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Optimal Management Strategy of a Battery-Based Storage System to Improve Renewable Energy Integration in Distribution Networks

Samuele Grillo, *Member, IEEE*, Mattia Marinelli, *Member, IEEE*, Stefano Massucco, *Member, IEEE*, and Federico Silvestro, *Member, IEEE*

Abstract—The paper proposes the modeling and the optimal management of a hot-temperature (sodium nickel chloride) battery system coupled with wind generators connected to a medium voltage grid. A discrete-time model of the storage device reproducing the battery main dynamics (i.e., state of charge, temperature, current, protection, and limitation systems) has been developed. The model has been validated through some experimental tests. An optimal management strategy has been implemented based on a forward dynamic programming algorithm, specifically developed to exploit the energy price arbitrage along the optimization time horizon (“generation shifting”). Taking advantage of this strategy wind generation performances can be enhanced and adapted to load demand, obtaining an increased economic gain measured by the difference between the economic revenue obtained with and without the proposed generation shifting policy.

Index Terms—Battery plants, dynamic programming, power generation dispatch, renewable power generation, smart grids, storage systems.

NOMENCLATURE

The following symbols are defined in this paper.

DAM	Day ahead market.
PCC	Point of common coupling.
SNC	Sodium nickel chloride battery.
SOC	State of charge.

I. INTRODUCTION

IN THESE YEARS electric power systems are experiencing quite a big revolution due to the increase of power generators fed by renewable sources like wind and sun. In addition to that, this trend has been mixing with the concurrent course

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S. Grillo is with the Dipartimento di Elettrotecnica, Politecnico di Milano, piazza L. da Vinci 32, I-20133 Milano, Italy (e-mail: samuele.grillo@polimi.it).

M. Marinelli, S. Massucco, and F. Silvestro are with the Department of Naval Architecture and Electrical Engineering, University of Genova, via all’Opera Pia 11/A, I-16145 Genova, Italy (e-mail: mattia.marinelli@unige.it; stefano.massucco@unige.it; federico.silvestro@unige.it).

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in power generation practice of preferring distributed and dispersed medium and small power generators instead of few localized large power plants [1]. Beyond the great benefits that the combination of these two tendencies can achieve, there are still some significant drawbacks [2], [3]. In fact the intermittency which naturally characterizes the power production of renewable sources is one of the main concerns and some actions both from a technical and a regulatory point of view (e.g., adequate reservoir and incentive tariffs) have to be envisaged. The combination of intermittency and diffusion may also bring out and worsen problems in transmission and distribution networks. Using a traditional approach the solution can be provided only by transmission and distribution equipment reinforcement, which is, for sure, the most costly way to work out the complex problems posed by this new context.

A different solution is offered by energy storage devices which can be used to effectively improve renewable energy sources behavior from a grid perspective. Moreover storage systems can be exploited by owners and investors to mitigate the uncertainty deriving from renewable energy randomness. In fact, energy storage can be seen not only as an “energy buffer” to be used to keep the energy delivered at PCC as close as possible to the declared value at DAM closure, but also as reservoirs that can store the energy produced by renewable energy sources in off-peak periods in order to sell it when the energy price rises (on-peak periods) [4], [5]. This use of storage devices is similar to what done in the management of water basins: i) energy production during the day and, especially, during on-peak hours; ii) pumping of water to the basin—and, consequently, power consumption—at night, when energy price is usually low.

However, for the moment, the integrated storage and energy sources systems are not generally allowed to draw energy from the grid and so this policy cannot be applied unless the energy stored in the reservoirs is that produced by the local energy sources themselves. This difference let the management strategy previously described be defined as “generation shifting” since it is not an increase of load when price is low (as a consequence of a general decrease of power demand) but a shift in power production.

The “energy buffer” function that storage devices can accomplish is extremely important, but is strictly related to the regulatory framework. Although the intermittent nature of renewable energy sources is considered a problem, regulatory rules slightly penalize bad forecasts and slightly incentivize good practices.

Consequently the mere respect of forecasted generation profiles is not sufficiently remunerative. In order to justify the installation of storage system it is necessary to identify management procedures that increment the final outcome. The proposed “generation shifting,” in principle, can be applied in every configuration and in every regulatory framework.

The aim of this paper is twofold. On one hand the discrete-time model which implements the battery main dynamics (i.e., state of charge, temperature, current, protection, and limitation systems) is described. The models are strongly nonlinear and this fact requires a complexity reduction through a linearization of some parameters in order to obtain a closed-form solution of the discrete-time dynamic behavior of the batteries and the use of an algorithm suited for handling the intrinsic correlation with time introduced by the storage devices.

On the other hand an economical cost-benefit analysis has been performed. Taking advantage of the increased capabilities given by the combined use of renewable energy sources and storage devices, wind generation can be enhanced and adapted to load demand, obtaining an economical gain.

A dynamic-programming based algorithm [6] has been developed in order to define the optimal generation profile of the whole generation facility. Given an estimation of battery life and of economic gain the battery maximum expected cost to reach the break even point before the end of battery life has been evaluated.

In order to carry out the proposed analysis a simulated test facility representative of an on-the-field test site has been set up. The model of the storage equipment, made up of 280 17.8 kW-rated units, has been derived both from literature and experimental tests on a specific SNC battery. The wind generation profiles have been derived from a statistical analysis of the power production of six 850 kW-rated wind generators located in Sicily (Italy).

II. PROBLEM FORMULATION

A. The Optimization Problem

The optimization problem which lies under the “generation shifting” objective can be formulated as the maximization of a profit function. This profit derives from the coordinated management of renewable energy resources and storage facilities. The problem can be viewed as finding the optimal value of energy sold to the grid using both renewable sources and storage devices. Let

$$J := f(\mathbf{E}, \mathbf{u} | \mathbf{E}_{\text{ren}}, c) \quad (1)$$

be the total profit deriving from selling, at the price specified by c , the amount of energy \mathbf{E} , which is the algebraic sum of \mathbf{E}_{ren} , the energy that renewable sources are foreseen to produce, and $\mathbf{E}_{\text{stg}}(\mathbf{u})$, the energy produced/stored by the batteries according to what defined by the control vector \mathbf{u} which sets the mission of the storage devices. Thus, the solution of the problem can be expressed as finding the optimal values of the control vector \mathbf{u} so as to maximize the overall profit

$$J^* = \max_{\mathbf{u}} J. \quad (2)$$

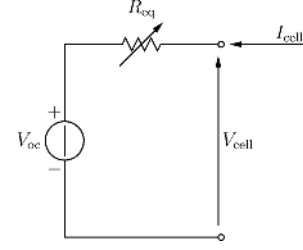


Fig. 1. First order model of SNC cell (V_{oc} is the open-circuit cell voltage and $R_{eq} = R_{eq}(SOC, T)$ is the equivalent cell resistance).

The energy \mathbf{E} on which the maximization is carried out is the production profile exposed to the grid by the plant. As shown in (1), J directly depends on the production forecasts of both renewable energy sources and energy market prices, which are supposed to be given. For what concerns energy prices, it is worth noting that energy can be paid according to some bilateral contracts, thus making the prices be known *a priori*.

B. Discrete-Time Models for Storage Equipment

The models of the energy storage equipment are intrinsically continuous. However, the plan of the amount of energy that will be provided to the grid is settled in the DAM some hours—usually one day—before the actual exchange would take place and on a (quarter-)hourly basis. This means that within the scheduler framework the coupling between energy storage devices and renewable energy sources is done by means of averaged models.

The proposed model of the SNC battery is composed by a set of N units, each of which with nominal values of 17.8 kW-14.2 kWh [7]. Each unit is composed by n_p parallels of n_s cells connected in series. It is assumed that all the cells are perfectly balanced and thus the tasks requested to the storage system are equally divided among the N units that constitute the storage system.

Under these assumptions all the dynamics are built in the single equivalent cell. The modeled dynamics regard SOC behavior, electrochemical conversion, and thermal characterization. The model used in the present work is shown in Fig. 1 [8]. Usually, complete models involve the presence of at least one parallel R-C branch in series with R_{eq} in order to take account of mid- and fast-acting dynamics and describe the battery behavior in a more complete way [9]. However, the exact characterization on the batteries is out of the scope of the present work, which is mainly focused on the long-term management of this kind of storage devices.

The discrete-time model of the storage device system can be expressed as

$$\begin{cases} \Delta x_{\text{soc}} = x_{\text{soc}_{i+1}} - x_{\text{soc}_i} = -\frac{I_{\text{stg}}}{N n_p C} \Delta t \\ V_{\text{stg}} = n_s V_{oc} - \frac{n_s}{N n_p} I_{\text{stg}} R_{eq} \\ P_R = \frac{n_s}{N n_p} I_{\text{stg}}^2 R_{eq} \\ \Delta E = E_{i+1} - E_i = (V_{\text{stg}} I_{\text{stg}} - P_{aux}) \Delta t \\ \Delta T = T_{i+1} - T_i = \frac{T - T_i}{R_{th}} \Delta t + P_R \Delta t + Q_{aux} \Delta t_{act} \end{cases} \quad (3)$$

where $I_{\text{stg}} = N I_{\text{batt}} = N n_p I_{\text{cell}}$ is the sum of the battery currents, C is the cell capacity, $V_{\text{stg}} = V_{\text{batt}} = n_s V_{\text{cell}}$ is the battery voltage, R_{eq} is the cell equivalent resistance, $n_s / R_{eq} N n_p$ is the overall equivalent resistance of the storage device, P_R is

TABLE I
VALUES OF THE MAIN BATTERY PARAMETERS

C	V_{int}	I_{nom}	P_{aux}		Q_{aux}		R_{th}	C_{th}	N	n_p	n_s	\hat{T}
			heater	cooler	heater	cooler						
Ah	V	A	W	W	W _{th}	W _{th}	K/W _{th}	kJ/K	—	—	—	°C
32	2.58	32	190	60	190	8250	2.5	80.64	280	2	108	25

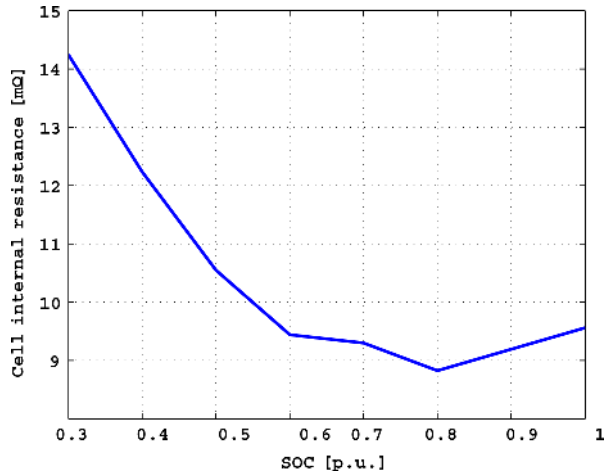


Fig. 2. Cell internal resistance during a controlled discharging cycle at 300 °C.

the thermal power dissipated due to Joule effect, E is the electrical energy flowing through the batteries, T_i is the temperature of the storage system at time i , P_{aux} is the electrical power used by auxiliary services (i.e., heaters and coolers), R_{th} and C_{th} are heat resistance and capacity, Q_{aux} is the heat transfer due to auxiliary service intervention, \hat{T} is the room temperature, and $\Delta t_{\text{act}} \leq \Delta t$ is the amount of time auxiliary services are active. The numerical values of these parameters are reported in Table I.

One of the main drawbacks of hot-temperature batteries is that, even though provided with good thermal shields, they have thermal losses due to natural cooling. For the 17.8 kW module used in the present work these losses reach the value of almost 110 W_{th} at the cell internal nominal working temperature of 300 °C. Moreover, if left in stand-by, the batteries cool down to room temperature (25 °C) in 7 days. These two values (i.e., thermal losses and cooling time) were used to estimate the thermal parameters of the battery model. In fact the equivalent thermal resistance R_{th} has been evaluated as the ratio between the temperature gap (275 °C) and the thermal losses (W_{th}) whereas the thermal time constant ($3\tau = 3R_{\text{th}}C_{\text{th}} = 168$ h) has been used to estimate the thermal capacity.

In order to use this model the solutions for SOC, temperature and supplied energy—the “state variables” of problem (3)—have been derived in closed form using a symbolic resolution tool. Being a nonlinear function of SOC and temperature, the equivalent internal resistance was linearized through least squares minimization in order to obtain convergence for the symbolic resolution process.

1) *Equivalent Internal Resistance Linearization*: The equivalent internal cell resistance for the considered SNC battery can be written as

$$R_{\text{eq}} = (k_1 + m(x_{\text{soc}} - k_2))(1 + \alpha(T - 300)) \quad (4)$$

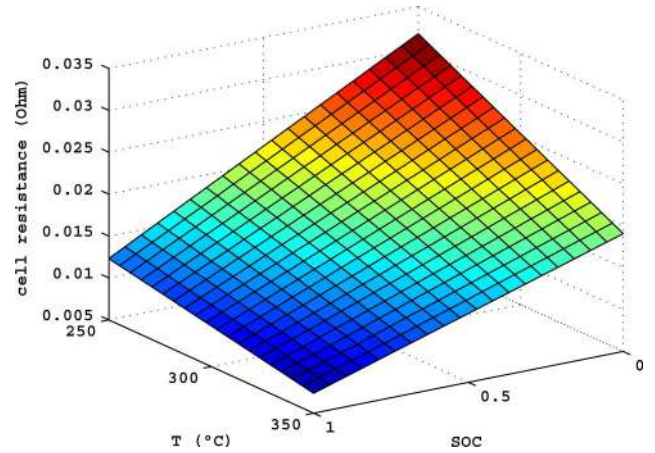


Fig. 3. Plot of the nonlinear cell equivalent resistance, function of SOC and temperature as described in (4).

TABLE II
VALUES OF THE PARAMETERS OF THE EXPRESSION OF INTERNAL RESISTANCE AS FUNCTION OF SOC AND TEMPERATURE

k_1	k_2	m	α
Ω	—	Ω	$^{\circ}\text{C}^{-1}$
0.0118	-0.875	-0.0156	-0.005

where k_1 is a constant term, k_2 is the reference value for SOC (i.e., that through which the internal resistance is only function of temperature), m is the weight of dependence on SOC, and α is the thermal coefficient. Function (4) has been derived from [10]–[12] while the parameters were estimated from experimental measurements provided by the battery manufacturer. Data, shown in Fig. 2, have been derived by measuring the ratio between voltage step amplitudes and the corresponding currents during a controlled discharging cycle from SOC = 1 to SOC = 0.3 with cell temperature within 300 °C ± 5%. For the considered SNC batteries these parameters were set to the values shown in Table II [13]. The plot of function (4) is shown in Fig. 3. Data and parameters of the adopted model are related to the activity mentioned in [7].

The least squares minimization algorithm was used to find the coefficients—values are reported in Table III—of the plane

$$\hat{R}_{\text{eq}} = \hat{k}_1 x_{\text{soc}} + \hat{k}_2 T + \hat{k}_3 \quad (5)$$

that best approximate the surface (4) according to

$$\min_{\hat{k}_1, \hat{k}_2, \hat{k}_3 \in \mathbb{R}} \|\hat{R}_{\text{eq}} - R_{\text{eq}}\|^2. \quad (6)$$

Fig. 4 shows the error done in using the linear model instead of the nonlinear one. It can be clearly seen that the average error is below 5% and that it increases at border conditions (i.e., low/high SOC and low/high temperatures) where the battery is

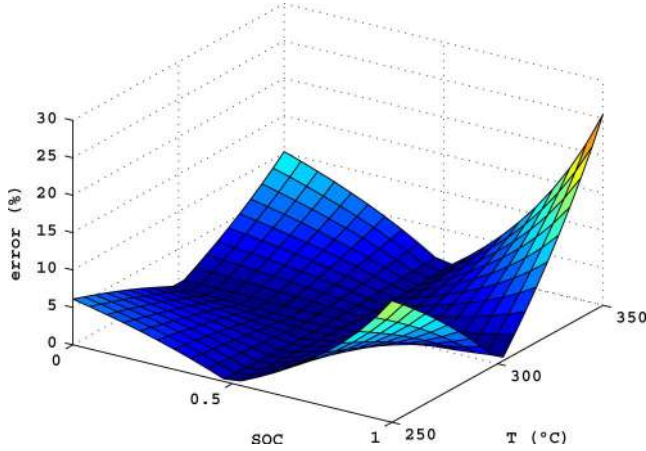


Fig. 4. Percentage error between the nonlinear and the linear models of the internal cell resistance.

TABLE III

VALUES OF THE PARAMETERS OF THE LINEAR APPROXIMATION OF THE INTERNAL RESISTANCE

\bar{k}_1	\bar{k}_2	\bar{k}_3
mΩ	Ω/°C	mΩ
-15.5	$-8.816 \cdot 10^{-5}$	51.86

likely to dwell only occasionally due to the intervention of the protection and limitation systems.

C. Dynamic Programming Algorithm

The dynamic programming algorithm was used to solve problem (3). The usual set-up of backward dynamic programming could not be used in this context [6]. In fact, using this approach, the algorithm starts from the final state, let say at time T , and goes backward to the initial state, let say at time t_0 , minimizing the overall cost through a recursive definition of the cost itself. However, in the problem under study it cannot be identified *a priori* a final state to which the whole system should converge because there are neither a desired SOC nor a particular state of the battery (in terms of temperature, protections, auxiliary services) that should be reached as an objective for the optimization. For this reason the forward approach has been followed.

Let a generic dynamical system be defined as

$$\mathbf{x}_{t+1} = \mathbf{f}_t(\mathbf{x}_t, \mathbf{u}_t), \quad t = 0, 1, \dots, T-1 \quad (7)$$

where \mathbf{x}_t is the n -dimensional state vector at time t , being $x_0 = \hat{x}$ the initial condition and \mathbf{u}_t the control vector that “brings” the system from state \mathbf{x}_t to state \mathbf{x}_{t+1} . Let also assume that for every time t the state space of the admissible states is reduced to non-empty subsets of \mathbb{R}^n

$$\mathbf{x}_t \in X_t \subseteq \mathbb{R}^n, \quad t = 0, 1, \dots, T \quad (8)$$

and that, similarly, the control vector is constrained to belong to nonempty subsets of \mathbb{R}^n that can generally depend on the current state vector

$$\mathbf{u}_t \in U_t(\mathbf{x}_t) \subseteq \mathbb{R}^n, \quad t = 0, 1, \dots, T. \quad (9)$$

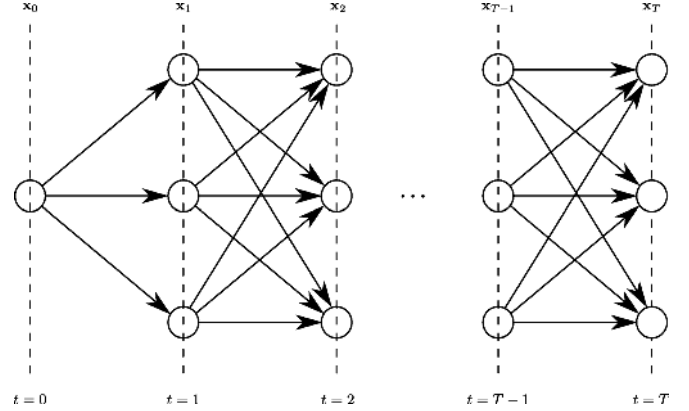


Fig. 5. Graph representing the maximization process.

The cost function to be maximized can thus be written as

$$J = \sum_{t=0}^T h_t(\mathbf{x}_t, \mathbf{u}_t) \quad (10)$$

where h_t is the transition cost from state \mathbf{x}_t to state \mathbf{x}_{t+1} using the control vector \mathbf{u}_t . The graph associated to this problem is depicted in Fig. 5.

The problem of finding the optimal value of energy sold to the grid at PCC can be written as in (10). Obviously this is a case of a maximization problem and the “cost” function J should be more properly called “profit” function. However, since this term has been widely accepted and there cannot be misunderstandings about the nature of this function, J will be called cost function throughout this paper.

Let the space vector \mathbf{x}_t be defined as

$$\begin{pmatrix} x_{\text{soc}_t} \\ x_{\text{temp}_t} \\ x_{\text{aux}_t} \end{pmatrix} \quad (11)$$

where the three components are the state of charge, battery temperature and auxiliary services activation state. The control vector \mathbf{u} is the energy supplied to the grid through the PCC. Obviously, for every instant, the energy requested from (supplied to) the battery is the difference between the energy generated by the wind farm E_{ren_t} and u_t . It is worth noting that while x_{aux_t} is a boolean variable and x_{temp_t} is a state variable used only to trigger auxiliary services activation and protection and limitation systems, x_{soc_t} is the state variable that rules over the maximization process. In fact the transition from a certain SOC at time t to another SOC value at time $t+1$ is achieved through a supply of energy to or from the battery, thus modifying the amount of energy that can be supplied to the grid and, consequently, the revenue.

This means that the state of charge is not only a state variable, but also a control variable. In evaluating the transitions from one state to another all possible states of charge should be considered. If this were done the problem would have no solution since there are infinite combinations due to the fact that there are infinite states of charge.

The first remark to this scenario is that starting from a state of charge not all states of charge can be reached. In fact some transitions would involve currents above the limits, thus making the

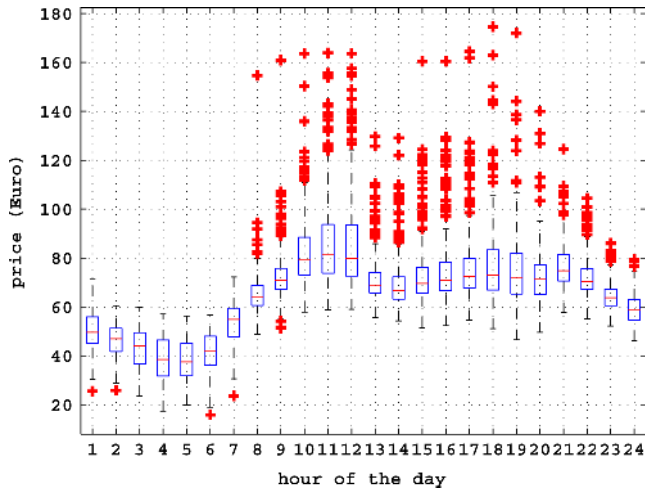


Fig. 8. Box plot graph for 2010 week day Italian energy prices.

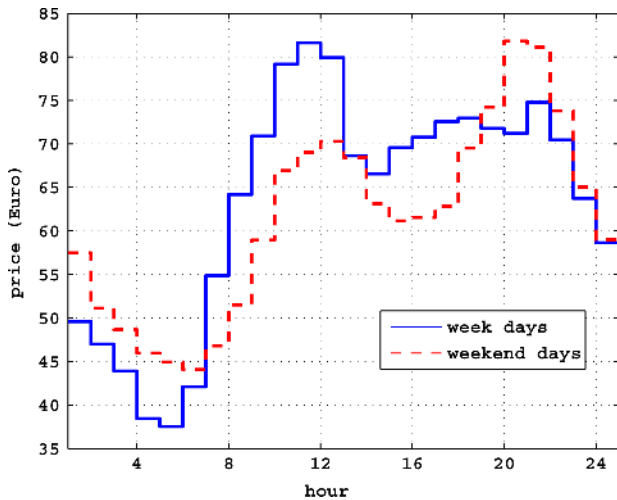


Fig. 9. Mean energy prices for the Italian Power Exchange (IPEX) in 2010.

energy Price as it comes from the DAM closure). The values were split between week days and weekend days, since some difference may occur in spread (the distance between peak and valley prices) and in peak price location. In Fig. 8 the statistically obtained box plots of 2010 weekday Italian energy prices are shown.

From this study two mean profiles (i.e., one representative of week days and the other of weekend days) have been derived. These profiles are made up of the median value for each hour (Fig. 9).

For what concerns renewable power production profiles, the generated power of six 850 kW-rated wind turbines located in Sicily (Italy) have been measured with a 5-s sample time in a one-year campaign and have been analyzed. From this statistical analysis, similar to that carried out for energy prices, a power production profile for the whole set of turbines have been derived [see Fig. 10(a)] starting from the median values. It is worth noting that the peak production value shown in Fig. 10(a) is far below the rated value of the wind power plant (5 MW). This is because the production profile was built from the median production values. Nevertheless this assumption is sound since the energy related to this profile sums up to approximately 21 GWh per day which correspond to approximately 7.6 GWh in a year,

which is the equivalent production of the whole wind power plant operating at nominal rated power for 1500 h, reasonably close to the standard wind farm production equivalent time in Italy.

Obviously the location of the peak in power production depends on the site from which wind data come. In order to avoid this dependence of the final results on the peak power production location the peak has been shifted twenty-three times, keeping constant the integral energy value, as shown in Fig. 10.

The results obtained by applying the 24 power production profiles are shown in Fig. 11. The economical gain is evaluated with respect to the profit from selling the energy harvested from the wind without the presence of the storage devices

$$\begin{aligned} \text{gain} &= \sum_{t=1}^T c_t (E_{\text{ren}_t} + E_{\text{stg}_t}) - c_t E_{\text{ren}_t} \\ &= \sum_{t=1}^T c_t E_{\text{stg}_t}. \end{aligned} \quad (13)$$

From this formulation it is straightforward that the storage system should accomplish the “generation shifting” in order to have a positive gain.

Each of the 24 gain values pairs have been used to define the yearly gain (i.e., 52 times the weekly gain, made up of five week-day gain and two weekend-day gain) for the twenty-four values (Fig. 12). It is clear that the best exploitation of the storage system occurs during night time when the wind production is at its peak and the cost of energy is low. The maximum gain is obtained when the wind peak overlaps with the week day energy minimum price. For this case the break down of the main storage system parameters is shown in Fig. 13.

In these first simulations no constraint has been set on the final state of charge of the storage system and the starting SOC was set to 0.2 pu. It has been also verified that the maximum gain was obtained with final SOC equal to 0.2 pu. New simulations were set up in order to find the sensitiveness of economical gain to the initial SOC of the storage system. In these simulations the constraint on the final SOC was set. For each simulation the storage system was forced to come back to the initial state of charge by applying a penalty weight to the final states different to that corresponding to the starting SOC. This action was necessary in order to avoid the distortion of the results. In fact, if there were not this kind of constraint the scheduler could use the energy exceeding the minimum value, regarding it as some sort of “dowry” coming from the previous day. In this way energy can be sold at peak price hours without taking account of the fact that the energy dowry has been stored at the expense of a possible gain, i.e., with a hidden cost. During operation this kind of behavior could be acceptable, but in the presented study, which considers a “mean behavior” in order to find the profitability of an investment, it is unacceptable. By forcing the storage system to return to the starting SOC value this misbehavior is avoided. The week and weekend days gain for different starting SOC values are shown in Fig. 14. From this plot is clear that the maximum gain is obtained when the starting SOC is minimum, thus validating the results obtained by first round of simulations. This is

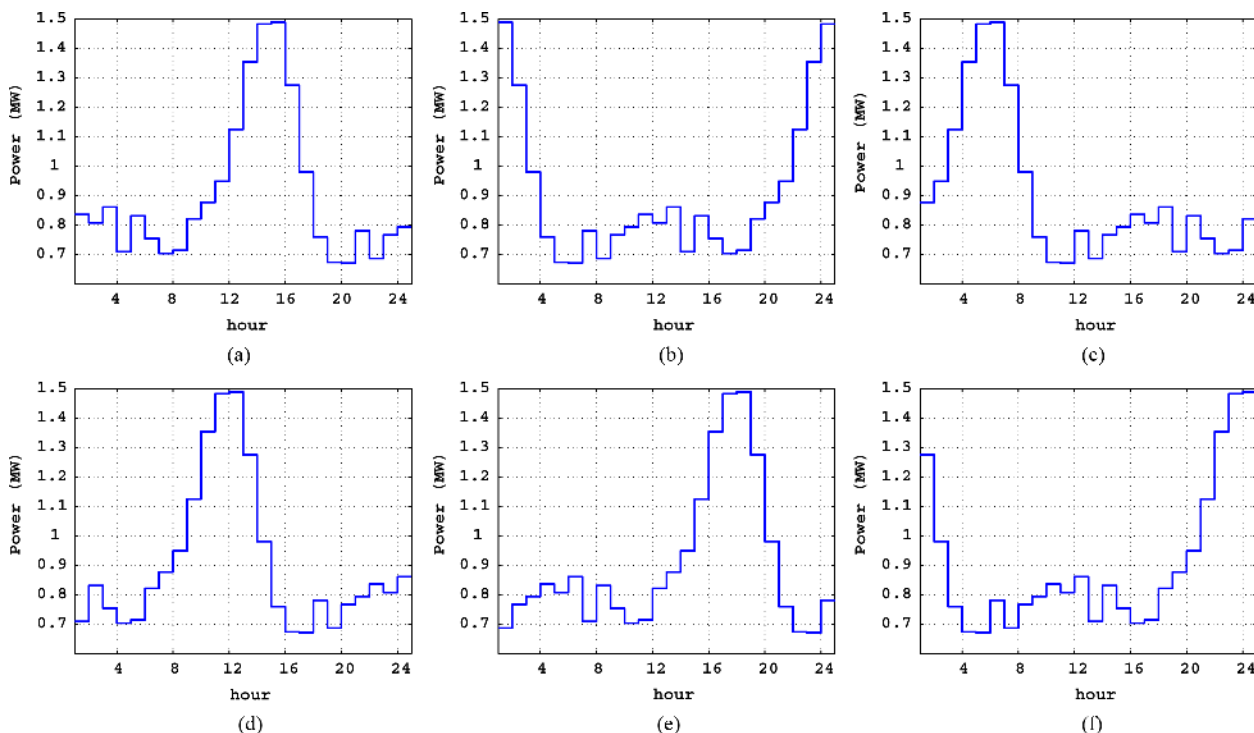


Fig. 10. Power profiles of wind turbines generation used for the simulations (a) the original wind profile, with peak at $t = 15$, coming from the statistical analysis on wind measurements (b)–(f) five examples of the “peak shifting” procedure used for obtaining the sensitiveness of the revenue with respect to the time at which the wind peak occurs.

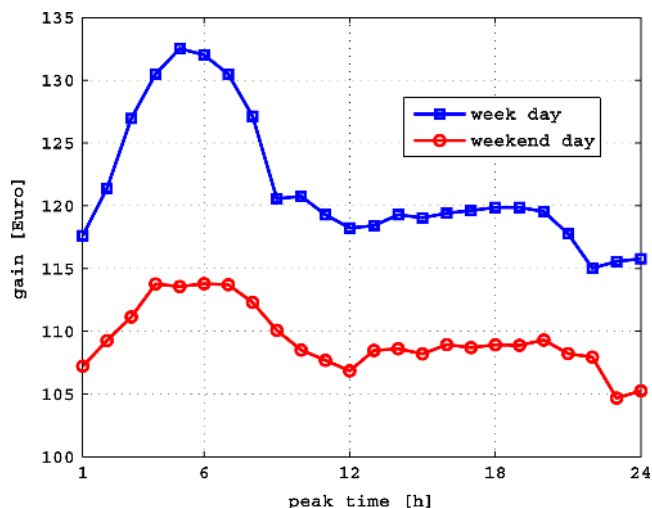


Fig. 11. Economical gains for week and weekend days obtained by exploiting the coupling of the storage system with the wind farm.

also a demonstration that, in the absence of further knowledge on wind or energy price forecasts spanning more than one day, a management strategy that tries to decouple subsequent days is more valuable.

IV. CONCLUSION

The paper has addressed the problem of renewable generation integration into the grid by proposing an optimization algorithm capable of suggesting optimal management strategies for a combined wind power generation and storage system. A forward dynamic-programming based algorithm has been developed in order to define the optimal generation profile of the

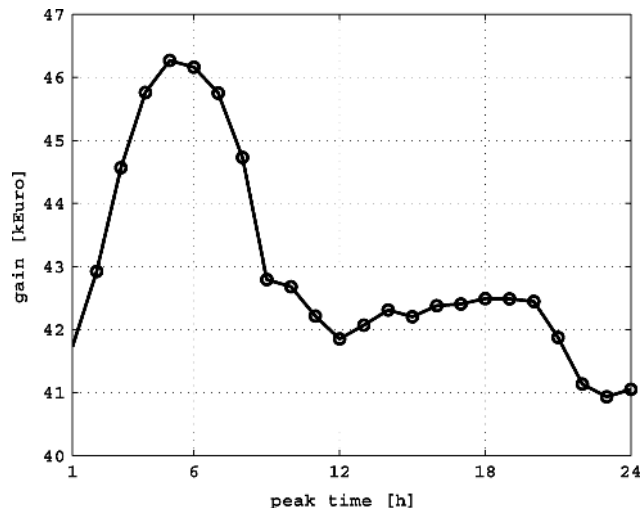


Fig. 12. Estimated yearly gain obtained from the week and weekend days results.

whole generation facility thus allowing the better exploitation of the intrinsically intermittent wind power generation. A discrete-time model of the storage device has been developed in order to introduce the main battery system dynamics (i.e., state of charge, temperature, current, protection, and limitation systems) in the optimization algorithm.

Storage system integration and coordinated management with renewable energy sources can open the way to larger level of renewable penetration into electric distribution networks. Under proper and reasonable assumptions of battery life and of economic gain the maximum expected battery cost to reach a revenue before the end of the battery life has been evaluated.

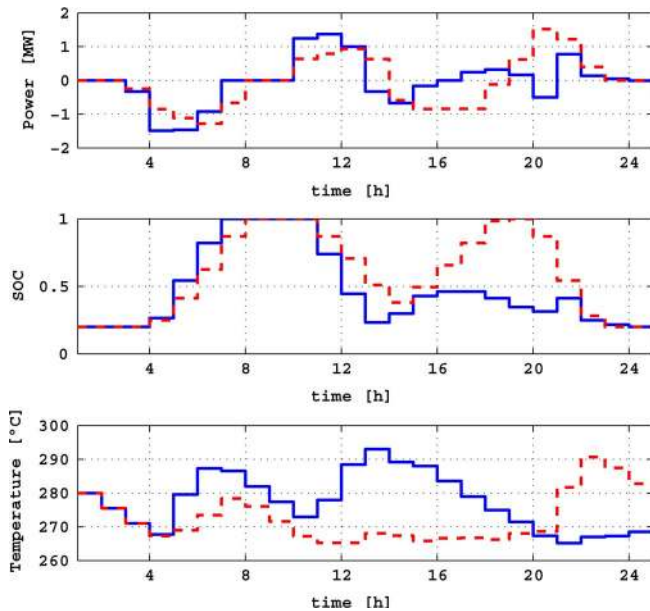


Fig. 13. Breakdown of the main parameters of the storage system (power supplied to or requested from the storage system, state of charge and storage system temperature) for the simulation with wind peak production at $t = 5$. Blue solid lines correspond to weekday simulation, red dashed lines correspond to weekend day simulation.

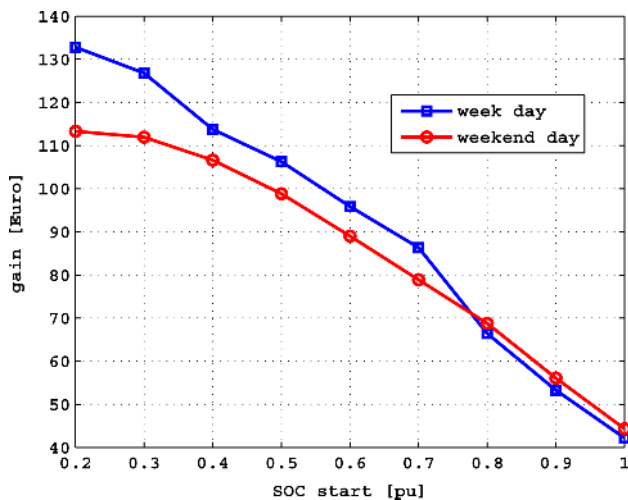


Fig. 14. Estimated daily gain obtained starting from different states of charge of the storage system.

The renewable integration study has been tested by simulation of a real scenario offered by six medium sized wind generators and the results have shown a good exploitation of the energy price arbitrage during the optimization time horizon by adequately operating a generation shifting. The economical gain has been evaluated by considering the ratio between the economic revenue obtained with and without the proposed generation shifting policy).

Future expected investigations will concern medium-to-long term analyses of the coupled wind generation park with the analyzed storage system, dynamic model validation, analysis of potential ancillary services provided by the combined plant.

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Samuele Grillo (S'05–M'09) was born in Alessandria, Italy, in 1980. He received the Laurea degree in electronic engineering and the Ph.D. degree in power systems (with a thesis on application of neural networks to power system security assessment) from the University of Genoa, Genoa, Italy, in 2004 and 2008, respectively.

Currently he is Assistant Professor with the Department of Electrical Engineering, Politecnico di Milano, Milan, Italy. His research interests include smart grids, optimization and control techniques, and neural networks and their application to power systems (i.e., security assessment, load and production forecast, local and small generation management).



Mattia Marinelli (S'10–M'12) was born in Genoa, Italy, in 1983. He received the B.Sc. and M.Sc. degrees in electrical engineering and the European Ph.D. degree in power systems from the University of Genoa in 2005, 2007, and 2011, respectively.

He is currently holding a Postdoc contract. His research interests regard wind and solar data analysis, distributed generators (mainly wind turbines), electromechanical and electrochemical storage modeling for integration studies of renewable energy sources in power systems.



Stefano Massucco (M'80) was born in Genoa, Italy, in 1954. He received the Laurea degree in electrical engineering from the University of Genoa, Genoa, Italy, in 1979.

During 1979–1987, he was with the Electrical Engineering Department, Genoa University, CREL—the Electrical Research Center of ENEL (Italian Electricity Board), Milano, Italy, and ANSALDO S.p.A., Genoa. Since 2000, he has been Full Professor in Power Systems Automation at the University of Genoa. His main research interests are in the field of electric energy systems and distributed generation modeling, control, and management, power systems analysis and simulation, and smart grids.

Prof. Massucco is a member of the Italian Electrotechnical Committee, the CIGRE Working Group 601 of the Study Committee C4 for Review of on-line Dynamic Security Assessment Tools and Techniques, the Scientific Committee of FIRE the Italian Federation for Rational Use of Energy, and is the Delegate of Genova University Rector for energy saving policies.



Federico Silvestro (S'01–M'03) was born in Genoa, Italy, in 1973. He received the electrical engineering degree and the Ph.D. degree in electric power systems from the University of Genoa, Italy, in 1998 and 2002, respectively.

He is currently Assistant Professor with the Naval Architecture and Electric Engineering Department, University of Genoa. He is a member of the CIGRE Working Group 04 of Study Committee C1 for Application and Required Developments of Dynamic Models to Support Practical Planning. His research interests include distributed generation, smart grids, dynamic security assessment, and knowledge-based systems applied to power systems.