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Providing Reactive Power Support from Photovoltaics for Voltage Profile Improvement in Distribution Networks

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Abstract— The increasing prevalence of distributed generation, particularly photovoltaic (PV)-based sources, in electricity distribution networks underscores the need for comprehensive studies on their impact on network operation. This paper addresses the significance of leveraging PV inverters to provide both capacitive and inductive reactive power support, thereby reducing the necessity for additional investments. By incorporating PVs in this dual role, the distribution network gains enhanced flexibility in managing voltage profiles, reducing dependency on additional investments in infrastructure. This dual functionality addresses the dynamic needs of the grid, offering a sustainable solution to optimize the network's overall performance while harnessing the inherent capabilities of PV technology. In this investigation, Python-based Particle Swarm Optimization (PSO) and Firefly algorithms (FA) have been applied to ascertain the optimal amount of reactive power support for enhancing the voltage profile of the network, and the effectiveness of the algorithms are compared. The algorithms take into account the reactive power limits inherent in PV plants within the distribution network, and optimize the reactive power support that should be taken from each PV that won't result in any curtailment in PVs' active power generation, i.e., only the remaining capacity of the inverter is allowed for the reactive power support, if needed. The network is modeled, analyzed, and simulated using the DIgSILENT PowerFactory program, with seamless integration between the network model and the optimization algorithm facilitated through Python. The obtained results demonstrate that reactive power support from PV plants yields positive effects on the overall voltage profile of the network.

Keywords— Particle swarm optimization; Firefly algorithm; Photovoltaics; Reactive power; Voltage profile improvement; Distribution network.

1. INTRODUCTION

Renewable energy, particularly solar power, is increasingly vital due to environmental concerns from fossil fuel depletion, offering a sustainable solution to reduce pollution and associated damages [1]. The increasing interest in distributed generation plants has prompted an increased focus on understanding their impacts on electricity transmission and distribution networks. While the prevailing notion of "generation at the point of consumption" is widely believed to enhance grid performance by minimizing technical losses and achieving a voltage profile closer to the desired levels, inadequately planned distributed generation, falling significantly below or exceeding the grid's requirements, can result in suboptimal network performance.

In such scenarios, the investment required for the sustainable operation of the distribution system increases, necessitating interventions by distribution system operators (DSOs). Commonly implemented interventions include the replacement of existing lines with

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higher current-carrying capacity lines, the addition of new lines/connections to the grid, and the compensation of reactive power using capacitors.

The capability of photovoltaic (PV) inverters to generate or absorb reactive power provides an opportunity for cost-effective compensation activities, potentially reducing operational expenses. However, the effectiveness of such compensatory measures is contingent upon well-designed algorithms that optimize the reactive power support from individual PV systems.

In the Turkish regulatory landscape [2, 3], PV power plants with capacities below 30 MW, whether licensed or unlicensed, connected to the distribution system at the medium voltage (MV) level, are exempt from the obligation to provide reactive power support, voltage regulation and power factor requirement. This exemption, applicable to both licensed and unlicensed generation plants integrated into the distribution system, shapes the operational dynamics and investment considerations for PV power plants in Turkey.

While the current regulations do not mandate reactive power support from distributed generation plants connected to the distribution system, the increasing interest in these plants, especially in countries like Turkey where specific regulations for reactive power support from these plants are yet to be defined, has accelerated theoretical studies. These studies explore the potential of utilizing reactive power support from PV plants to mitigate grid losses and regulate voltage levels [4-7]. However, existing studies primarily focus on voltage improvement through tracking the voltage at the point of common coupling (PCC) of a single PV plant, neglecting the overall voltage profile of the network.

With advancing technology, optimization methods inspired by natural processes are gaining prominence. These methods mimic the logic of natural phenomena to solve complex problems and often prove effective in finding accurate solutions. In this regard, Swarm Optimization provides a solution by simulating the collective behavior of a group.

Particle Swarm Optimization (PSO) and Firefly Algorithm (FA) stand as two prominent examples of Swarm Optimization. PSO is an optimization technique where a group of particles moves through the solution space of a specific problem, aiming to find the best solution. Each particle adjusts its position and velocity to move towards the optimal solution. This process allows for information exchange among particles, guiding them towards better solutions. Various versions and adaptations of the Particle Swarm Optimization (PSO) algorithm have been developed to address specific challenges in optimization tasks [8]. For instance, studies have proposed modified PSO algorithms with adaptive inertia weight and learning factors [9], as well as hybrid PSO algorithms combined with other optimization techniques [10]. These variations aim to improve the convergence speed, solution quality, and robustness of the PSO algorithm in different optimization scenarios.

On the other hand, The Firefly Algorithm (FA) is a metaheuristic optimization algorithm inspired by the light production and interaction of fireflies in nature [11]. This algorithm models the interaction of fireflies with the light intensity in the solution space to optimize solutions [12]. Each firefly represents a potential solution and occupies a position in the solution space. Brighter fireflies attract less bright ones, thereby guiding towards better solutions [13].

The Firefly Algorithm employs a population-based approach where each firefly updates its position based on its distance and brightness compared to others. This interaction, attracting brighter fireflies, mimics the collective behavior of the population, directing towards accurate solutions in the solution space. Thus, FA aims to find the most optimal solution. Firefly

Algorithm is commonly used for multimodal optimization problems and has been successfully applied in various optimization domains. Furthermore, studies have explored the algorithm's performance with different parameter settings and variations [14].

Both algorithms possess unique features and may be suitable for different optimization problems. While PSO ensures rapid convergence, FA may explore the solution space more extensively. Therefore, these algorithms have a broad range of applications and can be successfully applied to various optimization problems.

This study aims to address this gap by introducing a Python-based Particle Swarm Optimization (PSO) and Firefly algorithms specifically tailored to optimize the reactive power support from each PV plant's inverters, contributing to the overall enhancement of the network's voltage profile. The integration of this algorithm with the DIgSILENT PowerFactory application for network modeling and analysis is elucidated. Furthermore, the study evaluates the performance of both algorithms, assessing their effectiveness in optimizing reactive power support while not imposing constraints on the existing active power generation of the plants and taking into account the achievable reactive power limits from the inverters [15].

This paper meticulously outlines the application of an algorithm designed for optimizing reactive power support in the context of distributed PV generation. By seamlessly integrating this algorithm with the PowerFactory program, the study demonstrates its practical application within a distribution network. The primary objective is to showcase the algorithm's efficacy in enhancing the overall voltage profile, underscoring its potential as a valuable tool for optimizing reactive power support in the presence of distributed PV generation.

2. MATERIALS AND METHODS

In this study, analyses were conducted on the distribution system operated by Adıyaman Kahramanmaraş Electricity Distribution Inc. (AKEDAŞ) in the provinces of Kahramanmaraş and Adıyaman in Turkey, as depicted in the Geographic Information System (GIS) diagram in Fig. 1 and single-line diagram provided in Fig. 2 for the Adıyaman Substation-City 1 feeder. The distribution network comprises 249 MV/LV transformers, 508 distribution cable having a total of 139 km and a total installed capacity of 11.792 GW distributed across 12 PV plants, with their respective locations indicated on the GIS diagram.

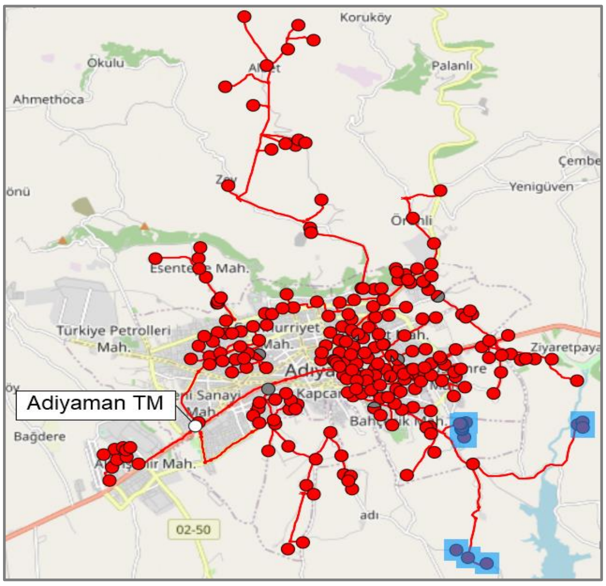

Fig. 1. Geographic information system of Adıyaman substation city 1 feeder.

In Digsilent PowerFactory, PV plants are represented as "PV Systems," allowing for accurate modeling of their active power generation during simulation time. These models utilize data such as radiation and temperature specific to the geographic location of the PV system to predict its active power generation over time. An algorithm based on PSO was developed in Python to calculate the optimal level of reactive power support required from the PV plants. This algorithm was seamlessly integrated with the DIgSILENT PowerFactory application, which is employed for network modeling and analysis. The subsequent sections detail reactive power limits of PV inverters, the PSO algorithm and its integration with the PowerFactory model through the Python code.

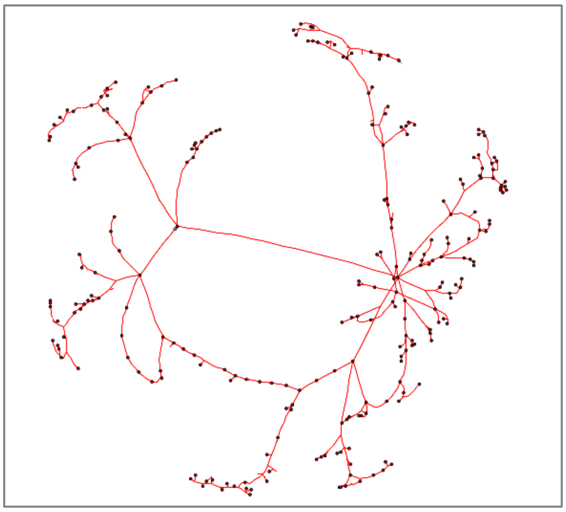

Fig. 2. Single line diagram of Adıyaman substation city 1 feeder.

2.1. PV Inverter Reactive Power Limits

There are three fundamental factors that limit the reactive power support achievable from PV inverters:

a) Inverter Current (Capacity) Limit:

The reactive power limits from the inverter, considering the current (capacity) limit perspective, are defined by the equations:

$$P^2 + Q^2 = S^2 \tag{1}$$

$$-\sqrt{S^2 - P^2} \leq Q \leq \sqrt{S^2 - P^2} \tag{2}$$

This equation defines a circle centered at the origin with a radius S, where S is the apparent power. The reactive power support limit that the PV can contribute is greater when the active power generation is low.

b) Voltage Limit:

For stable operation, the reactive power limit that can be provided from the inverter to the grid, considering the voltage limit perspective, is given by:

$$-\sqrt{\frac{V_g * V_t}{x_{eq}} - P^2} - \frac{V_g^2}{x_{eq}} \leq Q \leq \sqrt{\frac{V_g * V_t}{x_{eq}} - P^2} - \frac{V_g^2}{x_{eq}} \tag{3}$$

In this equation, V_g represents the voltage of the grid to which the PV is connected, V_t is the output voltage of the inverter, x_{eq} and represents the equivalent impedance between the PV connection point and the inverter. This equation defines a circle with a radius of $\sqrt{\frac{V_g * V_t}{x_{eq}}}$ in per unit (p.u.) centered at $(0, -\frac{V_g^2}{x_{eq}})$. When both current and voltage limits are considered together, the inverter can provide reactive power support within the scanned area shown in Fig. 3.

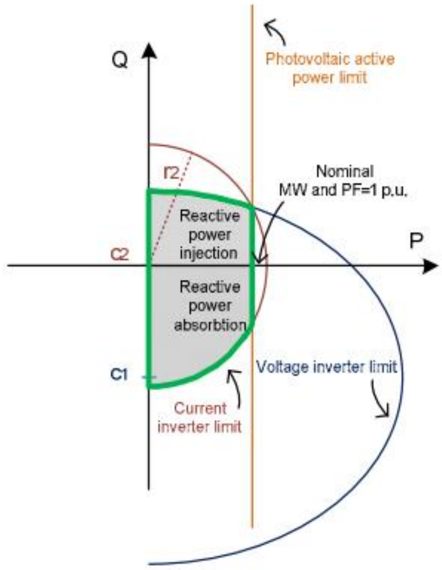

Fig. 3. Current and voltage limits of inverter.

c) Power Factor Limit:

Finally, each inverter has permissible power factor limits inherent to its design. While these limits vary depending on the technology used, most inverters can operate within power factor values ranging between 0.8 capacitive to 0.8 inductive. The reactive power limits (p.u.) that can be obtained from the inverter, considering the power factor limit perspective, are given by:

$$-\sqrt{1-pf_{cap}^2} \leq Q \leq \sqrt{1-pf_{ind}^2} \tag{4}$$

Here, pf_{cap}^2 and pf_{ind}^2 represent the minimum power factor values when the PV inverter operates in capacitive and inductive modes, respectively. In light of these limits, the minimum and maximum reactive power that can be obtained from PV plants in per unit (p.u.) are expressed as follows:

$$Q_{min} = \max(-\sqrt{S^2-P^2},\ -\sqrt{\frac{V_g * V_t}{x_{eq}} - P^2} - \frac{V_g^2}{x_{eq}},\ -\sqrt{1-pf_{cap}^2}) \tag{5}$$

$$Q_{max} = \min(\sqrt{S^2-P^2},\ \sqrt{\frac{V_g * V_t}{x_{eq}} - P^2} - \frac{V_g^2}{x_{eq}},\ \sqrt{1-pf_{ind}^2}) \tag{6}$$

2.2. Particle Swarm Optimization

The Particle Swarm Optimization (PSO) Algorithm is a nature-inspired optimization technique that draws inspiration from the collective behavior of bird flocking or fish schooling to enhance the efficiency of optimization processes [16, 17]. In this algorithm, particles represent candidate solutions, and their movement is governed by a set of rules designed to improve their positions within a solution space. Fundamental components of the Particle Swarm Optimization Algorithm are described below, shedding light on what each represents within the context of an optimization problem:

- **Particle:** Within the algorithmic framework, each particle symbolizes a potential configuration or setting for a PV inverter within the distribution network.

- **Fitness Function:** This parameter represents the objective function value associated with a particular solution. In essence, the fitness function quantifies the effectiveness or quality of a specific reactive power support strategy. A higher fitness function value indicates a more optimal solution that enhances the network's voltage profile.
- **Velocity:** Within the algorithmic framework, velocity represents the rate of change of a particle's position in the solution space. It illustrates how particles explore the solution space by moving towards more promising regions guided by their own best position (personal best) and the global best position found by the swarm.
- **Personal Best (P_{best}) and Global Best (G_{best}):** P_{best} represents the best position a particle has achieved so far, while G_{best} represents the best position found by any particle in the entire swarm. These positions guide the movement of particles towards promising regions of the solution space.
- **Inertia Weight:** In this optimization framework, the inertia weight serves as a parameter that controls the impact of the particle's previous velocity on its current velocity. It balances exploration and exploitation phases of the optimization process, influencing the rate at which particles explore the solution space.
- **Particle Update Equation:** The movement and position of each particle is determined by an update equation, which combines its current velocity, personal best, global best, and a randomization parameter. This equation guides particles towards promising regions of the solution space while allowing for exploration and exploitation. The velocity and position update equations are given in Eq. (7) and Eq. (8), respectively.

$$v_{i,t} = W.v_{i,t-1} + c_1 * r_1 * \left(P_{best_{i,t-1}} - x_{i,t-1}\right) + c_2 * r_2 * (G_{best_{t-1}} - x_{i,t-1}) \quad (7)$$

$$x_{i,t} = x_{i,t-1} + v_{i,t} \; * \; (t_i - t_{i-1}) \quad (8)$$

where $v_{i,t}$ is the velocity of the ith particle at iteration t, W represents the inertia weight controlling the impact of the particle's previous velocity $v_{i,t-1}$, c_1 and c_2 are acceleration coefficients determining the influence of the particle's personal best $P_{best_{i,t-1}}$ and the global best $G_{best_{t-1}}$ on its movement, respectively. r_1 and r_2 are random numbers sampled from a uniform distribution used for personal best and global best updates. $x_{i,t-1}$ denotes the position of the ith particle at the previous iteration $t-1$, and $G_{best_{t-1}}$ indicating the global best position found by any particle in the entire swarm at iteration $t-1$.

The PSO algorithm's flowchart, as presented in Fig. 4, offers a distinct method of emulating natural behaviors that delivers fresh insights into tackling optimization issues, while omitting velocity as a guiding parameter. The stop criterion is determined by running the algorithm multiple times until it converges to a satisfactory solution within a maximum iteration count, indicating that the algorithm has provided a sufficiently good result. The PSO algorithm is chosen for its ability to effectively handle complex optimization problems, such as optimizing reactive power support from PV plant inverters in electrical networks. Its inspiration from collective animal behavior, which exhibits intelligent and adaptive movement patterns to achieve optimal solutions, makes it particularly well-suited for finding optimal solutions in dynamic and nonlinear optimization environments. Additionally, the algorithm's flexibility in not imposing constraints on the active power generation of the plants aligns with the need to enhance the voltage profile without compromising the overall power generation capabilities of the PV plants.

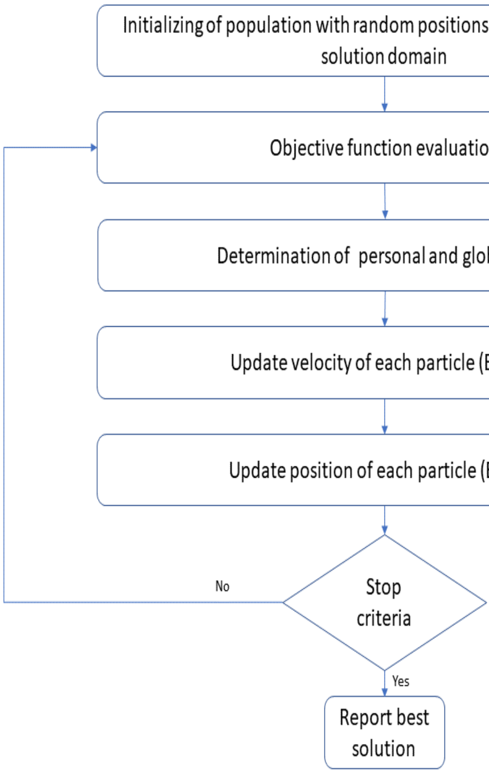

Fig. 4. Flowchart of the PSO algorithm.

2.3. Firefly Algorithm

The Firefly Algorithm (FA) draws inspiration from the flashing behavior of fireflies to optimize light communication within a swarm, aiming to improve efficiency [18, 19]. In this technique, fireflies represent potential solutions, and their movement is guided by rules to enhance their positions in the solution space. Here's a breakdown of key components within the algorithm:

- Firefly: Each firefly symbolizes a configuration or setting for a PV inverter within the distribution network.
- Brightness: This parameter indicates the fitness function value associated with a solution, quantifying the quality of a reactive power support strategy. Higher brightness signifies a more optimal solution, enhancing the network's voltage profile.
- Attractiveness: Attractiveness illustrates how different configurations of PV inverters interact regarding reactive power support. Fireflies are attracted to brighter individuals, with stronger attraction when brightness is higher. Attractiveness diminishes with distance between fireflies, reflecting closer fireflies' greater influence on each other.
- Fitness function: This metric evaluates each solution's efficacy in improving the network's voltage profile. By iteratively assessing solutions based on brightness, the Firefly Algorithm converges towards an optimal configuration of PV inverters, ensuring efficient reactive power support and network stability.

$$\beta(r) = \beta_0 * e^{-\gamma r^2} \tag{9}$$

where β_0 is the firefly attractiveness value at r = 0 and γ is the media light absorption coefficient.

$$x_i(t+1) = x_i(t) + \beta_0 * e^{-\gamma r^2} * (x_i - x_j) + \alpha\varepsilon_i \tag{10}$$

where $\beta_0 * e^{-\gamma r^2}$ is due to the attraction of the firefly x_j and $\alpha\varepsilon_i$ is a randomization parameter.

The flowchart of the Firefly Algorithm depicted in Fig. 5 provides a distinct approach to mimicking natural behaviors, offering novel perspectives on addressing optimization challenges without relying on velocity as a guiding parameter. The algorithm's success depends on its skill in utilizing brightness and attraction principles to swiftly traverse the solution space.

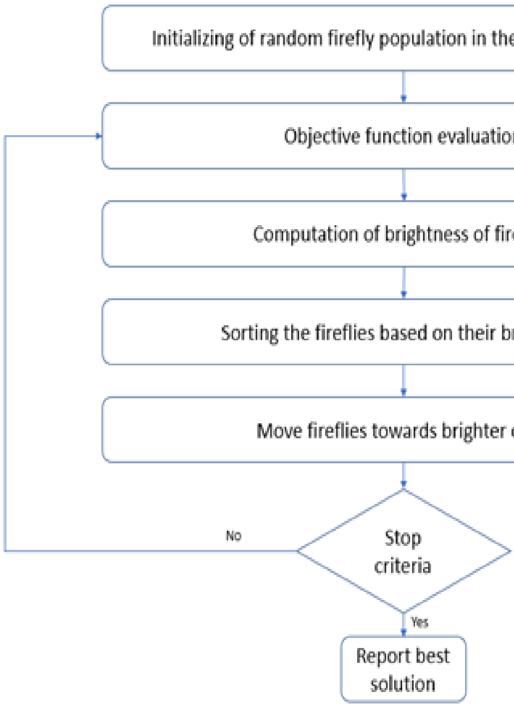

Fig. 5. Flowchart of the firefly algorithm.

2.4. DIgSILENT Integration

DIgSILENT PowerFactory is a network modeling and analysis program that enables remote access to the network model using Python-based code. This access facilitates the modification of the model, execution of analyses, and retrieval of parameters and analysis results for each equipment component within the network. This section will elucidate the process of accessing the network model created in the PowerFactory program through Python and applying an optimization algorithm to the PV systems on the network, employing code snippets.

To begin, the PowerFactory version and edition need to be added to the operating system path. Once integrated, the PowerFactory module is imported, and both application and user objects are initialized. The project is then activated for further analysis. Upon activation, relevant objects and equipment are retrieved for modification. For time-specific analyses, one can adjust parameters using the working hour setting object. The load flow is executed using its dedicated object, while adjustments to PV cell reactive power outputs are made through the PV equipment settings. Post-load flow, the grid's voltage profile is assessed by examining its busbars, providing insights into network stability and performance.

The fitness function for PSO and Firefly algorithms, which will determine the optimal reactive power support from PVs after necessary objects and equipment are arrested, is provided in Algorithm 1. The fitness function is that the bus voltages in the grid are close to ideal (all bus voltages are 1 p.u.). Therefore, in the fitness function, the voltage of the terminals after load flow is read and the voltage deviation index is calculated by summing the distances to 1 p.u.

Algorithm 1. Fitness function

Fitness Function: {
1. Set reactive power support (inductive or reactive) calculated by optimization algorithms for that iteration for each PV in the network
2. Execute load flow
3. Get terminal voltages in p.u.
4. Calculate voltage violation index (VVI) by Eq. (11)

}.

$$VVI = \sum |V_{terminal} - 1| \tag{11}$$

Following the establishment of the fitness function, the PSO algorithm, delineated in the preceding section's flowchart and pseudo code - given in Algorithm 2 - is employed to evaluate the requisite reactive power support from individual PV systems within the grid, with the objective of improving the grid's voltage profile. Note that the lower the value of Eq. (11) the higher the fitness.

Algorithm 2. PSO algorithm

```
Begin
1.  Load flow analysis with no reactive power support from PVs and calculation of reactive
    power limits (Eq. (5) and Eq. (6))
2.  Generate initial population with random position and velocities,
3.  Define the objective function f(x) (Eq. (11)) and evaluate initial fitness of each particle,
4.  While (t<iter_max)
        For i= 1 to n
            Evaluate fitness of the particle i
            if (fitness >  P_best_{i,t})
                P_best_{i,t}= fitness
            if (fitness >  G_best_t)
                G_best_t= fitness
            Update velocity of particle i from Eq. (7)
            Update position of particle i from Eq. (8)
        t = t+ 1
5.  Post process results and visualization
```

3. SIMULATION AND RESULTS

The study evaluates the effectiveness of using a Particle Swarm Optimization algorithm in a reactive power optimization strategy for PV systems to improve the voltage profile of the grid. The evaluation is conducted during an active hour when the feeder takes in reactive power from the substation causing potential drops in the voltage profile at the endpoints due to prolonged line losses. Load flow analyses were carried out in the designated operational state under two conditions: one without any reactive power support from the PV systems on the grid and the other with optimal reactive power support from each PV system.

The optimization process was executed multiple times to demonstrate the effectiveness of both algorithms, and the statistical analysis of the simulation results is summarized in Table 1. As depicted in the Table, the PSO algorithm effectively determines the optimal reactive power support for PVs, resulting in a minimum improvement of 17.8% and a maximum improvement of 20.94% in the voltage violation index across multiple runs compared to no reactive power support scenario.

Table 1. Statistical measures of multiple runs of algorithms.

Algorithm	Component	Min.	Max	Average	Standard deviation
PSO	VVI Improvement	17.8%	20.94%	19.34%	0.94%
FA	VVI Improvement	17.9%	20.89%	19.25%	0.87%

Additionally, the distribution of the improvement in the voltage violation index for various runs is illustrated in Fig. 5. Notably, the PSO algorithm consistently yields reliable results, as evidenced by the narrow range of variation in the results.

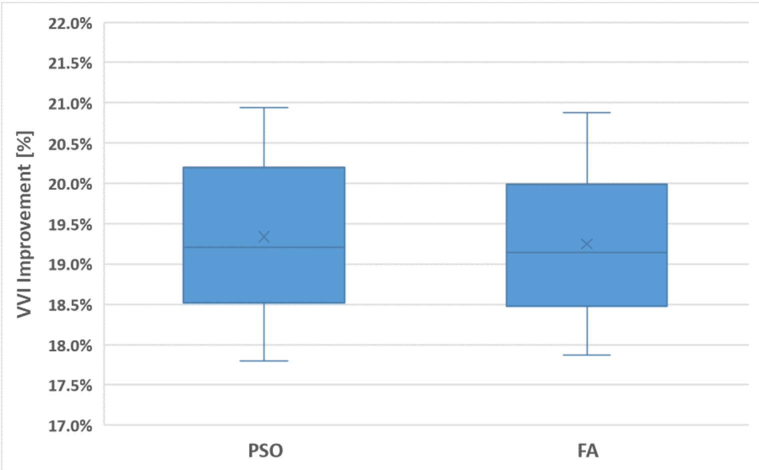

Fig. 5. Distribution of voltage violation index improvement for multiple runs of algorithms.

When comparing the performance of the two algorithms, it's observed that both PSO and FA algorithms exhibit similar effectiveness in improving the voltage violation index.

The statistical analysis presented in Table 1 shows that the FA algorithm achieves a minimum improvement of 17.9% and a maximum improvement of 20.89%, with an average improvement of 19.25% and a standard deviation of 0.87%. Although the differences between the two algorithms' performances are marginal, further examination reveals nuanced variations in their optimization capabilities.

A sample of resulting voltage profiles for both scenarios is given in Fig. 6. As shown in the diagram, substituting reactive power from PV inverters for the substation leads to a slight variation in voltages at the PV plant PCC point and neighboring centers from the nominal 1 p.u. Nonetheless, it eventually advances the overall voltage profile of the grid, drawing it nearer to 1 p.u. and successfully alleviating the voltage reduction problem at the endpoints of the feeder.

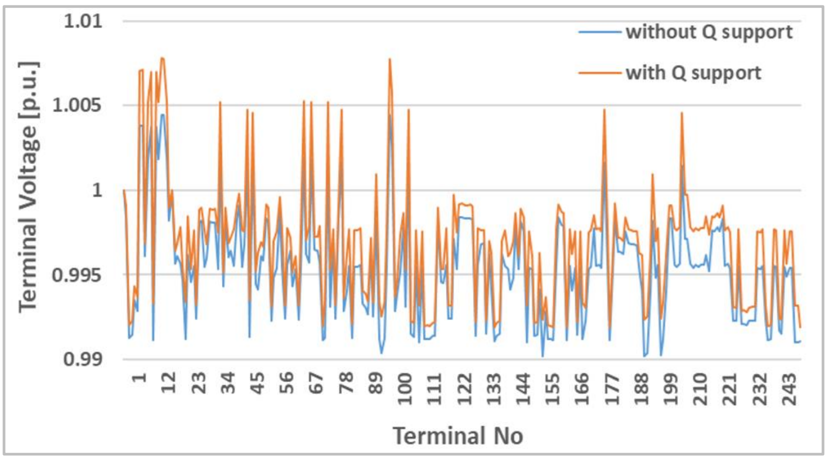

Fig. 6. Network voltage profile before and after reactive power optimization.

The power flow result of the feeder after optimum reactive power support is given in Fig. 7. Installed capacity, active power generation of the PV units in the simulation hour as well as the optimum reactive power support should be taken by each PV unit in the network and the apparent powers are given in Table 2. As seen from the Table, most of the PVs are operating at inductive mode (supplying reactive power to network) while few are operating at reactive mode (absorbing reactive power from the network).

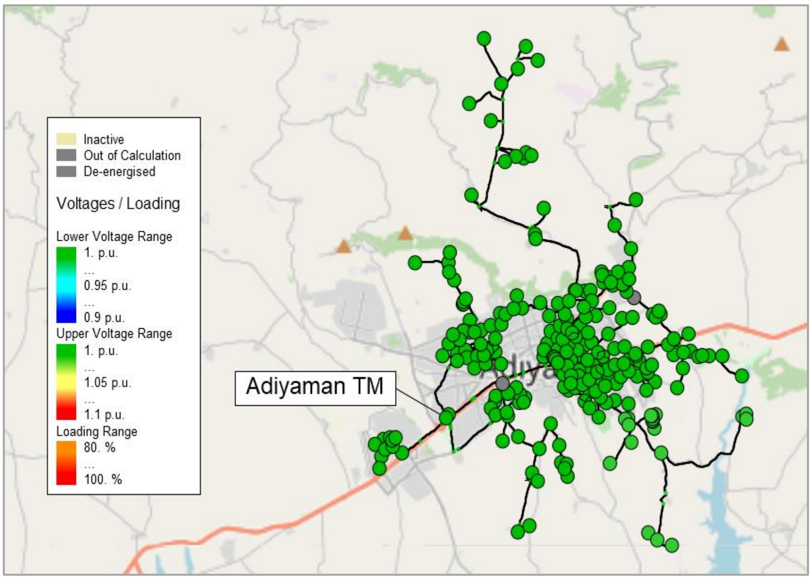

Fig. 7. Network voltage profile with reactive power support.

Table 2. Optimum reactive power support for PVs in the network.

PV name	Installed capacity of PV inverter [kVA]	Active power generation at simulation hour [kW]	Optimum reactive power support [kW]	Apparent power with Q support [kW]
A.KADIR EROGLU PV	1000	727.35	164.8479	788.50
FAMOR PV	1000	728.035	120.6196	825.46
GAZI KAYA PV	1000	727.35	171.3626	827.98
HASAN BASRI KAYA PV	1000	727.349	309.8605	801.93
INCI5_1 PV	920	669.793	-195.4699	676.61
INCI5_2 PV	920	669.793	188.5269	829.18
NAZAN BAGCI PV	1000	727.348	395.5988	766.94
ORMES 2 PV	960	698.942	329.3234	716.90
ORMES 3 PV	1000	727.329	236.7602	778.28
ORMES 4 PV	1000	727.341	-469.5989	728.01
SINAN BAGCI PV	1000	727.35	344.4116	807.34
ZEYNAL EROGLU PV	1000	727.35	11.68802	729.26

4. CONCLUSIONS

In the current regulatory landscape of small-scale distributed generation plants connected to medium-voltage level grids in Turkey, there is no explicit requirement for these plants to provide reactive power. However, recognizing the potential benefits, especially in terms of enhancing the grid voltage profile, opens up avenues for exploring the role of PV inverters in supplying reactive power.

The prospect of receiving reactive power support from PV inverters gains significance when the grid's voltage profile falls below the desired level. In such instances, the implementation of regulations addressing the situation could prompt the deployment of inverters to bolster the grid's reactive power capabilities. This strategic approach not only contributes to voltage stability, but also presents a cost-effective alternative to additional compensation investments.

Moreover, by having the closest PV power plant address the reactive power requirements of the feeder, there is a potential reduction in the overall reactive power drawn or supplied by the feeder to the substation. This, in turn, diminishes the reactive power obtained by the substation from the broader transmission system. As a result, distributed generation plants play a crucial role in providing reactive power support directly to the substation.

This decentralized reactive power support enables the substation to mitigate the risk of incurring reactive power penalties imposed by TEİAŞ, the transmission system operator in Turkey, should the substation exceed the designated reactive power thresholds. By actively participating in reactive power management, distributed generation plants contribute not only to local grid stability but also to the broader efficiency and reliability of the entire electricity distribution system.

While the proposed algorithm offers several advantages in optimizing reactive power support from PV inverters, it's essential to acknowledge its limitations and situations where its applicability may be constrained. Firstly, as heuristic methods, both PSO and FA algorithms do not guarantee the best solution. While they efficiently explore the solution space and converge towards promising solutions, there's no assurance of finding the optimal solution, especially in complex and dynamic network environments. Moreover, the algorithm lacks real-time monitoring capabilities due to its independence from a SCADA system. This means that it cannot perceive instantaneous changes in active consumption/generation status. Instead, the algorithm relies on historical generation/consumption data obtained from the DSO for testing purposes, which may not always reflect current operating conditions accurately. Additionally, the algorithm's applicability may be limited by its ability to address network faults and restoration scenarios (operational scenarios). Since the algorithm operates based on the existing network model, any modifications or updates required to accommodate fault scenarios would need to be manually implemented in the model. This can pose challenges in accurately simulating and optimizing reactive power support in dynamically changing network conditions.

In conclusion, while acknowledging the limitations of the proposed algorithm, it's important to recognize its significant potential in enhancing the efficiency and reliability of distributed generation systems. By optimizing reactive power support from PV inverters, the algorithm offers a cost-effective solution to bolster grid stability and mitigate voltage profile fluctuations. Moreover, its ability to adapt to changing network conditions and contribute to decentralized reactive power management underscores its value in modern electricity distribution systems.

Looking ahead, further research and development efforts can focus on refining the algorithm's capabilities, addressing its limitations, and integrating real-time monitoring features to enhance its applicability in dynamic grid environments. With continued advancements in optimization techniques and grid management strategies, the role of distributed generation plants in providing reactive power support is poised to become increasingly vital in ensuring the resilience and sustainability of electricity distribution networks.

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