

Article

Battery Energy Storage Contribution to System Adequacy

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Abstract: The objective of this paper is to evaluate the contribution of energy storage systems to resource adequacy of power systems experiencing increased levels of renewables penetration. To this end, a coherent methodology for the assessment of system capacity adequacy and the calculation of energy storage capacity value is presented, utilizing the Monte Carlo technique. The main focus is on short-duration storage, mainly battery energy storage systems (BESS), whose capacity values are determined for different power and energy configurations. Alternative operating policies (OPs) are implemented, prioritizing system cost or reliability, to demonstrate the significant effect storage management may have on its contribution to system adequacy. A medium-sized island system is used as a study case, applying a mixed integer linear programming (MILP) generation scheduling model to simulate BESS and system operation under each OP, in order to determine capacity contribution and overall performance in terms of renewable energy sources (RES) penetration, system operating cost and BESS lifetime expectancy. This study reveals that BESS contribution to system adequacy can be significant (capacity credit values up to ~85%), with energy capacity proving to be the most significant parameter. Energy storage may at the same time enhance system reliability, reduce generation cost and support RES integration, provided that it is appropriately managed; a combined reliability-oriented and cost-driven management approach is shown to yield optimal results.

Keywords: battery energy storage; resource adequacy; capacity value; Monte Carlo; generation management



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1. Introduction

Future targets for operation of power systems foresee high penetration of renewable energy sources (RES) as well as gradual decarbonization of the electricity sector. Specifically, for the power systems of non-interconnected islands (NIIs), which are characterized by increased CO₂ emissions and operating costs due to their reliance on oil-fired generation, the elevation of renewables participation in their energy mix in place of existing thermal production is imperative. However, increased penetration of stochastic RES, such as wind and solar generation, substituting dispatchable units, may eventually compromise resource adequacy of these systems.

To date, energy storage introduction is a decisive factor to enable RES uptake in saturated small island grids, where absorption of renewable energy is impeded by technical and security constraints that eventually impose a ceiling to the renewable hosting capacity of such systems [1,2]. Multiple benefits associated with the introduction of storage include the mitigation of RES curtailments, the provision of ancillary services, the reduction in variable generation cost, etc. [3–5]. At the same time, energy storage systems (ESS) can become a key factor to support resource adequacy by extending their role into firm capacity providers.

Over recent years, a discussion has been initiated on the contribution of ESS to resource adequacy and the feasibility of substituting conventional thermal generation to address security of supply issues. The contribution of generation to system adequacy is typically evaluated using the concept of capacity value (or capacity credit) and the popular metric

of the Effective Load Carrying Capability (ELCC) [6]. Capacity value is defined as the amount of extra load that can be served due to the addition of a generating unit, without a reduction in the reliability of the system [7]. Alternative metrics have been proposed in the literature to quantify the capacity value of ESS as well, such as the Equivalent Firm Capacity (EFC) and the Equivalent Conventional Capacity (ECC) [8].

The impact of ESS on system reliability has been studied by adopting different perspectives and operating strategies [9–18]. Mitigating loss of load events via storage, assuming perfect foresight of upcoming production shortfalls or adopting adequacy-oriented operating strategies for the ESS, is common to achieve the maximum capacity value [9,11–13]. The authors of [9] implemented an optimal storage strategy for minimizing adequacy metrics, allowing small ESS to fully recharge overnight. In [12], the contribution of storage to system ramping adequacy is investigated, resolving ramping capability limitations of conventional generators in situations of high wind penetration. In [13], ESS are utilized exclusively to mitigate system stress events, when available generation capacity falls short of the total system demand. Peak shaving functionality of ESS is broadly used as a solid strategy for resource adequacy enhancement [10,14,15]. In [10], storage systems contribute to system adequacy by shifting peak consumption to low demand periods; the analysis considers all ESS characteristics including charging and discharging rates. In [14], daily peak shaving functionality is implemented and adequacy metrics are calculated through an analytical method. In [15], the capacity credit of energy storage measured in terms of its peak reduction potential is compared with its scarcity value-based capacity credit. Other approaches introduce economic considerations to resource adequacy estimation [16], adopting a market-oriented operation schedule for storage and modifying it in case of generation shortfalls [17]. The authors of [18] highlight the importance of the assumed management of storage for its contribution to system reliability, demonstrating that the introduction of storage does not always guarantee an improvement of the respective metrics.

Most of the literature explores factors that determine the capacity value of ESS and proposes alternative methods for its calculation [8,19,20]. In [19], the authors develop a methodology for the calculation of capacity value of distribution-level ESSs for a small-scale test power system, accounting for their availability in a simplified way, and the effects of technical properties of energy storage and system conditions are investigated. The author of [20] apply a modified method for ELCC estimation to demonstrate that the capacity contribution of storage tends to saturate above a certain capacity level. In [8], the well-established capacity value metrics are summarized, evaluation algorithms are presented and the impact of storage sizing and efficiency on its contribution to resource adequacy is explored.

The capacity adequacy gap left by retiring conventional units and the potential for energy storage to fill this gap is an extremely topical question investigated in several works [8,21–23]. The authors of [21] calculate the capacity value of battery energy storage systems (BESS) of different sizes accounting for various photovoltaic (PV) capacity levels, while considering the possibility of deferring the installation of new conventional peaking generation through the coordinated operation of solar and storage. In [22], an interconnected island experiencing high wind penetration is studied, whose peaking units are effectively replaced by an ESS. In [8], a new capacity value metric is introduced to quantify the capacity of peaking units which could be displaced by ESS.

The benefits of joint operation of RES and storage are highlighted in several studies, in terms of achievable capacity value [24–30]. In [25], different energy storage management strategies are adopted in order to mitigate system inadequacies, meet a target RES penetration or achieve both objectives at the same time. The authors of [26] demonstrate the advantages through the coordinated operation of such units. Similarly, in [28], it is proven that the joint operation of solar power plants with thermal energy storage increases the capacity value of these assets. The authors of [29] studied the coupled operation of ESS and PVs and applied alternative management policies, improving system reliability by

executing a peak shaving strategy. Alternative operating strategies for BESS are applied in [30], similar as in [25], from the perspective of both system and wind farm operators.

The majority of the existing literature investigates the contribution of energy storage facilities integrated into large interconnected continental power systems or elementary test power systems. Furthermore, most studies lack a balanced approach regarding the ESS operating policy, either adopting resource adequacy-oriented strategies that ignore other aspects of system performance or disregard their capacity contribution enhancement. ESS are often represented in an oversimplified manner in adequacy studies, disregarding their reliability characteristics and availability limitations and failing to account for the deterioration induced by the applied operating policies.

This paper primarily aims to shed light on energy storage contribution to capacity adequacy of island systems, giving due consideration to their operating strategies. Notably, in a competitive market environment, where storage would participate as an independent profit-driven entity, its operating pattern and resulting contribution to resource adequacy would be dictated by the prevailing market conditions and the participation strategies selected by its operators. In isolated island systems, however, lacking competitive generation markets, the operating strategy of centrally dispatched storage assets needs to be set by the system operator considering different and often conflicting objectives. To this end, alternative operating policies (OP) are developed and evaluated in terms of the achieved storage contribution to resource adequacy, but also as regards overall system performance, to validate the suitability of each policy and address the fundamental question of whether a storage operated in a realistic manner, i.e., enhancing system economics and supporting RES penetration, will contribute sufficiently to capacity adequacy. Three policies are evaluated in the paper:

- OP1—*Cost driven*: BESS are operating in a market-oriented manner that maximizes economic benefits;
- OP2—*Reliability driven*: BESS execute peak shaving on a daily basis throughout the year, in order to maximize resource adequacy contribution;
- OP3—*Hybrid policy*: peak shaving is prioritized only on high demand days, while a cost-driven approach is adopted for the rest of the year.

A coherent methodology is developed for the assessment of resource adequacy and capacity value of energy storage, utilizing the Monte Carlo technique. Through a *resource adequacy model* (RAM), the well-established reliability metrics of Loss of Load Expectation (LOLE) and Expected Energy Not Supplied (EENS) are calculated and capacity value is assessed via the EFC and ECC metrics. The RAM employs an availability model for BESS within the Monte Carlo simulations (MCS) and utilizes annual storage operation profiles generated by a *unit commitment and economic dispatch* (UC-ED) model, which constitutes a detailed optimization methodology for the generation scheduling of the autonomous power system consisting of thermal units, RES and centrally managed BESS, built upon the mixed integer linear programming approach (MILP). The alternative policies are implemented inside the UC-ED model, which delivers the annual system operating and economic results. The OP-dependent impact on storage lifetime expectancy is evaluated *ex-post*, assuming Li-ion batteries.

The remainder of this paper is organized as follows. Section 2 describes in detail the rationale behind each operating policy and presents the UC-ED model formulation. In Section 3, the RAM model is developed and the applied BESS capacity value estimation method is outlined. The description of the case study follows in Section 4. Section 5 presents the results from the introduction of BESS on both adequacy and overall island system operation. The main conclusions are summarized in Section 6.

2. BESS Operating Policies and UC-ED Model Formulation

2.1. Outline of Operating Policies

2.1.1. Operating Policy 1—Cost Driven

OP1 is the baseline to create a realistic operating pattern of a BESS, driven by overall system operating cost and performance objectives, as are the variable generation cost of the system and RES energy absorption, both enhanced through energy arbitrage functionality and the provision of fast reserves, critical for the security of isolated system and the integration of stochastic RES. In this policy, batteries will operate in the market, aiming to provide flexibility and reduce system cost; however, BESS energy arbitrage and peak shaving functionality may be limited, as battery stations of limited energy capacity are primarily utilized as fast reserve-providing assets in island systems [31]. This is illustrated in Figure 1, where the residual system load (demand minus RES contribution) is shown when the alternative policies are applied. With OP1 (blue line in Figure 1a), demand peaks are only moderately mitigated, indicating that arbitrage is performed sparingly with this policy.

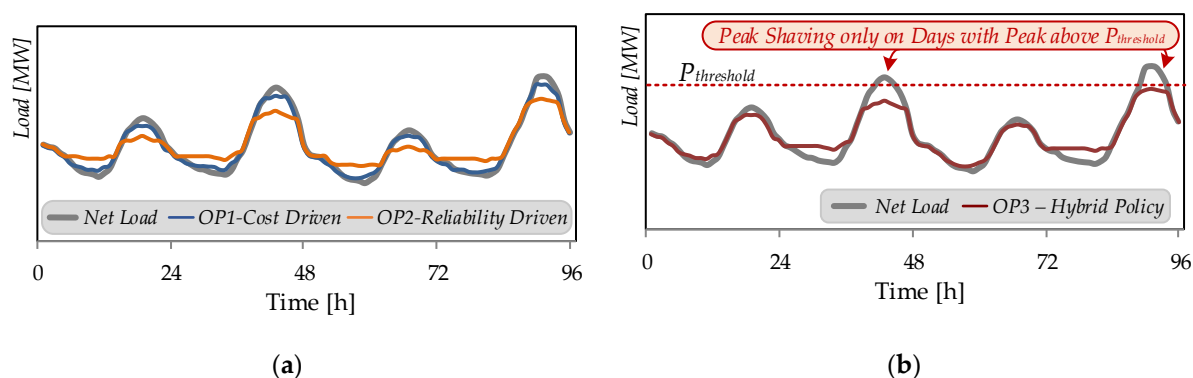


Figure 1. Daily load curve shaping for over an indicative 4-day period with the implementation of the alternative policies: (a) OP1 vs. OP2; (b) OP3.

2.1.2. Operating Policy 2—Reliability Driven

Given that high demand intervals are most critical for resource adequacy of a power system [32], this operating policy places emphasis on the elimination of peaks of the load curve, prioritizing the arbitrage functionality of the BESS on a daily basis seeking to maximize the capacity value of the storage asset. This is illustrated with the orange line in Figure 1a, where the difference in comparison to OP1 is apparent. Nevertheless, enforcing a daily peak shaving operation will prove non-optimal both for system economics and BESS degradation, as it will perform one full charge–discharge cycle per day, compromising the lifetime expectancy of the batteries.

2.1.3. Operating Policy 3—Hybrid Policy

OP3 aims at combining the advantages of the OP1 and OP2, in order to obtain a high capacity value out of storage, with a minimum burden on system operating cost and battery longevity. In this policy, peak shaving is performed only on high demand days, which are most crucial from a resource adequacy viewpoint. A simple criterion for selecting such days is the load exceeding a *threshold value* ($P_{\text{threshold}}$), determined by the system operator. Application of this strategy is illustrated in Figure 1b. The residual demand is shaped exactly in the same way as through OP1, except on high demand days where the performance resembles that of OP2.

2.2. UC-ED Model Fundamentals

A unit commitment and economic dispatch model is developed, incorporating the alternative policies considered, to reproduce the management of the island system in each case and capture the impact of each operating policy on system and BESS performance.

The generation scheduling problem adopts a cost-optimal approach and is formulated as a MILP problem with a 24 h look-ahead horizon and hourly dispatch intervals, as explained in more detail in [2,33] and amended in [31] to integrate centrally dispatched energy storage. MILP is a state-of-the-art optimization method for modeling the generation scheduling problem of power systems, effectively handling both binary and continuous variables and tracing optimal solutions in reasonable computational times [34,35]. The UC-ED model incorporates all technical and economic characteristics of the thermal generation fleet and the storage, as well as system-level constraints, including reserve requirements and real-time management constraints for the production level of intermittent renewables.

The objective function (1) of the UC-ED model is composed of the variable generation cost (C_p), startup/shut down costs ($C_{su/sd}$) and operating/maintenance costs ($C_{O\&M}$) of thermal units. The term of C_{peak} is necessary for the activation of the peak shaving mode, as explained in more detail in the following, while the rightmost term of (1), C_{sl} , stands for the cost of slack variables, allowing the relaxation of constraints to ensure a feasible solution of the optimization problem.

$$\min \{ C_p + C_{su} + C_{sd} + C_{O\&M} + C_{peak} + C_{sl} \} \quad (1)$$

The active power equilibrium is presented in (2) and ensures that the output power of committed thermal units ($P_{u,t}$), distributed photovoltaics ($P_{PV,t}^f$) and wind farms (WFs) after curtailments ($P_{W,t}^f - X_{w,t}$), the discharge of BESS ($P_{\xi,t}^d$) and the energy not served ($P_{ens,t}$) equals the load demand ($P_{L,t}$) and BESS charging ($P_{\xi,t}^c$) per time interval t .

$$\sum_u P_{u,t} + P_{PV,t}^f + (P_{W,t}^f - X_{w,t}) + \sum_{\xi} P_{\xi,t}^d + P_{ens,t} = P_{L,t} + \sum_{\xi} P_{\xi,t}^c \quad (2)$$

Constraints (3) and (4) impose the commitment status ($st_{u,t}$) and the start-up and shut-down states ($su_{u,t}$ and $sd_{u,t}$) of each thermal unit. Constraints (5) and (6) ensure that minimum up (T_u^{run}) and down (T_u^{stop}) times of each unit are observed. Constraints (7) and (8) restrict the output power of each unit by its ramp rates (RU_u , RD_u , RSU_u , RSD_u). Additionally, constraints (9) and (10) limit the output of conventional units by their maximum (P_u^{max}) and minimum (P_u^{min}) permissible loading, accounting for their contribution to positive and negative reserves ($r_{u,t,r}^{up/dn}$) per reserve type and time interval.

$$su_{u,t} + sd_{u,t} \leq 1 \quad (3)$$

$$su_{u,t} - sd_{u,t} = st_{u,t} - st_{u,t-1} \quad (4)$$

$$\sum_{k=t-T_u^{stop}+1}^t sd_{u,k} \leq 1 - st_{u,t} \quad (5)$$

$$\sum_{k=t-T_u^{run}+1}^t su_{u,k} \leq st_{u,t} \quad (6)$$

$$P_{u,t} - P_{u,t-1} \leq RU_u \cdot st_{u,t} + RSU_u \cdot su_{u,t}, \forall t > 1 \quad (7)$$

$$P_{u,t-1} - P_{u,t} \leq RD_u \cdot st_{u,t} + RSD_u \cdot sd_{u,t}, \forall t > 1 \quad (8)$$

$$P_{u,t} \leq P_u^{max} \cdot st_{u,t} - \sum_{r \in \{pr, sr, tr\}} r_{u,t,r}^{up} \quad (9)$$

$$P_{u,t} \geq P_u^{min} \cdot st_{u,t} + \sum_{r \in \{pr, sr\}} r_{u,t,r}^{dn} \quad (10)$$

The fundamental constraints related to the logical status of commitment of BESS are (11)–(14). Constraint (11) bounds the charge and discharge power of BESS to the maximum levels ($P_{\xi}^{c/d}$), while (12) ensures that BESS cannot charge and discharge at the same time, exploiting the binary variables $st_{\xi,t}^c$ and $st_{\xi,t}^d$. Constraint (13) determines the state of

charge ($\text{SoC}_{\xi, t}$) of BESS unit ξ , taking into consideration its charging and discharging efficiency, bound in (14) by its minimum ($\underline{E}_{\xi}$) and maximum ($\overline{E}_{\xi}$) levels.

$$0 \leq P_{\xi, t}^{c/d} \leq \overline{P_{\xi, t}^{c/d}} \cdot \text{st}_{\xi, t}^{c/d} \quad (11)$$

$$\text{st}_{\xi, t}^c + \text{st}_{\xi, t}^d \leq 1 \quad (12)$$

$$\text{SoC}_{\xi, t} = \text{SoC}_{\xi, t-1} + P_{\xi, t}^c \cdot n_{\xi}^c - P_{\xi, t}^d / n_{\xi}^d \quad (13)$$

$$\underline{E}_{\xi} \leq \text{SoC}_{\xi, t} \leq \overline{E}_{\xi} \quad (14)$$

Constraints (11)–(14) apply to all three operating policies; however, additional constraints apply when implementing OP2 and OP3. For OP2, the virtual cost term C_{peak} , defined in (15), is introduced in (1) to penalize daily peaks ($P_{\text{peak}, t}$) and thus prioritize peak shaving functionality, depending on the value of penalty factor φ_{peak} . Equations (16)–(17) are implemented for the identification of residual load peaks during one day period (T_D). The residual load $P_{R, t}$ includes demand and battery charging load, reduced by available RES generation and BESS discharging, as in Equation (22) below including BESS. The non-linear terms of (15) and (17) are properly linearized and incorporated in the MILP UC-ED model according to [36,37], respectively.

$$C_{\text{peak}} = \sum_t (\varphi_{\text{peak}} \cdot P_{\text{peak}, t}^2) \quad (15)$$

$$P_{\text{avg}} = \frac{\sum_{t \in T_D} P_{R, t}}{T_D} \quad (16)$$

$$P_{\text{peak}, t} = \max\{P_{R, t}, P_{\text{avg}}\} \quad (17)$$

In OP3, BESS peak shaving operation is initiated only when the peak demand of the dispatch day exceeds a predefined *threshold* ($P_{\text{threshold}}$), (18), in which case φ_{peak} receives the same value as in OP2, enforcing peak shaving through arbitrage. Otherwise, the system operates as in OP1. In (18), the residual load is used, before BESS action.

$$\varphi_{\text{peak}} \rightarrow \begin{cases} = 0, & \text{if } P_{\text{threshold}} \geq \max_{t \in T_D} (P_{L, t} - P_{W, t}^f - P_{PV, t}^f) \\ > 0, & \text{if } P_{\text{threshold}} > \max_{t \in T_D} (P_{L, t} - P_{W, t}^f - P_{PV, t}^f) \end{cases} \quad (18)$$

Additional UC-ED constraints, related to wind power limitations and the quantification of reserves requirements, are described in Appendix A and apply to all OPs.

3. Methodology for Assessing the Contribution of Energy Storage to Resource Adequacy

3.1. Resource Adequacy Evaluation Methodology

Monte Carlo simulation is a state-of-the-art analysis technique for stochastic problems and the principal technique to address resource adequacy in power systems incorporating energy storage facilities [38]. MCS evaluates system adequacy through a sequence of annual simulations accounting for the stochastic nature of uncertainties impacting adequacy [39]. A dominant uncertainty is the full/partial unavailability of thermal units to deliver their rated capacity, modeled in this paper by a two-state model. The time duration that a unit is available until its next failure (TTF—time to failure) and the time for the unit to repair after a failure (TTR—time to repair) are random variables following exponential distributions, with means $\lambda = 1/\text{MTTF}$ and $\mu = 1/\text{MTTR}$, respectively, where the Mean Time to Failure (MTTF) and Mean Time to Repair (MTTR) are expressed in hours. Sampling sequential values of the TTF and the TTR random variables carried out by using Equations (19) and (20), where U and U' are sequences of random numbers uniformly distributed in $[0,1]$ ([39]):

$$\text{TTF} = -\text{MTTF} \cdot \ln U \quad (19)$$

$$TTR = -MTTR \cdot \ln U' \quad (20)$$

The standard reliability metric used for conventional units is the FOR (forced outage ratio) indicator, related to MTTF and MTTR as in (21) [32].

$$FOR[\%] = \frac{MTTR}{MTTR + MTTF} \cdot 100\% \quad (21)$$

After generating annual availability histories with hourly resolution for each thermal unit, in the form of chronological up-down-up cycles, the cumulative available thermal capacity (ATC) of the system was obtained, combining the operating cycles of all units. This process is illustrated in Figure 2a. ATC will be compared to the residual load (P_R) that the dispatchable thermal generation is required to serve, given by the system load demand, incremented by BESS charging power and reduced by the available RES production and BESS discharge. The BESS operating profile was determined by the UC-ED model described in Section 2. The construction of $P_{R,t,s}$ timeseries for every sample year of the MCS is shown in Figure 2b.

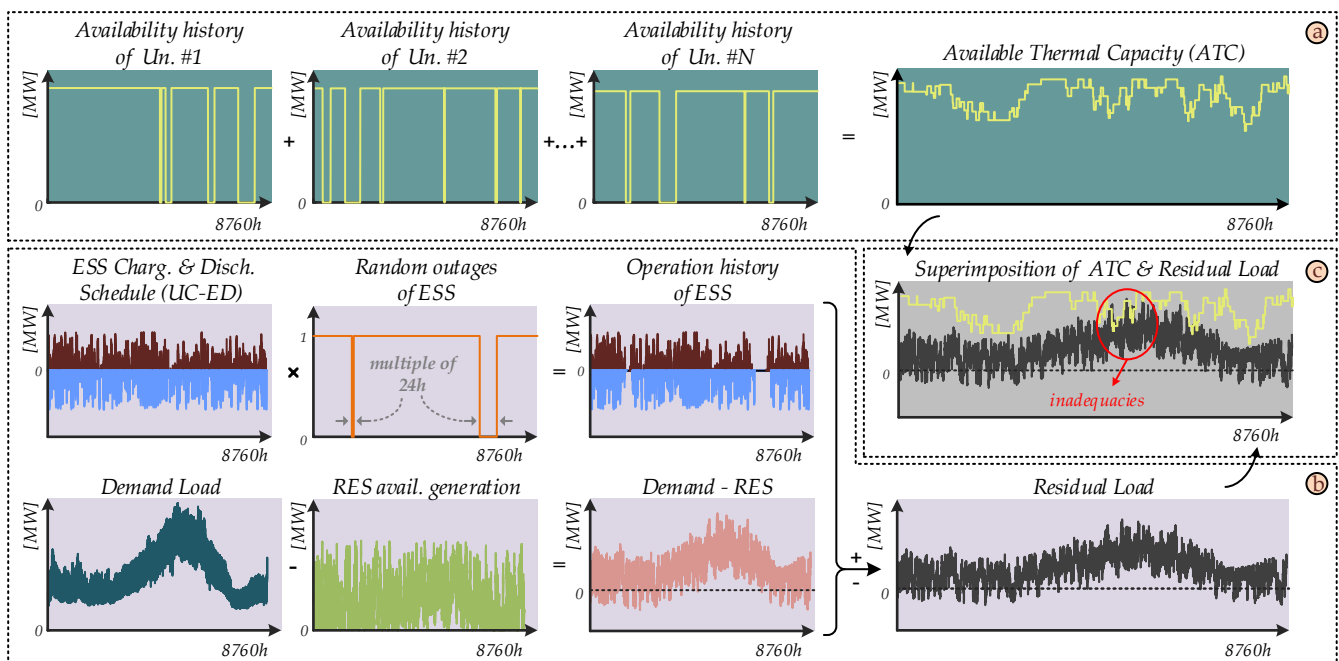


Figure 2. One sample year of the MCS process: (a) ATC modeling; (b) residual load modeling; (c) superimposition of ATC and residual load.

Same as for thermal units, BESS unavailability due to forced outages needs to also be accounted for. This is modeled on a daily basis, facilitating the inclusion of modified residual load profiles. When BESS is not available, based on its randomly generated availability intervals, its charging and discharging powers are excluded from residual load calculation, as in (22):

$$P_{R,t,s} = \begin{cases} P_{L,t} - P_{W,t}^f - P_{PV,t}^f + \sum_{\xi} P_{\xi,t}^c - \sum_{\xi} P_{\xi,t}^d, & \text{for days that BESS is available} \\ P_{L,t} - P_{W,t}^f - P_{PV,t}^f, & \text{for days that BESS is unavailable} \end{cases} \quad (22)$$

The ATC and $P_{R,t,s}$ timeseries were then compared to identify capacity inadequacies (Figure 2c), i.e., intervals where $P_{R,t,s}$ exceeds ATC, allowing the evaluation of the appropriate reliability indices for the particular MCS sample year, specifically, the loss of load duration (LLD) and the energy not supplied (ENS). LLD in (23) is the annual number of hours that load curtailments have to be imposed (i.e., a generation inadequacy is noted),

while ENS in (24) stands for the total load energy (MWh) curtailed on an annual basis for the specific sample year.

$$LLD_s = \sum_{t=1}^{8760} (ATC_{t,s} < P_{R,t,s}) \quad (23)$$

$$ENS_s = \sum_{t=1}^{8760} \max(0, P_{R,t,s} - ATC_{t,s}) \quad (24)$$

The system reliability indices LOLE and EENS are estimated in (25) and (26) as the mean values of LLD_s and ENS_s over the ensemble of N_{MCS} sampling years [39].

$$LOLE_{N_{MCS}} = \frac{\sum_{s=1}^{N_{MCS}} LLD_s}{N_{MCS}} \quad (25)$$

$$EENS_{N_{MCS}} = \frac{\sum_{s=1}^{N_{MCS}} ENS_s}{N_{MCS}} \quad (26)$$

As the number of sample years increases in the MCS process, the target reliability indicators converge towards their final value. The convergence criterion used in this paper to terminate the MCS process was set at 1% and it was applied to the EENS, which has the lowest convergence speed compared to other indices [39]. The accuracy of the MCS is defined in (27), where σ is the standard deviation, obtained by the quadratic root of the EENS variance after N_{MCS} samples, given by (28).

$$a = \frac{\sigma}{EENS_{N_{MCS}}} \quad (27)$$

$$\sigma^2 = \frac{1}{N_{MCS} \cdot (N_{MCS} - 1)} \sum_{s=1}^{N_{MCS}} (ENS_s - EENS_{N_{MCS}})^2 \quad (28)$$

3.2. Capacity Value Assessment

The capacity value of BESS is typically quantified through the EFC and ECC metrics, providing the capacity of an “equivalent production asset” that brings about the same system adequacy enhancement as the introduction of storage in question. Whilst EFC refers to a perfectly reliable “equivalent production asset”, ECC benchmarks storage against realistic conventional generation with a non-zero FOR.

An iterative process is implemented to calculate the EFC and ECC metrics. Generation capacity, with a zero FOR for the EFC and non-zero for the ECC, was gradually added in increments (G_{step} in MW) to the base case (BC) scenario, until the $EENS$ reached the same level as the BESS configuration under investigation ($EENS^{ESS}$). Adequacy recalculation was performed at every increase in generation capacity. For EFC calculation, the capacity increment can be directly subtracted from demand, as it is always available. The procedure is illustrated in the flowcharts of Figure 3a,b. Both metrics are expressed in MW or normalized as ratios of calculated capacity value over the rated capacity of the ESS under study.

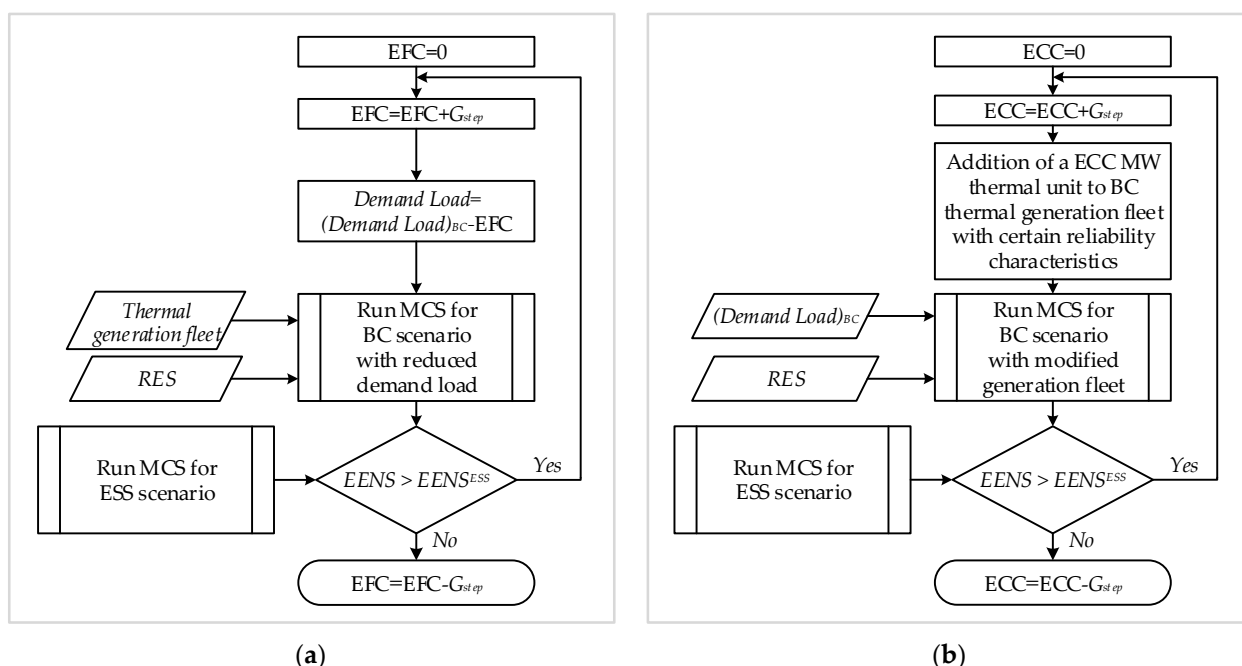


Figure 3. Methodology for calculating capacity value metrics: (a) EFC; (b) ECC.

4. Study Case NII System and Analysis Scenarios

The island power system described in [40] was selected as the study case, with certain modifications in the thermal fleet to serve the purposes of this study. Peak demand is 228.4 MW with a load factor of 44%. The system includes 13 heavy fuel oil (HFO) and 2 light fuel oil (LFO) units, whose basic technical and reliability characteristics are listed in Table 1. Additional data can be found in [40]. Installed PV and WF capacity values are 36 and 70 MW and the respective feed-in tariffs are 350 and 90 EUR/MWh. The crude oil price is USD 85/barrel, using an exchange rate of USD 1.10/EUR.

Table 1. Main characteristics of conventional units of the study case system ¹.

Unit No.	Type	Fuel	$P^{\max}$ (MW)	FOR (%)	MTTF (h)
1	Steam	HFO	15	10%	24
2–3	OCGT	LFO	25	8%	24
4–5	ICE	HFO	12	10%	24
6–8	ICE	HFO	23	10%	24
9–15	ICE	HFO	17	10%	24

¹ Steam: Steam turbines, OCGT: Open-Cycle Gas Turbines, ICE: Internal Combustion (reciprocating) Engines.

A centrally dispatched Li-ion battery system is considered, with a roundtrip efficiency of 85% and minimum and maximum SoC levels set at 15% and 95% of its installed energy capacity. A minimum energy reserve of 30 min of operation at rated BESS power was maintained on top of the minimum SoC level to ensure sustained provision of upward reserves. Similarly, a 5 min charging margin was maintained below maximum SoC to ensure provision of negative fast-response reserves. The FOR of the BESS was set at 2%, with an MTTR of 1 day per outage. The BESS configurations investigated include capacities from 10 to 40 MW, while installed energy capacity is 2/4/8 h expressed on rated BESS power base. As a result of the minimum and maximum SoC level restrictions and energy margins maintained for reserves provision, the exploitable capacity of 2, 4 and 8 h systems corresponds to 1, 2.6 and 5.8 h of operation at rated power.

RAM was developed in MATLAB [41]. The optimization UC-ED model was implemented in GAMS [42], using the CPLEX optimizer [43]. All simulations were performed on a 3.20 GHz Intel Core i7 processor with 16 GB of RAM, running 64-bit Windows.

5. Results and Discussion

5.1. System Operation under the Alternative Policies

A three-day period of high demand was used to demonstrate the operation of the island system and BESS using the three alternative operating policies. Operation without BESS and the coverage of the required primary reserves are illustrated in Figure 4. The same three-day period is presented in Figure 5 assuming the presence of a 30 MW/8 h BESS, for each OP. In Figures 4 and 5, *Net Load* represents the demand load, excluding any additional demand for BESS charging.

In the base-case (BC) scenario without storage, shown in Figure 4, the system cannot accommodate all available wind production and RES curtailments that take place on certain days, as thermal units need to operate above their minimum loading levels (TM) to provide down-regulation reserves (Figure 4a). In this scenario, primary reserves are only provided by thermal units. Upward reserves requirements are determined by the loss of the largest online unit (N-1 criterion) or the abrupt loss of RES generation [31]; downward requirements are set as a percentage of demand (Figure 4b).

In the presence of storage operated according to OP1, the BESS mainly contributes primary reserves to enhance RES penetration, without any substantial exchange of energy (Figure 5c), as this leads to minimum operating cost of the system. With OP2, on the other hand, the BESS is discharged on a daily basis, reducing demand peaks, as shown in Figure 5a, to achieve maximum benefits in terms of resource adequacy. BESS charging relies on wind power, but also on thermal generation in the valley hours, leading to an increase in conventional production compared to OP1, alongside the reduction observed in the peak hours, albeit at the expense of greatly increased BESS cycling. Under OP3, peak shaving takes place in the last two days, where the residual demand exceeds $P_{\text{threshold}}$, here selected at 148 MW (70% of the annual peak thermal demand), while cost-driven operation was adopted on the first day. On an annual basis, the peak shaving mode was implemented on only 48 days, which of course depends on the selection of $P_{\text{threshold}}$.

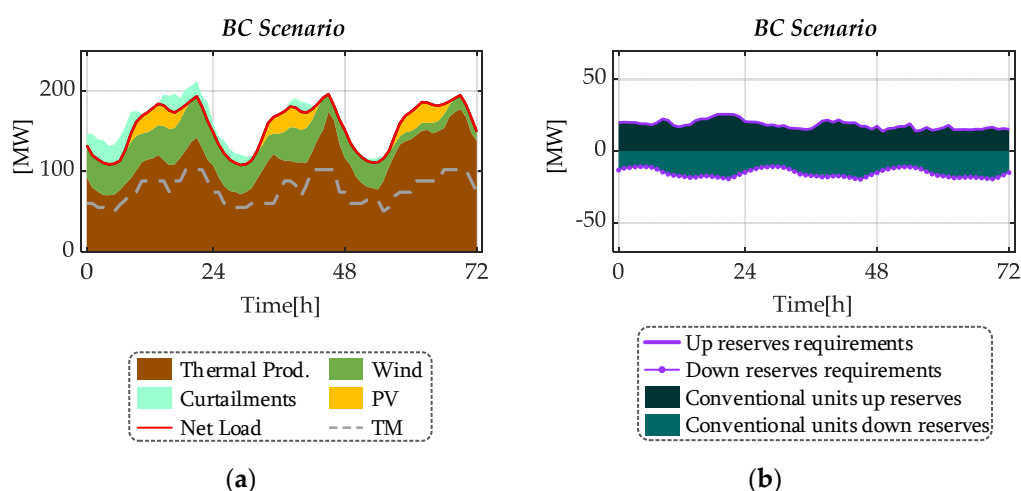


Figure 4. Base-case (BC) scenario without storage. (a) Generation mix and (b) provision of primary up/down reserves by conventional units over a three-day period.

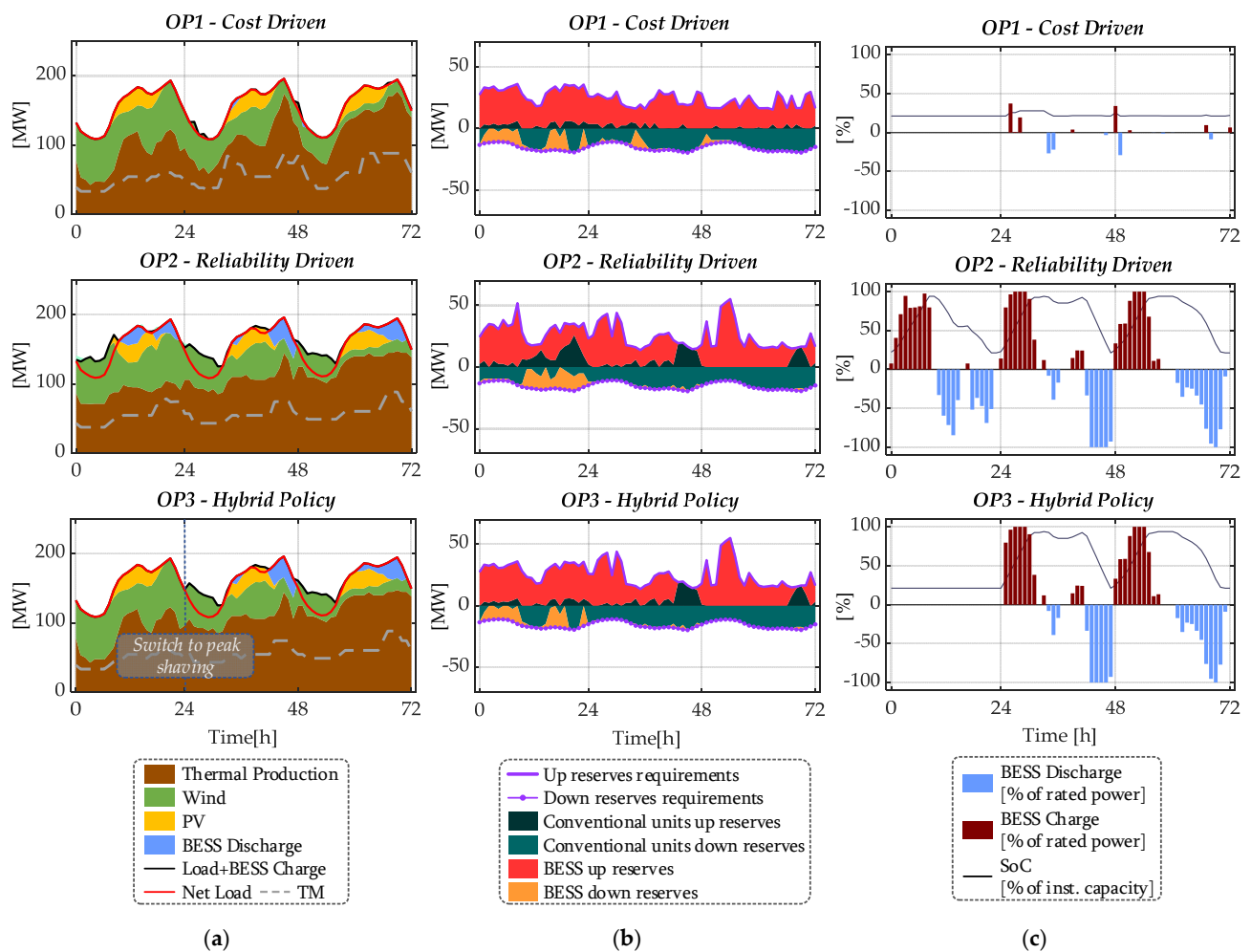


Figure 5. (a) Generation mix; (b) contribution of conventional units and BESS to system primary up/down reserves and (c) BESS operation over the same three-day period under the three OPs.

5.2. BESS Contribution to Resource Adequacy

Figure 6 presents the reliability indices EENS and LOLE calculated for different BESS configurations under the three alternative policies. Without any storage, the island system faces a resource adequacy deficit, with the LOLE reaching 9.87 h and EENS 112.6 MWh per annum. Applying OP1, where the storage operates without consideration of the reliability needs of the system, improvement in resource adequacy is minimal regardless of the BESS size, with a very modest reduction in LOLE, down by only 2.25 h even for the largest BESS considered and in spite of its substantial capacity. Under OP1, BESS capacity was utilized to provide fast response reserves, allowing a more efficient unit commitment and load dispatch for the thermal units, which in turn led to RES penetration uptake and a resulting reduction in generation cost. The level of energy arbitrage is very limited, as the conventional generation mix does not present any important spread in terms of its variable cost between valley and peak hours, to balance the cost of cycling energy through the batteries.

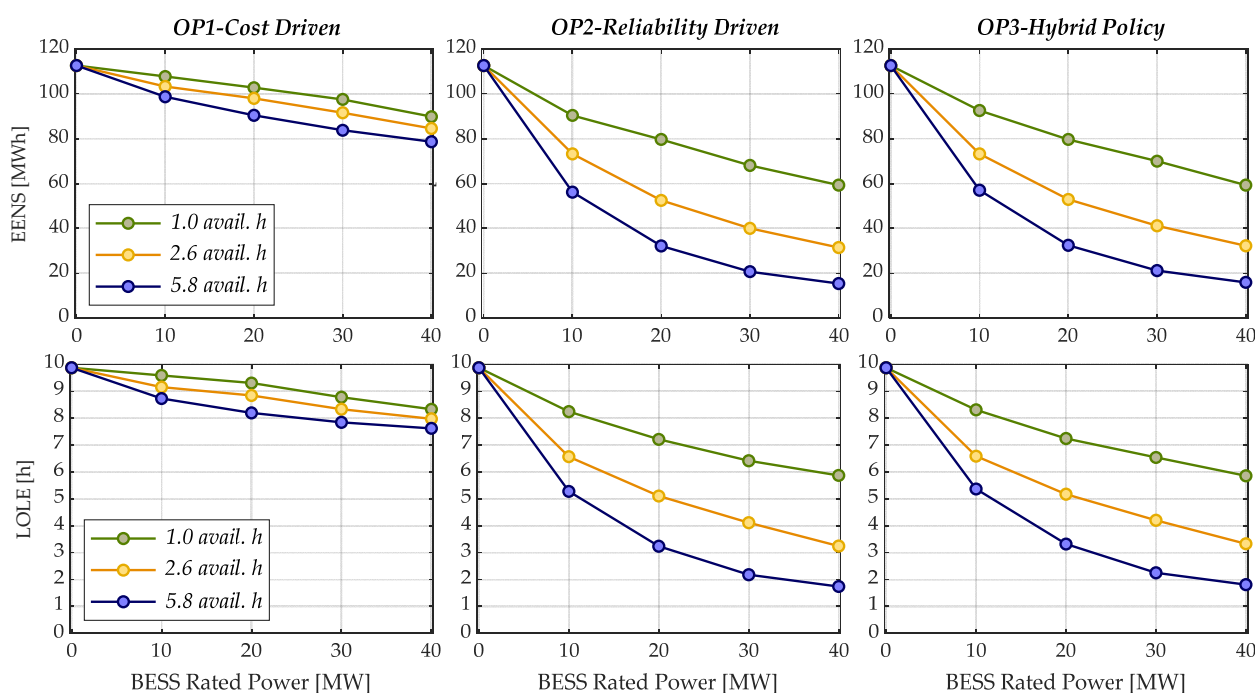


Figure 6. EENS and LOLE achieved by different BESS configurations for the alternative OPs.

On the other hand, OP2 is entirely reliability-oriented, disregarding any potential impact on system cost due to suboptimal BESS exploitation. As shown in Figure 6, the reliability indices improved substantially, with EENS decreasing by 86.3% for EENS the largest BESS configuration examined (40 MW/5.8 available hours), while storages of very modest capacities can achieve good results.

The results obtained by the hybrid policy OP3 indicate that targeted peak shaving in high demand days, as applied in this policy, practically achieves the same benefits for system adequacy as the reliability-oriented policy OP2 (reduction in EENS by 85.8% for the largest BESS considered), even though peak shaving only takes place on 48 days over the year, rather than on a daily basis.

The necessary sample years for MCS to reach the desired level of convergence depends on the selected indicator, with EENS requiring more sample years to achieve the targeted accuracy level. The number of sample years needed for the results of Figure 6 ranged from ~10.000 to ~90.000 and the respective computational time ranged from ~3' to ~20'. In Figure 7, the convergence of EENS is illustrated for one indicative scenario.

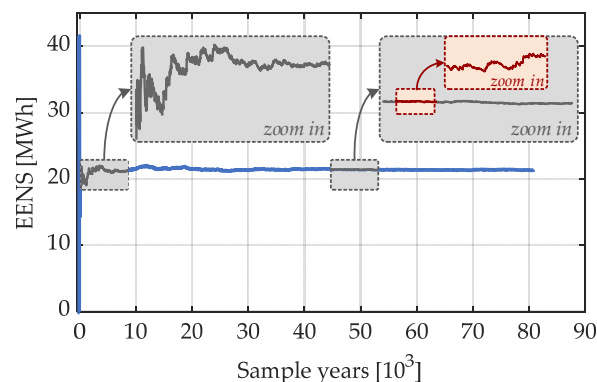


Figure 7. EENS vs. sample years convergence trajectory for a BESS of 30 MW/5.8 h operating under OP3.

Figure 8 depicts the residual load curve, as shaped after the implementation of the alternative OPs for a 30 MW/8 h installed capacity BESS. While in Figure 8a a daily peak

shaving operation is observed under OP2, the hybrid policy OP3 leads to a seasonal implementation during the high demand summer period, as shown in Figure 8b.

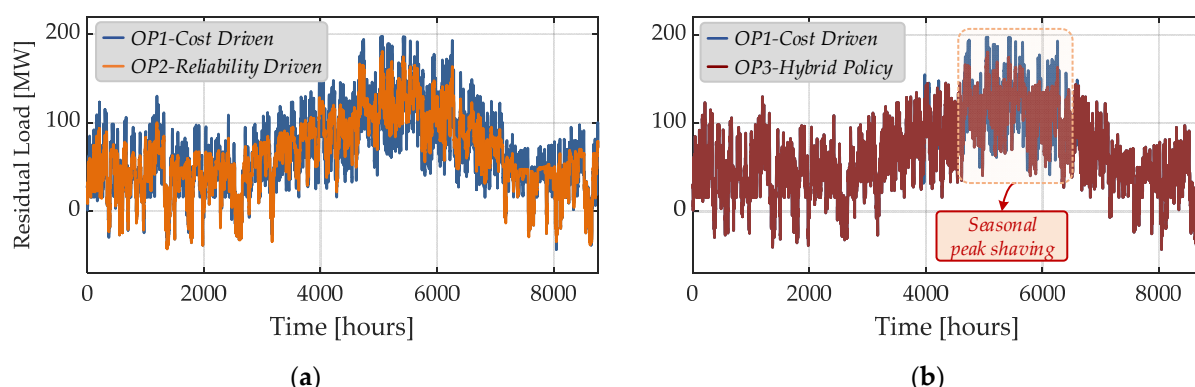


Figure 8. Peak shaving implementation over the year under (a) OP2 and (b) OP3.

The threshold value for OP3 was selected to avoid excessive peak shaving, without sacrificing the resource adequacy benefits from this functionality, as documented by the diagrams in Figure 9. The number of days per year with peak shaving activation for each $P_{\text{threshold}}$ is presented in Table 2.

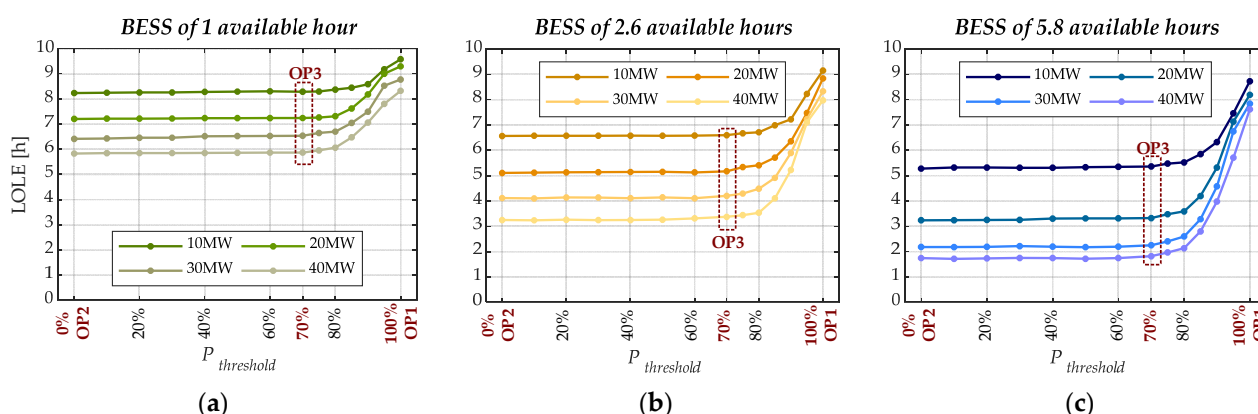


Figure 9. Sensitivity analysis of LOLE results with respect to $P_{\text{threshold}}$, for all BESS configurations considered: (a) 1 h; (b) 2.6; (c) 5.8 h.

Table 2. Number of days per year with peak shaving activation per $P_{\text{threshold}}$ value.

$P_{\text{threshold}}$ (%)	Peak Shaving Days	$P_{\text{threshold}}$ (%)	Peak Shaving Days	$P_{\text{threshold}}$ (%)	Peak Shaving Days
0%	365	50%	148	85%	14
10%	362	60%	95	90%	9
20%	346	70%	48	95%	3
30%	306	75%	29	100%	0
40%	229	80%	23		

5.3. BESS Capacity Value

The capacity value of the examined BESS configurations under the three policies is evaluated in Figures 10 and 11 using the EFC and ECC metrics. Capacity value is expressed in MW and normalized on the installed battery power. EENS is the system reliability index used to determine EFC and ECC, while a new Open Cycle Gas Turbine (OCGT) unit, with the characteristics given in [44], is the conventional generation benchmark for ECC calculations. ECC values are always greater than EFC, as EFC represents the

capacity of an ideal, perfectly reliable conventional unit to achieve the same contribution in system adequacy.

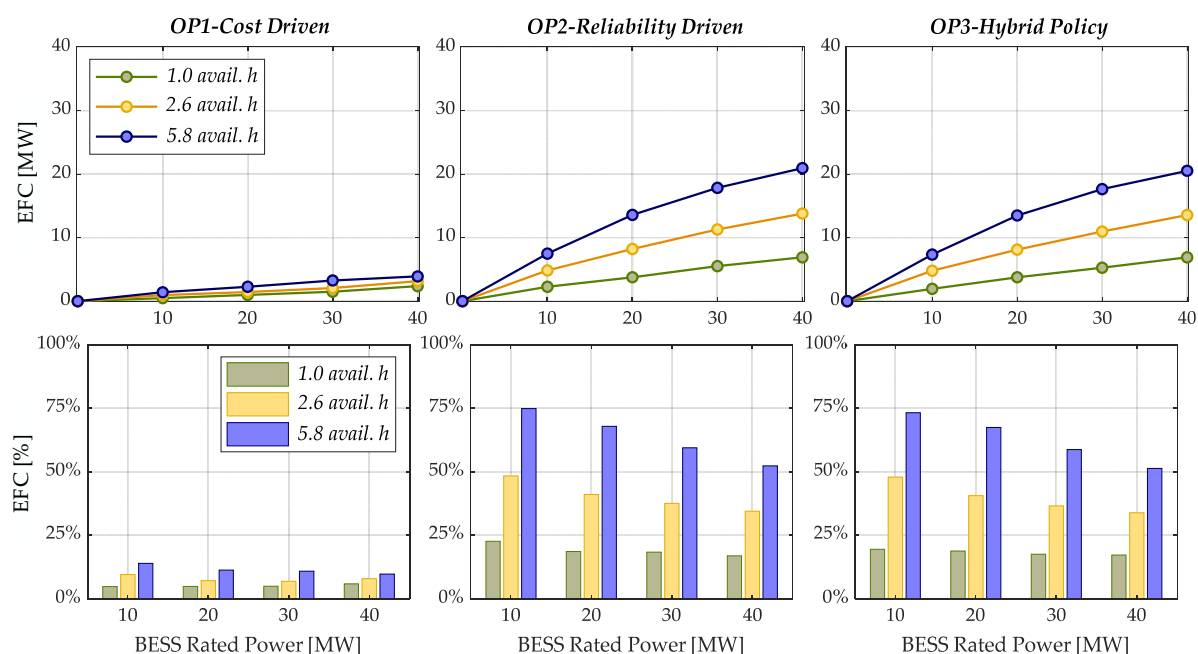


Figure 10. Capacity value of BESS using the EFC metric for the three alternative OPs.

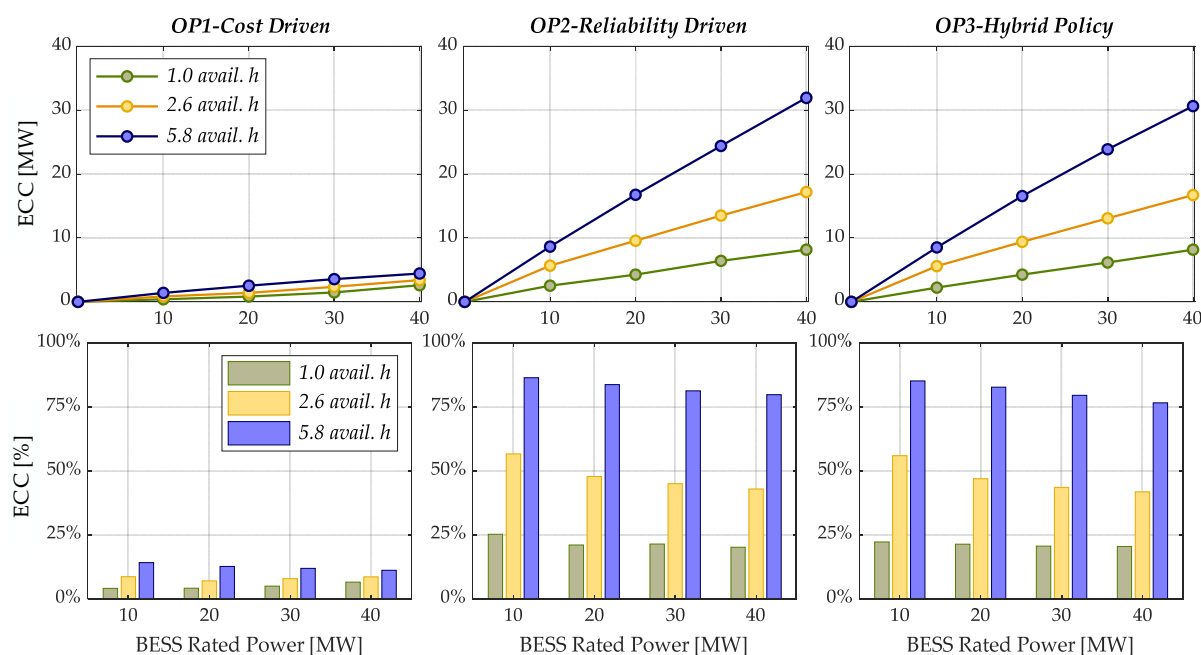


Figure 11. Capacity value of BESS using the ECC metric for the three alternative OPs.

The capacity value of storage obtained under OP1 is very limited, not exceeding 15%, while the same BESS will achieve substantially higher contributions under the other two policies, confirming the fact that peak shaving is the primary mechanism for storage to support resource adequacy of the system. The results obtained with the other two policies are quite similar, with the daily peak shaving operation enforced in OP2 leading to insignificant gains in comparison to the more targeted functionality of OP3.

From Figures 10 and 11, it is clear that, while the capacity value of storage is bound by its installed power capacity, the decisive factor determining its contribution to system

adequacy is energy capacity, expressed by its duration. For example, the EFC of the 20 MW BESS varies between 18.8% and 67.8% with its duration, largely due to the fact that higher energy capacities allow more effective utilization of available BESS power for load leveling purposes. It is also noted that the normalized capacity contribution is reduced for storages of a higher rated power. In fact, the contribution of storage to the capacity adequacy of a specific system tends to saturate at higher capacities, reaching a maximum that reflects the limitations in achievable load leveling of a given daily load curve.

The significance of storage duration for the achieved peak reduction and therefore its contribution to system adequacy is easily understood through the simplified peak shaving functionality depicted in Figure 12, a deterministic approach often used to quantify the capacity credit of storage [14,45]. Trimming of residual load peaks achieved by a 20 MW BESS becomes more effective as its energy capacity increases. BESS of low capacity, e.g., 1 or 2.6 h, even though they have sufficient power capability, do not have the necessary reserves to provide the energy in the load curve peak, as opposed to the larger BESS of 20 MW/5.8 available hours, which manages to fully utilize its rated power for peak shaving purposes. Notably, the duration required for a storage to claim its full capacity credit becomes higher as the rated power increases.

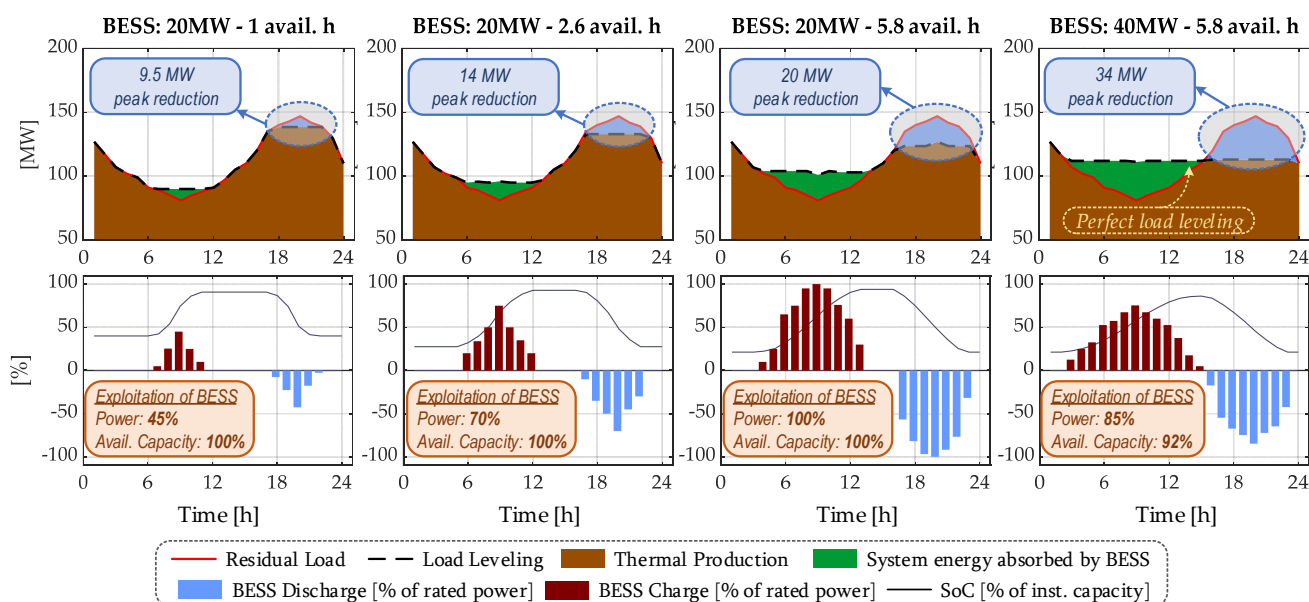


Figure 12. Daily load leveling achieved and corresponding BESS operation for different BESS sizes.

The last diagram on the right in Figure 12 explains the saturation that BESS contribution to peak reduction will eventually reach, beyond a capacity level. Assuming a BESS of 40 MW/5.8 available hours, a completely leveled residual load curve can be achieved utilizing only a fraction of the BESS full rated power (85% or 34 MW). In such a case, any further increase in the power or energy capacity of the batteries would not result in more effective peak reduction and hence increased BESS capacity value.

The impact of BESS duration on the capacity value of storage and its maximum contribution to capacity adequacy for a given system are strongly dependent on the characteristics of the residual load demand. In principle, the storage contribution will be enhanced for a peaky daily load curve shape, which in turn is created at increased PV penetration levels giving rise to the so-called “duck” curve shape [46].

5.4. Impact of OPs on System and BESS Performance

The selection of a BESS operating policy for the island system would not rely solely on reliability considerations, but it should consider additional factors, primarily the impact on the generation cost of the system and the achieved enhancement of RES integration.

The annual RES penetration level achieved with each operating policy is presented in Figure 13, with the three policies proving to be practically equivalent in this respect. The introduction of battery storage leads to a drastic increase in RES uptake, driven by BESS rated power, rather than its energy storage capacity. This increase is primarily related to the provision of fast reserves to cover system needs and saturates at a battery capacity of ~20 MW, regardless of its duration and system operating policy, as RES curtailments become fully exploited.

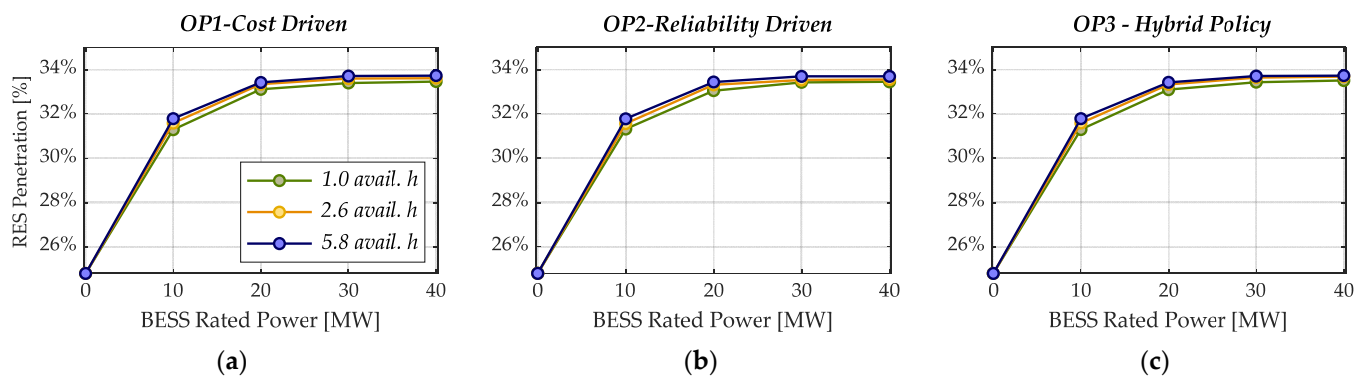


Figure 13. RES energy penetration, % of annual load demand, when (a) OP1, (b) OP2 and (c) OP3 are applied.

In Figure 14, the annual energy production of thermal units is presented for the same scenarios. The increased RES penetration leads to a reduction in thermal output; however this varies considerably by the operating policy selected. Whilst OP1 presents the largest gains, OP2 and OP3 are characterized by increased thermal outputs as a result of increased BESS charging needs and therefore losses to execute peak shaving. This is expectedly more pronounced in OP2, where arbitrage takes place on a regular basis.

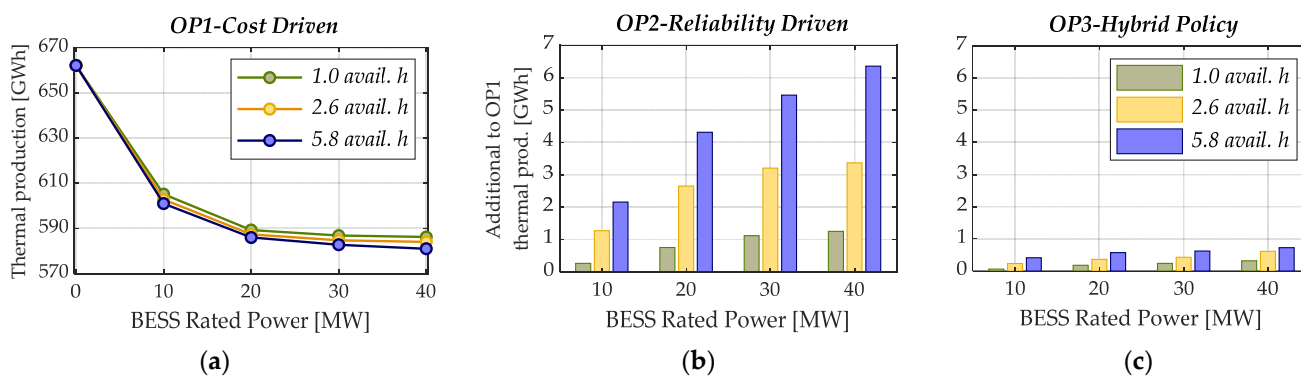


Figure 14. (a) Annual thermal production under policy OP1; increment when (b) OP2 and (c) OP3 are applied, compared to OP1.

With the remuneration of exploited RES energy curtailments being lower than the cost of substituted conventional energy (90 EUR/MWh wind energy tariff vs. 143.7 EUR/MWh average variable cost of thermal units), increases in RES penetration lead to decreased system costs in Figure 15 (consisting of the variable cost of conventional units plus the remuneration of RES). The increased output of thermal units in OP2 comes at the expense of a substantial increment in the generation cost of the system compared to OP1 (Figure 15b), unlike the hybrid policy OP3, which leads to a very moderate increase in system cost.

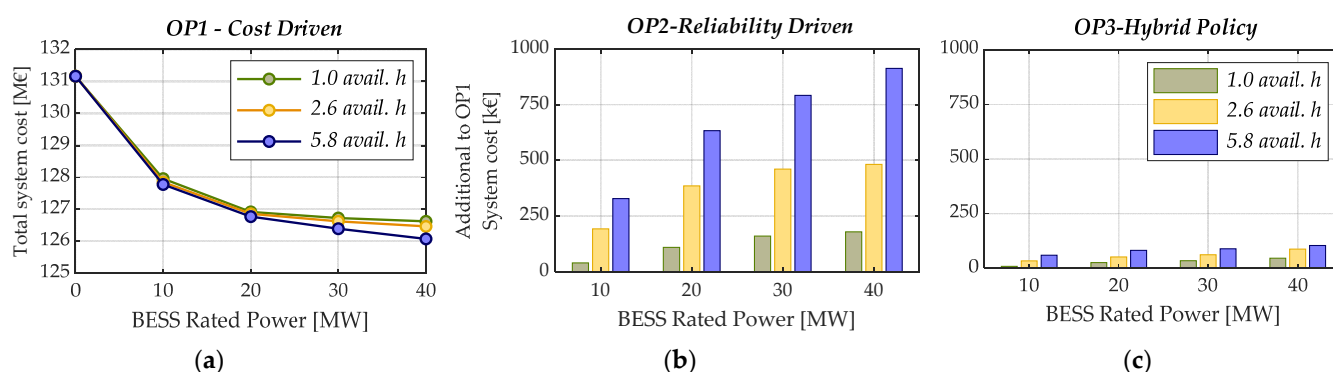


Figure 15. (a) Annual variable generation cost of the system with policy OP1; increment when (b) OP2 and (c) OP3 are applied, compared to OP1.

The impact of the applied OP on batteries' lifetime expectations is illustrated in Figure 16, indicatively for one BESS duration (8 h installation), evaluated according to the methodology described in [47]. The nominal lifetime of BESS is assumed to be 15 years. As anticipated, the daily cycling of the batteries in OP2 drastically reduces its lifetime, which becomes prohibitively short for a realistic BESS investment. OP1 is the most advantageous, with OP3 inducing only a moderate deterioration in battery lifetime.

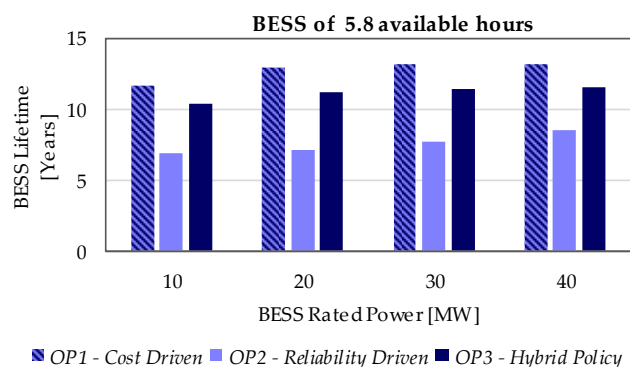


Figure 16. BESS lifetime expectancy for the three OPs. BESS configurations of 5.8 h available capacity.

6. Conclusions

In this paper, the contribution of storage to resource adequacy of isolated power systems was investigated for a large array of BESS configurations, giving due consideration to the operating policy adopted by the system operator. The Monte Carlo technique was applied for resource adequacy assessment, while system operation, including storage, was determined using a UC-ED model built upon MILP approach. A medium sized island system with substantial RES installed capacity was used as a study case.

A salient conclusion of the investigation conducted is that storage may provide a substantial capacity contribution only when a reliability-driven operating policy is adopted, primarily through a peak shaving functionality, which may conflict with other objectives sought after via the introduction of storage. Hence, BESS capacity credit in the reliability-driven policy OP2 ranges from ca. 25% to 85%, depending on BESS power and capacity, the corresponding contribution is limited to only 5–15% with the cost-oriented OP1. At the same time, however, OP2 increases system cost by up to ~1 MEUR and reduces battery lifetime by up to 5 years compared to OP1, for the specific case study. The best compromise is achieved by combining a cost-oriented management approach with targeted load-leveling in high demand periods. This may maximize, at the same time, reliability and generation cost benefits, while avoiding an excessive impact on battery lifetime.

As far as BESS characteristics are concerned, energy capacity (duration) is most significant in achieving maximum resource adequacy contribution, which gradually diminishes

as their power ratings increase. In terms of normalized capacity credit, values up to ~85% can be achieved with suitably sized and operated systems.

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Abbreviations

ATC	Available thermal capacity
BC	Base case
BESS	Battery energy storage system
ECC	Equivalent conventional capacity
EENS	Expected Energy Not Supplied
EFC	Equivalent firm capacity
ELCC	Effective load carrying capability
ENS	Energy not supplied
ESS	Energy storage systems
HFO	Heavy fuel oil
ICE	Internal Combustion Engine
LFO	Light fuel oil
LLD	Loss of load duration
LOLE	Loss of Load Expectation
MCS	Monte Carlo simulations
MILP	Mixed integer linear programming
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
NII	Non-interconnected island
OCGT	Open Cycle Gas Turbine
OP	Operating policy
PV	Photovoltaic
RAM	Resource adequacy model
RES	Renewable energy sources
SoC	State of Charge
TTF	Time to failure
TTR	Time to repair
UC-ED	Unit commitment and economic dispatch
WF	Wind farm
<i>Indices</i>	
t	Time interval (period) of optimization horizon
u	Thermal unit
ξ	Energy storage system
r	Reserve type {pr, sr, tr}, for primary, secondary and tertiary reserves
s	Monte Carlo sample

Binary variables

$sd_{u,t}$	Binary variable equal to 1 if unit u shuts down in dispatch period t
$st_{u,t}$	Binary variable equal to 1 if unit u is dispatched during period t
$su_{u,t}$	Binary variable equal to 1 if unit u starts up in dispatch period t
$st_{\xi,t}^c$	Binary variable equal to 1 if BESS ξ is charging in dispatch period t
$st_{\xi,t}^d$	Binary variable equal to 1 if BESS ξ is discharging in dispatch period t

Continuous variables

$ATC_{t,s}$	Available thermal capacity of dispatch period for each Monte Carlo sample s (MW)
C_p	Total variable generation cost of all operating thermal units over the dispatch horizon (EUR)
C_{su}	Total startup cost over the dispatch horizon (EUR)
C_{sd}	Total shut down cost over the dispatch horizon (EUR)
$C_{O\&M}$	Total operation and maintenance cost over the dispatch horizon (EUR)
C_{sl}	Total cost of slack variables over the dispatch horizon (EUR)
C_{peak}	Cost for penalization peak demand served by thermal units over the dispatch horizon (EUR)
$EENS_{N_{MCS}}$	Value of indicator EENS over N_{MCS} Monte Carlo samples
ENS_s	Annual total load energy curtailed on each Monte Carlo sample s (MWh)
LLD_s	Annual number of hours with load curtailments on each Monte Carlo sample s (h)
$LOLE_{N_{MCS}}$	Value of indicator LOLE over N_{MCS} Monte Carlo samples
N_{MCS}	Number of sampling years of Monte Carlo simulations
$P_{ens,t}$	Energy not served in dispatch period t (MW)
$P_{u,t}$	Production level of thermal unit u (MW)
$P_{W_{max,t}}^D$	Dynamic limitation of wind power for period t (MW)
$P_{W_{max,t}}^{ML}$	Minimum loading limitation of wind power for period t (MW)
$P_{\xi,t}^c$	Charging power of BESS ξ in dispatch period t (MW)
$P_{\xi,t}^d$	Discharging power of BESS ξ in dispatch period t (MW)
P_{avg}	Daily average power output of committed thermal units (MW)
$P_{peak,t}$	Slack variable for peak shaving in dispatch period t (MW)
$P_{R,t}$	Residual load demand of dispatch period t (MW)
$P_{R,t,s}$	Residual load demand of dispatch period t for each Monte Carlo sample s (MW)
$r_{u,t,r}^{up/dn}$	Type r reserve (up or down) provided by unit u in dispatch period t (MW)
$SoC_{\xi,t}$	State of charge of BESS ξ in dispatch period t (MWh)
TTF	Random variable of time to failure (h)
TTR	Random variable of time to repair (h)
$X_{t,r}^{up/dn}$	Slack variable violating of reserves requirements (up or down) constraints in dispatch period t (MW)
$X_{w,t}$	Wind curtailments in dispatch period t (MW)
a	Accuracy of $EENS_{N_{MCS}}$ value over the Monte Carlo simulations
σ	Standard deviation of $EENS_{N_{MCS}}$ value over the Monte Carlo simulations
<i>Parameters</i>	
$\overline{E}_{\xi}$	Maximum permissible storage capacity of BESS ξ (MWh)
$\underline{E}_{\xi}$	Minimum permissible storage capacity of BESS ξ (MWh)
G_{step}	Step-value for EFC and ECC calculation (MW)
l_{pv}	Coefficient quantifying proportion of PV power that may be suddenly lost
l_w	Coefficient quantifying proportion of wind power that may be suddenly lost
$MTTF$	Mean time to failure (h)
$MTTR$	Mean time to repair (h)
n_{ξ}^c	Charging efficiency (%)
n_{ξ}^d	Discharging efficiency (%)

$P_{PV, t}^f$	Total forecasted PV production for dispatch period t (MW)
$P_{W, t}^f$	Total forecasted wind production for dispatch period t (MW)
$P_{L, t}$	Total forecasted demand for dispatch period (MW)
$p_u^{\max}$	Maximum power output of unit u
$p_u^{\min}$	Minimum power output of unit u
$\overline{P}_{\xi}^c$	Maximum permissible charging power of BESS ξ (MW)
$\overline{P}_{\xi}^d$	Minimum permissible discharging power of BESS ξ (MW)
$P^{\text{threshold}}$	Threshold value for peak shaving activation (MW)
$R_{u,pr}^{\text{up}}$	Primary up reserve capability of thermal unit u (MW)
$R_{\xi,pr}^{\text{up}}$	Primary up reserve capability of BESS ξ (MW)
$rr_{r, t}^{\text{up/dn}}$	Type r reserve requirements (up or down) in dispatch period t (MW)
RD_u	Ramp down rate of thermal unit u for online operation (MWh)
RSD_u	Ramp down rate of thermal unit u for the shut-down (MWh)
RSU_u	Ramp up rate of thermal unit u for the startup (MWh)
RU_u	Ramp up rate of thermal unit u for online operation (MWh)
T_u^{stop}	Minimum offline time of u after shut-down (h)
T_u^{run}	Minimum online time of u after startup (h)
T_D	Hours of day of dispatch (h)
φ_{peak}	Penalty factor for peak load demand (EUR/MW)

Appendix A

Appendix A.1 Wind Power Limitations

Wind generation operating in NII systems is subjected to output power curtailments via set-points dispatched to individual wind farms. No curtailments are imposed on PV generation due to the small scale and distributed nature of island PV facilities. Rejected wind energy is not compensated.

Acceptable wind penetration is restricted by the minimum loading ($P_{W_{\max, t}}^{\text{ML}}$) and dynamic limitations ($P_{W_{\max, t}}^{\text{D}}$) [1], expressed through Equations (A1) and (A2). Equation (A1) ensures that the minimum loading levels of online thermal units are respected, taking into account the additional room created by the charging capability of ESSs. Non-linearities of (A1) are linearized according to [37].

$$P_{W_{\max, t}}^{\text{ML}} = P_{L, t} + \sum_{\xi} (\min\{\overline{P}_{\xi}^c, \overline{E}_{\xi} - \text{SoC}_{\xi, t}\}) - P_{PV, t} - \sum_u (p_u^{\min} \cdot st_{u, t}) \quad (\text{A1})$$

The dynamic limitation (A2) maintains security of operation by ensuring that the primary reserves provided by online thermal units ($R_{u,pr}^{\text{up}}$) and the ESS ($R_{\xi,pr}^{\text{up}}$) suffice to cover any sudden loss of renewable generation, quantified in (A2) using the empirical coefficients l_w and l_{PV} [2].

$$P_{W_{\max, t}}^{\text{D}} = \frac{\sum_u (R_{u,pr}^{\text{up}} \cdot st_{u, t}) + \sum_{\xi} R_{\xi,pr}^{\text{up}} - l_{PV} \cdot P_{PV, t}}{l_w} \quad (\text{A2})$$

The wind energy absorption capability of the system is given by the minimum of $P_{W_{\max, t}}^{\text{ML}}$ and $P_{W_{\max, t}}^{\text{D}}$ and it is distributed to individual WFs in proportion to their installed capacities.

Appendix A.2 Operating Reserves

Active power reserves (r) are distinguished as primary, secondary and tertiary, depending on their deployment times. Primary reserves ($r = pr$) are activated within a few seconds, following disturbances in the active power equilibrium of the system. Secondary ($r = sr$) and tertiary ($r = tr$, spinning and non-spinning) reserves correspond to activation times of 5 and 20 min, respectively. Reserves are provided both by thermal units and energy storage systems, to meet the requirements of the system based on constraints (A3)–(A5),

where reserve substitutability is assumed. The amounts of positive ($r_{\xi, t, sr}^{up}$) and negative ($r_{\xi, t, sr}^{dn}$) reserves provided by storage are subject to constraints (A6) and (A7). Slack variables $\chi_{t, r}^{up/dn}$ in constraints (A3)–(A5) allow the relaxation of these constraints for the sake of feasibility of the solution.

$$\sum_u r_{u, t, pr}^{up/dn} + \sum_u r_{\xi, t, pr}^{up/dn} + \chi_{t, pr}^{up/dn} \geq rr_{pr, t}^{up/dn} \quad (A3)$$

$$\underbrace{\sum_u r_{u, t, pr}^{up/dn} + \sum_u r_{\xi, t, pr}^{up/dn} - rr_{pr, t}^{up/dn}}_{\text{if } \chi_{t, pr}^{up/dn} = 0} + \sum_u r_{u, t, sr}^{up/dn} + \sum_u r_{\xi, t, sr}^{up/dn} + \chi_{t, sr}^{up/dn} \geq rr_{sr, t}^{up/dn} \quad (A4)$$

$$\underbrace{\sum_u r_{u, t, sr}^{up} + \sum_u r_{\xi, t, sr}^{up} - rr_{sr, t}^{up}}_{\text{if } \chi_{t, sr}^{up} = 0} + \sum_u r_{u, t, tr}^{up} + \sum_u r_{\xi, t, tr}^{up} + \chi_{t, tr}^{up} \geq rr_{tr, t}^{up} \quad (A5)$$

$$P_{\xi, t}^d + \sum_r r_{\xi, t, r}^{up} \leq \overline{P}_{\xi}^d + P_{\xi, t}^c \quad (A6)$$

$$P_{\xi, t}^c + \sum_r r_{\xi, t, r}^{dn} \leq \overline{P}_{\xi}^c + P_{\xi, t}^d \quad (A7)$$

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