OPTIMIZATION OF FULLY RENEWABLE AND DISPATCHABLE GREEN-HYDROGEN POWER-TO-POWER PLANTS WITH SEASONAL STORAGES

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ABSTRACT

Solar PV and wind turbines are the two most economically competitive renewable technologies. However, their intermittency and seasonality call for the need of short-term and long-term energy storages. The objective of this work is the assess the economic advantage of using green hydrogen as a long-term (seasonal) energy storage compared to batteries. As basis of design, we consider Sicily with its PV and wind production profiles as well as its electricity demand. Three Aggregated Energy Systems are considered: (i) PV + wind + lithium-ion battery, (ii) PV + wind + Power-to-Power system (with electrolyser, H² storage unit and one or more gas turbines) and (iii) hybrid PV + wind + battery + power-to-power. The optimal design is determined with the optimization code developed by Politecnico di Milano, based on an accurate Mixed Integer Linear Programming formulation for the design and operational problem of Aggregated Energy Systems (microgrids, virtual power plants, energy districts, district heating networks, etc). Results show that the configuration with the hybrid storage solution achieves the lowest cost of electricity but the economic advantage compared to the benchmark battery storage depends mainly on the H² storage cost. If H² is stored in pressurized pipes, the economic gain compared to batteries is limited (215 €/MWh vs. 213 €/MWh in the current scenario, 123 €/MWh vs. 128 €/MWh with 2050 projections). The advantage becomes considerable if a more economic geological H² storage system is available: 192 €/MWh vs. 213 €/MWh in the current scenario, 97 €/MWh vs. 128 €/MWh for the 2050 scenario. In the optimized management strategy, batteries are exploited for short-term (daily and weekly) cycles, while H2-based storage is used for long-term seasonal cycles.

Keywords: Power-to-Power, Aggregated Energy System, Seasonal storage, Optimization, Green-hydrogen.

NOMENCLATURE

- AEL Alkaline Electrolysers
- AES Aggregated Energy System
- BESS Battery Energy Storage System
- CAPEX Capital Expenditures
- CRF Capital Recovery Factor
- EOH Equivalent Operating Hour
- KPI Key Performance Indicator
- LCOE Levelized Cost of Electricity
- MILP Mixed-Integer Linear Programming
- O&M Operation and Maintenance
- OCGT Open Cycle Gas Turbine
- OEM Original Equipment Manufacturer
- OPEX Operation Expenditures
- P2P Power-to-Power
- PEM Proton Exchange Membrane
- PV Photovoltaics
- RES Renewable Energy Sources
- TAC Total Annual Cost
- TSO Transmission System Operator

INTRODUCTION

In the last decade, many governments are pushing towards a strong reduction of greenhouse gas emissions, favouring a higher usage of Renewable Energy Sources (RES), especially solar and wind energy, representing two of the most promising renewable technologies in the energy sector (IRENA, 2021). However, solar and wind energies as stand-alone systems are not only intermittent and fluctuating but also non-programmable resources, characterized by periodical changes in their production curve, with both short (day/night, cloudy/sunny) and long (seasonal) variations. For this reason, finding a technically feasible and economically affordable way to store the excess energy, is fundamental to mitigate the impacts of nonpredictable generation on the power grids.

In this framework, the H_2 molecule can be efficiently exploited as energy carrier and H_2 generation, when coupled with renewables, can limit the impacts of their intermittent nature and smooth their production. Because of its physical properties, hydrogen is one of the few energy carriers suitable for long storage duration (i.e., seasonal storage solutions) (IEA, 2019). Seasonal storages can compensate the fluctuations caused by renewables, increasing grid stability and reliability, saving, in the meanwhile, a significant amount of the power produced that, due to the mismatch between generation and consumption curves, otherwise would be curtailed and lost.

Already several studies have been published on seasonal storage systems, investigating the different available alternatives for large-scale (GWh) solutions. Matos et al. (2019) reviewed a number of underground energy storage solutions for RES integration. Following a similar methodology, Zareipour et al. (2010) analysed the state of technology, installations, and challenges of different storage systems, underlining advantages and drawbacks behind each alternative. Recently, the interest in large-scale H2-based storage systems is growing: the HyUnder project (Landinger, 2013) was the first European-wide assessment of the potential for H_2 storage underground. Currently, there are a number of ambitious ongoing projects involving hydrogen production and storage such as the Hyflexpower and the North $H₂$ projects.

Fully-renewable Power-to-Power (P2P) system based on H² has been extensively studied also in the literature: Crespi et al. (2021) propose a mathematical model to optimize a P2P plant in order to identify the optimal capacity of the system components to supply a constant electric load. Gabrielli et al. (2018) developed a novel Mixed-Integer Linear Programming (MILP) methodology capable of designing and operating an Aggregated Energy System (AES) to supply the power and heat demand to a Swiss neighbourhood, featuring H_2 -based seasonal storage. Similarly, Castelli et al. (2022) investigated the optimal design and operation of a fully renewable AES including a seasonal hydrogen storage system with a hydrogen-fired combined cycle, PV panels, and batteries for short-term storage, through a MILP optimization problem.

Starting from the already developed concept presented in Gabrielli et al. (2018) and in Castelli et. al (2022), the objective of this work is the assess the economic advantage of using green hydrogen as a long-term (seasonal) energy storage compared to batteries. As case study, we consider Sicily with its PV and wind production profiles as well as its electricity demand. Three AESs are considered: (i) PV + wind + lithium-ion Battery Energy Storage System (BESS), (ii) $PV + wind + P2P$ system (with electrolyser, H₂ storage unit and one or more gas turbines) and (iii) hybrid $PV +$ $wind + BESS + P2P$. The optimal design is determined with the optimization code developed by Politecnico di Milano. It is based on an accurate Mixed Integer Linear Programming formulation including the design and operational problem of AESs (microgrids, virtual power plants, energy districts, district heating networks, etc).

METHODOLOGY

Fully-renewable AESs description

The general layout of the AESs under study is schematized in [Figure 1.](#page-1-0) The range of technologies considered in the superstructure includes (i) PV fields, (ii) wind farms, (iii) BESS and (iv) hydrogen-based P2P system (electrolyser, compressor, pressurized hydrogen storage and gas turbines). In order to store the excess of renewable energy from one period of the year to another, two options of seasonal storage are considered: 1) electrochemical storage via the BESS and 2) a P2P storage exploiting H_2 as energy vector.

Figure 1. *Generic representation of the AES under study.*

Lithium-ion batteries have been selected as the reference technology for the BESS, as they are the most common electrochemical storage solution employed for stationary applications because of their fast dynamic response, high power density, long service life and low selfdischarge rate (Kebede et al., 2021).

Regarding the P2P system, different technologies must be selected. The electrolyser is based on a Proton Exchange Membrane (PEM) technology. With respect to Alkaline Electrolysers (AEL), PEM electrolyser operates at a higher pressure (30÷90 bar) and temperature (up to $100 \degree C$) (Buttler and Spliethoff, 2018), leading to better conversion efficiencies and lower power required to compress the H_2 produced up to the storage pressure. Moreover, PEM electrolyser are known to be very flexible in terms of both load variation and dynamic response (very low minimum load and few seconds required from minimum to full load) and they can easily match sudden variations of the renewable generation (IEA, 2019). Two separate options are instead considered for the $H₂$ storage: hydrogen can be stored at high pressure (500 bar) in steel pipes or, alternatively, in underground storage such as rock caverns at a lower pressure (between 20 and 200 bar) (Landinger, 2013). Lined rock caverns are rock caverns lined with a thin impermeable liner and surrounded by rock mass carrying the load of the compressed gas stored. Their main advantages are flexibility and a limited dependency on the host rock. Steel pipes are metallic vessels typically used for stocking compressed fluids. Such type of storage is most expensive than underground systems (approximately 10 times more) but today it is one of the few hydrogen storage solutions which is not site-dependent. As gas-to-power technology, Open Cycle Gas Turbine (OCGT) has been adopted since most of Original Equipment Manufacturers

(OEMs) already committed to developing H_2 -ready gas turbines by 2030 (ETN, 2020) and compared to other potential H_2 conversion technologies such as internal combustion engines and fuel cells, they present several advantages when used for peaking applications with few operating hours in a year. This is the case for seasonal storage systems, characterized by a limited number of charge/discharge cycles in a year. Indeed, OCGTs are not only very flexible and fast machines, designed for frequent turn-ons and turn-offs and short operations, but they achieve good conversion efficiencies (37÷40%) at a relatively low investment cost (1000÷300 €/kW) (Farmer, 2021). Such characteristics, make this technology particularly suitable for P2P applications.

Problem statement

The approach used for the design of the AES consists of two main steps: (i) first select the representative or typical periods (i.e. design days) that well characterize the most typical operating conditions under which the plant is expected to be operated and (ii) find the optimal design and the seasonal management of the entire system from a techno-economic standpoint, minimizing the total annual costs. This methodology is applied for a grid-connected, large scale and fully-renewable AES, capable of entirely satisfying a given fraction of the regional demand of the considered location. The problem has been formulated as a MILP optimization problem by means of the Python-based open-source optimization modelling language Pyomo and solved by the commercial MIP solver Gurobi (Gurobi, 2022). Formulating this kind of problem as a MILP optimization problem means ensuring the global optimality of the solution, namely a high-quality solution, relying on a rigorous method capable of managing problems with a high number of variables and constraints, and exploiting efficient and off-the-shelf commercial algorithms (i.e., Gurobi® and CPLEX). In order to preserve the computational tractability of the optimization problem, it is common practice to reduce the temporal scale of the MILP by accurately selecting few design days to represent the entire year (Hoffmann et al., 2020). Among the available techniques in literature, the k-MILP clustering algorithm (Zatti et al., 2019) has been used for the extraction of the most representative design days because, other than the typical days, it allows the selection extreme days (i.e. those characterized by a minimum of renewable production or a maximum of electricity demand) which represent critical conditions and are fundamental for a reliable plant design.

The AES, whichever layout is selected by the optimization model, has to fully meet the regional electricity demand over the whole year, shifting the excess of the renewable production from the summer to the winter through the installation of one or more seasonal storage technology. The overall problem can be formulated as follows. Given:

- Regional hourly PV and wind generation, electricity load in each of the design days considered
- The catalogue of recent (2021) OCGTs available on the market ranging from 30 to 314 MW of power output, with related performance maps at part-load, investment, and operating costs
- Technical performances and economic characterization of all plant components (electrolyser, PV, wind, storage technologies)

The target of the optimization algorithm is to define the optimal AES design and its operation over a typical year minimizing the Total Annual Cost (TAC) function, expressed as the sum of annualized capital (CAPEX) and operating (OPEX) costs. At the same time, the following constraints must be satisfied:

- Fully cover a given fraction of the electric regional demand
- Units and storage operational constraints (ramping) rates, start-up/shut-down trajectories, minimum up/down times, part-load efficiency maps, storage levels management via charge/discharge, etc.)
- Hourly electricity and hydrogen balances
- Maximum capacity available of storages
- Cyclic management of the seasonal storage system (i.e. same storage level at the beginning and at the end of the year)

Optimization model

The optimization problem of AES design can be mathematically formulated as a two-stage stochastic MILP consisting of two optimization problems for each stage, mutually dependent:

- Design problem: units selection and sizing, including the choice of the energy vector (i.e., electricity and hydrogen) for the seasonal energy storage.
- Operation problem: selection of the best AES dispatch strategy, including hourly exchange of electricity between the system and electric grid, commitment status and production levels of each unit, storage management strategy and energy exchanges between all system components.

A detailed description of the general mathematical formulation of a two-stage stochastic MILP problem and the associated solution methods can be found in Birge and Louveaux (2011).

The simultaneous design and operational problem can be stated as follows. Given a set of dispatchable (OCGT, electrolyzer) and non-dispatchable generators (PV, Wind) and energy storages (BESS, H_2 storage) with their respective size ranges (i.e. minimum/maximum installable power or capacity), performance characterization and production curves, the optimization problem must decide which units install and select the associated sizes, also considering, at the same time, the optimal management

strategy of the system with the objective of minimizing the Total Annual Cost (TAC).

For this category of problems, involving design decisions, the TAC represents a good choice for the objective function, since it is an economic indicator including both capital (CAPEX) and operational (OPEX) expenditures. In the TAC expression, capital expenditures are annualized via the Capital Recovery Factor (CRF) (Short et al. 1995), assumed to be equal to 10% for this study. The investment costs are computed as the sum of the installation cost of each unit (i.e. green-field AES design). The operating costs are constituted by the Operation and Maintenance (O&M) costs which include (i) fixed costs depending only on machines and storage installed capacity, (ii) variable costs and (iii) start-up costs, based on the number of start-ups over the year.

The variable O&M term of the BESS includes the cost associated with battery cell degradation with use, expressed as a throughput cost (Sauer and Wenzl, 2008) (Wang et al., 2014). This O&M cost can be estimated as the replacement cost of the BESS allocated to the total expected energy discharged through its entire lifetime.

The optimal solution of the optimization problem is subject to several constraints that must be satisfied. Design constraints ensure that the size of dispatchable machines selected is within the specified range defined by the minimum and maximum power while the installable capacity of non-dispatchable and storage units is limited only by an upper bound as these technologies are modelled as modular components. Moreover, additional constraints are necessary to guarantee that the operation of the system is accurately described. Those include constraints defining

the input-output constitutive relationships, minimum load capability, start-up trajectories, ramp rates of conversion units, storage level evolution, minimum and maximum charge and discharge rates of energy storages and system energy balances. The detailed mathematical description of the same methodology applied to a similar optimization problem can be found in the work of Castelli et al. (2022).

CASE STUDY

The previously presented methodology is applied to determine the optimal configuration and seasonal storage management of an AES designed to supply 10% of the electricity demand of the Sicily region (Italy) for a current and a future scenario (2050), considering three different seasonal storage options (BESS, P2P and both).

Regarding the electrolyser, it is assumed to be operated always at nominal conditions (i.e. at design temperature and pressure) with constant efficiency. The power consumptions of the H_2 compressor are lumped with the auxiliaries of the electrolyser, therefore the net efficiency of the electrolyser already accounts for power spent for the H_2 compression up to the storage pressure. The former value is dependent on the $H₂$ delivery pressure, assumed constant and imposed by the H_2 storage type (equal to 500 bar for steel pipes and 200 bar for line rock cavern), so two different values are used for this parameter according to the storage solution adopted. Variations in the H_2 storage pressure due to charge and discharge operations are not considered to preserve the linearity of the problem. Negligible self-discharge losses have been assumed for the H_2 storage.

Figure 2. *Electrical power (a) and efficiency (b) approximation: MILP maps vs real data.*

Table 1. *Coefficients for the part-load performance curve linearization with the mean and the maximum linearization error for each OCGT power range.*

OCGT category	Power range $\mathbf{M}\mathbf{W}_{\text{el}}$	$K_{1,i}$ [MW _{el} /MW _{fuel}]	$K_{2,i}$ [MW _{el} /MW _{fuel}]	$K_{3,i}$ [MW _e]	Average error	Max error
OCGT1	30-80	0.529	-0.105	-3.010	3.0%	6.2%
OCGT2	80-116	0.495	-0.081	-10.890	0.8%	4.1%
OCGT3	16-314	0.497	-0.091	-20.055	.8%	4.9%

The data used to model the OCGTs were taken from a recent catalogue of machines reported in the Gas Turbine World Handbook (Farmer, 2021). For each unit in the catalogue, the part-load performance curves were derived starting from the known nominal conditions, following the methodology proposed by Gülen (2019). Then, OCGT models were aggregated according to their power rating in several categories for each power range (30-80 MW, 80-116 MW, 116-314 MW).

$$
P_{i,t}^{el} = K_{1,i} \cdot Q_{i,t}^{in} + K_{2,i} \cdot Q_i^{nom} + K_{3,i} \qquad \begin{array}{c} \forall i \\ \in \{OCGT1, \\ OCGT2, \\ OGGT3 \} \end{array} \tag{1}
$$

Each OCGT category is represented in the MILP model by a corresponding equivalent machine (OCGT1, OCGT2, OCGT3) with the variable size in the power range predefined. Then, the best-fit coefficients associated with each OCGT category *i* $(K_{1,i}, K_{3,i}, K_{3,i})$ that linearize the input-output relationship have been estimated (reported in [Table 1\)](#page-4-0). Eq. (1) expresses the constitutive equation linking the electrical power output $(P_{i,t}^{el})$ with the fuel thermal input $(Q_{i,t}^{in})$ and the nominal fuel input (Q_i^{nom}) , associated with the OCGT size. [Figure 2](#page-3-0) shows the real performance curves of existing gas turbine models versus their linear approximation in the MILP model. The maximum error committed on the estimate of OCGT output power by the linear approximation is below 6%.

As electrochemical storage options, three categories of lithium-ion batteries (BESS1, BESS2 and BESS3) were considered, characterized by different discharge durations: 4 h, 12 h and 20 h, respectively. Each BESS can be charged and discharged completely, exploiting all the available capacity, and constant charging and discharging efficiencies have been assumed. BESS2 and BESS3 costs were computed starting from cost data available for BESS1 (Kebede et al. 2021)(Cole et al. 2021) by weighting the cost of each unit (battery, inverter and balance of system) according to discharge duration. A self-discharge loss equal to 3% of the storage level per month has been considered for each BESS model.

The hourly PV and wind generation and electric load profiles of the year 2018 were taken from the Italian Transmission System Operator (TSO) website (Download center, Terna). The hourly electricity load profile has the same shape as the regional one but it has been rescaled by a factor of 0.1: the profile of electricity demand obtained in this way is characterized by a peak of 297 MW and an annual electricity generation of 1756.8 GWh/year and corresponds to the 10% of the overall electricity demand of Sicily. Starting from this yearly data, 18 design days (12 typical + 6 extremes) were selected via the k-MILP clustering algorithm. The 6 extreme days are chosen as follows: three feature the maximum peak conditions (i.e., peak of electricity demand, solar and wind generation), two feature the lowest of solar and wind generation and the last one is freely chosen by the clustering algorithm itself to capture any possible "unusual" trend not seized by these criteria.

Table 2. *Main technical and economic parameters for each technology considered in the optimization model.*

	Dispatchable conversion technologies				
OCGT category	$OCGT1$ (Farmer, 2021)	OCGT2 (Farmer, 2021)	OCGT3 (Farmer, 2021)		
Power range [MW _{el}]	$30.8 - 57.0$	$80 - 116.5$	$144.1 - 314.0$		
Efficiency range $[\%]$	$37.2 - 40.1$	$36.4 - 38.3$	$34.8 - 38.6$		
Inv. Cost $\left[\frac{\epsilon}{kW_{el}}\right]$	$376.5 - 261.0$	$276.3 - 202.9$	$227.7 - 154.3$		
		PEM Electrolyzer (IRENA, 2019c)			
Power range [MW _{el}]	0-1500				
	Current value		Future value (2050)		
Efficiency (EE-to-LHV)	60%		75%		
Inv. Cost $\left[\frac{\epsilon}{kW_{el}}\right]$	800		400		
PV OM fix $\left[\frac{\epsilon}{kW\text{-year}}\right]$	32		16		
	Non-dispatchable technologies (IRENA, 2019a) (IRENA, 2019b)				

Other than the time-varying series, the optimizer required as input the techno-economic characterization of all the units constituting the AES. [Table 2](#page-4-1) reports the main parameters of the model for each unit, with their power ranges, efficiencies and investment costs considered. The upper bounds on the maximum PV and Wind capacity that could be installed and aggregated with the AES have been selected considering the value provided by TERNA in their projections on the renewable installations in Sicily for the year 2050, according to the Distributed Energy scenario (Terna and Snam, 2022) and multiplying these numbers by the corresponding percentage of the regional load that should be covered by the AES (i.e. 10%)

AES configurations

The optimal design and operation of the AES are analysed for three configurations differing in the seasonal storage solution adopted:

- 1) **BESS-only available**, referred to as "pure BESS" case.
- 2) **P2P-only available**:
	- a. H_2 stored in steel pipes storage vessels (high-cost solution), referred to as "P2P – pipes" configuration

b. H_2 stored in a line rock cavern (low-cost solution), referred to as "P2P – cavern" configuration

3) **P2P and BESS both available**:

- a. H² stored in steel pipes storage vessels (high-cost solution), referred to as "hybrid – pipes" configuration
- b. H² stored in a line rock cavern (low-cost solution), referred to as "hybrid – cavern" configuration

The techno-economic feasibility of the abovementioned configurations has been assessed in two different scenarios: the *current (i.e. reference) scenario*, assuming the current costs and performances of the technologies, and the *future (i.e. 2050) scenario*, representative of a situation where the AES is built in the future. In the latter scenario, cost reductions for batteries, electrolyzer technology and renewables have been taken into account according to the projections available in the literature (IRENA, 2019c)(IRENA, 2019a)(IRENA, 2019b)(Kebede et al., 2021). The goal is to critically analyse the differences among the optimal AES final design and management under these changing conditions and to understand strengths and weaknesses of the seasonal storage solutions adopted.

RESULTS

The design and operational optimization problem was solved with Gurobi® 9.5 (Gurobi, 2022). A maximum time limit of 1 hour is set for each optimization run. [Table 3](#page-6-0) reports the optimal AES design and the economic Key Performance Indicators (KPIs) found by the optimizer for all the configurations.

BESS-only configuration

Where BESS is the only available storage solution, the optimal design choice, in both the scenarios (current and 2050) is to couple the renewable generation with two very large BESS (thousands of MWh) characterized by different storage durations: a 4-hour and a 10-hour BESS. In this way, the BESS featuring the largest storage duration and capacity (BESS2) can be exploited with a lower frequency, for interday operations while the BESS with the higher c-rate (BESS1) is used, because of its fast dynamic, for shorter and more frequent intra-day cycles, mainly to accommodate periodic variations in the renewable generation. The LCOE achieved by such configuration in the reference cost scenario is 214.6 €/MWh. This number decreases to 128.1 €/MWh for the 2050 scenario.

P2P-only configurations

In P2P-based configurations, the optimal AES design is dependent on the type of H_2 storage technology adopted: if the H_2 is stored in the more expensive steel pipes, the storage optimal volume is contained as much as possible by (i) increasing the renewable generation capacity and (ii) the electrolyzer size. Since the renewable-generated electricity

is cheaper than the one generated with H_2 -based GTs, in order to contain the LCOE of the system, all the renewable capacity available is exploited and the P2P system is used as long-term storage to shift the production in hours where renewable generation is low or absent, to provide the backup power.

Compared to the current scenario, in 2050 the AES shows a similar design, except for the size of the H_2 storage which is reduced from 182.7 to 101.9 GWh. To better understand the storage behavior, the number of equivalent full-cycles (i.e. 100% charge/discharge) have been computed and reported in the Appendix [\(Table](#page-10-0) *5*): in 2050 scenario, the H_2 storage performs almost the double equivalent cycles, going from 3.4 to 6.5, meaning that such system does not work as "pure" seasonal storage but is charged and discharged with weekly and monthly frequency. Instead, when a low-cost solution is available for the H_2 storage, such as the rock cavern, a relatively larger storage volume can be exploited and the seasonal behavior is more evident. Thanks to the large storage capacity, the installed power of the electrolyzer and of the most expensive renewable technology (i.e. wind) can be both reduced. This is especially true for the 2050 scenario, where

the wind installed capacity is reduced to 601 MW and the electrolyzer rated power to 684 MW.

In terms of OCGT installation, the optimal choice for the conversion of the green H_2 into electricity is to install a large OCGT2 supported by three smaller OCGT1 with a nominal output power ranging between 32 and 57 MW, working as backups. OCGT3 is never installed because it is not economically convenient to operate such a large GTs for

few hours a year, despite the higher efficiency. From the number of Equivalent Operating Hours (EOH) of the installed OGCT (see in the Appendix), it can be noted that all of them are operated in a peaking regime (i.e. less than 3000 EOH a year) in each configuration, with the largest OCGT (i.e. OCGT2) not even achieving 1000 EOH in the current scenario. The utilization rate of OCGT2 increases in the 2050 scenario in terms of EOH.

Figure 3. *Example of the AES optimal operation strategy in all the design days considered (hybrid cavern configuration, 2050 scenario). Dark vertical lines are used to separate different design days.*

The P2P configuration based on pipes storage achieves a LCOE of 361 ϵ /MWh and this number is expected to be halved in future scenario (178.5 ϵ /MWh), mainly due to the cost reduction of the electrolyzer and the renewable installations. For the cavern storage, the LCOE is equal to 224.4 and 99 ϵ /MWh, respectively for reference and 2050 scenario. The cost reduction in this case is even more pronounced and the LCOE referred to 2050 scenario is more than halved thanks to technologies cost reduction and performance improvements.

Hybrid configurations

In the hybrid configurations, both storage options are present in the optimal design. In the pipes storage configuration, the solution is similar to the BESS-only case in terms of AES design, given the small size of the P2P system (small electrolyzer, OCGT and H₂ storage). A slightly lower LCOE can be achieved (213.2 €/MWh for current and 122.6 ϵ /MWh for future scenario). In this configuration, the H_2 storage can be exploited for infraseasonal and monthly periods with medium-long storage

durations (see [Figure 5a](#page-8-0) showing the yearly trend of pipes storage level) for which the use of a BESS is avoided because of self-discharge. However, the high cost of pipes discourages the installation of a large H_2 -storage system with a full seasonal capability.

Conversely, when geological storage is considered, such as the rock cavern case, the entire P2P seasonal potential is unlocked. From the number of equivalent full cycles of the two storage systems in [Table](#page-10-0) *5* (Appendix), it is evident how the two BESS are cycled relatively frequently (> 100 cycles a year, meaning an average value of three full cycles every three days) while the H_2 cavern has the typical number of cycles of a seasonal storage (1.4 for current, 4.7 for future scenario). The seasonal behavior is confirmed by looking at the trend of the yearly storage level, visible in [Figure 5b](#page-8-0). As both storage options are presented, the optimal operational strategy consists in exploiting the BESS for daily and intra-daily cycles while longer storage durations will be more efficiently handled by the larger H_2 storage. In 2050 scenario, the contribution of the P2P system becomes more prominent while the size of the two BESS is significantly reduced.

Figure 4. *Storage level of the seasonal H² storage for the hybrid-pipes (a) and hybrid-cavern (b) configurations, respectively, in the reference scenario.*

[Figure 3](#page-7-0) shows the AES operation behavior in all 18 design days selected for the hybrid cavern configuration in the future scenario. During the central hours of the day, the excess electricity from renewable generation is supplied to the electrolyzer to produce green H_2 and store it in the rock cavern. A minor fraction is used also to charge the two BESS. Later, the H₂ is discharged from the cavern to power the OCGTs, which together with BESS1 and BESS2, provide the required electricity to meet the load in the hours of the day where the renewable production is low or completely absent (e.g. at nighttime).

Configuration comparison

Comparing the AES design obtained in the different configurations, it can be demonstrated how a hybrid storage system (BESS + P2P) offers several advantages over their respective separated solutions: the combination of both BESS and hydrogen storage has led to the best design configuration, able to achieve (in both the scenarios), the minimum TAC and the lowest LCOE. If a low-cost option is available to store the H_2 , the LCOE reduction of the hybrid case with respect to the BESS-only configuration is even more pronounced: in the current scenario, the hybrid cavern is able to achieve a LCOE below 200 ϵ /MWh (192 E/MWh) and potentially, in the future, the LCOE could drop below 100 €/MWh (97 €/MWh), a remarkable achievement for a fully-renewable and fully-dispatchable system. This result could be made possible by devising an optimal AES management that exploits the good properties of the H² molecule as a long-term storage energy vector and, at the same time, relies on the fast dynamics characterizing the battery storage to match rapid variations in the renewable generation occurring on an hourly and daily basis, for which the use of a P2P storage system would not be cost-effective.

Figure 5. *LCOE of different AES configurations for the current and future scenario.*

CONCLUSIONS

This work investigated several design configurations for a fully-renewable and fully-dispatchable AES able to cover 10% of the electricity demand of the Sicily region, in Italy. Different long-term storage options have been explored and compared to each other to accommodate daily and seasonal variations in renewable productions.

Batteries turned out to be a promising storage solution for durations limited to daily and intra-daily horizons. For longer durations, factors such as the self-discharge rate and the high cost will not make the BESS solution economically convenient. In particular, AES configurations based on a BESS seasonal storage system resulted in very large battery sizes, difficult to implement in practice. Several aspects not discussed in this study would discourage the use of electrochemical batteries as seasonal storage such as aging and degradation, limited lifetime $(H₂$ storage has a 4 or 5 times longer lifetime), availability of rare minerals and critical materials for their manufacturing and environmental impact (e.g. land use and disposal).

Conversely, P2P storage has been proven to be more effective for long-term shifts of renewable production because, despite the low round-trip efficiency, the lower storage cost favors higher system capacities, especially in the presence of a geological storage system. Similarly, results show that the configuration with the hybrid storage solution achieves the lowest LCOE but the economic advantage compared to the benchmark BESS-only system depends mainly on the H_2 storage cost: if H_2 is stored in pressurized pipes, the economic gain is marginal (215 ϵ /MWh vs. 213 ϵ /MWh in the current scenario, 123 ϵ /MWh vs. 128 €/MWh with 2050 projections). The cost reduction is more significant if a low-cost H_2 storage (e.g., a cavern) is available: under this configuration, LCOE in the order of 192 ε /MWh for the current scenario and 97 ε /MWh for the 2050 scenario can be achieved.

REFERENCES

- Ahluwalia, R. K., T. Q. Hua, J. K. Peng, and R. Kumar. 2010. 2010 DOE Hydrogen Program Review *System Level Analysis of Hydrogen Storage Options*. Crystal City, Virginia.
- Birge, John R., and François Louveaux. 2011. Springer Series in Operations Research and Financial Engineering *Introduction to Stochastic Programming*.
- Buttler, Alexander, and Hartmut Spliethoff. 2018. "Current Status of Water Electrolysis for Energy Storage, Grid Balancing and Sector Coupling via Power-to-Gas and Power-to-Liquids: A Review." *Renewable and Sustainable Energy Reviews* 82(February 2017): 2440–54.
- Castelli, Alessandro Francesco, Lorenzo Pilotti, and Emanuele Martelli. 2022. "Optimal Design and Operation Planning of VPP Based on Hydrogen." In *ASME Turbo Expo Conference Proceedings*, , 1–11.
- Cole, Wesley, A Will Frazier, and Chad Augustine. 2021. National Renewable Energy Laboratory (NREL) *Cost Projections for Utility-Scale Battery Storage: 2021 Update*. www.nrel.gov/publications. (November 30, 2020).
- Crespi, Elena, Paolo Colbertaldo, Giulio Guandalini, and Stefano Campanari. 2021. "Design of Hybrid Powerto-Power Systems for Continuous Clean PV-Based Energy Supply." *International Journal of Hydrogen Energy* 46(26): 13691–708. https://linkinghub.elsevier.com/retrieve/pii/S036031 9920335928 (April 22, 2021).
- "Download Center Terna Spa." https://www.terna.it/en/electric-system/transparencyreport/download-center (June 10, 2022).
- European Turbine Network. 2020. *ETN Global. Hydrogen Gas Turbines:The Path Towards a Zero-Carbon Gas Turbine*.
- Farmer, Robert. 2021. "2021 GTW Handbook." *Volume 36*. https://gasturbineworld.com/shop/annualhandbook/2021-handbook-volume-36/ (January 24, 2022).
- Gabrielli, Paolo, Matteo Gazzani, Emanuele Martelli, and Marco Mazzotti. 2018. "Optimal Design of Multi-Energy Systems with Seasonal Storage." *Applied*

Energy 219(May 2017): 408–24. https://doi.org/10.1016/j.apenergy.2017.07.142.

- Gülen, S. Can. 2019. Gas Turbines for Electric Power Generation *Gas Turbines for Electric Power Generation*. Cambridge University Press.
- Gurobi Optimization, LLC. 2022. "Gurobi Optimizer Reference Manual." https://www.gurobi.com.
- Hoffmann, Maximilian, Leander Kotzur, Detlef Stolten, and Martin Robinius. 2020. "A Review on Time Series Aggregation Methods for Energy System Models." *Energies* 13(3): 641. https://www.mdpi.com/1996- 1073/13/3/641 (December 7, 2020).
- IEA. 2019. *The Future of Hydrogen*. OECD. https://www.oecd-ilibrary.org/energy/the-future-ofhydrogen_1e0514c4-en.
- IRENA. 2019a. November International Renewable Energy Agency *Future of Solar Photovoltaic: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects (A Global Energy Transformation: Paper)*.
- IRENA. 2019b. IRENA. *Future of Wind: Deployment, Investment, Technology, Grid Integration and Socio-Economic Aspects*.
- IRENA. 2019c. Report prepared for the 2nd Hydrogen Energy Ministerial Meeting in Tokyo, Japan *Hydrogen: A Renewable Energy Perspective*. https://irena.org/publications/2019/Sep/Hydrogen-Arenewable-energy-perspective.
- IRENA. 2021. IRENA. *World Energy Transitions Outlook*.
- Kebede, Abraham Alem et al. 2021. "Techno-Economic Analysis of Lithium-Ion and Lead-Acid Batteries in Stationary Energy Storage Application." *Journal of Energy Storage* 40(May): 102748.
- Landinger, Hubert. 2013. "Benchmarking of Large Scale Hydrogen Underground Storage." *HyUnder project* (August).
- Matos, Catarina R., Júlio F. Carneiro, and Patrícia P. Silva. 2019. "Overview of Large-Scale Underground Energy Storage Technologies for Integration of Renewable Energies and Criteria for Reservoir Identification." *Journal of Energy Storage* 21(March 2018): 241–58.
- Sauer, Dirk Uwe, and Heinz Wenzl. 2008. "Comparison of Different Approaches for Lifetime Prediction of Electrochemical Systems-Using Lead-Acid Batteries as Example." *Journal of Power Sources* 176(2): 534– 46.
- Short, Walter, Dj Packey, and Thomas Holt. 1995. "A Manual for the Economic Evaluation of Energy Efficiency and Renewable Energy Technologies." *Renewable Energy* 95(March): 73–81. http://large.stanford.edu/publications/coal/references /troughnet/market/docs/5173.pdf (February 28, 2022).
- Terna, and Snam. 2022. 3 Paper Knowledge . Toward a Media History of Documents *Documento Di Descrizione Degli Scenari 2022*.

https://www.terna.it/it/sistema-elettrico/rete/pianosviluppo-rete/scenari/previsioni-domanda-elettrica.

- Wang, John et al. 2014. "Degradation of Lithium Ion Batteries Employing Graphite Negatives and Nickel-Cobalt-Manganese Oxide + Spinel Manganese Oxide Positives: Part 1, Aging Mechanisms and Life Estimation." *Journal of Power Sources* 269: 937–48.
- Zareipour, Hamidreza, Marc Beaudin, Anthony Schellenberglabe, and William Rosehart. 2010. "Energy Storage for Mitigating the Variability of Renewable Electricity Sources: An Updated Review." *Energy for Sustainable Development* 14(4): 302–14.
- Zatti, Matteo et al. 2019. "K-MILP: A Novel Clustering Approach to Select Typical and Extreme Days for Multi-Energy Systems Design Optimization." *Energy* 181: 1051–63.

https://doi.org/10.1016/j.energy.2019.05.044.

APPENDIX

[Table](#page-10-1) *4* shows the number of Equivalent Operating Hours (EOH) of the electrolyzer and OCGT for each AES configuration considered.

[Table](#page-10-0) 5 reports the number of equivalent full (i.e. 100%) depth-of-discharge) charge-discharge cycles of the storage technologies.

Configuration P2P - pipes P2P - cavern Hybrid - pipes Hybrid - cavern *Scenario current future current future current future current future* Electrolyzer 2217 1908 2656 2754 1924 1765 2575 2635 OCGT1 – s1 2729 1615 2732 2587 884 2954 2069 2989 OCGT1 – s2 | 2566 | 2661 | 2567 | 2876 | 0 | 0 | 0 | 2460 OCGT1 – s3 | 1501 | 1524 | 1843 | 1786 | 0 | 0 | 0 | 2515 OCGT2 | 973 | 1824 | 863 | 1231 | 0 | 0 | 0 | 0

Table 4. *Number of Equivalent Operating Hours (EOH) for the electrolyzer and OCGTs.*

