Comparison of Metaheuristic Algorithms for Photovoltaic Systems Allocation in a Power Distribution Feeder

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***Abstract*—The government's endorsement of renewable energy objectives and the requirement to use carbon-free energy sources to keep up with the growth in energy consumption have expanded the integration of solar photovoltaic (PV) systems in distribution networks. However, an excessive PV penetration may lead to operational threshold violations. PV system allocation that is optimal in terms of placement and sizing can enhance power quality and grid performance. We formulate the allocation of PV systems as a combinatorial mixed-integer nonlinear model to maximize the distribution network PV hosting capacity (PVHC). We chose three differential evolution (DE) mutation strategies, namely $DE/rand/1/bin$, $DE/current\text{-}to\text{-}best/1/bin$, and $DE/rand/1/either\text{-}or$, and the vortex search (VS) algorithm to solve that optimization problem. This study aims to identify the method that solves the PV allocation problem with higher quality. We performed manual parameter tuning to set both the population and iteration numbers for each algorithm. In addition, for the DE mutation strategies, we set the scale factor and crossover rate parameters. The results show that the VS provides the highest grid PVHC.**

***Index Terms*—differential evolution, distribution system, hosting capacity, metaheuristic algorithm, photovoltaic allocation, vortex search.**

I. Introduction

Small-scale generators attached to distribution feeders or the customer side of the meter at the distribution level are known as distributed generation (DG) units. The government's acceptance of renewable energy objectives and the need to satisfy growing energy demand with carbon-free energy sources have led to a rise in integrating renewable DG units into distribution networks, primarily solar photovoltaic (PV) systems [1].

The vast connection of distributed PV generation to distribution feeders requires careful planning owing to potential negative consequences on service quality and technological limits, despite the technical, environmental, and financial advantages of deploying DG units. These effects include an increase in voltage, overloading grid equipment, reverse power flow, and deterioration in grid power quality [2]. Therefore, it is necessary to allocate DG units optimally to prevent these technical issues.

Works [3]–[6] solved the optimal placement and sizing of DG units in distribution networks using metaheuristic algorithms. In [3], the authors separately minimized power losses and bus voltage deviations using the differential evolution (DE) algorithm. References [4], [5] included the power factor of each DG unit as a design variable. In [4], the objective function minimized the power imported from the substation, and DE was employed. The particle swarm optimization and genetic algorithm (GA) optimization methods were used in [5] for minimizing the annual energy losses and bus voltage deviations, considering the installation of single and double DG units. Work [6] proposed a hybrid approach that employs the Chu-Beasley GA at the master stage and the vortex search (VS) algorithm at the slave stage.

To optimize the allocation of PV systems, we implemented three DE mutation strategies and the VS algorithm. This work aims to determine which algorithm provides better quality solutions by comparing their results. DE is a stochastic search method that employs mutation, crossover, and selection oper-

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ators [7]. We employed the following three mutation strategies: $DE/rand/1/bin$, $DE/current\text{-}to\text{-}best/1/bin$, and $DE/rand/1/either\text{-}or$. VS is a single-solution-based metaheuristic inspired by the vortex pattern [8]. Additionally, we performed manual parameter tuning of the control parameters for each algorithm.

The remaining sections of this work have the following structure: Section II presents the optimization model for the PV allocation problem. Section III describes the metaheuristic algorithm design and its computational implementation. Section IV presents briefly the DE and VS search mechanisms. The case study is shown in Section V. Section VI provides the results of the manual parameter tuning and solutions reached for each algorithm. Lastly, Section VII provides the concluding remarks.

II. PV Allocation Problem

The PV allocation problem, i.e. siting and sizing of PV systems in the distribution network, is stated as follows: "From a set of candidate locations and some PV systems, what is the best placement, installed capacity, and power factor for each PV power plant to be connected to a distribution feeder to ensure compliance with operational constraints imposed by both the grid and PV power plants?". Three classes of optimization techniques can solve this problem: (i) Classical optimization methods, which directly solve mathematical models, provide exact solutions but may become computationally intractable for large-scale problems; (ii) Intelligent search methods, known as metaheuristic algorithms, offer flexibility and adaptability and can find near-optimal solutions for complex optimization problems beyond the reach of classical techniques; and (iii) Hybrid methods, which combine the strengths of metaheuristics and classical optimization techniques [9].

The nonlinear power flow equations lead to a non-convex feasible space [10]. The mathematical formulation of the optimal PV allocation problem includes power flow equations as equality constraints, which makes it a non-convex optimization problem. The design variables are integers (location) and continuous (size and power factor) values. Therefore, the optimization model for the PV allocation problem is constrained, non-convex, nonlinear, and mixed-integer. Due to these characteristics, we chose metaheuristic algorithms to solve that problem.

The PV hosting capacity (HC) is the amount of solar PV generation that the distribution grid can accommodate [11]. The objective function of the optimization model maximizes the PV HC (PVHC), that is, the sum of each PV power plant's installed capacity, as follows:

$$\max \sum_{p \in \Omega_{PV}} P_p^{inst} \tag{1}$$

where Ω_{PV} is the set of buses in which PV systems can be connected, P_p^{inst} is the installed capacity of the PV power plant at bus p, Since installing PV power plants impacts the distribution network operation, we must perform a power flow analysis to evaluate that impact on network parameters, such as bus voltages and line currents. Therefore, the operational state of the grid is determined by the following nonlinear power flow equations:

$$P_k^{PV} - P_k^D = V_k \sum_{km \in \Omega_L} V_m (G_{km} \cos\theta_{km} + B_{km} \sin\theta_{km}) \tag{2}$$

$$Q_k^{PV} - Q_k^D = V_k \sum_{km \in \Omega_L} V_m (G_{km} \sin\theta_{km} - B_{km} \cos\theta_{km}) \tag{3}$$

$$Q_k^{INV} = \delta \frac{P_k^{PV}}{pf_k} \sqrt{1 - pf_k^2} \qquad \forall k = p \in \Omega_{PV} \tag{4}$$

where k is a bus from the set of distribution network's buses (Ω_B); $P_k^{PV} = P_p^{inst}$ and $Q_k^{PV} = Q_k^{INV} \forall k = p \in \Omega_{PV}$ represent the active and reactive powers of the p-th PV power plant connected at bus k, respectively; the Q_k^{PV} given by (4) is the reactive power injected or absorbed by the PV system into the grid and is a function of both the output active power and the set power factor (pf_k); δ is the power factor type and is defined as either 1 or -1 to represent a leading and lagging power factor, respectively; P_k^D and Q_k^D are the active and reactive power demand on the bus k, respectively; V_k and V_m are the voltage magnitudes on the buses k and m, respectively; Ω_L is the set of lines; the conductance, susceptance, and voltage angle difference on the line linking buses k and m are represented by G_{km}, B_{km}, and θ_{km}, respectively.

$$\sum_{k \in \Omega_B} b_k = N \qquad \forall b_k \in \{0,1\}, \quad \forall k = p \in \Omega_{PV} \tag{5}$$

The sum of the binary variables b_k, denoting if a PV system is installed at bus k, must be equal to the quantity of PV systems that are installed (N), according to (5). The inequality constraints of the optimization model are the following:

$$b_p P_p^{min} \leq P_p^{inst} \leq b_p P_p^{max} \quad \forall b_p \in \{0,1\}, \ \forall p \in \Omega_{PV} \tag{6}$$

$$pf_p^{min} \leq pf_p \leq pf_p^{max} \qquad \forall p \in \Omega_{PV} \tag{7}$$

$$V_k^{min} \leq V_k \leq V_k^{max} \qquad \forall k \in \Omega_B \tag{8}$$

$$0 \leq I_{km} \leq I_{km}^{rated} \qquad \forall km \in \Omega_L \tag{9}$$

$$P_{slack} \geq P_{rpf} \tag{10}$$

The boundaries of the PV system's installed capacity and PV inverter power factor at bus p are given by (6) and (7), respectively. Inequalities (8) and (9) limit the voltage magnitude at bus k and avoid overloading related to the current through the line km, respectively. To some extent reverse power flow is allowed at the feeder-head. Therefore, the active power at slack or swing bus must be greater than the reverse power flow threshold (P_{rpf}) as in (10). Note that P_{rpf} is a negative number.

In summary, the constraints include the nonlinear power flow equations, boundaries of each PV system's installed capacity and power factor, and thresholds of bus voltages, current through the conductors, and reverse power flow at the feeder-head.

III. Metaheuristic Design and Implementation

This section outlines the design and implementation of the metaheuristic, including aspects such as solution encoding, the initial population, evaluation of the quality of a candidate solution, and the constraint handling.

A. Solution Encoding

The design variables are each PV system's location, installed capacity, power factor type (δ), and power factor value (pf). Figure 1 depicts a solution vector comprising four types of design variables. Location variables are discrete (integers), but we represent them as continuous values. So, all the elements of the solution vector are continuous values. To get the location number, the corresponding variables are rounded to the nearest integer number. α is a real value in the range [0,1] that allows representing δ in the algorithm and is given by (11). α values less than 0.5 indicate a leading power factor, while α values greater than or equal to 0.5 represent a lagging power factor. Since N represents the quantity of PV systems that will be installed, each part of the vector will have N elements, and the solution vector will have a total of $N \times 4$ elements.

$$\delta = \begin{cases} -1 & \text{if } \alpha \geq 0.5 \\ 1 & \text{otherwise} \end{cases} \tag{11}$$

B. Initial Population

In the population initialization process, one solution vector (or individual) equals the variable's lower bounds. The remaining individuals are randomly generated between the lower and upper boundaries of the design variables. It ensures that at least one individual from the population is feasible.

C. Objective Function Value and Feasibility

The quality of a candidate solution is defined by its objective function value (OFV) and its feasibility. The power flow analysis allows us to obtain the OFV and verify the feasibility of the solution. It is possible to determine the current and power flow through the lines from the power flow outputs (i.e., the magnitude and phase angle of the bus voltages). Therefore, we can check if the bus voltages, line currents, and reverse power flow constraints are satisfied. We perform the power flow analysis of the distribution grid using an open-source simulation tool called OpenDSS [12].

D. Constraint Handling

We implemented a repair method to guarantee that only one PV system would be connected in each potential location. A random number is chosen one at a time from a list of potential sites using this repair process. This selection process is carried out N times. After a number is selected, it is eliminated from the list of places, making it impossible to choose the same number again. The location repair procedure does not guarantee the solution's feasibility; it only ensures that unique locations will be in the solution vector. The metaheuristic executes the repair procedure every time the search mechanisms (i.e., the DE and VS algorithms) generate new candidate solutions. Each infeasible solution has a degree of infeasibility computed as follows:

$$S = w_1(V^f - V^{max}) + w_2(I_{km}^f - I_{km}^{rated}) - w_3(P_{rpf} - P_{slack}) \tag{12}$$

where w_1, w_2, w_3 are the weights of each constraint violation; V^f is the maximum bus voltage of the feeder; and I_{km}^f is obtained as follows: First, for each line, the conductor (or cable) current is divided by its current rating, and the maximum value is saved in a list. Then, we get the maximum value of that list and multiply it by its corresponding ampacity. A feasible solution is always better than an infeasible one. Among infeasible solutions, the one with the lowest infeasibility value is the best.

E. Metaheuristic Framework

Figure 2 depicts the metaheuristic design steps. The steps in blue boxes are problem-dependent. While the search mechanism (or algorithm), such as GA, DE, VS, among others, generally is not for a specific optimization problem, instead it can be employed for solving several optimization problems.

This work employs simulation-based optimization, where optimization is the primary method that uses simulation as a subcomponent. The metaheuristic conducts the optimization process, whereas the simulation method is the power flow analysis that enables objective function evaluation and constraint satisfaction verification.

IV. Search Mechanisms

Figure 1 shows three-fourths of the design variables are continuous. We chose the DE and VS algorithms because both are well-suited for continuous optimization problems. In addition, DE has already been used to solve the optimal DG allocation problem [3], [4] and is simpler to code than other evolutionary algorithms [13]. The VS algorithm is a single-solution-based algorithm that requires setting only the maximum iteration ($iter$) and neighborhood solution (NP) numbers, and its computational implementation is simple. Some works have compared the DE performance with other population-based algorithms, such as GA and particle swarm optimization. This paper compares a population-based algorithm with a single-solution-based algorithm.

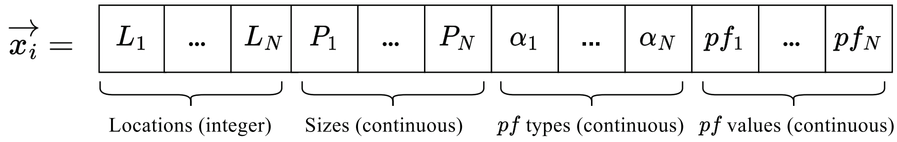

Fig. 1. Encoding of the solution vector.

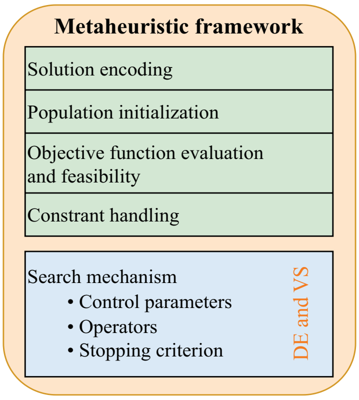

Fig. 2. Metaheuristic design.

A. Differential Evolution

DE is an evolutionary algorithm for real parameter optimization developed by Storn and Price in 1995 [7]. It is a population-based stochastic search mechanism that seeks the best solution over continuous search spaces. The main idea behind the algorithm is to generate trial vectors. First, the mutation operator creates the mutated or donor vector by adding a weighted difference between two individuals to a third. Next, a trial individual is created by recombining the donor with the target vector.

After the population initialization and the objective function evaluation, the algorithm executes the following four steps at each iteration for each individual:

1) Random choice of three different solutions from the population;
2) The creation of the trial individual by applying the mutation and crossover operators;
3) Verifying the variable boundaries of the trial individual, if some variable of the trial individual is beyond the search range, it must be returned to the feasible search range;
4) Selection of the best solution by comparing the OFV and infeasibility degree of the trial and current individuals.

DE is characterized by three control parameters that define its performance in achieving high-quality solutions: the population number (NP), scale or differentiation factor (F), and crossover rate (Cr). A predefined number of iterations (or generations) ($iter$) is the stopping criterion for the algorithm.

To solve the optimal PV allocation problem, we employed the following three different mutation strategies:

1) $DE/rand/1/bin$: This is the classic mutation scheme, which creates an i-th mutant individual ($\vec{m}_{i,it}$) at iteration it and uses a binomial crossover as follows:

$$\vec{m}_{i,it} = \vec{x}_{r1,it} + F(\vec{x}_{r2,it} - \vec{x}_{r3,it}) \tag{13}$$

where $\vec{x}_{r1,it}$, $\vec{x}_{r2,it}$, and $\vec{x}_{r3,it}$ are three random solutions from the population, which are mutually different and also different from the current individual.

2) $DE/current\text{-}to\text{-}best/1/bin$: This strategy mutates the current i-th individual $\vec{x}_{i,it}$ by adding two scaled difference vectors, as follows:

$$\vec{m}_{i,it} = \vec{x}_{i,it} + F(\vec{x}_{best,it} - \vec{x}_{i,it}) + F(\vec{x}_{r1,it} - \vec{x}_{r2,it}) \tag{14}$$

where $\vec{x}_{best,it}$ is the best individual in the population, $\vec{x}_{r1,it}$, and $\vec{x}_{r2,it}$ are two random solutions from the population. The current, base, and difference vectors must be different.

3) $DE/rand/1/either\text{-}or$: The mutant vectors that are pure mutants (such as in the classic DE) occur with a probability of P_F, and those that are pure recombinants happen with a probability of $1 - P_F$, as follows:

$$\vec{m}_{i,it} = \begin{cases} \vec{x}_{r1} + F(\vec{x}_{r2} - \vec{x}_{r3}), & \text{if } rand() < P_F \\ \vec{x}_{r1} + K(\vec{x}_{r2} + \vec{x}_{r3} - 2\vec{x}_{r1}), & \text{otherwise} \end{cases} \tag{15}$$

$rand()$ is a uniformly distributed random number within the range of $(0, 1)$ and $K = 0.5(F + 1)$.

B. Vortex Search

The VS is a single-solution-based algorithm for solving bound-constrained global optimization problems. It mimics the vortex flow phenomenon and uses an adaptive step size adjustment to balance the exploration and exploitation of the search. VS uses the inverse incomplete gamma function to decrease the radius at each iteration [8]. A real positive number a is an input of the lower incomplete gamma function. In the VS algorithm, that parameter a defines the resolution of the search. At each iteration it, the value of a_{it} is computed as follows:

$$a_{it} = a_0 - \frac{it}{iter} \tag{16}$$

where a_0 is equal to 1 to ensure full coverage of the search space at the first iteration.

V. Case Study

We tested the three DE mutation strategies and the VS algorithm for the PV allocation problem in a real medium-voltage distribution feeder model shown in [14]. There are eight candidate locations, and we are allocating three PV systems. The distribution feeder has a residential load profile with a peak demand of 4580 kW at 19:00. From the measurements at the feeder-head, we consider two operating points for the power flow analysis, whose load values in per unit (p.u.) (selecting the peak demand as the base) are 0.668 and 0.501 for the first and second operating points, respectively. The active power outputs of the PV systems are equal to their installed capacities.

The PV inverter rating is 10% higher than the installed capacity of the PV system ($S^{\text{INV}} = 1.1P^{\text{inst}}$) so that it can inject or absorb reactive power at a power factor of 0.9, even when the PV system is injecting its total active power output. The minimum and maximum voltage thresholds are 0.95 p.u. and 1.05 p.u., respectively. The current threshold for each conductor is its rated current, $P_{rpf} = -10000$ kW, and $w_1 = w_2 = w_3 = \frac{1}{3}$. The allowed ranges of the location variables, installed capacities (in kW), α, and pf are [0.5, 8.49], [1000, 7000], [0, 1], and [0.9, 1], respectively. For the parameter tuning and comparison of each algorithm, we fixed the number of objective function evaluations to 500. We tested the algorithms on a workstation running Windows 10 with an Intel®Core™i7-4770 2.6 GHz processor and 16 GB of RAM.

VI. Results

We implemented the algorithms in Python 3.9. The py-dss-interface package, particularly version 2.0.2, enables access to OpenDSS version 9.6.1.3 via dynamic link library (DLL) interface. We tuned the parameters for every search mechanism. The parameter tuning comprises two stages. The first stage, just for the three DE strategies, concerns tuning the F and Cr control parameters, whereas the second one determines the best values of NP and $iter$ for all algorithms. In the first stage, we set NP = 10 and $iter$ = 50 and modify both F and Cr parameters in the range of [0.1, 1] with a step size of 0.1, resulting in 100 possible combinations. The final value of each (F, Cr) combination is the average of the final OFV for five different runs, and we chose the combination that yielded the highest mean PVHC. Figure 3 shows the heatmaps for the three DE strategies. Warmer tones, such as red and orange, indicate higher mean OFVs, while cooler tones, like dark green, represent lower values. The best combinations of (F, Cr) were (0.8, 1.0), (0.6, 0.8), and (0.5, 0.6) for the first, second, and third mutation strategies, respectively.

In the second stage of the parameter tuning, with the best (F, Cr) parameters found in the first stage, the following five (NP, $iter$) combinations were tested: (5, 100), (10, 50), (20, 25), (25, 20), and (50, 10). Table I displays the mean PVHC for five runs of each (NP, $iter$) combination. The (10, 50) combination reached the highest mean OFV for every algorithm.

Once the control parameters were set, we executed each search mechanism 30 times. The following performance metrics were chosen to compare the algorithms: the mean, best, worst, standard deviation (std dev) OFVs, and the mean runtime. The results of each metric are shown in Table II. The VS algorithm has the highest values for both the PVHC mean and the PVHC. The $DE/current\text{-}to\text{-}best/1/bin$ mutation strategy presents the best values for the worst and std dev PVHC.

Figure 4 shows the convergence of the best run for each algorithm. There are higher variations in the OFV in the first 20 iterations, approximately, and after that iteration, the value of the PVHC presents minor modifications. Table III displays the locations, installed capacities, and power factors of the three PV systems, founded by the best solution of the VS algorithm (PVHC= 12399.87 kW). The power factor at the fourth and fifth locations is leading, whereas the PV inverter at the eighth location is operating with a lagging power factor. Additionally, the maximum values of bus voltage and line thermal load of the feeder for the best solution are 1.05 p.u. and 99%, respectively, and $P^{slack} = -9367.236$ kW. Since the bus voltage reaches the maximum threshold, overvoltage is the main constraint for reaching higher PVHC levels.

VII. Concluding Remarks

This work presented the application of two algorithms, namely differential evolution (DE) and vortex search (VS), for optimizing the allocation (placement and sizing) of solar photovoltaic (PV) power plants into a power distribution network. We implemented and compared four search mechanisms: three different DE mutation strategies, namely $DE/rand/1/bin$, $DE/current\text{-}to\text{-}best/1/bin$, and $DE/rand/1/either\text{-}or$, along with the VS algorithm. Moreover, a manual parameter tuning process that comprises two stages was presented. The results showed the VS algorithm outperformed the DE mutation strategies, as it yielded the highest values for two metrics: the PV hosting capacity (HC) mean and PV HC.

Future work would be to solve the proposed optimization model using a commercial optimization solver and compare the quality of its result with the best solution obtained by the VS algorithm.

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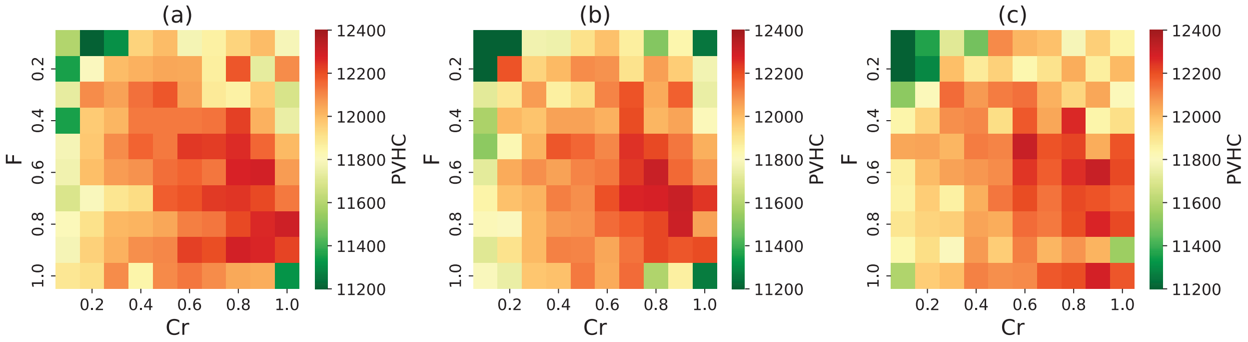

Fig. 3. Mean OFV of (a) $DE/rand/1/bin$, (b) $DE/current\text{-}to\text{-}best/1/bin$, and (c) $DE/rand/1/either\text{-}or$.

TABLE I
RESULTS FOR THE FIVE (NP, $iter$) COMBINATIONS

NP	$iter$	Mean PVHC [kW]			
		$DE/rand/1/bin$	$DE/current\text{-}to\text{-}best/1/bin$	$DE/rand/1/either\text{-}or$	VS
5	100	10727.20	11389.75	9290.33	11904.82
10	50	**12119.34**	**12109.58**	**12108.07**	**12234.23**
20	25	12016.84	12059.76	12016.29	12174.89
25	20	12056.97	12086.16	12060.51	12080.85
50	10	11916.46	11915.57	11871.18	12065.85

TABLE II
PARAMETERS AND METRICS FOR THE SEARCH MECHANISMS

Algorithm	Parameter (F, Cr)	PVHC [kW]				Mean runtime [s]
		Mean	**Best**	**Worst**	**std dev**	
$DE/rand/1/bin$	(0.8, 1)	12139.67	12318.21	11008.02	244.79	243
$DE/current\text{-}to\text{-}best/1/bin$	(0.6, 0.8)	12129.25	12272.28	**11960.76**	**86.57**	**239**
$DE/rand/1/either\text{-}or$	(0.5, 0.6)	12023.26	12223.57	11807.49	108.28	247
VS	–	**12182.72**	**12399.87**	11639.4	155.41	275

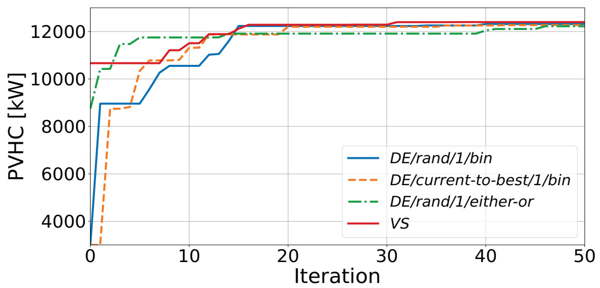

Fig. 4. PVHC over iterations of the best run for each algorithm.

TABLE III
BEST SOLUTION FOUND BY THE VS ALGORITHM

PV system	Location	Distance [km]	Size [kW]	Power factor
#1	4th	6.41	5257.63	0.991
#2	5th	8.01	6029.06	0.967
#3	8th	7.46	1113.17	0.998^{-}

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