Enhancing photovoltaic hosting capacity in distribution networks by optimal allocation and operation of static var compensators

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***Abstract*—This paper presents a novel two-stage optimization approach for the optimal sizing of static var compensators and their operational management to maximize the photovoltaic integration capacity of distribution systems. In the first stage, the optimal locations for fixed size photovoltaic (PV) systems are determined to minimize the sum of total voltage violations. In the second phase, the size of the PV units are resized and the optimal size, number, location, and operating strategy of the SVC units are determined to maximize PV hosting capacity. In both phases, the Marine Predators algorithm is used for the solution optimization equations. The performance of the proposed approach and solution method is validated on modified 33-node and 141-node radial distribution networks. The results are discussed from the point of view of the maximum hosting capacity and compared with the Grey Wolf Optimization and Whale Optimization algorithms in terms of computational performance.**

***Index Terms*—Distributed generation, Distribution Networks, Marine Predators Algorithm, Static VAR compensator**

I. Introduction

Increasing the penetration of renewable distributed generation (RDG), particularly photovoltaics (PV), is a promising approach to addressing global environmental and energy challenges. The popular uses for the PV systems include improving voltage profiles, reducing energy losses and harmful emissions, reducing dependence on fossil fuels, and deferring transmission grid upgrades. On the other hand, excessive use of PV systems may disrupt the operation of the system. Researchers have therefore attempted to solve the main difficulties associated with large-scale penetration of PVs, such as overloading of distribution lines and overvoltage problems [1].

From the customer's perspective, RDG units provide backup generation and sell the excess energy to the utilities. To take advantage of the potential benefits of RDG units, utilities have begun to adapt their infrastructure to accommodate more RDG units in their distribution systems.

The transition from no PV penetration to large-scale PV penetration follows three main phases in a distribution network. In the first phase with low PV penetration, local consumption is much higher than PV production and PV units have minimal adverse impacts on the network. In the second phase, PV output exceeds the power consumption, and there are noticeable adverse effects of PV generation. Finally, when the penetration of PV systems is very high, a large amount of PV output is injected into the network. The negative impacts can reach unacceptable levels, which involves some additional precautions to alleviate them. The maximum cumulative PV generation capacity that a grid can support without violating any operational restrictions is called the PV hosting capacity (PVHC) of the grid.

Several researches have focused on solving the voltage quality problems while integrating PVs into medium voltage (MV) and low voltage (LV) grids. Aziz and Ketjoy found that the LV grids could handle higher relative penetration of PV systems than the MV grids, but voltage problems such as overvoltages in the MV grid were less when compared to LV grids [2]. Another study focused on controlling the reactive and active power of PV units using inverters to create the possibility of connecting more units to the grid [3]. The research proposed to minimize the negative impact of PV output on the voltage level of the system based on new strategies and laws proposed for Volt-VAr and Volt-Watt coordination of the PVs. In other words, the voltage profiles so do the system's power quality can be improved by throttling the extra active power of the PV systems during overvoltage problems and adjusting the reactive power control of the system during undervoltage problems. In summary, it is an important task to develop techniques that enable maximum PVHC while keeping the operational constraints of the grid within the specified limits [4].

Approaches to assess the maximum PVHC using probabilistic and deterministic methods were discussed in the literature [5]–[8]. Electric utilities worldwide are trying to develop policies to enhance PVHC while keeping acceptable grid performance. Specific methods to improve PVHC involve using various energy storage system units, smart inverter technologies, load tap changing transformers, and static var compensator (SVC) [9]–[12]. Nonetheless, there is still a need for general and flexible criteria for PV system connection, including a straightforward method for evaluating PVHC without violating grid operating limits [13].

Installing an SVC in the distribution grid is one of the practical and economical means of improving PVHC, as SVC can perform voltage adjustments by releasing or absorbing reactive power [14], [15]. The SVCs can continuously consume and compensate reactive power and respond quickly to voltage fluctuations.

This study presents a two-stage framework for maximizing PVHC in an active distribution network by identifying the optimal location, size, and operating strategy of SVCs. In the first stage, the optimal locations of PV units are determined to minimize the voltage profile improvement function. Then, the optimal location, size, and operation strategy of the SVC units are determined along with the resizing of the PV units to maximize the PVHC without causing any voltage violation problems in the system.

Since the proposed formulation is a Mixed-Integer Nonlinear Programming (MINLP) problem, solving the problem with classical optimization algorithms involves scalability and convergence problems due to the non-convex nature of the problem and the integer, binary, and continuous control parameters. Although there have been many efforts to optimally size and allocate distributed generation units, finding an optimal solution using heuristic methods is still a challenge. In contrast, heuristic methods are better suited for non-linear constrained optimization problems as they can handle both the integer and continuous control variables in an optimization cycle. For this reason, the use of alternative optimization techniques, such as meta-heuristics, should be explored to find the maximum PVHC while having SVC units. The Marine Predators Algorithm (MPA) [16] is used as a representative meta-heuristic solution algorithm for both stages. The proposed two-stage optimization method is applied to 141-bus and 33-bus radial distribution test systems. The coding of all relevant processes is done in MATLAB 2021a environment.

This paper,

- proposes an efficient method for improving PVHC, which plays an essential role in determining the capability of a distribution system to support more PV generation.
- explores the possible advantages of optimal SVC planning to improve PVHC by eliminating voltage violation problems due to large-scale PV generation.
- extends the conventional PV allocation problem with the management of SVC operation to maximize the PVHC.
- takes into account weather-related volatilities of the load and PV generation with a 72-hour optimization period (one representative day for each season).
- uses real load patterns and PV power characteristics of a Turkish area.
- adapts the MPA algorithm for the proposed problem and extends it with an additional stopping criterion to improve the convergence properties.
- provides a better performance in finding a near global solution for different scenarios compared to other meta-heuristic algorithms such as Whale Optimization Algorithm (WOA) [17] and Grey Wolf Optimizer (GWO) [18].

The rest of the paper is organized as follows. The objective function formulations are discussed in section II. Section III briefly describes the MPA and focuses on the implementation of the optimization problem. Simulation results of 33-bus and 141-bus test system applications are presented in section IV. Final remarks and conclusions are summarized in section V.

II. Problem Formulation

A constrained optimization problem can mathematically expressed as follow;

$$\underset{w.r.t\ \mathbf{X}}{\text{minimize}}\ OF(\mathbf{X}) \tag{1}$$

$$\mathbf{X} = \{\overrightarrow{L}_{PV}, \overrightarrow{S}_{PV}, \overrightarrow{L}_{SVC}, \overrightarrow{S}_{SVC}, \overrightarrow{O}_{SVC}\}$$

$$\text{subject to :} \begin{cases} g_i(\mathbf{X}) \geq 0, & i = 1, 2, ..., m \\ h_i(\mathbf{X}) = 0, & i = 1, 2, ..., p \end{cases}$$

where $\overrightarrow{S}$ and $\overrightarrow{L}$ represent the size and location vectors of the units, $\overrightarrow{O}_{SVC}$ denotes to the operation strategy of the SVC units. The terms $g_i(\mathbf{X})$ and $h_i(\mathbf{X})$ represent the i^{th} inequality and eequality constraints for the control variable vector $\mathbf{X}$. In the Eq. (1), the terms of m and p denote the numbers of inequality and the equality constraints.

In this work, a two-stage allocation approach is used to find the maximum PVHC of the grid. In the first stage, the optimization process determines the optimal locations of the PV units to minimize the voltage violation. In the second stage, the PVHC of the grid is maximized by optimizing the locations, sizes, and operating strategy of the SVC units for the PV locations determined in the first stage. The objective functions of the optimization stages are defined below.

A. Voltage violation (VV) objective function

The VV objective function is expressed as [19]:

$$OF_{\text{VV}} = \sum_{i=1}^{N_T} [\sum_{j=1}^{N_{BUS}} (V_{i,j} - K_{i,j})^2] \tag{2}$$

$$K_{i,j} = \begin{cases} V_{i,j}, & if\ \ 0.95V_{ref} \leq V_{i,j} \leq 1.05V_{ref} \\ 1.05V_{ref} & if\ \ V_{i,j} \geq 1.05V_{ref} \\ 0.95V_{ref} & if\ \ V_{i,j} \leq 0.95V_{ref} \end{cases} \tag{3}$$

where N_T is the total duration of the optimization period, N_{BUS} is the number of busses in the feeder, and $V_{i,j}$ is the j^{th} bus voltage magnitude at hour i, calculated by forward/backward sweep (FBS) power flow [20] method. The reference voltage (V_{ref}) is assumed as 1 p.u in this study.

B. PV hosting capacity (PVHC) objective function

The proposed objective function for maximizing the PV size in the network is defined as follows;

$$OF_{\text{PVHC}} = \frac{1 + \sum_{i=1}^{N_T} (\sum_{j=1}^{N_{BUS}} P_{i,j})}{\sum_{n=1}^{N_{PV}} S_{PV}} \quad (4)$$

$$P_{i,j} = \begin{cases} 0, & \text{if } 0.95V_{ref} < V_j^i < 1.05V_{ref} \\ b \times (2 - \frac{it}{it_{max}}), & \text{if other} \end{cases} \quad (5)$$

where the maximum number of iterations in the optimization process and the current iteration are shown with it_{max} and it, respectively. The term b is a fixed quantity used to penalize the objective function for the violating voltage magnitudes.

C. Constraints

The proposed formulations for the network inequality and equality constraints, including voltage magnitude limitations, nodal power balance equations, PV output limits, and SVC unit constraints, are given in [21].

1) Power balance:

$$\begin{aligned} P_{\text{MG}_i} + P_{\text{PV}_i} - P_{\text{load}_i} - P_{\text{losses}_i} &= 0 \\ Q_{\text{MG}_i} - Q_{\text{load}_i} - Q_{\text{losses}_i} + Q_{\text{SVC}_i} &= 0 \\ i = 1, 2, \cdots, N_{\text{T}} & \end{aligned} \quad (6)$$

where P_{MG} is the active and Q_{MG} is the reactive power supplied from the main grid at the slack bus. P_{PV} is the total active power generated by PVs and Q_{SVC} is the reactive power injected or observed by SVC units. The active and reactive system loads and line losses are represented by P_{load}, P_{losses}, Q_{load}, and Q_{losses}.

2) Generation constraints:

$$P_{\text{MG}_i} \leq P_{\text{MG}_{max}} \quad (7)$$

$$Q_{\text{MG}_i} \leq Q_{\text{MG}_{max}} \quad (8)$$

$$P_{\text{PV}} \leq P_{\text{PV}_{max}} \quad (9)$$

III. Optimization Process

A. Marine Predators Algorithm

Faramarzi et al. [16] developed MPA, which mimics the lifestyle of marine predators and their prey. In MPA, the prey and predator are viewed as search representatives since the marines are searching for the prey, while the prey itself is looking for its food. The algorithm is classified as the meta-heuristic technique, and it starts the optimization process with a random set of solutions and tries to evaluate the solutions using the local and global search questions to find the near-optimal solution. The details of the mathematical formulation used in the MPA algorithm can be found in [22].

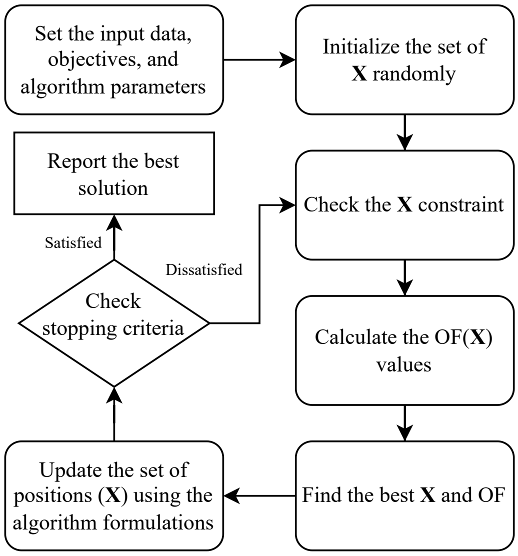

Fig. 1. The flowchart of the optimization process for heuristic methods.

B. Implementation of optimization algorithms

The implementation of the proposed MPA, GWO, and WOA to solve the optimization model comprises the following steps shown in Fig. 1.

IV. Simulation Result and Discussion

A. Load characteristics and system data

The proposed formulations are applied to 141-bus and 33-bus radial networks. The details of the line data, peak load data, and the daily load curves are taken from the Turkish medium voltage distribution feeder [1], [23]. The load curves for the three illustrative days are shown in Fig. 2. Note that the curve's peaks and valleys are critical for considered under and over-voltage problems, respectively.

B. PV models

Seasonal averages are used for the power outputs of PV units. The scaled values for PV outputs [1], [23] are illustrated in Figure 3. According to yearly PV outputs, the average capacity factor for PV units was found as 34%. The same output patterns and capacity factors are used for all PV units since the length of the feeder is short enough to consider the identical atmospheric conditions.

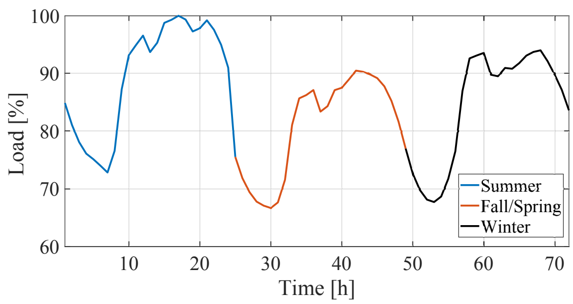

Fig. 2. Scaled load curve.

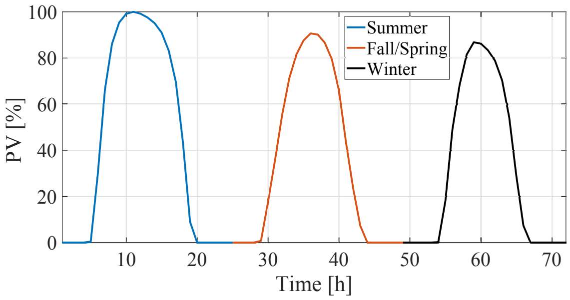

Fig. 3. Estimated scaled PV output.

C. Test system results

The constrained single objective formulation for the first stage of the optimization process can be expressed mathematically as follows.

$$\underset{w.r.t\ \mathbf{X}}{\text{minimize}}\ \ OF_{\text{VV}}(\mathbf{X}) \tag{10}$$

$$\mathbf{X} = \{\overrightarrow{L}_{PV}\}$$

$$\text{subject to}: \begin{cases} g_i(\mathbf{X}) \geq 0, & i = 1, 2, ..., m \\ h_i(\mathbf{X}) = 0, & i = 1, 2, ..., p \\ \overrightarrow{S}_{PV} = 100kW \end{cases}$$

Note that all the PV sizes are assumed to be 100 kW in this stage. In order to ensure the near optimality of the PV locations obtained by MPA, objective function statistics (average, standard deviation, and the best) are compared to those obtained by GWO and WOA in Table I. Note that the average objective functions and corresponding standard deviations are the results of fifty independent runs, where the optimal locations correspond to the best objective function values.

TABLE I
COMPARISON OF THE PERFORMANCE OF THE ALGORITHMS

		Average	STD	Best Fitness	PV locations
33-bus	MPA	0.1926	0.0001	0.1924	14, 15, 16, 17, 18, 31, 32, and 33
	GWO	0.1941	0.0008	0.1928	
	WOA	0.1926	0.0001	0.1924	
141-bus	MPA	0.1884	0.0017	0.1856	45, 46, 47, 48, 49, 50, 51, 52, 77, 82, 83, 84, 85, 86, and 87
	GWO	0.1945	0.0020	0.1922	
	WOA	0.1927	0.0040	0.1880	

The total size of the installed PV units was found to be 800 kW for the 33-bus system and 1500 kW for the 141-bus system. The average and best solutions found by MPA and WOA are the same for the 33-bus system. Moreover, they show a smaller standard deviation than GWA, indicating more uniform solutions. On the other hand, MPA provides the best values in terms of the average, best and standard deviations of the solutions for the 141-bus system.

The second stage of the optimization process aims to maximize the PVHC by optimizing the PV sizes whose locations are already determined by the first stage. In addition, SVC locations, sizes, and operation strategies are also optimized to achieve the same objective. It can be mathematically expressed as:

$$\underset{w.r.t\ \mathbf{X}}{\text{minimize}}\ \ OF_{\text{PVHC}}(\mathbf{X}) \tag{11}$$

$$\{\overrightarrow{S}_{PV}, \overrightarrow{L}_{SVC}, \overrightarrow{S}_{SVC}, \overrightarrow{O}_{SVC}\}$$

$$\text{subject to}: \begin{cases} g_i(\mathbf{X}) \geq 0, & i = 1, 2, ..., m \\ h_i(\mathbf{X}) = 0, & i = 1, 2, ..., p \end{cases}$$

The resulting statistics of the objective functions obtained by MPA are compared to the ones obtained by GWO and WOA, again for the fifty independent runs. The results are tabulated in Table II. The results show that MPA has a better ability to find near-optimal solutions. In the 33-bus system, MPA achieves the smallest best fitness value (2.165E-04), corresponding to the highest PVHC of 4.62 MW installed at the 8 locations determined by the previous stage. It is the maximum PVHC that can be integrated into the system without any voltage violations and is 9-10% greater than the values obtained by the other methods. Moreover, MPA shows the minimum standard deviation when compared to the other two methods. On the other hand, although the MPA achieves the highest PVHC, there are no significant differences between the statistics of the three methods for the 141-bus test system.

The optimal number, locations, and sizes of SVCs determined by MPA for the 33-bus system are illustrated in Table III, together with the optimal sizes of 8 PV units. There are 13 SVCs with a total size of 2.4 MVAr, and the total PV size is 4.62 MW. The optimal number, locations, and the sizes of SVCs determined by MPA for the 141-bus system are illustrated in Table IV, together with the optimal sizes of 15 PV units. There are 20 SVCs with a total size of 3.83 MVAr, and the total PV size is 14.55 MW.

TABLE II
COMPARISON OF THE PERFORMANCE OF THE ALGORITHMS IN SECOND STAGE

		Average	STD	best Fitness	total PV sizes [MW]
33-bus	MPA	2.212E-04	3.491E-06	2.165E-04	4.62
	GWO	2.404E-04	3.617E-06	2.353E-04	4.25
	WOA	2.447E-04	3.956E-06	2.375E-04	4.21
141-bus	MPA	3.235E-03	5.652E-05	3.163E-03	14.55
	GWO	3.311E-03	7.652E-05	3.194E-03	14.40
	WOA	3.264E-03	6.095E-05	3.194E-03	14.40

TABLE III
THE OPTIMAL SIZES OF THE PV AND SVC UNITS FOR 33 BUS SYSTEM.

#	L_{PV}	S_{PV} [kW]	L_{SVC}	S_{SVC} [kVar]
1	14	520	2	10
2	15	110	3	280
3	16	110	4	10
4	17	450	5	60
5	18	500	6	300
6	31	1000	13	300
7	32	940	16	300
8	33	990	21	280
9			25	110
10			28	10
11			29	300
12			31	140
13			33	300
total		4.62 MW		2.40 MVar

TABLE IV
THE OPTIMAL SIZES OF THE PV AND SVC UNITS FOR THE 141-BUS SYSTEM FOUND BY MPA ALGORITHM.

#	L_{PV}	S_{PV} [kW]	L_{SVC}	S_{SVC} [kVar]
1	45	830	9	40
2	46	1980	27	10
3	47	1960	31	10
4	48	2000	41	30
5	49	400	48	300
6	50	330	52	300
7	51	1360	62	300
8	52	270	63	300
9	77	300	79	300
10	82	1980	80	280
11	83	180	81	300
12	84	260	82	300
13	85	1290	85	300
14	86	990	86	300
15	87	420	87	210
16			101	160
17			105	10
18			114	70
19			130	10
20			141	300
total		14.55 MW		3.83 MVar

Voltage magnitude profiles of the 33 bus test system are illustrated in Figures 4 and 5 for the base case and the best MPA solution, respectively. Each color in the figures corresponds to different simulation hours of the three representative days. All the voltage magnitude violations of the base case conditions are eliminated while increasing the PVHC to 4.62 MW (477.5% increase compared to stage-1 results). Fig. 6 shows the optimal strategy for the SVCs to eliminate the voltage violation throughout the simulation period. Note that the daytime overvoltages due to increased PV power penetration and the nighttime undervoltages due to the absence of PV power are eliminated with the appropriate management of the SVC reactive power injection.

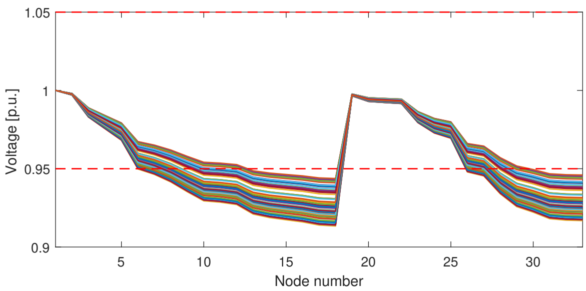

Fig. 4. The voltage profile for the base case in 33-bus system.

Voltage magnitude profiles of the 141 bus test system are illustrated in Fig. 7 and 8 for the base case and the best MPA solution, respectively. All the voltage magnitude violations of the base case conditions are eliminated while increasing the PVHC to 14.55 MW (870% increase compared to stage-1 results). Fig. 9 shows the optimal operating strategy for the SVCs, which eliminates the daytime overvoltages due to increased PV power penetration and the nighttime undervoltages due to the absence of PV power.

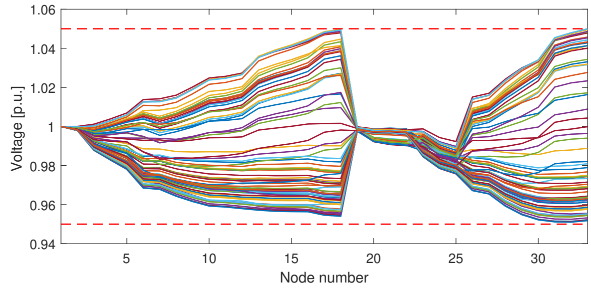

Fig. 5. The voltage profile for the best solution in 33-bus system.

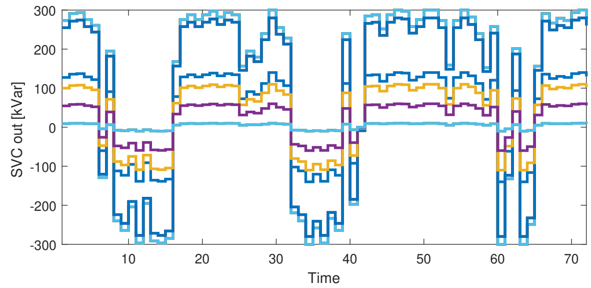

Fig. 6. The optimal strategy of SVCs for the best solution in 33-bus system.

V. CONCLUSIONS

In this paper, a method for maximizing the hosting capacity of PV systems in radial distribution networks was proposed. The proposed two-stage model was solved using an MPA-based heuristic approach. The first stage aimed to determine the near-optimal locations of PV units with a fixed size of 100 kW. The optimization problem was formulated to minimize the voltage violations in the networks. Then, in the second phase, the proposed algorithm determined the maximum size of the PV units by the SVC units. The new objective function for the optimization process was developed to maximize the PV penetration in the system while taking advantage of the SVC units (which still have the voltage violation in the times when the PV cannot generate electric power) to improve the voltage profile of the system based on solving all the voltage violation problems.

The results show that the PVHC of the 33-bus test system and 141-bus test system is increased by 477.5% and 870%, respectively, compared to corresponding stage-1 results. In addition to PVHC increase, the solutions also mitigate the network's voltage violation problems.

We are planning to maximize the hosting capacity of different RDG units in a future study where we will consider several objectives in a multi-objective optimization framework.

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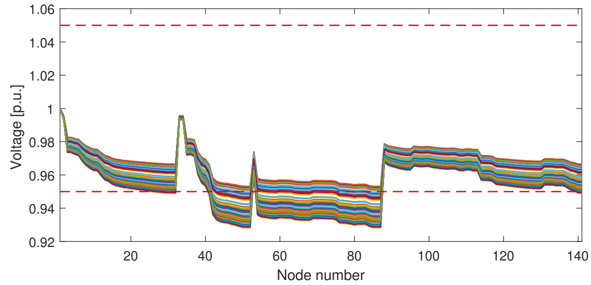

Fig. 7. The voltage profile for the base case in 141-bus system.

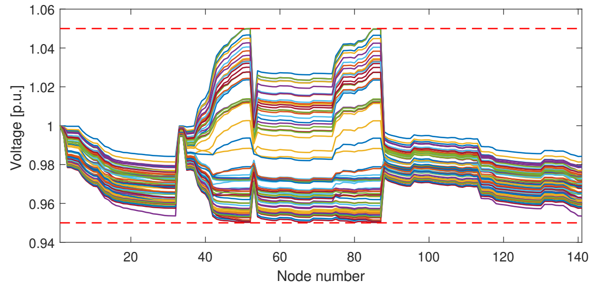

Fig. 8. The voltage profile for the best solution in 141-bus system.

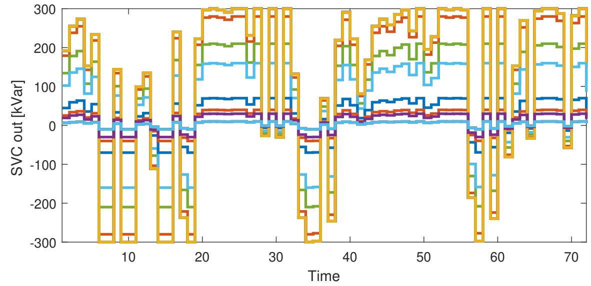

Fig. 9. The optimal strategy of SVCs for the best solution in 141-bus system.

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