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Analysis of the applicability and results of swarm intelligence tools for the positioning of Energy Storage Systems

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ABSTRACT

The integration of renewable energy is transforming traditional energy systems, blurring the distinction between producers and consumers and shifting towards a distributed grid network. This change demands innovative approaches to optimize Energy Storage Systems (ESS) and manage grid incidents efficiently, all without significant infrastructural changes. While optimization algorithms like Swarm Intelligence are gaining traction, critical aspects, such as worst-case scenario analysis in distribution networks, remain underexplored. This study addresses this gap by applying stochastic optimization techniques to determine the optimal placement and capacity of ESS in a medium voltage radial distribution system, using the IEEE 33-bus model. The findings highlight the importance of considering worst-case scenarios, offering a balanced evaluation of current methodologies. This research provides valuable insights for improving system flexibility and resilience, contributing to more effective and practical energy optimization strategies in real-world applications.

1. Introduction

The digital and ecological transition in the energy sector has introduced significant challenges, particularly with the increasing integration of renewable energies. This shift has not only expanded the number of large renewable energy producers but has also redefined traditional consumption patterns, creating a blurred distinction between producers and consumers. As a result, the electrical system is undergoing a fundamental transformation, evolving from a traditional cascading model to a distributed network. This new network requires advanced protection, management, monitoring, load balancing, and generation tools.

Despite these advancements, a critical gap remains in the literature regarding the effective management of this evolving energy landscape, particularly concerning the optimization of Energy Storage Systems (ESS) in a way that minimizes infrastructural changes. Addressing this gap is crucial, as modifications to existing infrastructure can incur significant costs. Therefore, the motivation for this study is rooted in the need to develop innovative optimization strategies that enhance system flexibility and efficiency without extensive infrastructural overhauls.

Specifically, this research focuses on the application of stochastic optimization tools to determine the optimal placement of ESS, aiming to improve the system's resilience to grid congestion and incidents. While existing studies have explored various optimization algorithms, such as those based on Swarm Intelligence, there is a notable lack of research addressing the stochastic aspects of ESS location optimization under worst-case scenario analysis. This study aims to fill that gap by examining the effectiveness of these methods in a medium voltage radial distribution system, using the IEEE 33-bus radial model as a test case.

The contribution of this work lies in its detailed analysis of how stochastic optimization tools can enhance grid flexibility and efficiency, particularly in the face of incidents that cause congestion, especially on how the power applied to the system is distributed to stabilize the system, depending on the number of ESS applied and their maximum power. By addressing this overlooked area in the literature, the research provides valuable insights that can guide future studies in optimizing distributed energy resources.

This document is structured as follows: First, the state of the art is presented, focusing on the context, objectives, and analysis of current solutions and alternatives in the literature. Next, various case studies are discussed to assess the applicability of the proposed solutions. The mathematical and computational methodologies used to obtain the results are then detailed, followed by a comprehensive analysis of these results across different scenarios. Finally, the study concludes with proposals for future research directions and a summary of key findings.

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2. State of the art

Several projects and case studies have explored the integration of flexibility and dynamic monitoring in power grids. One notable example is the project by Viesgo, which implemented dynamic monitoring in its distribution network to optimize transmission capacity and integrate wind generation systems [1]. Additionally, utilities like ERCOT in Texas and ELIA in Belgium have adopted ampacity forecasting and distributed monitoring systems to dynamically manage their network capacities in real-time [2,3]. These initiatives have demonstrated the economic and technical benefits of using ampacity forecasts and flexible technologies to optimize the utilization of renewable resources and enhance grid reliability. Furthermore, a study conducted at MINES ParisTech highlighted the economic advantages of ampacity forecasts within the electricity market [4].

Collectively, these projects and studies underscore the critical role of flexibility and dynamic monitoring in the effective integration of energy resources and the safe, efficient operation of power grids. They illustrate how system flexibility, coupled with ampacity management, enables the system to adapt to changes in load and generation. Flexibility allows for more efficient use of line capacity by adjusting power distribution in real-time based on generation and demand. Moreover, it facilitates the use of energy storage systems to absorb excess generation during low demand periods and release stored energy during high demand periods, maintaining line ampacity within safe limits.

The following section presents an analysis of various control and optimization techniques discussed in the literature, applied to electrical distribution systems. It examines existing tools and their impact on system flexibility, offering insights into their application in systems similar to the 33-bus radial network.

2.1. Flexibility of the network

Despite all the advantages that the presence of renewable energies has brought to the electricity system, they have also caused problems concerning the uncertainty and variability of their operation. The capacity of the electricity system to face both problems is defined as flexibility [5]. According to the Danish Energy Agency [6]:

> *The term flexibility describes the ability of a power system to cope with variability and uncertainty in both generation and demand while maintaining a satisfactory level of reliability at a reasonable cost over different time horizons.*

The economic profitability of flexibility, often calculated alongside the opportunity cost, is a crucial metric [5]. This metric assesses the economic benefit of the system's ability to adapt to adverse conditions that could otherwise diminish performance. By offsetting part of the flexibility cost, it inherently ties into the system's opportunity cost.

Flexibility resources are tools that enhance the power system's resilience to changes that might affect the quality and continuity of the power supply [7]. These resources are especially critical in systems with significant renewable energy integration [8–10]. Key resources identified in the literature for analysis include Conventional Generation (CG), Energy Storage Systems (ESS), Demand Response (DR), Dynamic Line Rating (DLR), Wind Turbines (WT), and Photovoltaic Systems (PV) [8].

2.2. Congestion of the electric distribution network

According to the literature, in the context of the power distribution network, congestion in the power grid is defined as the set of technological, legal, or methodological constraints that prevent meeting the system demand [8,11–13], i.e., a congested situation occurs when the demand for electric power exceeds the capacity of the power grid to supply it. Therefore, the basic task of a congestion management procedure is to provide additional power to congested areas. For this, the ability to ensure continuity of supply without a decrease in system reliability and security must be available [4]. In general, if the power system does not meet the expectations of its users in terms of supply quantity, this could be considered congestion.

Based on the specific characteristics of congestion in the distribution network, congestion management methods must be able to address both voltage and overload problems using all the resources provided by Congestion Management (CM), DR, and DLR mechanisms [8,14,15]; and other control devices. A sequence of typical objectives of CM methods in distribution networks is to [11]:

- meets voltage quality requirements in terms of magnitude and degree of balance;
- to give priority to important customers, especially when the capacity of the flexibilities is limited;
- generate optimal scheduling and network configuration in different circumstances to maximize the benefits to customers, the utility, and the network;
- proposes a backup scheme in response to failures.

Additionally, the U.S. Department of Energy (DOE) has been involved in projects field-testing Dynamic Line Rating (DLR) systems, which use real-time data from sensors to dynamically manage line capacities. These efforts have proven beneficial in increasing transmission capacity, reducing grid congestion, and improving the reliability of power supplies [16].

2.3. Energy storage systems

By bridging gaps between non-concurrent renewable energy sources (RES)-based power output [17] and demand in the mid-voltage (MV) and low-voltage (LV) distribution networks, ESSs play a significant role as flexibility sources (FS) in active network management (ANM) schemes [18]. The ESS may offer both active power and reactive power flexibility services, which qualifies them as a multifunctional FS for ANM requirements. With current technological advancements, ESSs can serve as cost-effective FSs and offer a variety of technical ancillary/flexibility services, including voltage control through active power management and frequency control by active power injection.

However, while ESSs are being charged, they add to the system load. When charging at a higher current rate (i.e., fast charging), ESSs can stress the distribution system, particularly at the integration point [19]. The additional load from charging ESSs may negatively impact the distribution network, as demonstrated in section 0. This increased load can elevate the network's overall peak load, leading to negative voltage fluctuations that can damage distribution transformers [18]. To address these challenges, advanced grid solutions such as Active Network Management (ANM) schemes are employed.

In the field of batteries integrated into the distribution system as a compensation tool, Ahmed A. Raouf et al. [11], present an analysis regarding the distribution of this tool along the distribution system, assigning a voltage profile improvement index to quantify the impact of ESS on the system (see Eq. (1)).

$$VPII_h = \frac{\sum_{i=1}^{N} V_{i,h}^{a}}{\sum_{i=1}^{N} V_{i,h}^{b}} \tag{1}$$

2.4. Swarm intelligence applied to electrical systems: ESS location optimization

In the field of power system optimization, Swarm Intelligence algorithms are booming in application due to their resilience and opportunities [22–25]. This type of algorithm is an optimization technique used to solve complex and difficult problems approximately [26,27]. Unlike classical optimization algorithms, metaheuristic algorithms are

Table 1
Comparison of methodologies and findings from various references.

Ref.	Objective	Methodology	Outcome/ Results	Limitations/ Future Work
[20]	Analyze BESS for congestion management	Simulation-based approach with various scenarios	Identified BESS placement improves flexibility	Further research needed on large-scale systems
[3]	Optimize renewable integration	Use of optimization algorithms for ESS placement	Enhanced renewable integration and system stability	Limited consideration of storage technology
[6]	Address uncertainty in power systems	Stochastic methods combined with optimization	Improved handling of variability in renewables	Requires advanced forecasting techniques
[12]	Review optimization algorithms	Comparative study of various algorithms	BA identified as highly effective for IEEE 33-bus	Further validation needed in different networks
[21]	Develop the Bat Algorithm (BA)	Algorithm inspired by bat echolocation	Effective for solving complex optimization problems	High computational effort for large-scale applications
Current Study	Optimize BESS placement using BA	BA simulation in MATLAB, Python, and Power Factory	Achieved optimal BESS configuration, reducing congestion	Explore scalability and integration with real-world systems

more general and versatile, making them suitable for problems that do not have an analytical solution or for which finding the optimal solution is computationally infeasible due to their size or complexity [21]. Therefore, this stochastic methodology is increasingly used in the field of ESS location optimization, where computing the totality of options is unfeasible in most cases. Although this tool has an important potential, yet to be exploited, there are authors who propose different types of swarm intelligence applied to these systems. Within the literature reviewed, seven optimization algorithms have been identified as typically applied to the analysis in the power system. In [12] five are analyzed, being these; particle swarm optimization (PSO), Firefly Algorithm (FA), Novel Bat Algorithm (NBA), Krill Herd (KH) algorithm, and Coyote Optimization Algorithm (COA), which the first three stand out for their applicability in small-scale distribution networks.

- Particle Swarm Optimization (PSO). Developed by Kennedy and Eberhart in 1995 [26], this algorithm has a long history in optimization systems, not especially in the electrical field, but in the experimental mathematical field. This algorithm bases its operation on the swarm behavior, considering the different possible solutions calculated for each iteration as a particle that composes this swarm and that, as one of them approaches a more optimal result, the rest of the swarm (or possible results) follow it, always maintaining a randomness factor. This algorithm has been the main inspiration for all those algorithms that came later, inspired by animal behavior.
- Firefly Algorithm (FA). As a natural continuation of the operation of the PSO, the Firefly Algorithm was developed by Xin-She Yang [27]. This algorithm seeks to adapt the PSO to the behavior of fireflies that, although they attract each other as other swarms might do, their ability to attract and be attracted depends on physiological factors of the fireflies themselves, including an extra factor to provide flexibility to the configuration of the optimization system and its algorithm.
- Novel Bat Algorithm (NBA). The Bat Algorithm (BA), developed by Xin-She Yang [21], is inspired by the behavior of bats to search for the optimization of mathematical functions, redesigning his previous FA.

In order to provide a comparative context that summarizes the methodologies and results of previous studies in the area of power system optimization with the use of energy storage systems (BESS), a comparison table is presented below. This table summarizes the objectives, methodologies, results and limitations of the most relevant works cited in the introduction, as well as the main findings of the present study. In this way, it facilitates the visualization of the contributions of different approaches and highlights the progress made in optimizing the location and capacity of BESS to improve the efficiency and flexibility of electricity systems under congestion scenarios (see Table 1).

3. Design of the case study

For decades, the IEEE has provided standardized test models to perform different research on similar systems, allowing the authors to have some agreement between the structures to be analyzed and facilitating the comparison of the different studies [28].

The distribution system to be used for this work's analysis (33-bus distribution system) was born in 1989 to study the impact of distribution system reconfiguration on losses and load balancing [29]. Since then, this model has gained popularity and is present in a large number of publications, each analyzing different aspects of the system. Since 1989, the original work of Baran and Wu [29] has undergone a few modifications in the literature. Noting the need to adapt it to today's new energy paradigm, the work of Sarineh Hacopian Dolatabadi, et al. [28], makes some updates to the original system.

The 33-bus distribution system's original configuration includes 33 buses, 32 fixed lines, 5 switchable lines, and no reactive power compensation devices. The proposed architecture shown in Fig. 1, however, is a 12.66 (kV) system with a single feeder substation, four DG units, two systems for compensating reactive electricity, 33 buses, and three looping branches (switchable tie lines). When they are voltage-controlled, the buses 18, 22, 25, and 33 that contain DG units can be regarded as PV buses, and the allowed bus voltages during system operation should be kept to a maximum of 0.95 to 1.05 (p.u.). The combined active and reactive demand is 3.715 MW and 2.3 MV Ar, respectively. Table 4 lists the bus data for the proposed test benchmark, offered in both balanced and unbalanced variants to serve also as a test benchmark for imbalanced distribution systems studies.

The statistics for the generating units, including their production cost functions, are shown in Table 2. It is evident that the quadratic elements of the cost functions are minimal and the average quadratic function is roughly linear due to the relatively low amount of DG power generating outputs compared to larger units (more than 100 MW) in transmission systems.

This updated version by Hacopian, et al. [28] and applied to Power Factory by Mostafa Malekpour, et al. [30] will be used, making some slight modifications to allow the system to act together with the algorithm. In this way, different static cases will be defined to detect the

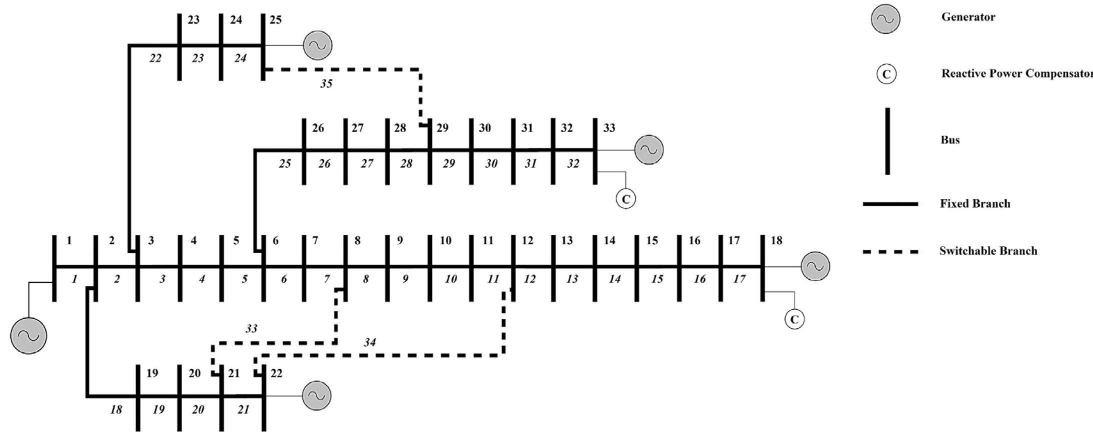

Fig. 1. The enhanced IEEE 33 bus distribution test system [28].

Table 2
Generators data of the Enhanced IEEE 33 Bus Distribution Test System [28].

Bus Number	Active Capacity (MW)	Reactive Capacity (MV AR)	Type	Cost Function ($/h)
1	4	2.5	Feeder (Conventional Generation)	$0.003P^2 + 12P + 240$
18	0.2	0	DG	$0.0026P^2 + 10.26P + 210$
22	0.2	0	DG	$0.0026P^2 + 10.26P + 210$
25	0.2	0	DG	$0.0026P^2 + 10.26P + 210$
33	0.2	0	DG	$0.0026P^2 + 10.26P + 210$

Table 3
Reactive power compensators data [28].

Bus Number	Type	Reactive Capacity (MV AR)
18	Capacitive	0.4
33	Capacitive	0.6

injection of active power necessary to optimize system congestion, to subsequently observe the flexibility that these energy storage systems would bring to the system. The fact that these cases are analyzed statically will limit the ability of the system to determine flow problems due to variations in load flows, as well as the possibility of reverse flow to cascade flow. However, a static analysis is considered sufficiently appropriate for the analysis of the impact and distribution of ESS power within the literature [28,30], thus saving computational effort and system complexity.

Each case is described in more detail below, reflecting the needs and characteristics of the system in each incident situation:

3.1. Case 0

Case 0 represents the original state of the IEEE 33-bus radial system, as updated by [28]. In this scenario, generators are added, and load and generation values are specified (see Tables 4, 2, and 3). As a baseline, we will search for the optimal "battery position + battery capacity" solution to observe how modifications can improve system performance.

The initial state of Case 0 reveals issues with voltage levels in buses 6–18 and 26–33, where voltages fall below 0.95 p.u. (see Fig. 2). Installing ESSs can help stabilize these buses and bring their voltage levels closer to 1 p.u.

To enable the algorithm to interact with the power system, minor modifications were made, such as integrating ESSs at every bus (initially set to 0, so the system functions as if no ESSs were connected) and not considering reactive power compensators.

3.2. Case 1

As shown in Table 5 and in Fig. 2, case 1 is similar to case 0, with the difference that there are no active generators in the system, either due to a problem in the system or because the energy production by the generators cannot be carried out due to any environmental factor.

The modified system is identical to the previous one, keeping the generators in the "Out of Service" category. At the same time, their voltage characteristics are compared with the situation in the previous case, it can be seen that the absence of the generators causes a worsening of the situation in the system buses, increasing the need for the system to implement corrective measures.

3.3. Case 2

The second case presents the casuistry of adding new branches to the original system, increasing the total load of the system from a 33-bus system to a 41-bus system.

The system has two new branches (see Table 6 and Fig. 2), whose buses comprise buses 34-35-36-37 and 38-39-40-41. A large deterioration in the voltage quality of the buses is observed, compared to case 0. Once again it is clear that system solutions need to be implemented to meet the appropriate quality requirements for the network user (see Table 7).

3.4. Case 3

The last case presents a somewhat atypical situation. For undetermined reasons, the different branches of the original system have been isolated, i.e. the lines that make the connections between buses 2–19, 3–23, and 6–26 are in "Out of Service" status (see Fig. 2). This disconnection causes an absolute dependence of the branches concerning their generators, these generators are designed for a much lower energy input than is necessary to meet the needs of the system. On the contrary, looking at the voltage levels, one could conclude that, not only the system status has improved, but also that the main requirement of keeping the voltage levels within the margins imposed by the criterion has been fulfilled. It must be considered that we are only looking at the state of voltage in the system, there being (evidently) many other relevant magnitudes that require attention.

We can see how the simulation program itself, in an attempt to "solve" the situation and be able to perform the simulation, has allowed the generators to produce more than they really could, in some cases even exceeding 650% of their original value. This situation is unsustainable, so finding a solution is key.

Table 4
Bus data of the Enhanced IEEE 33 bus Distribution Test System [28].

Both Test Systems						Unbalanced Three-phase Test System		
Bus Number	Type	Active Demand (MW)	Reactive Demand (MV AR)	Minimum Voltage (p u)	Maximum Voltage (p u)	Number of Phases	Connection Type	Number of Wires
1	Reference	0	0	1	1	3 (ABC)	Y	3
2	PQ	0.1	0.06	1.05	0.95	2 (AB)	Y	3
3	PQ	0.09	0.04	1.05	0.95	1 (A)	Y	3
4	PQ	0.12	0.08	1.05	0.95	2 (BC)	Y	3
5	PQ	0.06	0.03	1.05	0.95	1 (B)	Y	3
6	PQ	0.06	0.02	1.05	0.95	1 (C)	Y	3
7	PQ	0.2	0.1	1.05	0.95	3 (ABC)	D	3
8	PQ	0.06	0.1	1.05	0.95	3 (ABC)	Y	3
9	PQ	0.06	0.02	1.05	0.95	1 (A)	Y	3
10	PQ	0.045	0.02	1.05	0.95	1 (B)	Y	3
11	PQ	0.06	0.03	1.05	0.95	1 (C)	Y	3
12	PQ	0.06	0.035	1.05	0.95	1 (A)	Y	4
13	PQ	0.12	0.035	1.05	0.95	1 (B)	Y	4
14	PQ	0.06	0.08	1.05	0.95	2 (AC)	Y	4
15	PQ	0.06	0.01	1.05	0.95	1 (C)	Y	4
16	PQ	0.06	0.02	1.05	0.95	1 (A)	Y	4
17	PQ	0.06	0.02	1.05	0.95	1 (B)	Y	4
18	PQ/PV	0.09	0.04	1.05	0.95	1 (C)	Y	4
19	PQ	0.09	0.04	1.05	0.95	1 (A)	Y	3
20	PQ	0.09	0.04	1.05	0.95	1 (B)	Y	3
21	PQ	0.09	0.04	1.05	0.95	1 (C)	Y	3
22	PQ/PV	0.09	0.04	1.05	0.95	1 (A)	Y	3
23	PQ	0.09	0.05	1.05	0.95	1 (B)	Y	3
24	PQ	0.42	0.2	1.05	0.95	3 (ABC)	Y	3
25	PQ/PV	0.42	0.2	1.05	0.95	3 (ABC)	D	3
26	PQ	0.06	0.025	1.05	0.95	1 (C)	Y	3
27	PQ	0.06	0.025	1.05	0.95	1 (A)	Y	3
28	PQ	0.06	0.02	1.05	0.95	1 (B)	Y	3
29	PQ	0.12	0.07	1.05	0.95	2 (AB)	Y	4
30	PQ	0.2	0.6	1.05	0.95	1 (C)	Y	4
31	PQ	0.15	0.07	1.05	0.95	2 (BC)	Y	4
32	PQ	0.21	0.1	1.05	0.95	3 (ABC)	Y	4
33	PQ/PV	0.06	0.04	1.05	0.95	1 (A)	Y	4

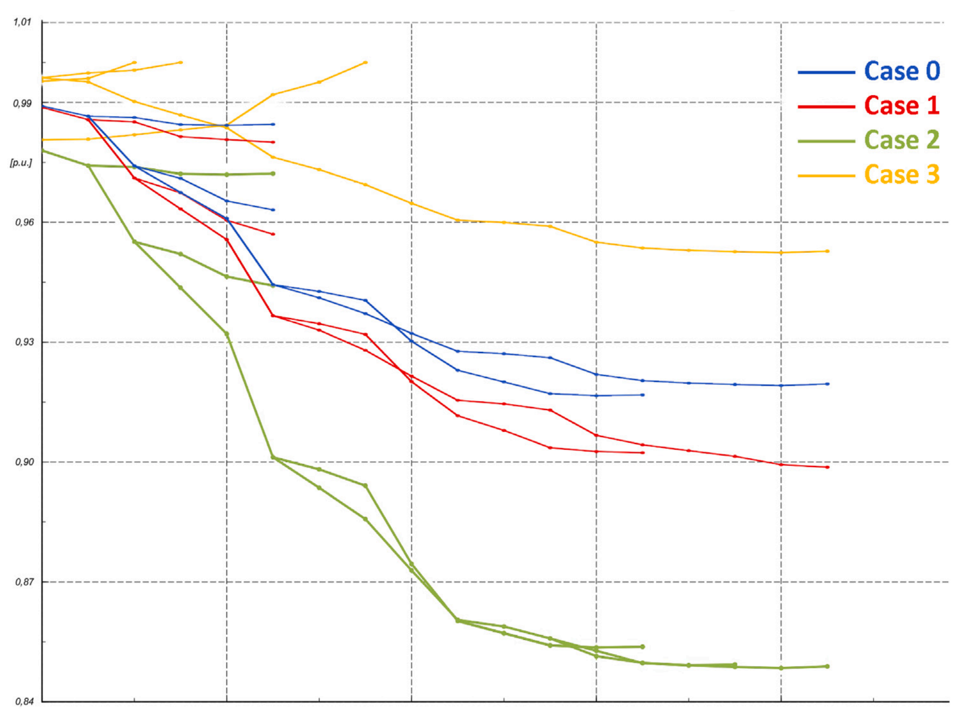

Fig. 2. System profile of case 0, initial state.

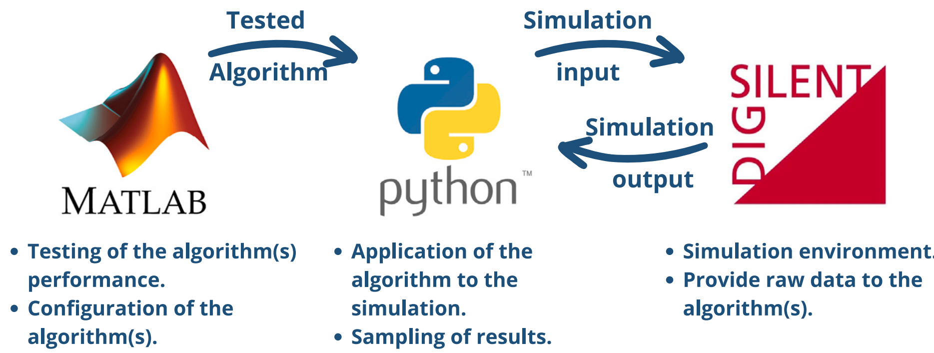

Fig. 3. Distribution and functions of the software applicable to the study.

Table 5
List of analyzed cases.

Case N°	Incident situation
0	None (Reference).
1	All generators are out of service.
2	Two new branches are added (total = 41 bus).
3	Branches are isolated.

4. Methodology

To determine the optimal position and capacity of BESS for enhancing an electrical system's effectiveness against congestion caused by incidents, it is necessary to analyze and evaluate relevant software tools for simulation.

Based on the previously conducted state of the art review, it has been concluded from [12] that various optimization algorithms exist, with the Bat Algorithm (BA) being identified as the most suitable for the majority of cases analyzed in the IEEE 33-bus network. Consequently, a simulation will be performed using the BA to determine the optimal BESS position and capacity for mitigating system congestion in different scenarios.

The BA is an optimization technique inspired by the behavior of bats. Similar to other swarm intelligence algorithms, like Particle Swarm Optimization (PSO), the Bat Algorithm simulates the collective behavior of a group of individuals to find optimal solutions to complex problems.

In this algorithm [21], the inspiration comes from how bats use echolocation to navigate and hunt prey. Bats emit sounds and listen to the echoes that bounce off objects to determine their location and size.

Here's how the algorithm works:

- Bats as particles: Each bat represents a possible solution to the optimization problem.
- Movement towards better solutions: The bats "fly" through the search space, adjusting their positions based on the best solutions found so far. They use their speed, frequency, and sound intensity to explore new areas.
- Exploration and exploitation: Bats adjust the intensity and frequency of their "calls" (signals) to balance the search between exploring new areas (exploration) and honing in on the best solutions found (exploitation).
- Global optimization: Over time, the bats converge around the best solutions, continually refining their positions to find the optimal value desired.

This algorithm is useful for solving complex problems where an optimal solution needs to be found among many possibilities, such as in planning, design, or resource management.

This evaluation will be carried out in three main steps using Matlab, Python, and Power Factory. This combination of applications will facilitate the evaluation, adaptation, and simulation of the BA in the 33-bus system, as illustrated in Fig. 3. Analyzing and evaluating these software tools will enable the simulation of the situations under study and the identification of the most effective BESS configuration.

To begin with the BA code, various tools will be employed. The initial step will involve verifying the correct functioning of the algorithm using Matlab (2022b).

An example of what has been done is presented below. A population of bats is initialized (in this case 50) and the number of iterations or "movements" to be performed per "bat" is designated (also 50). With these variables defined and the data of the original algorithm from [21], the optimization of the Beale function is proposed.

The Beale function looks like Fig. 4 in a three-dimensional environment. As can be seen, the minimum point is difficult to discern, although the environment in which it will be located can be intuited. As Beale is a studied function, we know in advance the minimum point, which will be the target of this algorithm. Thus, we have a function in which we know the optimal point that the algorithm will have to identify. If we start the MatLab code (applying it to the Beale function), we obtain the following results:

As can be seen in Fig. 6, after completing the 50 iterations with the 50 bats, a result of $f_{best} = (2.98507, 0.49594)$ has been obtained, showing a minimum error (in this case, specifically 1.32%). Another appreciable factor in Fig. 5, and characteristic of the Bat Algorithm, is the behavior of the possible results or "bats". This is detailed in Fig. 6, where those divergent bats and the point where most of the bats have converged are highlighted.

Of course, the number of iterations or bats can be modified to optimize the computational resources to the maximum. Some cases contain a substantial error, so in the analysis of Table 8 the computational effort applied to the algorithm is extended to refine the result. This has a direct effect on the simulation time, which, although they are now admissible amounts of time when applied to a complex system can become a limiting factor in terms of the system's computability.

The main tool for running the simulation was an Intel(R) Core(TM) i7-7700HQ CPU @ 2.80 GHz, 2808 MHz with 4 main cores and 8 logical processors.

5. Results

Following the creation of ten iterations of the software, it is deemed that the program aligns with the project's initial objectives, as it can furnish the user with pertinent solutions to accommodate the system's intricate scenarios. Subsequently, the scrutiny and evaluation of the system's attained outcomes commenced.

Table 6
Bus data of the Enhanced IEEE 33 bus Distribution Test System.

Bus number	Type	Active Demand (MW)	Reactive Demand (MW AR)	Minimum Voltage (p u)	Maximum Voltage (p u)	Number of Phases	Connection Type	Number of Wires
34	PQ	0.2	0.6	1.05	0.95	1 (C)	Y	4
35	PQ	0.15	0.07	1.05	0.95	2 (BC)	Y	4
36	PQ	0.21	0.1	1.05	0.95	3 (ABC)	Y	4
37	PQ/PV	0.06	0.04	1.05	0.95	1 (A)	Y	4
38	PQ	0.2	0.6	1.05	0.95	1 (C)	Y	4
39	PQ	0.15	0.07	1.05	0.95	2 (BC)	Y	4
40	PQ	0.21	0.1	1.05	0.95	3 (ABC)	Y	4
41	PQ/PV	0.06	0.04	1.05	0.95	1 (A)	Y	4

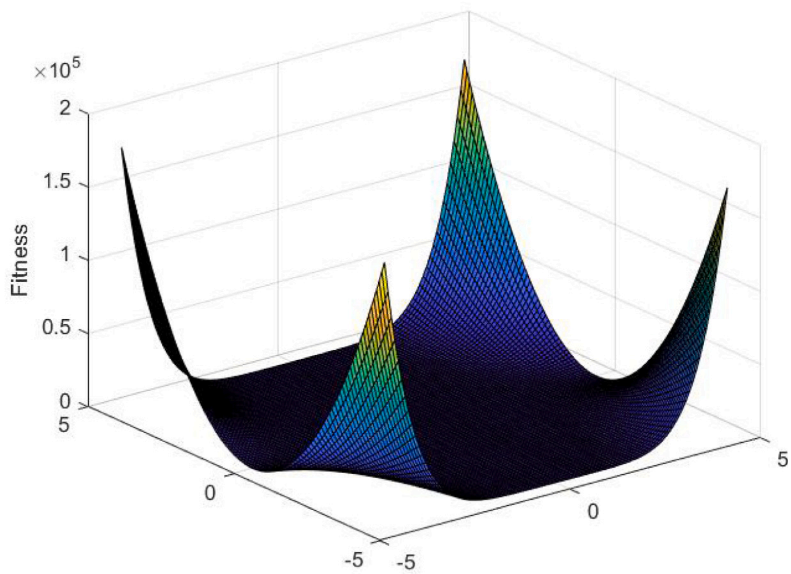

Fig. 4. Beale Function 3D representation.

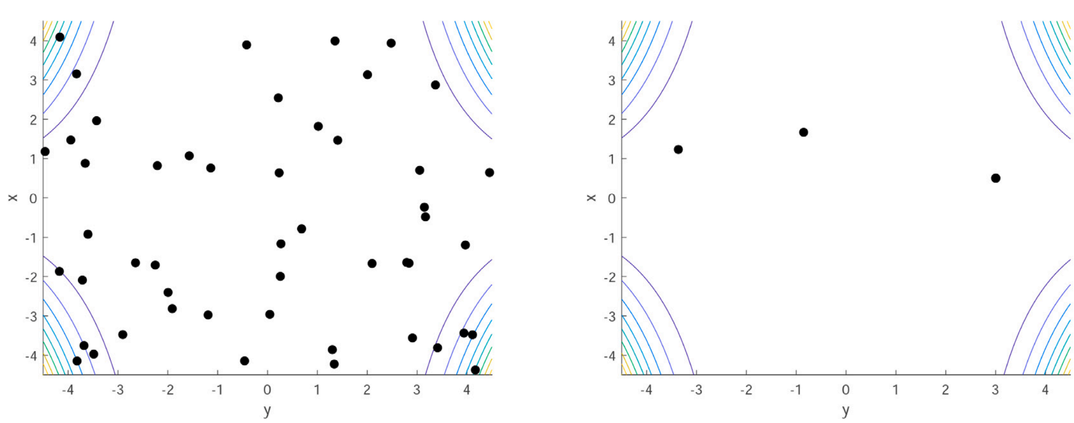

Fig. 5. Graphical expression (2D) of the location of the results in (a) the initial interaction and (b) the final iteration.

Table 7
Generators data of the Enhanced IEEE 33 Bus Distribution Test System.

Bus number	Active Capacity (MW)	Reactive Capacity (MW AR)	Type	Cost Function ($/h)
37	0.2	0	DG	$0.0026P^2 + 10.26P + 210$
41	0.2	0	DG	$0.0026P^2 + 10.26P + 210$

5.1. Case 0

In order to verify the program's efficacy, a reiteration of the same test conducted on version 8 was undertaken. This involved executing 150 iterations with a 10/5 ratio, focusing solely on the implementation of a single ESS. A comparison between the system's performance before and after ESS integration is depicted in [Figure 56], with the solution derived from the system, where two ESS units (0.816 MW on Bus 29 and 0.884 MW on Bus 15) were applied (see Fig. 7).

Expanding the investigation to include additional storage units, the data depicted in the current images pertains to the utilization of two

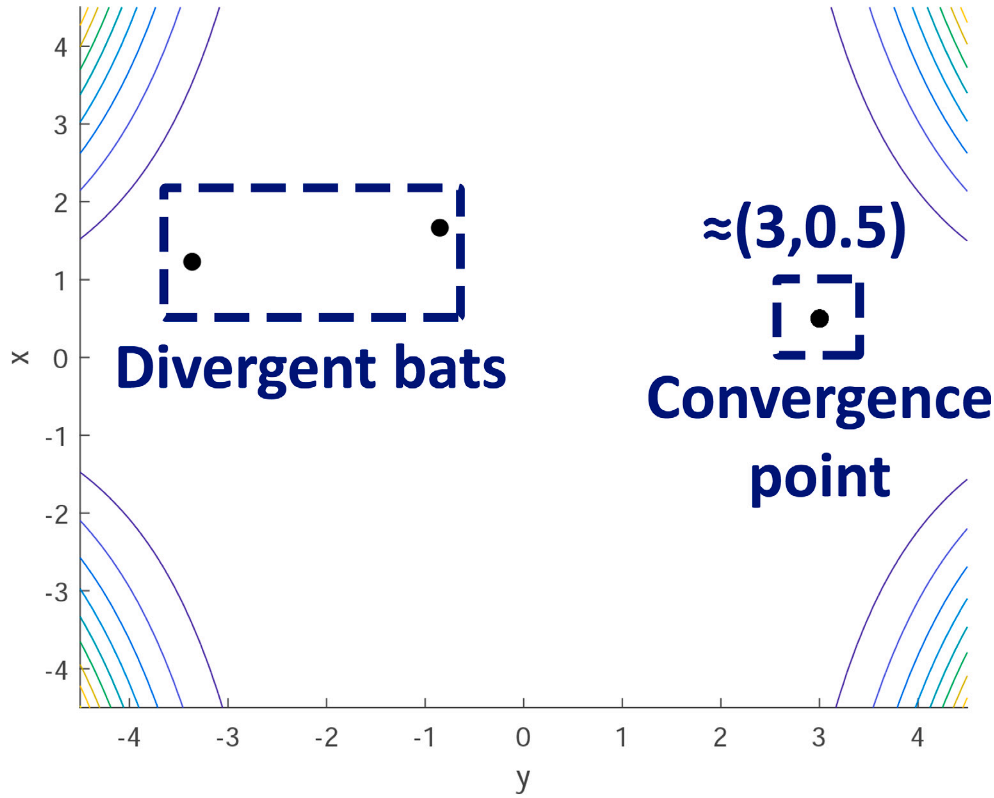

Fig. 6. Final status after 50 iterations of 50 bats, descriptive picture.

Table 8
Comparison of results by varying the movement/bat ratio.

Function	Launches	50/50*		100/100*		250/250*		500/500*	
		ϵ	t_{sim} (s)	ϵ	t_{sim} (s)	ϵ	t_{sim} (s)	ϵ	t_{sim} (s)
Beale	150	0.047**	14.58	0.017**	40.28	0.00%	224.18	0.00%	931.66
Ackley	150	0.008**	13.76	0.00%	40.26	0.00%	226.69	***	***
McCormick	150	0.31%	14.71	0.37%	40.18	0.00%	220.45	0.00%	959.65
Eggholder	150	13.34%	13.77	8.65%	39.59	4.19%	226.37	2.81%	948.48
Goldstein Price	150	29.44%	14.52	0.69%	38.82	0.00%	217.53	***	***

* movement/bat ratio.
** absolute error (no percentual) due to division by zero.
*** it is not considered relevant to perform the calculation.

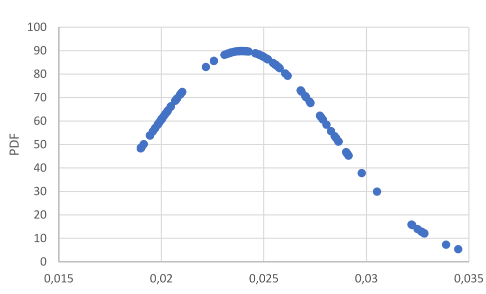

Fig. 7. Normal function of error with one ESS.

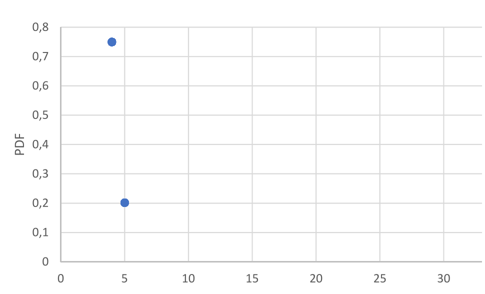

Fig. 8. Normal function of the buses that do not meet the criterion with one ESS.

ESS. It is noteworthy to highlight that, with the implementation of two ESS, the outcomes consistently adhere to the criterion of maintaining all buses within the prescribed parameters. Hence, there will be no equivalent to Fig. 8 in this section (see Figs. 9–14).

The tables presented above illustrate the values observed in the implementation of two ESS. Now, let us examine the scenario when three ESS are employed:

Upon comparing the previously presented Figures, several patterns and traits emerge:

- In the baseline scenario (case 0), no viable solutions are identified that fulfill all predefined criteria. However, this issue is rectified with the introduction of two ESS, resulting in the fulfillment of requirements in 100% of the outcomes (see Figs. 15–18).

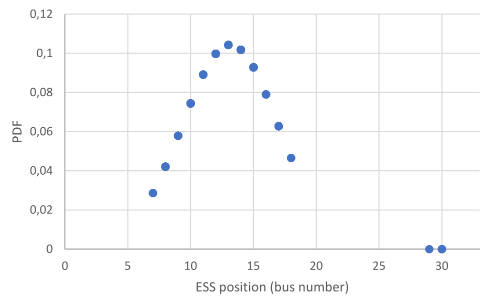

Fig. 9. Normal function of ESS position with one ESS.

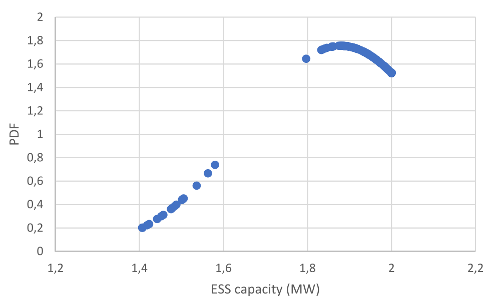

Fig. 10. Normal function of ESS active power with one ESS.

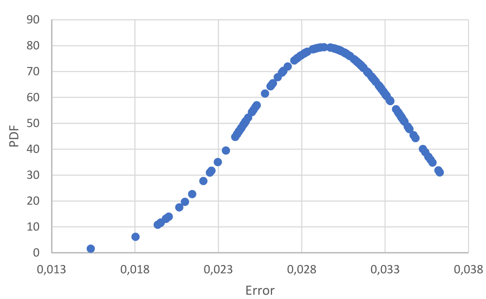

Fig. 11. Normal function of error with two ESS.

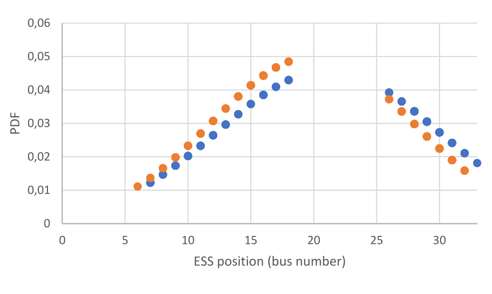

Fig. 12. Normal function of V10 of ESS position with two ESS.

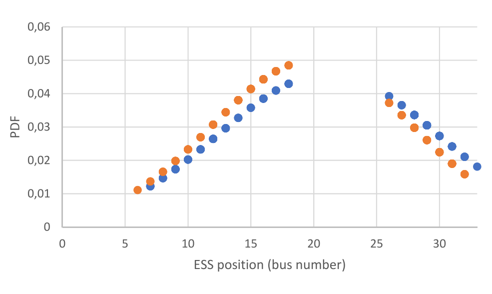

Fig. 13. Normal function of ESS position with two ESS.

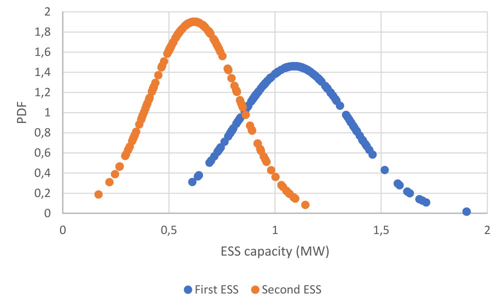

Fig. 14. Normal function of ESS active power with two ESS.

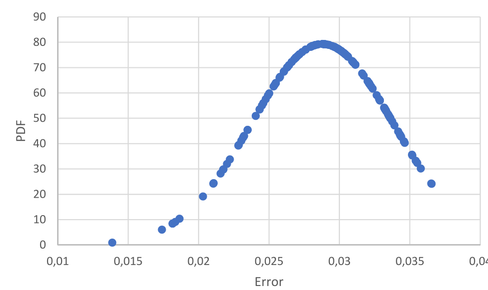

Fig. 15. Normal function of error with two ESS.

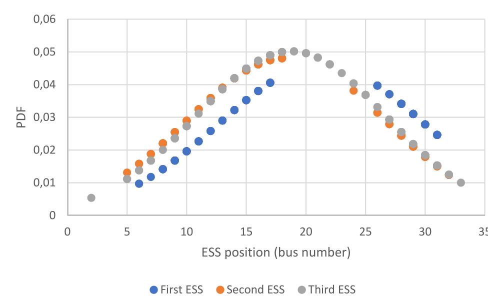

Fig. 16. Normal function of V10 of ESS position with three ESS.

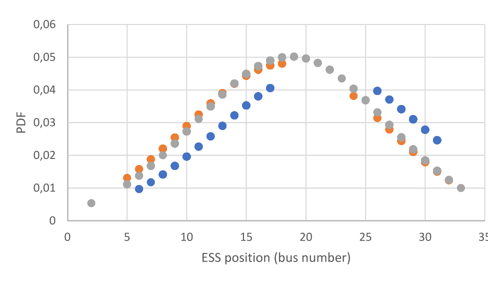

Fig. 17. Normal function of ESS position with two ESS.

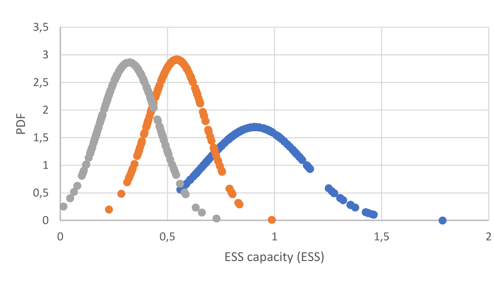

Fig. 18. Normal function of ESS active power with three ESS.

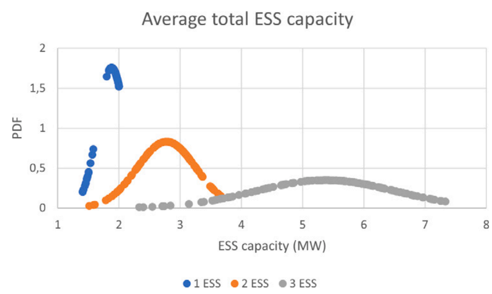

Fig. 19. Normal function of total ESS active power for one, two, and three ESS.

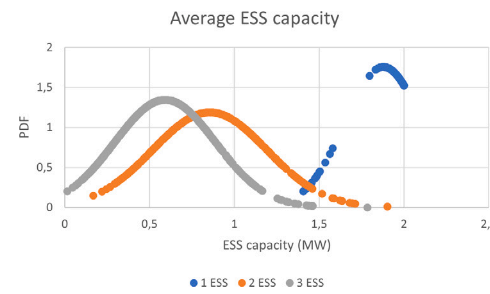

Fig. 20. Normal function of ESS active power for one, two, and three ESS.

- There exists a slight inclination towards an increase in the overall system load, alongside a noteworthy decrease in the average load of each ESS, as depicted in Figs. 19 and 20.
- Likewise, an increase in the average error is noted (refer to Fig. 21), nearing the predefined threshold of 5%. Hence, it can be inferred that the greater the number of ESS, the more optimized the system distribution will become.

5.2. Case 1

These results, corroborated by the data obtained by the simulator, are consistent and meet the system's needs. In this case, a certain similarity is observed with that obtained in case 0, but the integration of a single ESS for system voltage stabilization is also insufficient. Thus, the simulator results shown in Fig. 22 show the case of the application of two ESS (1.044 MW on Bus 10 and 0.905 on Bus 17).

5.3. Case 2

This case presents a scenario where the original system of 33 buses has expanded to 41, with the addition of two divergences. When applying the program to this case, as shown in Fig. 22, the results are still as expected. Unlike the 33-bus system, the 41-bus system requires three ESSs to meet the voltage requirements for all its buses, whereas the 33-bus system only needed two ESSs.

The need for three ESSs is likely due to the addition of the two new branches extending from the main network. Fig. 22 demonstrates that applying three ESSs, as specified by the program, keeps the voltage levels across all buses within the necessary margins to meet quality requirements for consumers.

5.4. Case 3

As presented in previous sections, case 3 exhibits certain unique characteristics compared to the other cases. Unlike the others, case 3 already meets the voltage level requirements but does so by overstressing the system generators. This indicates the presence of an important factor that the program currently does not consider.

This case highlights the need to increase the number of parameters in the program to ensure that the system provides the user with the necessary quality and safety for correct energy consumption. Given that the solution criteria in this project have been limited to voltage levels, it is assumed that the results may not be sufficiently appropriate to deem the system suitable from a more realistic perspective.

As expected, the proposed solutions appear promising. However, unlike the other cases, in case 3, there is no number of ESSs that is insufficient to stabilize the system voltage. Yet, Table 9 reveals multiple inconsistencies:

One of the first inconsistencies detected is that the program presents the same bus twice in the same solution, due to the lack of a function to ensure that the buses are not repeated. This is considered a bug.

Table 9
Comparison of results by varying the movement/bat ratio.

ESS quantity	G1	G2	G3	G4	ESS locations			
					G1	G2	G3	G4
0	100	197, 4	517, 7	669, 9				
1	100	197, 4	517, 7	669, 9	12			
2	100	99, 6	517, 7	669, 9	8	19		
3	100	87, 5	517, 7	669, 9	8, 18	22		
4	100	197, 4	476, 9	641, 8	13		23	27
5	100	88, 3	290, 9	669, 9	6, 15, 18	22	24	
6	100	94, 3	517, 7	566, 4	6, 13, 15	22		26

The second inconsistency is the significant overstress on the generators to achieve optimal voltage levels, which would be unfeasible in reality. However, it is possible to reduce this overstress by integrating ESSs into different branches, as shown in Table 9, which decreases the burden on the main generators.

These results indicate that the program needs to consider more variables than just bus voltage levels to fully meet its objectives.

6. Limitations of the study and future lines of research

In analyzing the results we must be aware of the limitations of the study. Firstly, storage technologies play a critical role in the effectiveness of the proposed optimization methods. The study assumes the availability of advanced Energy Storage Systems (ESS) with specific characteristics, such as capacity, efficiency, and response time, which directly impact system stability and flexibility. Future research should validate these assumptions by examining various storage technologies, including battery types, their degradation rates, and the economic implications of their deployment.

Similarly, the integration of renewable energy sources is a key consideration. The variability and unpredictability of renewables, such as solar and wind power, introduce additional complexity into the optimization process. This study assumes a certain level of penetration and reliability of these sources, but further research should explore scenarios with varying levels of renewable integration, including the impact of geographic and temporal factors on system performance.

Moreover, relevant constraints such as grid infrastructure limitations, regulatory policies, and environmental considerations are not fully explored in the current analysis. These constraints could significantly affect the feasibility and outcomes of the optimization strategies proposed. Future studies should incorporate these factors to provide a more comprehensive evaluation of the program's applicability.

These avenues of research highlight the potential for further development and refinement of the program, ensuring it remains a valuable tool for optimizing and analyzing electricity systems.

7. Conclusions

In conclusion, the present study has achieved its proposed objectives through the development of an electrical systems optimization program

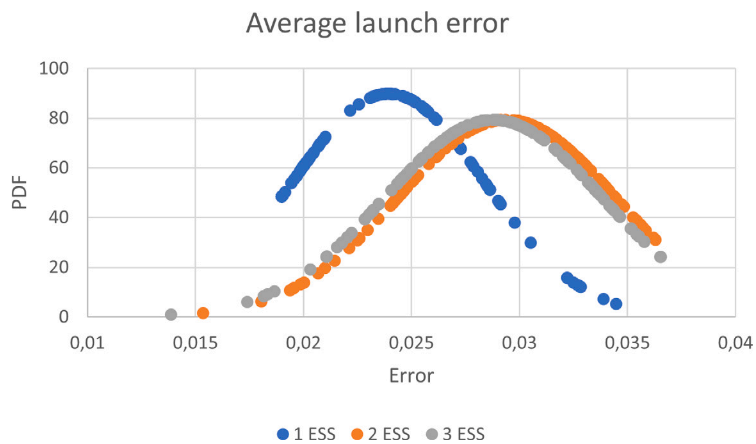

Fig. 21. Normal function of V10 error with one, two, and three ESS.

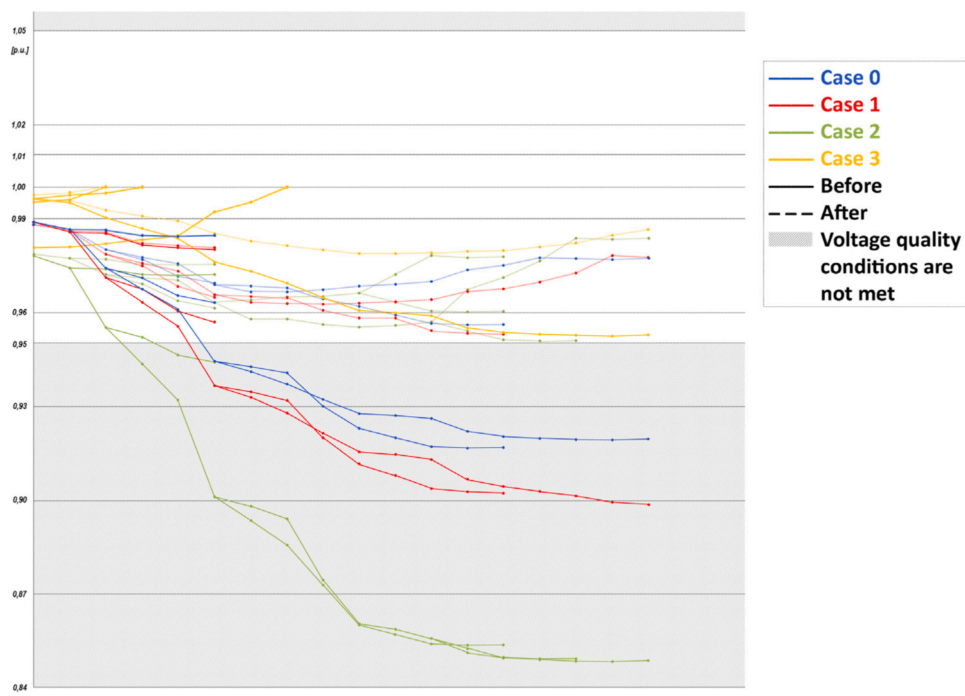

Fig. 22. Comparison of before and after ESS installation in case 0, case 1, case 2, and case 3.

that allows the user to tailor their system to their needs, providing necessary flexibility through energy storage systems (ESS). This study has implemented advanced optimization techniques and has considered both deterministic and stochastic aspects to address the uncertainty and variability inherent in modern electrical systems. Despite these achievements, new needs have been identified that could enhance the program's results and make the scalability of the analysis more efficient.

The developed program demonstrates a notable capacity to enhance the flexibility and efficiency of medium voltage distribution systems using ESS, which is crucial for managing congestion scenarios in the network. The application of stochastic techniques has proven effective in addressing the uncertainty and variability inherent in modern electrical systems, providing robust and adaptable solutions. The configuration and application of algorithms can significantly vary in their outcomes, suggesting that future research should carefully consider how these algorithms are configured and applied to obtain more consistent and accurate results. Furthermore, the study has validated its findings through extensive simulations in MATLAB and Python, demonstrating the practical applicability of the conclusions in real power systems. The possibility of applying this approach to real systems has been discussed and is an important step towards practical implementation.

The study's findings were supported by simulations conducted in MATLAB and Python, which provide a preliminary indication of their applicability to real power systems. The potential for applying this approach in real-world scenarios has been considered, representing an initial step towards practical implementation.

This work contributes to the field of electrical engineering by providing an innovative tool for the optimization of electrical systems, improving the management and use of ESS in distribution networks. The developed methodology is adaptable to different system needs, opening the door to its application in other contexts, such as increasing flexibility in response to the rise in energy consumption from electric vehicles or analyzing transmission capacity. Additionally, the study has expanded the literature review with recent and relevant studies, highlighting the evolution of methodologies and technologies in the field of ESS, and providing an updated and relevant framework for future research.

In terms of areas for improvement and future lines of research, further optimization of the algorithm is suggested to further enhance its performance and efficiency. Incorporating machine learning techniques could enable the program to learn from previous responses and optimize its performance in similar future cases, reducing unnecessary computational effort. It is also important to explore the applicability of the methodology to other system needs, such as managing transmission capacity and adapting to increases in energy consumption. Encouraging collaboration between researchers and industry professionals to standardize methodologies and compare results will ensure the replicability and validity of future studies. Finally, it is crucial to emphasize the novelty of the study compared to other similar works, highlighting how it addresses the limitations of previous research and contributes significantly to advancing knowledge in ESS optimization.

CRediT authorship contribution statement

Asier Divasson-J: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Itxaso Aranzabal Santamaria:** Writing – review & editing, Supervision, Conceptualization. **Miren T. Bedialauneta Landaribar:** Supervision. **Paula Castillo Aguirre:** Software.

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Declaration of competing interest

We declare that there is no conflict of interest regarding the publication of our manuscript.

Data availability

No data was used for the research described in the article.

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