Journal of Energy Storage 57 (2023) 106306

Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est

Research Papers

Towards 100% renewable energy systems: The role of hydrogen and batteries

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A R T I C L E I N F O

Keywords:
Renewable energy systems
Renewable energy sources
Hydrogen
Battery
Energy storage
Optimisation

A B S T R A C T

New challenges arise for the accurate modelling of energy systems with a high share of renewable energy. In this context, energy storage technologies become key elements to manage fluctuations in renewable energy sources and electricity demand. The aim of this work is to investigate the role of batteries and hydrogen storage in achieving a 100% renewable energy system. First, the impact of time series clustering on the multi-year planning of energy systems that rely heavily on energy storage is assessed. The results show good accuracy, even for a small number of representative days, which is necessary to limit the computational burden of the optimisation problem. Then, different configurations of carbon-free energy systems are considered by varying the energy storage solution: only-battery, only-hydrogen, and hybrid scenarios. An island energy system based on photovoltaics and floating offshore wind turbines is used as a demonstrative case study. It is shown that the cost of the only-battery configuration is 155% higher than the cost of the hydrogen-based scenarios. The reason is that the long-term hydrogen-based storage, despite its low round-trip efficiency, avoids costly oversizing of batteries and wind turbines throughout the analysed period. In the selected case study, hydrogen storage reduces the total rated power of the wind farm by about 5 times compared to the only-battery system. Hydrogen-based solutions are therefore crucial in 100% renewable energy systems to achieve energy self-sufficiency in a cost-effective way.

1. Introduction

In recent years, there has been growing interest in developing sustainable energy systems based on renewable energy sources (RESs). The deployment of RESs at a large scale is the first step in the transition to a low-carbon economy. However, the fluctuating behaviour of variable RESs, e.g., wind and solar, leads to new challenges in terms of electric grid management and energy storage. The installed capacity of electrical energy storage (EES) systems is thus expected to increase significantly in the coming years. Energy storage solutions can be of different types: mechanical, electrochemical, chemical, electrical and thermal [1,2]. Batteries offer high efficiency and fast response time [3], making them ideal candidates when small size and short-term energy storage is needed. Hydrogen is also expected to become essential as a storage solution in RES-based scenarios due to its long-term storage capability and high energy density [4]. Hydrogen can be generated in a sustainable way through water electrolysis powered by renewable energy [5]. Once hydrogen is produced, it can be stored and later reconverted into electricity according to the so-called power-to-power (PtP) route. Moreover, and differently from a closed battery (pure role of electrical storage), hydrogen can assume other roles: as feedstock for production of gaseous and liquid synthetic chemicals via dedicated power-to-X (PtX) routes in

Abbreviations: BATT, Battery; CAPEX, Capital Expenditures; DG, Diesel Generator; EES, Electrical Energy Storage; ELY, Electrolyser; FC, Fuel Cell; HRES, Hybrid Renewable Energy System; HT, Hydrogen Tank; HYB, Hybrid; LP, Linear Programming; MILP, Mixed Integer Linear Programming; NPC, Net Present Cost; OB, Only-Battery; OF, Objective Function; OH, Only-Hydrogen; OPEX, Operating Expenditures; PEM, Proton-Exchange Membrane; PtP, Power-to-Power; PtX, Power-to-X; PV, Photovoltaic; RD, Representative Day; RES, Renewable Energy Source; TRAD, Traditional; WT, Wind Turbine.

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https://doi.org/10.1016/j.est.2022.106306
Received 2 November 2022; Received in revised form 27 November 2022; Accepted 29 November 2022
Available online 8 December 2022

a cross-sector perspective [6]. As highlighted by Lund et al. [7], an integrated cross-sector approach can promote a large penetration of renewable energy sources, by providing additional flexibility in the energy system. In this context, the potential integration of the electricity, heat, transport and industrial sectors - as part of a smart energy system - has been shown to be beneficial in achieving 100% renewable energy supply [8]. Indeed, sector coupling can mitigate the need for grid expansion and storage capacity [9].

In islands, diesel generators (DGs) are still the most widespread choice for electricity production [10,11]. Local RESs can represent an effective solution to mitigate DG-related pollution problems and reduce the cost of electricity [12]. However, the adoption of EES solutions is crucial to improve the RES exploitation and enhance the reliability of the power supply service. Accurate sizing of the energy storage is thus necessary when dealing with hybrid renewable energy systems (HRESs) for stand-alone applications [13]. In this context, in the literature, increasing attention has recently been paid to the optimal design of stand-alone HRESs to minimise the system cost while keeping the energy provision reliable and less polluting [14]. As reported in the review by Liu et al. [15], the combination of PV, wind, diesel, and batteries was proven to be feasible, cost-effective, and with a low environmental impact. Prina et al. [16] showed that the cost of energy supply increases exponentially as the share of variable RESs increases; the most challenging and expensive phase of the energy transition is from 70% to 100% of the RES share. High-RES penetration, indeed, entails the oversizing of the HRES components, with consequent sharp rise in the cost of energy [17]. In this context, the use of hydrogen was found to be effective in limiting the cost increase when pursuing full-RES system configurations in off-grid insular communities [18]. The hybridisation of batteries with hydrogen can represent a cost-effective choice when relying on local RESs in isolated areas [19]. A 35% cost reduction was reported for the hybrid hydrogen-battery configuration compared to the only-battery system in a 100% RES-based scenario [20].

As shown in the review article by Chang et al. [21], there is a wide range of tools for modelling energy systems: from commercially available software, to open-access modelling frameworks, and in-house proprietary tools. Current research trends seek to address cross-sector synergies and improved temporal detail, with an increasing focus on open-access models. Several modelling methods have been used to investigate the decarbonisation of islands. HOMER is a well-known commercial software mainly used for the optimal sizing of RES-based energy systems at the micro-grid level. It can combine many components and perform optimisation and sensitivity analyses, which simplifies the evaluation of the most favourable system configuration [22,23]. Metaheuristic-based models are also widely employed for micro-grid applications to perform the optimal design of HRESs [24]. When dealing with the energy planning at the whole-island level, established modelling frameworks include EnergyPLAN, TIMES and OSeMOSYS [25]. They were originally designed for applications at the country level, but have been applied extensively at the island level as well [15]. These tools typically use the linear programming (LP) or mixed integer linear programming (MILP) techniques to solve the energy planning problem. TIMES [26] and OSeMOSYS [27] are based on a multi-year time horizon approach, which allows overcoming intrinsic problems associated with a single-year formulation. Indeed, the single-year-based framework cannot describe important phenomena, such as an increase in energy demand over the project lifetime, changes in long-term behaviour of RESs and changes in the cost of technologies over time. However, in multi-year capacity expansion models, time series must be approximated to reduce the computational burden of the simulation. Each year is generally divided into time slices, which are identified by a season, a day type (i.e., day of a season) and a daily time bracket (i.e., fraction of the day) [28]. Increasing the number of time slices improves the accuracy of the time series representation, but at the expense of a more complex problem. The study of scenarios with high RES penetration, and the consequent introduction of EES solutions in energy systems, makes the correct representation of time series even more important [29]. Novo et al. [30] addressed this issue by investigating techniques to reduce the number of time slices and limit the computational time when dealing with multi-year energy system models. In particular, they evaluated the advantages of time series clustering and showed good accuracy of results when only a few representative days (RDs) are used. The benefits of representative days have also been demonstrated in other works, where a single-year modelling approach has been adopted [31–33]. Gabrielli et al. [31] pointed out that the interconnection of RDs (based on the chronological order of days over the year) is necessary to accurately model multi-energy systems with seasonal energy storage [31]. Consistent with this finding, Kotzur et al. [32] showed that uncoupled representative periods are not suitable for modelling energy systems based on high-capacity energy storage. Hoffmann et al. [33] reported that the optimal choice of aggregation methods depends on the mathematical structure of the energy system optimisation model. They also showed that the use of representative days is the Pareto-optimal aggregation approach when storage is considered.

This work assesses the impact of time series clustering in the long-term planning of energy systems, making use of interconnected clustered representative days. OSeMOSYS, an open-source multi-year modelling framework, was employed in the present study, further investigating the methodology introduced in [30]. Specifically, a comparative assessment of the traditional and updated OSeMOSYS versions was conducted to evaluate the effectiveness of the proposed methodology to model the multi-year evolution of renewable-based energy systems that rely heavily on energy storage. The island of Pantelleria (in southern Italy) was considered as a demonstrative case study for this analysis. A relatively simple reference energy system was used to better highlight the impact of interconnected clustered RDs in modelling long-term energy storage. Then, different configurations of carbon-free power systems were analysed by varying the EES solution to shed light on the role of batteries and hydrogen in achieving 100% renewable energy systems. Specifically, the only-battery, only-hydrogen, and hybrid (i.e., battery plus hydrogen) configurations were examined.

The structure of this work is the following: Section 2 describes the methodology that has been developed for the energy system modelling. This section also presents the selected case study and the various scenarios that will be investigated. The main results are then shown and discussed in Section 3, and finally, the key conclusions are summed up in Section 4.

2. Materials and methods

This section depicts the overall methodology implemented in this paper to explore the future role of batteries and hydrogen in energy systems with a high share of renewable energy. First, the modelling framework used is depicted. Then, the model of the insular energy system is presented along with the main techno-economic assumptions. Finally, the strategy identified for the development of different energy scenarios is described.

2.1. Modelling framework

The energy model has been developed using OSeMOSYS, an LP-/MILP-based, open-source, multi-year energy modelling framework [27]. In this work, both the conventional OSeMOSYS version [34] and the enhanced version presented by Novo et al. [30] were used. For both versions, an additional set of equations was introduced to enable a discussion about the storage systems analysed in this article.

The structure of OSeMOSYS is based on the following elements: sets, which determine the model structure; parameters, which are the model inputs; variables, which are the outputs of the model; and equations, which relate parameters and variables. Each parameter and variable is a function of one or more sets.

The physical model structure is based on the following sets: *regions*, which are areas where the balance between supply and demand is guaranteed; *fuels*, which are the energy commodities; *technologies*, which are the elements that transform, import or export *fuels*; and *storages*, which are used to store *fuels* between time intervals.

The objective function (OF) is to minimise the net present cost (NPC) of the energy system [35]. As shown in Eq. (1), OF is given by the sum of the discounted costs of all *technologies* (*t*) and *storages* (*s*) over all *regions* (*r*) and *years* (*y*). The discounted costs can include capital, fixed and variable terms.

$$OF = min\left(\sum_{r}\sum_{y}\left(\sum_{t} TotalDiscountedCostByTechnology_{r,t,y} + \sum_{s} TotalDiscountedStorageCost_{r,s,y}\right)\right) \tag{1}$$

where the $TotalDiscutedCostByTechnology_{r,t,y}$ is the total discounted cost of the *t*-th *technology* in the *y*-th *year*, and $TotalDiscountedStorageCost_{r,s,y}$ is the total discounted cost of the *s*-th storage in the *y*-th year.

The key decision variables are the annual installed capacity of *technologies* and *storages* in each *year* and the activity of *technologies* and *storages* (i.e., a measure of their operation) in each time interval.

2.1.1. TRAD method

The time representation in the common version of OSeMOSYS is the same as that of typical LP/MILP-based frameworks for long-term optimal expansion planning of energy systems [27]. It makes use of five *sets*: *years (y)*, *seasons (ls)*, *daytypes (ld)*, *dailytimebrackets (lh)* and *timeslices (l)*. Each modelled *year* consists of several *seasons* (e.g., spring, summer); *daytypes* (e.g., weekdays, weekends) recur in every *season*; and every *daytype* consists of several *dailytimebrackets* (e.g., morning, afternoon). The combination of a *season*, a *daytype*, and a *dailytimebracket* represents a *timeslice*. All time-related input profiles (e.g., power load profiles, variable RES capacity factors) are obtained by averaging original (e.g., hourly) time series. This process - which is performed based on how *seasons*, *daytypes* and *dailytimebrackets* recur over the year - is necessary to reduce the complexity of the problem and allow the resolution of multi-year optimal planning problems [28]. Nevertheless, such a practice tends to flatten peaks and troughs, favouring low-cost variable renewables and underestimating the total system cost [36]. Especially, this conventional approach (named TRAD from now on) may lead to a weak dimensioning of energy storage systems [37].

Accurate representation of energy storage becomes increasingly important as the share of electricity from renewable sources increases. Concerning the energy storage modelling, OSeMOSYS enables energy to be either stored or discharged during a *timeslice* as long as the storage level remains within specified minimum and maximum values. A timeline of *timeslices* is obtained by assigning each *timeslice* to a *season*, a *daytype* and a *dailytimebracket*, which is needed for a correct modelling of the energy storage. However, as discussed in [38], it is not necessary to verify that the storage levels are within their boundaries at each time interval over the year. Indeed, based on the TRAD time representation, extreme storage level values can only occur during the first and last week of a specific *season,* and during the first and last occurrences of a particular *daytype*.

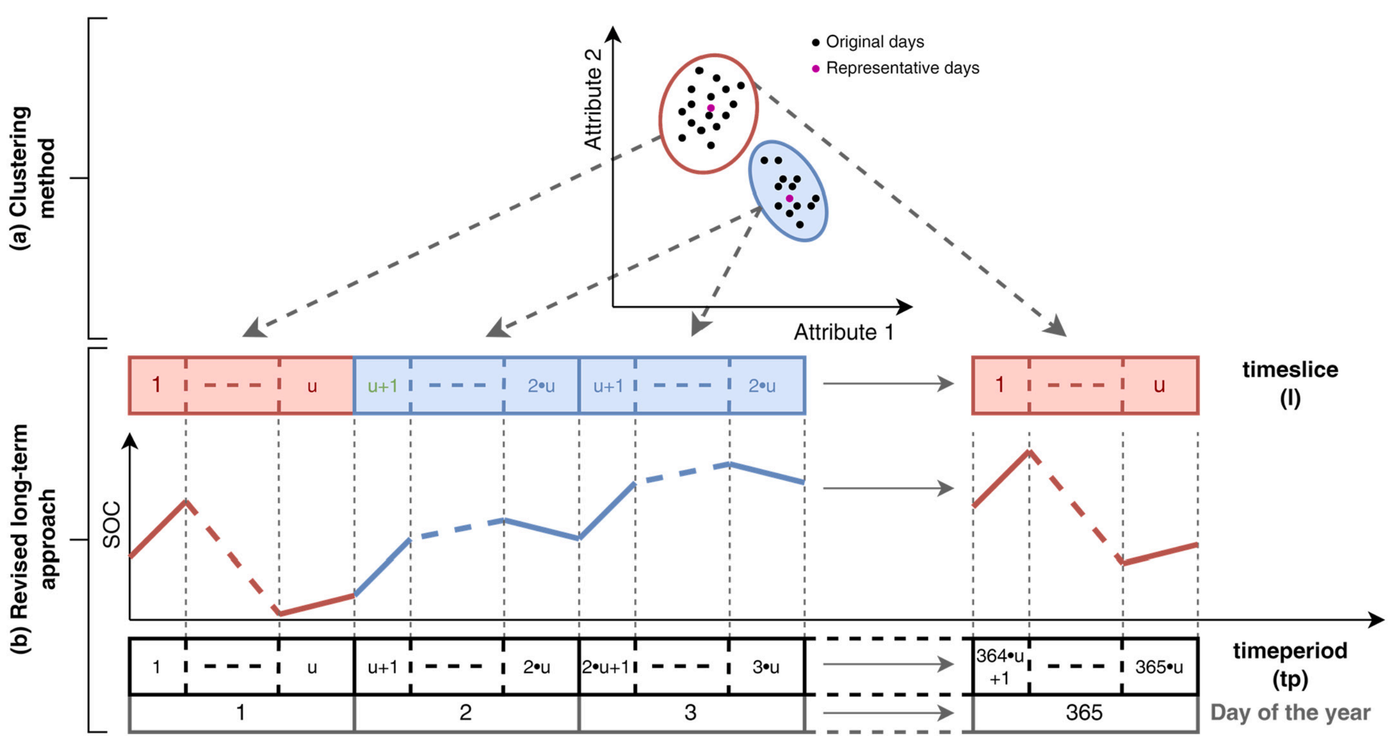

Fig. 1. NEW method: Temporal framework with interconnected clustered representative days (modified from [30]). For the sake of clarity, a clustering process with two attributes is shown in the figure. However, in this analysis the clustering was performed considering three attributes: PV and wind capacity factors, and electricity demand. This figure also refers to a clustering process with two representative days. SOC is the State-Of-Charge of the storage.

2.1.2. NEW method

In this analysis we considered, and further investigated, the OSeMOSYS update proposed by Novo et al. [30], where interconnected clustered representative days were implemented to improve the modelling of energy systems with high RES share [39].

In contrast to TRAD, where sequential averaging of time series is performed, in the NEW method representative days are defined using a clustering procedure based on specific attributes, namely time series profiles of RES supply and electricity demand.

As displayed in Fig. 1, the first step is to cluster the time series: the aim is to merge all days of the year into a predefined number of groups (representative days) so that the group members are as similar as possible. The clustering process was performed through the k-means algorithm [32]. According to this technique, clusters are created by minimising the squared error between the empirical mean of a cluster and all candidates in the cluster. More specifically, it is minimised a distance measure of some attributes between each group member. The major advantage related to the k-means method is that the total value of the original time series is preserved for each attribute. In this work, the following attributes were considered for the clustering: PV capacity factor, wind capacity factor and electricity demand. At the end of the clustering procedure, each day of the year is assigned to one of the representative days.

Fig. 1 also shows that each day consists of a certain number (u) of time intervals. Section 2.2 provides details on the accuracy that has been adopted for the intraday variability (Table 2). The number of *timeslices* of the model is thus given by u multiplied by the number of representative days.

The TRAD framework was then revised to allow the implementation of clustered time series while considering the chronological order of the representative days (and thus *timeslices*) throughout the year. This chronological sequence is necessary for the modelling of the energy storage.

In particular, a new temporal *set,* called *timeperiod (tp)*, was introduced to account for the chronology of *timeslices* over the course of the year. The number of *timeperiods* is equal to u (i.e., the time intervals of a day) multiplied by the number of days in a year. Each *timeperiod* is assigned a *timeslice* on the basis of the RD associated with the day of that *timeperiod*. The introduction of *timeperiods* eliminates the need for *seasons*, *daytypes* and *dailytimebrackets*, which are required instead in the TRAD method.

As shown in Fig. 1, the energy balance of the *storage,* and thus its State-Of-Charge (SOC) variation, is always the same when a certain *timeslice* occurs in the year. However, the SOC at the beginning of each *timeperiod tp* is evaluated based on the SOC at the beginning of the previous *timeperiod tp-1* and the SOC variation in the *timeslice* associated with the *timeperiod tp-1.* This formulation allows successive time intervals of the year to be interconnected and was introduced to model the *storages* and describe their long-term operating cycles when dealing with clustered time series. It should be noted that, unlike the TRAD method, it is necessary to verify that the storage level (i.e., SOC value) remains within the SOC limits for each time interval during the year.

A sensitivity analysis on the number of representative days must be performed to assess a reasonable trade-off between accuracy and computational time.

This paper goes beyond the work developed in [30], assessing the suitability of NEW for an isolated, 100% renewable-based energy system with a hybrid hydrogen-battery storage. Moreover, it aims to evaluate the role of storage systems with different durations on a long-term scale. It should be marked that the rated power and rated energy of storage systems are sized separately in OSeMOSYS, with different costs associated to power-related components (which are modelled as *technologies*) and energy-related components (which are modelled as *storages*). While this approach performs well for a hydrogen-based PtP solution, it is not suitable for batteries. In fact, many electrochemical storage technologies (e.g., Li-ion batteries, NaS batteries) are characterised by a well-defined range of energy-to-power ratios. For these EES systems, OSeMOSYS (both TRAD and NEW methods) has been updated by introducing lower and upper bounds on the ratio between the energy size and the power size. The new parameters and storage equations, along with the modified OSeMOSYS code, are included in Section 3 of the Supplementary Material.

2.2. Energy model

The island of Pantelleria was considered as a case study in this analysis. It is located in the Strait of Sicily, south of Italy, and is not electrically connected to the mainland. This medium-sized island is a good example of several other insular locations across the Mediterranean area and thus represents a valuable case study to investigate solutions for local energy self-sufficiency of remote sites [28].

The reference energy system of Pantelleria used in this work is displayed in Fig. 2. It includes one *fuel*, five *technologies* and two *storages*. A *storage* set and at least one *technology* set are needed to model a storage system in OSeMOSYS. *Technologies* are, indeed, associated to a certain *storage* to enable its charging and discharging.

Electricity (ELC) is the *fuel*, which has an associated final demand. The *technologies* are the following: photovoltaic power plants (PV), floating offshore wind turbines (WT), electrolyser (ELY), fuel cell (FC), and battery technology ($BATT_t$). Two different *storages* were considered: the hydrogen tank (HT) and the battery storage ($BATT_s$). The ELY and FC are needed, respectively, to charge and discharge the hydrogen tank. Analogously, the $BATT_t$ technology was included for the charging/discharging of the $BATT_s$ storage.

Proton-Exchange Membrane (PEM) electrolysers were considered for hydrogen production because of their excellent dynamic behaviour, making them suitable for coupling with variable RESs [40]. The PEM typology was also chosen for the fuel cell component. As for the BATT component, Li-ion batteries were considered because of their high roundtrip efficiency, low self-discharge rate and wide cycling modulation range [18]. Pressurised vessels were assumed for the hydrogen storage tank.

The investigation of renewables-based future energy scenarios requires an accurate definition of the installable power limits of different technologies. A precise estimate can be very challenging at a national level; nevertheless, it is more practicable at the scale of a small island. The PV technical potential for the island of Pantelleria amounts to 10.8 MW [28]. Such value was obtained as a sum of the 6 MW ground-mounted PV potential established by the local municipality based on available land, and the 4.8 MW rooftop PV potential, which would be reached with an average per-capita installed capacity of around 0.60 kW_{PV}/person. Concerning wind power, the installation of onshore wind

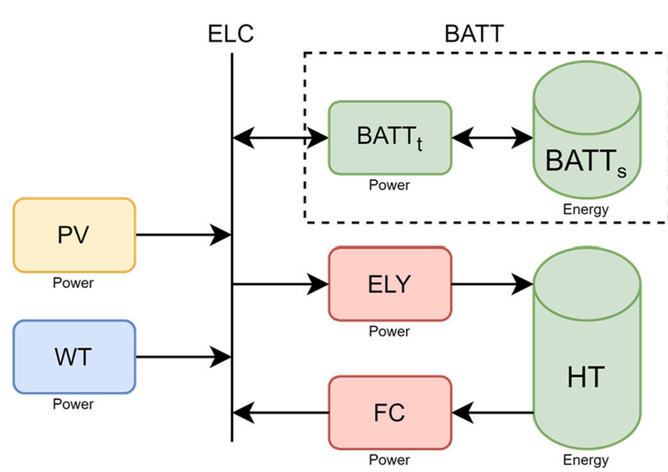

Fig. 2. Reference energy system of the analysed case study.

Table 1
Techno-economic assumptions (CAPEX and replacement) of components involved in the energy system.

	Capital cost (2021)	Capital cost (2030)	Capital cost (2040)	Operational life (years)	Ref.
PV	1022 k€/MW	523 k€/MW	405 k€/MW	25 y	[47]
WT	3705 k€/MW	2181 k€/MW	2025 k€/MW	25 y	[48]
BATT	500 k€/MW	332 k€/MW	304 k€/MW	10 y	[42,49]
	154 k€/MWh	102 k€/MWh	89 k€/MWh		
ELY	1300 k€/MW	1000 k€/MW	775 k€/MW	20 y	[43,44]
	(40% stack)	(40% stack)	(40% stack)	(stack: 10 y)	
FC	1520 k€/MW	800 k€/MW	650 k€/MW	20	[43–45]
	(50% stack)	(50% stack)	(50% stack)	(stack: 10 y)	
HT	15 k€/MWh	15 k€/MWh	15 k€/MWh	20	[50]

turbines of any size is currently forbidden by the Sicilian regional law [41]. Although public authorities are currently engaged in a discussion on the topic, it was assumed that the current legislative framework is not modified in this analysis. Therefore, exclusively offshore wind turbines were considered. In addition, because of the very high depths that characterise the sea in the Strait of Sicily, offshore wind turbines were supposed to be installed on floating platforms, with a significant increase in the overall cost of wind power. Specifically, floating wind turbines with a rated power of 2 MW each were considered in this work.

The annual electrical demand in Pantelleria amounted to approximately 27.3 GWh in 2021, with a power peak of 10.5 MW in the summer period due to tourism. It has been assumed that the electrical load has an annual increase of 1.5%, mainly because of the introduction of electric vehicles [28]. A seasonal behaviour is also present in the RES production profiles: PV (annual production of 1610 kWh/kW) has a peak in the summer period, whereas floating offshore wind (annual production of 3580 kWh/kW) is characterised by greater productivity in the winter months, from around January to March. The strong intra-annual variability of both RES supply and electrical demand profiles suggests that energy storage systems are necessary to optimise the exploitation of local RESs and, thus, achieve higher levels of renewable penetration.

Table 1 summarises the main techno-economic assumptions to estimate the CAPEX and replacement costs of the components involved in the Pantelleria energy system. The values of the operational life are also shown to know when replacements take place. Cost projections were used for all the components to consider any cost reductions over the model period, with intermediate values obtained through interpolation. As suggested by Cole et al. [42], the cost of the battery component was divided into power- and energy-related contributions. Cost projections of the PEM electrolyser and PEM fuel cell were taken from [43]. It was assumed that the ELY and FC stack replacements occur every 10 years [44]. The stack replacement cost was computed as a percentage of the CAPEX: 40% for ELY [43] and 50% for FC [45]. OPEX were assessed as a fraction of the CAPEX per year [46]. No cost evolution over time was considered for the hydrogen tank since the technology of steel pressure vessels is already mature [45]. Finally, an annual discount rate equal to 4% was adopted in this analysis [46].

The charging and discharging efficiency of BATT was set to 95%. A value of 60% was assumed for the efficiency of the PEM electrolyser [46], while 51% was used for the efficiency of the PEM fuel cell [44]. An energy-to-power ratio range between 0.5 and 2 was considered for the BATT component (Li-ion typology).

As shown in Table 2, each day was divided into 5 daily time brackets to consider the intraday variability of electricity consumption and renewable energy production. This detail on the daily variation (which was used for both the TRAD and NEW methods) is consistent with assumptions generally made in the literature for long-term energy expansion models [37]. The partitioning of days into time intervals is common in long-term energy models and is necessary to limit the computational cost and to ensure the solvability of the problem.

Table 2
Daily time brackets in every representative day (for both TRAD and NEW methods).

Daily time bracket	Start hour	End hour
1	0	6
2	6	10
3	10	14
4	14	18
5	18	24

The identification of the cost-optimal configuration of the energy system is allowed from the first year (2021) onwards. The evolution of the energy system configuration over the years is related to the increase in the total energy demand and to the cost-learning curves of the involved components (see Table 1).

2.3. Scenario setting

The validation of the NEW method was done by performing a sensitivity analysis on the number of representative days, which was increased up to 365. For the validation, the energy simulation was performed over 1 year in order to solve the full time-scale model (i.e., 365 representative days), which was used as a reference. The effectiveness of TRAD as a function of the number of RDs was also analysed for comparison purposes. In NEW, the required number of RDs was obtained by performing the clustering procedure described in Section 2.1.2. In TRAD, the RDs were instead derived by changing the number of *seasons* and considering a single *daytype* for each *season*. It should be noted that the same number of RDs for TRAD and NEW also implies the same number of *timeslices*.

For each case characterised by a certain number (i) of RDs, the relative error in the objective function (i.e., the net present cost of the system) was evaluated as follows:

$$RE_{TRAD/NEW,i} = \frac{OF_{TRAD/NEW,i} - OF_{TRAD,365}}{OF_{TRAD,365}} \tag{2}$$

where $RE_{TRAD/NEW,\,i}$ is the relative error of the TRAD/NEW method with i RDs, and $OF_{TRAD/NEW,\,i}$ is the objective function of the TRAD/NEW method with i RDs.

The goal of this sensitivity is to find the minimum number of RDs that can lead to an accurate representation of the objective function and component sizes. This RD number was then used to investigate the multi-year evolution of the Pantelleria energy system (from year 2021 to year 2040). More specifically, different scenarios have been analysed by varying the configuration of the EES system:

1. Only-battery scenario: the sizes of the hydrogen-based P2P components (ELY, FC and HT) are set to zero.
2. Only-hydrogen scenario: the size of the battery is set to zero.
3. Hybrid scenario: no size constraints are set on the EES solutions (i.e., hydrogen and batteries).

3. Results and discussion

Simulations were performed on a desktop computer with an Intel® Xeon® CPU E3-1245 v5 @ 3.50GHz CPU and 32 GB RAM. The IBM

ILOG® CPLEX® Optimization Studio software was employed as solver of the MILP models, imposing a relative MIP gap tolerance of 0.01%.

Representative days were introduced to reduce the complexity of the MILP-based optimisation framework (Section 3.1). Their influence was assessed using a single-year model to allow the resolution of the full-scale problem (with all 365 days of the year). The aim was to identify a sufficiently accurate model to then address the design of multi-year renewable energy systems (Section 3.2).

3.1. Impact of representative days

The energy system optimisation was run several times performing a sensitivity analysis on the number of representative days: from 6 RDs up to the full-scale solution (i.e., 365 RDs). The goal was to evaluate the minimum number of RDs needed to obtain an accurate approximation of the full-scale objective function. Moreover, both NEW and TRAD methods were applied to assess the effectiveness of interconnected clustered RDs in the modelling of hydrogen-based EES systems. This analysis was performed on a single year, using the electrical demand profiles and technology costs expected for the year 2040.

The relative error of the objective function with respect to the full-scale model is depicted in Fig. 3a. It can be noted that the relative error of NEW is always lower than that of TRAD, thus showing that the NEW approach provides better accuracy in estimating the total system cost. When using very few representative days, from 6 to 12, the relative error of the traditional method is close to −50%. In contrast, the NEW technique can find an optimal system configuration with relative error of around 10%. For both methods, the objective function tends to converge by increasing the RD number until reaching the same value when 365 representative days are considered.

As displayed in Fig. 3b, the use of RDs effectively reduces the computational burden of the problem. The computational time of the TRAD approach increases from 2.3 s at 6 RDs to 4679 s at 365 RDs. Moreover, a 23-fold increase can be observed in the NEW approach when moving from 6 RDs to the full-scale solution. Although additional variables have been added in the NEW approach (related to the modelling of the storage component), the TRAD time curve is characterised by a greater slope. This can be due to an increase in the number of binary parameters needed to assign a certain *timeslice* to a *season* in the TRAD method [30].

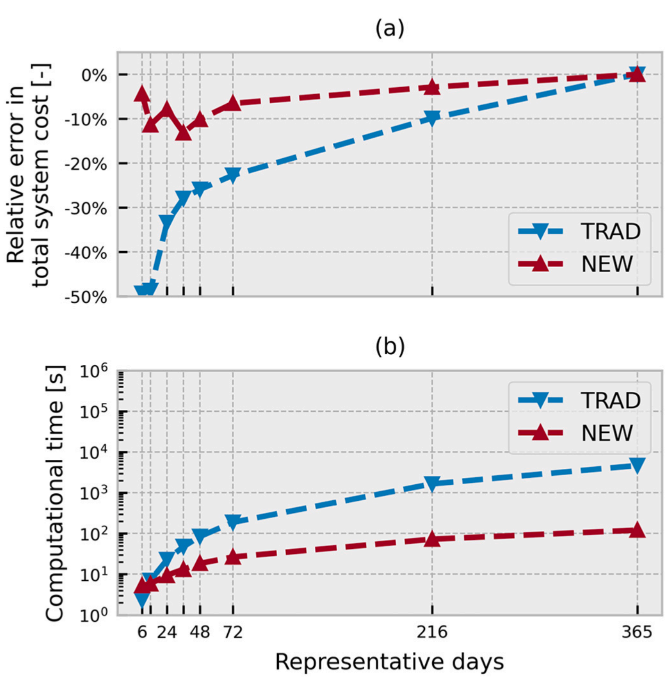

Fig. 3. - Relative error in total system cost (a) and computational time (b) for NEW and TRAD methods as a function of the number of representative days.

Main sizing outcomes as a function of the number of RDs are displayed in Fig. 4, where the dashed black lines refer to the full-scale solution. The rated power of the PV and WT technologies is well approximated over the entire RD interval for both the TRAD and NEW methods. The optimal PV size is always equal to 10.8 MW, which corresponds to the upper boundary of the PV size decision variable, as pointed out in Section 2.2. Unlike the TRAD approach, the NEW technique can accurately evaluate the battery size, i.e., rated power and energy, even when very few representative days are used. The benefits of NEW are also evident in estimating the size of the hydrogen-based components, i.e., electrolyser, fuel cell and hydrogen tank. The ELY and FC sizes quickly converge close to the full-scale solution when the NEW approach is used. Compared to TRAD, NEW also identifies a more accurate value of the HT rated energy in all the RD configurations. As for the TRAD technique, the HT capacity is almost null in the range from 6 to 12 RDs. The error on the HT capacity reaches −35% of the full-scale size when using 24–48 RDs and then gradually improves to the full-scale solution. By contrast, considering the NEW method, the underestimation of the HT rated energy is always less than 12% from 12 RDs onwards. The use of interconnected clustered RDs (i.e., the NEW approach) is thus effective in predicting the long-term storage capacity of the hydrogen tank, whose optimal rated energy (1365 MWh) is much higher than that of the battery (1.73 MWh).

Overall, representative days have been demonstrated to reduce the required simulation time while maintaining a good accuracy in the OF estimation. They were thus employed for the development of the 20-year energy system model of Pantelleria island, whose full-scale resolution is unfeasible with the available hardware.

It should be noted that the current work is mainly focused on validating the newly introduced methodology in an energy system characterised by long-term energy storage and on developing a comparative discussion about the functionality of batteries and hydrogen in a 100% renewable energy scenario. However, the obtained results show that this methodology could also be extended to the modelling of more complex energy systems, thanks to the reduced computational effort ensured by the use of time slices and the improved reliability of the model.

3.2. Scenarios comparative assessment

The multi-year energy model of Pantelleria, from 2021 to 2040, is here presented for the NEW approach and considering 48 RDs (240 *timeslices*), which were shown to provide accurate sizing results (see Section 3.1). Three different scenarios have been investigated by varying the EES solution: only-battery (OB), only-hydrogen (OH) and hybrid (HYB) configurations.

The breakdown of the net present cost of the three scenarios is displayed in Fig. 5. The system configuration with hybrid storage is the most cost-effective solution with an NPC of 87.9 M€, followed by the only-hydrogen case, whose NPC is slightly higher (90.2 M€). A 155% NPC increase can be observed when changing from the hybrid to the only-battery storage system (224.8 M€). As shown in Fig. 5, approximately 70% of the OB cost is due to the wind farm subsystem. The battery storage also covers a relevant share of the cost (23%). It should be noted that the WT cost decreases significantly, by roughly 4.5 times, when the hydrogen-based PtP solution is included in the energy system (i.e., OH and HYB scenarios). The implementation of hydrogen storage is thus highly effective in limiting the costs when aiming at 100% renewable energy systems. In this case study, the PV cost share is the same for the three scenarios since the optimal PV rated power is always equal to the maximum installable PV power, i.e., 10.8 MW.

The main sizing results over the selected time horizon are reported in Fig. 6 for the OB, OH and HYB scenarios. The corresponding sizing values are specified in the Appendix, Table A.1.

As shown in Fig. 6a, in the only-battery scenario, the WT size

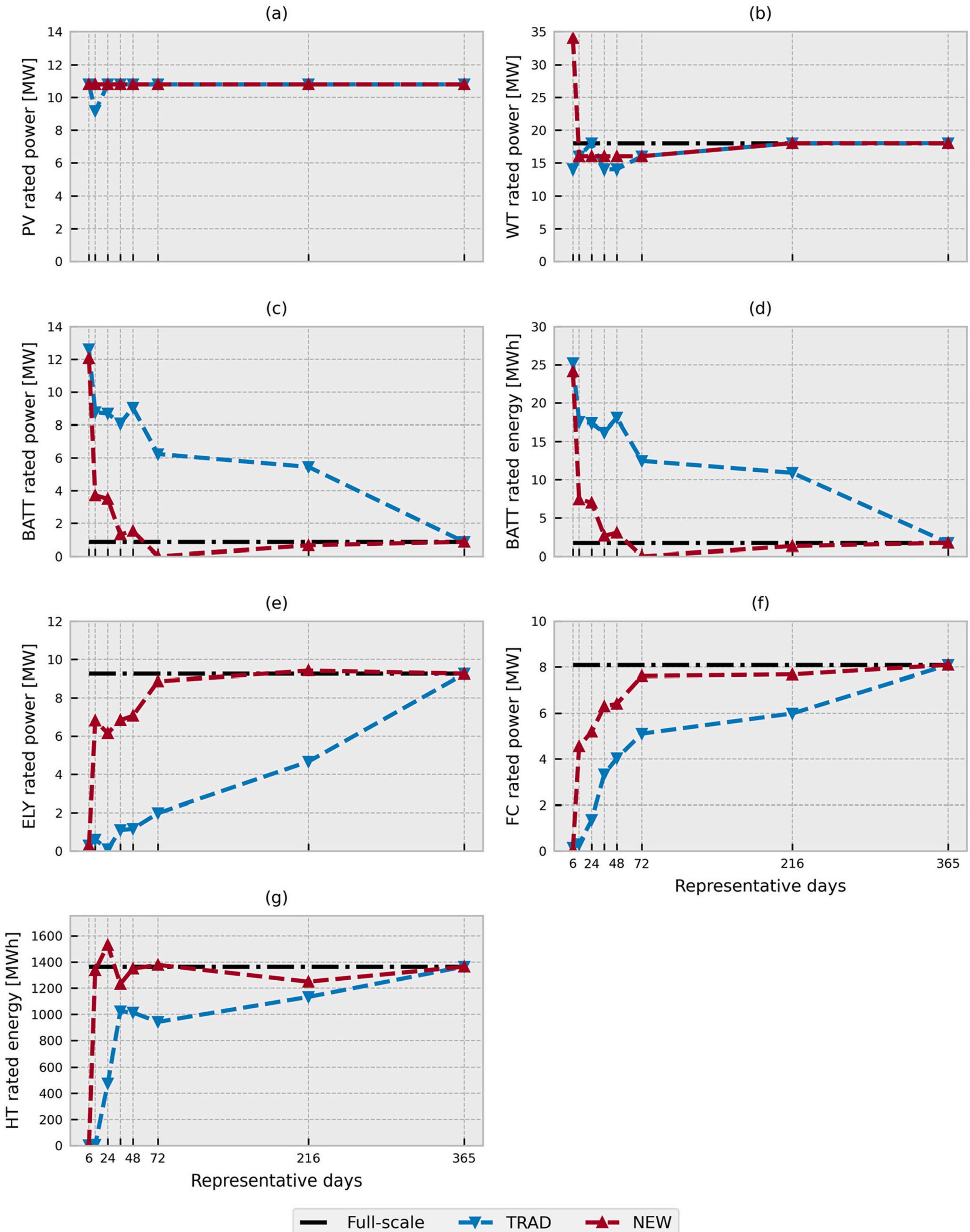

Fig. 4. PV rated power (a), WT rated power (b), BATT rated power (c), BATT rated energy (d), ELY rated power (e), FC rated power (f) and HT rated energy (g) in 2040 for TRAD and NEW methods as a function of the number of representative days. The full-scale solution refers to 365 representative days.

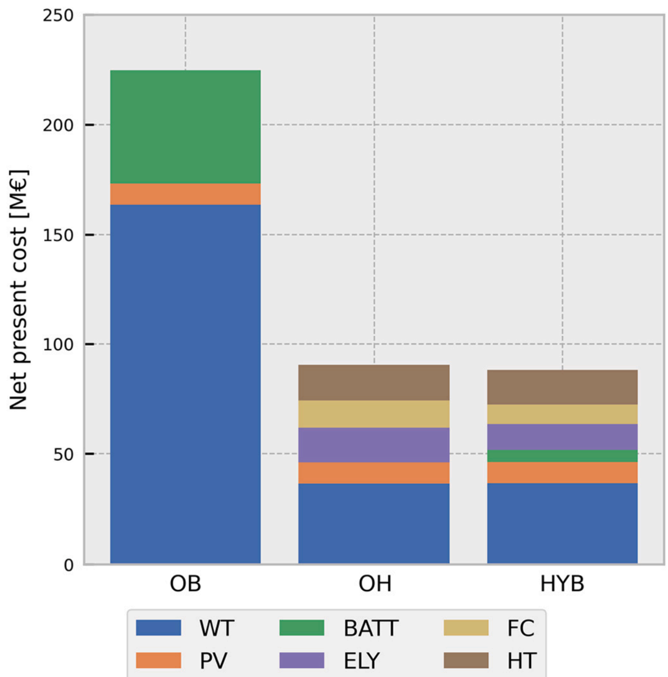

Fig. 5. Breakdown of the net present cost (over 20 years project lifetime) in the only-battery (OB), only-hydrogen (OH) and hybrid (HYB) scenarios.

increases from 42 MW in 2021 to 72 MW in 2040 to cope with the increase in load over years on the island of Pantelleria. The large WT size of the OB scenario is also accompanied by a high-capacity battery, whose rated power and energy (in the year 2040) are 46.9 MW and 93.8 MWh, respectively (i.e., energy to power ratio of 2 h). It can be noted that, in the OB scenario, the installed battery size has a maximum value in the year 2030 (Fig. 6b and c). From 2030 onwards, the increase in the annual electrical demand is thus mainly addressed by increasing the WT rated power installed per year, which turns out to be a cost-optimal planning strategy according to the cost projections reported in Table 1.

At the beginning of the project period, the OH and HYB cases require a WT size of 10 MW, which is about 4 times smaller than that needed in the OB scenario (Fig. 6a). However, large-size hydrogen storage is computed for the OH and HYB scenarios, from 842–851 MWh in 2021 to 1391–1403 MWh in 2040 (Fig. 6e). As previously shown in Fig. 5, the H_2-based power-to-power solution is essential in lowering the cost of the energy system. In particular, the most cost-effective solution involves the presence of a hybrid storage system that combines battery and hydrogen technologies. In the HYB scenario, considering the year 2020, the rated energy of the battery is 73 times smaller than that of the hydrogen tank (11.6 MWh of BATT compared to 842 MWh of HT). This size discrepancy further increases over the years: in 2040, indeed, the rated energy of BATT is 4.7 MWh, while 1391 MWh are foreseen for the HT. The adoption of batteries has almost no impact on the long-term capacity of the hydrogen tank, which is roughly the same in the OH and HYB scenarios. However, batteries in the HYB case are useful to reduce the rated power of the ELY and FC components with respect to the OH case. As displayed in Fig. 6d, in 2021, the ELY size changes from 5.5 MW (OH) to 3.5 MW (HYB) and the FC size changes from 5.3 MW (OH) to 3.4 MW (HYB). This is because the short-term BATT storage intervenes in support of the H_2-based PtP to cover the electrical demand peaks, thus avoiding oversizing the rated power of the hydrogen equipment.

It is also worth noting that, in the OH and HYB scenarios, the increase in the WT rated power (from 10 MW in 2021 to 14 MW in 2040) is lower compared to the OB scenario. It is, indeed, more convenient to invest in a greater hydrogen-based storage (and, thus, improve the actual RES exploitation) rather than further increasing the size of the wind farm. Moreover, it can be observed that the sizing results in 2040 for the multi-year model differ slightly from the values of the single-year simulation with the same RD number (see Section 3.1). This is because, in the multi-year approach, the sizing results at the end of the simulation are influenced by the evolution of the energy system during previous years.

Fig. 7 shows the profile of the energy stored in the hydrogen tank expected for the year 2040 in the HYB scenario. This trend is typical of a long-term storage system: the HT is filled during the first part of the year and then emptied mainly during the summer because of the higher electrical demand. Therefore, the HT function is essential to maintain a reliable electricity supply service throughout the entire year. On the contrary, BATT operates daily and acts as a short-term energy buffer.

The average round-trip efficiency of the hydrogen-based PtP is 31%, i.e., 60% of ELY efficiency multiplied by 51% of FC efficiency. This value is three times lower than the average round-trip efficiency of the BATT-based PtP (90%), given by the product of the BATT charging (95%) and discharging (95%) efficiencies. However, even if the hydrogen route is much less efficient than the battery route, hydrogen was found to be crucial to achieve a cost-optimal 100% renewable energy system. Due to the cost-effective long-term storage capability of HTs, hydrogen makes it possible to better exploit local renewable energy sources, thus avoiding a costly oversizing of the RES power plants. On the island of Pantelleria, in 2021, the WT rated power is 10 MW in the HYB and OH scenarios and 42 MW in the OB scenario, and this difference in size increases over the years (14 MW compared to 72 MW in 2040).

It is also worth noting that, in the H_2-based PtP, the rated energy and power are decoupled and belong to different components, which is a key feature in RES-based applications when a long-duration EES system is required. In fact, as for the hybrid scenario, in 2040 the rated power of ELY and FC is 8.7 MW and 6 MW, respectively; whereas the rated energy of the hydrogen tank is around 1400 MWh, which is needed to cope with the seasonal variation of the electrical demand in Pantelleria. On the contrary, the rated energy-to-power ratio is constrained in the BATT solution and depends on the BATT technology adopted. Finally, self-discharge losses, which were not implemented in this analysis, would shift the results further in favour of hydrogen. They are, in fact, null for the hydrogen storage but not negligible for the battery solution, especially when dealing with high-capacity storage systems. However, as shown in the HYB scenario, batteries are effective and still needed - due to their high efficiency and fast response - to support the RES-based energy system in daily operation.

4. Conclusions

In this work, time series clustering was used to improve the modelling of energy systems with a high share of renewable energy. Different EES configurations (i.e., only-battery, only-hydrogen, and hybrid) were investigated to disclose the role of batteries and hydrogen in 100% renewable-based systems. The main conclusions are summarised below:

- The use of interconnected clustered representative days (NEW method) was shown to be effective to address the modelling of energy systems with long-term energy storage. Few representative days are needed to obtain an accurate representation of the objective function (NPC) and the component sizes. Due to the reduced computational effort, this method can be extended to the modelling of more complex energy systems.
- Hydrogen storage plays a key role in achieving cost-effective system configurations that rely entirely on local RESs. In the case study of Pantelleria, the NPC of the only-battery energy system is 155% higher than that of the hybrid (hydrogen + battery) alternative.
- In the HYB configuration, batteries assume anyway a useful role as short-term energy buffer, supporting the energy system in daily operation and reducing the installed rated power of the ELY and FC components.

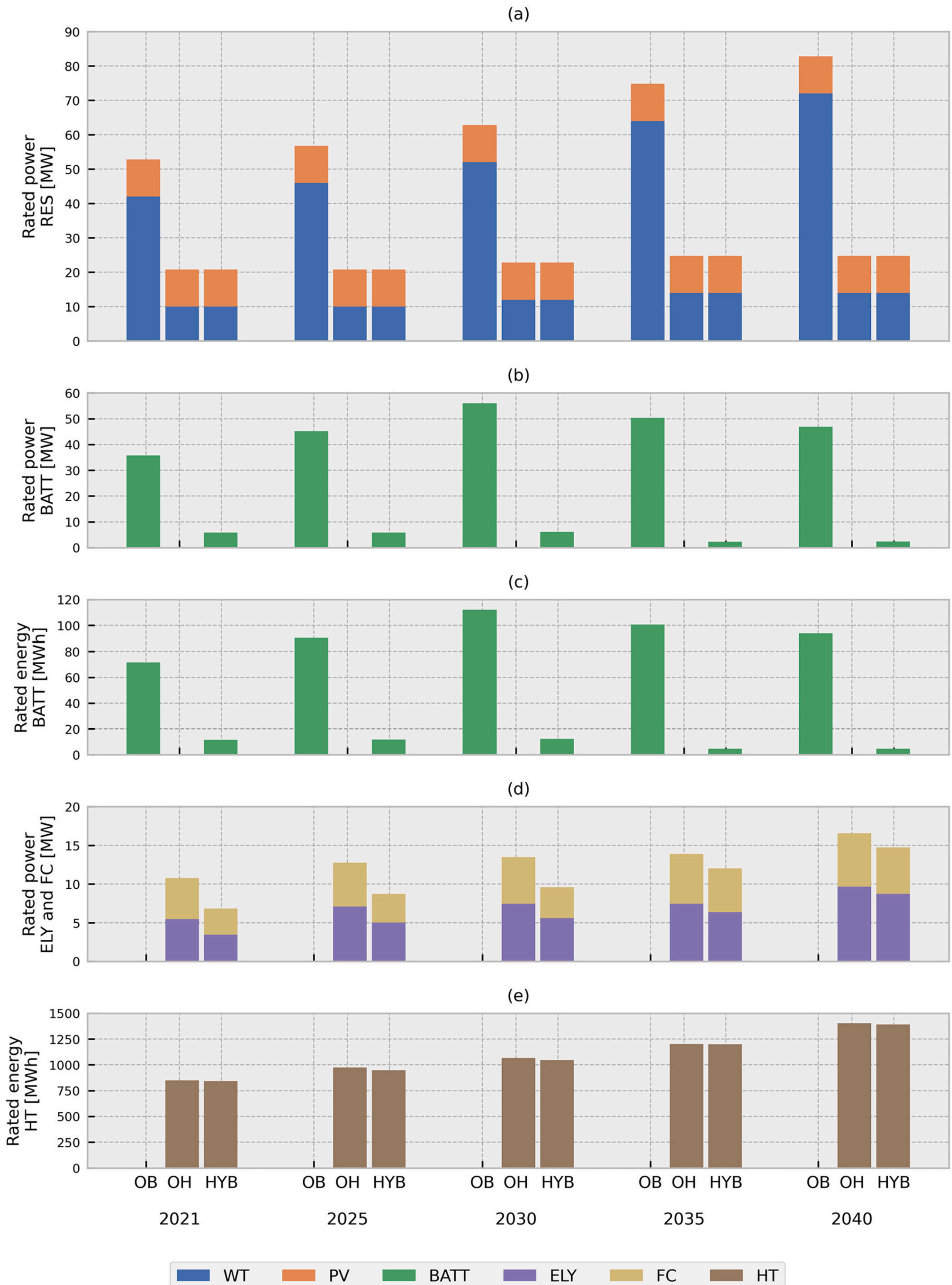

Fig. 6. Main sizing results in the only-battery (OB), only-hydrogen (OH) and hybrid (HYB) scenarios: rated power of PV and WT (a); rated power of BATT (b), rated energy of BATT (c), rated power of ELY and FC (d); and rated energy of HT (e).

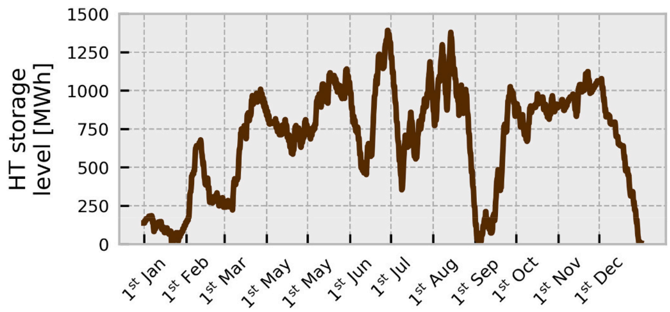

Fig. 7. Energy stored in the HT storage over the year (2040) in the HYB scenario.

- Although the hydrogen-based pathway is less efficient (about three times lower) than the battery-based pathway, the advantage of hydrogen lies in the low-cost high-capacity hydrogen tanks, which become crucial in RES-based energy systems to address the seasonal behaviour of renewable production and electrical demand. Long-term storage of hydrogen enhances the exploitation of renewable energy, avoiding costly oversizing of renewable generators. As an example, in 2040 the WT rated power in the hydrogen-based scenarios (i.e., OH and HYB) is around 5 times lower than that needed in the OB scenario.

Based on the methodology proposed in this work, future steps will address the development of a spatially resolved model of the Pantelleria energy system, considering a multi-nodal approach for a more accurate assessment of RES production across the island. The impact of intraday variability on sizing results deserves also to be investigated in future works.

CRediT authorship contribution statement

Paolo Marocco: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Resources. **Riccardo Novo:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Resources. **Andrea Lanzini:** Writing – review & editing, Supervision. **Giuliana Mattiazzo:** Writing – review & editing, Supervision. **Massimo Santarelli:** Writing – review & editing, Supervision.

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

Data will be made available on request.

Appendix A

Main sizing results of the 3 scenarios (OB, OH and HYB) are listed in Table A.1 for the years 2021, 2030 and 2040.

Table A.1
Main sizing results in the only-battery (OB), only-hydrogen (OH) and hybrid (HYB) scenarios in 2021, 2030 and 2040 years.

Scenarios		WT [MW]	PV [MW]	BATT [MW]	BATT [MWh]	ELY [MW]	FC [MW]	HT [MWh]
	OB	42	10.8	35.8	71.6	–	–	–
2021	OH	10	10.8	–	–	5.5	5.3	850.9
	HYB	10	10.8	5.8	11.6	3.5	3.4	842
	OB	52	10.8	56	112.1	–	–	–
2030	OH	12	10.8	–	–	7.4	6	1067.7
	HYB	12	10.8	6.1	12.3	5.6	4	1047.4
	OB	72	10.8	46.9	93.8	–	–	–
2040	OH	14	10.8	–	–	9.7	6.9	1403
	HYB	14	10.8	2.4	4.7	8.7	6	1391.3

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.est.2022.106306.

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