Centralized Volt-VAR-Watt Optimization for Real Distribution Grids

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Abstract—The increasing integration of distributed energy resources (DERs) into distribution grids can pose challenges to power quality. Specifically, distributed photovoltaic (PV) systems can cause issues, such as voltage fluctuations, due to their intermittent nature. PV inverter control deployment is necessary to minimize these issues. The existing local inverter control methods might not adequately address the broader grid concerns. As such, this work proposes an optimization-based volt-var watt centralized control method to optimize the output of PV across the grid and solve the voltage issues with high levels of PV integration. The proposed methodology is validated on a medium IEEE 123-bus and a large 3,989-bus distribution network. Simulation results show significant improvement in the overall voltage profiles, and thus, the proposed method proves to be effective in enhancing the overall system performance.

Index Terms—Centralized inverter control, distribution system voltage management, nonlinear optimal power flow

I. INTRODUCTION

The rapid growth of inverter-based distributed energy resources (DERs) is driven by the progress in power electronic devices and the increased flexibility in grid operations. Photovoltaic (PV) generation stands out as the swiftest expanding power generation system within renewable DERs, experiencing substantial growth during the past decade [1]. The extensive incorporation of PV into distribution networks has introduced several challenges, including voltage levels, reverse power flow, and complications in configuring protective relays. Numerous approaches have been proposed to address the operational challenges in distribution networks that incorporate PV units and keep the service voltage within the American National Standards Institute range [2]. Based on previous literature, controlling the PV smart inverter might solve these problems.

Voltage control in distribution grids featuring PV units revolves around two primary aspects: control devices and techniques. Conventional control components include capacitor banks and on-load tap changers (OLTCs) [3]. The operational strategies of these mechanical devices are typically slow. In contrast, DERs, comprising PV units and energy storage systems, are integrated into distribution networks using smart inverters and can offer a significantly swifter regulation approach. The involvement of PV inverters in voltage control and their synchronization with other devices has gained substantial interest in recent times [4]. Further, there is an increasing interest in leveraging the PV inverter’s reactive power capability to enhance performance, which reduces active power losses.

Numerous control approaches have been identified in the existing literature on the volt-var (reactive power control) strategies, as outlined in IEEE Std. 1547-2018 [5]. In volt-var methods, the control of the inverters involves adjusting their operation to either absorb or provide reactive power to regulate voltage levels. The effectiveness of this approach is limited due to the inverter’s reactive power output constraints, which can be inefficient in reducing voltage violations during certain conditions, particularly during periods of high PV generation and off-peak times. Further, the distribution system’s low X/R ratio contributes to voltage regulation, relying on reactive and active power. Consequently, the active power output of the PV inverters can be regarded as an additional control variable for maintaining voltage stability [6].

The control strategies discussed in various studies can be categorized into two main types: local control methods and centralized control methods. Local control techniques involve using nearby measurements, such as voltage levels and/or generated power [7], to manage and restrict voltage rise or drop events. There are some significant concerns over local controllers; for example, local controllers might not be adaptable to dynamic changes in grid conditions or varying grid requirements, and localized decisions made by individual inverters might inadvertently contribute to grid instability [8].

On the other hand, the centralized control approach uses data gathered from different locations through communication channels. All necessary information is transmitted to the central controllers and subjected to processing. Subsequently, control directives are issued to the voltage regulation components, considering the holistic perspective of the distribution network [9]. This advantage enables the formulation of control decisions that are more effective and optimal. The power quality issues associated with a centralized weak grid-connected PV system are discussed in [10]. The study in [11] focuses on the instabilities and dynamic interactions in a centralized, vector-controlled voltage-source converter that connects a single-stage, utility-scale PV system to a high-impedance grid, considering the dynamic resistance of the PV system, using active stabilization techniques to ensure the stability of the entire system in compliance with the IEEE standard 519-2014 [12]. According to [13], a novel Volt-VAR control method can be implemented in a centralized PV system to address the issue of power fluctuations caused by long-distance power transmissions. Moreover, the centralized control strategy in [14] was implemented in conjunction with local droop controllers and a hierarchical coordination approach that tackles...
an optimization challenge to minimize overall system losses; however, the models in [9], [14] are solved through conic relaxation, a scenario-based stochastic optimization approach, or a linear distribution optimal power flow (OPF) model, which might not give an exact solution or might sometimes cause infeasibility for the extensive distribution system.

The study of optimal power flow (OPF) methodology has been extensive in recent days, leading to significant advancements in the field. However, a critical gap remains in the application, especially when it comes to addressing the complex challenges of voltage management in radial distribution networks. This area has yet to be explored thoroughly and needs substantial research. Moreover, despite the advancements in OPF methodologies, more comprehensive studies are required on the centralized control approach for inverters are needed. This area holds immense potential for enhancing grid stability and efficiency. As such, this paper proposes a nonlinear OPF-based volt-var-watt centralized control for inverters for voltage management in the distribution grid. The main contributions of this paper are: (i) a nonlinear OPF-based effective centralized voltage management mechanism to reduce the voltage fluctuations for both voltage rise and voltage drop for 24-hour simulations, and (ii) the model is validated on a large real distribution system network consisting of 3989 buses from Portland General Electric (PGE). The rest of the paper is organized as follows. Section II discusses the problem and solution strategy. Case studies and simulation results are discussed in Section III, and Section IV concludes the paper.

II. PROBLEM FORMULATION AND SOLUTION METHODOLOGY

A. Problem Formulation

Fig. 1 shows a simple one-line diagram of a power system. The complex constant load connected to bus \( i \in N \) is represented as \( S_i^2 \), where the real and reactive power load are represented by \( p_i^g \) and \( q_i^g \), respectively, and \( N \) is the set of all buses. The line impedance, \( z_{ij} \), connected between bus \( i \in N \) and bus \( j \in N \), is expressed by \( z_{ij} = R_{ij} + jX_{ij} \). The conductance and susceptance connected at bus \( i \in N \) can be expressed as \( G_{ii} \) and \( B_{ii} \), respectively. The power balance equation at bus \( i \in N \) is as follows:

\[
\begin{align*}
\sum_{j=1}^{n} V_j G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij} &= p_i^g - p_i^l, \quad (1a) \\
\sum_{j=1}^{n} V_j G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij} &= q_i^g - q_i^l + V_i^2 B_{ii}, \quad (1b)
\end{align*}
\]

Fig. 1: Simple one-line diagram of a distribution system.

Here, conductance \( G_{ij} \) and susceptance \( B_{ij} \) are calculated by the formula \( G_{ij} = \frac{R_{ij}}{R_{ij}^2 + X_{ij}^2} \) and \( B_{ij} = \frac{-X_{ij}}{R_{ij}^2 + X_{ij}^2} \) by using the resistance, \( R_{ij} \) and reactance, \( X_{ij}, \) and \( \theta_{ij} = \theta_i - \theta_j \). The DERs’ real and reactive power injection is expressed as \( p_{i}^g \) and \( q_{i}^g \) at bus \( i \in N \). The DERs are designed as a voltage source in the formulation to get the maximum real and reactive power support between their operating limits. The modeling of the transformer has been replicated from [15]. In power flow problems, the power balance equations, \( (1a) \) are used to solve for the power flow variables, \( (\theta_i, V_i, p_i^g, q_i^g) \). The real and reactive power injection variables \( p_{i}^g \) and \( q_{i}^g \) have their respective minimum and maximum limits. They are:

\[
0 \leq p_{i}^g \leq \bar{p}_{i}^g, \quad (2) \quad 0 \leq q_{i}^g \leq \bar{q}_{i}^g
\]

The (\( \bar{p} \)) and (\( \bar{q} \)) represent the minimum and maximum of variables, respectively. The power flow problem can be solved by solving \( (1) \) and \( (2) \).

Solving power flow problems in large radial networks reveals notable voltage drops across various network sections. Further, the proliferation of DERs leads to substantial voltage deviations in specific areas. These voltage deviations, both drops and rises, have the potential to cause significant complications within the distribution network.

B. Solution Methodology

The voltage issues can be mitigated by dispatching the active and reactive power from the PV smart inverters through volt-var-watt control. According to IEEE std. 1547-2018, [5], the DER reactive power injection should not be constrained up to 44% of the nameplate’s apparent power rating, and the curtailment of active power to meet reactive power constraints is permissible. So, an efficient volt-var-watt injection and curtailment methodology are required for voltage management. An optimization-based centralized voltage management approach can be very efficient in this regard.

1) Optimization Methodology: The nonlinear optimization-based voltage management method is used here. The nonlinear optimization has been solved through the interior point method (IPM) algorithm. The efficacy and validation of the IPM algorithm for solving the nonlinear OPF algorithm has been demonstrated in [16]. For this voltage management methodology, the minimization of real power loss of the network is considered the objective function to construct the optimization problem:

\[
f = \min \sum_{i} \sum_{j} |P_{ij} - P_{ji}|
\]

where \( P_{ij} \) and \( P_{ji} \) are the power leaving bus \( i \) toward bus \( j \) and the power received in bus \( j \) from bus \( i \), respectively. The power balance equations in \( (1) \) will form the equality constraints, and the DERs’ active and reactive power limit \( (2) \) will form a part of the inequality constraints of the optimization problem. The optimization problem will also have the bus voltage angle and bus voltage magnitude limits. So, the overall optimization problem can be written as:

Objective function, (3) (4a)
subject to, (1) - (2) and:

\[
\begin{align*}
\theta_i & \leq \theta_i \leq \bar{\theta}_i \\
V_i & \leq V_i \leq \bar{V}_i
\end{align*}
\]

(4b)

The solution variables for the optimization problem are the same as the power flow problems, i.e., \([\theta_i, V_i, p_{ij}, q_{ij}]^T\). Henceforth, \(\Phi = [\theta_i, V_i, p_{ij}, q_{ij}]^T\) will be used for the ease of writing. Moreover, the equality and inequality constraints can be expressed as \(h(\Phi)\) and \(g(\Phi)\), respectively. The inequality constraints are converted into an equality constraint by adding two non-negative slack variables, that is, \(\sigma = [\sigma_1, \sigma_2, \ldots, \sigma_r]^T\) and \(\Omega = [\Omega_1, \Omega_2, \ldots, \Omega_r]^T\), where \(r\) is the variable’s size. A barrier function can be constructed using \(\log(\sigma_j)\) and \(\log(\Omega_j)\) equivalent to (3) when \(\Omega_j, \sigma_j > 0\). Based on the barrier function and constraints, the Lagrangian function can be written as:

\[
\mathcal{L} = f - \mu \left( \sum_{j=1}^{r} \log(\sigma_j) + \sum_{j=1}^{r} \log(\Omega_j) \right) - \lambda^T h(\Phi) - \gamma^T \left( \Omega - \Phi - \Phi \right) - \xi^T \left( \Phi + \sigma - \Phi \right)
\]

(5)

where \(\lambda, \gamma, \xi\) are Lagrange multipliers. \(\mu\) is the barrier parameter. The Newton direction \(\Delta \Phi, \Delta \lambda, \Delta \sigma, \Delta \Omega, \Delta \xi, \) and \(\Delta \gamma\) can be calculated by solving the following correction equations:

\[
\begin{bmatrix} H & (J^T) \\ J & 0 \end{bmatrix} \begin{bmatrix} \Delta \Phi \\ \Delta \lambda \end{bmatrix} = \begin{bmatrix} \mathcal{L}_\Phi \\ \mathcal{L}_\lambda \end{bmatrix}
\]

(6)

\[
\Delta \sigma = -\mathcal{L}_\xi - \nabla_{\Phi, g} \mathcal{L}(\Phi) \Delta \Phi; \quad \Delta \Omega = \mathcal{L}_\gamma + \nabla_{\Phi, g} \mathcal{L}(\Phi) \Delta \Phi
\]

(7)

\[
\Delta \xi = -\sigma^{-1} \mathcal{L}_{\sigma} - \sigma^{-1} \mathcal{L}_{\sigma} \Delta \sigma; \quad \Delta \gamma = -\Omega^{-1} [\mathcal{L}_\Omega + \gamma \Delta \Omega]
\]

(8)

where \(H\) and \(J\) are the Hessian and Jacobian matrices, respectively. \(\mathcal{L}_\Phi, \mathcal{L}_\lambda, \mathcal{L}_\sigma, \mathcal{L}_\Omega, \mathcal{L}_\xi, \) and \(\mathcal{L}_\gamma\) denote the residuals of the perturbed Karush–Kuhn–Tucker conditions [17]. With these values, the primal \((\sigma_p)\) and dual \((\alpha_d)\) step sizes are calculated. After computing (6) to (8), the update steps for \(\Phi, \lambda, \mu, \xi, \Omega, \) and \(\gamma\) can be computed. From these values, the complementary gap size can be calculated by \(\text{Gap} = \sum_{i=1}^{r} (\Omega_i \gamma_i - \sigma_i \xi_i)\). When the complementary gap becomes smaller than the tolerance, the iteration stops and finds the optimal points for all variables.

2) Overall Solution Methodology: When the power flow problem discussed in II-A is solved, in some instances, the voltage goes beyond the standard voltage limit of 0.95 p.u. to 1.05 p.u. for the distribution system. This voltage violation can be for the voltage drop or the voltage rise, or both. First, the power flow problem is solved in one-time step and checked to see if the voltage is within its range. If the voltage violates the voltage range, then the optimization process starts. The upper \((\bar{V}_i)\) and lower \((V_i)\) limits of the voltage magnitude variables for the optimization algorithm are set between 0.95 p.u. and 1.05 p.u., while the voltage angle’s \(\theta_i\) maximum and minimum limits are set as \(+\pi\) to \(-\pi\). Then the IPM algorithm solves the optimization problem in (4) and finds the optimal set points \((p_{ij}^d\) and \(q_{ij}^d\) for the DEPs). It is worth mentioning that a good initialization helps speed up the solution process and helps to prevent overlapping and inconsistent solutions. The voltage magnitude and voltage angle variables \(V_i\) and \(\theta_i\) are initialized as the average of their minimum and maximum values. The proposed method then fixed the DEPs’ real and reactive power output as solved through the optimization process and kept the voltage between the required voltage limit. The overall procedure is shown in Fig. 2.

![Fig. 2: Conceptual diagram for the proposed voltage management method.](image)

III. CASE STUDIES AND SIMULATION RESULTS

The proposed methodology is simulated in a Windows machine with Intel(R) Core i7 2.60 GHz and 16-GB memory in the MATLAB platform’s optimization toolbox. The system is tested with a medium distribution system (IEEE 123-bus distribution network [18]) and one large real distribution system with 3,989 buses. The power flow simulation is done by making the OPF formulation’s objective function zero and removing the voltage magnitude and voltage angle limit constraints. All the simulations are done in 24-time steps replicating 24 hours of the day. The OpenDSS [19] default irradiance and load profile multiplier settings for 24 hours are used for the simulation.

A. IEEE 123-Bus Distribution Network

The proposed model is tested with a medium IEEE 123-bus distribution network test case. The network data and network topology are adopted from [18]. Three DEPs (PV) are installed at buses 67, 100, and 108. The system has three OLTC transformers between buses 11-38, 28-39, and 123-128. The total number of variables that need to be solved for this problem is 575 in each time step. The total simulation time taken is 46.23 seconds, so on average, each time step of the simulation takes 1.93 seconds.

The voltage profile for the IEEE 123-bus system before and after the proposed method is shown in Fig. 3. The 24 curves depict the voltage profile for the 24 hours. The voltage deviation (VD) for all 24 hours has been calculated based on \(VD_i = (V_{i}^{ref} - V_i)/V_{i}^{ref} \times 100\%\). Here, \(V_{i}^{ref}\) is the reference voltage of the network (1.0 p.u.), and \(V_{i}^{ref}\) is the voltage deviation of the \(i^{th}\) bus of the network. The maximum voltage deviation before and after the proposed control is also calculated. The 24-hour maximum voltage deviation in each time step is plotted in Fig. 4.
Fig. 3: Voltage profile of IEEE 123-bus distribution network: (a) before the proposed control; (b) after the proposed control.

Fig. 4: Maximum voltage deviation in each hour for IEEE 123-bus distribution network: (a) before and (b) after the proposed control approach.

Fig. 5: Topology of PGE distribution system with DER locations highlighted in red.

Fig. 6: Voltage profile of the large real distribution system of PGE; (a) before the proposed control: (b) after the proposed control.

Fig. 7: Voltage profile after the proposed control, which shows that the voltage profile has significantly improved. Now, most bus voltage magnitudes are within the standard limit; however, there are still some instances where the voltage is below 0.95 p.u. and the minimum voltage is 0.935 p.u. This is because the lower limit of the OPF is used as 0.93 p.u. If 0.95 p.u. is used as a lower limit, some of the DERs’ set points violate IEEE std. 1547-2018. So, soft constraints are considered in this case. Moreover, after the proposed control, the voltage deviation reduces to 7%.

All DERs’ real and reactive power output is plotted in Fig. 8. Before the proposed control, the DERs were performing on 100% power factor output, as configured in the model.
and hence, the reactive power output is zero; however, after applying the proposed control strategy, the DERs supplied reactive power in accordance with IEEE std. 1547-2018; hence, the real power amount has changed and improved the overall performance.

IV. CONCLUSIONS

This paper introduces a centralized control strategy based on volt-var-watt operations for PV systems to enhance the overall system performance in practical distribution networks. The control algorithm conducts OPF to generate optimal set points to the PV to maintain the voltage quality. Through simulations conducted on an IEEE test case and a real-world distribution network, significant improvements in the voltage profile are observed, accompanied by a notable reduction in voltage deviation; thus, the proposed method proves to be effective in maintaining the power quality in the distribution feeders with high levels of PV integration. For real-world applications, this methodology needs to be integrated into the Advanced Distribution Management Systems (ADMS) and Distributed Energy Resource Management Systems (DERMS) for various grid use cases, such as voltage regulation, peak demand management, and reverse power flow mitigation. One of the main challenges will be to collect data from different meters, sensors, and devices and the computational capabilities of the grid control systems for adaptability and scalability.

REFERENCES