TECHNO-ECONOMIC COMPARISON OF LITHIUM-ION AND VANADIUM REDOX FLOW BATTERY WITH TARGET COST DEFINITION FOR A DOMESTIC SCENARIO

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ABSTRACT

This study aims to conduct a techno-economic comparison of two battery technologies suitable for storing renewable electricity: lithium-ion battery (LiB) and vanadium redox flow battery (VRFB). The analysis is conducted using a Mixed Integer Linear Program (MILP) to determine the optimal use of locally produced renewable energy, coming from either a photovoltaic solar or wind source, in order to minimize the expenses of a domestic user, for an Italian case study. The investigated batteries added to the outlined energy system are modeled considering variable efficiencies and distinct degradation characteristics. Post-optimization investment analysis incorporates realistic life expectancy and component replacement for each technology. Different sizes for the batteries are investigated in a sensitivity analysis to evaluate the impact of energy and power sizes on the Net Present Value (NPV) and the Discounted Payback Period (DPBP) of the investment upon storage deployment. Results indicate that pairing storage with photovoltaic systems proves more profitable than with wind farms, given comparable battery sizes, but storage profitability remains insufficient for both technologies. To reach profitability within 10 years from the storage installation in a domestic system producing solar energy, batteries should decrease their initial cost by at least 17-51%. In particular, the most successful VRFB, with 6 hours of discharging time, should decrease its total specific cost from about 366 €/kWh to about 241-305 €/kWh, while the most successful lithium-ion battery, with 4 hours of discharging time, should decrease its cost from about 397 €/kWh to about 196-217 €/kWh.

1 INTRODUCTION

1.1 Background and state of the art

Energy storage systems have the potential to enhance the flexibility and stability of the grid (IRENA, 2020). This enhancement can facilitate the integration of renewable energy sources, thereby advancing efforts to achieve future decarbonization objectives (European Commission, 2019). Storage systems can mitigate temporal mismatches between production and demand in electricity systems through load-shifting and increase the value of the produced renewable energy. For example, storage can reduce electricity bills when installed in small domestic systems, such as renewable energy communities, by increasing the utilization of the renewable source installed, and increase the self-sufficiency of the locally produced renewable energy.

Among the technologies suitable for stationary storage of renewable energy for bill management, lithium-ion and vanadium redox flow emerge as the most promising solution from an economical point of view (Schmidt *et al.*, 2019). Lithium-ion batteries represent a technologically mature option with high efficiency. In contrast, vanadium flow batteries stand out as novel batteries, with high stability, safety, a long lifecycle, and the possibility to independently size energy and power capacities, making them suitable for long-duration energy storage (Alotto, *et al.* 2014).

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In order to evaluate the revenue coming from storage system installation alongside renewable energy in the context of domestic systems with high renewable penetration, realistic scenarios are investigated, giving more reliable information compared to the utilization of the sole metric of capital cost or levelized cost of storage to compare different technologies for a particular application.
In literature, generic storage systems have been analyzed with optimization models, without focusing on a particular efficiency characterization or technology-specific model, to evaluate the effects of renewable energy penetration on the profitability of storage systems (Spodniak *et al.*, 2018). Generic or simple storage models, for example, assume constant battery efficiency and do not assume any degradation (Yarlagadda, *et al.,* 2020) and are easier to implement; however, they can lead to errors in the evaluation of the profitability and revenue of the system. Other works show that literature models considering constant battery efficiency lead to substantial errors in evaluating the economic revenue of lithium-ion or vanadium redox flow batteries (Cremoncini *et al.*, 2023; Jafari *et al.*, 2020).

1.2 Paper contribution

This study conducts a techno-economic analysis comparing lithium-ion and vanadium redox flow batteries of various sizes. The assessment evaluates the economic value these storage systems generate when integrated into a domestic renewable system, generating energy from either wind or photovoltaic (PV) plants. The focus is on optimizing renewable energy storage and dispatching in a small renewable energy system situated in Italy to increase the amount of self-sufficiency from the grid and reduce the expenses from the electricity purchased from the grid.

The main contribution of this research is incorporating detailed and technology-specific models for comparing lithium-ion and vanadium redox flow batteries. These models account for variable efficiencies and maximum charging and discharging rates and explore the economic implications of cyclic degradation, expected battery life, and replacement costs throughout the entire investment period. This work gives cost targets for the investigated technologies needed to reach profitability in the investigated scenario and guarantee the future deployment of batteries to store renewable energy.

2 METHOD

2.1 Problem formulation

The optimization problem is formulated as follows. Given: (i) size, efficiency, power and state of charge limits of the battery storage system (either lithium-ion battery or vanadium RFB); (ii) renewable energy production curve; (iii) time-dependent demand of electricity; (iv) time-dependent price of selling and purchasing electricity. Determine for each *i*-th period i of a time horizon T: (i) the battery charging and discharging power; (ii) the battery state of charge; (iii) the power exchanged with the grid; to maximize the revenue associated with selling and purchasing electricity from the grid, ensuring that the energy demand is always satisfied.

The optimization problem is addressed using a Mixed Integer Linear Program (MILP) with a one-hour resolution time and a 24-hour time horizon. The formulation assumes perfect forecasts of energy prices, renewable energy production, and electricity demand for the upcoming 24 hours.

The battery storage models include detailed performance characterization, and the efficiencies are expressed as a function of the charging/discharging power of the battery. Additionally, for the lithium-ion battery, the maximum charging and discharging powers are limited as a function of the state of charge of the battery, and the model evaluates the annual cyclic degradation of the lithium-ion battery, providing insights into its lifespan and assessing replacement costs over the investment period.

2.2 Parameters and variables

The optimization model is described firstly by introducing the known parameters and the decision variables subject to optimization. The mathematical model is subsequently outlined, detailing the objective function and all associated constraints. In the current problem, the index *i* denotes the i-th

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period of the day, selected from the set of hours in a day T = {1, ..., 24}. The optimization is independently solved for each day *d* for the set of days in a year D = {1, ..., 365}.

The problem relies on a set of parameters, which can be either constant or time-varying:

- $\widehat{P}_{EL}$ (i,d) [kW] – Power demanded by the domestic user, with i ∈ T and d ∈ D;
- $\widehat{P}_{RES}$ (i,d) [kW] – Power generated by the renewable plant, with i ∈ T and d ∈ D;
- $\widehat{P}_{nom,c}$ and $\widehat{P}_{nom,d}$ [kW] – Maximum charging and discharging powers of the battery;
- $\widehat{E}_{nom}$ [kWh] – Rated output energy of the battery;
- $\widehat{P}_{g,max}$ [kW] – Maximum power that can be exchanged with the grid;
- $\hat{f}_{prod}$ [-] – Fraction of the demanded energy covered by the renewable plant on a yearly basis;
- $S\hat{o}C_{min}$ and $S\hat{o}C_{max}$ [kWh] – Minimum and maximum state of energy of the battery;
- $S\hat{o}C_0$ [kWh] - Initial state of energy of the battery;
- $\hat{c}_p$ (i,d) [€/kWh] – Price of purchased electricity from the grid, with i ∈ T and d ∈ D;
- $\hat{c}_s$ (i,d) [€/kWh] – Price of sold electricity to the grid, with i ∈ T and d ∈ D;
- $\hat{c}^v{}_{O\&M}$ [€/kWh] – Variable O&M costs of the battery;

The problem makes use of the following continuous or binary decision variables:

- $P_{RES,u}$ (i,d) ∈ $\mathbb{R}^+$ [kW] – Useful power produced from the renewable plant, with *i* ∈ T and *d* ∈ D;
- P_{curt} (i,d) ∈ $\mathbb{R}^+$ [kW] – Curtailed power from the renewable plant, with *i* ∈ T and *d* ∈ D;
- $P_{g,s}$ (i,d) and $P_{g,p}$ (i,d) ∈ $\mathbb{R}^+$ [kW] – Power sold and purchased from the grid, with *i* ∈ T and *d* ∈ D;
- $P_{b,c}$ (i,d) and $P_{b,d}$ (i,d) ∈ $\mathbb{R}^+$ [kW] – Charging and discharging battery powers, with *i* ∈ T and *d* ∈ D;
- $P_{in,c}$ (i,d) and $P_{in,d}$ (i,d) ∈ $\mathbb{R}^+$ [kW] – Internal charging and discharging battery powers, with *i* ∈ T and *d* ∈ D;
- η_c (i,d) and η_d (i,d) ∈ $\mathbb{R}$ [-] – Charging and discharging DC/AC efficiencies of the battery, with *i* ∈ T and *d* ∈ D;
- SoE (i,d) ∈ $\mathbb{R}^+$ [kWh] – State of energy of the battery, with *i* ∈ T and *d* ∈ D;
- k_b (i,d) ∈ {0,1} – Binary variable indicating whether the battery is in a charging (1) or discharging state (0), with *i* ∈ T and *d* ∈ D;
- k_{onoff} (i,d) ∈ {0,1} – Binary variable indicating whether the battery is an on (1) or off (0) state, with *i* ∈ T and *d* ∈ D;
- k_g (i,d) ∈ {0,1} – Binary variable indicating whether the energy is being bought (1) or sold (0) to the grid, with *i* ∈ T and *d* ∈ D.

2.3 Objective function

The optimization problem consists of the maximization of the daily revenue coming from the energy sold to the grid minus the expenses for the energy purchased and the operational costs of storage (O&M):

$$Rev(d) = \tau \cdot \sum_{i \in T} \hat{c}_s(i,d) \cdot P_{g,s}(i,d) - \tau \cdot \sum_{i \in T} \hat{c}_p(i,d) \cdot P_{g,p}(i,d) - \tau \cdot \hat{c}^v_{O\&M} \cdot \sum_{i \in T} P_{b,d}(i,d) \quad (1)$$

Where τ is the time interval of the problem, equal to one hour.

2.4 Constraints

The power balance within the system, valid for every *i* ∈ T and *d* ∈ D, is given as follows:

$$P^u_{RES}(i,d) = P_{g,s}(i,d) - P_{g,p}(i,d) + P_{b,c}(i,d) - P_{b,d}(i,d) + \hat{P}_{EL}(i,d) \quad (2)$$

$$\hat{P}_{RES}(i,d) = P^u_{RES}(i,d) + P_{curt}(i,d) \quad (3)$$

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Grid power is subjected to the following constraints to avoid simultaneously selling and buying electricity from the grid:

$$P_{g,p}(i,d) \leq k_g(i,d) \cdot \hat{P}_{g,max} \tag{4}$$

$$P_{g,s}(i,d) \leq (1 - k_g(i,d)) \cdot \hat{P}_{g,max} \tag{5}$$

The power of the storage is subjected to different constraints to avoid simultaneously charging and discharging the battery and for maximum power when active:

$$P_{b,c}(i,d) \leq k_b(i,d) \cdot \hat{P}_{nom,c} \tag{6}$$

$$P_{b,d}(i,d) \leq (1 - k_b(i,d)) \cdot \hat{P}_{nom,d} \tag{7}$$

$$P_{b,x}(i,d) \leq k_{onoff}(i,d) \cdot \hat{P}_{nom,x} \tag{8}$$

Where the subscript *x* indicates either charging or discharging. The constraints in equations (6)-(8) are also valid for the internal battery powers $P_{in,c}$ and $P_{in,d}$. The internal battery powers are additional variables used in this work to solve the problem as a MILP (Mixed Integer Linear Program), even when the efficiencies are non-linear. These powers appear in the definition of the battery's state of energy (SoE):

$$SoE(i,d) = S\hat{o}E_0 + \tau \cdot \sum_{n=1}^{i} \eta_c(n,d) \cdot P_{b,c}(n,d) - \tau \cdot \sum_{n=1}^{i} \frac{1}{\eta_d(n,d)} \cdot P_{b,d}\,(n,d) =$$

$$= \tau \cdot \sum_{n=1}^{i} P_{in,c}(n,d) - \tau \cdot \sum_{n=1}^{i} P_{in,d}\,(n,d) \tag{9}$$

The internal battery powers are determined using a piecewise linearization technique. This is achieved by creating tangent lines that serve as approximations to the efficiency curves of the battery (Gonzalez-Castellanos *et al.*, 2020; Zugschwert *et al.*, 2021). These curves are non-linear and convex with respect to the problem. The linearization is defined by the following set of linearization constraints, valid for every $i \in$ T, $d \in$ D, and $j \in$ J:

$$P_{in,c}(i,d) \leq \hat{a}_c(j) \cdot P_{b,c}(i,d) + \hat{b}_c(j) \cdot P_{nom,c} + BM \cdot \big(1 - k_b(i,d)\big) + BM \cdot (1 - k_{onoff}(i,d)) \tag{10}$$

$$P_{in,d}(i,d) \geq \hat{a}_d(j) \cdot P_{b,d}(i,d) + \hat{b}_d(j) \cdot P_{nom,d} - BM \cdot k_b(i,d) - BM \cdot (1 - k_{onoff}(i,d)) \tag{11}$$

Where BM is a large constant parameter used to deactivate these constraints when the battery is not operating or when it is either charging or discharging. At the same time, $\hat{a}_x(j)$ and $\hat{b}_x(j)$ in the set J are the coefficients of the tangent lines resulting from the piecewise approximation of the efficiency curves.

Additionally, the lithium-ion battery is modelled with constraints that limit its maximum charging and discharging power as a function of the state of charge, valid for every $i \in$ T, $d \in$ D and $l \in$ L:

$$P_{b,x}(i,d) \leq (\hat{a}_{lim,x}\ (l) \cdot SoC(i,d) + \hat{b}_{lim,x}(l)) \cdot P_{nom,x} \tag{12}$$

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$$SoC(i,d) = \frac{SoE(i,d) \cdot \bar{\eta}_d}{\hat{E}_{nom}} \tag{13}$$

Where the subscript x indicates either charging or discharging, and $\hat{a}_{lim,x}\ (l)$ and $\hat{b}_{lim,x}\ (l)$, in the set L are the coefficients of the tangent lines resulting from the piecewise approximation of the maximum charging/discharging rates of the lithium-ion battery. *SoC* is the state of charge of the battery and $\bar{\eta}_d$ is the average discharging efficiency of the storage.

The state of energy of the battery (SoE) is subject to the following constraints:

$$S\hat{o}C_{min} \cdot \frac{\hat{E}_{nom}}{\bar{\eta}_d} \leq SoE \leq S\hat{o}C_{max} \cdot \frac{\hat{E}_{nom}}{\bar{\eta}_d} \tag{14}$$

$$SoE(24,d) = S\hat{o}E_0 = S\hat{o}C_0 \cdot \frac{\hat{E}_{nom}}{\bar{\eta}_d} \tag{15}$$

2.5 Economic modelling

Results in terms of investment profitability are compared using the following indexes: Discounted Payback Period (DPBP) and Net Present Value (NPV). Assuming to have constant annual net cash flows (CF_n), the Net Present Value at the end of the investment, after N_y years, is calculated as follows:

$$NPV = -C_{0,tot} + \sum_{n=1}^{N_y} \frac{CF_n}{\left(1 + r_{dy}\right)^n} \ \ [€] \tag{16}$$

Where $C_{0,tot}$ is the total discounted cost of the storage system, and r_{dy} is the annual discount rate. The Discounted Payback Period measures the time the investment takes to recover the initial costs and equals the time the NPV becomes positive.

$C_{0,tot}$ is the sum of initial (C_0) and discounted replacement costs of the battery storage (C_0^{rep}):

$$C_{0,tot} = C_0 + C_0^{rep} \ \ [€] \tag{17}$$

$$C_0 = \hat{E}_{nom} \cdot \hat{c}_E + \hat{P}_{nom,d} \cdot \hat{c}_P \ \ [€] \tag{18}$$

$$C_{0,inv} = \hat{c}_{inv} \cdot \hat{P}_{nom,d} \ \ [€] \tag{19}$$

$$C_0^{rep} = (\hat{E}_{nom} \cdot \hat{c}_E^{rep} + \hat{P}_{nom,d} \cdot \hat{c}_P^{rep}) \cdot f^{rep} \ \ [€] \tag{20}$$

Replacement costs, are actualized using the replacement factor f^{rep}, evaluated using the formulation from (Zakeri and Syri, 2015) in equation (21). The LiB is subject to only energy-specific replacement costs, while the VRFB is subject only to power-specific replacement costs.

$$f^{rep} = \sum_{n=1}^{n^{rep}} \frac{1}{\left(1 + r_{dy}\right)^{n \cdot t^{rep}}} \ \ [-] \tag{21}$$

Where n^{rep} and t^{rep} are the number of replacements and the replacement interval of a storage system throughout the investment period. For the vanadium battery, the replacement interval is fixed and equal

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to 10 years, after which the membrane and electrodes are replaced (Mongird *et al.*, 2020). For the lithium-ion battery, the replacement interval equals the battery's lifetime, after which the battery pack is replaced (the cost of replacement equals the initial specific energy cost of the LiB). To calculate the lithium battery's lifetime due to cyclic aging, a rain-flow counting algorithm analyzes its state of charge profile, as in (Luo *et al.*, 2021), evaluating the cyclic degradation as a function of the number of cycles and their depth of discharge, using the characteristic life curve from (Jafari *et al.*, 2020). The actual LiB life is calculated as the minimum value between its variable cyclic life, expressed in years and calculated as mentioned above, and its calendar life, equal to 10 years, after which the battery is replaced (Mongird *et al.*, 2020).

For both battery technologies, the technical degradation effects, such as nominal capacity loss throughout their operational life, are discarded, but the economic effects of the degradation are considered. For the lithium-ion battery, the degradation of capacity is reflected in the dependency of its life on the cyclic operation and on the need to replace the entire battery due to unrecoverable capacity loss after its life is due. For the vanadium redox flow battery, the capacity degradation, which can be reversed cheaply (Rodby et al., 2020), is assumed to be mitigated with regular battery maintenance, the costs of which are included inside the battery O&M costs. On the other hand, part of the VRFB is periodically replaced after a fixed period, as mentioned above.

The annual net cash flows (CF_n) of the investment remain constant each year and is calculated as follows:

$$CF_n = \Delta Rev - C^f_{O\&M} = Rev - Rev_{ref} - \hat{c}^f{}_{O\&M} \cdot C_0 \quad [€/year] \tag{22}$$

The net cash flow is calculated by subtracting the total fixed operational costs of the system from the net revenue generated by the investment (ΔRev). *Rev* equals the annual revenue from the system, calculated as the sum of the values of the objective functions through the year, while Rev_{ref} is the annual revenue evaluated for the reference case, i.e. the case without a storage system. The annual operational costs of the HESS are divided into (i) variable O&M costs, embedded inside the objective function of the optimization, (ii) fixed O&M costs ($C^f_{O\&M}$), calculated as a fraction of the capital cost (C_0).

3 CASE STUDY

The optimization problem is solved for an Italian case using historical data for renewable energy production, electricity demand, and prices. The demand corresponds to the Italian national grid profile for the year 2023 and it is representative of a typical aggregated load from a group of domestic users. The demand profile is scaled down to an aggregated demand with a peak power consumption equal to 100 kW. The considered renewable energy sources (RES) are wind or solar photovoltaic (PV) power plants, assumed to be located in central Italy (Lat: 41.91; Lon:12.16). The average capacity factor of the wind plant, composed of an array of horizontal small wind turbines, equals 20.5%, while the average capacity factor of the solar photovoltaic plant, composed of an array of crystalline silicon modules, equals 17.7%. Both renewable power plants are assumed to have a system efficiency, considering the losses of cables, power inverters, and dirt, of 88%. Both lithium-ion and vanadium redox flow battery (RFB) technologies are tested for different sizes of renewable power plants. The system's technical parameters and data sources are described in Table 1.

The problem is solved for a system in which the wind farm and solar PV plant have the same yearly energy production, which amounts to 60, 80, or 100% of the yearly electricity demand from the user. This translates into different renewable plant sizes. In the context of this analysis, the renewable production profile is not influenced by the size of the renewable plant.

The system's economic parameters, operational values, and data sources are described in Table 2. The economic conditions under which the energy is exchanged on the grid follow Italian regulations, and electricity prices are valid for 2023. In particular, the energy sold to the grid, coming from renewable sources, is paid at the minimum price of 44 €/MWh for the PV source and 55.2 €/MWh for the wind

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source (ARERA, 2023b). On the other hand, the cost of the energy bought from the grid is calculated by adding all the variable cost entries sustained by a domestic user purchasing electricity on the market under the market regulator rules (ARERA, 2023a).

Table 1: System's technical characteristics

Description		Value	Unit	Data source
Rated demand power		100	kW	(Terna spa, 2024)
RES power	Wind	175-291	kW	(Davis *et al.,* 2023; RSE, 2012)
	Solar PV	202-337	kW	(Huld *et al.*, 2012)
Rated battery energy		43-716	kWh	-
Nominal discharging time	Lithium-ion	4-8	h	-
	Vanadium RFB	4-8	h	-
Mean battery efficiency	Lithium-ion	83	%	(Gonzalez-Castellanos *et al.*, 2020)
	Vanadium RFB	65	%	(Zugschwert *et al.*, 2021)
State of charge range	Lithium-ion	20-100	%	-
	Vanadium RFB	0-100	%	-
Initial state of charge		30	%	-

Table 2: System's economic and operating parameters

Description		Value	Unit	Data source
Electricity price range	Selling price	44-55.2	€/MWh	(ARERA, 2023b)
	Buying price	156-425	€/MWh	(ARERA, 2023a)
Energy specific cost	Lithium-ion	321	€/kWh	(Cole and Karmakar, 2023)[a]
	Vanadium RFB	186	€/kWh	(Cremoncini *et al.*, 2024)
Power specific cost	Lithium-ion	304	€/kW	(Cole and Karmakar, 2023)[a]
	Vanadium RFB	1080	€/kW	(Cremoncini *et al.*, 2024)
Replacement cost	Lithium-ion	321	€/kWh	(Cole and Karmakar, 2023)[a]
	Vanadium RFB	350	€/kW	(Cremoncini *et al.,* 2024)
O&M cost	Fixed	0.43	%/year	(Mongird *et al.*, 2020)[b]
	Variable	0.45	€/MWh	(Mongird *et al.*, 2020)[b]
Calendar life	Lithium-ion	10	years	(Mongird *et al.*, 2020)[b]
	Vanadium RFB	20	years	(Mongird *et al.*, 2020)[b]
Replacement time	Vanadium RFB	10	years	(Mongird *et al.*, 2020)[b]
Investment time		20	years	-
Annual discount rate		8	%	(Schmidt *et al.*, 2019)

[a]An exchange rate of 1.082 $/€, the annual average rate for the year 2023, was used to convert costs from $ to € (Exchange Rates UK, 2023).
[b]An exchange rate of 1.142 $/€, the annual average rate for the year 2020, was used to convert costs from $ to € (Exchange Rates UK, 2020).

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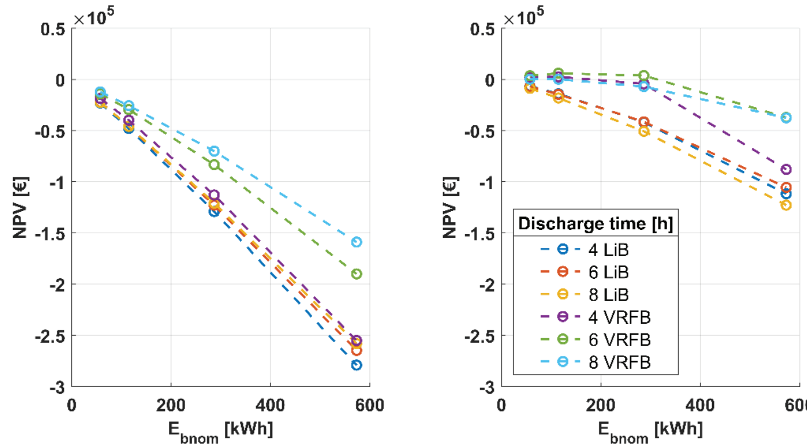
4 RESULTS

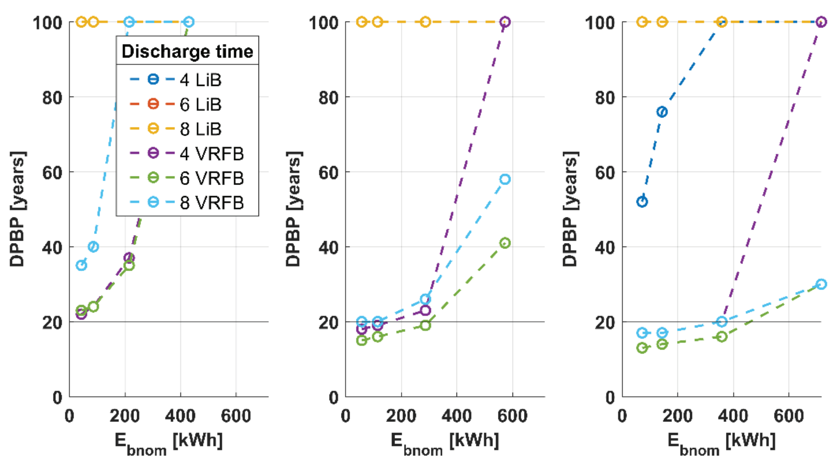
4.1 Net Present Value and Discounted Payback Period sensitivity analysis

To compare lithium-ion (LiB) and vanadium redox flow batteries (VRFB), the problem was solved for different instances, assuming to have different battery capacities to store energy from either a wind farm or a solar PV plant. Each battery is sized to have an energy capacity equal to 5-10-25-50% of the daily electricity produced by the RES. Both batteries are analyzed in a discharge time range of 4-6-8 hours. For the lithium-ion battery, the energy-to-power ratio or discharging time is increased by reducing the size of the inverter.



(a) (b)

Figure 1: Net Present Value of the investment for different storage sizes alongside (a) wind farm or (b) solar PV plant annually producing 80% of the total energy demand



(a) (b) (c)

Figure 2: Discounted Payback Period of the investment for different storage sizes on a solar PV plant annually producing (a) 60%, (b) 80% or (c) 100 % of the total energy demand

Figure 1 shows results in terms of sensitivity analysis for Net Present Value (NPV) of a system producing electricity using either a wind or a solar plant. For this analysis, the electricity produced over a year equals 80% of the total energy demand, and different storage sizes are installed. Results show that the NPV after 20 years of investment is negative for most cases and that the larger storage capacities decrease the NPV. Installing storage alongside the wind farm generates less net revenue than installing the same size alongside the solar PV plant because the nature of the wind power leads to a bigger

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mismatch between production and consumption, resulting in a smaller increase in self-sufficiency with the battery compared to the PV plant case. Consequently, the avoided expenses in the wind case are always insufficient to cover the cost of the installed battery. On the other hand, in the case of a PV plant with a peak power of 270 kW (80% of renewable coverage), the battery with the highest NPV is the 6h VRFB, with a capacity of 115 kWh. The NPV for this case is negligible with respect to the initial cost of the storage, which indicates a bad investment, due to the high initial costs of the storage. Similar conclusions can be drawn from the analysis of the Discounted Payback Period, as shown in Figure 2.

Figure 2 shows investment results in terms of Discounted Payback Period (DPBP) for the solar PV case, for different sizes of the renewable plant, annually producing 60, 80, or 100% of the energy demand. The amount of installed renewable sources dramatically influences the outcome of the investment and the preferred battery size. The most successful battery is the 6-hour VRFB (DPBP of 13-14 years) with a small capacity (5-10% of the daily energy produced by the RES) for the 100% renewable production scenario. The LiB has a poor performance, and for most tested sizes the DPBP is greater than 100 years.

4.2 Identification of battery cost targets

Since the investment is not profitable for the investigated case, this section identifies cost targets to make the storage installation profitable for the PV plant. Considering a battery capacity equal to 10% of the daily electricity produced by the renewable plant, Table 3 highlights the desired cost reduction needed for the storage to obtain a DPBP of 10 years. The most successful sizes investigated are VRFB with a discharging time of 4-6 hours and LiB with a discharging time of 4 hours. Current and target cost results refer to the storage system's initial cost without considering the actualized replacement costs. The target cost and desired cost reduction ranges in Table 3 reflect different scenarios where the PV plant produces either 60, 80, or 100% of the annual energy demand. The cost reduction needed to obtain the same DPBP for the wind case is always above 73%.

Table 3: Current, target cost and desired cost reduction ranges for a battery with a capacity equal to 10% of the daily electricity produced by the PV plant for different discharging times to guarantee a 10-year DPBP

Battery type	Discharging time [h]	Current system cost [€/kWh]	Target system cost [€/kWh]	Desired cost reduction [%]
Lithium-ion battery	4	397	196-217	45-51%
Vanadium RFB	4	456	299-340	25-34%
	6	366	241-305	17-34%

Even if the lithium-ion battery has a lower initial cost than the vanadium battery, it constitutes a worse investment case. The LiB needs replacement during the course of the investment and incurs greater costs, having an average life of 10 years in the investigated scenarios due to calendar aging. The replacement increases the overall system cost and reduces the net revenue. This translates into a greater desired cost reduction to guarantee the profitability of the LiB compared to the VRFB.

4.3 Influence of storage on energy self-sufficiency

From a technical point of view, self-sufficiency (f_{self}), meaning the share of annual energy demand covered by the local renewable plant, increases with the amount of installed storage capacity and power, as shown in Figure 3 for the solar PV plant.

The value of self-sufficiency increases with the amount of installed RES and the best-performing storage is the VRFB with 4h of discharging time. The VRFB outperforms the LiB of the same rated capacity and power, because the LiB has a smaller usable capacity, having a minimum state of charge equal to 20%. Using a 4h VRFB with a capacity equal to 50% of the daily PV production, the annual self-sufficiency increases from 38-43% (depending on the renewable source production, going from 60

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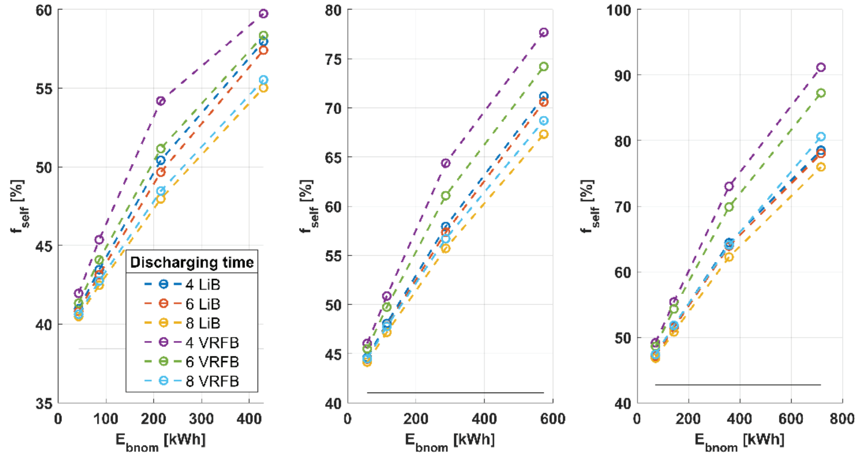
to 100% of the demanded annual energy) to 60-91%, while a LiB of the same size increases the self-sufficiency only up to 58-79%.



(a) (b) (c)

Figure 3: Self-sufficiency achieved with different storage sizes on a solar PV plant annually producing (a) 60%, (b) 80%, or (c) 100 % of the total energy demand

5 CONCLUSIONS

This study conducts a techno-economic comparison between lithium-ion batteries (LiB) and vanadium redox flow batteries (VRFB). The analysis evaluates the potential profitability of integrating energy storage with renewable sources, namely photovoltaic (PV) and wind, in a domestic energy system for an Italian case study. The model includes detailed and technology-specific models for the investigated batteries, accounting for variable efficiencies as a function of the charging and discharging power, and variable maximum charging and discharging rates as a function of the state of charge. The analysis explores the economic implications of expected battery life and replacement costs throughout the entire investment period. Different sizes are investigated for both batteries to evaluate the impact of energy and power sizes on the Net Present Value (NPV) and on the Discounted Payback Period (DPBP) of the investment. Each battery is tested for an energy capacity of 5% to 50% of the daily renewable energy source (RES) output. Both batteries are analyzed for a discharging time range of 4-8 hours. The renewable plant is sized to produce a variable amount (from 60% to 100%) of the annual electrical demand.

Findings highlight that pairing batteries with photovoltaic systems yields higher profits for the same storage size in the Italian case study, compared to the pairing with a wind farm. Nevertheless, current storage profitability remains insufficient for widespread adoption of the battery technology in the investigated scenarios due to high storage system costs. This suggests that further cost reductions are necessary to incentivize investment in energy storage deployment. The battery that guarantees the highest profitability for the case generating energy from the PV plant is the 6-hour VRFB, producing a minimum DPBP of 13 years, when the renewable coverage equals 100% of the annual demanded energy. The best energy capacity of this battery equals 72 kWh, corresponds to 5% of the average daily energy output generated by the PV plant (337 kW). Specific cost targets are identified to increase renewable energy storage profitability in the investigated case study, lowering the DPBP to a desired value of 10 years. A VRFB with a 6-hour discharging time should decrease its total system cost, from 366 €/kWh to about 241-305 €/kWh, while a LiB with a 4-hour discharging time needs to decrease its cost from 397 €/kWh to 196-217 €/kWh. The VRFB outperforms a LiB of the same size when evaluating the self-sufficiency of demanded energy. A 4h VRFB can increase the annual self-sufficiency of the domestic system from baseline values of 38-43% to 60-91%, for a RES plant producing 60-100% of the annual demand.

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NOMENCLATURE

η	efficiency	(-)
τ	time step length	(h)
a, b	coefficients of the tangent approximating line	(-)
C, c	cost or specific cost, price of electricity	(€/kWh, €/kW)
CF	net cash flow	(€/year)
d	day index	(-)
DPBP	discounted payback period	(years)
E	energy	(kWh)
i	time step index	(-)
k	binary variable	(-)
N_y	number of years of the investment	(years)
NPV	net present value	(€)
P	power	(kW)
r_{dy}	annual discount rate	(-)
Rev	economic revenue	(€/day)
SoC	state of charge	(-)
SoE	state of energy	(kWh)
t	time interval	(years)

Subscript/superscript

0	initial state, initial/actualized cost
b	battery
c	charging
curt	curtailed
d	discharging
EL	electrical demand
f	fixed
g	grid
in	internal
lim	limits, coefficients
max	maximum
min	minimum
n	year index
nom	nominal, rated
O&M	operation and maintenance
onoff	state of the battery
p	purchasing
rep	replacement
RES	renewable energy source
s	selling
u	useful
v	variable

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