Data-driven decentralized volt/var control for smart PV inverters in distribution systems

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≪Voltage regulation≫,≪Decentralized control structure≫, ≪Neural network≫, ≪Reactive power≫, ≪Renewable energy systems≫

Abstract

The growing penetration of renewable energy sources (RES) in modern grids may result in severe voltage violation problems due to high stochastic features. Conventional centralized approaches could provide optimal solutions for voltage regulation while with great communication burdens. Control methods based on local information usually have non-optimal results and cannot always guarantee voltage security. This paper proposes a neural network-based decentralized strategy for volt/var control using inverter reactive power capacity. Learning from optimal power flow (OPF) results of historical data, the developed controller can provide optimal results approximate to centralized solutions and outperform local control methods in minimizing the power loss. The proposed method is tested on the IEEE 33-bus system and simulation results illustrate the effectiveness in voltage regulation and loss minimization.

Introduction

Renewable energy resources (e.g., solar PV and wind) have been deeply participated in modern distribution power system development, playing essential roles in achieving the sustainable goal. However, due to their high stochastic and uncertain nature, the increased penetration of renewables brings voltage stability issues and has attracted global attention in recent years [1].

Voltage stability is one of the necessary prerequisites and basic guarantees for secure power grid operations. Voltage/Var control (VVC) can mitigate the voltage violation and reduce the power loss. Some devices are developed to provide reactive power support, such as static Var compensators (SVCs) and static Var generations (SVGs) [2]. As the interface of renewables, inverters are proved to be a cost-effective and flexible device for reactive power support and voltage regulation [3] [4], which are controlled based on power injection demand.

Centralized control methods are widely used for voltage control with PV inverters. However, the determined optimal setpoint may change once the system power varies. Then the optimal power flow (OPF) needs to be recalculated, which brings heavy communication and computational burdens to power grids [5].

Some distributed control strategies are developed to alleviate these burdens. Under designed communication topology, agents can achieve desired goals based on neighbor information [6]. The alternative path in the topology can also avoid single-point failure occuring in conventional centralized methods. But it still needs frequent power flow calculations and considerable communication resources.

Decentralized control approaches are developed to further reduce the demand in communication, which only uses local information to operate without mutual interactions. The droop control is proposed through the approximately linear relationship of reactive power and voltage amplitude [7]. Under scenarios with fluctuating power flow, it can react quickly to local bus voltages without considering changes of other buses. However, the general linear droop curve cannot give the optimal response of reactive power support under local voltage change. The results are non-optimal, and voltage security may not be guaranteed.

In recent years, data-driven methods have attracted much attention, like data-driven OPF [8], deep reinforcement learning [9]. But most of these works are centralized methods with a high communication burden. Ref [10] proposes a data-driven local control method where the local voltage/reactive power relationship is assumed as a piecewise linear function to be identified with historical data. However, a piece-wise linear function cannot perfectly describe the underlying voltage/reactive power relationship. Thus the developed local control method cannot achieve optimal results.

Based on the above analysis, this paper proposes a decentralized method to regulate voltages, which can provide approximate optimal solutions under fluctuating loads and PV generations. The OPF calculation is performed in a centralized manner using historical PV and load data. Then multiple optimal power settings and corresponding voltages are obtained for different PV systems located at various buses. The neural network is trained by these optimal scatters (Q,V) to find underlying relationships between local bus voltage and reactive power support. Next, the trained network functions as a local controller, which gives out optimal local voltage control curves. At last, using developed local controllers, simulations on IEEE 33-bus system are presented to show the effectiveness of proposed method, which can achieve secure voltage regulation and perform comparably to centralized OPF.

This paper is organized as follows. Section II gives the problem formulation and presents conventional voltage control methods. Section III introduces the proposed method and the operation process. Section IV performs the simulation based on the IEEE 33 bus case with actual fluctuating PV and load data, showing the effectiveness of the approach in voltage regulation. At last, the conclusion is given in Section V.

Problem Formulation and Conventional Method

This section presents the Voltage/Var control principle with the implementation of PV inverters. Then, the conventional centralized approach is introduced. It provides the optimal power setting for reference by calculating OPF on historical data.

Voltage/Var Control Using PV Inverter

The impedance in transmission lines will cause voltage drops during power flow. To avoid the risk of severe voltage deviation under fluctuated power flow, volt/var control is used to mitigate the violation. The principle is as follows [1]. As the branch shown in Fig. 1, the voltage drop across the series impedance can be expressed as

$$\Delta V = \left(\frac{P+jQ}{V_j}\right)^* (R+jX) = \frac{PR+QX}{V_j} + j\frac{PX-QR}{V_j} \tag{1}$$

with i and j of the send and to buses. This paper analyzes the High Voltage (HV) level system with a low R/X ratio, so the effect of resistance can be ignored, then it obtains

$$\Delta V = \frac{QX}{V_j} + j\frac{PX}{V_j} \tag{2}$$

As the approximation of voltage triangle shown in figure 1, effects of the imaginary component can be omitted, and it gets

$$|\Delta V| = \left(\frac{PR+QX}{V_j}\right) \tag{3}$$

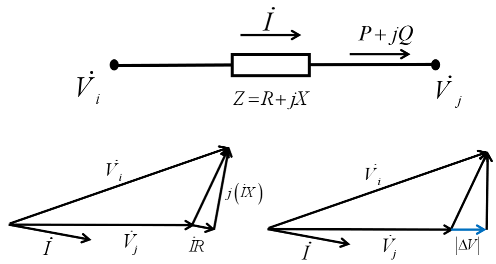


Fig. 1: Branch power flow and voltage triangle.

From equation (3), the voltage deviation is affected by both active and reactive power. But due to the low R/X ratio, the reactive power contributes more to the voltage drop. So reactive power can be used to regulate voltage.

Different devices can be applied to provide reactive power support. Compared with other var support devices, inverters have already been added to grids as the interface for PV generators, so the inverter-based volt/var control is more cost-effective and flexible[3] [4]. Since the PV usually works on Max Power Point Tracking (MPPT) mode for more generation, assume the active power output of the inverter is P_{pv} with power capacity S_{inv}, then the reactive power capacity can be determined by

$$Q_{pv} = \sqrt{S_{inv}^2 - P_{pv}^2} \tag{4}$$

where the Q_{inv} is the Qg_{max} of PV generator outputs.

The consideration of the capacity constraint on inverter reactive power is reasonable. The fluctuated PV active power output affects the reactive power that the inverter can supply. Therefore, inverter-based volt/var control has dynamic reactive power capacity compared to devices with fixed one.

The volt/var control principle and the reactive power support from inverters have been presented above. Next, it will introduce conventional centralized OPF to obtain the reference optimal power settings based on historical data.

Conventional Centralized Approach

Conventional centralized control can achieve optimal results with global communication. To implement OPF on historical data, the selected power flow model and its calculation process are presented below.

Assume there are N buses in the grid, and their voltage amplitudes are denoted as V_i $(i = 1, 2, ..., N)$. The $DistFlow$ model is uesd to describe the AC power flow in general network as follows [11].

$$p_i = \sum_{j \in B_i^D} P_{ij} - \sum_{k \in B_i^U} (P_{ki} - R_{ik} l_{ki}) \tag{5}$$

$$q_i = \sum_{j \in B_i^D} Q_{ij} - \sum_{k \in B_i^U} (Q_{ki} - X_{ik} l_{ki}) \tag{6}$$

$$v_i = v_j + 2(R_{ij}P_{ij} + X_{ij}Q_{ij}) - \left(R_{ij}^2 + X_{ij}^2\right) l_{ij} \tag{7}$$

$$v_i l_{ij} = P_{ij}^2 + Q_{ij}^2 \tag{8}$$

with $k \in B_i^U$, $j \in B_i^D$. B is the feeder bus set, B_i^D and B_i^U are respectively the downstream and upstream bus sets of bus i. p_i and q_i represent the power injections of bus i, and are equal to $Pg_i - Pd_i$, Qg_i respectively.

Power injection from generators are denoted as Pg_i, Qg_i. Active power load demand is noted as Pd_i. The branch current, active and reactive power flow on the branch ij are noted as I_{ij}, P_{ij}, Q_{ij}. And $v_i = V_i^2$, $l_{ij} = \left|I_{ij}\right|^2$. Line impedances are described as R_{ij}, X_{ij} which induce line losses. The target of centralized

OPF is to minimize the line loss.

$$\min_{Pg,Qg,Pd} \sum_{i=1}^{N} \sum_{j \in B_i^D} R_{ij} l_{ij} \tag{9}$$

There are boundary limits of variables

$$V_{\min} \leq V_i \leq V_{\max}, \quad l_{ij} \leq l_{ij\max} \tag{10}$$

$$P_{ij}^2 + Q_{ij}^2 \leq S_{ij\max}^2 \tag{11}$$

$$Pg_{i\min} \leq Pg_i \leq Pg_{i\max}, \quad -Qg_{i\max} \leq Qg_i \leq Qg_{i\max} \tag{12}$$

The upper and lower limits of voltage amplitude are denoted as V_{max} and V_{min}. The square of current magnitude should be less than the maximum value $l_{ij\max}$. Also, the line power flow should not exceed the upper limit $S_{ij\max}$. From equation (4), the reactive power support from the PV has a capacity limit Qg_{max}, which varies with PV active power output.

Based on these constraints and with desired optimization target, conventional centralized OPF can be conducted to generate optimal power settings for PV volt/var control in grids. But this approach requires extensive communication resources and cannot provide the optimal set point for real-time local control when global communication is not triggered. As analyzed above, there are certain relationships between bus power injection and bus voltage deviation. Meanwhile, certain rules of electricity consumption exist, and so does the sunshine. So OPF results on historical data similar to desired scenarios may provide information to find local volt/var control curve approximate to the centralized performance. And the neural network has a solid ability to dig and fit the underlying relationship. Therefore, a neural network-based decentralized approach will be developed for effective local volt/var control in the following section.

The Proposed Data-driven Decentralized Approach

Motivated by recent advancements in machine learning techniques and based on the centralized OPF described above, we will develop a data-driven decentralized approach to achieve near-optimal results without communication. The principle is to use neural networks to identify the underlying relationship between local voltage and reactive power support from optimal operations. Then the trained networks function as local controllers for PV inverters.

Principle of Neural Net Fitting

The basic structure of a neural network is as follows. There are input, hidden, and output layers. When inputs enter the hidden layer, the data is weighed, and biases are added. These sums are the input of the activation function. The output of the nonlinear activation function is the transferred signal intensity of input data, which is distributed over a limited range, such as [0,1]. The sigmoid function is used here.

$$f(x) = \frac{1}{1+e^{-x}} \tag{13}$$

with the $f(x) \in (-1,1)$ for $x \in (-\infty,+\infty)$. It restricts the hidden neurons' output to a limited extent. The activation function itself needs to be differentiable for reverse optimization of neural parameters using strategies such as gradient descent.

There can be multiple hidden layers. But theoretically, a neural network with a single hidden layer is enough to approach arbitrary functions. This fitting capability is enabled by the nonlinear activation function, through which the nonlinear relationships between system input and output can be mapped successfully. So the neural network can work effectively in function approximation. As shown in Figure 2, the neural network used has a single hidden layer with 10 neurons. The training process can be conducted conveniently by powerful modern software, such as MATLAB.

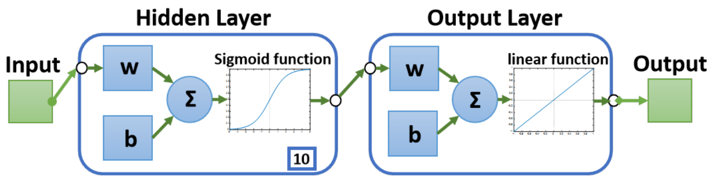


Fig. 2: Two-layer feed-forward neural network structure.

Based on the above analysis, though there are complex relationships between bus voltage and optimal reactive power setting, the neural net fitting provides a competent approach to fit them.

The Proposed Approach

In this section, the proposed method will be introduced, along with the functioning process.

First, it uses the conventional centralized method to calculate OPF for historical data. Then the neural network is applied to fit the underlying relationships between local voltage and optimal reactive power setpoint of PV inverters. So each PV inverter will obtain a local neural network to provide the approximate optimal reactive power setpoint under the variation of bus voltage due to the fluctuations of load and PV. At last, the local controller based on the trained neural network can achieve near-optimal performance in a decentralized way. The whole process is presented in Fig. 3.

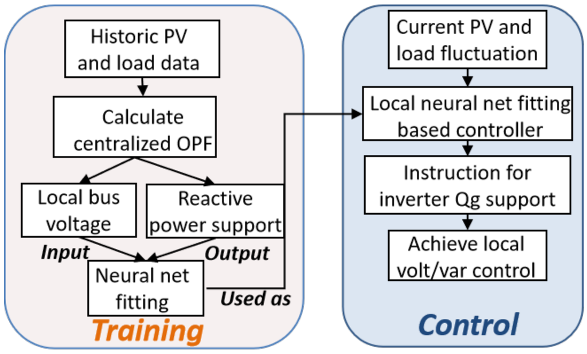


Fig. 3: Process of proposed data-driven decentralized control.

Some details are as follows. The neural network for each PV inverter is trained based on centralized OPF results performed on historical PV and load data. The local voltage of the inverter is as input and the corresponding optimal power setting is as the output. The trained neural network determines the inverter Q_g support only upon local voltage amplitude in the real-time operation.

Therefore, the proposed method has both advantages of centralized and local methods, with solutions near centralized optimal results but without communication requirements.

Case Study

To demonstrate the effectiveness of proposed data-driven decentralized control method, the IEEE 33 bus case (case33) from matpower is studied. Comparisons are made for the proposed method with the conventional centralized and local control methods.

The PV and load data of one month are from [12]. The load data is from the 'Office 2' in the 'Consumption' module, and the PV data is from 'PV GECAD LASIE' in the 'PV Generation' module. 15 weekdays are selected as historical data to perform centralized OPF and generate the training set. Remained 5 weekdays are applied as current data to test the performance of the proposed method.

Based on the IEEE 33-bus system, changing loads are added to several buses (5, 10, 16, 26, 33) and vary from 0.02 MVA to 0.12MVA in every bus. PVs are installed in another buses (6, 12, 18, 24, 32). They are connected to the grid by inverters, enabling 1.6 MVA power capacity for reactive power support of

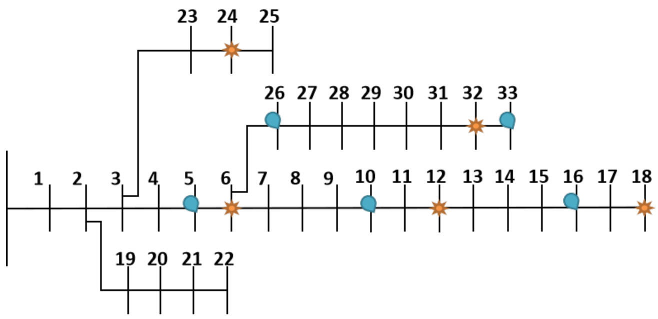
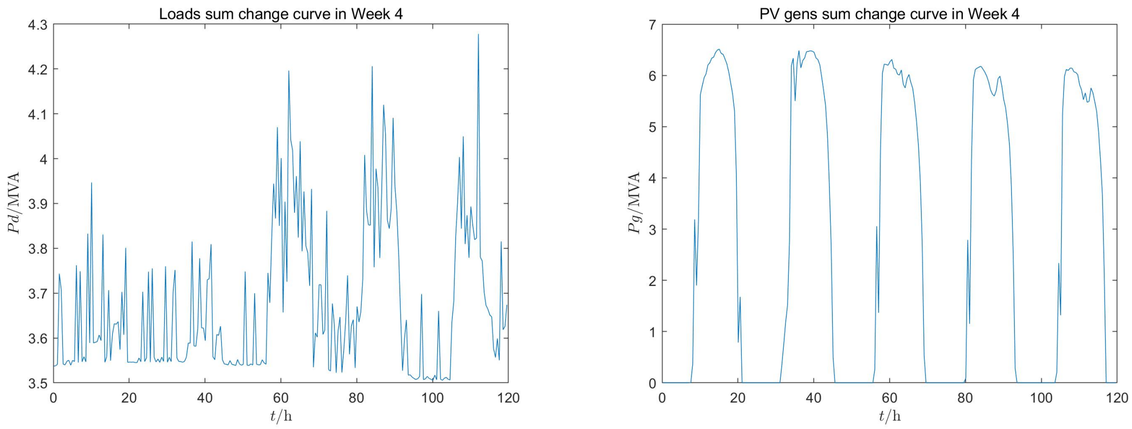


Fig. 4: The 33 bus case topology

each connected bus. The grid topology is shown in Fig. 4, where blue denotes varying loads and the sun for fluctuated PVs. The load and PV test data are demonstrated in Fig. 5, fluctuating during the 120 hours (5 weekdays).



(a) Load sum of 5 weekdays

(b) PV generation sum of 5 weekdays

Fig. 5: Power fluctuation in the grid.

Fig. 6 shows the voltage control results of OPF without reactive power support from PV inverter (denoted as w/o Q), centralized approach (denoted as OPF), and proposed approach (denoted as NN), and the detail in Fig. 8. It can be observed that, without the reactive power support from PV inverters (i.e., w/o Q curve), the voltage security boundary will be violated. Also, by comparing the results of OPF and NN, it shows that the proposed method can effectively control voltage under its boundary without violation, and the performance is close to the centralized method. So the proposed approach can guarantee voltage security, and the outcome approximate centralized optimization results.

Fig. 7 shows the results of the reactive power output of PV inverters under the centralized approach (OPF) and the proposed method (NN). Based on the voltage/var control principle, the reactive power output effectively supports the voltage regulation. It can be observed that the reactive power output of each inverter under the proposed method is approximate to that under the centralized method. This illustrates that the proposed decentralized approach achieves close results as the centralized control method due to similar reactive power generation for support.

Fig. 9 demonstrates results of line loss under the centralized approach (OPF), droop control method (Droop) and the proposed method (NN). The droop control is based on $V_m = V_m^* - m\left(Q_g - Q_g^*\right)$, with V_m^* and Q_g^* as the setting point [13]. Since the inverter reactive power capacity ΔQ varies with time, adaptive control is used here for comparison, which has a changed slope $m = \frac{\Delta Q}{\Delta V}$. It shows that the proposed method achieves similar line loss as the centralized method, while droop control, the conventional decentralized method, has much higher line loss. Therefore, the proposed method can achieve optimal

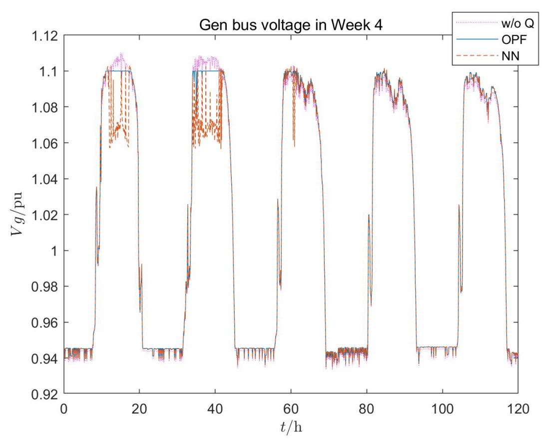


Fig. 6: Overall voltage change curves

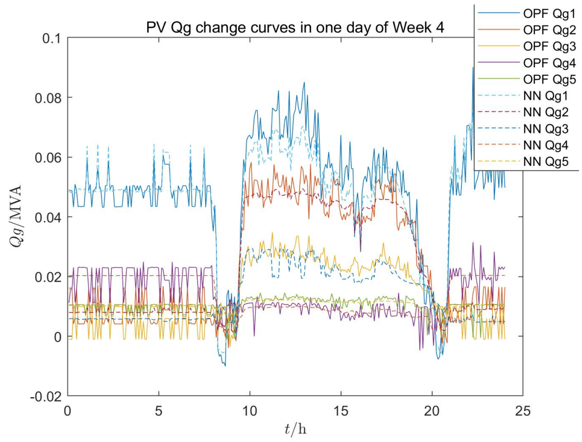
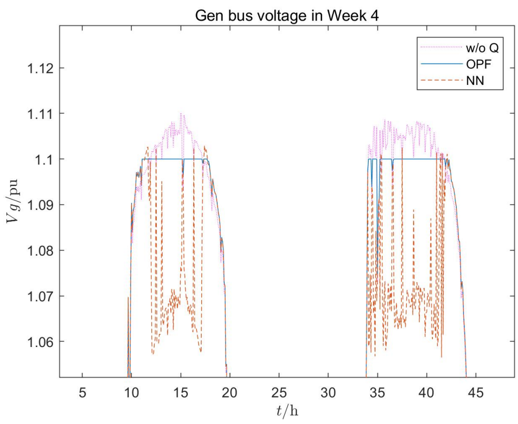
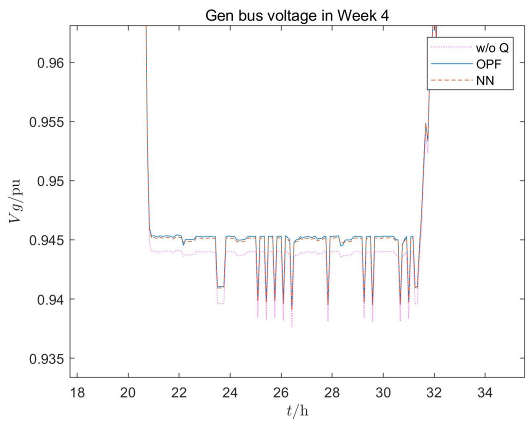


Fig. 7: Q_g change curves in one day of Week 4.



(a) Detail in upper voltage boundary (zoomed in)



(b) Detail in lower voltage boundary (zoomed in)

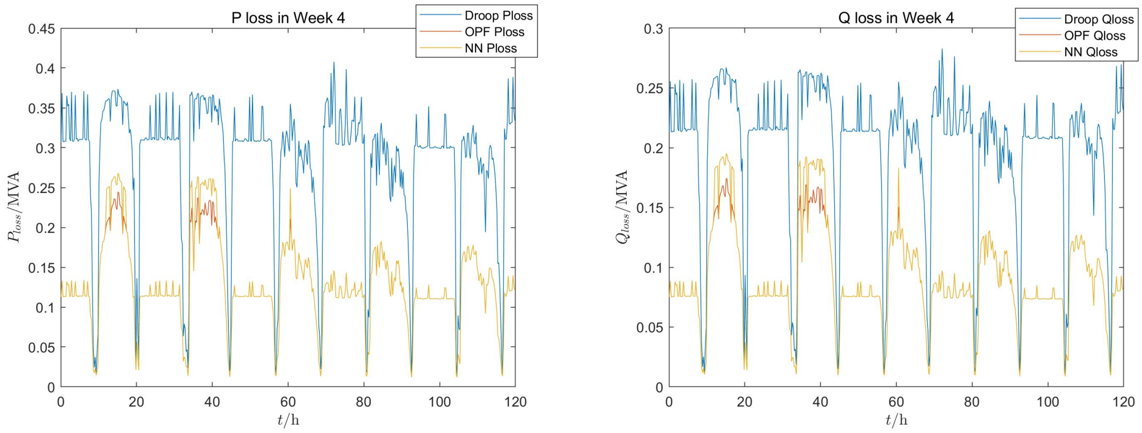
Fig. 8: Gen bus voltage in bus 18 of Week 4 under 3 control approaches

results in a decentralized manner, while droop control cannot.

The above simulation results comparisons show that the proposed approach has approximate performances of centralized OPF but works in a decentralized way. It can mitigate the voltage violation and guarantee voltage security while minimizing the line loss. Therefore, those advantages enable this decentralized method to provide near-optimal solutions effectively, under constantly changing loads and PVs, and without communication.

Conclusion

This paper proposes a neural network-based decentralized approach for volt/var control by inverter reactive power capacity. Neural net fitting is used to train local controllers from centralized OPF results on historical data. As neural networks can describe underlying relationships between voltage and optimal reactive power support, approximate optimal solutions will be provided by local controllers with fluctuating loads and PVs. In this way, inverter reactive power setpoints are optimized without communication. Simulations are conducted based on the IEEE 33 bus case, with fluctuated PVs and loads. The obtained results illustrate the effectiveness of the proposed method in both voltage regulation and loss minimization. Overall, this decentralized approach provides near-optimal solutions for voltage regulation using inverters, which are cost-effective and easy to implement.



(a) P line loss of 5 weekdays

(b) Q line loss of 5 weekdays

Fig. 9: Line losses comparison of 3 control approaches

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