This article is a submitted version. Please cite the published version:

https://doi.org/10.1016/j.est.2024.113404

Submittee

Distributed battery energy storage systems for deferring distribution network reinforcements under sustained load growth scenarios

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Abstract

Energy storage systems can be leveraged in electricity distribution network planning as mitigation alternatives to traditional grid reinforcements if they are strategically installed and operated to reduce congestion and voltage limit violations. This paper examines the technical and economic viability of distributed battery energy storage systems, owned by the system operator, as an alternative to distribution network reinforcements. The case study analyzes the installation of battery energy storage systems in a real 500-bus Spanish medium voltage grid under sustained load growth scenarios. The results show that, in general, dedicated battery energy storage systems are only a cost-efficient alternative in distribution system planning under very specific conditions, such as when low load growth rates are expected. Nevertheless, they are only required for peak shaving during a few days per year. For the analyzed case study, the recoverable portion of their total cost through deferral of distribution system upgrades is higher than the fraction of cycles required for peak shaving under all sustained load growth scenarios. Therefore, it is explored if mobile battery energy storage systems, capital grants, and revenue stacking can enable battery energy storage systems to become an efficient distribution system planning alternative.

Keywords

Distribution network planning, energy storage systems, reinforcements, genetic algorithms.

Nomenclature

- BESS Battery energy storage system
- DN Distribution network
- DNP Distribution network planning
- DSO Distribution system operator
- DG Distributed generation
- ESS Energy storage system
- GA Genetic algorithm
- HV High voltage
- LV Low voltage
- MV Medium voltage

1. Introduction

Electricity distribution networks (DNs) are undergoing a major transition driven by the increasing penetration of distributed energy resources (DERs). Higher electrification and the need to integrate higher shares of DERs have put a spotlight on distribution network planning (DNP). Distribution system operators (DSOs) are facing new challenges due to growing electrification of energy demand and DERs connected to DNs. However, the digitalization of grids allows DSOs to benefit from valuable services achieved by a smart operation of DERs. Therefore, strategically installed and operated DERs, such as energy storage

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systems (ESSs), could be leveraged in DNP as non-wires alternatives to traditional reinforcements in DNs [1]. In the European Union, Article 36 of the directive (EU) 2019/944 does not generally allow DSOs to own, develop, manage, or operate ESSs unless they are fully integrated network components (i.e., cannot be used to buy or sell electricity in electricity markets) and have received approval from the national regulatory authority. Nevertheless, the European Commission has recently recommended system operators to further assess whether ESSs can be a more cost-effective alternative to conventional investments in DN upgrades [2].

In this context, the study of the optimal sizing and location of distributed ESSs in DNP has gained attraction in the scientific literature [3]. ESSs are highly flexible DERs that can be used for different applications and planning objectives [4]. The most common application, considered in [5–7], is obtaining a benefit from energy arbitrage by charging the ESS when electricity is cheap and generating energy by discharging the ESS during high demand periods. However, ESS can also be used to provide benefits during the future operation of the DN by reducing energy losses, enhancing voltage regulation, improving reliability, and avoiding overloads of network equipment [8]. Furthermore, ESS installed at DNs could provide services to the transmission network and to reduce the uncertainty from DG [9]. All these applications offer different benefits to the power system: transmission and distribution grid reinforcements deferral, frequency and non-frequency ancillary services, energy arbitrage, reduction in peaking generation capacity, higher integration of intermittent renewable energy, and emissions reduction [10]. Nevertheless, the specific conditions under which ESSs could become a viable alternative as a grid asset for deferring grid reinforcements in DNs have not been sufficiently addressed in the literature. Most studies combine several of the aforementioned benefits in the objective function to minimize the total cost of the system [5–7,10] or perform a multi-objective optimization [8,11]. However, objectives that bring greater benefits to the power system (e.g., energy arbitrage, resiliency, etc.) are more prominent in determining the optimal solution in these papers. Moreover, they do not study when the installation of ESS can be used in practice to defer or avoid network reinforcements under future sustained load growth scenarios.

On the other hand, some authors have focused on analyzing how ESSs can be strategically used as a mitigation alternative for grid congestion in DNs [12–17]. Optimal charging and discharging scheduling of BESSs have been addressed to defer substation reinforcements [12], to avoid voltage and overload problems [13], and to reduce EV charging peak load [14], but none of these papers optimize a combination of BESS installation and grid upgrade investment decisions. The optimal sizing of distributed BESS in DNs for voltage regulation and peak load shaving under high solar photovoltaic penetrations is addressed in [15]. In [16], it is analyzed how distribution system security of supply can be enhanced by providing the additional required capacity through a combination of ESS and real-time thermal rating monitoring. Nevertheless, the probabilistic analysis used in [16] does not perform any optimization, only the mitigation of congestion at the substation is studied in detail (i.e., the distribution network is not modelled) and the cost of conventional reinforcements is roughly approximated as a function of the distance from the substation. A techno-economic analysis of installing ESSs to mitigate grid congestion caused by high EV uptakes in several distribution grids is studied in [17], but varying peak load and load growth conditions are not evaluated.

The main objective of this study is to assess whether the optimal installation of battery energy storage systems (BESSs) can be a techno-economic alternative to postpone investments in network reinforcements under sustained load growth scenarios. This paper focuses on DNP, hence BESSs are viewed as fully integrated network components owned and operated by the DSO to reduce the loading of the DN during peak demand periods. The optimal combination of investments in network reinforcements and BESSs is obtained with the proposed methodology, which employs a genetic algorithm (GA) that optimally locates and sizes distributed BESSs to minimize investment costs in the DN. This paper contributes by analyzing the technical and economic viability of distributed BESSs as an alternative to DN upgrades under different sustained load growth scenarios for a real 500-bus Spanish DN. This case study highlights important considerations that have not been addressed in the literature but are fundamental to understanding the value of BESS network planning alternatives in DNs. For instance, the results inform about the share of the total costs throughout the useful life of BESS that can be recovered from distribution upgrade deferrals under different load growth scenarios.

The results show that, generally, dedicated BESSs are not a cost-efficient alternative in DNP unless low load growth rates are expected. Nevertheless, they are only necessary for peak shaving during a few days per year and the recoverable portion of their total cost through deferral of DN reinforcements is higher than the fraction of cycles required for peak shaving under all analyzed sustained load growth scenarios in the

case study. Additionally, this paper evaluates various options for improving the profitability of BESS investments. These options include mobile BESSs, capital grants, and revenue stacking with other BESS services. Recent studies have identified mobile BESSs as an emerging resource for improving resilience [18,19], increasing the share of renewable energy and electric vehicle fast charging stations [20], and reducing generation curtailment and energy losses [21]. To the authors' knowledge, this study is the first to assess whether moving a BESS to another location could offset the additional shipping and installation costs by reducing the project duration when investing in a BESS as a network planning alternative. A BESS may only defer network reinforcements for a couple of years when high load growth rates are expected, but it could still be a valuable asset for other DNs.

The remainder of this paper is organized as follows. Section II describes the proposed methodology for evaluating the distributed installation of ESSs in DNs as an alternative to defer investments in distribution network reinforcement. Section III applies this methodology to a real Spanish DN, which serves as a case study. Then, in Section IV, the results of the case study are studied under different load growth rates. Finally, conclusions are drawn in Section V.

2. Methodology

This section presents a deterministic model that combines distributed BESSs and traditional network reinforcements in DNP. As aforementioned, intelligent planning and operation of distributed BESSs can provide several benefits to DNs such as reducing the loading of the DN during peak demand hours. Thus, DSOs can optimize their costs in DNP by considering the installation of distributed BESSs as an option to postpone or avoid traditional network reinforcements. This methodology aims to find the optimal combination of distributed BESSs and network reinforcements that minimize DNP costs while satisfying the grid operational limits. Equivalent annual costs are used to fairly compare these grid assets with different lifetimes. The average useful life of BESSs is significantly shorter than that of power lines and transformers.

This paper assumes that the DSO will own and operate the distributed BESSs as a flexible network asset to reduce distribution system costs. Note that the unbundling of the electricity sector in many countries does not currently allow DSOs to gain profits from arbitrage in wholesale electricity markets. Initially, the only system benefit considered by this methodology to motivate DSO investments in BESS as a network asset is the deferral of DN reinforcements. Therefore, it is assumed that the DSOs will operate BESSs based on a peak-shaving strategy to reduce the loading of DN equipment during days with high demand. Reconfiguration, contingencies, and other singular operating conditions are not modeled in the proposed methodology. Nevertheless, a sensitivity regarding stacking benefits from other ancillary services provided by distributed BESS will also be analyzed later in the case study.

Regarding the distributed installation of BESSs, the proposed methodology optimizes its location and capacity. The methods employed to find the optimal location, sizing, and control strategies of ESSs in DNP can be classified into four categories: analytical methods, exhaustive search, mathematical programming, and metaheuristics [22]. The main issue with analytical methods is that they do not perform any optimization. On the other hand, exhaustive search methods guarantee finding the optimal solution within a discrete search space, but they require long computing times and are not practical for large-scale DNP studies. Moreover, various mathematical programming techniques have been developed to convert the optimal power flow problem for siting and sizing ESSs into mixed-integer linear programming (MILP) [23] or mixed-integer second-order cone programming model (MISOCP) [9]. Finally, the high complexity behind this problem, which involves large amounts of binary decision variables and the nonlinear relationships of power flows in electricity systems, has also resulted in many papers that propose different meta-heuristic algorithms to solve this optimization problem [3]. While metaheuristics do not guarantee convergence to the global optimum, many authors have shown that a variety of them can produce reasonable solutions in practice, including Genetic Algorithms (GA) [5,24,25], Non-dominated Sorting Genetic Algorithm – II (NSGA-II) [8], Differential Evolution [26], Particle Swarm Optimization [27], and Artificial Bee Colony [28]. The proposed methodology uses a GA to handle this complexity and allow its application for large-scale real DNs.

The input data sets for this model include electrical and economic data for utility-scale BESSs, consisting of a catalog with techno-economic data for new network equipment, electrical and topological data of the DN, and daily load profiles for all loads and DG units. The model outputs are the optimal location and size of BESS units, network reinforcements, and DNP equivalent annual cost.

a. Genetic Algorithm (GA)

The objective of the DSO in DNP is to define investments according to planning criteria to maintain a reliable and efficient distribution electric system. In this paper, both distributed BESSs and traditional network reinforcements are considered as candidate investments to avoid thermal and voltage limit violations. Although the unit cost of BESSs (C/kWh) is considered as a constant input parameter, the overall cost of BESSs investments is derived from the number of BESSs and their capacity (kWh). Thus, the decision variables for installing distributed BESSs are their capacity and location. These decisions are modeled in the GA by characterizing individuals based on the capacity and allocation node for each distributed BESS. The first element (i.e., odd entries) determines its capacity, denoted as x_i , and the second (i.e., even entries) gives the DN bus where it is installed, denoted as z_i . The codification of the individuals in the GA is illustrated with an example for three BESSs in Fig. 1.

BESS 1		BESS 2		BESS 3		
x_1 [MWh]	Z_1	x_2 [MWh]	Z_2	<i>x</i> ₃ [MWh]	<i>Z</i> ₃	
250	34	1500	497	725	421	

Fig. 1. Illustrative example of GA individual chromosome codification for 3 BESSs.

The objective function of the model (1) is to minimize the equivalent annual cost of all investments in distributed BESSs (C^{BESS}) and traditional network reinforcements (C^{DNR}). As aforementioned, equivalent annual costs are used to fairly compare the cost of these grid assets which have significantly different useful lives².

$$\min C^{BESS} + C^{DNR} \tag{1}$$

The annual cost of BESS (2) is obtained as the sum of all installed capacities multiplied by their annualized cost (*EAC^{BESS}*), expressed in ϵ /MWh-yr.

$$C^{BESS} = EAC^{BESS} \sum_{i} \cdot x_i$$
⁽²⁾

On the other hand, the annual cost of investments in DN reinforcements is derived as a function of the siting and sizing of BESS decisions (3). Note that traditional network reinforcements are not considered as decision variables. Each individual in the GA population represents a fixed set of BESS installations and the DSO can only solve the remaining grid limit violations by reinforcing the DN. The optimal DN reinforcement decisions are always the same for a given set of BESS installations. For instance, if the size of the BESSs performing peak-shaving is not enough to resolve the congestion of a power line, then that power line will have to be upgraded. Section II.b describes in detail the function to obtain the annual cost of investments in DN reinforcements.

$$C^{DNR} = f(x_i, z_i) \tag{3}$$

Besides, the installation of distributed BESSs is constrained to a maximum BESS capacity (\bar{X}) that can be installed at a single bus (4). Finally, constraints (5) and (6) guarantee that BESSs are installed in one of the candidate buses. The variable z_i denotes the bus at which the BESS is installed, so it is defined as an integer variable (6). If no investment in BESS is made, z_i takes a value of zero. Otherwise, it takes the value of the bus where the BESS is installed and, thus, the maximum value z_i can take is the number of buses (N^{BUS}) in the DN.

$$x_i \le \bar{X} \tag{4}$$

$$0 \le z_i \le N^{BUS} \tag{5}$$

$$z_i \in \mathbb{Z} \tag{6}$$

² In this paper, it is assumed a useful life of 16 years for BESSs and 40 years for power lines and transformers

Fig. 2 shows a flowchart of the GA. After reading the input data, an initial population is created with randomly selected individuals. Then, the necessary reinforcements are computed (see Section II.B.), and the fitness function is evaluated for each population individual using the inner optimization output. If GA does not converge, a new generation of candidate solutions is used for the next iteration. This new population is generated by mutation and recombination of the genomes from selected individuals with the best fitness values. The GA stops when the maximum number of iterations is reached, or the best fitness function value has converged.



Fig. 2. Flowchart of GA.

b. Computation of required investments in network reinforcements

This section describes how network reinforcements are selected for each individual in the GA, which determines a fixed set of BESS installations. First, the power profile of the distributed BESSs is added at the nodes where they are installed. The generation/consumption profile for each BESS is computed based on its capacity and assuming it is operated to perform peak-shaving to reduce the aggregate peak load in the DN. Then, a power flow analysis is run. Any overloads of power lines or transformers are solved by investing in a new element with a higher power rating. On the other hand, resolving voltage limit violations is not as simple. The reinforcement of a branch reduces its voltage drop, but it also affects the voltage of all downstream nodes in radial DNs. To select which branches should be reinforced first, all branches are ranked by a KPI that measures the resulting voltage deviations after reinforcing that branch to reduce its voltage drop:

$$KPI = \sum_{i} \left(Vdev_{i} - M_{i,l}^{VReinf} \cdot \left(1 - \frac{1}{n_{l}^{MAX}}\right) \right)$$
(7)

where V dev is the vector of voltage deviations from the limit at each bus *i*, M^{VReinf} is the sensitivity matrix that measures the impact of reinforcing branch *l* on the voltage of bus *i*, and n_l^{MAX} is the maximum number

of equivalent parallel lines of branch l to reinforce. That enforces the monotonicity of decreasing nominal ampacities is applied by imposing an upper limit on n_l^{MAX} so that the nominal capacity of branch l cannot exceed the capacity of its upstream branch. Once the KPI for each branch is computed, the candidate branch with the lowest KPI value is reinforced.

3. Case study

A real 20kV rural DN, operated by i-DE in Spain, is analyzed in this case study. This DN consists of 500 buses and 504 branches, but it is operated radially with five open branches. Its power lines extend over a distance of 243 km and it is connected to the high voltage grid by means of a 20 MVA HV/MV substation. In the case study, it is assumed that there are no technical violations at LV, allowing consumers and DG to be represented as the aggregation of demand and generation at the distribution MV/LV transformers. Based on their location and type (i.e., industrial or residential), their hourly loading profile for a peak demand day is assigned. First, unitary hourly profiles are obtained from the measured aggregated hourly demand of each type of customer, differentiated by access tariff, in Spain [29]. Then, these unitary profiles are multiplied by the contracted power at each connection point.



Fig. 3. Loading of HV/MV substation for a peak load day in the base case scenario.

An equipment catalog for new network equipment (i.e., BESSs, power lines and transformers) is also given as input to the model. As shown in Fig. 3, the aggregate load curve has a nighttime peak that lasts for 3 hours. Therefore, it is assumed that the DSO can invest in a battery BESS that can provide a maximum of 3MW for 4 hours³. In the base scenario, peak demand plus power losses results in a substation load of 20.24 MVA, slightly exceeding the substation capacity limit by 1%. An annual equivalent cost for BESS of 40.6 ϵ/kWh -yr.⁴ is used for this case study [30]. In addition, the cost of power lines and transformers is determined based on the reference investment and operation and maintenance values defined by the Spanish regulation [31]. Then, the equivalent annual cost is calculated for each asset, considering a discount rate of 5.58% [32] and an expected useful life of 40 years for power lines and transformers [31] and 16 years for ESSs [30].

4. Results

³ Given that evening peak lasts for 3 hours, it is assumed that the battery will be discharged at its rated power for a maximum of 4 hours. Besides, the rated power of the BESSs is limited to 3MW because the difference between the peak demand and the demand at off-peak hours at midday does not exceed 3MW of the scenarios.

⁴ This reference value is derived by annualizing the installation, operation and decommission reference costs for a 1MW-4h lithium ferrophosphate (LFP) BESS over a lifetime of 16 years.

This section presents the results of the case study which analyzes the techno-economic viability of the distributed BESSs in DNP as an alternative to DN reinforcements under different load growth scenarios. The GA has been implemented using the off-the-shelf GA solver in MATLAB and MATPOWER [33] is employed for power flow analysis.

First, the GA-based model is used to optimally locate and size distributed BESS to reduce the cost of conventional network reinforcements in a scenario where the rating of the substation transformer is exceeded during peak demand hours. From a DNP perspective, peak shaving is only required when the limits of the existing DN infrastructure are exceeded. The aggregate load profile for this base case scenario was presented previously in Fig. 3. It is assumed that this profile is representative of the 20 days with highest demand in the year. The optimal investment decision according to the GA model for this base case scenario is to install a 715 kWh BESS at bus 498, which is located at the end of the sub-feeder with highest peak demand. This result seems very promising as it yields a 50000 €/yr. annual cost savings from deferring conventional investments in DN reinforcements, mainly from avoiding the investment in a new substation transformer. Nevertheless, this result is just an illustration for one scenario and the aggregate load will probably continue to increase over the project lifetime.

Fig. 4 illustrates the annual cost reduction achieved by installing a 715 kWh BESS at bus 498 for different peak loading levels of the HV/MV substation. In Fig. 4, the annual cost savings are obtained as equivalent annual cost savings from the deferral of grid reinforcements minus the equivalent annual cost of the BESS. This sensitivity analysis shows that there is only a narrow margin for load growth where BESS is an economic alternative to defer network reinforcements. If the substation is not overloaded, installing BESS can defer a few power line reinforcements, but it is not an economical solution. This is illustrated in Fig. 4, where the deferral of power line upgrades for some loading intervals compensates for part of the BESS cost, but it is not sufficient to justify an investment on BESS. On the other hand, when the overload of the substation transformer is small, it is more economical to reduce its loading by installing a BESS with just enough capacity to avoid the congestion of the transformer. Upgrading the substation transformer to a higher rating (e.g. 40 MVA) will have the same cost if its original rating is expected to be exceeded by 1 MVA or 19 MVA. However, because of very high unit costs (in ϵ /MWh) for BESS installation, it is only efficient to install BESS if the overload of the substation is small.



Fig. 4. Evolution of the annual cost reduction from installing a 715kWh BESS at bus 498 as the aggregate peak demand is increased.

Where permitted by the regulation, the DSO may consider other options to improve the economic viability of BESS investments such as mobile BESSs, capital grants, and stacking multiple services provided to the power system by BESSs. Although the installation of third-party-owned BESS is beyond the scope of this

study, the revenue stacking analysis could also inform the BESS owner of the fraction of the BESS cost that can be recovered by providing a flexibility service to defer network reinforcements.

a. Sensitivity to peak demand growth

The net present value (NPV) of investing in a 715kWh BESS at bus 498 (the optimal solution selected by the GA) is analyzed for different constant interannual growth rates of peak demand over the 16-year period of the BESS lifetime in the upper plot of Fig. 5. When demand grows very slowly, the BESS is effective in keeping the loading of power lines and transformers below their nominal rating during several years. The bottom plot in Fig. 5 shows that the number of years that the BESS can postpone the reinforcement of the HV/MV substation sharply decreases for higher load growth rates. This can be seen in Fig. 5 where the NPV of installing this BESS is only positive for interannual growth rates up to 0.16%. Alternatively, in this case study the BESS should be enough to defer the substation reinforcement for at least 5 or 6 years. Although the BESS investment can yield high distribution system cost reductions for small load growth is slightly higher than expected. Therefore, for distributed BESS to be an efficient alternative to traditional DN upgrades, considering network investment deferral as the only revenue stream to justify the investment on distributed BESS, the expected aggregated peak demand growth rate should be low and the load forecast should also have a very low uncertainty.



Fig. 5. NPV of investing on a 715kWh BESS at bus 498 (upper plot) and number of years the substation reinforcement is deferred (lower plot) for different interannual growth rates of peak demand during a 16-year period.

b. Mobile battery energy storage systems

Mobile BESSs have been considered by estimating the annual cost of the project for a smaller time window (see Annex A). The project length indicates the amount of time the mobile BESS unit is installed at each location during its useful life. For instance, a project length of 8 years means that the BESS unit that is installed at 2 different DNs and is used for peak shaving during 8 eight years at each of them. The total cost of mobile BESS increases significantly as the project length decreases because the BESS unit is moved more frequently and this results in higher project-related costs (e.g., shipping and installing the BESS at the new site) that have to be assumed at every different location. On the other hand, the advantage of mobile BESS units is that they are a more flexible option, as they can still be used for peak shaving at another location if the load growth becomes too high and the BESS unit is no longer able to defer a network reinforcement. Nevertheless, in Fig. 6 the window of load growth where BESS is an economic alternative

to network reinforcements is not significantly extended because its annual equivalent costs are still considerably high. Therefore, the main drawbacks for mobile BESSs are uncertainties in estimating the costs of mobile BESSs, increased project complexity and lower cost reductions for small load growth rates.



Fig. 6. NPV of investing a 715kWh mobile BESS at bus 498 for different interannual growth rates of peak demand and different project lengths (i.e., years the mobile BESS remains in this location).

c. BESS cost reduction and revenue stacking

Learning rates, capital grants and stacking multiple ancillary services are modeled based on the assumption that each of these options could allow for a reduction in the fraction of the cost of the BESS asset that will need to be recovered through the deferral of network upgrades. Despite the recent increase in BESS costs due to inflation, it is expected that utility-scale BESS costs will reduce by 25% in 2030 based on a 7% learning rate [30]. In Fig. 7, this scenario (depicted in orange) does not provide much improvement. Thus, further revenue streams or BESS cost reduction will be required to make BESSs an interesting alternative under higher load growth scenarios. A reduction of 75% of BESS costs is required in this case study for the investment to be profitable under all load growth considered scenarios.



Fig. 7. NPV of investing a 715kWh BESS at bus 498 for different interannual growth rates of peak demand during a 16-year period. The different curves represent fractions of the total BESS cost that must be recovered from deferring investments in traditional network reinforcements.

Where allowed by the regulation, stacking the benefits of multiple ancillary services could significantly increase the viability of installing BESS for DSOs, as shown in Fig. 7. This could be achieved because the number of peak days per year when the BESS is required for peak shaving is small (e.g., 20 peak days in this case study). Note that only 10% of the BESS cycles over its lifetime will be used for peak shaving, and from Fig. 7, at least 25% of the total BESS cost is expected to be recovered under all load growth rates considered. Thus, in this case study, the BESS unit, by deferring network investments, would recover at least a portion of its installation cost proportional to the percentage of cycles over its useful life that it is used for peak shaving. Where allowed by the regulation, combining peak shaving with the provision of other grid services should be considered to make installing BESS a profitable alternative in DNP, especially when high load growth rates are expected.

This result is also interesting from the perspective of third-party owned BESS, as it informs on the value for the distribution system of a peak shaving service to defer network reinforcements. BESS owned by third parties can participate in electricity markets and have a wider range of revenue streams. Although DSOs would not own the BESS, they could contract congestion management and voltage control services from third parties only while they are needed. In the European Union, this alternative is currently being discussed in the proposal for the Network Code on Demand Response [34].

5. Conclusions

This paper has analyzed whether the installation of distributed BESSs could be a techno-economic alternative to conventional network reinforcements under sustained load growth scenarios in a case study for a real 500-bus Spanish DN. The results illustrate that installing dedicated distributed BESSs can reduce peak loading in DNs and, thus, reduce the need for grid reinforcements in DNP. Nevertheless, the conditions under which BESSs become a cost-effective alternative are very specific, requiring small interannual load growth rates. These results highlight that BESS costs are still high compared to traditional DN reinforcements, which remain the best option when very high load growth is expected since power lines and transformers can provide electricity continuously if their rating is not exceeded. The reason for investing in BESS when small interannual load growths are expected is that the BESS is only required for a few peak load hours. Therefore, dedicated BESSs are not usually a cost-effective option to delay network reinforcements in DN unless the DSO is certain that low load growth rates are expected. This study could be extended in future research to analyze more grids and scenarios (e.g., non-uniform load growth, future sustainable development scenarios with high adoption of heat pumps and electric vehicles, etc.).

Moreover, the extended project duration of 16 years makes it difficult to recover the investments if demand is expected to rapidly increase. The capacity of BESS becomes insufficient to maintain the grid within its operating limits during peak load hours in a few years. Mobile BESSs could be interesting for shortening the project duration and redeploying the BESS at another location. However, there is very little information on the total costs for mobile BESS projects. The estimates for this paper result in high costs of transporting and installing the BESS at different locations. In this case study, considering BESSs as mobile assets is not enough to make them a cost-efficient DNP alternative for medium or high sustained load growth scenarios.

On the other hand, BESSs are only required for peak shaving during a few days per year. For all scenarios of sustained load growth in the case study, the portion of their total cost that could be recovered through deferral of network reinforcements was higher than the fraction of total cycles required for peak shaving over their lifetime. In this case study, the system benefits achieved by grid reinforcement deferral would cover around 25% of the investment under almost all interannual load growth rates that have been studied. Given that the BESS would only be used for peak-shaving during a few peak load days during the year, there is still room to leverage the BESS to provide other ancillary services that would provide additional benefits. If it is allowed by the regulation, DSOs should consider combining network reinforcements deferral with other system benefits (e.g., resilience) to make them a cost-efficient network asset. Future work will analyze the synergies that emerge from combining the deferral of investments in network reinforcements with other benefits such as enhanced system reliability.

Furthermore, an emerging alternative is that DSOs do not own the BESS, but they contract congestion management and voltage control services from third parties only when they are needed. Future work should

compare the installation of DSO-owned BESSs with flexibility services provided by BESSs and DERs owned by third parties.

Acknowledgements

The authors would like thank Dr. Jose Pablo Chaves-Ávila and David Martín for their helpful guiding comments. This paper is based on the research carried out in the Flexener project, funded by the "Centro para el Desarrollo Tecnológico Industrial" (CDTI) of the Spanish Ministry of Science and Innovation, financed by the call "Misiones CDTI 2019" (project MIG-20201002).

References

- B. Mukhopadhyay, D. Das, Optimal multi-objective long-term sizing of distributed energy resources and hourly power scheduling in a grid-tied microgrid, Sustainable Energy, Grids and Networks 30 (2022) 100632. https://doi.org/10.1016/j.segan.2022.100632.
- [2] European Commission, COMMISSION RECOMMENDATION of 14 March 2023 on Energy Storage Underpinning a decarbonised and secure EU energy system, 2023. https://eur-lex.europa.eu/legalcontent/EN/TXT/?uri=CELEX:32023H0320(01) (accessed July 23, 2023).
- [3] L.A. Wong, V.K. Ramachandaramurthy, P. Taylor, J.B. Ekanayake, S.L. Walker, S. Padmanaban, Review on the optimal placement, sizing and control of an energy storage system in the distribution network, J Energy Storage 21 (2019) 489– 504. https://doi.org/10.1016/j.est.2018.12.015.
- [4] H. Saboori, R. Hemmati, S.M.S. Ghiasi, S. Dehghan, Energy storage planning in electric power distribution networks A state-of-the-art review, Renewable and Sustainable Energy Reviews 79 (2017) 1108–1121. https://doi.org/10.1016/j.rser.2017.05.171.
- [5] G. Carpinelli, G. Celli, S. Mocci, F. Mottola, F. Pilo, D. Proto, Optimal Integration of Distributed Energy Storage Devices in Smart Grids, IEEE Trans Smart Grid 4 (2013) 985–995. https://doi.org/10.1109/TSG.2012.2231100.
- [6] H. Saboori, R. Hemmati, Maximizing DISCO profit in active distribution networks by optimal planning of energy storage systems and distributed generators, Renewable and Sustainable Energy Reviews 71 (2017) 365–372. https://doi.org/10.1016/j.rser.2016.12.066.
- [7] S.F. Santos, D.Z. Fitiwi, M. Shafie-Khah, A.W. Bizuayehu, C.M.P. Cabrita, J.P.S. Catalao, New Multistage and Stochastic Mathematical Model for Maximizing RES Hosting Capacity—Part I: Problem Formulation, IEEE Trans Sustain Energy 8 (2017) 304–319. https://doi.org/10.1109/TSTE.2016.2598400.
- [8] G. Celli, F. Pilo, G. Pisano, G.G. Soma, Distribution energy storage investment prioritization with a real coded multiobjective Genetic Algorithm, Electric Power Systems Research 163 (2018) 154–163. https://doi.org/10.1016/j.epsr.2018.06.008.
- [9] J.H. Yi, R. Cherkaoui, M. Paolone, D. Shchetinin, K. Knezovic, Optimal Co-Planning of ESSs and Line Reinforcement Considering the Dispatchability of Active Distribution Networks, IEEE Transactions on Power Systems 38 (2023) 2485– 2499. https://doi.org/10.1109/TPWRS.2022.3181069.
- [10] C. Gu, J. Wang, Y. Zhang, Q. Li, Y. Chen, Optimal energy storage planning for stacked benefits in power distribution network, Renew Energy 195 (2022) 366–380. https://doi.org/10.1016/j.renene.2022.06.029.
- [11] N.B. Arias, J.C. Lopez, S. Hashemi, J.F. Franco, M.J. Rider, Multi-Objective Sizing of Battery Energy Storage Systems for Stackable Grid Applications, IEEE Trans Smart Grid 12 (2021) 2708–2721. https://doi.org/10.1109/TSG.2020.3042186.
- [12] H. Mehrjerdi, E. Rakhshani, A. Iqbal, Substation expansion deferral by multi-objective battery storage scheduling ensuring minimum cost, J Energy Storage 27 (2020) 101119. https://doi.org/10.1016/j.est.2019.101119.
- [13] W. van Westering, H. Hellendoorn, Low voltage power grid congestion reduction using a community battery: Design principles, control and experimental validation, International Journal of Electrical Power & Energy Systems 114 (2020) 105349. https://doi.org/10.1016/j.ijepes.2019.06.007.
- [14] L. Yao, Z. Damiran, W.H. Lim, Optimal Charging and Discharging Scheduling for Electric Vehicles in a Parking Station with Photovoltaic System and Energy Storage System, Energies (Basel) 10 (2017) 550. https://doi.org/10.3390/en10040550.
- [15] Y. Yang, H. Li, A. Aichhorn, J. Zheng, M. Greenleaf, Sizing Strategy of Distributed Battery Storage System With High Penetration of Photovoltaic for Voltage Regulation and Peak Load Shaving, IEEE Trans Smart Grid 5 (2014) 982–991. https://doi.org/10.1109/TSG.2013.2282504.

- [16] D.M. Greenwood, N.S. Wade, P.C. Taylor, P. Papadopoulos, N. Heyward, A Probabilistic Method Combining Electrical Energy Storage and Real-Time Thermal Ratings to Defer Network Reinforcement, IEEE Trans Sustain Energy 8 (2017) 374–384. https://doi.org/10.1109/TSTE.2016.2600320.
- [17] A. Navon, R. Nitskansky, E. Lipman, J. Belikov, N. Gal, A. Orda, Y. Levron, Energy storage for mitigating grid congestion caused by electric vehicles: A techno-economic analysis using a computationally efficient graph-based methodology, J Energy Storage 58 (2023) 106324. https://doi.org/10.1016/j.est.2022.106324.
- [18] J. Kim, Y. Dvorkin, Enhancing Distribution System Resilience With Mobile Energy Storage and Microgrids, IEEE Trans Smart Grid 10 (2018) 4996–5006. https://doi.org/10.1109/TSG.2018.2872521.
- [19] H. Saboori, Enhancing resilience and sustainability of distribution networks by emergency operation of a truck-mounted mobile battery energy storage fleet, Sustainable Energy, Grids and Networks 34 (2023) 101037. https://doi.org/10.1016/j.segan.2023.101037.
- [20] H.M.A. Ahmed, H.F. Sindi, M.A. Azzouz, A.S.A. Awad, Optimal Sizing and Scheduling of Mobile Energy Storage Toward High Penetration Levels of Renewable Energy and Fast Charging Stations, IEEE Transactions on Energy Conversion 37 (2022) 1075–1086. https://doi.org/10.1109/TEC.2021.3116234.
- [21] S. Xia, Z. Wang, X. Gao, W. Li, Optimal planning of mobile energy storage in active distribution network, IET Smart Grid (2023). https://doi.org/10.1049/stg2.12139.
- [22] M. Zidar, P.S. Georgilakis, N.D. Hatziargyriou, T. Capuder, D. Škrlec, Review of energy storage allocation in power distribution networks: applications, methods and future research, IET Generation, Transmission & Distribution 10 (2016) 645–652. https://doi.org/10.1049/iet-gtd.2015.0447.
- [23] Y.M. Atwa, E.F. El-Saadany, Optimal Allocation of ESS in Distribution Systems With a High Penetration of Wind Energy, IEEE Transactions on Power Systems 25 (2010) 1815–1822. https://doi.org/10.1109/TPWRS.2010.2045663.
- [24] O. Babacan, W. Torre, J. Kleissl, Siting and sizing of distributed energy storage to mitigate voltage impact by solar PV in distribution systems, Solar Energy 146 (2017) 199–208. https://doi.org/10.1016/j.solener.2017.02.047.
- [25] M.H. Roos, D.A.M. Geldtmeijer, H.P. Nguyen, J. Morren, J.G. Slootweg, Optimizing the technical and economic value of energy storage systems in LV networks for DNO applications, Sustainable Energy, Grids and Networks 16 (2018) 207– 216. https://doi.org/10.1016/j.segan.2018.08.001.
- [26] Y. Zhang, Z.Y. Dong, F. Luo, Y. Zheng, K. Meng, K.P. Wong, Optimal allocation of battery energy storage systems in distribution networks with high wind power penetration, IET Renewable Power Generation 10 (2016) 1105–1113. https://doi.org/10.1049/iet-rpg.2015.0542.
- [27] Y. Zheng, Z.Y. Dong, F.J. Luo, K. Meng, J. Qiu, K.P. Wong, Optimal Allocation of Energy Storage System for Risk Mitigation of DISCOs With High Renewable Penetrations, IEEE Transactions on Power Systems 29 (2014) 212–220. https://doi.org/10.1109/TPWRS.2013.2278850.
- [28] J.J. Jamian, M.W. Mustafa, H. Mokhlis, M.A. Baharudin, Simulation study on optimal placement and sizing of Battery Switching Station units using Artificial Bee Colony algorithm, International Journal of Electrical Power & Energy Systems 55 (2014) 592–601. https://doi.org/10.1016/j.ijepes.2013.10.009.
- [29] REE, ESIOS, (2023). https://www.esios.ree.es/en (accessed March 5, 2024).
- [30] V. Viswanathan, K. Mongird, R. Franks, X. Li, V. Sprenkle, R. Baxter, 2022 Grid Energy Storage Technology Cost and Performance Assessment, 2022.
- [31] Orden IET/2660/2015, Ministerio de Industria, Energía y Turismo, 2015. https://www.boe.es/buscar/doc.php?id=BOE-A-2015-13488 (accessed September 2, 2022).
- [32] CNMC, Acuerdo por el que se aprueba la propuesta de metodología de cálculo de la tasa de retribución financiera de las actividades de transporte y distribución de energía eléctrica para el segundo periodo regulatorio 2020-2025, 2018.
- [33] R.D. Zimmerman, C.E. Murillo-Sánchez, R.J. Thomas, MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education, IEEE Transactions on Power Systems 26 (2011) 12–19. https://doi.org/10.1109/TPWRS.2010.2051168.
- [34] ENTSO-e, DSO Entity & ENTSO-E Public consultation on Network Code for Demand Response, 2023. https://consultations.entsoe.eu/markets/public-consultation-networkcode-demand-response/ (accessed March 5, 2024).

Annex A

The cost of mobile BESS has been estimated by breaking down the components of investment cost for a 1MW-4h LFP battery in [30]. The first category accounts for the cost of the mobile BESS that will be exploited over the battery lifetime of 16 years in different locations. The BESS cost includes the battery

modules, container, cabling, switchgear, HVAC, power conversion equipment, and energy management system. On the other hand, there are project-related costs for shipping and installing the BESS that will have to be assumed at each different location and, thus, have to be recovered while the BESS stays at that location. This second category includes project development, engineering and construction, system integration (including shipment of the BESS to the new site and onsite installation of HVAC, fire, and power conversion equipment), and grid integration. The resulting equivalent annual costs for BESS, depending on the years that the BESS remains at each location, are shown in Table I.

Years at the same location	16	8	4	2	1
Equivalent annual cost [€/kWh-yr.]	40,60	51,04	73,08	117,86	207,77

Table I. Equivalent annual cost for mobile BESS given the number of years that the BESS stays at each location.