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Renewable Hydrogen Energy Communities layouts towards off-grid operation

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ABSTRACT

Solar hydrogen technology, i.e. producing green hydrogen by electrolysis fed by solar panels, is gaining attention as studies show it can compete with traditional electric batteries. Contemporary, the interest in the realization of Renewable Energy Community driven by the recent adoption in almost all the EU Countries of the RED II Directive is increasing. To match innovative technologies and new business models making the energy demand and the production closer in terms of time and space, the feasibility of Renewable Hydrogen Energy Community is explored. To determine the profitability of these solutions and size and operate the energy system, energy and economic analyses are needed as well as the optimization of its performance. A building complex with 180 kWp of PhotoVoltaics was studied using hourly real data on energy loads and production. Storage capacities ranging from 500 to 2000 kWh were simulated for hydrogen and electric battery options. The cost of investment and operation was also analyzed for the years 2020, 2030, and 2040 to evaluate changes in technology readiness level as well as accounting for the strong changes in electricity tariff due to the geopolitical issues effects on the market. The analysis was conducted using the DECAPLAN™ digital platform, which employs a mixed integer linear programming solver. Finally, the dispatch on hourly base has been compared for the same two months in 2019, 2020 and 2021 corresponding to pre, during and after pandemic restrictions.

1. Introduction

Energy transition called by scientists [1] is dealing with the constraints of reality [2] actually highlighting the inadequate infrastructures to allow it [3] when locally high power of new renewable energy plant is planned to be installed or widespread of prosumers activities in asking bidirectionality to the Grid, conceived as centralized mono-directional infrastructure. Electricity sector is the first and main subject of the transition [4] since electrification is seen a growing trend of heating and transport sectors with a yearly 3 % growth [5] seeing the huge increase in electric renewables installations in the last two decades mainly with the centralized approach [6] of installing new RES power plant connected to the grid [7] with the benefit of reducing the Primary Energy Factor, as defined by the International Energy Agency [5], of the Power Grid [8]. Here, the further stress on the grid by new connected production comes [9]. At centralized level, the balancing issues caused by the mismatch between demand and production [10] leads to the inclusion of storage facilities [11]. However, they are limited in size [12] and, subsequently, in impact on the grid operation due to the high costs [13]. A different case is for pumped hydro but geographical features and justice of transition rule are the main obstacles for further installations [14]. It comes the consideration of the energy balance at National level as the sum of energy balances at smaller and smaller scales [15] entailing, with the limitation to the electrical energy, the important role of local energy communities [16]. Local electricity balance means reducing the changes [17], and subsequent stress, on the Grid infrastructures together with a new focus on local emission factors [18] linked to local energy mixes [19]. The direct consequence is the decentralized search for renewable energy plants [20], accounting for multiple generation types and units, i.e. a polygeneration system, and, then, the setting up of the Renewable Energy Community (REC) concept recently codified in the EU Directive REDII [21]. Moreover, the codified incentive schemes supporting the Self-Consumption [22] aim at providing the shared added value in terms of environmental and financial impact of the energy chain to the community members [23].

PV on the roof, hot water storage, electric batteries in the basement are the most used tools made available to the citizens to participate to this new entity being the way to store the local renewable production [24] by converting it into stored heat or storing electricity to put back. In

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Nomenclature

BAU	Business As Usual
CAPEX	Capital Expense
CL	Calendar Life
DUCV	During-Covid
DNI	Direct Normal Irradiation
DOD	Depth of Discharge
DPBP	Discounted Payback Period
EES	Electrochemical Energy Storage
EU	European Union
IRR	Internal Rate of Return
LCOE	Localized Cost of Electricity
LHV	Lower Heating Value
MILP	Mixed-Integer Linear Programming
MINLP	Mixed-Integer Non-Linear Programming
MP	Master Planning
NC	Number of Cycles
NP	New Price
NPV	Net Present Value
NSC	No Self-Consumption
ODP	Optimal Dispatch Planning
OP	Old Price
OPEX	Operational Expenses
POCV	Post-Covid
PRCV	Pre-Covid
PV	PhotoVoltaics
REC	Renewable Energy Community
RES	Renewable Energy Sources
ROI	Return of the Investment
SC	Self-Consumption
SOC	State OF Charge
TCO	Total Cost of Ownership
WSC	With Self-Consumption

the case of batteries, the diffusion is limited to residential size, around few kWh thanks to the fully economic support as the case of SuperBonus 110 % in Italy [22]. Beside them, innovative technologies are taking place such hydrogen energy systems [25]. Similarly, centralized approach for assisting the Grid is taking place first even with the limitations in size and impact due to the high costs [26]. Later, small scale hydrogen energy systems based on reversible cell like the reversible solid oxide cells are seeing interest [27] and their application to different types of buildings [28] offering the production and utilization of hydrogen as a service for the buildings [29] and in cooperation with other sectors like the mobility [30].

Few applications of reversible cells to the building sectors are available in literature as reviewed in [27,31] and since buildings are the unit of energy production and consumption in a community [32], the application to such a scale is of primary interest [33]. Furthermore, the contemporary adoption of optimal energy management strategies [34] and tailored energy systems design [35] to make the local renewable energy production meeting the load profiles [36] implies the strong decrease of the electrical energy exchange in the REC boundaries made possible thanks to the adoption of diversified production [37] and detailed choice of storage systems [38].

In this paper, a Renewable Hydrogen Energy Community to be set, composed by five buildings equipped with a total of 180 kWp of PV array is designed by master planning and optimal dispatching focusing on the role of hydrogen based technologies to maximize the Self Consumption, to annual the electricity export to the Grid in comparison with electric batteries accounting for the changes in loads before, during and after the pandemic in the monitored period of almost 4 years (2018–2021).

2. Materials and methods

In this section, the methods used for data collection and analysis are described. The DECAPLAN™ digital platform [39] is proprietary digital of a start-up company spin-off of Nanyang Technological University. The DECAPLAN™ has been developed for designing power plants, microgrids, and industrial and building estates characterised by high energy mix by establishing the best plant arrangement and choosing among database (DB) the most suitable commercially available components. The DECAPLAN™ allows for concurrently optimising the best multi-energy plant design and operation by solving the energy dispatch for given electricity, cooling and other demands. In this paper, the optimal solution is addressed to minimise the primary energy consumption and the greenhouse pollutant emissions (CO_2) by maximising the Net Present Value (NPV) at the same time. The mathematical formulation of the DECAPLAN™ objective function enables the digital platform to search for the best solutions taking the Operational Expenses (OPEX), the Localized Cost of Electricity (LCOE), the Return of the Investment (ROI), and other parameters into consideration. More details on the modelling approach and the optimisation strategy are given in the next section.

The proposed system layout includes several components, with the main ones being the electrolyser and fuel cell, as well as their management. This section presents the mathematical formulation for the Master Planning (MP) and the Optimal Dispatch Planning (ODP), along with a description of the main features of the DECAPLAN™ digital platform. The simulation tool for the hydrogen energy system was developed using a modular approach at the component level. To set up the polygeneration plant simulator, steady-state 0-D component models were adopted as per the method proposed by the DECAPLAN™ digital platform algorithm. The DECAPLAN™ includes various solvers such as quadratic programming, mixed-integer linear programming (MILP), and mixed-integer non-linear programming (MINLP). Research has shown that the mixed-integer quadratic programming technique used by the DECAPLAN™ digital platform is robust and efficient, as demonstrated by comparisons with a hybrid heuristic algorithm based on GA and PSO solvers [40] and other mathematical approaches [41,42]. Additionally, the use of stochastic algorithms has been found to potentially lead to suboptimal results in master-planning problems [43]. Fig. 1 provides a complementary block diagram to understand the optimization process flow that the end-users need to perform, specifically the optimal dispatch block diagram DECAPLAN™.

The algorithm consists of three parts: the *input layer*, where conditions such as temperature, DNI, and precipitation profiles, as well as plant demands and costs, are inputted; the *optimal dispatch layer*, where the algorithm matches and connects components, ensuring that conservation equations are not violated; and the *output layer*, where the optimal dispatch strategy for the power plant and its associated costs are presented. Additionally, the algorithm uses a modular approach to simulate power systems and incorporates a database of component performance maps to evaluate costs, degradation, and maintenance. In detail, the three layers are:

Input Layer: In this step, the input for solving the optimal dispatch problem includes boundary conditions such as temperature, DNI, and rain profiles. Additionally, the electric, heating and cooling loads, as well as the costs associated with plant operations, are also input. In the case of solving the optimal dispatch problem standalone, the plant configuration is defined by the end user. However, in the case of master planning, the supervisory algorithm provides the plant configuration and optimized selection of components from the database.

Optimal Dispatch Layer: In this step, the DECAPLAN™ optimal dispatch routine matches and connects the components, ensuring that

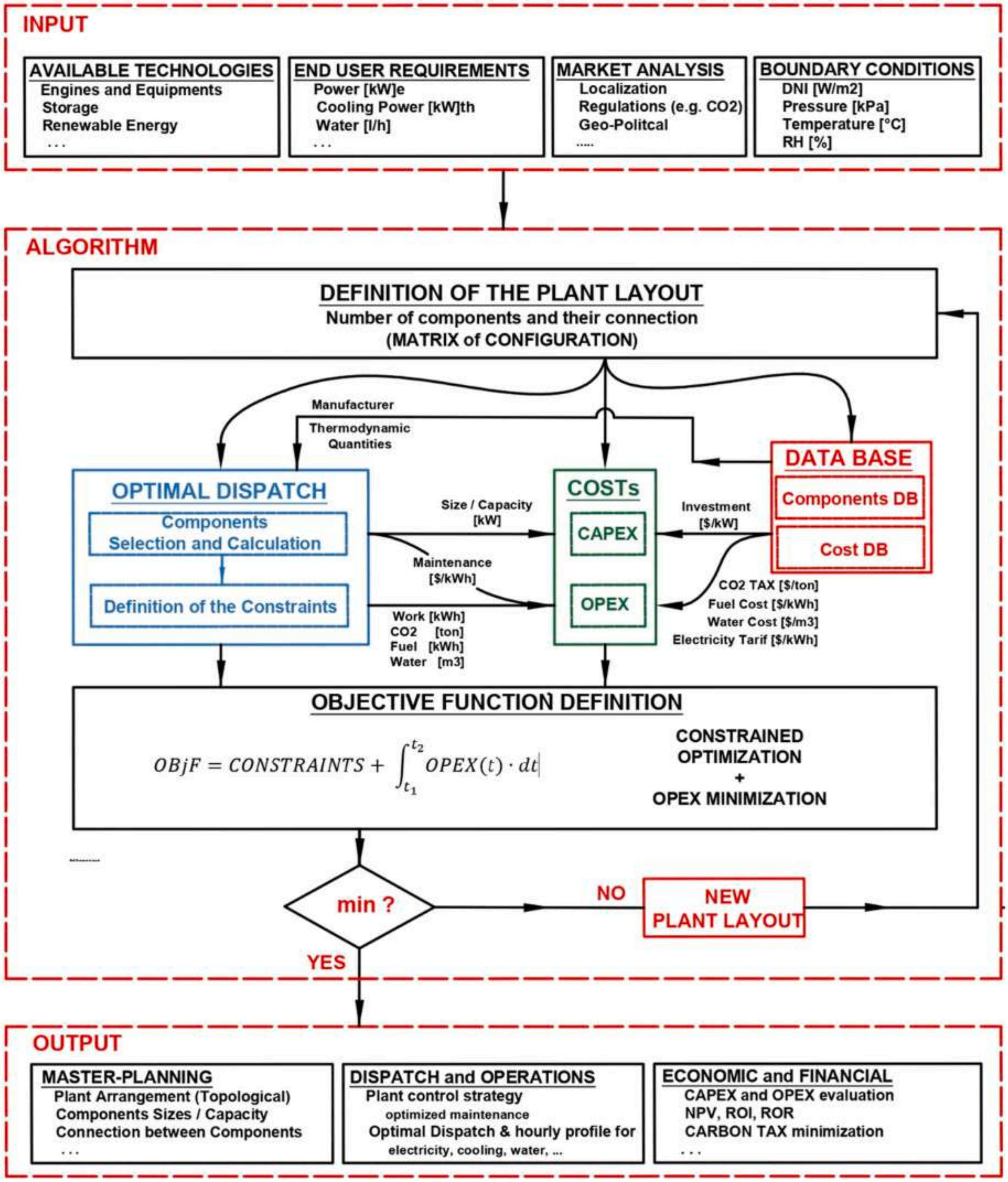


Fig. 1. The block diagram of DECAPLAN™ digital platform.

mass flow rates, temperatures, pressures, and conservation equations are not violated. Each component contributes to defining the objective function and adding constraints and partial objective functions related to the component operations. Through this modular approach, it is possible to simulate any type of power system within the limitations of computational costs and the number of variables involved in the optimization. The solver iterates the Lagrangian multipliers (in the case of the quadratic programming approach) until convergence is achieved. As a result of solving the optimal dispatch problem, the DECAPLAN™ software determines which components will be operated at what load during the specified time interval.

Output Layer: The final outcome of the calculations is the optimal dispatch strategy for the polygeneration power plant, which includes the definition of plant operations and set points for controlled variables. The output also includes a techno-economic breakdown of operating costs, scheduled maintenance, and the performance deterioration of components due to plant operations.

As for the techno-economic optimization, the modelling of the Capital Expense (CAPEX) and Operating Expense (OPEX) is discussed, along with the details of the objective function used for the evaluations.

The system being analyzed in this study is a complex of five fully electrified buildings, where all energy needs are met through electric-driven appliances. Consumption and production datasets are used and divided in 3 intervals: (i) pre-COVID-19, (ii) during COVID-19 and (iii) post COVID-19. Data consists of hourly electricity consumption and production data of 5 buildings located in Naples, Italy covering the

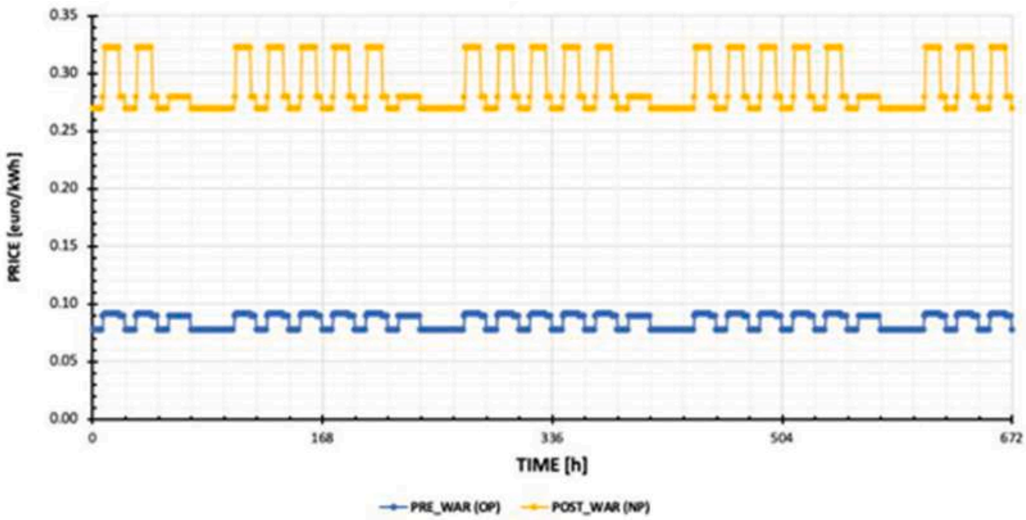


Fig. 2. Hourly trends of electricity tariff before and after geopolitical issues.

period of February 1st, 2018 to November 30th, 2021. The production data includes hourly data on the electricity generated by installed photovoltaics during the same period. Electricity prices, which were split into three categories based on the national grid tariff related to the different times of use, were taken from energy bills and did not include taxes. The weekly breakdown of tariffs into three categories: F1 for working hours during weekdays, 8:00 to 18:00; F2 for a few hours surrounding the F1 interval, 7:00–8:00 and 18:00–23:00 and most of Saturday 7:00 to 23:00; and F3 for all nighttime, the entire Sunday and it is valid for holidays. Fig. 2 shows this trend during the week highlighting the BAU price as well as, in yellow, the price after the geopolitical issues of February 2022.

The DECAPLAN platform is utilized to conduct Master Planning and Optimal Dispatch, integrating production, storage, and consumption. The system components are modeled using the DECAPLAN™ Digital Platform database (component libraries) and validated using real manufacturers' data. Additionally, economic parameters such as investment and operational costs are associated with each component. The technical data of the technological components and their mathematical formulation in the model are detailed below.

2.1. Solar PV

The solar PV component in the model is represented by a lumped performance model, that includes in the optimal tilt angles and azimuth, in respect of the geographical location, according to the methodologies reported in [44]. This approach allows for the calculation of both the performance of the Solar PV and the Capital Investment (C_{0PV}) by taking into account manufacturing parameters such as the reference Solar PV cell temperature (TCR), the type of Solar PV (mono or polycrystalline) and the reference (nominal) Solar PV efficiency. During off-design conditions, the actual efficiency is determined by normalized maps relating the reference efficiency, the DNI and PV cell temperature to the actual DNI and cell temperature (T). The efficiency generally increases as the cell temperature decreases. Typically, 0 °C is used as the minimum value. Therefore, it is expressed as a function of:

$$\eta_{PV} = f\left(\eta_{PV_R}, \frac{DNI}{DNI_R}, \frac{T}{T_R}\right) \tag{1}$$

The power generated by the solar PV system is calculated accounting for the number of PV modules (N_{PV}), the direct normal irradiance (DNI), the PV area (S_{PVN}) and the ambient temperature, as shown in Equation (2).

$$P_{PV} = N_{PV} \bullet DNI \bullet S_{PV_N} \bullet \eta_{PV} \tag{2}$$

The net power output given by equation (2) is consider in DC. In case that the implementation of an inverter is required for generating AC, a 0.95 inverted peak efficiency is taken into consideration.

The cost of the PV system (C_{0PV}) is determined by the relationship between the type of PV technology used and its performance. The authors have compiled a database of various PV modules based on manufacturer data and costs in [44]. In cases where costs are not provided, cost functions based on factorized methods are used to evaluate the cost of the PV system. According to IRENA [45], the average efficiency of PV modules has been steadily increasing since 2006 and is expected to continue to do so through 2030. The efficiency of multicrystalline PV panels was 13.2 % in 2006 and 14.7 % for monocrystalline PV panels, and by 2018, it has risen to 24.2 % set by researchers in the United States and the Republic of Korea, which is close to the lab record of 26.7 % for silicon. It is worth of note that in [45] the cost of the PV, C_{OPV} does not include the balance of the system, since it drastically depends of the specificity of each Solar PV installation.

2.2. Hydrogen storage and utilization systems

The H_2 Storage System (H2-ST) model includes three main components: the Electrolyser, the H_2 Storage Tank and the Fuel Cell (FC). These three components work together to enable hydrogen charging, storing, and discharging, similar to Electrochemical Energy Storage (EES) systems. The model takes into account operating parameters such as the charging efficiency ($\eta_{Electrolyzer}$), discharging efficiency (η_{FC}), the State of Charge (SOC_{H2ST}), and the maximum storage capacity (E_{H2ST}) of the H_2 storage tank. The FC and Electrolyser are selected from the DECAPLAN™ Digital platform database, and their costs, efficiencies, and off-design performance are also taken into consideration. Additionally, secondary losses have been factored into the efficiencies of the two components. The H_2 mass or volume flow rate can be calculated by considering the Lower Heating Value (LHV) and the specific weight of hydrogen. The SOC, or state of charge, in this paper, is defined as the ratio of actual energy stored in the EES at a given time (t + 1) to the nominal capacity. It is a non-dimensional parameter and bounded by minimum and maximum SOC values. The ODP, or optimal dispatch problem, has inequality constraints expressed by the energy conservation equation and capacity at time step (t + 1) established as the capacity at time step (t) plus energy injected during charge or minus energy taken during discharge. An equality constraint is also introduced to ensure energy conservation over the EES's entire period of operation, which can

Table 1
CAPEX Comparison of different plant layouts towards 2040 scenarios.

		kWh	[-]	CAPEX [EURO]
2020	H2	500	1	€ 905.844
		1000	2	€ 1.412.942
		1500	3	€ 1.845.871
		2000	4	€ 2.236.724
	BATT	500	5	€ 299.749
		1000	6	€ 613.076
		1500	7	€ 841.745
		2000	8	€ 1.062.766
2030	H2	500	9	€ 500.967
		1000	10	€ 794.289
		1500	11	€ 1.044.709
		2000	12	€ 1.270.791
	BATT	500	13	€ 178.754
		1000	14	€ 306.474
		1500	15	€ 427.669
		2000	16	€ 544.810
2040	H2	500	17	€ 356.943
		1000	18	€ 568.134
		1500	19	€ 748.437
		2000	20	€ 911.216
	BATT	500	21	€ 132.851
		1000	22	€ 231.654
		1500	23	€ 325.408
		2000	24	€ 416.027

be adapted to weekly, monthly, or yearly time steps. The cost of a hydrogen system is determined by the cost of its main components, as illustrated by Equation (3).

$$C_{0H_2} = C_{0_{FC}} + C_{0_{ELZY}} + C_{0_{H2-ST}} \tag{3}$$

The cost of a fuel cell (C_{0H2}) is primarily influenced by the technology used (FC_{Type}), its capacity (P_{FC}), operating conditions and related efficiency (η_{FC}), and configuration. Equation (4) provides the formula for calculating this cost.

$$C_{0H2} = f\left(FC_{Type}, P_{FC}, \eta_{FC}\right) \tag{4}$$

The cost of an electrolyzer (C_{0ELY})is largely determined by the technology employed (ELY_{Type}) (such as Alkaline or PEM), the capacity for producing hydrogen per hour (M_{H2}), the operating pressure (p_{ELY}), and the efficiency of the system (η_{ELY}). Equation (5) provides the formula for this cost.

$$C_{0ELY} = f\left(ELY_{Type}, M_{H_2}, \eta_{ELY}, p_{ELY},\right) \tag{5}$$

The final component of the system is the hydrogen storage tank. The cost of the storage tank ($C_{0H2\text{-}ST}$)is established based on several factors, including the capacity of the tank (V_{H2}), the insulation properties (s_{INSU}), and the operating pressure (p_{H2}). Equation (6) provides the formula for determining this cost.

$$C_{0H2-ST} = f\left(V_{H_2}, s_{INSU}, p_{H_2}\right) \tag{6}$$

2.3. Electrical energy storage systems

Choosing the appropriate EES is contingent on various factors and the specific needs of the end user. In recent years, various EES technologies have been developed for a range of applications, such as mobile phones, electric vehicles, micro-grids and poly-generation applications that are often paired with solar PV. The EES component model takes into account several operating parameters such as charge and discharge efficiency, State of Charge (SOC), Depth of Discharge (DOD), nominal capacity, circuit current and voltage, Calendar Life (CL), and Number of Cycles (NC). These parameters are related to the specific EES family (e.g.

Table 2
Comparison of different storage technologies and capacities versus different scenarios – NPV analysis.

				#1	#2	#3	#4	#5	#6	#7	#8
		kWh	[-]	PRCV_NSC_OP	PRCV_WSC_OP	DUCV_NSC_OP	DUCV_WSC_OP	POCV_NSC_OP	POCV_WSC_OP	POCV_NSC_NP	POCV_WSC_NP
2020	H2	500	1	-€ 754,179	-€ 264,825	-€ 784,712	-€ 134,424	-€ 786,614	-€ 274,107	-€ 494,728	€ 17,779
		1000	2	-€ 1,256,404	-€ 767,200	-€ 1,281,707	-€ 631,418	-€ 1,287,131	-€ 774,624	-€ 978,584	-€ 466,077
		1500	3	-€ 1,688,574	-€ 1,199,425	-€ 1,713,343	-€ 1,063,055	-€ 1,718,955	-€ 1,206,448	-€ 1,407,660	-€ 895,153
		2000	4	-€ 2,078,932	-€ 1,589,778	-€ 2,103,645	-€ 1,453,356	-€ 2,108,963	-€ 1,596,456	-€ 1,795,549	-€ 1,283,042
	BATT	500	5	-€ 126,190	€ 304,963	-€ 162,517	€ 317,186	-€ 158,097	€ 252,295	€ 187,106	€ 597,498
		1000	6	-€ 433,810	€ 53,274	-€ 472,868	€ 177,421	-€ 466,331	€ 46,176	-€ 109,096	€ 403,411
		1500	7	-€ 661,021	-€ 173,954	-€ 700,530	-€ 50,241	-€ 693,998	-€ 181,491	-€ 334,511	€ 177,996
		2000	8	-€ 881,360	-€ 394,370	-€ 920,565	-€ 270,277	-€ 914,563	-€ 402,056	-€ 553,931	-€ 41,424
2030	H2	500	9	-€ 340,661	€ 199,062	-€ 374,627	€ 342,603	-€ 373,983	€ 191,282	-€ 62,977	€ 502,288
		1000	10	-€ 629,236	-€ 89,924	-€ 658,142	€ 59,088	-€ 661,010	-€ 95,745	-€ 334,136	€ 231,129
		1500	11	-€ 878,425	-€ 339,191	-€ 906,952	-€ 189,722	-€ 910,334	-€ 345,069	-€ 580,476	-€ 15,211
		2000	12	-€ 1,103,841	-€ 564,623	-€ 1,132,364	-€ 415,134	-€ 1,135,940	-€ 570,675	-€ 804,776	-€ 239,511
	BATT	500	13	-€ 407	€ 450,386	-€ 40,936	€ 447,265	-€ 33,531	€ 391,225	€ 320,544	€ 745,299
		1000	14	-€ 121,890	€ 415,676	-€ 165,856	€ 551,077	-€ 155,074	€ 410,169	€ 213,787	€ 779,030
		1500	15	-€ 241,363	€ 296,032	-€ 286,044	€ 431,186	-€ 274,978	€ 290,287	€ 96,918	€ 662,183
		2000	16	-€ 357,827	€ 179,585	-€ 402,422	€ 314,808	-€ 391,686	€ 173,579	-€ 18,724	€ 546,541
2040	H2	500	17	-€ 188,668	€ 411,006	-€ 226,506	€ 570,416	-€ 222,529	€ 405,543	€ 106,711	€ 734,783
		1000	18	-€ 394,631	€ 204,573	-€ 429,716	€ 367,206	-€ 427,241	€ 200,831	-€ 81,849	€ 546,223
		1500	19	-€ 573,428	€ 25,593	-€ 608,769	€ 188,153	-€ 606,686	€ 21,386	-€ 258,979	€ 369,093
		2000	20	-€ 735,502	-€ 136,515	-€ 771,254	€ 25,668	-€ 769,133	-€ 141,061	-€ 420,357	€ 207,715
	BATT	500	21	€ 50,308	€ 521,110	€ 5,476	€ 502,240	€ 16,176	€ 455,414	€ 379,713	€ 818,951
		1000	22	-€ 41,287	€ 553,660	-€ 90,608	€ 689,990	-€ 75,635	€ 545,523	€ 304,769	€ 925,928
		1500	23	-€ 132,918	€ 464,528	-€ 183,483	€ 613,439	-€ 167,082	€ 460,990	€ 218,911	€ 846,983
		2000	24	-€ 222,646	€ 374,697	-€ 273,422	€ 523,500	-€ 257,091	€ 370,981	€ 130,455	€ 758,527

Table 3
Optimal Energy Storage Capacity versus different scenarios.

year	OBJ: –> NPV	BATT [kWh]	H_2 [kWh]
2020	Best performing Capacity	500	500
2030	Best performing Capacity	1000	500
2040	Best performing Capacity	1000	500

Lithium-Ion, Vanadium Redox), nominal capacity, and Capital Investment through implicit equation (7).

$$C_{0EL_{ST}} = f(Type, E_N, I, V, SOC, DOD, CL, N_C, \eta_{RTE},) \tag{7}$$

This information can be used to populate a EES Database (DB) to aid in selecting the most suitable component for the intended application. For stationary applications in remote islands, lithium-based EES have a high energy density compared to other EES options and offers high-power discharge and excellent round-trip efficiency. The depth of discharge for these chemistries can be between 80 % and 100 %, and the estimated central round-trip efficiency for Li-ion technologies ranges from 92 % to 96 %. Additionally, there has been a reduction in capital costs over the years making their use in stationary applications increasingly competitive.

2.4. Financial details

The Incentives provided by the Italian Ministry of Economy [22] considers the prize, in the form of incentive ($p_{Incentive}$) totally of 160 €/MWh for the electric work generated through renewable energy sources and internally consumed ($P_{INTERNAL}$). Accordingly, the incentive is quantified as:

$$INCENTIVE = \int_0^{365} P_{INTERNAL} \bullet p_{Incetive}(t) \bullet dt \tag{8}$$

The total incentive is the sum of the basic Self Consumption incentive of 110 €/MWh; the award for the avoided grid usage of 8 €/MWh and the avoided buy of the average day-ahead market price of around 42 €/MWh. According to a report from the International Renewable Energy

Table 4
Comparison of different storage technologies and capacities versus different scenarios – Yearly Cash Flow analysis.

				#1	#2	#3	#4	#5	#6	#7	#8
		kWh	[-]	PRCV_NSC_OP	PRCV_WSC_OP	DUCV_NSC_OP	DUCV_WSC_OP	POCV_NSC_OP	POCV_WSC_OP	POCV_NSC_NP	POCV_WSC_NP
2020	H2	500	1	€ 13,787	€ 58,828	€ 11,117	€ 70,796	€ 10,942	€ 57,976	€ 37,729	€ 84,764
		1000	2	€ 14,220	€ 59,262	€ 12,044	€ 71,723	€ 11,546	€ 58,580	€ 39,862	€ 86,897
		1500	3	€ 14,285	€ 59,326	€ 12,162	€ 71,842	€ 11,647	€ 58,682	€ 40,216	€ 87,250
		2000	4	€ 14,331	€ 59,372	€ 12,213	€ 71,892	€ 11,725	€ 58,759	€ 40,488	€ 87,522
	BATT	500	5	€ 15,623	€ 55,496	€ 12,594	€ 56,618	€ 13,000	€ 50,663	€ 44,680	€ 82,343
		1000	6	€ 16,112	€ 61,153	€ 12,867	€ 72,546	€ 13,467	€ 60,502	€ 46,252	€ 93,286
		1500	7	€ 16,244	€ 61,285	€ 12,960	€ 72,639	€ 13,559	€ 60,594	€ 46,550	€ 93,585
		2000	8	€ 16,300	€ 61,341	€ 13,050	€ 72,729	€ 13,601	€ 60,636	€ 46,697	€ 93,732
2030	H2	500	9	€ 14,566	€ 64,244	€ 11,595	€ 77,417	€ 11,654	€ 63,530	€ 40,196	€ 92,072
		1000	10	€ 14,964	€ 64,642	€ 12,495	€ 78,317	€ 12,231	€ 64,108	€ 42,230	€ 94,106
		1500	11	€ 15,070	€ 64,748	€ 12,642	€ 78,465	€ 12,332	€ 64,208	€ 42,604	€ 94,480
		2000	12	€ 15,129	€ 64,807	€ 12,704	€ 78,526	€ 12,376	€ 64,252	€ 42,768	€ 94,644
	BATT	500	13	€ 16,062	€ 57,738	€ 12,648	€ 57,452	€ 13,328	€ 52,309	€ 45,822	€ 84,803
		1000	14	€ 16,600	€ 66,274	€ 12,905	€ 78,700	€ 13,895	€ 65,769	€ 47,746	€ 99,620
		1500	15	€ 16,738	€ 66,416	€ 12,997	€ 78,820	€ 14,013	€ 65,889	€ 48,143	€ 100,019
		2000	16	€ 16,802	€ 66,480	€ 13,067	€ 78,890	€ 14,053	€ 65,929	€ 48,281	€ 100,157
2040	H2	500	17	€ 15,279	€ 70,477	€ 11,971	€ 85,107	€ 12,336	€ 69,976	€ 42,551	€ 100,191
		1000	18	€ 15,716	€ 70,914	€ 12,703	€ 85,839	€ 12,930	€ 70,570	€ 44,628	€ 102,268
		1500	19	€ 15,837	€ 71,035	€ 12,818	€ 85,954	€ 13,009	€ 70,649	€ 44,919	€ 102,559
		2000	20	€ 15,899	€ 71,097	€ 12,845	€ 85,981	€ 13,039	€ 70,680	€ 45,048	€ 102,688
	BATT	500	21	€ 16,521	€ 60,016	€ 12,695	€ 58,284	€ 13,677	€ 53,987	€ 47,040	€ 87,350
		1000	22	€ 17,127	€ 72,071	€ 12,944	€ 84,582	€ 14,318	€ 71,324	€ 49,229	€ 106,235
		1500	23	€ 17,297	€ 72,495	€ 13,025	€ 86,161	€ 14,530	€ 72,170	€ 49,954	€ 107,594
		2000	24	€ 17,369	€ 72,567	€ 13,087	€ 86,223	€ 14,586	€ 72,226	€ 50,152	€ 107,793

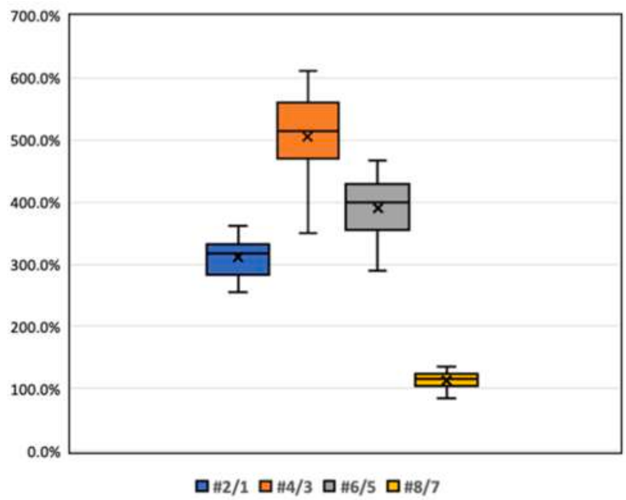


Fig. 3. Yearly Cash Flow increase between Cases with and without Self Consumption.

Agency (IRENA) [45], the cost of renewable energy sources, coupled with energy storage and hydrogen technologies, is projected to decrease significantly in the coming years. The Levelized Cost of Energy (LCOE) for solar PV technology is expected to drop from an average of 0.14 $/kWh in 2018 to an average of 0.03 $/kWh in 2050. This decrease is driven by two main factors: the ability of manufacturers to produce solar PV modules at lower costs while maintaining high reliability and durability and the development and commercialization of materials and technologies that can increase energy conversion efficiency. In micro-grid and off-grid applications, solar PV modules are often paired with EES systems. The IRENA report predicts that new EES technologies will enable higher round-trip efficiencies and longer battery lifetimes in the next decade. Hydrogen-based technologies are also gaining popularity for their potential to integrate with renewable energy sources and for peak shaving operations.

2.5. Techno-economic analysis key performance indicators

In this section, the financial model and indicators are outlined. The economic feasibility of the proposed solutions involves incorporating the costs of capital investment and operation into the overall analysis. Capital expenditure (CAPEX) covers the cost of components, construction, piping, and installation, such as the PV array for power generation, electrolyzer, fuel cell, and hydrogen tank for the hydrogen scenario, and battery facilities for the electrical storage scenario. β represents the binary variable that activates the option of H_2 based storage ($\beta = 1$) or Electrochemical based one ($\beta = 0$). These costs are calculated using Equation (9).

$$C_{APEX} = C_{0_{PV}} + (C_{0_{FC}} + C_{0_{EYZ}} + C_{0_{H2-ST}}) \bullet \beta + C_{0_{EL_{ST}}} \bullet (1-\beta) \tag{9}$$

The costs of operation (OPEX) include plant running costs, such as the cost of purchased (p_{el}^{IMP} is expressed in €/MWh and P_{IMP} expressed in MW), and sold electricity, as well as maintenance costs (expressed in €) which have both variable (M_{EOH}) and fixed (M_0) components based on component equivalent operating hours (EOH). The overall cost of operation is calculated by Equation (10), where k represents the k-th component of the plant layout

$$O_{PEX} = \int_0^{365} P_{IMP} \bullet p_{el^{IMP}}(t) \bullet dt + \sum_{k=1}^{N_{COMPONENT}} \left[M_0 + \int_0^{365} M_{EOH}(t) \bullet dt \right]_k \tag{10}$$

Investors and stakeholders typically use financial indicators such as Net Present Value (NPV), Internal Rate of Return (IRR), Discounted Payback Period (DPBP), and Total Cost of Ownership (TCO) to evaluate the viability and risk of a project.

The most commonly used financial indicator for determining the feasibility of a project is the NPV. This parameter considers various factors such as the yearly cash flow, the interest rate, inflation, and system's lifetime. It is calculated by subtracting the yearly costs from the yearly revenues, as seen in Equation (20). A compact form of the NPV is presented in Equation (11).

$$NPV = \sum_{k=1}^{N} \frac{CF_k}{(1+i)^k} - C_{APEX} \tag{11}$$

The Discounted PayBack Period (DPBP) is a metric that determines the number of years needed for the Net Present Value (NPV) of a project to reach zero. This is calculated by using Equation (12).

$$DPBP = \{N_{YR} | NPV = 0\} \tag{12}$$

This financial indicator is useful for assessing the risk of an investment and also for understanding the potential for growth in revenue. For example, if two projects have the same NPV, the project with the shorter DPBP will generally have a higher return on investment over the lifetime of the project. Additionally, a shorter DPBP also means less exposure to risk.

The Internal Rate of Return (IRR) is a metric used to determine the profitability of potential investments by determining the interest rate at which the net present value (NPV) of the investment is equal to zero. This can be calculated using Equation (13).

$$IRR = \{i | NPV = 0\} \tag{13}$$

The IRR is used to measure the annual growth rate of an investment, while the Discounted Payback Period (DPBP) measures the total growth of an investment from start to finish.

Another metric used to evaluate the feasibility of a project is the Total Cost of Ownership (TCO). This metric considers all costs associated with an investment, including initial costs, operating costs, maintenance costs, and in some cases, residual value. In this study, the TCO is calculated using a methodology outlined in a specific reference and is represented by Equation (14).

$$TCO_{Ny} = \frac{C_{APEX}}{Ny} + O_{PEX} \tag{14}$$

The TCO is calculated on an annualized basis and is used as the primary objective for the planning problem as it is less affected by variations in operating costs.

Meeting the electricity load demands is achieved by reducing the ObF and adhering to the system limitations. A mathematical optimization method known as MILP is utilized to find the optimal solution. Equation (15) shows the OPEX that needs to be maximized.

$$ObF - Searchminof : O_{PEX} = \int_0^{365} P_{IMP} \bullet p_{el}(t) \bullet dt - \int_0^{365} P_{Internal} \bullet p_{incetive}(t) \bullet dt \tag{15}$$

Finally, Equation (16) takes into account the limitations on energy flow and its distribution.

$$P_{LOAD} \bullet \Delta t = P_{PV} \bullet \Delta t + P_{IMP} \bullet \Delta t + P_{ST}^{-} \bullet \Delta t - P_{ST}^{+} \bullet \Delta t - P_{EXP} \bullet \Delta t \tag{16}$$

The findings will be discussed in the following section.

3. Results and discussion

In this section, the authors present the results of the techno-economic optimisation carried out by the DECAPLAN™ Digital Platform, considering different energy storage capacities and types of storage versus eight scenarios. The authors have discussed the details of the different energy storage technologies and the related capital costs (CAPEX) in

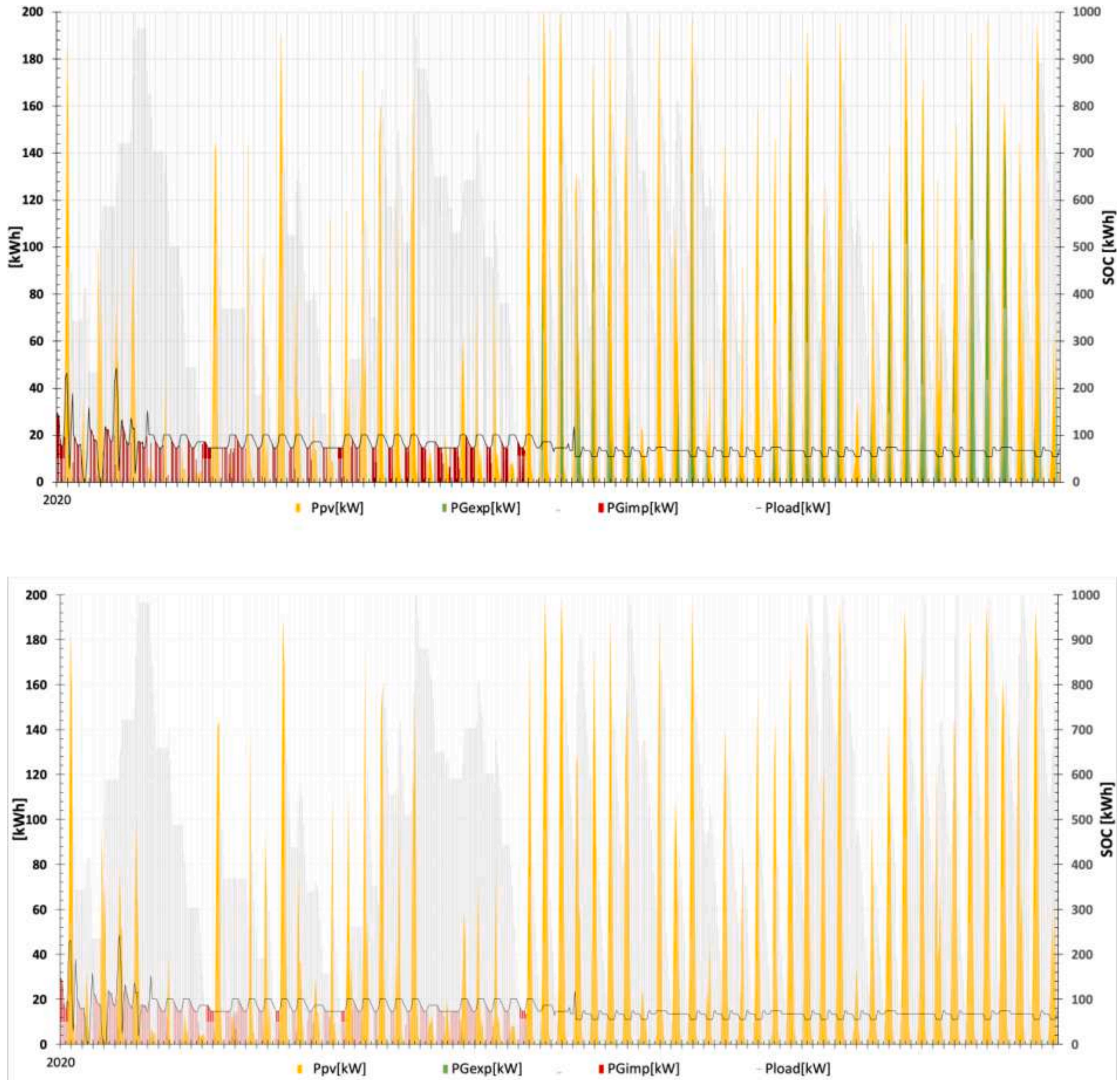


Fig. 4. 1000 kWh H_2 Storage – Case #1 and Case #2.

another paper [44], highlighting how the different technology's costs will decrease for 2020, 2030 and 2040 scenarios. Regarding the different scenarios the authors have investigated in this paper, eight different scenarios in which energy consumption and the related costs differ in respect of the system operations before, during and after the COVID-19 pandemic, and also in respect of the price of the electricity before (Old Price – OP) and after (New Price – NP) the energy crisis, partially related to the war, and to the incentives that the Italian Government have enabled for the Self-Consumption of electricity generated by Renewable Energy Resources, namely PV in this paper.

Accordingly, the different scenarios are listed below:

- #1 PRCV_NSC_OP (Pre-Covid No Self-Consumption Old Price)
- #2 PRCV_WSC_OP (Pre-Covid With Self-Consumption Old Price)
- #3 DUCV_NSC_OP (During-Covid No Self-Consumption Old Price)
- #4 DUCV_WSC_OP (During-Covid With Self-Consumption Old Price)
- #5 POCV_NSC_OP (Post-Covid No Self-Consumption Old Price)
- #6 POCV_WSC_OP (Post-Covid With Self-Consumption Old Price)
- #7 POCV_NSC_NP (Post-Covid No Self-Consumption New Price)
- #8 POCV_WSC_NP (Post-Covid With Self-Consumption New Price)

The optimisation aimed to understand the best capacity of the energy storage technologies in respect of the different scenarios, assuming an installed capacity of 715 solar PV, with a nominal peak capacity 250Wp. According to [45], the solar PV nominal efficiency has different values for 2020, 2030 and 2040 optimisation. Regarding cases #7 and #8, the effect of the energy crisis related to the geopolitical issues of February 2022 have been mentioned in Fig. 2, where the Old Price (OP) and the New Price (NP) are before and after this event, respectively.

3.1. Techno-economic analysis

The results of the technical analysis have been summarised in Tables 2 and 4 for the net present value and for the yearly cash flow, respectively. Indeed, while the net present value accounts for CAPEX and OPEX concurrently, giving an immediate result on the financial viability of the various scenarios, the results presented for the yearly cash flow allow an understanding on how the selection of the optimal energy storage technologies and related capacity, leads to optimal operating strategies in a day to day system operations. CAPEX and OPEX are presented for the 2040 cases in Table 1. Indeed, as a result of the

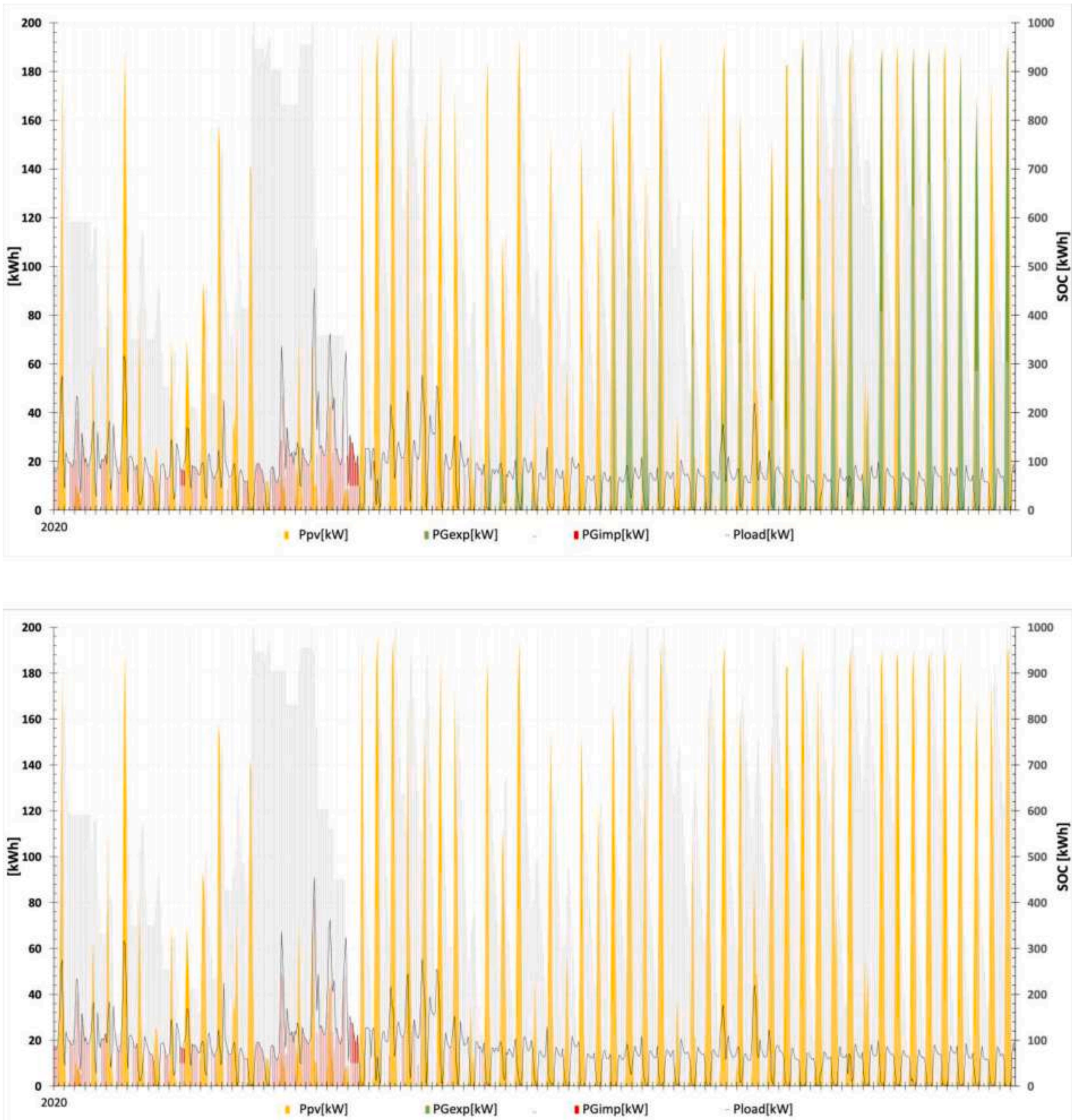


Fig. 5. 1000 kWh H_2 Storage – Case #3 and Case #4.

MILP-based optimisation, the DECAPLAN™ Digital Platform allows for solving the hourly optimal dispatch problem, supporting and establishing the definition of the optimal plant operating strategy, as presented by the authors in another paper [46].

Looking at the 2020 scenario and at cases #1, #3 and #5 in Table 2, it is interesting to understand that none of the energy storage configurations (1–8) leads to an economically viable NPV. Indeed, both the Battery and the H_2 Storage solutions have a negative value of NPV. When the government provides the Incentive for Self-Consumption of electricity, rewarded at 160 Euro/MWh, the most effective scenario (4 and 5) with 500 kWh and 1000 kWh of Battery Capacity allows for a positive – even if only minimal - NPV in cases #2, #4 and #6. In the last two columns of Table 2, the optimisation results show how the increased electricity price tariff helps and supports the penetration of energy storage technologies on a larger scale. Indeed, for the 500 kWh Battery Energy Storage, when #7 is compared with #5, the NPV becomes positive, resulting in a value NPV#7 = +187 k€ versus NPV# = − 158 k€.

The economic viability of larger-scale energy storage design becomes even more convenient in case #8, and positive NPV can be observed for the cases 500, 1000 and 1500 kWh of Battery Energy Storage. For 500 kWh, indeed, when compared with case #7, for 500 kWh, the NPV#8 = +597 k€. Furthermore, case #8 also shows a positive NPV#8 for the 500 kWh H_2 Energy Storage.

In the scenarios 2030 and 2040, according to the reduction of the CAPEX [44] of the storage technologies and the improvements of the performances in terms of lifecycle durability and efficiencies (PV and ESS round trip efficiency), the economic viability of larger scale energy storages also becomes sustainable. Indeed, comparing the 500 kWh H_2 and Battery Energy Storages, NPV#8 for cases 2030_9 and 2030_13 becomes + 502 k€ and + 745 k€, respectively, while looking at 2040_17 and 2040_21, NPV#8 increases even more up to + 734 k€ and + 819 k€. The Energy Storage capacity that maximises the NPV is different between H_2 and Battery Energy Storage for 2030 and 2040 scenarios, indeed for 2020, the positive NPV is for both the technology 500 kWh,

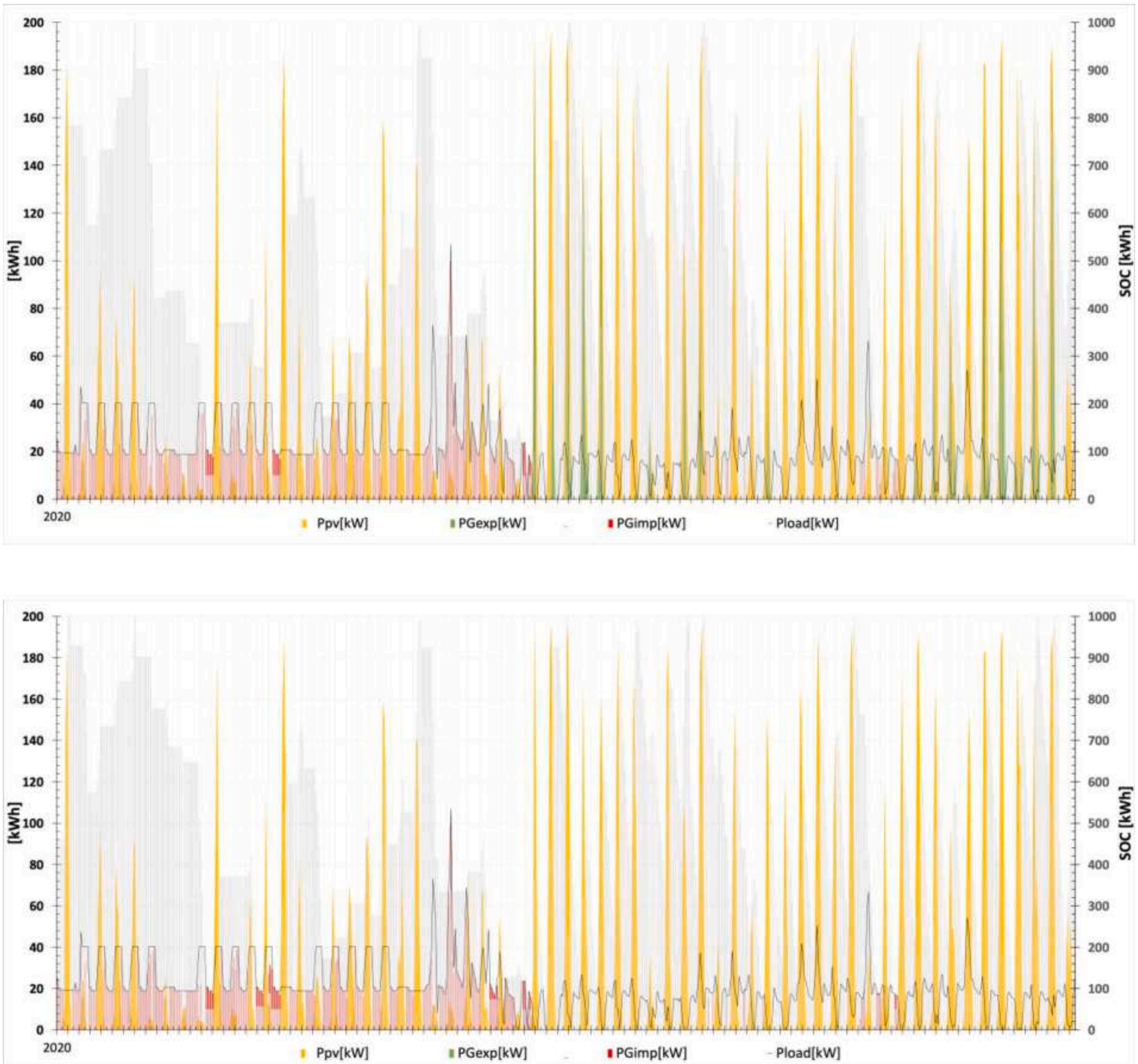


Fig. 6. 1000 kWh H_2 Storage – Case #5 and Case #6.

while 2030 and 2040 show that 500 kWh is the optimal capacity for the H_2 Energy Storage and 1000 kWh for the Battery Energy Storage. Indeed, the NPV#8 in cases 2030_14 and 2040_22 is + 779 k€ and + 925 k€, respectively, leading to +4.5 % and +13 % higher NPV when compared with 500 kWh Battery Energy storage capacity. A summary of the optimal capacities in respect of the different scenarios 2020, 2030 and 2040 is given in Table 3.

Table 4 shows the detailed economic results for the different scenarios focusing on the yearly Cash Flow (CF_y) obtained by integrating RES with energy storage solutions of different capacities.

A general trend can be derived by observing the relationship between the size of the storage technologies and the yearly Cash Flow. In all the configurations, the larger the storage capacity, the higher the cash flow. Indeed, a larger storage capacity allows for better peak shaving operations that directly imply a reduction of the purchase of electricity at higher prices when the system can rely on a larger discharging capacity of the time. When the Self-Consumption is incentivised, the yearly cash flow increases drastically – up to 600 % in cases #2, #4 and #6 when compared with #1, #3 and #5, while for case #8, the increase is limited to about 100 % when compared with #7. The candlestick chart with more details of the variability of the % for each case is given in Fig. 3. It highlights that the maximum benefit related to the Self Consumption incentive is during the Covid-19 pandemic. It is essential to highlight that the in the evaluation of the different scenarios, the excess of the electricity generated and exported to the grid has not been included in the economic analysis since there is no remuneration for the kWh exported to the grid in the specific case studies. This aspect justifies why the yearly Cash Flow in some cases is higher for the H_2 storage in respect of Battery Storage. Accordingly, taking #4 into consideration 2020_1 and 2020_5 case studies, the electric work exported to the grid is 0.0 kWh and 27697.48 kWh, respectively.

Thus, if it is true on one hand that 2020_1yearly Cash flow is + 70 k€, and the equivalent yearly Cash Flow for 2020_5 is only + 56 k€, is also true that if the electric work exported to the grid had been monetized, the yearly Cash flow related to the battery scenario would have been higher.

Another consideration that can be deduced from the analysis of data in Table 4 and Fig. 3 is that cases #7 and #8, characterized by a significantly higher cost of the electricity to be purchased, present a lower % benefit from the incentives, and this is due to the fact that dispatching operating strategy already has tried to maximize the internal self-consumption, even if without the incentives. Indeed, it can be

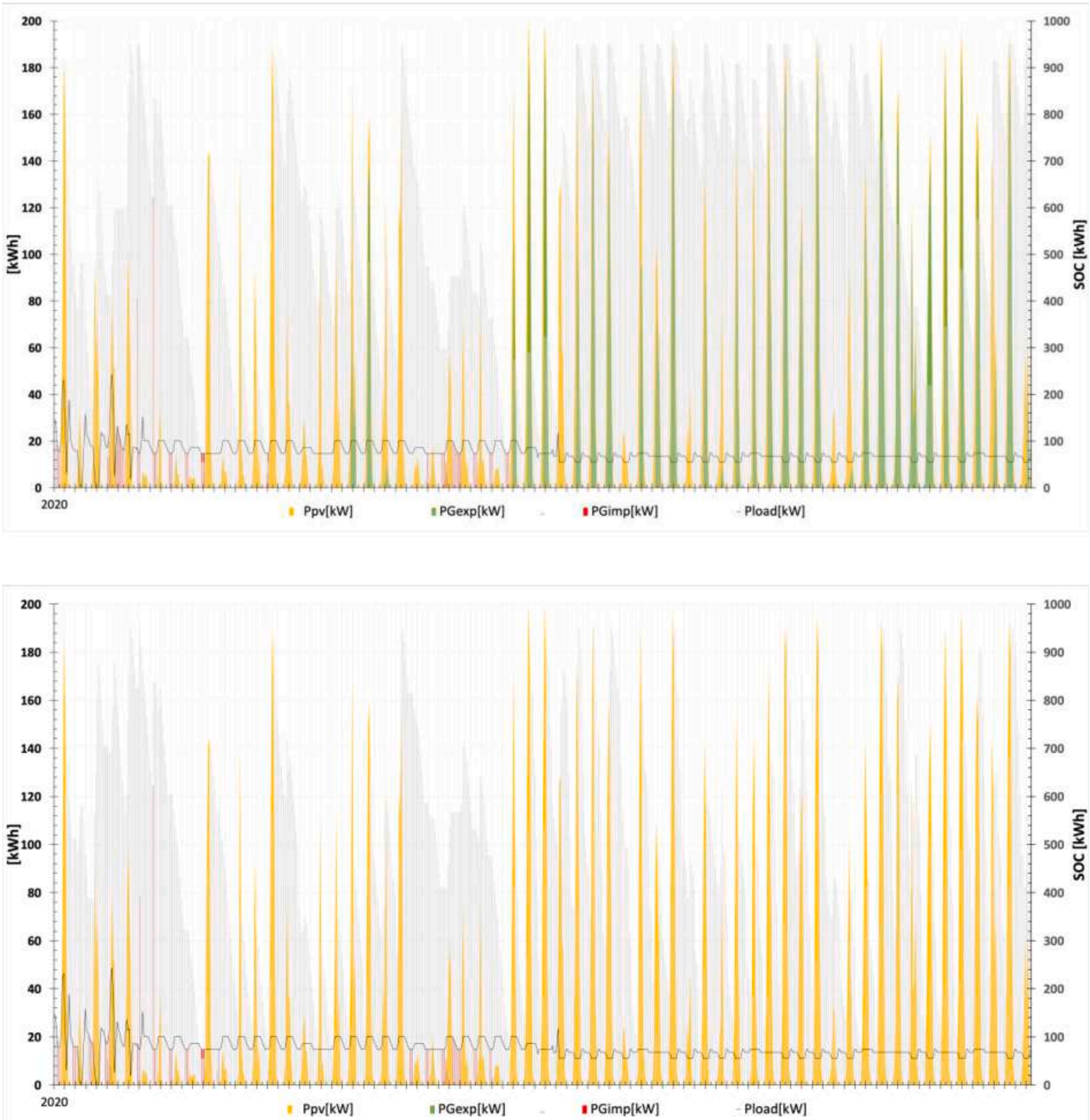


Fig. 7. 1000 kWh EE Storage – Case #1 and Case #2.

observed that the variability range of increased yearly cash flow of case #8 is between +80 % and 125 % higher compared to case #7. In absolute value, the increase of the storage capacity results in an increase in the yearly cash flow in all of the scenarios. Still, it is worth of note that on relative percentage values, this trend is the opposite. This is because the higher the energy storage capacity, the higher the losses due to round-trip efficiency.

3.2. Self-consumption and optimal operations

In this section, the authors present the comparison of optimal dispatch profiles with and without Self-Consumptions, for the different cases (#1 to #6), for the prices of the 2020 scenarios, and assuming the 1000 kWh storage capacity, both for H_2 and Battery Energy Storage. The comparison is carried out for the same two months for 2019, 2020 and 2021, respectively. Indeed, during the pre (#1, #2), during (#3, #4) and post (#5, #6) Covid-19 pandemic, end-user electricity utilisation differs, and the electricity source affects the load demand. Data on the electricity consumption have been collected in situ by a proper smart-metering station and sampled every hour. Accordingly, it is possible to understand how the pre, during, and post-pandemic scenarios lead to different load demand profiles characterised by different trends and peaks. This is the first element that required DECAPLAN™ Digital Platform to perform complex calculations for accounting for the load variability in the overall optimisation process.

In Figs. 4 to 6, the black line represents the load demand (P_{load}), the red area is the electricity imported from the grid (P_{imp}), the yellow area is the electricity generated by the PV (P_{PV}), the grey area is the state of charge of the energy storage technology (0–100 %), and the green area is the electricity exported (P_{exp}) to the grid.

The aim of this section is to understand and discuss how the Self-Consumption Incentives promoted by regulatory agencies at a National Level affect and influence the optimal design and operations of multi-energy systems characterised by high penetration of renewable

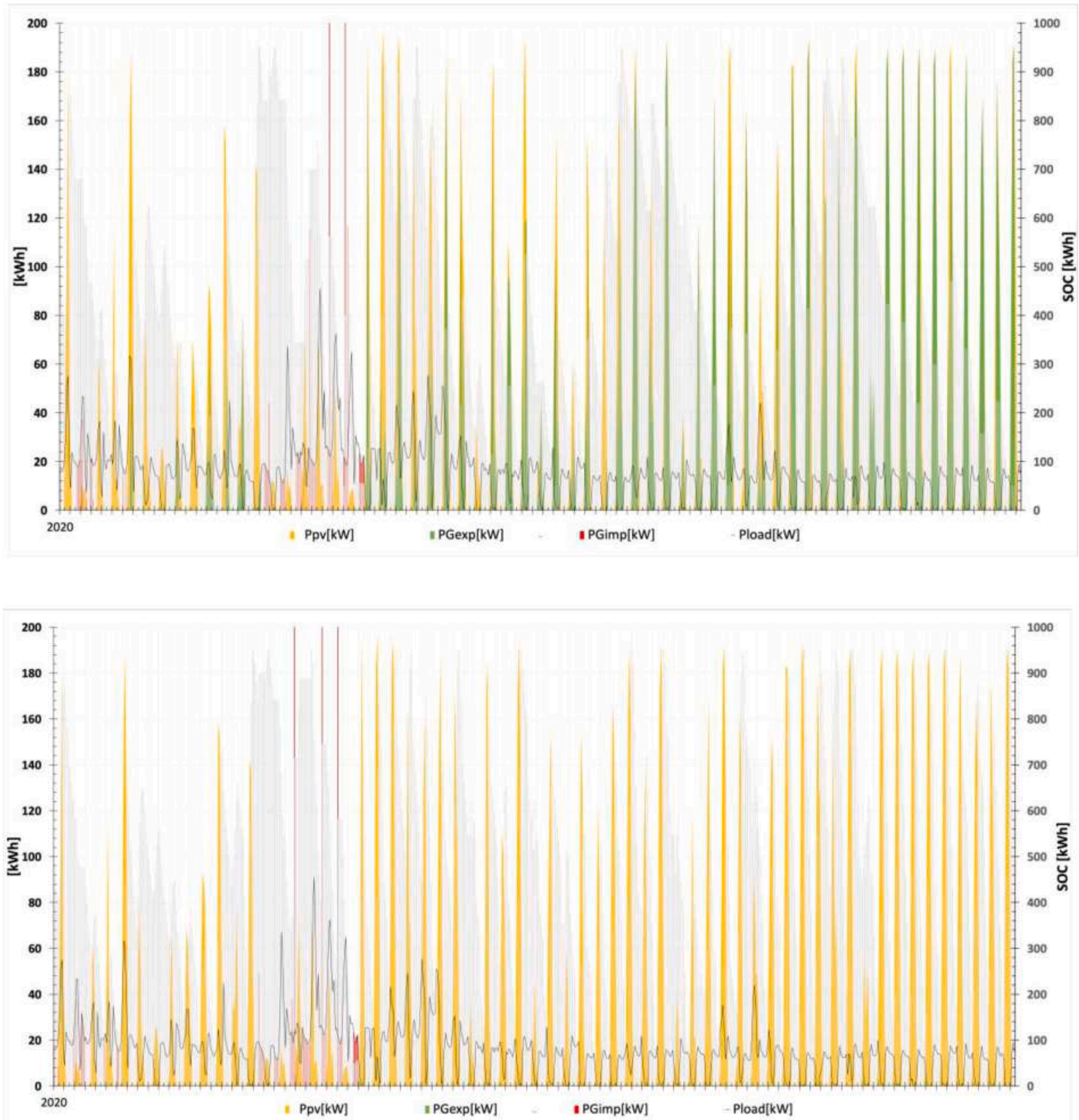


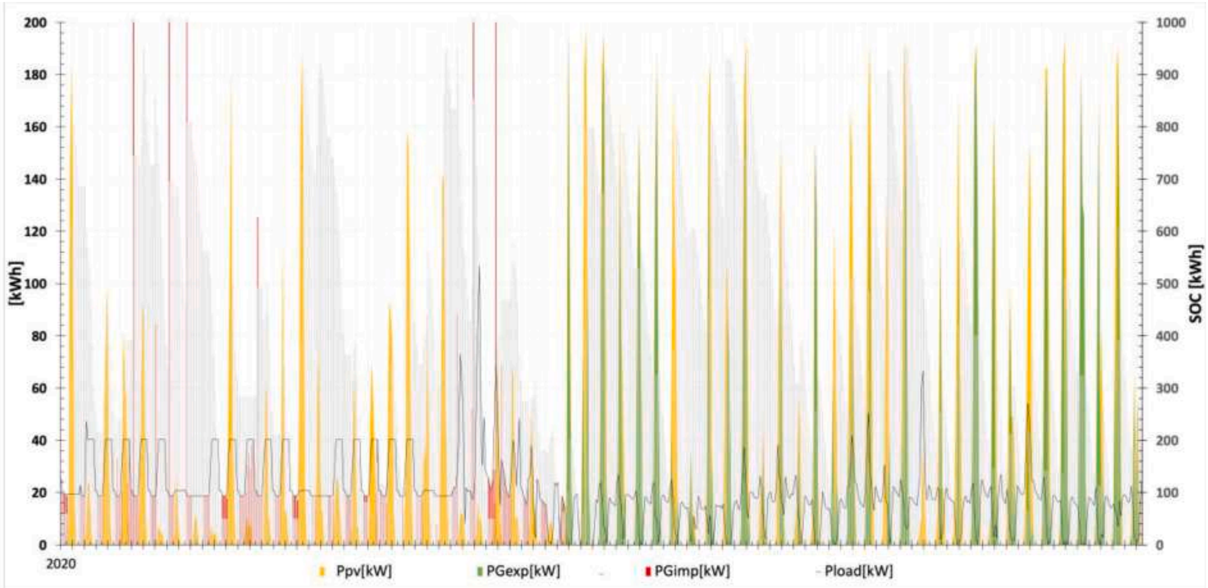
Fig. 8. 1000 kWh EE Storage – Case #3 and Case #4.

energy resources and novel energy storage solutions. The scenarios based on 1000 kWh H_2 Storage are presented in Figs. 4 to 6, while the 1000 kWh Battery Storage is given in Figs. 7 to 9. The charts on the left represent the scenario without Self-Consumptions, and the charts on the right represent the scenario with Self-Consumption.

The first immediate observation that results from the comparison of the different cases given in Figs. 4 to 6 is related to the fact that with 1000 kWh H_2 storage, when the incentives are subsidised, there is no surplus of electricity exported to the grid. Indeed, it can be observed that in all the right charts, there is no green area since during the period with the highest solar availability, the system is self-sustained and with the optimised control strategy of the energy storage, it is not required to export electricity. It is also worth of note that during the hot season, in almost all cases, the system does not import electricity from the grid. The control strategy proposed by the optimised results given by DECAP-LAN™ Digital Platform shows different energy storage management in respect of the time period (pre, during and after post Covid-19 pandemic) and with respect of the Self-Consumption incentive. the load profile related to The former aspect, related to the different periods, affects the duty cycle of 1000 kWh H_2 storage, especially in the first month of the chart, where the load demand is higher due to the seasonality (winter/spring), the latter aspect, related to the Self-Consumption of the incentives, affects the management of the 1000 kWh H_2 storage by increasing the number of the duty cycle since it is more convenient to self-generate in this case than export and import to the grid in peak/off-peak tariff.

Looking at the scenario equipped with 1000 kWh Battery storage, results are given in Figs. 7 to 9. Similar consideration can be carried out also in this case on the way that the Self-Consumption Incentives influence the capability of the system to export and self-consume the electricity generated and stored by the system.

The competitive advantage gained by the higher round-trip efficiency of the 1000 kWh Battery storage when compared to the 1000 kWh H_2 storage is clearly shown in Fig. 9 Case#6, where in respect of



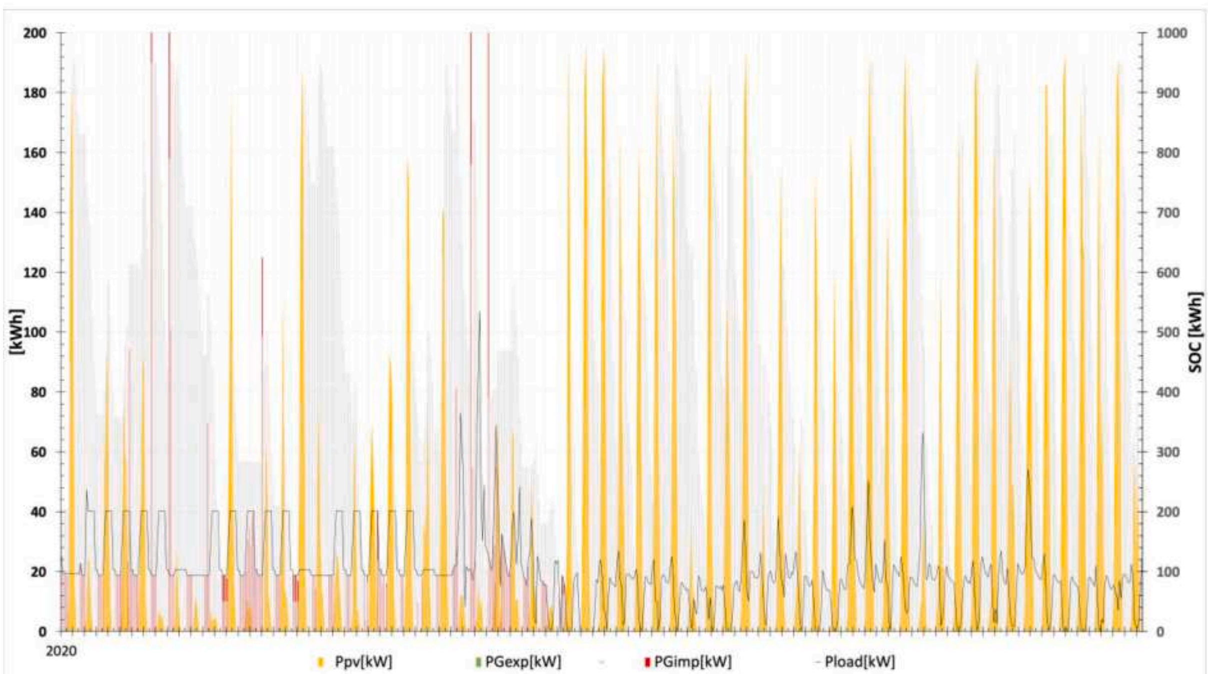


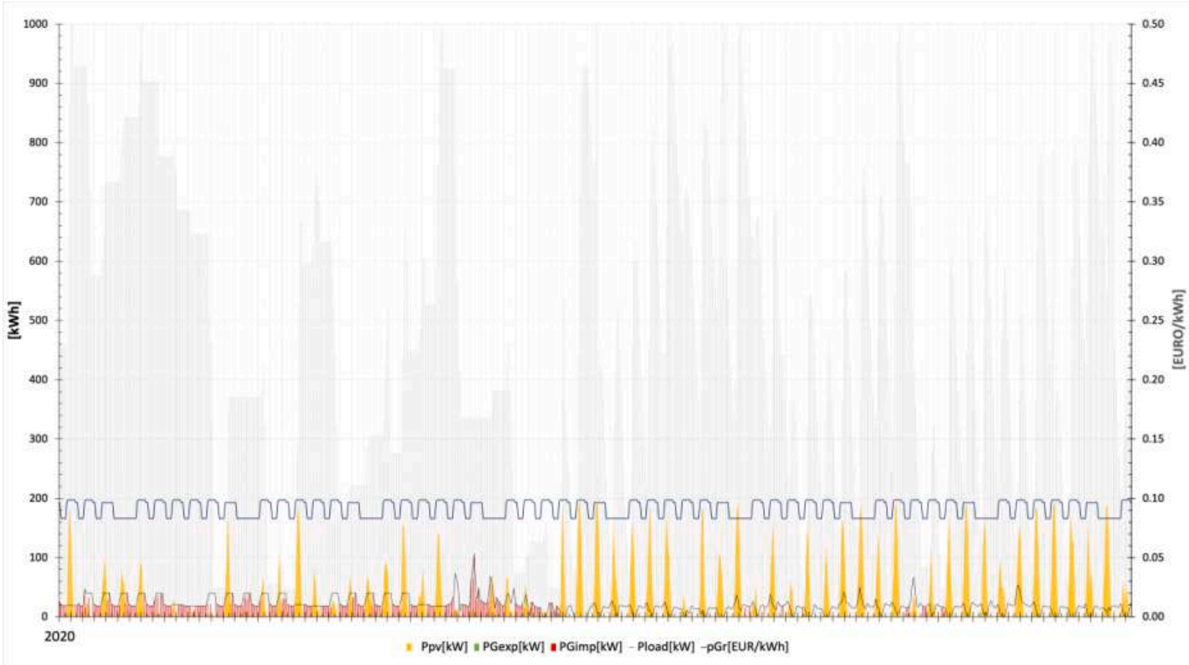
Fig. 9. 1000 kWh EE Storage – Case #5 and Case #6.

Fig. 6 Case#6, the system equipped with the 1000 kWh Battery storage does not require to import any electricity from the grid during the second month of operation, where solar availability is higher. Furthermore, the other aspect connected to the higher round trip efficiency is shown by the number of full charge/discharge cycles among the time series in all the scenarios. Indeed, the higher the round-trip efficiency, the lower the losses and the higher the flexibility of operating the system with reduced yearly cash flow.

The support at a National Level for the Self-Consumption of renewable energy-generated electricity brings benefits related to the multi-energy system's economic viability. Indeed, a decentralised – relatively small - self-sustained energy community that does not export and inject power into the national grid is actively supporting the optimal operation of national grids as well, reducing the TSO and DSO complications of dealing with the uncertain and highly unpredictable distributed generation of electricity derived by renewable energy resources, especially when of small capacity. Furthermore, the subsidising of Self-Consumption incentives also supports the long-term trajectory where demand response and arbitrage/ancillary services will become more and more important for giving national grid reliability and stability, with reduced impact on the carbon emissions.

3.3. *Price variability and optimal operations*

The other analysis carried out by the authors is related to understanding and discussing which implication derives from the optimal control strategy of the system when that the electricity price varies. Indeed, for Cases #6 and #8, 1000 kWh H_2 and Battery storage, the profile of the optimal dispatch strategy of the system for the two months of operations have been presented in Figs. 10 and 11. In these analyses,



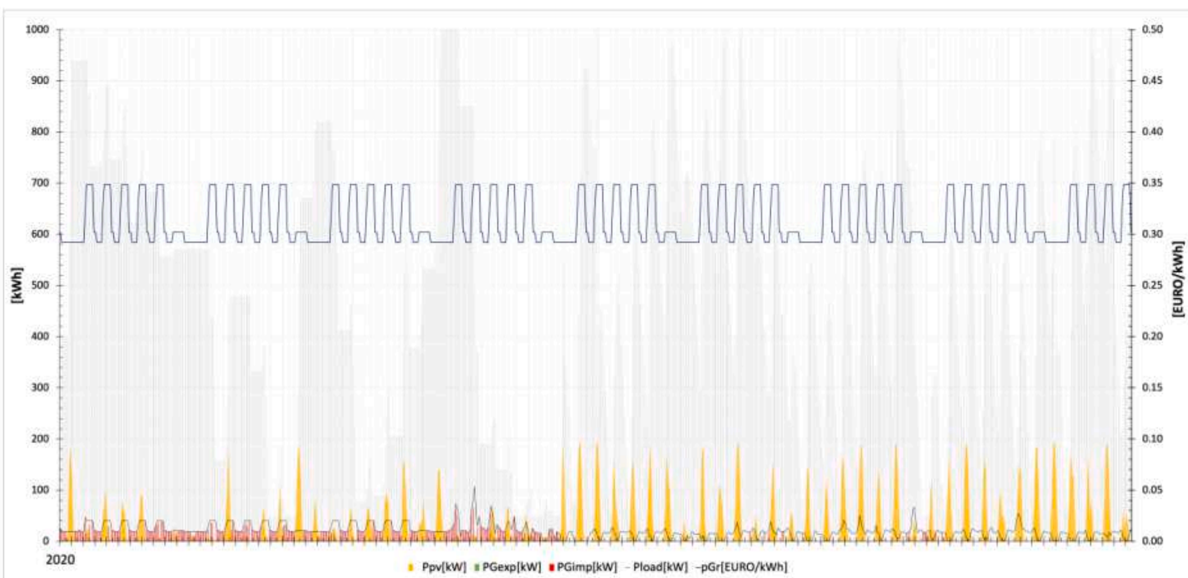


Fig. 10. 1000 kWh H_2 Storage – Case #6 and Case #8.

the authors have tried to emphasise how the control strategy of the system, sustained by the Self-Consumption incentives, is affected by the electricity price variability, with the Old Price and New Price, presented in Fig. 2.

Fig. 10 shows how the increase of almost 300 % of the electricity price from the OP to the NP, affects the duty cycle of the 1000 kWh H_2 storage. Indeed, despite the higher losses related to the relatively small round-trip efficiency of the storage system, the optimal control strategy addressed to maximise the yearly cash flow (reducing the OPEX), allows for more charge/discharge cycles for enabling a more effective peak shaving of the purchase of the electricity (Pimp).

Indeed, even if the overall system efficiency decreases due to the losses occurring during the storage duty cycle, the positive outcome on the electricity bill justifies this control strategy. A similar trend, even more evident, can be encountered in Fig. 11, where the higher round trip efficiency of the 1000 kWh Battery storage systems allows for better operations and reduced OPEX, as per Table 3 in the previous section. Indeed, thanks to the implementation of the most suitable technology of Energy Storage and its related optimal capacity, thanks to the optimised dispatching profile provided by DECAPLAN™ Digital Platform, the yearly cash flow of case #8 are at least 40 % higher than that of case #7. Combining the results given in Figs. 10 and 11 with Table 3, it can be summarized that the yearly cash flow (savings on the running cost of the system if it is not equipped with PV and Storage solutions) for 1000 H_2 Storage 48 % higher when NP is in place versus OP. The benefit becomes 55 % for the 1000 Battery Storage since its round-trip efficiency is higher.

The authors have also compared the scenario for the full-time period post-Covid-19 pandemic, considering the New Price of the electricity, and 1000 kWh H_2 and Battery storage solutions have been compared as well, as depicted in Figs. 12 and 13. Also, in this case, the higher round trip efficiency of the 1000 kWh battery storage allows for more duty

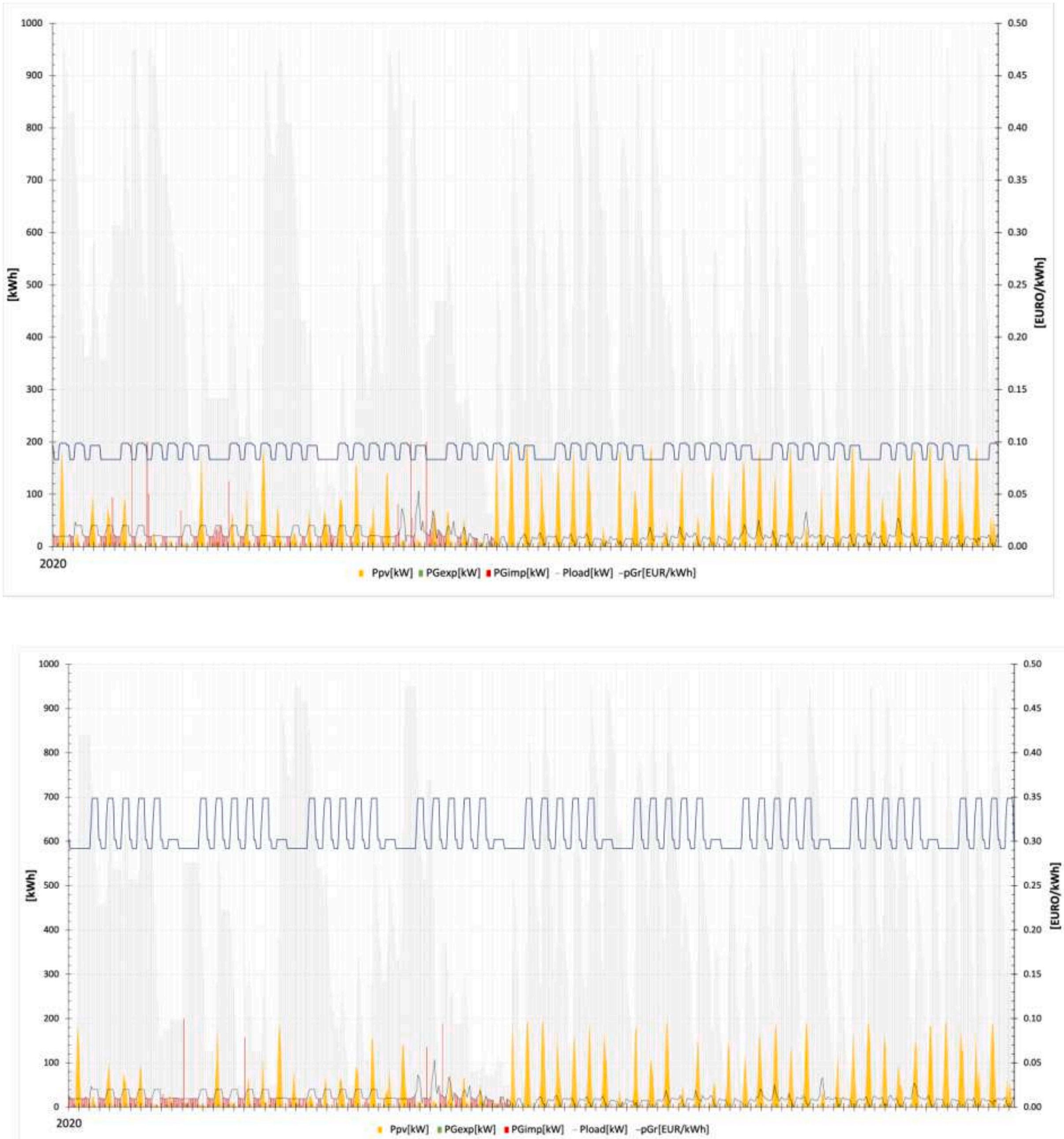


Fig. 11. 1000 kWh Battery Storage – Case #6 and Case #8.

cycle of the period, even if as already shown in Tables 1 and 3, also the H_2-based storage provides for the beneficial economic viability of the solution.

4. Conclusions

In the paper, the authors investigate the implementation of solar-based power systems equipped with energy storage technologies in a Renewable Energy Community composed of 5 fully electrified buildings. One of the main problems of long-term energy storage is related to the huge capacity and the large footprint occupancy required to allocate the storage system, especially looking at electrochemical energy storage. The authors filled the gap in the existing literature by providing an extensive techno-economic assessment of the implementation of H_2-based storage solutions applied to the Renewable Energy Community framework. Furthermore, a competitive advantage of H_2-based storage is to allow flexibility of the system operation by implementing H_2 as an energy carrier. Accordingly, H_2 can also be adapted for heating and transportation purposes – should there be excess in satisfying the energy demands or if economic viability allows.

The paper aims to investigate which parameters affect more significantly the optimal selection of the system equipment such as solar PV, Fuel Cell, Electrolyser, Electrochemical Energy Storage and H_2 storage in meeting the global call for CO_2 reduction, financial and economic viability and, at the same time, ensuring high reliability and availability of the power system. Accordingly, the authors have been adopting the DECAPLAN™ Digital Platform to optimise the Master-Planning and optimal dispatch problems. By relying on a Hybrid Genetic Algorithm/MILP solver, the DECAPLAN™ Digital Platform allowed for optimising multiple scenarios for NPV maximisation and OPEX minimisation for multiple scenarios.

Indeed, calculations have been carried out for load demands before,

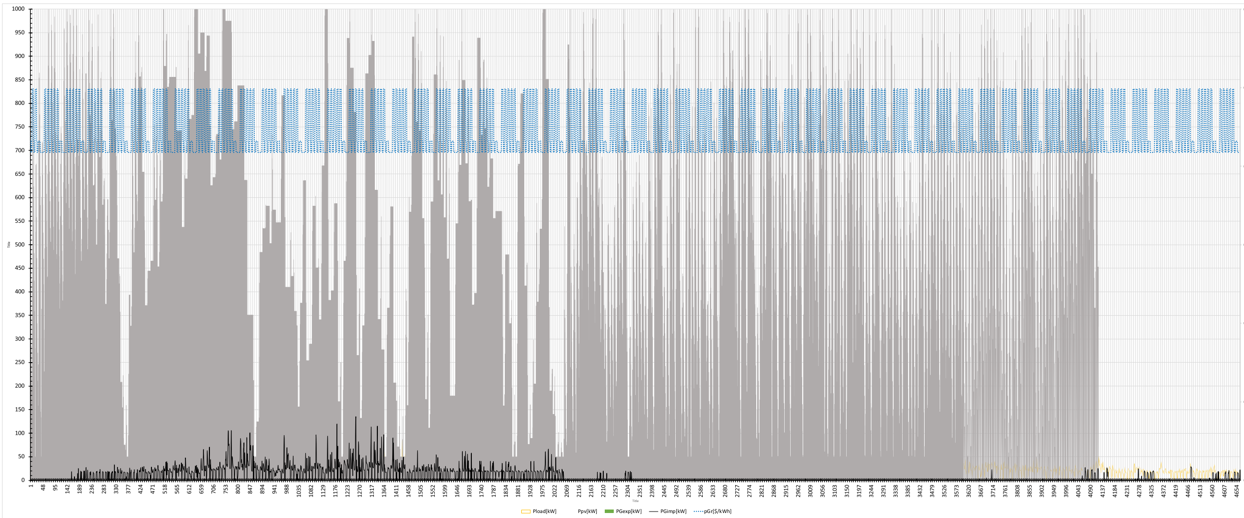


Fig. 12. Case#8-1000 kWh H_2 Storage full period.

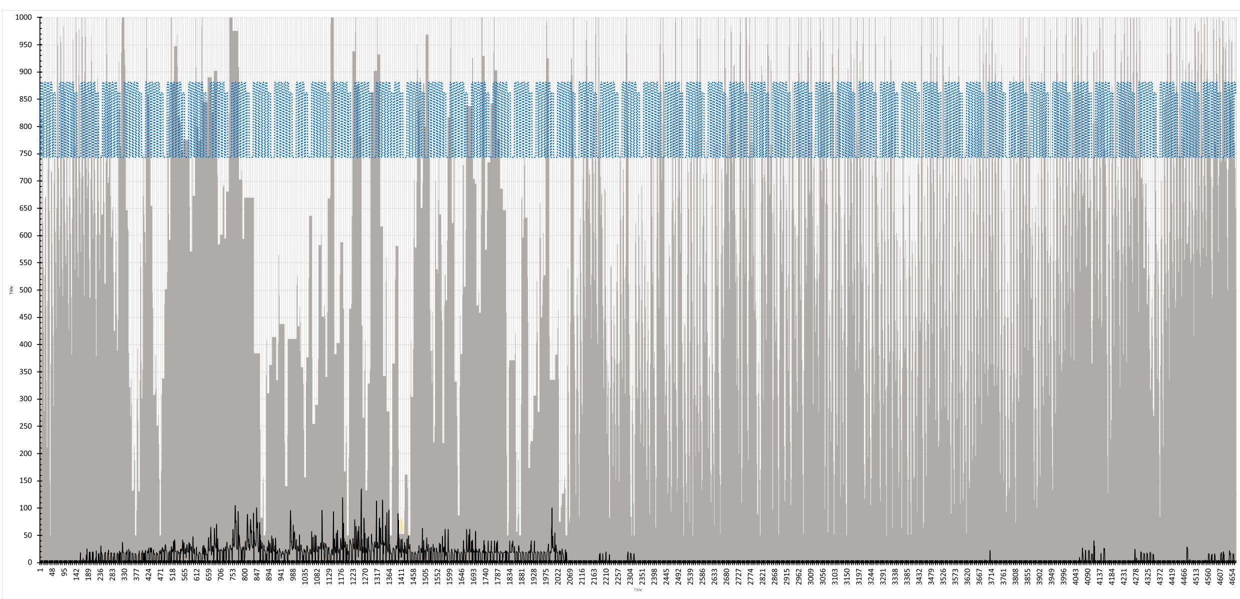


Fig. 13. Case#8-1000 kWh Battery Storage full period.

during and after COVID-19 pandemic, including the electricity price variability due to the energy crisis started in 2021/2022. Among the optimisation parameters, the scenarios of 2020, 2030 and 2040 have been investigated, considering the various technologies' improvement and the reduction of the related CAPEX due to the maturity of the technologies. The introduction of Incentives at the National Level for Self-Consumption has also been considered, with a value of 160 €/MWh.

Results show that given a 200 kWp installed solar PV capacity, the optimal storage capacity based on the H_2 storage is 500 kWh, while it ranges up to 1000 kWh when Batteries are considered. The lower round-trip efficiency plays a role in downsizing the H_2-based storage capacity. At the same time, the reduced CAPEX related to smaller storage makes the solution attractive, especially in the post-Covid-19 scenario.

Introducing Self-Consumption Incentives allows more flexibility for distributed energy resources from a design perspective, allowing for larger storage potential. Indeed, it will be beneficial for the seasonality of a distributed energy system and for supporting the national grid in reducing the noise and the impure frequencies derived from the injection into the national grid of the electricity generated through intermittent renewable energy resources.

On the financial aspect, the paper put the basis for future investigations on how financing mechanisms could make the solution more attractive for investors and government agencies since the annual return on the investment for some of the 2030 and 2040 scenarios assumes values up to 15 % and 25 %, respectively. Indeed, to increase the financial viability of the solutions, in further work the authors plan to include Carbon Certificates, Carbon Tax and Carbon Trade mechanisms.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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