Received: 11 January 2021 | Revised: 14 September 2021 | Accepted: 7 October 2021

DOI: 10.1049/rpg2.12339

IET Renewable Power Generation

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH PAPER

Co-optimization of active power curtailment, load shedding and spinning reserve deficits through hybrid approach: Comparison of electrochemical storage technologies

Pavlos Nikolaidis[1] | **Andreas Poullikkas**[2]

[1] Department of Electrical Engineering, Cyprus University of Technology, Limassol, Cyprus

[2] Cyprus Energy Regulatory Authority, Nicosia, Cyprus

Correspondence
Andreas Poullikkas, Cyprus Energy Regulatory Authority, P.O. Box 24936, 1305 Nicosia, Cyprus.
Email: andreas.poullikkas@eecei.cut.ac.cy

Abstract

Under the constraints of fossil-fuel reserves depletion and climate change, the expansion of intermittent renewable generation creates a lot of power integration issues which undeniably disturb the overall system stability. Optimally planned, electricity storage systems are capable of managing the variability and uncertainty of renewable energy sources, guaranteeing power balance and ensuring feasible and economical operation. Here, the outcomes derived by a Genetic algorithm-driven priority list approach is provided, which effectively quantifies the impact of intermittent renewable energy sources on total production cost and the benefits of electricity storage. The experimental evaluation on three benchmark scenarios shows that cost improvements exist in terms of thermal generation improvement, lower renewable generation curtailment and load shedding avoidance cost. Zinc-air battery offers the highest net present value at relatively low PV penetration levels. Increased penetration levels favour Li-ion batteries followed by Pb-acid and Vanadium-redox flow batteries. In general, the viability of each storage device depends on the renewable penetration level, promoting the technologies with lower capital costs at limited shares, whereas at higher contribution frameworks systems with higher performance features become preferable.

1 | INTRODUCTION

The depletion of fossil-fuel reserves, global warming and associated extreme weather conditions have motivated European Union to expand the share of intermittent renewable energy sources (RES) for electricity production. This transformed power grids into active complex systems with bidirectional flows that increase the uncertainty at both generation, transmission and distribution sections. In addition, the imposed electrification of transport and heating/cooling sectors is responsible for the radical reshaping of electricity demand profiles, making the day-ahead scheduling an even more challenging optimization task for modern power systems. Besides achieving minimum total production cost, the today's generation schedule must satisfy a larger set of different complex constraints. These include generation constraints in the presence of renewable generation, network constraints affected by the distributed energy resources, bilateral contracts enclosing independent electricity provision, corrective security actions in sudden load variation or outage circumstances, and so on [1].

The simultaneous increase in electricity demand and reduction of conventional sources contribution in power generation create a lot of integration issues. The uncertainty and variability in net load caused by the increasing penetration of renewable generation undeniably disturb the overall system stability and reliability [2]. Hence, adequate operating reserves are required to cover the uncertainty caused by forecast errors, whereas sufficient ramping capability is necessary to address the variability issues which often occur at high time resolutions [3]. Since RES do not inherently contribute to flexibility, increasing their penetration levels leads to even more limited flexibility frameworks. Despite this irreversible circumstance, energy policies empower the independent system operators, marketers and regulators to focus on the minimization of RES curtailment, load shedding and spinning reserve deficits, calling for alternative approaches that increase flexibility.

Electricity storage (ES) is attracting increasing interest as a potential candidate for power grid applications that facilitate a shift from the currently passive to an active network via time-shifting [4]. Optimal planning of ES ensures supply continuity and reliability and guarantees the energy generation-demand balance across the power chain [5]. Although extensive research has been made around the concept of unit commitment (UC), the term of storage has not been treated properly, since in some cases it acts as load while in others it functions as a generator. This way, appropriate decisions relating to the exact time, the total duration as well as the optimum amount of energy for the charging, storage and discharging procedures are of great importance to at least conserve the convexity of the overall UC optimization process. In such cases, electrochemical storage becomes advantageous in terms of response time, autonomy and scalability [6]. Based on realistic models, it is crucial to examine for solutions that are capable of extracting more comprehensive outcomes relating to storage. Apart from the direct fuel-cost savings, further credits including increased security, reliability and dispatchability can also be achieved.

The authors in [7], proposed a hybrid algorithm that combines the advantages of a generalized Lagrange relaxation and advanced priority list methods to solve the large-scale nonlinear mixed-integer UC problem. They focused on short-term simulations to address the sharp decreases of renewable energy output which result in power outages and minimize the ramp-rate of thermal generating units. An alternative method is presented in [8], where a UC solution was achieved utilizing a novel metaheuristic algorithm named binary whale optimization algorithm. A study found in [9], compared the two-stage and multi-stage stochastic UC providing a continuous-time formulation in which an underlying load scenario tree is used to define the baseline day-ahead dispatch, commitment and reserve capacity.

In [10], a new technique was conducted to strengthen the performance of particle swarm optimization by making use of sine/cosine acceleration coefficients, while a different approach relying on distributionally robust optimization models is given in [11]. This approach aims at minimizing the worst-case expected cost of a probability distribution of the uncertain parameters including renewable generation. The authors in [12] consider the temporal and spatial correlations of multiple wind farms, introducing a data-adaptive uncertainty set and extreme scenarios to reformulate the robust optimization. In contrast to these approaches which belong to what may be termed as “supervised learning”, the work in [13] constitutes an approximate dynamic-based approach wherein no a priori target information is available. Instead, it is based on reinforcement learning that exploits a single-agent technique known as fuzzy Q learning. However, none of the aforementioned research works have considered electricity storage to cope with the uncertainty of RES.

The authors in [14] proposed an optimal scheduling to retain the frequency dynamic security by considering demand response programs and fast-acting ES technologies. Although the system operating cost was reduced, wind curtailment was prohibited and the frequency security was guaranteed, the formulation was based on only three non-probabilistic scenarios regarding the wind turbine uncertainties. Energy storage schemes were also considered in [15] showing considerable market-based improvements when utilized for RES support in energy and spinning reserve procurement, whereas the impact of forecast errors on in wind and solar generation outputs was assessed in [16]. Apart from the largest online unit or percentage of the system load, spinning reserve should consider the stochastic nature of system behaviour and component failures. As a result, a changing spinning reserve influences the cost and therefore, its absolute amount should be determined carefully. The authors in [17] classified the probabilistic approaches into three classes according to the method by which they optimize this requirement.

Regarding the co-optimization of RES curtailment, energy and reserves not served, some representative research works are distinguished by both the proposed formulation of spinning reserve requirement and solution method. For instance, [18] considered N-1 criterion to offer an optimal schedule via mixed integer linear programming. The variable solar and wind power outputs were modelled via uncertainty sets and the solution was given by an adaptive semi-infinite program in [19]. Two further studies treated RES as negative load utilizing robust [20] and clustering-based [21] spinning reserves requirement. The UC task was conducted via binary grey-wolf optimizer and imperialistic competition algorithm, respectively. Stochastic programming was combined with both forecast confidence level and scenario-based formulations [22], while a mixed-integer cone programming approach was presented in [23] combined with data-adaptive robust models. In [24], effective prevention of premature convergence was achieved through a chaotic differential evolution mechanism over conservative reserve formulations. The authors in [25] presented quality solutions to robust UC utilizing Gaussian process-based Bayesian optimization in the presence of increased RES penetrations. Compared to traditional solutions, higher convergence accuracy was also reported in [26], relying on hybrid particle swarm optimization.

To the best of our knowledge and based on the most recent and relevant literature, there has not yet been a comprehensive work which dealt with the simultaneous load shedding, RES curtailment and spinning reserve optimization tasks by making use of storage. The term of load shedding is proposed to be conducted either as a coordination of active power loss reduction and optimal allocation of thyristor-controlled series capacitor [27] or an optimizable variable to prevent transmission lines from being overloaded under line contingency [28]. To strengthen the benefit list of ES systems, a few research works assume their participation in combined stationary and mobile applications or promote their installation at the same location where RES is connected to store the excess renewable generation [15, 29]. Although mathematical methods including Lagrange relaxation, Benders' decomposition and branch-and-bound constitute promising approaches with respect to convergence time and constraints treatment, in the presence of identical units fall into oscillations due to unnecessary commitments/de-commitments of identical heat-rate generators [30]. On the other hand, heuristic techniques rely on rule-based transitions and involve stochastic approach in moving from one solution to another. Hence, even the magnitude of their sub-optimality and overall dimensionality are difficult to be estimated.

To ameliorate the expensive requirement of dimensionality whilst providing high quality solution with traceable constraints satisfaction, hybrid methods are proposed. Utilizing the merits of mathematical and heuristic methods, our proposed solution aims at finding better trade-offs between exploration and exploitation. Specifically, to avoid local solutions that lead to premature convergence and increase the solving accuracy at reasonable computational efforts, during the searching process we exploit the stochastic transition of a heuristic approach to progressively discover optimal generation output based on improved recommendations. Based on the updated configuration of the constructed priority list, the available generating units are committed until the system-wide constraints are satisfied. The pre-process task takes place to provide an initial solution to the UC problem. The hybrid approach consists in delivering updated recommendations with respect to net load demand, by making use of the advances of Genetic algorithm. Motivated by the previously described concept, in this work we present a different approach for the co-optimization of active power curtailment, load shedding and spinning reserve deficits. Based on a hybrid optimization mechanism, we determine both the operating strategy and optimal size for realistic storage implementations. Moreover, we compare different technologies according to their performance characteristics, utilizing actual data of generation and demand and relying on robust unit commitment formulations. Our comparisons account for: (1) The most recent technological variations in development status and cost metrics in research and (2) distinguished metrics for the power-related and energy-related costs.

The contribution of this work is three-fold: (1) A comprehensive formulation of UC including the ES parameters under volatile net demand is presented, (2) the total production cost is simultaneously optimized with the spinning reserve deficits and RES integration conserving the maximum reliability, and (3) the hybrid solution offers computationally tractable schedules at reasonable execution times distinguishing the power and energy related components of the considered ES system. The rest of the paper is organized as follows. In the following Section, we define the UC problem along with the most important unit-specific and system-wide constraints in the presence of storage. Also, we introduce the penalty terms of RES curtailment, load shedding and reserve not served. Section 3 provides the methodology adopted for simulation purposes and the case study system is demonstrated and explained in detail. In Section 4, the numerical results regarding the weekly and annual simulations are evaluated and discussed, while the conclusions are drawn in Section 5.

2 | UNIT COMMITMENT PROBLEM FORMULATION

Intelligent scheduling is of utmost importance for the seamless integration of uncertain and volatile renewable generation. In order to explore and evaluate the efficacy of ES systems, we consolidate into the objective function the terms of *RES* curtailment (*RES-CUT*), energy not served (*ENS*) and reserve not served (*RNS*). Also, our methodology takes into account both the system-wide and unit-specific constraints in the presence of storage, the formulation of which is provided below.

The total production cost (*TPC*) is calculated by means of fuel cost (C_F), start-up cost (C_{SU}), cost for the curtailed RES ($C_{RES\text{-}CUT}$), cost of energy (C_{ENS}) and spinning reserve (C_{RNS}) not served. For N generating units and total T time intervals, a formulation for the UC problem is as follows:

$$\min \sum_{t=1}^{T} \left\{ \sum_{i=1}^{N} \left\{ \left[C_{F_i}^t + \left(1 - U_i^{t-1}\right) C_{SU_i}^t \right] U_i^t \right\} + C_{RES-CUT}^t + C_{ENS}^t + C_{RNS}^t \right\} \tag{1}$$

$$s.t.$$

$$\sum_{i=1}^{N} P_i^t - P_{dis}^t = P_{netD}^t + P_{ch}^t \tag{2}$$

$$\sum_{i=1}^{N} P_{i,\max\_cap}^t \geq P_{netD}^t + SR^t - \left(P_s^t + P_{ch}^t\right) \tag{3}$$

$$P_{i,\min}^t . U_i^t \leq P_i^t \leq P_{i,\max}^t . U_i^t \tag{4}$$

$$\sum_{t=td}^{t-1} (1 - U_i^t) \geq MD_i \tag{5}$$

$$\sum_{t=tu}^{t-1} U_i^t \geq MU_i \tag{6}$$

$$P_i^t - P_i^{t-1} \leq RU_i \tag{7}$$

$$P_i^{t-1} - P_i^t \leq RD_i \tag{8}$$

The discrete, binary variable U_i^t, represents the status (on/off) of each generating unit, holding the value "1" or "0" if the *i*th unit is on-line or off-line at the particular time *t*, respectively, according to $U_i^t \in \{1, 0\}$. $C_{F_i}^t$ depends on the production level of each generator P_i^t and its cost coefficients a_i, b_i and c_i measured in €/h, €/MWh and €/MW^{2}h, respectively. It is determined via the following quadratic function.

$$C_{F_i}^t = f\left(P_i^t\right) = a_i + b_i . P_i^t + c_i . \left(P_i^t\right)^2 \tag{9}$$

Start-up cost can be treated as warmth-dependent, corresponding to a hot, warm or cold condition of each generating unit, according to the duration that the unit has been off-loaded. In our formulation, $C^t_{SU_i}$ is considered as warmth-independent and thus it can be approximated by a constant value for each unit. Penalizing the three terms of *RES-CUT*, *ENS* and *RNS* by reasonable costs (e.g. c_{res}, c_{ens} and c_{rns}), an opportunity is given to the objective to enlarge the feasible solution space and consequent convergence rate. However, this degrades the level of system security and reliability which is the scope of our proposed solution. $C_{RES\text{-}CUT}$, C_{ENS} and C_{RNS} are estimated based on the following formulations:

$$C^t_{RES-CUT} = P^t_{RES-CUT} \cdot c_{res} \tag{10}$$

$$0 \le P^t_{RES-CUT} \le P^t_{RES} \tag{11}$$

$$C^t_{ENS} = c_{ens} \left\{ P^t_{netD} - \sum_{i=1}^{N} P^t_i \right\} \tag{12}$$

$$C^t_{RNS} = c_{rns} \left\{ SR^t - \left[\sum_{i=1}^{N} P^t_{i,max-cap} - P^t_{netD} \right] \right\} \tag{13}$$

The comprehensive formulation of the objective (1) can now be used to account for the total cost in all periods T. The system-wide constraints of power balance and spinning reserve are modelled by making use of the decision variables U^t_i and P^t_i. In Equation (2), it is ensured that the sum of the power produced from all committed units meets the net load demand (P^t_{netD}) at each time-interval, considering the contribution of storage ($\sum P^t_i - P^t_{dis}$) and renewable generation ($P^t_{netD} = P^t_D - P^t_{RES}$). Constraint (3) is used to guarantee the spinning reserve requirements SR^t based on the maximum ramping capability of each unit ($P^t_{i,\max\_cap}$) along with the direct (P^t_s) and indirect (P^t_{cb}) storage participation.

The maximum and minimum rated MW-output, $P^t_{i,\max}$ and $P^t_{i,\min}$, that confine the generating units to operate within their boundaries are represented by constraint (4). Each generator can change its status from "0" to "1" and vice versa satisfying the respective constraints (5) and (6). t_u and t_d express the time a unit has started-up or shut-down, respectively, whereas MU_i and MD_i define the required minimum up and down time-intervals that must be elapsed. Two further constraints are needed to determine the ramping-up (RU_i) and ramping-down (RD_i) capabilities between consecutive periods. Consequently, Equations (7) or (8) take place when the power output of a certain generator increases or decreases. A further constraint regards the must-run units which remain on-line during the whole period or certain time-intervals.

Emphasizing on fixed, expected values of uncertain injections d, the compact formulation of deterministic UC can be expressed as:

TABLE 1 Parameters and variables

Parameters			Variables	
Net demand	P_{netD}	MW	Unit status	U
Start-up cost	C_{SU}	€	Power output	P
Curtailment cost	c_{RES}	€	Fuel cost	C_F
Energy not-served	c_{ENS}	€	Spinning reserve	SR
Reserve not-served	c_{RNS}	€		
Maximum power	P_{max}	MW	Stored power	P_s
Minimum power	P_{min}	MW	Charge power	P_{cb}
Ramp-Up rate Ramp-Down rate	RU RD	MW/h MW/h	Discharge -»- Stored energy	P_{dis} E_s
Minimum-Up time	MU	h	Charge energy	E_{cb}
Minimum-Down time	MD	h	Discharge –»-	E_{dis}
Initial conditions	$I.C.$	h	RES power	P_{RES}
Identical units num.	η		Uncertainty set	D
Charging efficiency	n_{cb}	%	Uncertain resource	D
Discharging efficiency	n_{dis}	%		
Depth of discharge	DoD	%	Investment cost	IC
Rated power	P_{rated}	MW	Profitable return	PR
Energy capacity	E_{cap}	MW		
Balance of plant	C_{BOP}	€/kW	Replacement cost	C_R
Power conversion	C_{PCS}	€/kW		
Energy storage medium	C_{ESM}	€/kWh	Inflation rate	i_R
Fixed O&M cost	C_f	€/kW-y	Self-discharge	SD
Variable O&M cost	C_v	€/MWh		
Useful lifetime	L	y		

$$\min_{U,P} \left(C^T_{SU} U + C^T_F \right) \tag{14}$$

$$s.t.\ I.P = d \tag{15}$$

Therefore, the equivalent robust UC objective is determined via the following equation:

$$\min_{U} \left\{ C^T_{SU} U + \max_{d \in D} \left[\min_{P} \left(C^T_F \right) \right] \right\} \tag{16}$$

I represents the selector of uncertainty resources, while D denotes the uncertainty set [31]. All parameters and variables used are listed in Table 1.

3 | METHODOLOGY AND CASE STUDY SYSTEM

Robust unit commitment formulations account for the worst-case scenario and involve different uncertainty factors relating to load forecasting, renewable power output and unintentional generation outages. In this work, we utilize the advances of priority-list schemes to provide the optimal UC schedule and genetic algorithm (GA) as a tool to drive the optimization and optimally define the ES parameters of charging and discharging power output [32]. In contrast to other mathematical approaches, priority-list method does not suffer from the identical heat-rate sensitivity. Thus, it offers a great advantage in systems which consist of several generators possessing identical heat-rate coefficients and start-up costs. The general concept around priority list consists in committing conventional generators until the net load demand is satisfied, based on the order of increasing production cost [33]. The optimal priority is given based on the ranking achieved based on the following function:

$$R_i = \frac{d\left(f\left(P_i\right)\right)}{dP_i}\Big|_{P_i = \frac{P_{i,min}+P_{i,max}}{2}}^{\forall i} \tag{17}$$

This way, the determined commitment status can be regulated through the employed algorithm constructed to optimize the ES variables of P_{ch} and P_{dis}, considering different technologies. Allowing P_{dis} to vary between DoD and P_{RES}, the exact time and duration of charging and storage forms a nonlinear problem which can appropriately conducted via Genetic algorithm. Compared to mathematical techniques, GA occurs advantageous in convergence time, whereas in contrast to classical heuristic algorithms it progressively leads to high-quality solutions modifying a population of recommendations using random processes [34]. The main steps comprising the process include the initial population generation and its evaluation, selection of the best candidate, crossover and mutation. The general criterion for convergence is 'a no change in the solution for n generations' [35].

Based on this motivation, GA decreases the contribution of variable renewable generation to satisfy the spinning reserve requirements subject to the ramping capability of the committed units defined by priority list schemes. In the presence of storage, GA regulates the charging state such that all constraints are satisfied and decides on how to allocate the discharged energy in order to minimize the total production cost. The solution consists in finding both the optimal UC schedules and the size of the intended ES system based on actual annual data.

Inspired from the previously described advancements, in this study we assess our proposed approach, adopting a benchmark experimental setup, described in [36]. We consider an isolated power system with 20 generating units characterized by identical cost coefficients and start-up costs. Their respective characteristics are listed in Table 2.

Moreover, we consider the half-hourly load demand regarding the year of 2018 as depicted in Figure 1. Since the demand profiles vary according to the time and the type of the day (e.g. weekday or weekend) as well as the season, we provide the total hourly-summed, weekly profiles for each season in Figure 2. As can be seen, the peak demand occurs during summer days, whereas a much more mitigated load profile is observed in spring.

TABLE 2 Characteristics of thermal generating units

	Grp1	Grp2	Grp3	Grp4	Grp5	Grp 6
P_{min} (MW)	4	30	8.75	14.5	66	66
P_{max} (MW)	37	58	17	17	124	216
a (€/h)	0.107	0.141	0.011	0.219	0.033	0.020
b (€/MWh)	33.92	31.07	31.12	25.83	28.35	21.60
c (€/MW^{2}h)	474.5	501.4	77.4	93.8	618.0	1238.4
SU (€)	104	5786	66	66	9200	208
RU (MW/h)	75	30	15	15	63	180
RD (MW/h)	75	15	15	15	63	180
MU (h)	1	2	1	1	12	8
MD (h)	0.5	8	2	2	8	6
$I.C.$ (h)	−1	−8	−2	−2	12	8
η	4	6*	3	3	2*	2

*One unit in the particular group is constantly in must-run mode.

Identifying that the robustness and economic efficiency of a solution can vary according to the generation and transmission parameters as well as the overall topology of a power system, we appropriately model the operating reserve requirements to form the following dynamical expression.

$$SR^t = \max_t \left\{ \left(\xi_1 . P_D^t + \xi_2 . P_{RES}^t\right), \max_{i=1:N, i\neq j} \left\{U_i^t . P_i^t\right\} \right\} \tag{18}$$

To take into account the errors due to the deviations between the actual and forecasted values, the uncertainty in load demand and renewable energy is modelled with the aid of ξ_1 and ξ_2. The non-responsive nature of electricity demand along with the still limited electrification degrees concerning the heating/cooling and transportation sectors, require a spinning reserve no greater than 5% ($\xi_1 = 5\%$) of the total electricity demand. On the other hand, the total amount of the domestic renewable sources (both wind and PV) utilized for electricity production is taken into account due to isolation ($\xi_2 = 100\%$). The respective RES contribution is illustrated in Figure 3, where the summed overall energy for each season is provided. To highlight the contrast between overall, seasonal penetration and variable actual contribution, we include the power output from PV and wind regarding a random day per month in Figure 4.

Finally, N-1 criterion is considered as the most adequate for islanded power systems and thus, we postulate the worst case of a failure on the second biggest generator. In (18), j represents the biggest in terms of P_{max} generating unit.

The relationship between the charged, stored and discharged energy is modelled based on a formulation that takes into account the dynamic losses due to the energy conversion and parasitic self-discharge rate (SDR). As a result, the imposed by GA charging energy, E_{ch}^t, is reduced due to the charging losses according to charging efficiency, n_{ch}, resulting to:

$$E_s^t = n_{ch}\, E_{ch}^t \tag{19}$$

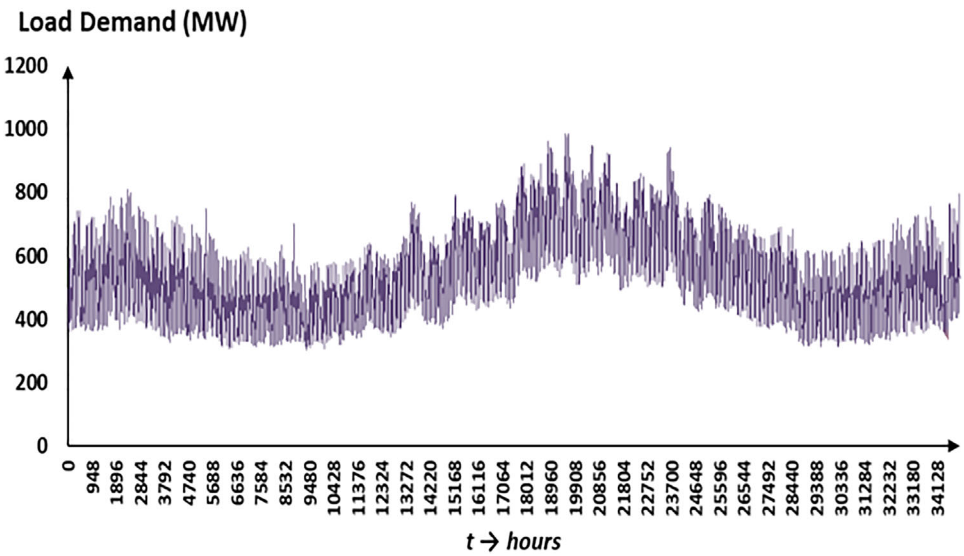

FIGURE 1 Annual electricity load variation during the entire year of 2018

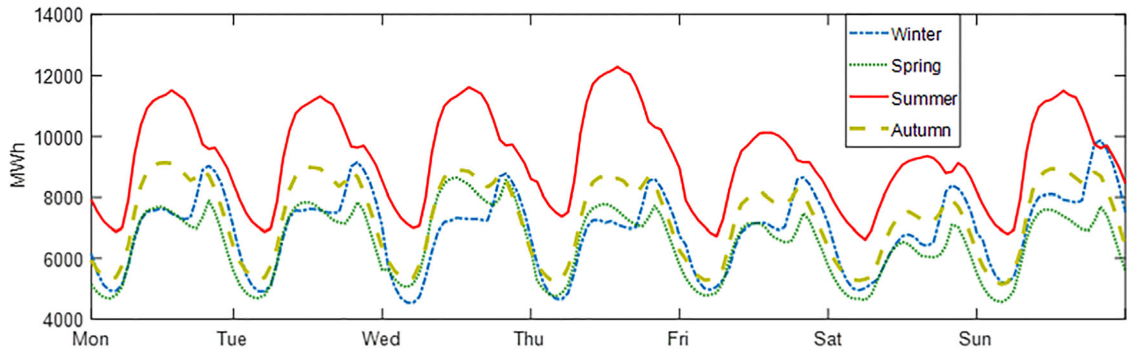

FIGURE 2 Weekly hourly-summed load demand per season

At the end of the process, the stored energy is degraded according to SDR and the storage duration t_s, to give the final:

$$E_s^{t+t_s} = E_s^t \,.(1 - SDR)^{t_s} \tag{20}$$

Finally, the discharging energy, $E_{dis}^{t+t_s}$, decrease based on the discharging efficiency n_{dis} to read as:

$$E_{dis}^{t+t_s} = n_{dis}\, E_s^{t+t_s} \tag{21}$$

To comprehensively assess the impact of ES on system operation, we perform weekly simulations for the year of 2018. The necessary data, obtained from the Cyprus Energy Regulatory Authority (CERA), regarding the half-hourly power demand of the island of Cyprus during the whole year of 2018 along with the real-time generation from the domestic RES [37].

Analysing the impact of variable energy resources on total production cost, we examine the economic feasibility of storage technologies with different performance features (including efficiency, depth of discharge, self-discharge rate, power and energy related cost components). For example, to conserve high reliability level at the same total production cost, the optimal size of a storage facility with greater efficiency will be sufficiently less than a system possessing low efficiency and high *SDR* or *DoD*. On the contrary, a storage technology with high performance metrics do not necessarily provide less production cost if its inherent cost components are quite higher than others. As a result, the various technologies must be assessed in terms of their profitable return considering different renewable penetration levels.

Three case studies are carried out to evaluate the profitable return derived by the application of ES. While the first scenario constitutes the actual, base case, two further scenarios consider a 250% and 500% increase in PV contribution. Aiming at minimizing the RES curtailment, load shedding and spinning reserve deficits, we repeat the simulations varying the parameters of round-trip efficiency and self-discharge rate concerning each individual ES technology.

Once the optimal storage size, in terms of power (P_{rated}) and energy (E_{cap}), along with the annual profitable return (APR) are determined, the selected ES facilities are subjected into life-cycle cost analysis. The life-cycle cost in net present value (NPV) for

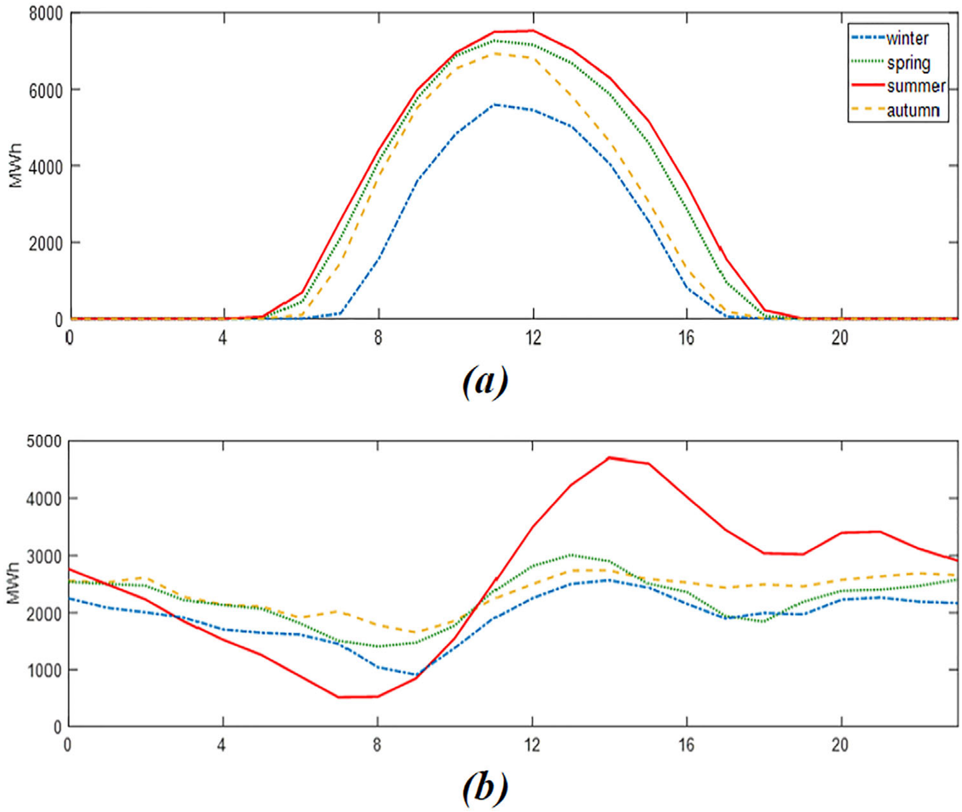

FIGURE 3 Daily hourly-summed (a) PV and (b) wind penetration per season

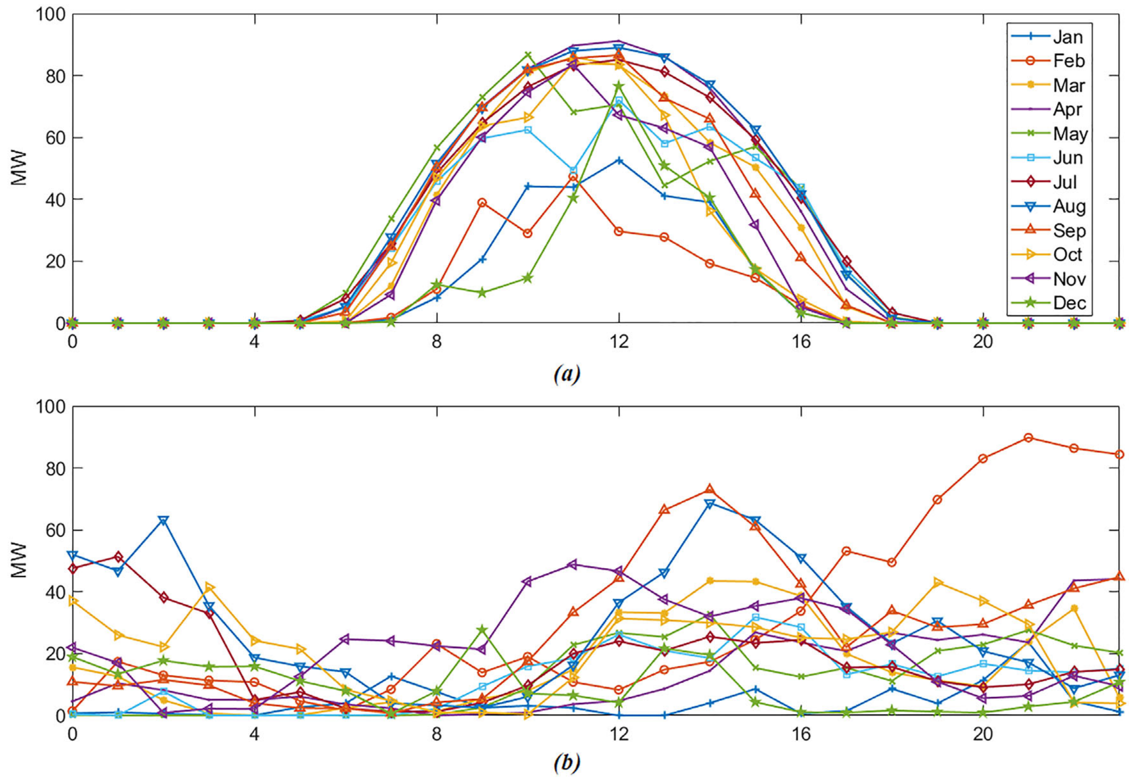

FIGURE 4 Daily (a) PV and (b) wind contribution per month

TABLE 3 Technical characteristics and cost metrics of ES technologies [42, 43]

	Pb-acid	Zn-air	Na-S	Li-ion	VRB
SDR (%)	0.01–0.02	~0	~0	0.03	~0
Round-trip efficiency (%)	85–90	50	89-92	~100	85
DoD (%)	80	100	100	80	100
BOP (€/kW)	110–552	110–552	110–552	110–552	110–552
PCS (€/kW)	53–166	0–110	0–110	0–110	0–110
ESM (€/kWh)	184–460	9–55	276–552	552–2300	138–920
Fixed O&M (€/kW-year)	3.95	–	18.4	2.47	4.2
Variable O&M (€/MWh)	0.18	–	0.37	0.50	0.25

each technology k can be computed as:

$$NPV_k = -IC^k(t) + \sum_{t=0}^{L} \frac{APR^k(t) - C^k_{O\&M}(t) - C^k_R(t)}{(1+i_R)^t} \tag{22}$$

IC^k is the investment cost composed by the balance of the plant (C_{BOP}), the power conversion system (C_{PCS}) and energy storage medium (C_{ESM}) as presented in Equation (23).

$$IC = E_{cap}.C^*_{ESM} + P_{rated}.(C_{PCS} + C_{BOP}) \tag{23}$$

On the contrary, the replacement cost (C_R) concerns only the energy storage medium for analyses regarding a few years ($L <$ 20) and may occur either due to the end of useful lifetime or the elapsed efficient cycles. In both cases, C^*_{ESM} takes into account the depth of discharge (DoD) corresponding to the oversized C_{ESM}/DoD for each individual technology. $C^k_{O\&M}$ expresses the operation and maintenance costs based on fixed and variable components with the help of Equation (24).

$$C_{O\&M} = C_{f-O\&M}.P_{rated} + C_{v-O\&M}.E_{dis} \tag{24}$$

The selected electrochemical storage technologies include lead-acid (Pb-acid), zinc-air (Zn-air), sodium-sulphur (Na-S) and lithium-ion (Li-ion) batteries and vanadium-redox (VRB) flow batteries. The participating systems are tabulated in Table 3 along with their main characteristics.

4 | RESULTS AND DISCUSSION

In order to gain a broad overview regarding the impact of RES in UC scheduling, we first take a look at the results derived from the priority-list schemes. The curtailed renewable energy is weighted by a penalty estimated by Equation (25) [38].

$$c_{res} = \max_{t=1:T} \left\{ \frac{\partial F_t}{\partial P^t_{netD}} \right\} \tag{25}$$

TABLE 4 Results concerning the test-case studies without storage

Scenario	PV	ξ_2	TFC (M€)	RES-CUT (GWh)	ENS (GWh)	RNS (GWh)
Base	×1	1	263.6	0.099	0.018	6.136
2	×2.5	0.5	249.0	6.849	4.219	6.663
3	×5	0.2	234.9	180.2	13.15	8.582

This way, RES producers receive the fair payback of the average hourly summed fuel cost (F_t) derived from the conventional generating units. Load shedding and *RNS* are penalized by 950 and 850 €/MWh, respectively, according to [39, 40]. Increasing the contribution of PV, the net load decreases limiting the ramping capability of the system which is strictly proportional to the spinning reserve provision. Aiming at minimizing the total production cost, the priority-list method targets on lowering the spinning reserve requirement. Up to a certain penetration level this can be achieved with the aid of penalty cost c_{rns} and Equation (13). At higher penetration levels, especially during the 2nd and 3rd scenarios, optimization results in RES curtailment to expand both the conventional contribution and flexibility. If the conventional generation is able to recover the curtailed energy, no load shedding has to take place, otherwise the penalty cost due to the energy not served is calculated by Equation (12). The results derived from the UC solution without the storage contribution for the assumed scenarios are depicted in Table 4.

As a common practise, the spinning reserve requirement due to RES contribution in the second and third case studies was set at 50% and 20%, respectively, considering the dispersity of PVs across the island. Although the total fuel cost seems to decrease with the increasing contribution of renewable generation, one can be observed is that the curtailed RES as well as the services not served increase. This leads to a dramatic increase concerning the *TPC* allowing the storage facilities to benefit from their participation.

Applying GA as a tool to drive optimization in lower *TPC* solutions, we expect that the optimum solution will be

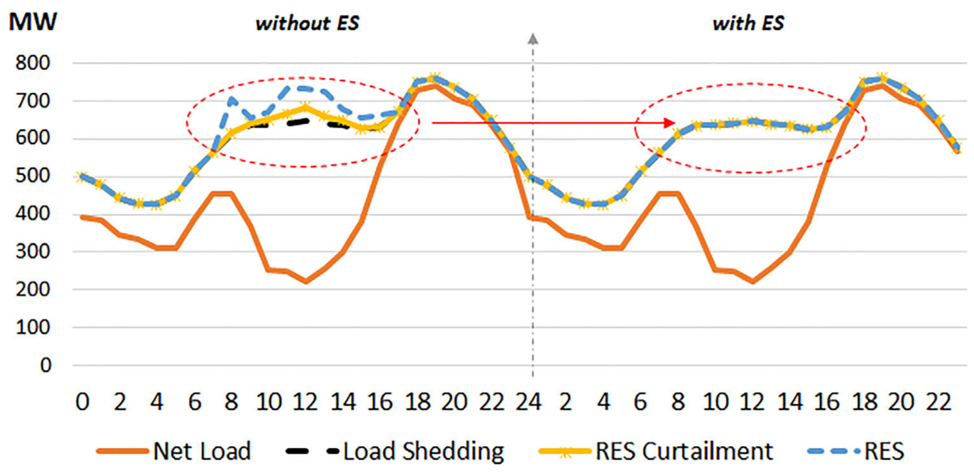

FIGURE 5 Optimal UC schedule obtained without ES and with ES

TABLE 5 Results concerning the test-case studies in the presence of storage

Scenario	PV	ξ_2	TFC (M€)	RES-CUT (GWh)	ENS (GWh)	RNS (GWh)
Base	×1	1	258.3	–	–	0.0043
2	×2.5	0.5	242.9	–	–	0.0803
3	×5	0.2	229.4	–	–	0.0952

reached by optimizing both the active power curtailment, load shedding and spinning reserve deficits. Varying the parameters of round-trip efficiency and hourly self-discharge rate for each technology, the derived results are provided in Table 5.

As we expected, RES curtailment and load shedding are eliminated by all participating technologies and the reserve not served is almost zero. GA successfully regulates the charging power to store the curtailed renewable generation whilst lowering the spinning reserve requirements. The stored energy, after being subjected into self-discharge degradation, can facilitate in load shedding while the excess energy can contribute as a firm input to peak load reduction. Figure 5 illustrates a representative example of the storage influence on UC schedule.

Depending on its special technical and economic features, each storage technology possesses different *TPC*. Performing simulations over the 52 short-term horizons of 336 half-hours of the entire year, we obtain the annual profitable return and required system size considering the optimal scheduling in the presence of storage. Based on these findings (included in Table 6), we assess the impact of different electrochemical storage systems assuming a lifespan of 15 years.

With the aid of Table 3 and setting the discount rate at 2.5%, we assess the technologies according to both their minimum and maximum performance. The minimum performance is defined by minimum overall features (e.g. minimum efficiency, depth of discharge, cycling and calendar life/maximum costs and self-discharge rate) whereas a maximum performance is achieved when minimum costs and maximum technical characteristics are taken into consideration.

Figure 6 shows the cumulative cost obtained from the three test-case studies. As can be seen, all technologies constitute infeasible solutions mainly due to their increased replacement costs which bring a negative impact in terms of NPV. In case of 500% PV contribution, Zn-air batteries provide an initial positive trend which quickly alternates sign and passes to the negative semi-plane because of the assumed weak performance characteristics. The respective outcomes when maximum performance features were considered are demonstrated in Figure 7. As can be observed, the replacement costs concerning the technologies were minimized, allowing the ES facilities to reach positive NPV representation. The outcomes derived from the experimental evaluation validate the effectiveness of our hybrid approach. In Figure 8, further comparisons with respect to capital, replacement, fixed and variable O&M costs are illustrated, revealing the consistency of our formulation for the optimal size of ES.

In the base case, despite their low efficiency and high replacement rate, Zn-air batteries provides the maximum potential mainly due to their reduced investment costs. On the other hand, possessing highest performance and cost, Li-ion follows the positive trend achieving a payback period around twelve years. In the second scenario (PV = 250%), all technologies offer feasible solutions with Zn-air and Li-ion terminating simultaneously at the 15th year. During the third case study, the technical performance constitutes the greatest impact on *NPV*. The increased penetration of PV systems allows Li-ion to reach a peak performance, followed by Pb-acid batteries and VRB flow batteries. This is confirmed by Zn-air batteries which, despite their precedence during the initial 4–5 years, they constitute the less suitable choice at the end of the examined lifespan. The results obtained by applying the proposed Genetic-algorithm driven priority list approach on the three case studies are depicted in Figure 9 in terms of total

TABLE 6 Results concerning the test-case studies without storage

	Case-study	Pb-acid	Zn-air	Na-S	Li-ion	VRB
APR (M€)	Base	0.107	0.105	0.107	0.109	0.107
	2	1.25	1.23	1.24	1.28	1.25
	3	2.27	2.26	2.27	2.28	2.27
P_{rated} (MW)	Base	87.3	102.7	92.4	51.3	87.3
	2	94.1	110.7	99.6	55.3	94.1
	3	305.7	359.6	323.7	179.8	305.7
E_{cap} (MWh)	Base	218.1	256.6	231	128.3	218.1
	2	470.3	553.3	498	276.6	470.3
	3	2445	2877	2589	1438	2445

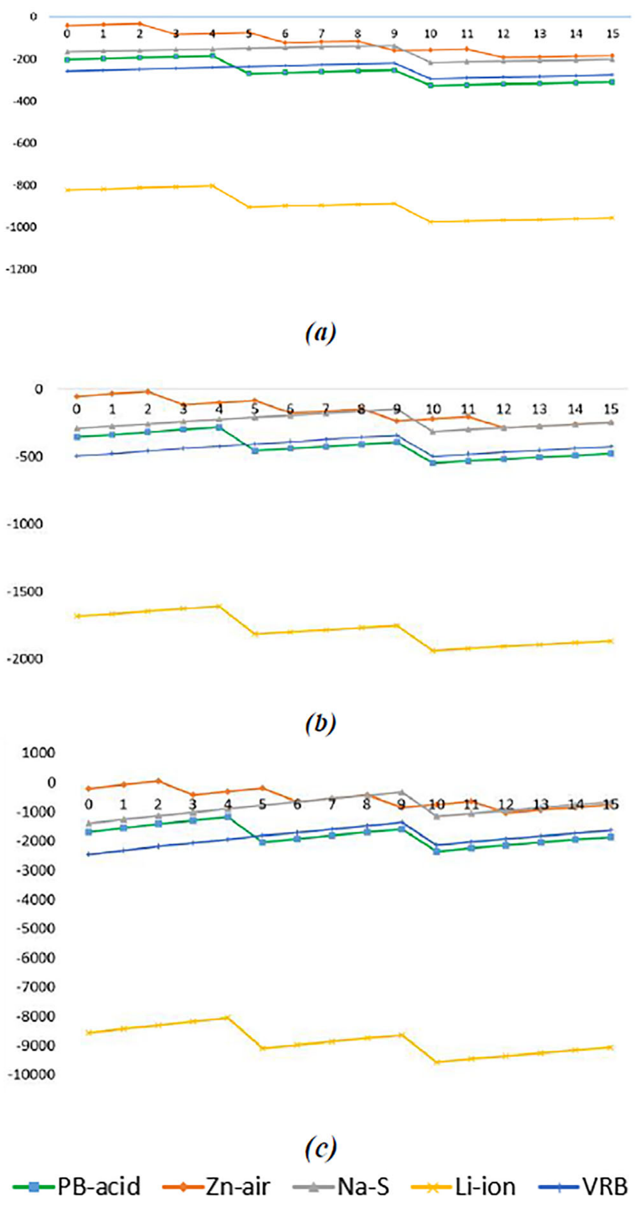

FIGURE 6 Cumulative cost (M€) obtained from the test-cases of (a) 100%, (b) 250%, and (c) 500% PV penetration and minimum ES performance

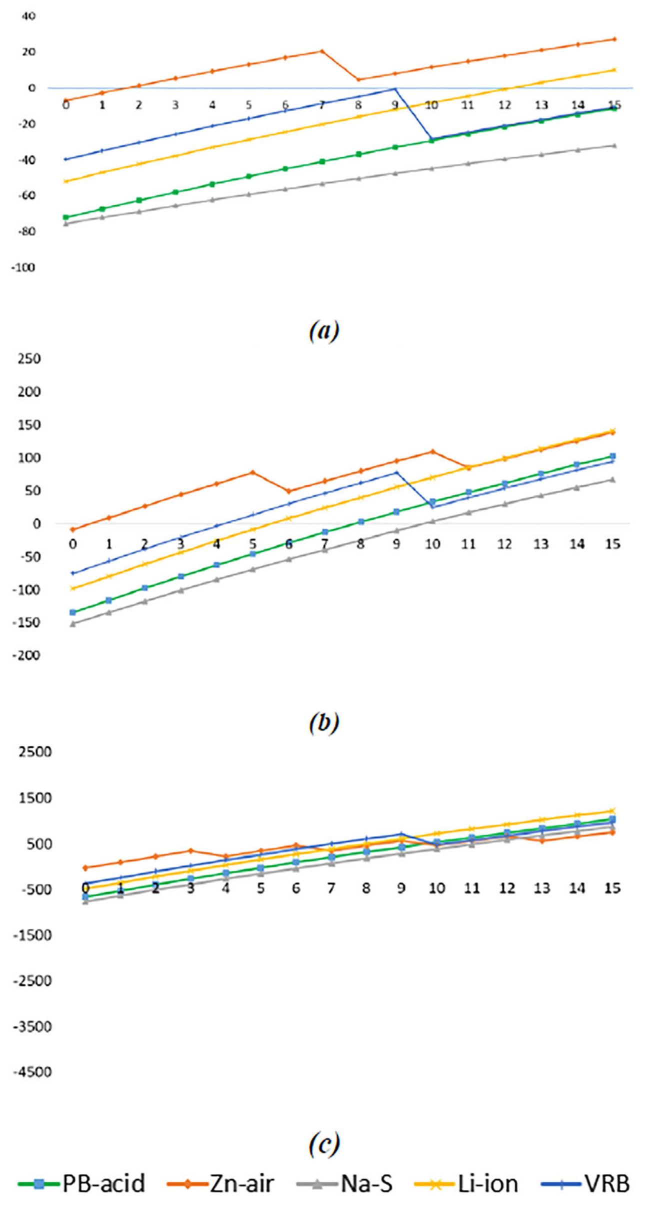

FIGURE 7 Cumulative cost (M€) obtained from the test-cases of (a) 100%, (b) 250% and (c) 500% PV penetration and maximum ES performance

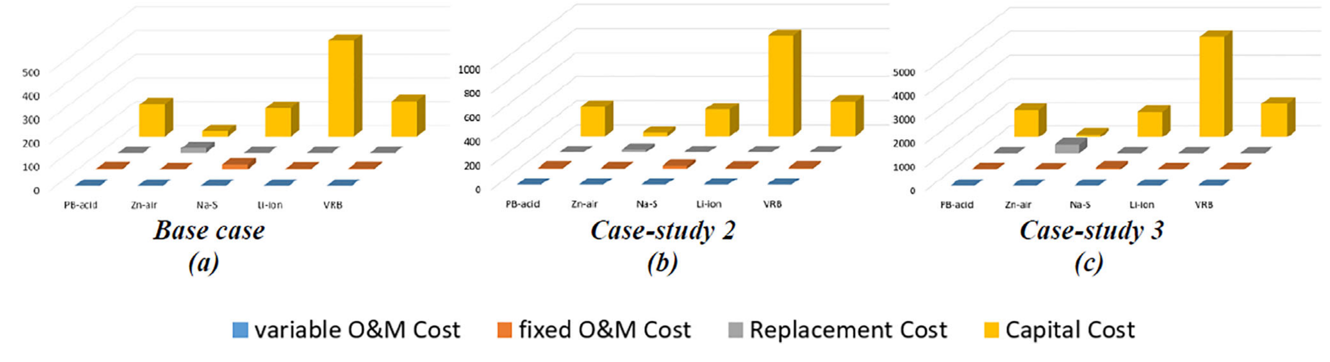

FIGURE 8 Investment and operation cost (M€) of ES technologies for the test cases (a) 100%, (b) 250% and (c) 500% PV penetration levels

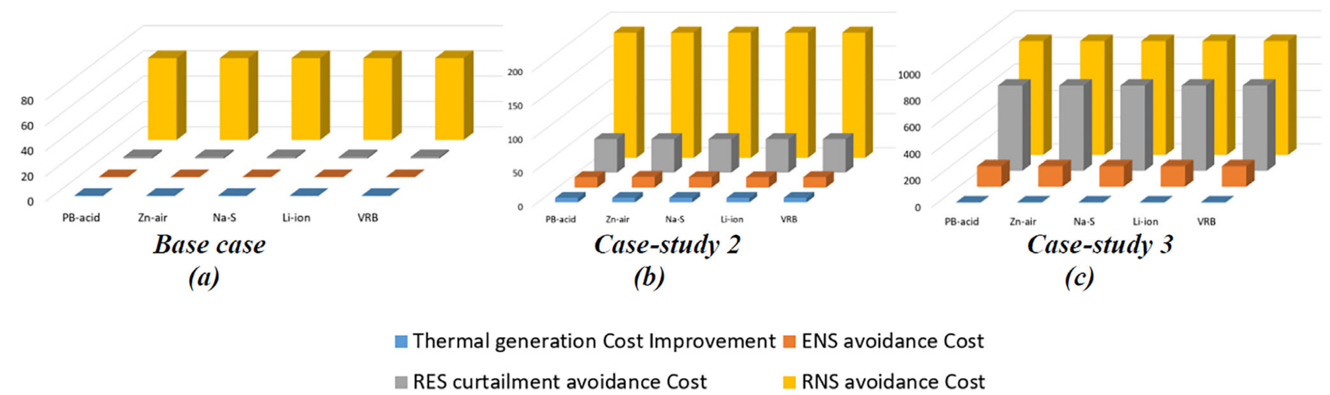

FIGURE 9 Cost improvements (M€) in the presence of ES technologies for the test cases (a) 100%, (b) 250% and (c) 500% PV penetration levels

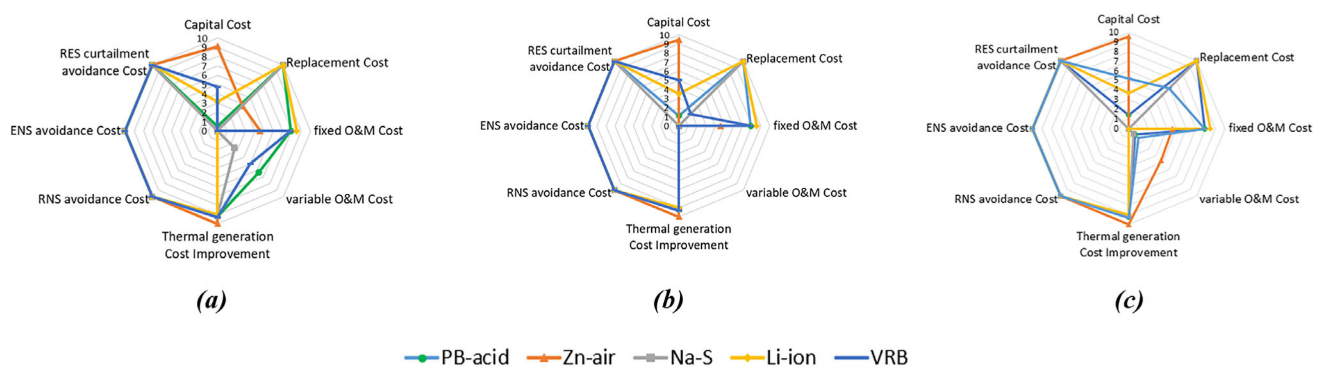

FIGURE 10 Normalized costs obtained from the test-cases of (a) 100%, (b) 250% and (c) 500% PV penetration

production cost improvements and penalty avoidance costs by technology.

Finally, to get some comparative results, we normalize the inflated costs based on the following formulation [41].

$$Rank\ \left(f_i\right) = 10\frac{f^* - f_i}{f^*} \tag{26}$$

f^* represents the maximum value between all candidates considered in each case study, whereas f_i is the actual value of each candidate. In this regard, the lowest values for the expenses including capital, replacement, fixed and variable O&M costs correspond to higher rankings (e.g. 10). A less beneficial approach gives lower rank estimates while the worst would approximate zero. On the contrary, the profitable values of avoidance credits in terms of RES curtailment, thermal generation, *ENS* and *RNS* avoidance costs are approximated by Equation (27).

$$Rank\ \left(f_i\right) = 10 - \frac{f_i - f_*}{f_*} \tag{27}$$

where f_* represents the minimum value between all candidates considered. For completeness sake, we present the normalized values in Figure 10.

5 | CONCLUSION

Electricity storage is attracting increasing interest as a potential candidate for power grid applications that facilitate a shift from the currently passive to an active network via time-shifting. In this work we have presented a different approach for the co-optimization of active power curtailment, load shedding and spinning reserve deficits. Utilizing the advances of priority-list schemes and genetic algorithm as a tool to drive the optimization, we provided the optimal unit commitment schedules and we defined the appropriate electricity storage parameters of charging and discharging power output. Based on actual data, the thermal generation of the power system of Cyprus was optimally scheduled for the year 2018 in the absence and presence of storage. Lead-acid, zinc-air, sodium-sulphur, lithium-ion batteries and vanadium-redox flow batteries were selected to minimize the renewable generation curtailment, energy not served and spinning reserve not served. Once optimally sized, the participating technologies subjected into life-cycle cost analysis considering both their minimum and maximum performance characteristics.

The derived results showed that the total fuel cost of thermal generating units is strongly affected by the uncertain and volatile behaviour of renewable sources, while improvements in terms of profitable return exist when electricity storage was integrated. The findings of our extensive evaluation are summarized as follows: (1) All technologies provide infeasible solutions when their minimum performance has been taken into account mainly due to increased replacement costs which deteriorate the net present value; (2) possessing the lowest investment cost, zinc-air batteries provide the maximum potential in the base case; (3) Despite their highest capital investment, at higher PV penetration levels ($PV = 250\%$) lithium-ion terminates with zinc-air when life-cycle costs consider the maximum performance features; (4) Maximum penetration of PV systems ($PV = 500\%$) allows Li-ion to reach a peak performance, followed by Pb-acid batteries and VRB flow batteries. Although the economic feasibility of the electricity storage components used has been examined based on the optimal capacity considering different technologies, their optimal allocation into the power network has not been considered.

Due to the small-scale and isolated system examined in this study, a single-bus model was considered neglecting the transmission losses. As for future directions, we indicate the multi-bus formulations, increased generating units and consolidation of network losses into the UC objective. We reckon that hybrid approach would provide great performance by adding complexity to the overall optimization task.

FUNDING

None.

CONFLICT OF INTEREST STATEMENT

There is no conflict of interest.

PERMISSION TO REPRODUCE MATERIALS FROM OTHER SOURCES

None.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Pavlos Nikolaidis https://orcid.org/0000-0002-5956-8800
Andreas Poullikkas https://orcid.org/0000-0003-3703-4901

REFERENCES

1. Aghaei, J., Shayanfar, H., Amjady, N.: Incorporating power system security into market-clearing of day-ahead joint energy and reserves auctions. Eur. Trans. Electr. Power 20(2), 140–156 (2010)
2. Mahmutoğulları, A.İ., Shabbir, A., Özlem, Ç. & Selim, A.: The value of multi-stage stochastic programming in risk-averse unit commitment under uncertainty. IEEE Trans. Power Syst. 34(5), 3667–3676 (2019)
3. Kwon, H., Park, J.K., Kim, D., Yi, J., Park, H.: A flexible ramping capacity model for generation scheduling with high levels of wind energy penetration. Energies 9(12), 1040 (2016)
4. Nikolaidis, P., Poullikkas, A.: Sustainable services to enhance flexibility in the upcoming smart grids. Sustaining Resources for Tomorrow, pp. 245–274, Springer, Berlin (2020)
5. Nikolaidis, P., Chatzis, S., Poullikkas, A.: Renewable energy integration through optimal unit commitment and electricity storage in weak power networks. Int. J. Sustain. Energy 38(4), 398–414 (2018)
6. Nikolaidis, P., Poullikkas, A.: A comparative review of electrical energy storage systems for better sustainability. J. Power Technol. 97(3), 220–245 (2017)
7. Lu, S., Wang, M., Kuo, M., Tsou, M., Liao, R.: Optimal unit commitment by considering high penetration of renewable energy and ramp rate of thermal units-a case study in Taiwan. Appl. Sci. 9(3), 421–435 (2019)
8. Kumar, V., Kumar, D.: Binary whale optimization algorithm and its application to unit commitment problem. Neural Comput. Appl. 32(7), 2095–2123 (2020)
9. Hreinsson, K., Scaglione, A., Analui, B.: Continuous time multi-stage stochastic unit commitment with storage. IEEE Trans. Power Syst. 34(6), 4476–4489 (2019)
10. Boqtob, O., El Moussaoui, H., El Markhi, H., Lamhamdi, T.: Optimal robust unit commitment of microgrid using hybrid particle swarm optimization with sine cosine acceleration coefficients. Int. J. Renew. Energy Res. 9(3), 1125–1134 (2019)
11. Babaei, S., Member, S., Zhao, C., Fan, L.: A data-driven model of virtual power plants in day-ahead unit commitment. IEEE Trans. Power Syst. 34(6), 5125–5135 (2019)
12. Zhou, B., et al.: Data-adaptive robust unit commitment in the hybrid AC /DC power system. Appl. Energy 254(May), 113784 (2019)
13. Kumar, N., Rajneesh, N.: A fuzzy reinforcement learning approach to thermal unit commitment problem. Neural Comput. Appl. 31(3), 737–750 (2019)
14. Sedighizadeh, M., Esmaili, M., Mousavi-taghiabadi, S.M.: Optimal energy and reserve scheduling for power systems considering frequency dynamics, energy storage systems and wind turbines. J. Clean. Prod. 228, 341–358 (2019)
15. Banshwar, A., Kumar, N., Raj, Y., Shrivastava, R.: Market-based participation of energy storage scheme to support renewable energy sources for the procurement of energy and spinning reserve Procurement Cost of Energy Procurement Cost of Reserve. Renew. Energy 135, 326–344 (2019)

16. Nguyen, T.N.H., Yabe, K., Ito, M., Dao, V.T., Ishii, H., Hayashi, Y.: Spinning reserve quantification considering confidence levels of forecast in systems with high wind and solar power penetration. IEEJ Trans. Electr. Electron. Eng. 14(9), 1304–1313 (2019)
17. Wang, M.Q., Yang, M., Liu, Y., Han, X.S., Wu, Q.: Electrical Power and Energy Systems Optimizing probabilistic spinning reserve by an umbrella contingencies constrained unit commitment. Int. J. Electr. Power Energy Syst. 109, 187–197 (2019)
18. Psarros, G.N., Papathanassiou, S.A.: Comparative assessment of priority listing and mixed integer linear programming unit commitment methods for non-interconnected island systems. Energies 12(4), 667 (2019)
19. Lorca, A., Sun, X.A.: Multistage robust unit commitment with dynamic uncertainty sets and energy storage. IEEE Trans. Power Syst. 32(3), 1678–1688, (2016)
20. Panwar, L.K., Reddy K, S., Verma, A., Panigrahi, B.K., Kumar, R.: Binary Grey Wolf Optimizer for large scale unit commitment problem. Swarm Evol. Comput. 38(May 2017), 251–266 (2018)
21. Subba, G.V., Ganesh, V., Rao, C.S.: Implementation of clustering based unit commitment employing imperialistic competition algorithm. Int. J. Electr. Power Energy Syst. 82, 621–628 (2016)
22. Håberg, M.: Fundamentals and recent developments in stochastic unit commitment. Electr. Power Energy Syst. 109(July), 38–48 (2019)
23. Zhou, B., Ai, X., Fang, J., Yao, W., Zuo, W.: Data-adaptive robust unit commitment in the hybrid AC /DC power system. Appl. Energy 254(Nov), 113784 (2019)
24. Lu, Y., Zhou, J., Qin, H., Wang, Y., Zhang, Y.: An adaptive chaotic differential evolution for the short-term hydrothermal generation scheduling problem. Energy Convers. Manag. 51(7), 1481–1490 (2010)
25. Nikolaidis, P., Chatzis, S.: Gaussian process-based Bayesian optimization for data-driven unit commitment. Int. J. Electr. Power Energy Syst. 130(February), 106930 (2021)
26. Zhu, X., Zhao, S., Yang, Z., Zhang, N., Xu, X.: A parallel meta-heuristic method for solving large scale unit commitment considering the integration of new energy sectors. Energy 238(C) 121829 (2021)
27. Sayed, F., Kamel, S., Yu, J., Jurado, F., Yu, J.: Optimal load shedding of power system including optimal TCSC allocation using moth swarm algorithm. Iran. J. Sci. Technol. Trans. Electr. Eng. 44(2), 741–765 (2020)
28. Kim, C., Kim, K., Balaprakash, P., Anitescu, M.: Graph convolutional neural networks for optimal load shedding under line contingency. In IEEE Power & Energy Society General Meeting, Atlanta, GA, pp. 1–5 (2019)
29. Hayajneh, H.S., Lainfiesta, M., Zhang, X.: Three birds one stone : A solution to maximize renewable generation, incentivize battery deployment, and promote green transportation. In: *IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*, Washington, DC, pp. 7–11 (2020)
30. Nikolaidis, P., Poullikkas, A.: Enhanced Lagrange Relaxation for the optimal unit commitment of identical generating units. IET Gener. Transm. Distrib. 14(18), 3920–3928 (2020)
31. Bertsimas, D., Litvinov, E., Sun, X.A., Zhao, J., Zheng, T.: Adaptive robust optimization for the security constrained unit commitment problem. IEEE Trans. Power Syst. 28(1), 52–63 (2013)
32. Georgiou, G.S., Nikolaidis, P., Lazari, L., Christodoulides, P.: A genetic algorithm driven linear programming for battery optimal scheduling in nearly zero energy buildings. In *2019 54th International Universities Power Engineering Conference (UPEC)*, Bucharest, Romania, pp. 1–6 (2019)
33. Nikolaidis, P., Poullikkas, A.: Increasing the photovoltaic hosting capacity in autonomous grids and microgrids via enhanced priority-list schemes and storage. Green Energy Sustain. 1(1), 1–21 (2021)
34. Nikolaidis, P., Fotiou, S., Kasparis, T., Poullikkas, A.: Dynamic analysis of high-response storage systems to minimize the generation ramping requirements. In *Proceedings of Mediterranean Conference on Power Generation, Transmission, Distribution and Energy Conversion (MEDPOWER 2020)*, Online conference, pp. 1–6 (2020)
35. Georgiou, G.S., Nikolaidis, P., Kalogirou, S.A., Christodoulides, P.: A hybrid optimization approach for autonomy enhancement of nearly-zero-energy buildings based on battery performance and artificial neural networks. Energies 13(14), 3680 (2020)
36. Nikolaidis, P., Chatzis, S., Poullikkas, A.: Optimal planning of electricity storage to minimize operating reserve requirements in an isolated island grid. Energy Syst. 1, 1–18 (2019)
37. CERA Annual report of cyprus energy regulatory authority (2017) www.cera.org.cy [Accessed 1 March 2021]
38. Nikolaidis, P., Poullikkas, A.: A novel cluster-based spinning reserve dynamic model for wind and PV power reinforcement. Energy 234, 121270 (2021)
39. Mercados, A.: Identification of appropriate generation and system adequacy standards for the internal electricity market. Final Report Prepared for the European Commission; Library, New York, NY, USA, (2016).
40. Al-shaalan, A.M.: Reliability evaluation in generation expansion planning based on the expected energy not served. J. King Saud Univ. Eng. Sci. 24(1), 11–18 (2014)
41. Nikolaidis, P., Poullikkas, A.: Cost metrics of electrical energy storage technologies in potential power system operations. Sustain. Energy Technol. Assessments 25, 43–59 (2018)
42. Nikolaidis, P., Chatzis, S., Poullikkas, A.: Life cycle cost analysis of electricity storage facilities in flexible power systems. Int. J. Sustain. Energy 38(8), 752–772 (2019)
43. Nikolaidis, P., Poullikkas, A.: Secondary battery technologies: a static potential for power. Energy Generation and Efficiency Technologies for Green Residential Buildings. pp. 191–207, IET, Stevenage, United Kingdom (2019)

How to cite this article: Nikolaidis, P., Poullikkas, A.: Co-optimization of active power curtailment, load shedding and spinning reserve deficits through hybrid approach: Comparison of electrochemical storage technologies. IET Renew. Power Gener. 16, 92–104 (2022). https://doi.org/10.1049/rpg2.12339