Optimal Allocation of Battery Energy Storage Systems in Distribution Networks Considering High PV Penetration

Oytun Babacan, *Student Member, IEEE,* William Torre, *Senior Member, IEEE,* and Jan Kleissl.

***Abstract*—The question of how energy storage can be used efficiently and effectively in distribution networks is open and ongoing. This work explores optimal allocation of battery energy storage systems (BESS) in distribution networks to maximize their support in integrating high penetration solar photovoltaics (PV). A genetic algorithm (GA)-based multi-layer multi-objective optimization model is developed that minimizes the voltage deviation caused by high PV penetration and decreases energy loss in the distribution system while also accounting for the BESS capital and operational lifetime. The optimization problem considers BESS unit capacities, BESS installation points in the network and the cumulative BESS capacity of the network as decision variables. Siting constraints that would play a practical role in resource allocation, such as construction limitations, environmental and visual impacts are not included in the model. A case study with the IEEE 8500-Node test feeder is carried out to discuss the effectiveness of the proposed method. The results show a clear connection between BESS sizing and siting decisions and voltage deviation reduction benefits in a distribution network.**

***Index Terms*—Distributed power generation, Energy storage, Hybrid power systems, Genetic algorithms, Power distribution, Power system planning**

I. Introduction

Planning and managing the electric distribution system is becoming more challenging due in part to the emergence of widespread distributed renewable generation. A less predictable system may lead to a variety of issues, ranging from sub-optimal financial planning to unreliable operation. Distributed storage is often considered as a viable tool to offset these impacts. Utility-scale storage systems such as compressed air, flywheels, or batteries have been studied for decades and can be used for a wide range of grid services such as frequency control [1], network voltage control [2] and peak shaving [3].

Optimal operation and allocation of energy storage systems have been studied in the literature looking for an optimal trade-off between technical and economic goals. These studies introduce problem definitions that usually focus on one or several of the following categories: storage operation [3], [4], storage sizing [5], [6], and storage siting [7], [8]. Many of these studies provide solutions to undesirable consequences arising from transforming the existing electric system with distributed renewable energy resources. The motivation for this particular work is to understand the benefits of having energy storage systems in distribution networks with high PV penetration. A particular interest is to fill the gap in understanding how battery energy storage system (BESS) sizing and siting influence the overall benefit of allocating such systems. This effort often requires a problem definition that captures a certain depth of all three categories listed above.

This paper is organized as follows: Section II introduces the methodology by providing a description of the objective function and its terms, the constraints and the implementation of the optimization routine. Section III presents the case study along with the data sources and the test circuit. Section IV concludes the paper with final remarks on the method.

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Oytun Babacan (obabacan@ucsd.edu) and Jan Kleissl (jkleissl@ucsd.edu) are with the Department of Mechanical and Aerospace Engineering, University of California San Diego, La Jolla, CA, 92093 USA

W. Torre (wtorre@ucsd.edu) is with the Center of Energy Research, University of California San Diego, La Jolla, CA, 92093 USA

II. Methodology

A. Problem Definition

The goal is to optimally size and site BESS for a given circuit with a penetration of distributed PV. The ultimate BESS configuration is determined by the three decision variables: the size of each BESS, installation node of each BESS, and total number of BESS in the circuit. The term "BESS configuration" is used herein to mean the set of these three decision variables.

The multi-objective optimization, given in (1), is formulated as a weighted sum method. Each weight is set to unity.

$$max\left\{[n_1\bar{L}_{\Delta E}+n_2\bar{V}_{\text{dev}}+n_3\bar{T}]\cdot\lambda_{\text{cost}}\right. \tag{1}$$

λ_{cost} is a multiplier that decreases the objective function as the aggregate BESS capacity increases. All terms are normalized by an appropriate quantity so that they lay within a similar range with comparable rates of change. Different weighting coefficients could be used but results indicate the present normalization is well-balanced and effective as formulated.

1) Reducing overall energy loss in the feeder: As PV penetration increases, required power supply from the substation during peak solar hours decreases and hence PV reduces energy loss in the network. However, as PV penetration nears 100% and exceeds, reverse power flow becomes an issue. BESSs can shift a portion of PV generation to peak net load hours, reducing congestion and thus energy loss and can store excess energy from the feeder, thereby avoiding reverse power flow. In principle BESSs can reduce energy loss in the

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feeder greater than PV systems achieve alone. The energy loss reduction achieved through the prescribed BESS scheduling is expressed in (2).

$$\bar{L}_{\Delta \mathrm{E}} = \frac{\sum_{i=1}^{T} (P_{L,i}^{\text{base}} - P_{L,i}^{\text{pv+bess}})}{\sum_{i=1}^{T} (P_{L,i}^{\text{base}} - P_{L,i}^{\text{pv}})} - 1 = \frac{\sum_{i=1}^{T} \Delta P_{L,i}^{\text{pv+bess}}}{\sum_{i=1}^{T} \Delta P_{L,i}^{\text{pv}}} - 1 \quad (2)$$

The superscripts *base*, *pv*, and *pv+bess* indicate separate power flow simulations – using the base circuit without PV or BESS support, the circuit with PV at load points, and the circuit with PV and BESS support, respectively. Energy loss for each case is determined by subtracting the *pv* and *pv+bess* cases from the *base* case. The impact of BESS support is the ratio of these two differences. The ratio is then normalized by subtracting from unity – in this way (2) nears unity for nonoperational BESSs after accounting for BESS idling losses.

2) Mitigating voltage deviations at PV generation points: Voltage deviations are caused by local variation in power supply and/or demand. A daily simulation is first run without BESS support to get a base case. Voltage variation at each node is determined as given in (3).

$$\Delta V_n = \sum_{i=1}^{T} \left(V_{n,i}^{\text{pv}} - V_{n,i}^{\text{ref}}\right), \quad \text{for each node n=1,...,N} \quad (3)$$

The voltage deviation caused by PV penetration is calculated based on a reference voltage $V^{\text{ref}} = 1$pu that is independent of time or location. Once known at each node and at time step, the nodal voltage deviation at all nodes is ranked based on per unit voltage difference (from highest to lowest).

The top X "critical nodes" are used to calculate a variance of voltage deviation to form a "network-wide" voltage deviation metric. Here, X is the total number of installed PV systems in the network. Critical nodes are considered so that the deviation metric is not averaged out by less-effected nodes (typically located far from PV systems) and BESS siting is more strongly coupled to the largest points of deviation.

After the variance for *pv* and *pv+bess* cases are calculated, the impact of BESS is determined by taking the ratio of these two variances. The normalization is done by subtracting the ratio from unity before summing for each time step to ensure proper scaling of $\bar{V}_{dev}$ against other parameters.

$$\bar{V}_{dev} = \sum_{i=1}^{T} \left(\frac{V_{dev,i}^{pv}}{V_{dev,t}^{pv+bess}} - 1\right) \quad (4)$$

3) Evaluation of battery degradation: A simple battery degradation model is used to assess the impact of various operating strategies in relation to the chosen system sizing and to rank different BESS sizes for each configuration. Such a ranking differentiates BESS configurations with similar $\bar{L}_{\Delta E}$ and $\bar{V}_{dev}$ through their expected operational life.

The total number of cycles the battery can endure for each scheduled discharge event within the day is assessed using (5) as proposed in [9].

$$L(x) = \left(\frac{u_0}{x}\right)^{u_1} e^{u_2 - u_3 x} \quad (5)$$

where x is the depth of discharge (DOD) for the event. The parameters u_i is determined by performing a best fit of (5) to the cell cycle life data of a battery of interest.

The overall effect of cycling to a battery is determined using an event-oriented ageing model as described in [10]. Many BESS operating schedules (i.e., discharge events) can occur based on local load and irradiance. Each schedule e impacts battery lifetime differently and so they are considered separately as shown in (6),

$$LC_e^{\text{event}} = \frac{\#DOD_e}{L(DOD_e)} \quad (6)$$

where $\#DOD_e$ is the number of events at DOD_e and L(DOD_e) is the corresponding estimated cycle life. This model captures the life impact, or "life cost", when the battery is operated at that particular DOD. The operational cost of dispatching $LC^{\text{operation}}$ is calculated in (7) by summing the life cost of each event e on each BESS m.

$$LC^{\text{operation}} = \sum_{m=1}^{M} \sum_{e=1}^{E} LC_{m,e}^{event} \quad (7)$$

A battery reaches its "end of lifetime" when its operational costs sum to unity. The performance of a BESS is assessed in (8) based on the number days of similar operation it can endure under such conditions until its end of lifetime.

$$\bar{T} = \frac{1}{LC^{\text{operation}}} \frac{1}{T_{\text{goal}}} \quad (8)$$

The total number of days of sustained operation is determined by dividing unity by $LC^{\text{operation}}$. T_{goal} is a predicted or desired operational lifetime and normalizes this value.

4) Assessing the performance of the investment: An economic analysis of BESS typically requires consideration of capital, operating and maintenance costs [11]. While the objectives of the optimization routine (reducing energy loss and voltage deviation and prolonging BESS lifetime) could be monetized considering current markets, the strength of the analysis comes from maximizing the utilization of BESSs based on market-independent performance metrics. An approach which considers explicit monetization has been shown to be effective in mitigating PV impacts by controlling customer behavior [4], though such an approach is not appropriate for this study, which considers utility-scale storage and feeder-level benefits (decreasing energy loss and voltage deviations).

In the optimization routine a BESS cost model is developed that considers the BESS capital cost, marginal benefit, and economies of scale. Consideration of capital cost is necessary because they bound BESS installations. Marginal benefits are considered because, beyond a certain aggregate capacity, the marginal benefit of each additional BESS begins to decrease but likely stays positive until there is no excess power on the feeder with which to charge. Economies of scale make estimating BESS installation cost challenging due cost discrepancies and large variations in the reported values and differing costs between different technologies accompanied with a lack of experimental performance data. In the optimization routine the capital cost is considered as a multiplier, λ_{cost}, to the objective function that penalizes larger BESS installments,

$$\lambda_{\text{cost}}(x) = \left(\frac{a}{x}\right)^b - b \cdot (x - a) \cdot 10^{-3} \tag{9}$$

where a is the smallest permissible BESS sizing, b is a small constant such as 0.020 and x is the total installed BESS capacity in kWh. b can be varied to achieve a desired form of $\lambda_{\text{cost}}(x)$. When $x = a$, $\lambda_{\text{cost}}(a)$ is unity.

$\lambda_{\text{cost}}(x)$ scales the objective function in (1). It is maximized when the capital cost of a chosen system x is minimum. As x increases, $\lambda_{\text{cost}}(x)$ decreases, reflecting the increasing capital cost of installing larger BESS. $\left(\frac{a}{x}\right)^b$ in (9) represents an increasing scale of operation where capital cost is dispersed among more BESS. As x gets relatively large, the per unit cost of additional units becomes constant due to a minimum expenditure independent of the quantity purchased. Each additional BESS unit δx installed to an existing BESS configuration x^* always decreases $\lambda_{\text{cost}}(x^* + \delta x)$. In this way, for the same conferred benefit, a cumulatively smaller BESS configuration is ranked higher compared to its larger. $\lambda_{\text{cost}}(x)$ represents capital costs qualitatively but could be reconfigured into a monetized cost model that reflects specific market characteristics.

B. Constraints

If a configuration is found to be optimal for a certain PV penetration but fails to converge to a feasible solution for a higher PV penetration, it is discarded. Usual restrictions stemming from power flow analysis are not listed here. The voltage regulators in the circuit are set to regulate voltage between $0.95pu$ and $1.05pu$ with $\pm 1pu$ band. BESS start the day with 20% state of charge (their reserve energy) and return to that reserve energy at the end of the day.

Reverse power flow is not allowed at the slack bus and BESS are scheduled to absorb excess generation. If a BESS configuration does not have the proper sizing to store this excess generation, it is discarded from the solution set. Smaller sized configurations are then declared infeasible.

C. Implementation of the Routine

Power flow simulations are conducted using OpenDSS [12], an electric power distribution system simulator. The simulations are solved in "daily" mode and have a time step of 15 minutes. The control mode for the solution is "static".

Battery dispatch for each system is primarily determined by a linear programming (LP) routine that minimizes the daily non-coincident peak demand [3]. The LP routine receives solar PV power and load forecasts as its inputs and sets a load reduction target. In principle, this target is adjusted throughout the day in response to forecast error. In this study, PV power and load data are provided to the LP routine as perfect forecasts, and consequently the battery dispatch is not affected by forecast error. For further detail about this routine see [3]. When reverse power flow from the circuit to the slack bus is imminent, battery dispatch is updated to charge the battery for the duration of the excess generation.

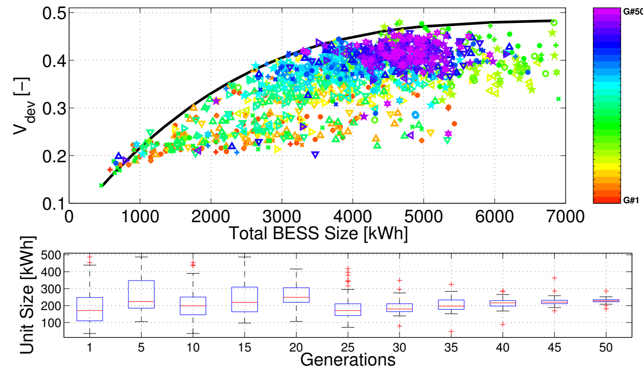

Fig. 1. GA simulation results for $b = 0.020$ and 50% PV penetration. Top: Reduction in voltage deviation in the network for each BESS configuration. Results of individuals belonging to different generations are marked with different colors. The polynomial fit in black depicts the decreasing marginal benefit as the total BESS size increases. Bottom: The progression of BESS unit sizes in the network with increasing generations. GA explores a wide range of unit sizes up to 500kWh and eventually converges to the proximity of 260kWh

Given the nonlinear nature of power flow analysis and fairly large solution space formed by the three decision variables, genetic algorithms (GA) are a viable global search algorithm option for this study. GA implementations are vast in literature and are proven to achieve near-optimality with good computational performances. For length considerations, a detailed explanation for GA routine is not included; however, details necessary to reproduce simulations are provided. At the start of the optimization, 50 solution sets ("individuals") are initialized by uniformly distributing the number of BESS (maximum of 25) and cumulative BESS capacity (maximum capacity equals total PV system capacity in kVA). These systems are sited by a random permutation among permissible nodes.

At each simulation cycle ("generation"), simulations for each individual are run for a clear day, cloudy day and overcast day. The objective function is calculated for each day and a fitness value for the individual is then determined by multiplying each day's result with its weather modifier (see Section III.A) and summing into a single value. After assigning a fitness value to each individual, the whole generation undergoes the GA operators: selection, crossover and mutation. This study uses 10% elitism and a tournament selection operator with a threshold value 0.80. Parameterized uniform crossover with a 0.50 swapping probability is applied for crossing over and in each generation two new randomly generated individuals are introduced to the solution set as part of the mutation.

In terms of BESS siting, the primary interest is utility-owned energy storage. Thus, the batteries are always located on medium voltage (MV) lines on the primary side of the load transformers. The initial conditions restrict the maximum number of BESS to 25 and the maximum cumulative BESS size to the total PV system capacity. Nevertheless, the optimization routine itself does restrict the rating or number of BESS that might be installed to the circuit. If favorable, the solution space may expand into much larger systems compared to the one that is initialized.

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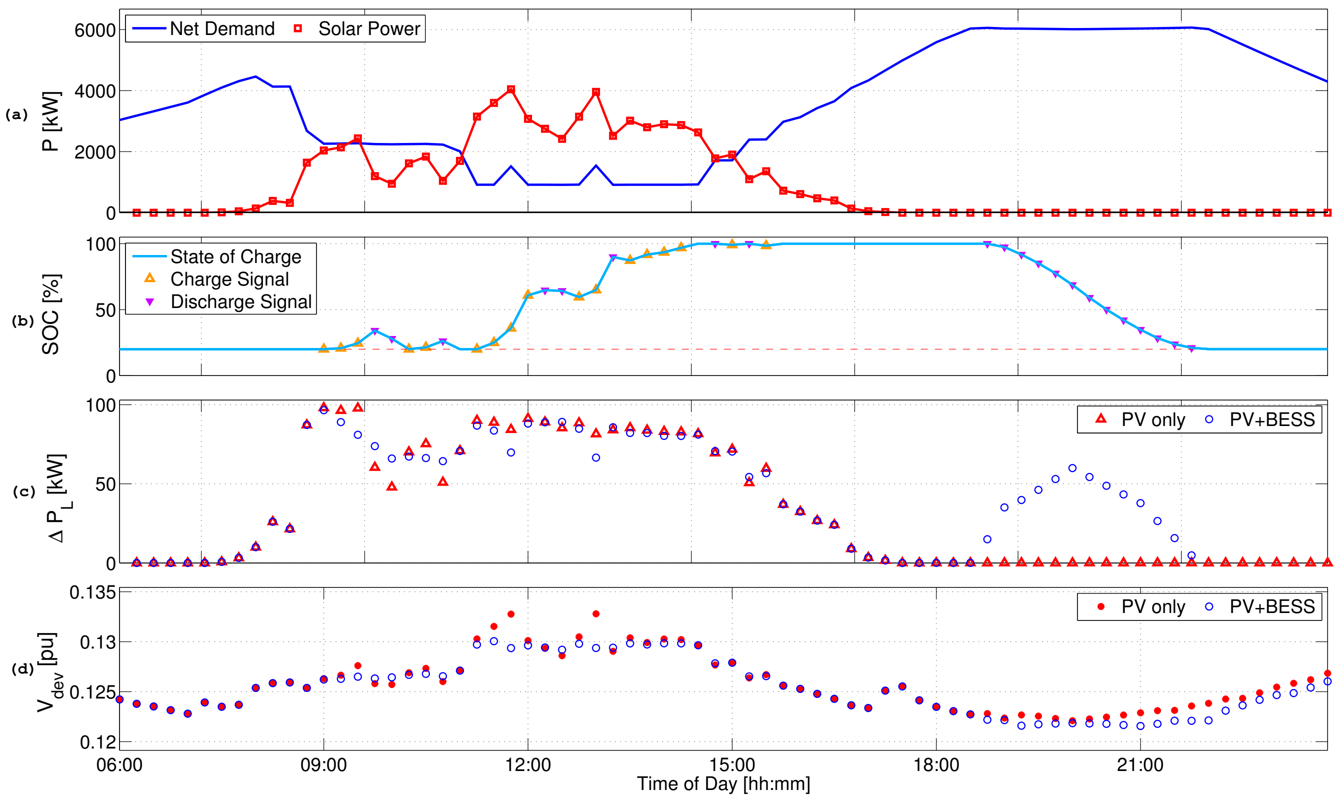

Fig. 2. Overview of a typical daily simulation. The case shown is 50% PV penetration and subject to a cloudy day. (a) the daily net demand and solar power generation in the circuit. (b) the change in the cumulative BESS state of charge with respect to charging and discharging signals. (c) energy loss reduction. (d) the voltage deviation with respect to $1pu$ reference line.

III. Case Study

A. Test Circuit and Data Sources

The IEEE 8500-Node test feeder with balanced 120V secondary loads on the service transformers is chosen as the benchmarking circuit. This circuit is a radial distribution feeder with multiple feeder regulators and capacitors [13] and is a suitable test feeder to assess the performance of the proposed algorithm as it is similar to a large feeder with many typical elements found in a residential distribution feeder.

The PV generation fleet is assumed to be composed of highly distributed rooftop systems located in direct proximity (i.e. secondary side of the service transformer) of respective load points. For each level of PV penetration, PV systems are sited randomly among the load points of the circuit until the desired penetration is reached. Each system is specified to have a capacity equal to the peak demand of that bus.

Testing and demonstration of the algorithm is carried out using 15 minute resolution demand and solar generation data. Generic demand profiles for residential buildings in San Diego are imported from the dataset provided by Open Energy Information (OpenEI) [14]. PV power output data from 2014 are collected from six real PV systems located at the campus of University of California, San Diego campus. The PV system tilt angles are $10°$ and $20°$ depending on the system and their azimuth angle is $180°$. Days representative of clear, cloudy and overcast conditions are chosen for the pool of days that are to be simulated. A weather modifier is calculated by taking the fraction that each of conditions occurs in the year. ($w_{\text{clear}} = 0.448$, $w_{\text{cloudy}} = 0.384$, $w_{\text{overcast}} = 0.168$)

B. Results and Discussion

Three sets of simulation are conducted to demonstrate how objective function performs. The stopping point for the GA routine is reached when either a maximum number of generations is simulated or several consecutive generations do not improve the solution. In this study, a minimum number of generations is set at 50. In these sets b is varied as 0.015, 0.020, and 0.025. The same initialization is used for all simulations, so that none of the simulations has an advantage in convergence rate over others due to a better starting set.

Typical daily BESS operation is shown in Figure 2a and 2b. This example shows a cloudy day with many ramp events on a circuit with 50% penetration. The BESS smooth the ramps with short discharge cycles between 9am and 1pm. Reverse power flow through the slack bus is predicted beforehand by simulating the feeder with PV and without BESS. In this example two reverse power flow events are eliminated at 11:45am and at 1pm. Prior to 6pm the BESS are fully charged and after 6pm are discharged to shave peak demand.

Figure 2c shows the impact of BESS operation on energy loss reduction. During hours of PV generation, PV systems decrease energy loss since demand consumes locally-generated power. The BESS minimally increase energy loss because they charge, thereby adding to the feeder load. During the

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TABLE I
SIMULATION RESULTS AND BESS CONFIGURATIONS FOR CHOSEN B VALUES CONSIDERING 50% PV PENETRATION. "OPTIMAL" IS THE INDIVIDUAL WITH THE HIGHEST FITNESS VALUE. "MEAN" INDICATES THE MEAN VALUE OF ALL SOLUTION SETS.

		Fitness value	Unit Size [kWh]	Total Size [kWh]	Unit [#]
$b = 0.015$	Optimal	1.5972	294	9122	31
	Mean	1.3995	230	3772	19
$b = 0.020$	Optimal	1.4969	285	4575	16
	Mean	1.3466	267	3804	15.8
$b = 0.025$	Optimal	1.4820	191	3439	18
	Mean	1.3560	230	3772	18.7

		Optimal	Mean	Best
$b = 0.015$	$\bar{L}_{\Delta E}$	0.4797	0.3184	0.5014
	$\bar{V}_{\text{dev}}$	0.5566	0.3605	0.5638
	$\bar{T}$	0.8310	0.8349	0.9545
	λ_{cost}	0.8553	-	-
$b = 0.020$	$\bar{L}_{\Delta E}$	0.3444	0.2792	0.4455
	$\bar{V}_{\text{dev}}$	0.4322	0.3302	0.4999
	$\bar{T}$	0.8698	0.8406	0.9553
	λ_{cost}	0.9118	-	-
$b = 0.025$	$\bar{L}_{\Delta E}$	0.2992	0.2887	0.4438
	$\bar{V}_{\text{dev}}$	0.4150	0.3563	0.4752
	$\bar{T}$	0.8719	0.8874	
	λ_{cost}	0.9253	230	3772

evening peak, the BESS dispatch and reduce energy loss significantly. Figure 2d shows the impact of BESS operation on voltage deviation. Here BESS dispatch supports fluctuates in PV generation and stabilizes the local voltage. Reduction in voltage deviation is largest during peak shaving.

GA simulation results for chosen values of b considering 50% PV penetration are summarized in Table I. These results show that the aggregate BESS capacity is directly influenced by b. Installing large BESS in the network becomes favorable with decreasing b and thereby decreasing capital costs. However, the unit size is not so heavily influenced by b. Despite the total BESS size increases almost 100% from $b = 0.020$ to $b = 0.025$, the individual units remain similarly sized but increased in quantity. The network benefits more from widely dispersed BESS than larger, central units.

As capital cost gets larger from $b = 0.020$ to $b = 0.025$, the total BESS capacity decreases as expected but, in return, the total BESS number increases. This behavior shows, for a smaller total capacity, locating more systems closer to critical nodes is more important than installing fewer larger BESS that are far from critical nodes. However, if λ_{cost} is tailored to consider a land-use cost, the optimization will have to favor a more centralized approach and decrease the number of BESSs.

Another interesting observation is the decreasing marginal benefit with increasing installed BESS capacity in the network. The polynomial fit in Figure 1 approximates the maximum for voltage deviation reduction $\bar{V}_{\text{dev}}$ that GA could achieve during its simulations. As the important nodes in the network are supported with sufficiently sized BESS, additional BESS capacity cannot benefit the network with a similar impact. This eventually limits the total BESS capacity installed in the network as additional BESS cannot justify its cost.

IV. CONCLUSION

The paper has proposed a multi-objective GA optimization routine that optimally allocates BESS in distribution networks. Simulations for the proposed methodology are carried out considering three forms of capital cost model. The results have shown that BESS operation can save energy loss in the network by enabling localized storage resources and mitigate voltage deviations at critical nodes. Cumulative BESS capacity in the network is primarily influenced by the cost model but individual BESS sizing and allocation are determined by the associated network-wide benefits they introduce. The proposed method can accommodate different economic models and dispatch schedules and optimally allocate utility-owned BESS according to the given scenarios of interest. Future studies will focus on exploiting these capabilities even further.

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