Assessment and Simulation of Strategies to Enhance Hosting Capacity and Reduce Power Losses in Distribution Networks

Ivo Benitez Cattani, *Member, IEEE*, Enrique Chaparro, *Member, IEEE*, and Benjamín Barán, *Senior Member, IEEE*

***Abstract*—Distribution systems are increasingly experiencing the penetration of photovoltaic (PV) systems. Although PV penetration is beneficial up to a point, beyond that point, it begins to generate issues related to voltage levels and grid stability. In modern distribution system planning, it is essential to identify an optimal operational point where the integration of PV supports the voltage profile rather than causing any adverse effects. The purpose of this paper is to explore and evaluate strategies to enhance Hosting Capacity and reduce Power Losses in distribution systems through an optimization algorithm that iteratively uses power-flow simulations and a Multi-Objective Genetic Algorithm. Different strategies taking advantage of conventional distribution system assets are formulated to avoid new system reinforcement. The strategies include Network Reconfiguration, Capacitor Switching, On-Load Tap Changer Switching, Volt-VAR Control Settings and the Combination of all strategies. To evaluate the efficiency of each approach, a comprehensive simulation study is conducted on the IEEE 123 bus distribution system modeled in OpenDSS, with an algorithm created in Python to control the optimization process.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/8853

***Index Terms*—PV system, Power Losses, Hosting Capacity, Multi-Objective Optimization.**

I. Introduction

Modern electric distribution systems are undergoing a major restructuring in order to accommodate the integration of Photovoltaic (PV) systems and meet increasing customer demands. Home PV systems are often installed on rooftops, exploiting the sun's vast energy to produce power locally. Investing in and owning PV systems seams very compelling to the utility customers since they can significantly reduce their reliance on the traditional power grid and achieve long-term savings. Due to these benefits, the number of PV owners is steadily increasing, creating distribution system operational and management challenges.

The challenges associated with PV penetration arise due to the traditional way that distribution systems were designed to handle only one-way power-flow. However, integrating PVs can feed power back into the grid; this can lead to issues such as overvoltage. There are strategies to increase the amount of PV that a system can safely accommodate. Hosting Capacity (HC) is the measure that refers to the maximum amount of PV systems that a power grid can house before compromising its safety.

Another major concern in power distribution is related to the losses that occur when electricity is distributed from substations to utility clients. Power distribution incurs unavoidable losses due to line resistance. Nevertheless, there are technical opportunities to minimize Power Losses and maximize energy utilization. Therefore, this paper aims to explore strategies that can significantly increase the HC and simultaneously reduce Power Losses.

Over the course of years, research works have been using the process of distribution system reconfiguration to reduce Power Losses [1]–[5]. In recent years, the reconfiguration has been also applied as a strategy for enhancing HC within modern power networks. In [6], an optimal power-flow method is used to explore the potential benefits from adopting static and dynamic network reconfiguration as options to increase the ability of distribution systems to host Distributed Generation (DG). The authors in [7] present a mathematical model to find the optimal network topology and detect the optimal DG allocation while considering network technical limits related to line capacity and voltage range. A stochastic approach was used in [8] to analyze the impact of network reconfiguration on improving photovoltaic Hosting Capacity.

Alternatively, smart inverter functions, like Volt-VAR can improve distribution voltage regulation and increase PV HC [9]. In [10]–[12], the efficiency of using Volt-VAR control to increase HC is evaluated. The studies presented in [13], [14] explore an additional advantage offered by smart inverters; these studies investigate the potential of employing Volt-VAR control strategies to mitigate Power Losses.

There are several ways to reduce Power Losses in distribution systems; one of the most commonly used is the installation of capacitor banks [15]. In [16], a strategy was developed for determining optimal set points for capacitor controls to minimize line losses at all load levels. The study outlined in [17] compares the results of simulation studies on selected criteria capacitor bank control to reduce the network losses

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and variability of voltage in Medium Voltage (MV) network. In [18], [19], the capacitor bank operation has been studied as a strategy to increase Hosting Capacity, where various HC enhancement techniques are examined.

An alternative strategy of increasing Hosting Capacity is using On-Load Tap Changer (OLTC). The effectiveness of this strategy was demonstrated in [20], and an investment analysis was performed comparing the cost of the OLTC-fitted transformer with the network reinforcement cost. In [21], the use of PV VAR absorption and OLTC transformers were assessed as techniques to increase the HC. The interactions of Low Voltage (LV) and Medium Voltage (MV) networks were assessed using Monte Carlo simulation. In addition to increasing HC, OLTC also proves valuable in minimizing Power Losses, as shown in [22], where an Artificial Neural Network technique was proposed for predicting optimum tap changing transformer ratio, which in turn minimize real Power Losses in an electrical power system. While reference [23] introduces an Ant Colony Optimization approach designed to determine the optimal settings of OLTC and Reactive Power Compensation Equipment. The goal is to enhance voltage stability within the system while concurrently minimizing Power Losses.

The studies mentioned above addressed the problems of enhancing HC and minimizing Power Losses individually, treating them as single-objective problems. Although our literature review identified research works in a multi-objective context, their approaches differ from those of the present study. For example, the research work by [24] also considers HC and Power Losses as a multi-objective problem, including a third objective function aimed at enhancing the system's base resilience. However, this study focuses on optimizing the placement and sizing of PV systems without incorporating the strategies used in the present study. Additionally, the research suggests future exploration of appropriate smart inverters functionalities of PV, which aligns with one of the strategies in our study—specifically, the use of Volt-VAR control settings.

In contrast, the research work presented in [25] considered strategies to adjust the voltage profile within a multi-objective framework to support HC, but it did not address the reduction of Power Losses in the system. This research suggested that future studies should compare the performance of various HC enhancement techniques and develop combinations of technics to achieve higher HC. This is precisely the focus of the present study, which uses four different strategies to improve HC, combines them to form a fifth strategy, and evaluates the performance of each one. Our study not only improves HC but also reduces Power Losses.

As far as the authors are aware, until date no existing paper has proposed an algorithm that employs all the strategies discussed in this work for multi-objective optimization to enhance HC and reduce Power Losses. Furthermore, no previous research has compared the performance of these strategies through several simulations.

All strategies proposed in this research tries to use pre-existing facilities within the power distribution system in order to mitigate costly network reinforcements. Initially, the Capacitor Switching, OLTC Switching, Volt-VAR Control Settings and Network Reconfiguration strategies are independently implemented on the IEEE 123-bus Feeder [26]. Subsequently, the Combination of all strategies is employed to assess the performance of each approach.

Addressing the optimization problem to increase HC and simultaneously reduce Power Losses requires the use of some multi-objective algorithm to optimize the referred objective functions. The literature demonstrates that Genetic Algorithms (GAs) are a promising tool for this kind of problem. Although GAs do not always guarantee a globally optimal solution, they are designed to find good, often near-optimal solutions [27]. The Non-Dominated Sorting Genetic Algorithm II (NSGA-II), which is based on Genetic Algorithms (GAs), has been successfully applied to a variety of multi-objective power system problems, such as those in [28], where NSGA-II has been implemented to optimal integration and sizing of DG in power network in order to maximize system loadability and minimize real Power Losses. In [29], NSGA-II was used in a management method of energy storage system in PV-integrated Electric Vehicle charging station to minimize the power purchase cost of charging stations and the power variance of the load. The work documented in [30] highlights the utilization of NSGA-II for addressing the optimal placement of additional switches for enhancing reliability with the objective functions of minimizing the number of switches and maximizing system reliability.

In [31], the NSGA-II was shown to achieve better results in a multi-objective optimization problem compared to other widely reported algorithms in the scientific literature, specifically the Pareto Archived Evolution Strategy (PAES) [32] and the Strength Pareto Evolutionary Algorithm (SPEA-II) [33].

Given the well-known effectiveness of NSGA-II, the optimization proposed in this paper is based on NSGA-II with two objective functions, HC maximization and Power Losses minimization, satisfying a set of constraints described further. The decision variables of each approach are: I) the line switching operations during each step of the Reconfiguration Strategy, II) the capacitor dispatch during each step of the Capacitor Switching Strategy, III) the OLTC operation during each step of the OLTC Switching Strategy, IV) the reactive power control of smart inverters during each step of the Volt-VAR Control Settings Strategy, and V) all mentioned decision variables are integrated for the Combination of all strategies. The NSGA-II algorithm manipulates these decision variables to improve the objective functions preventing the system from violating the constraints, particularly through managing active and reactive power, and controlling voltages and currents throughout the distribution system.

This research aims to provide a collaborative environment using open-source software platforms to facilitate its reproducibility and accessibility. Python [34] was used as the scripting language for implementing the optimization algorithm, while the Open Distribution System Simulator (OpenDSS)

[35] was employed to perform consecutive power-flow simulations during each optimization algorithm iteration. Python and OpenDSS were implemented working together through an interactive connection between the two platforms using a COM (Component Object Model) interface. This interface allows Python and OpenDSS to communicate and exchange information in a synchronized way. The simulations were conducted on a personal laptop equipped with an Intel Core i7-11390H CPU (3.40 GHz, 8 cores), 16 GB of RAM, and a 952 GB SSD.

The power-flow simulations were conducted in snapshot mode, representing a specific moment in time [36]. In other words, this is a steady-state study. The objective of the study is to test the performance of all strategies during the most challenging conditions, when PVs reach the maximum production, and the loads are at their lowest levels of the day.

II. Problem Formulation

A. Multi-Objective Optimization

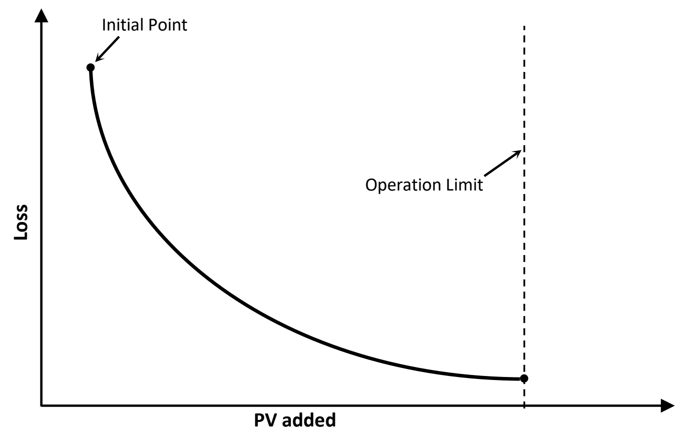
Multi-objective optimization is used in different real-world problems, aiming to find a set of solutions when contradictory or conflicting objective functions are being optimized. In other words, improving one objective leads to a degradation of another objective. The authors evaluated the conflicting nature of the objective functions proposed in this work.

1) Contradictoriness of the objective functions: Generally, power system multi-objective optimization problems request to maximize the performance of the system while minimizing the facility cost investments. This generates contradictory objective functions, since the enhancement of the power system comes with a price, while leading to gradual system improvement. In other words, the system becomes more efficient as the investment grows.

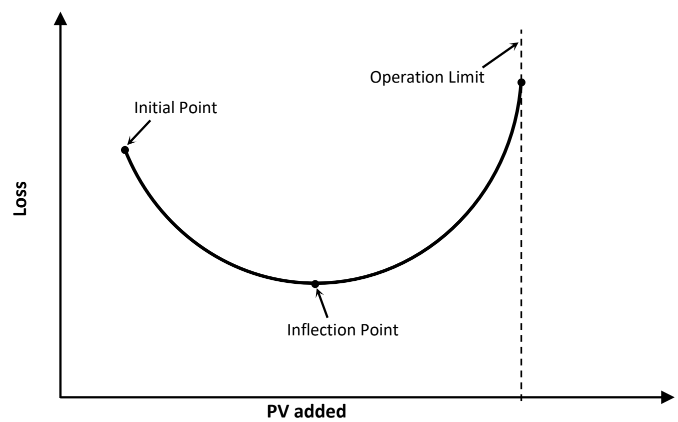
Nevertheless, the two objective functions presented in this paper are not evidently contradictory to each other as the aforementioned example. For this reason, before chosen this objective function as the main subject of this research, the authors tested the conflicting degree of this objective functions performing some power-flow simulations, integrating solar PV systems progressively into a distribution grid (detailed further in this document) to evaluate Power Losses associated with the specific quantities of PV introduced into the power system.

Fig. 1 provides a summarized illustration of several power-flow simulations performed on a power system with distributed PVs. The simulations were performed by successively increasing PV capacities from a low capacity (Initial Point) to a larger capacity until the power system operation limits were reached. Then, the same process was performed but the PVs positions were randomly altered. Throughout the simulations, it was found that the system displays two distinct patterns of response. In the first pattern, when locating the PVs in certain sites, the power system loss decreases as more PVs are installed on the system, this clearly indicates that the objective functions are not contradictory for some PVs positions, given that incorporating more PV generation capacity prior to exceeding the operation limit effectively decreases Power Losses, as depicted in the curve of Fig. 1a.

In contrast, when positioning the PVs in other sites, the curve behaves different as shown in Fig. 1b. The second pattern performs like the first one until an inflection point is reached. Beyond this point, the Power Losses initiate a rise in correlation with the increase in PV generation capacity. Hence, from the inflection point on, the second pattern shifts into a multi-objective optimization, since the Power Losses increase as more PV generation capacity is incorporated.



(a) Pattern-1



(b) Pattern-2

Fig. 1. Test results for different PV positions.

The outcomes of the simulations have produced interesting findings illustrating the complexity of the optimization problem. The PV locations influence the nature of the optimization problem, since the problem can manifest as either a purely mono-objective optimization or a fusion of mono-objective and multi-objective problem. Therefore, this compelling result has motivated the authors to delve deeper into these objective functions.

2) NSGA-II Algorithm: As mentioned earlier, the NSGA-II algorithm has been chosen as the optimization approach to enhance Hosting Capacity and mitigate Power Losses. NSGA-II algorithm is designed to find a set of optimal solutions known as Pareto set [37]. It is one of the most efficient multi-objective evolutionary algorithms using elitist approach which has great advantages in comparison to other evolutionary algorithms [38]. Fig. 2 shows two flowcharts, the one on the left provides a broad overview of the algorithm developed, while the flowchart on the right illustrates the HC & Loss step. It provides information about the iterative process to increase PV capacities of each individual (candidate solution) until the HC and Power Losses of the power system are determined.

Basically, the algorithm was developed in Python using the COM interface to communicate with OpenDSS whenever is necessary to perform power-flow simulations. All steps from the flowchart are detailed below.

Initialize: The user can initiate the algorithm once all NSGA-II parameters are configured in Python and the power system is modeled using OpenDSS.

Generate initial population: The algorithm randomly generates an initial population of 100 candidate solutions, referred to as individuals. The diverse set of potential solutions ensures that they represent viable solutions within the defined solution space. This randomness helps to explore a broad range of possibilities and avoid premature convergence on suboptimal solutions.

HC & Loss: As shown on the right flowchart, the HC & Loss step starts creating Random PV locations. To ensure a consistent evaluation of all individuals, all members of the population will have PVs installed at identical locations.

Two kinds of PV locations are randomly generated, Small-Scale PV and Large-Scale PV. Buses serving residential or commercial customers are eligible for random Small-Scale PV site selection; while three-phase buses are candidates to randomly generate Large-Scale PV locations. Similar to the approach in reference [39], the maximum allowable Small-Scale PV size installed on a bus is restricted by the total customers peak load at that bus. On the other hand, the maximum size for Large-Scale PV installations is fixed at 1 MW. Initially, only 10 Small-Scale PV sites are randomly generated for all individuals of the population.

The evaluation is performed sequentially for each member of the population. The initial value of each PV is 10 kVA. Each individual is evaluated according to the results of the power-flow calculation. The power-flow is performed as many times as needed, increasing each PV system in 10 kVA until the Power System Limit (PSL) is reached. New Small-Scale PVs locations are created when PVs achieve their maximum allowable PV size. Large-Scale PV sites are created only after 10 Small-Scale PV have collectively reached the allowable PV size.

Once the PSL is achieved, the individual HC has been found, and the value from the preceding stage ($\sum(PV - 10kVA)$), before any power system limits were breached, is established as the individual HC. Additionally, the Power Losses associated with this stage is stored.

Fitness Evaluation: The individuals are ranked based on their dominance relationship [37] and the ones that are not dominated by any other individual are assigned to the first Pareto front (non-dominated front). In addition, the individuals are also ranked using the Crowding Distance (measures how close an individual is to its neighbors) parameter.

Genetic Algorithm Operators: Genetic Algorithm (GA) Operators are applied; parents are selected using binary tournament. Then, parents generate offspring from crossover and mutation operators.

HC & Loss: Again, the HC & Loss step is implemented, this time, to find offspring's HC and Power Losses.

Offspring Fitness Evaluation: The offspring are evaluated according to the objective functions and a new rank with parents and offspring is calculated [37].

Survival Selection: The best 100 individuals are selected for the next generation.

Stopping Condition: This paper proposes a stopping criterion based on a maximum number of 100 iterations. If the Stopping Condition is not met, the loop keeps going as indicated in Fig. 2.

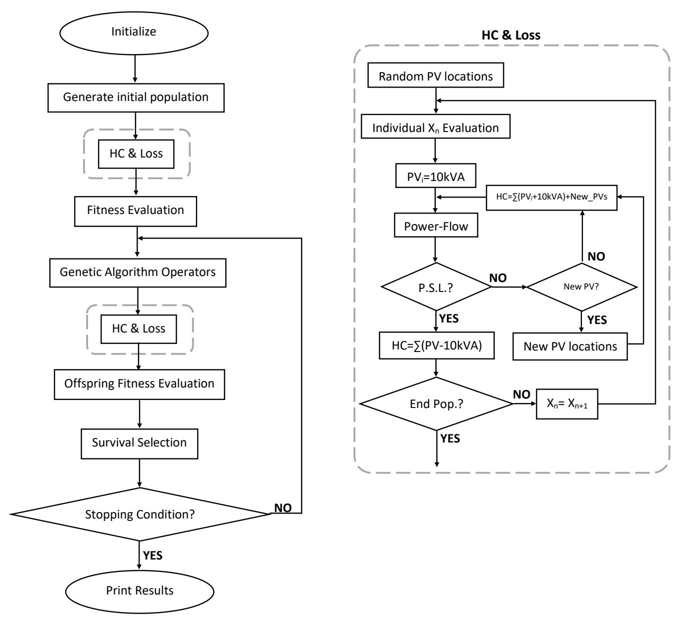


Fig. 2. Implemented NSGA-II flowchart.

3) Objective Functions: The first objective function aims to find the maximum amount of PVs that can be connected to a distribution system without compromising its safety or reliability. The HC is computed as the sum of all PV capacities in the system before constrains are violated. The mathematical formulation for the HC maximization is presented as

$$Max\left\{HC_{TOTAL}\right\} = Max\left\{\sum_{i=1}^{npv} HC_i\right\} \tag{1}$$

where

HC_{TOTAL} = total HC of the system
npv = number of system PVs
HC_i = power capacity of PVi

The other objective function to address is the minimization of the real Power Losses. Eq. (2) shows the objective function and provides an illustrative representation of the Power Losses calculated by OpenDSS during the power-flow simulations. Loss calculations are performed individually for every phase and branch within the distribution network. The accumulation of these branch losses corresponds to the overall power system loss. The mathematical expression of the minimization of real Power Losses is introduced as follows.

$$Min\left\{P_{TOTAL}\right\} = Min\underbrace{\left\{\sum_{j=1}^{nb} R_j.I_j^2\right\}}_{\text{OpenDSS}} \tag{2}$$

where

P_{TOTAL} = total real Power Losses of the system
nb = number of system branches
R_j = resistance of branch j
I_j = current of branch j

4) Constraints: The optimization problem is formulated considering different constraints that are described in the following equations.

Voltage limit constraint: The ANSI voltage limits must be satisfied for all steady-state bus voltages of the distribution system, as:

$$0.95 \leqslant V_{BUS} \leqslant 1.05, \qquad BUS = 1, 2, ..., N \tag{3}$$

where V_{BUS} is the per-unit voltage at the BUS-th.

Flow constraint: During the steady state condition, the maximum current through each line is restricted by the thermal limit of the feeder. Therefore, the following restriction must be addressed:

$$I_{branch} \leqslant I_{max}, \qquad branch = 1, 2, ..., N \tag{4}$$

where I_{branch} is the current that flows through the branch-th, and I_{max} is the thermal limit of that branch.

Voltage unbalance constraint: As detailed in [40], voltage unbalance is a power quality concern in distribution networks and the problems caused by voltage unbalance need to be prevented. To keep power quality within acceptable limits, this work proposes to restrict the voltage of each bus using the Voltage Unbalance Factor (VUF), which is the ratio between negative-sequence and positive-sequence voltages. The limits are set according to [41] as follows

$$VUF_{BUS} \leqslant 2\%, \qquad BUS = 1, 2, ..., N \tag{5}$$

where VUF_{BUS} is the Voltage Unbalance Factor at the BUS-th.

Voltage Deviation constraint: Besides overvoltage limits and voltage unbalance, the HC may also face limitations due to the impact of how much the PVs change the distribution system voltages. Voltage Deviation has the potential to cause voltages to suddenly swing above/below operating limits [42]. Furthermore, this can cause additional control (regulator/capacitor) operations or tripping of sensitive equipment. The Voltage Deviation constraint consists of comparing the percentage of voltage variation at each system bus before and after full PV comes online [39]. The following equation illustrates the Voltage Deviation limit at each bus:

$$Vdev_{BUS} \leqslant 3\%, \qquad BUS = 1, 2, ..., N \tag{6}$$

where $Vdev_{BUS}$ is the Voltage Deviation at the BUS-th.

Topology constraint: Most Distribution Systems operate with radial topology to facilitate the coordination and protection and to reduce the short-circuit current [43]. Hence, when the network reconfiguration is performed, a topology restriction is implemented to allow only the generation of radial solutions.

B. Encoding

Binary encoding, using “0” and “1” as the encoding symbol set, is most used in genetic algorithms. The encoding, decoding, replication, crossover and mutation of a binary encoded genetic algorithm can be easily implemented, and it has a strong global search capability [44]. Given its simplicity, the benefits it offers, and its seamless alignment with all decision variables proposed in this research, the binary encoding is chosen as the encoding method.

In this kind of encoding, a chromosome is the representation of an individual (candidate solution) in the population, while a gene constitutes an individual component within the decision variable. Fig. 3 shows the representation of the encoding structure implemented in this work.

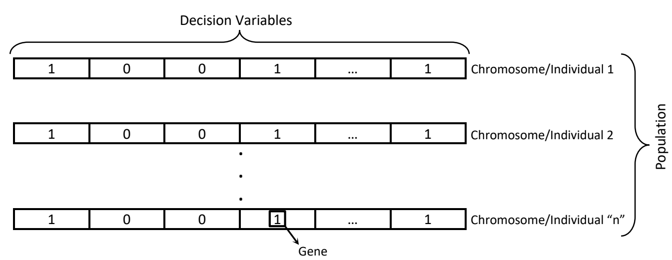


Fig. 3. Encoding structure.

1) Network Reconfiguration: Network Reconfiguration in distribution systems involves altering the status of sectionalizing switches, typically to enhance system performance [2]. Studies, such as [45], have demonstrated that binary encoding is a well-suited technique for network reconfiguration GA optimization due to its compatibility with the discrete nature of breaker states. Hence, the representation of each system topology in this research is carried out using a binary encoding, where the chromosomes have fixed length equal to the number of system breakers. Each gene is represented by a binary value that indicates the status of each breaker, a number "1" indicates a closed breaker while the number "0" represents an open breaker. Considering that most distribution systems follow a radial structure, only radial arrangements are studied in this research. Hence, all individuals are restricted to produce radial topology structures. In OpenDSS, the opening and closing of switches are controlled by adjusting the *"State"* property of each *"SwtControl"* element in the model.

2) Capacitor Switching: The dispatch of capacitors is widely used in distribution systems to inject reactive power, create voltage support and enhance the power factor. Capacitors are energized or de-energized regularly according to the changes in voltage and reactive power, which is one of the most common operation events in distribution systems [46]. The binary encoding for capacitor switching involves representing the on/off states of capacitors as binary values. Like the network reconfiguration encoding, each capacitor is associated with a binary digit (0 or 1) that indicates its switching state, where "0" indicates off-state, and "1" denotes on-state. The capacitor bank switching on OpenDSS is made manipulating the *"States"* property of each capacitor of the model.

3) OLTC Switching: Electric utilities use OLTC attached to Medium Voltage (MV) transformer to regulate voltage levels [47]. An OLTC comprises an autotransformer and a load tap changer mechanism. The voltage change is achieved through switching the taps of the series winding on the autotransformer [48]. OLTC has a limited number of tap positions; standard regulator contains usually 32 switching states, each step is typically designed to change 0.625% of voltage [49].

In this research, a binary representation of the 32 OLTC switching positions is proposed, where the position is numerically represented by its conversion from decimal to binary. For instance, a switching position represented by the decimal value “14” is converted into the binary sequence ($14_{DEC} = 001110_{BIN}$). Each OLTC will be represented by a binary number indicating its particular position. In OpenDSS, the adjustment of voltage regulators is done by modifying the *"Tap"* property of each voltage regulator in the model.

4) Volt-VAR Control Settings: The smart PV inverter can absorb and generate reactive power using the Volt-VAR Control Strategy to regulate voltage [50]. The use of inverter control systems may represent a solution for mitigating the problems associated with the penetration of PVs in distribution systems. Nevertheless, incorrect settings may lead to increase voltage issues and adverse influence on thermal conductor constraints. In [51], it was demonstrated that the best settings of smart inverter Volt-VAR Control differ by location and objective considered. In this paper, the objectives of smart inverter control settings were already discussed. However, the location where PVs are going to be connected to the system and the control settings may vary for each simulation.

Without implementing any voltage support method, the farther a user is from the main substation, the greater the voltage drop the user may experience. Hence, it is proposed to establish four different location ranges, enabling neighboring PVs to create clusters that contribute to voltage stability in their respective areas. This implies that each of the four regions will have a unique encoding that defines the Volt-VAR settings of the PVs that fall within that specific range. The classification of these ranges will be based on how far each PV system is from a substation. PV systems that are nearest to the substation will be grouped together, and those more distant will be categorized into subsequent groups. Fig. 4 offers an example of a distribution system showing how the four regions are defined by their distance from a substation.

Simultaneously, the Volt-VAR control settings of each PV group will be associated with an encoding that represents the Volt-VAR curve of the group. The proposal involves two curves defined by the IEEE Std 1547-2018 [52] (Category A and B setting curves), alongside two custom curves—one with no reactive power setting and the other exhibiting an aggressive setting. Fig. 5 illustrates these curves. These curves are represented in OpenDSS by setting the *"XYCurve"* elements for each *"InvControl"* object in the model.

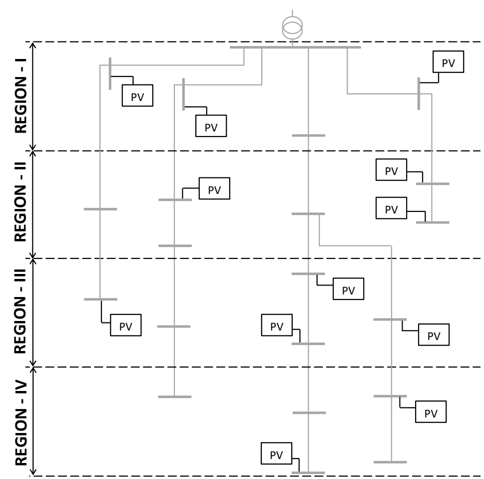


Fig. 4. Regions defined by the distance from substation.

5) Combination Approach: In the previous sections, different binary representations were employed. In the combination approach, the binary representations introduced earlier come together to form a unified solution. This process involves the integration of all strategies to create a single string that represents the entire solution.

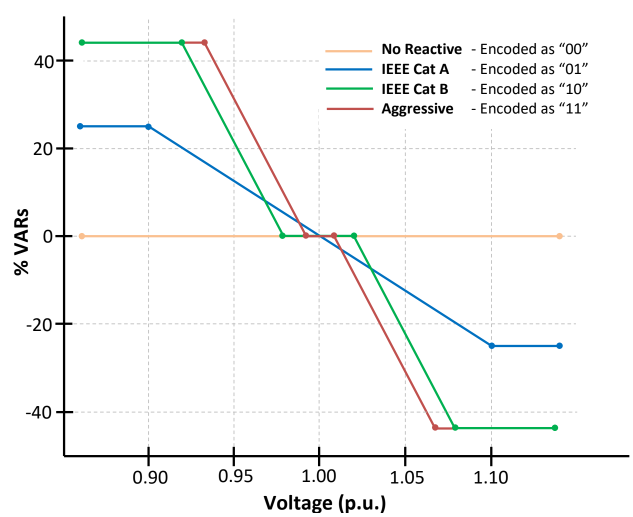


Fig. 5. Volt-VAR curve settings.

III. Simulation and Results

The IEEE 123 Node Test Feeder is widely used in power system studies. Nevertheless, this paper considers the radial network reconfiguration as one of the strategies to improve HC and reduce Power Losses. The IEEE 123 system, in its original form, is not able to perform system reconfiguration. Therefore, modifications have been made to enable topology changes using switching devices while preserving the system's radial structure and ensuring feeding all loads.

Fig. 6 shows the modified version of the IEEE 123 system. In contrast to the initial configuration featuring only 11 breakers, 8 new breakers were strategically located to allow the system reconfiguration. In addition, 12 new three-phase distribution lines were added. The new switching devices are represented by square black boxes, while the new lines are described by black dotted lines. All modifications made to the system are detailed in Table I.

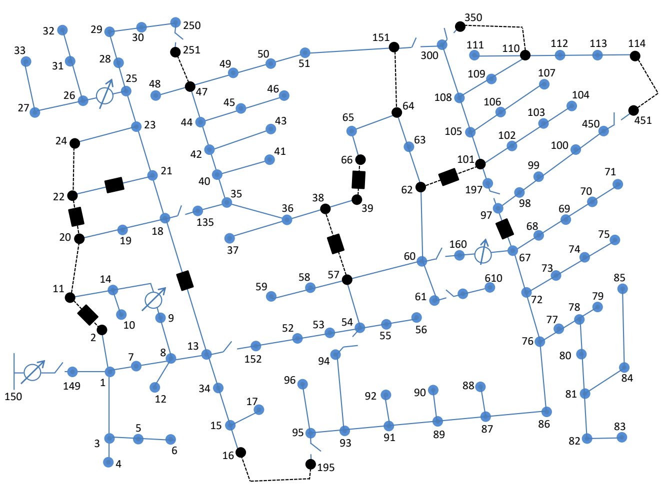


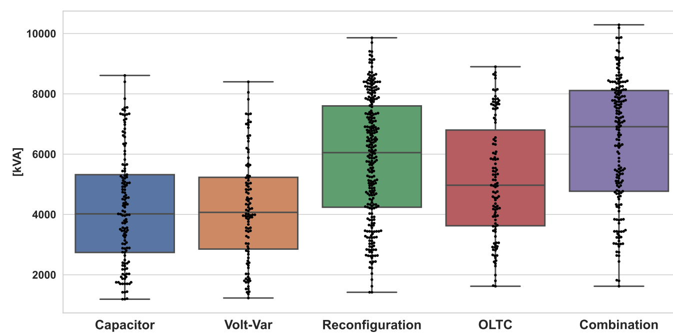
Fig. 6. Modified IEEE 123 Node Test Feeder.

The algorithm proposed was applied to the IEEE 123 bus system. All five strategies were simulated: Network Reconfiguration, Capacitor Switching, OLTC Switching, Volt-VAR Control Settings, and a Combination of all these strategies.

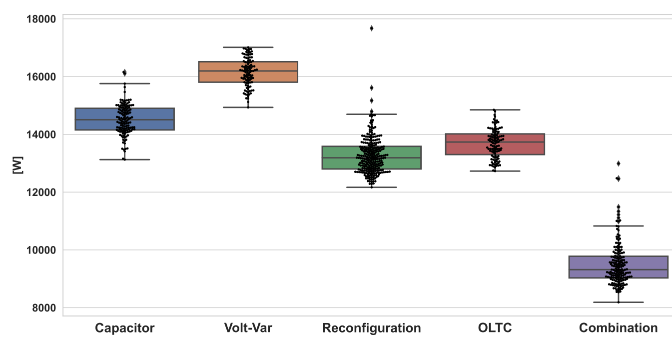
TABLE I
MODIFICATIONS MADE TO THE IEEE 123 SYSTEM

Bus A	Bus B	Line (m)	Switch
2	11	250	Yes
11	20	300	-
20	22	250	Yes
22	24	250	-
47	251	250	-
16	195	320	-
57	38	310	Yes
66	39	250	Yes
64	151	300	-
62	101	300	Yes
350	110	350	-
114	451	320	-
22	21	-	Yes
13	18	-	Yes
67	97	-	Yes

To ensure a fair comparison among the strategies, the PVs were placed in different positions for each simulation, but the positions remained consistent across all strategies. This was achieved using Python's *"random.seed(number)"* function, which initializes a random number generator to produce reproducible results. By using the same seed number, the same set of random PV positions was generated for all strategies. Different seeds were tested, gradually increasing the number from 0 to 100, resulting in 101 distinct sets of PV positions and, consequently, 101 simulations for each strategy. During this process, a clear trend emerged when comparing the strategies. It was concluded that further simulations were unnecessary, as the results had stabilized and additional seeds were unlikely to change the outcomes. To visualize the range and other characteristics of the responses, the results are represented using the box plots of Fig. 7.



(a) Hosting Capacity results



(b) Power Losses results

Fig. 7. Box plot representing the performance results of the five strategies.

From box plots of Fig. 7a, it is noted that the Combination Strategy exhibits higher values of HC results. On the other hand, box plots of Fig. 7b shows that the Combination Strategy has lower values in all parameters of Power Losses. This clearly suggests a better performance of the Combination Strategy in comparison to the other strategies.

As previously discussed, two different patterns of response were found (see Fig. 1), one exhibiting a mono-objective behavior and the other a multi-objective behavior. To evaluate how many times each strategy makes the transitions into a multi-objective problem, Table II displays the occurrences of responses exhibiting Pattern-1 and Pattern-2 of each strategy. The total solutions obtained in 101 simulations of each strategy are logically equal to the sum of Pattern-1 and Pattern-2. It can be noted that the Reconfiguration Strategy exhibits more outcomes among all strategies with 266 solutions. In addition, this strategy is the one that presents more multi-objective solutions, with 255 Pattern-2 solutions, followed by the Combination Strategy that has 137 Pattern-2 solutions. On the other hand, the Volt-VAR approach displays the fewest number of solutions, a total of 104, and only 6 of them meet the criteria for multi-objective solutions.

For a more detailed analysis of the presented results, the box plots have been quantified and presented numerically in Table III. This representation allows a precise examination and comparison of the data, enabling further examination of each strategy outcomes. The table shows each strategy smallest result (Min), the first quartile (Q1) that represents the value below which 25% of the strategy results fall, the second quartile (Q2) known as the median, the third quartile (Q3) that indicates the value below which 75% of the strategy results fall, the largest result (Max) and the number of outliers (Out) that are those results that deviate significantly from other results.

TABLE II
RESULT PATTERNS OF STRATEGIES

Strategy	Pattern-1	Pattern-2	Total
$Capacitor$	76	57	133
$Volt/Var$	98	6	104
$Reconfig.$	11	255	266
$OLTC$	82	29	111
$Combinat.$	46	137	183

Analyzing the median, first quartile, and third quartile results depicted in the boxplots, the Combination Strategy has the largest HC and the lowest Loss in all metrics. This proves that the Combination Strategy performs better than the other strategies. The Reconfiguration Strategy comes in second place, followed by OLTC Strategy. While the Volt-VAR and Capacitor strategies share the last position, with Volt-VAR displaying better performance in some metrics but poorer in others.

TABLE III
NUMERICAL RESULTS OF BOXPLOTS

Strategy	Objective F.	Min	Q1	Q2	Q3	Max	Out
$Capacitor$	HC (kVA)	1190	2740	4020	5320	8610	0
	Loss (W)	13125	14153	14507	14902	15757	2
$Volt/VAR$	HC (kVA)	1230	2852	4070	5232	8400	0
	Loss (W)	14933	15805	16194	16515	17012	0
$Reconfig.$	HC (kVA)	1420	4240	6050	7600	9860	0
	Loss (W)	12166	12802	13189	13584	14695	4
$OLTC$	HC (kVA)	1620	3625	4970	6800	8900	0
	Loss (W)	12728	13300	13734	14015	14849	0
$Combinat.$	HC (kVA)	1620	4770	6910	8110	10290	0
	Loss (W)	8186	9030	9317	9780	10828	10

The interquartile range (IQR) gives a measurement of how spread out the results are. It is computed by taking the difference between the third quartile (Q3) and the first quartile (Q1). Table IV summarize all boxplot IQR, it can be observed that in terms of numerical results and electric units, the IQR results express that Loss outcomes are irrelevant comparing to the HC outcomes, given that HC IQRs are expressed in thousands of kilovolt-amperes and Loss IQRs are around 7 hundred Watts.

The analysis made on IQRs reveals that there are no substantial distinctions among the Power Losses outcomes. This leads to the supposition that using Power Losses as an objective function may not be meaningful. Nevertheless, it should be noted that Table III implies that there are outliers in some Power Losses boxplots, indicating that some results significantly differ from the rest of the outcomes. Considering that IQR calculation ignores outliers, analyzing at least one of the results containing outliers might be interesting before discarding Power Losses as an objective function.

TABLE IV
BOXPLOT IQRS

Strategy	$HC_{IQR}(kVA)$	$LOSS_{IQR}(W)$
$Capacitor$	2580	749
$Volt/VAR$	2380	710
$Reconfig.$	3360	782
$OLTC$	3175	715
$Combinat.$	3340	750

Fig. 8 shows the Pareto Front generated from one of the 101 simulations executed using the Combination Strategy. It can be observed that there are 3 solutions with lower Power Losses and 2 solutions (outliers) with higher Power Losses. The figure highlights the most substantial difference in Power Losses values between Solution 1 and Solution 5 (Outlier), with a gap of 3688 [W]. The Pareto Front reveals the potential merit of treating Power Losses as an objective function.

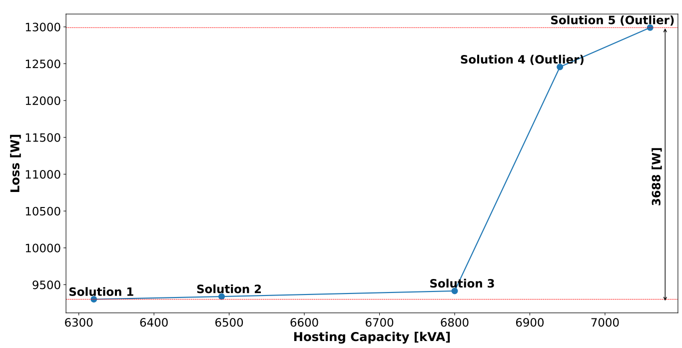


Fig. 8. Pareto Front containing outliers.

IV. CONCLUSION

This study explored various approaches aimed at enhancing Hosting Capacity and reducing Power Losses using conventional distribution system assets and avoiding extensive system reinforcements. The strategies under test were Network Reconfiguration, Capacitor Switching, OLTC Switching, Volt-VAR Control Settings and the Combination of all strategies. Through rigorous simulation and evaluation of the proposed strategies, it was concluded that the Combination of all strategies is the most effective, excelling in optimizing both objective functions. In this context, the Reconfiguration Strategy demonstrated substantial efficacy, securing the second position in performance. OLTC Switching followed as the next viable option; meanwhile, Volt-VAR Control Settings and Capacitor Switching exhibited similar performances and occupied the last position in terms of efficacy. When it comes to diversification, the Reconfiguration Strategy demonstrated to have more solutions after 101 simulations, presenting more multi-objective solutions.

In addition, the studies assessed managing Hosting Capacity and minimizing Power Losses within a multi-objective framework. The analysis revealed that dedicating considerable computational resources to address the problem in a multi-objective context may not always yield substantial benefits, as evidenced by the lack of significant improvement in Power Losses results in most of the cases. However, in some specific cases Power Losses reduction as an objective function can yield important improvements.

To evaluate the performance of the strategies proposed under a time-domain load flow analysis, the authors encourage future research that includes quasi-dynamic study to analyze further the behavior of the problem in a pure multi-objective context.

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