery (with respect to the nominal number of cycles $Ncyclemax$).

In the formula, E_{level} is the sum of the energy exchanged in the charging semi-cycle and in the discharging semi-cycle. This energy is subdivided into n_{pow} different levels, according with the amount of power exchanged at different charge levels. A higher energy level (i.e. a higher charge/discharge current) would represent a higher cost for the system due to a reduction of the BESS lifetime. The optimization is carried out over a daily timeframe and results are function of the BESS behavior in the previous optimization interval.

$CapMax_{residual}$ represents the residual capacity considering a capacity fade over the optimization period as function of the number of cycles carried out in the previous simulated period. It is computed adopting a linear relationship between capacity and number of cycles and assuming end-of-cycle-life reached at 80% of nominal capacity.

The second term of the objective function is the economical representation of the battery degradation at high DoD.

The BESS objective function (1) is subject to the following constraints, defined $\forall t$ in time, $\forall b$ in BESS, $\forall i$ in n_{SoC}, $\forall j$ in n_{η}, $\forall k$ in n_{POW}.

Chargeable and dischargeable power

$$0 \leq P_{up}[t,b] \leq u_{dis}[t,b] \cdot Pmax[b] \tag{2}$$

$$u_{ch}[t,b] \cdot Pmin[b] \leq P_{down}[t,b] \leq 0 \tag{3}$$

Where:

$$u_{ch}[t,b] + u_{dis}[t,b] \leq 1 \tag{4}$$

The binary variables $u_{ch}[t,b]$ and $u_{dis}[t,b]$ identify the activated charge state, and are used in (2) and (3) to limit the chargeable and dischargeable power between the minimum and the maximum limit; eq.(4) is needed to ensure that only one state (charge or discharge) is active in each time step and for each battery. However, chargeable and dischargeable powers are limited not only by the minimum and maximum powers respectively, but they also depend on the actual BESS state of charge. Equations (5) and (6) are needed to model this dependency.

$$P_{up}[t,b] \leq P_{max\_dis}[t,b] \tag{5}$$

$$P_{down}[t,b] \geq P_{min\_ch}[t,b] \tag{6}$$

$P_{max\_dis}[t,b]$ and $P_{min\_ch}[t,b]$ are respectively the maximum and the minimum powers that can be delivered and absorbed by the battery according with the actual SoC, as described below.

Maximum available chargeable and dischargeable power

In the literature, it is well known that for some storage technologies the (charge or discharge) power that can be actually exchanged depends on current SoC [8]. So, to model this aspect, the following constraints are introduced:

$$P_{max\_dis}[t,b] = \sum_{i=1}^{n_{soc}} u[t,b,i] \cdot PowStep_{dis}[i,b] \tag{7}$$

$$P_{min\_ch}[t,b] = \sum_{i=1}^{n_{soc}} u[t,b,i] \cdot PowStep_{ch}[i,b] \tag{8}$$

Where:

$$PowStep_{dis}[i,b] = (P_{max,SoC}[i,b] - P_{max,SoC}[i-1,b]) \cdot P_{max} \tag{9}$$

$$PowStep_{ch}[i,b] = (P_{min,SoC}[i,b] - P_{min,SoC}[i-1,b]) \cdot P_{min} \tag{10}$$

State of Charge

$$Cap_{min} \leq SoC\,[t,b] \leq Cap_{nom} \tag{11}$$

$$SoC\,[t,b] = -\frac{P_{up}[t,b]}{\eta_{dis}[t,b]} - P_{down}[t,b] * \eta_{ch}[t,b] + SoC\,[t-1,b] \tag{12}$$

Equation (12) defines the battery SoC at the time step *t* as the sum of the SoC at the previous time step, the charge and the discharge energy.

$$u(t,b,i=0) = 1 \tag{13}$$

$$SoC\,[t,b] \geq SoCStep[i,b] \cdot (u[t,b,i] + \varepsilon) \tag{14}$$

$$SoC\,[t,b] - SoCStep[i,b] \leq M \cdot u[t,b,i] \tag{15}$$

Equations (13-15) are needed to define the binary variable $u[t,b,i]$, which is equal to 1 only when the actual SoC of the BESS is higher than the minimum SoC of the considered interval *i*.

Energy constraints

$$E_{cycle}[b] = \sum_{t=0}^{24}\left(\frac{P_{up}[t,b]}{\eta_{dis}[t,b]} - P_{down}[t,b] \cdot \eta_{ch}[t,b]\right) \tag{16}$$

The energy exchanged over the optimization period (t=1,…24) by the battery is computed as the sum of cumulated and delivered energies for each time step, considering charge and discharge efficiencies. According with this definition, energy is always a positive quantity and $\eta_{dis}[t,b]$ and $\eta_{ch}[t,b]$ could be time dependent or flat on the base of chosen model complexity.

Not-linear efficiency constraints

In reality, BESS power depends also on the efficiency, which depends, in turn, on the C-rate (that is the ratio between actual charged, or discharged power, and the nominal power). However, as it can be noted in equations (16) and (17), this dependency implies the multiplication between two continuous variables (power and efficiency), that should be linearized to be implemented in the existing MILPmodel. In order to linearize these products, it has been chosen to adopt the binary expansion presented in [27].

First of all, it is necessary to introduce an auxiliary variable representing the C-rate:

$$P_{ratio}[t,b] = \frac{P_{up}[t,b] - P_{down}[t,b]}{\alpha[b] * Pmax[b]} \tag{17}$$

Where$\alpha[b]$ is the Energy/Power ratio, that means the ratio between the nominal capacity and the nominal power. Then a logic constraint, linearized using a classic BigM approach using equations (18) and (19), must be introduced in order to link C-rate and the efficiency discretization curve:

$$P_{ratio}[t,b] \geq PowThs_{\eta}[j,b] \cdot u_{ratio_{\eta}}[t,b,j] \tag{18}$$

$$P_{ratio}[t,b] - PowThs_{\eta}[j,b] \leq M \cdot u_{ratio_{\eta}}[t,b,j] \tag{19}$$

$PowThs_{\eta}[j,b]$ is defined as the inverse of the number of *j* intervals chosen to discretize the efficiency curve (i.e. if $j = 4$ discretization intervals are adopted, $PowThs_{\eta}[1,b]$ would be 0.25). In this way, equations (18) and (19) define the binary variable $u_{ratio_{\eta}}[t,b,j]$, which is activated only when C-rate is higher than the j-C-rate interval. In turn, $u_{ratio_{\eta}}[t,b,j]$ is used to define another binary variable $u_{\eta}[t,b,j]$ that allows to select in which range of efficiency the battery is operating:

$$u_{\eta}[t,b,j] = u_{ratio_{\eta}}[t,b,j] - u_{ratio_{\eta}}[t,b,j+1] \tag{20}$$

By means of binary variable $u_{\eta}[t,b,j]$ it is possible to implement the binary expansion model with equations (21) and (22). In this way it is finally possible to define $Pdw_{eta}[t,b]$ and $Pup_{eta}[t,b]$ (equations (23) and (24)) which represent the actual charged and discharged powers with efficiency already included.

$$Pdw_{eta_j}[t,b,j] = P_{down}[t,b] \cdot \eta_{ch}[j,b] \cdot u_{\eta}[t,b,j] \tag{21}$$

$$Pup_{eta_j}[t,b,j] = \frac{Pup[t,b]}{\eta_{dis}[j,b]} \cdot u_{\eta}[t,b,j] \tag{22}$$

$$Pdw_{eta}[t,b] = \sum_{j=1}^{n_{\eta}} Pdown_{eta_j}[t,b,j] \tag{23}$$

$$Pup_{eta}[t,b] = \sum_{j=1}^{n_{\eta}} Pup_{eta_j}[t,b,j] \tag{24}$$

In turn, Pdw_{eta_j} and Pup_{eta_j} are defined as:

Finally, the energy cycle over the optimization period is computed as:

$$E_{cycle}[b] = \sum_{t=0}^{24}(Pup_{eta}[t,b] - Pdown_{eta}[t,b]) \tag{21}$$

Battery cycle reduction

As already introduced, the battery cycle reduction with the increasing of C-rate is also modeled. This constraint is carried out splitting BESS production in different steps (n_{pow}), each one characterized by a permissible power range. The following equations, based on BigM approach, define the binary variable $u_{ratio_E}[t,b,j]$, used to select in which range of C-rate the battery is operating.

$$P_{ratio}[t,b] \geq PowThs_E[k,b] \cdot u_{ratio_E}[t,b,k] \quad (22)$$
$$P_{ratio}[t,b] - PowThs_E[k,b] \leq M \cdot u_{ratio_E}[t,b,k] \quad (23)$$

Where $PowThs_E[k,b]$ is defined as the ratio between 1 and the number of k C-rate intervals (i.e. if $k=4$ discretization intervals are adopted, $PowThs_E[1,b]$ would be 0.25). Consequently, the energy level is computed as:

$$E_{level}[t,b,\mathrm{k}] = (Pup_{eta}[t,b] - Pdown_{eta}[t,b]) \cdot u_{ratio_E}[t,b,\mathrm{k}] - (Pup_{eta}[t,b] - Pdown_{eta}[t,b]) \cdot u_{ratio_E}[t,b,\mathrm{k}+1] \quad (24)$$

Also in this case, it is necessary to linearize the product of the binary $u_{ratio_E}[t,b,k]$ and the continuous variable $(Pup_{eta} - Pdown_{eta})$.

Number of cycles

The daily effective number of cycles carried out by the battery is computed as the ratio between the daily exchanged energy and two times the residual battery capacity (two times because a total cycle, which is the double of the capacity, must be considered):

$$N°cycles_{eff}[b] = \frac{Ecycle[b]}{2 \cdot CapMax_{residual}[b]} \quad (25)$$

Capacity reduction

In the presented model, the battery capacity is not assumed constant, but it changes day by day according with the energy exchanged in previous time steps, or in other words, according with the number of cycles already cycled. BESS capacity has been modeled considering a linear reduction, with respect to cycles, from 100% of nominal capacity to 80% of nominal capacity (conventionally assumed as BESS end of life). In each day, capacity reduction is computed as the product between nominal capacity and the ratio between the carried out cycles in that day and the cycle life.

$$CMax_{residual}[b] = \sum_j \left(\widetilde{CMax_{residual}}[b] - Cap_{nom}[b] \cdot \frac{\sum_k N°cycles_{eff\_k}[b,k]}{N°cyclesmax[b]} \cdot \frac{20}{100}\right) \quad (26)$$

Where $\widetilde{CMax_{residual}}[b]$ is the residual capacity at the previous simulation period, which is the remaining capacity at the end of the day ahead the considered day, and $N°cycles_{eff\_k}[b,k]$ is the number of daily carried out cycles according with C-rate:

$$N°cycles_{eff}[b] = \frac{\sum_{t=0}^{24} E_{level}[t,b,\mathrm{k}]}{2 \cdot CapMax_{residual}[b]} \quad (31)$$

Additional cost at high DoD

BESS aging increases when BESS is operated at high Depth of Discharge (low SoC, when the battery completes the discharging phase). In order to model such behavior, an economic penalization, named $CostDoD[t,b]$, has been introduced in the objective function when battery is operated in the first intervals of the SoC discretization curve. Such intervals are detected by means of a new binary variable $w_{ch}[t,b]$, defined by equations (33-35), which is activated only when BESS starts a new charging phase (so at the end of a discharging phase)

$$CostDoD[t,b] \geq \sum_{i=1}^{n_{SoC}} u[t-1,b,i] \cdot c_{dod}[b,i] - M \cdot (1 - w_{ch}[t,b]) \quad (32)$$

$$u_{ch}[t,b] - u_{ch}[t-1,b] \leq w_{ch}[t,b] \quad (33)$$
$$u_{ch}[t,b] \geq w_{ch}[t,b] \quad (34)$$
$$1 - u_{ch}[t-1,b] \geq w_{ch}[t,b] \quad (35)$$

All the previously described BESS technical parameters have been set accordingly to experimental measures performed by Politecnico di Milano research group [28].

Secondary and tertiary reserve

In the developed model, BESS are exploited in order to provide secondary regulation and tertiary regulation reserve. The equations below define the up and down powers available for the reserves.

$$0 \leq Pup_{res}[t,b] \leq Pmax[b] \quad (36)$$
$$Pmin[b] \leq Pdown_{res}[t,b] \leq 0 \quad (37)$$
$$Pup_{res}[t,b] \leq P_{\max\_dis}[t,b] - Pup[t,b] - Pdown[t,b] \quad (38)$$
$$Pdown_{res}[t,b] \geq P_{\max\_ch}[t,b] - Pup[t,b] - Pdown[t,b] \quad (39)$$
$$SoC_{res}[t,b] = SoC[t,b] - Pdown_{res}[t,b] \cdot \eta_{ch}[b] - \frac{Pup_{res}[t,b]}{\eta_{dis}[b]} \quad (40)$$

Where $Pmax[b]$ and $Pmin[b]$ are the nominal powers for the tertiary reserve (both zonal and pool) and the half-band available for the secondary reserve. In (38) and (39), the increasing and decreasing powers available for the reserve are limited according to the difference between the battery maximum power and the power already employed in the energy balance using equation (36) and (37). Reserve contributions are also subject to SoC constraints in (40).

III. Models Set Up

The presented BESS model had been tested simulating a period of 7 days on a system characterized by 10 interconnected market zones; such a model is inspired to the Italian system (see Fig. 2).

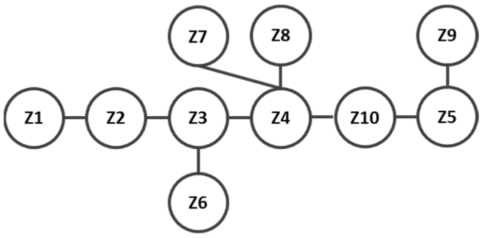

Figure 2. Model validation: network structure.

A Li-ion battery with a nominal power equal to 20 MW, a nominal capacity of 20 MWh and service life at 80% of DoD equal to 4000 cycles [29] has been installed to this purpose in each market zone. This technology is characterized by an almost constant maximum power (both for charging and discharging phase) curve as function of SoC, discretized adopting as n_{soc} 10 steps. As regarding the capital cost, 300 €/kWh has been chosen according to [30].

The model has been tested starting from the so-called "*Reference Model*" (hereafter *Ref.Model*), characterized by:

- modelling of the capacity fade;
- constant charge and discharge efficiencies equal to 0.95;
- absence of penalties correlated to BESS lifetime reduction due to high C-rate;
- absence of penalties correlated to BESS lifetime reduction due to high DoD;
- BESSs are not enabled to secondary/tertiary reserve services but can provide balancing service.

Consequently, the battery energy is simply computed with (16), adopting constant discharge and charge efficiencies.

The model assessment has been carried out by implementing model specifics (shown in previous chapter) one at a time:

- *"C-rate model"*, which considers a lifetime reduction due to high C-rate. Specifically, a service life of 5250 cycles below 0.5C and of 3500 cycles above 0.5C is considered. This functionality has been tested adding eq. (26-28).
- *"Non-Linear Efficiency model"*, characterized by a discharge/charge efficiency function of the battery C-rate. The efficiency curve shown in Fig. 3 (blue curve) has been discretized using as n_η 4 different steps (red curve). This functionality has been tested adding equations (17-25).
- *"Complete model"*: constraints of both *"C-rate model"* and *"Non-linear Efficiency model"* have been implemented.
- *"Complete model + reserve"*: BESS complete model has been regulated in order to provide also the reserve service on the ASM. This functionality has been tested adding equations (36-40).

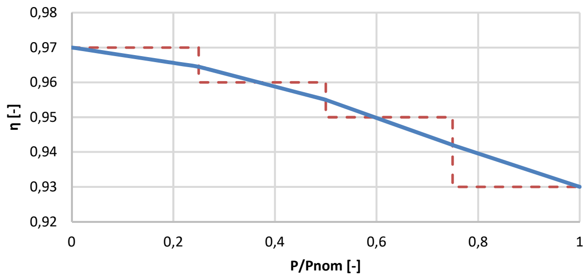

Figure 3. Charge and Discharge efficiency.

DoD constraints (32-35) had not been analyzed due to lack of real laboratory measurements or reliable/detailed data in literature. Moreover, DoD constraints are supposed to have marginal impact on BESS performances.

Table I. MODEL ASSESSMENT: SENSITIVITY REVIEW

Sensitivity Resume	Basic Equations (2-16)	Capacity Fade (29-30)	Cycle Life reduction with C-rate (26-28)	Variable (Dis)Charge Efficiency (17-25)	Reserve (36-40)
Ref.Model	✓	✓	X	X	X
C-rate Model	✓	✓	✓	X	X
Non-linear Efficiency Model	✓	✓	X	✓	X
Complete Model	✓	✓	✓	✓	X
Complete + Reserve	✓	✓	✓	✓	✓

The different models had been compared in terms of power curve of durability, ASM objective function, computational time, number of constraints. The comparison helps to check the correct implementation of the constraints and the impact of modeling some aspects of the BESS. The chart in Fig. 3 shows the battery durability production curve; in order to simplify chart interpretation, only the battery of market zone 1 is shown.

Applying the "*C-rate model"*, two levels of production can be distinguished because of different costs associated with different production levels: below and above 10 MW (corresponding to 0.5C, see arrows #1 in Figure 4). As a consequence, with "*C-rate model*" applied, BESS is frequently activated at lower power level with respect to *"Ref.Model"*.

The *"Non-linear efficiency model"* reduces the maximum delivered power (see focus #2 in Figure 4) because of the average constant efficiency adopted in the *"Ref model"* (equal to 0.95) is higher than the one of the *"Non-linear efficiency model"* at 1C. Furthermore, the number of hours in which BESS works at medium-low power increases with respect to the *"Ref model",* because of the higher efficiency at low C-rate (see focus #3 in Fig. 4).

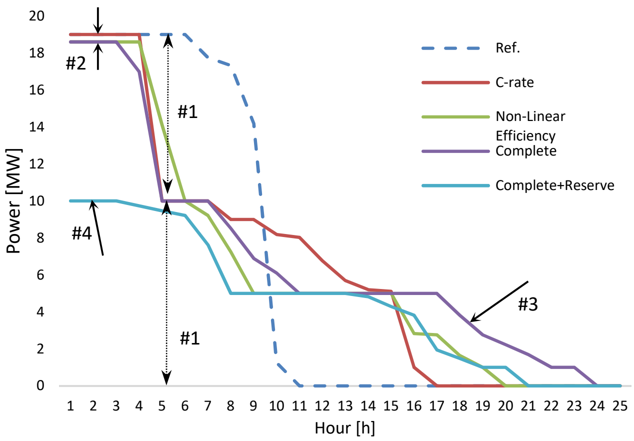

Figure 4. Battery delivered power in each model.

The introduction of *batteries reserve requirements* causes a significant reduction on the batteries injections (see focus #4 in Fig. 4) because of the need to preserve an available up and down regulation capacity.

The reduction of BESS production in the *"Complete model + reserve"* is consistent and is reflected in a lower battery objective function, quantifiable in 27.3% (from 66.05 k€ to 48.01 k€), i.e. in lower BESS exploitation costs. Significant is also the impact, in terms of objective function variation, of the *"C-rate model*": the BESS objective function reduces of 11% (from 66.05 k€ to 58.83 k€) against a rise of the production thanks to the lower cost at low C-rate. On the contrary, the objective function reduction caused by the *"Non-linear efficiency model"* is limited to 1.23% with respect to the "*Ref.Model"* (from 66.05 k€ to 65.24 k€), and it is mainly due to the decrease of the efficiency at high C-rates. Actually, over the simulation performed the C-rate resulted quite low. ASM asks BESS to contribute for time window equal or higher to one hour limiting, from the market point of view, the maximum C-rate BESS could be scheduled to; this motivate small efficiency fluctuations.

For each model, computational time and number of integer and continuous variables has been properly evaluated. The implementation of the variable efficiency as a function of the power exchanged (nonlinear constraints) (i.e. between power and variable efficiency in the *"Non-linear efficiency model*") has a very strong impact, adding 1152 binary quantities and 5616 constraints with respect to the "*Ref.Model*". Actually, affects significantly also the daily computational time: about three times the "*Ref.Model*".

TABLE II. ASSESSMENT RESULTS.

Model Specifics	BESS Objective Functions [k€]	BESS Exchanged Energy [MWh]	Daily Average Calculation Time [h]	N° of Integer Variables	N° of Constraints
Ref.Model	66.05	1759.8	0.30	5376	44582
C-rate Model	58.83	1878.8	0.31	5664	46886
Non-Linear efficiency	65.24	1738.1	1.36	6528	50198
Complete Model	60.70	1953.8	1.96	6816	52502
Complete+Reserve	48.01	1589.5	1.41	6816	53798

Model set up simulations validate the option to not model variable (dis)charge efficiency as a reasonable tradeoff, causing a marginal approximation in the objective function (1.23%) in order to achieve a strong reduction in the computational effort. Such a model is adopted in the study case reported in chapter IV.

Lastly, it should be interesting to analyze the impact of capacity fade, by comparing results, in terms of power curve od durability and cycled energy, obtained simulating one whole year adopting the "*Ref.Model*" with and without capacity fade.

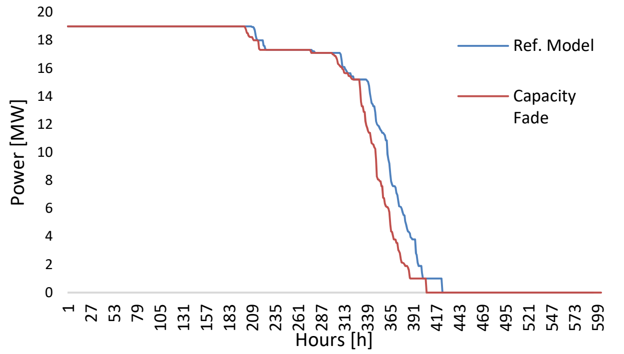

Figure 5: Battery delivered power in Reference and Capacity Fade models

As it can be noted (Fig. 5), capacity fade rightly causes a decrease of delivered power. Consequently, also the fluxed energy of a single BESS decreases from 14.1 GWh to 13.5 GWh, causing a reduction of about 3.8 % in one single year.

IV. CASE STUDY

Once validated, the tool proposed has been adopted in a realistic mid-term (2020) scenario tailored in the Italian system. BESS C-rate model has been adopted. Public data provided by Terna (Italian TSO [10]) and GME (Italian public company that operates power, gas and environmental markets [39]) were used to define the scenario in terms of:

- need of reserve (tertiary and secondary);
- balancing market need;
- list and characteristic of the hydro-thermal fleet enabled to participate to the ASM;
- network development.

A BESS equivalent model has been simulated in each geographical zone in order to investigate the economic benefit given by BESSs in relieving dispatching cost, from the point of view of the system operator (for this reason BESSs owner gains have not been considered).

Regarding BESSs sizing methodology, it has been chosen to adopt the lifespan criterion, which means sizing batteries in order to obtain a lifespan of about 12 years (adopting a reasonable BESSs calendar life [31]). Lifespan is function of the number of performed cycles, that are inversely proportional to the size, keeping the power constant. Different BESSs sizes have been considered: 5 MW, 10 MW, 20 MW, 40 MW and 60 MW with 1 hour as Energy/Power ratio. Table III reports the resulting installed capacity for each market zone.

TABLE III. SCENARIO CHARACTERIZATION.

Market Zone	Installed Capacity [MWh]	Installed Power [MW]	Secondary Reserve Half-Band [MW]	Investment Cost [€/kWh][1]	Cycle Life at 0.5C
North	10	10	1	350	4000
Center-North	20	20	2	350	4000
Center-South	10	10	1	350	4000
South	20	20	2	350	4000
Sicily	10	10	1	350	4000
Sardinia	10	10	1	350	4000

The economical profitability of investments in storage technologies and storage-related network services in the defined market scenario has been investigated in terms of BESS timespan (the time needed to reach BESS end of life) and cost saving for the system. Fig. 6 shows the duration curve related to the production of each BESS: it is possible to notice the different behavior of the battery in each different market zone and the influence of "*C-rate model*" implementation.

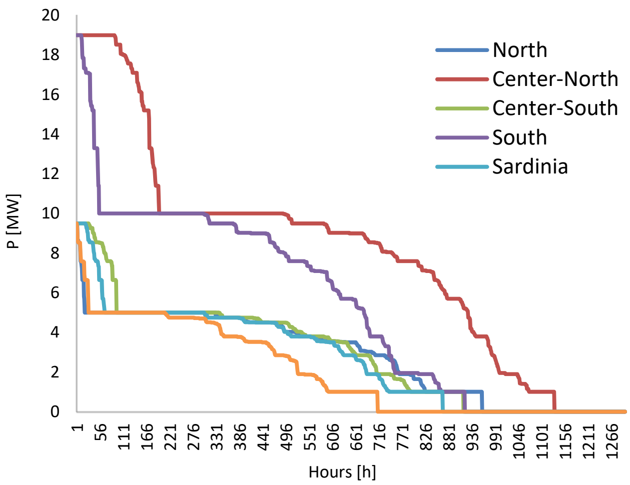

Figure 6. BESS delivered power in each zone.

Results, reported in Table IV, are detailed in terms of BESSs number of cycles carried-out in the simulated period and the corresponding cycle life and lifespan. It must be specified that the cycle life is computed taking into account the different degradation when battery works at various C-rate; whereas the lifespan is simply the ratio between the obtained cycle life and the number of carried-out cycles. These results depend on the chosen BESS sizes and specific scenario hypothesis adopted in each zone.

To properly access the economic benefit, in terms of cost saving for the system introduced by BESS deployment, the comparison of two different scenarios, with and without BESS, is reported. The system cost saving has been quantified in 12.1 M€ (Fig. 7), against a BESS cost of 2.4 M€ (this cost is related to batteries usage over a timespan of one year), resulting in an interesting economic viability of BESS exploitation. Should be noticed that this analysis disregard additional fix and variable costs (such as auxiliaries costs, operating and maintenance costs and site arrangement costs); actually, results obtained motivate to deepen the economic analysis and to evaluate regulatory framework schemes capable to effectively manage BESS units.

TABLE IV. BESS CYCLE LIFE AND LIFESPAN.

	Ncycles [cycles]	Cycle Life [cycles]	BESS Lifespan [years]
North	382.0	4967.2	13.0
Center-North	549.4	4803.2	8.7
Center-South	399.9	4893.8	12.2
South	363.4	4858.3	13.4
Sardinia	367.5	4880.4	13.3
Sicily	273.6	4989.5	18.2

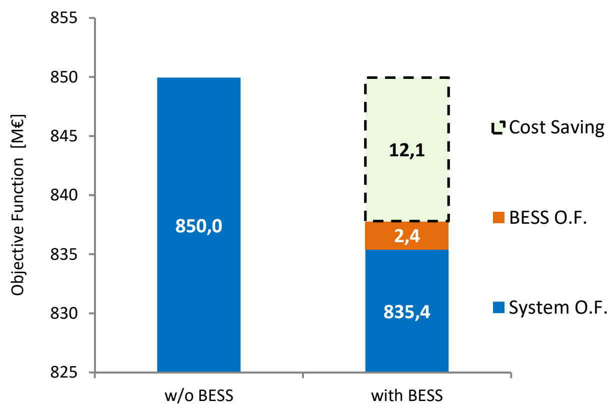

Figure 7. Comparison between total yearly system costs with and without BESS.

V. CONCLUSIONS

In this article, a MILP model suitable for evaluate BESS behavior and economic viability in the ASM has been developed and integrated in an ancillary services market simulator.

The accuracy of the model has been proved implementing one at a time the different BESS model specifics (constraints shown in chapter III) and analyzing batteries behavior during a period of 7 days on a 10-nodes-interconnected system. The validation phase was helpful in order to evaluate the impact of the different constraints in terms of model accuracy and computational effort. The validation phase reveals that BESS

[1] Specific investment cost is equal to 350 €/kWh.

behavior associated to the *C-Rate* model should not be neglected whilst the impact of the *Non-linear efficiency* model is not significant.

The presented model resulted suitable for investigating BESS impacts on ancillary services markets, in particular, in order to show a practical application useful in assessing potential cost savings associated with the deployment of BESS, the model has been applied to a mid-term scenario (2020) of the Italian ASM, simulating a whole year of exploitation.

Comparing the proposed model to the one commonly adopted in literature, results a higher complexity and consequently a higher accuracy in the BESS performances evaluation; at the same time, the mathematical formulation proposed resulted in a viable computation effort.

The presented model resulted to be useful for a BESS design consistent with ancillary service needs, giving to investors a computational tool capable to help in the decision-making phase.

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