

ANN-Based Adaptive Voltage Regulation for PV Distributed Generation Under Dynamic Cloud-Shading Conditions

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Abstract— High penetration of photovoltaic distributed generation (PVDG) makes voltage regulation a critical problem in medium-voltage feeders. Passing clouds change irradiance by more than 60 % within seconds, step voltage regulators (SVRs) are too slow to follow, and smart inverters lose volt-var capability because their available reactive power changes with the generated active power. This paper builds on an adaptive voltage control with dynamic voltage reference, in which each PVDG restores a 10 % reactive-power margin and shifts its reference when an upstream SVR changes tap. The proposed extension replaces the proportional-integral (PI) controllers of the PVDG with three artificial neural network (ANN) controllers: ANN-1 generates the maximum-power-point voltage, ANN-2 replaces the DC-link PI regulator, and ANN-3 replaces the reactive-power PI regulator. ANN-2 and ANN-3 are trained offline on a short-horizon predictive control law. Three 300 kW PVDGs, two SVRs and a reduced IEEE 34-node feeder are simulated with fractal cloud shading and a variable load. The ANN controller reduces the worst DC-link deviation after irradiance steps from 135 V to 33 V and the settling time from about 100 ms to about 30 ms. The adaptive reference keeps regulation capability for 99.8 % of the cloudy period against 54.6 % with a fixed reference. The ANN regulator lowers the voltage fluctuation index by 24 % under clear sky and 4 % under clouds, reference adaptations at nominal irradiance fall from 2520 to 210, and

SVR coordination cuts tap operations from 6 to 2.

Keywords— photovoltaic distributed generation, voltage control, adaptive voltage reference, artificial neural network, MPPT, volt-var control, step voltage regulator, cloud shading, MATLAB/Simulink.

1. INTRODUCTION

Distribution feeders were planned for one-way power flow, with the voltage falling from the substation to the feeder end and held within 0.95–1.05 p.u. by slow devices such as on-load tap changers, SVRs and capacitor banks. Photovoltaic distributed generation (PVDG) reverses power flow, can raise the voltage above the substation value, and injects power that varies with the weather within seconds [1]. The most demanding condition is the partly cloudy day, when irradiance can fall by more than half in a few seconds and recover as quickly [2][3]. In medium-voltage feeders with a high R/X ratio, voltage is strongly coupled to active power, so every irradiance ramp appears as a voltage fluctuation (Fig. 1).

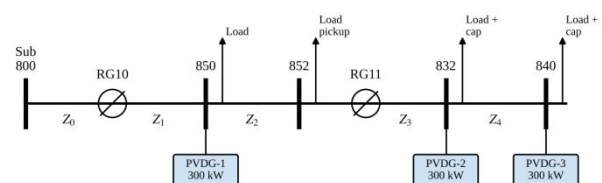


Fig. 1. Medium-voltage feeder with three PVDGs and two SVRs.

SVRs correct slow changes and have a dead band and a 30–60 s time delay, so they cannot

follow cloud-induced fluctuations. A smart inverter can instead regulate its own terminal voltage by injecting or absorbing reactive power, and volt-var control is preferred in medium-voltage networks because it does not reduce energy yield [4]. Its limitation is that the available reactive power $Q_{av} = \sqrt{(S_{nom}^2 - P_{PV}^2)}$ shrinks when the active power is high. Three problems follow: (i) a fixed-reference volt-var regulator can saturate for long periods [5]; (ii) each SVR tap step of about 0.625 % is opposed by the PVDG, consuming margin and causing antagonistic tap operations [6]; and (iii) the PI controllers of the DC-link and reactive-power loops, tuned for one operating point, show large transients, and the perturb-and-observe (P&O) search adds a permanent oscillation.

Landbrug et al. [7] solved the first two problems with an adaptive voltage reference and local SVR coordination, but kept PI regulators in the inner loops. ANNs are universal approximators [8] that can represent nonlinear control laws with feed-forward information. This paper therefore keeps the adaptive reference and coordination of [7] and replaces the PI controllers with ANN controllers. Its contributions are:

- a PVDG voltage control scheme in which all PI regulators are replaced by ANN controllers while the adaptive reference and SVR coordination are unchanged;
- an offline training procedure in which the ANNs learn a short-horizon predictive control law, with a 70/15/15 % data split and early stopping;
- a set of performance indices and a PI-versus-ANN comparison over nine time-domain case studies.

2. LITERATURE SURVEY

Much of the literature validates PV voltage control with power-flow studies at a resolution of minutes. Li et al. [1] used power factor control validated with 15-minute profiles, which cannot represent cloud transients. Tang et al. [9] proposed distributed coordinated reactive power control, but it reacts only to violations and leaves fluctuations inside the band. Xu et al. [10] designed hierarchical volt/var control with fixed droop references, Patari et al. [11] computed optimal set-points under communication latency, and Su et al. [12]

proposed spatial-temporal volt/var control, all with updates in minutes. Visser et al. [13] compared supercapacitors and curtailment in a low-voltage grid, and Rahman and Ganguly [5] used dual-stage model predictive control (MPC).

Dynamic studies include the Volt-PF mode of Sondharangalla et al. [14], the MPC and gradient-projection coordination of Jiao et al. [15], and the decentralised OLTC–PV control of Jafari et al. [6], but they use a fixed inverter voltage reference. Qu and Li [16] and Karbouj et al. [17] addressed limited reactive power and adaptive voltage control of a large PV plant. Turitsyn et al. [18] and Carvalho et al. [19] showed that local reactive power control provides much of the benefit of centralised schemes, and IEEE Std 1547-2018 [20] defines volt-var, volt-watt and power-factor functions. Table I summarises the main approaches.

TABLE I. SUMMARY OF REVIEWED VOLTAGE CONTROL APPROACHES

Ref.	Control approach	Validation	Voltage reference
[1]	PV power factor control	Static, 15 min	Fixed
[9]	Distributed coordinated Q control	Static, 5 min	Limits only
[10]	Hierarchical volt/var, droop PV	Power flow	Fixed
[11]	Distributed optimal P/Q	Power flow, 5 min	Band
[12]	Spatial-temporal volt/var	Power flow, 15 min	Optimal
[13]	Supercapacitor and curtailment	Power flow	Band
[6]	Decentralised OLTC and PV	Dynamic	Fixed
[14]	Volt-PF control mode	Time domain	Fixed
[15]	MPC and gradient projection	Time domain	Fixed
[7]	Adaptive reference + SVR coordination, PI	Time domain, cloud maps	Adaptive
This work	Adaptive reference + ANN controllers	Time domain, cloud maps	Adaptive

For maximum power point tracking (MPPT), P&O and incremental conductance are the most common methods [21][22]. Hill-climbing methods oscillate in steady state and can drift during irradiance ramps unless the step and period are well chosen [23]. Flexible power point tracking (FPPT) lets the array operate below the maximum power point to provide

reserve or limit power [24][25][26], which increases the available reactive power.

Multilayer perceptrons trained by back-propagation [27] were shown by Narendra and Parthasarathy [28] to be suitable for identification and control, and Parisini and Zoppoli [29] showed that a network can approximate a receding-horizon control law, so that optimisation is done offline. In PV systems, ANNs are used mainly for MPPT [30]; Messalti et al. [31] reported faster tracking and lower oscillation than fixed-step P&O. The research gaps are that (i) most methods use static analysis and fixed references, (ii) the adaptive-reference approach keeps PI inner loops, and (iii) ANNs have not been applied to all inner loops of a PVDG with an adaptive volt-var reference and SVR coordination.

3. EXISTING SYSTEM

In the existing system [7], each PVDG uses a local droop-type volt-var regulator with an adaptive limiter, an adaptive reference and SVR coordination, but its inner loops use conventional controllers: P&O with a PI DC-link regulator ($K_p = 1185 \text{ W/V}$, $K_i = 27 \text{ 800 W/(V}\cdot\text{s)}$) and a PI reactive-power regulator ($K_p = 1$, $K_i = 50 \text{ s}^{-1}$). Its limitations are:

- *P&O oscillation*: the P&O search adds a permanent 7.7 V peak-to-peak DC-link ripple and a power ripple that becomes a voltage disturbance.
- *Slow DC-link response*: the PI regulator must rebuild the power reference through its integrator, so the DC-link voltage collapses by up to 135 V after a sudden irradiance drop.
- *Single-point tuning*: fixed PI gains are tuned for one operating point and degrade under fast ramps.
- *Nominal-irradiance chattering*: the P&O ripple makes Q_{av} oscillate around the inverter limit and triggers 2520 reference adaptations in 20 minutes.
- *No feed-forward information*: the PI loops do not use the measured PV power or an internal model of the current loop.

TABLE II. EXISTING VERSUS PROPOSED SYSTEM

Aspect	Existing system	Proposed system
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MPPT reference	P&O, 3 V step	ANN-1 from G and T
DC-link loop	PI regulator	ANN-2 with PV-power feed-forward
Reactive loop	PI regulator	ANN-3 with internal model
Adaptive reference	Yes	Yes (unchanged)
SVR coordination	Yes	Yes (unchanged)

4. RESEARCH METHODOLOGY

The methodology models the PVDG and feeder, implements the conventional PI scheme, designs and trains the ANNs, replaces the PI blocks, and compares both versions in nine case studies. The same models are used for both versions, so differences result only from the controllers.

A. System Modelling

Each PVDG is a single-stage topology (Fig. 2) with a 297.8 kW array of 62 parallel strings of 24 KC200GT modules, a DC link, an averaged three-phase inverter and an RL filter. The module follows the single-diode model [32]:

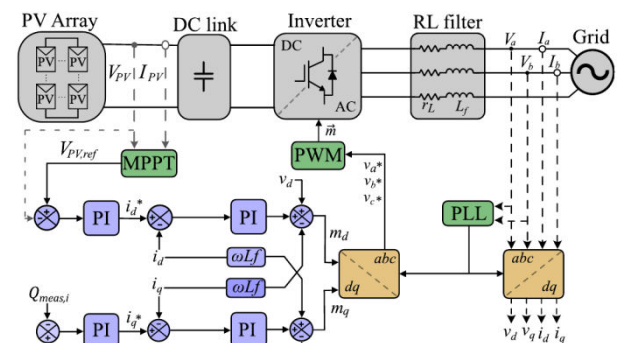


Fig. 2. PVDG topology and conventional PI control.

$$I = I_{ph} - I_0 \left[\exp \left(\frac{V + IR_s}{aV_t} \right) - 1 \right] - \frac{V + IR_s}{R_p} \quad (1)$$

The DC-link energy balance and the dq powers, with the d-axis aligned to the grid voltage using a phase-locked loop [33], are

$$C_{dc} V_{dc} \frac{dV_{dc}}{dt} = P_{PV}(V_{dc}, G, T) - P_{ac} \quad (2)$$

$$P_{ac} = \frac{3}{2} v_d i_d, \quad Q_{PV} = -\frac{3}{2} v_d i_q \quad (3)$$

The closed current loop is a 5 ms first-order lag, and measurements are filtered with a 20 ms time constant. The feeder is a reduced positive-sequence equivalent of the IEEE 34-node feeder [34] (24.9 kV, R/X = 1.44 at node 840) with SVRs RG10 and RG11, three 300 kVA PVDGs at nodes 850, 832 and 840, and about 50 % DG insertion. A 1200 s load profile with a 300 kW

pick-up at $t = 560$ s forces SVR operation. Cloud shading is synthesised with a fractal field (50 % cover, 40 % opacity, 7.7 m/s wind, 700 W/m² clear sky), giving irradiance swings of up to 63 % within 20 s with different shading instants at each PVDG. Table III lists the main parameters.

TABLE III. MAIN SYSTEM PARAMETERS

Parameter	Value
PV array (STC)	297.8 kW, 632 V (24 × 62 modules)
PVDG rating / locations	300 kVA at nodes 850, 832, 840
Base voltage / power	24.9 kV / 1 MVA
Initial feeder load	1.769 MW, 1.044 MVar
SVR delay / tap step	30 s / 0.625 % (± 16 taps)
SVR dead band	± 0.0085 p.u.
DC-link capacitor	20 mF
Simulation time / step	1200 s / 1 ms

B. Adaptive Voltage Control (Kept Unchanged)

The regulator of each PVDG is a droop law with an adaptive limiter set by the available reactive power:

$$Q_{ref} = k_{droop}(V_{ref, adap} - V_{meas}), |Q_{ref}| \leq Q_{av} \quad (4)$$

$$Q_{av, i}(t) = \pm \sqrt{S_{nom, i}^2 - P_{PV, i}(G, t)^2} \quad (5)$$

With a fixed reference, the PVDG can remain at Q_{av} for minutes (Fig. 3). In the adaptive scheme the reference is ramped at 0.004 p.u./s, within 0.95–1.05 p.u., until Q_{PV} falls to 90 % of Q_{av} , restoring a 10 % margin. An SVR tap change is recognised locally when the terminal voltage step satisfies

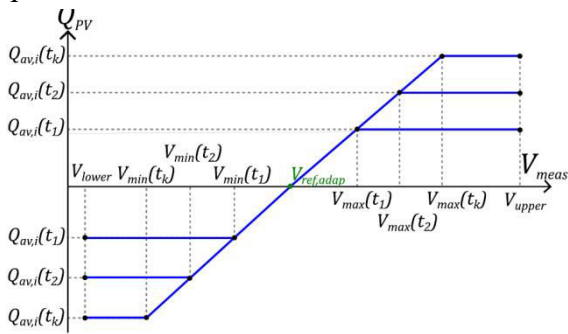


Fig. 3. Q-V droop with adaptive reactive-power limit.

$$0.85 \Delta V_{tap} \leq |\Delta V_{meas}| \leq 1.15 \Delta V_{tap} \quad (6)$$

and the reference is then shifted by one tap step $\Delta V_{tap} = 0.625$ %, so the PVDG follows the new voltage level instead of opposing it (Fig. 4). Large events such as faults are not mistaken for taps.

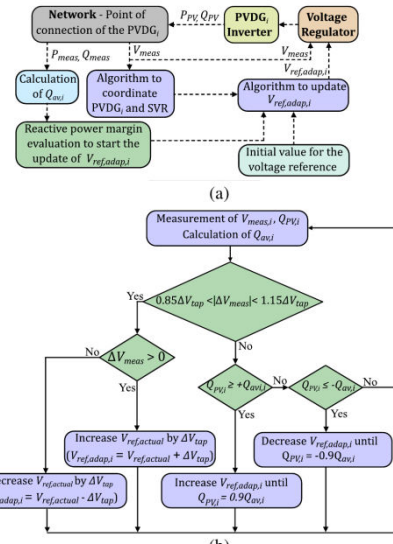


Fig. 4. Flowchart of the adaptive reference with SVR coordination.

The voltage regulation margin follows from $\Delta V \approx (R\Delta P + X\Delta Q)/V_{nom}$ [35]:

$$\Delta V_{PVDG} = \frac{R\Delta P_{PV} + X\Delta Q_{PV}}{V_{nom}} \quad (7)$$

$$\Delta Q_{marg, \pm} = \pm \sqrt{S_{nom, i}^2 - (P_{PV, 0} + \Delta P_{marg, -})^2} - Q_{PV, 0} \quad (8)$$

$$V_{ref, marg} = V_{ref, actual} + \Delta P_{marg, -} \frac{R}{V_{nom}} + \Delta Q_{marg, \pm} \frac{X}{V_{nom}} \quad (9)$$

where $\Delta P_{marg, -}$ is a negative active-power margin provided by FPPT. The references that the PVDG can follow lie between $V_{ref, marg, -}$ and $V_{ref, marg, +}$.

C. ANN Controller Design

Fig. 5 shows the proposed structure: ANN-1 and ANN-2 replace the MPPT block, and ANN-3 replaces the PI regulator in the voltage regulator. Each network is a two-hidden-layer perceptron with tansig hidden and purelin output layers:

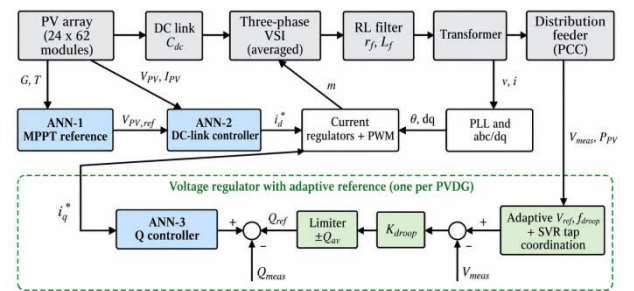


Fig. 5. Proposed PVDG control structure with ANN controllers.

$$y = W_3 \tanh(W_2 \tanh(W_1 \tilde{x} + b_1) + b_2) + b_3 \quad (10)$$

where $\tilde{x}$ is the normalised input. ANN-1 (2-10-10-1) maps irradiance G and temperature T to the maximum-power-point voltage, trained on 4000 exact MPP points (50–1100 W/m², 10–70 °C) found by golden-section search. ANN-2 (3-

12-12-1) replaces the DC-link PI regulator; its targets come from a short-horizon predictive controller (25 ms horizon, 241 candidate commands, 30 000 random states) [29], and it uses the measured PV power as feed-forward:

$$P_{ac}^* = P_{PV} + S_{nom} \text{ANN}_2\left(e_{dc}, \frac{P_{ac} - P_{PV}}{S_{nom}}, V_{dc}\right)$$

(11)

ANN-3 (2-10-10-1) replaces the reactive-power PI regulator. It keeps an internal model $\hat{Q}$ of the commanded reactive power, uses 60 ms predictive targets, and gives

$$u_Q = Q_{ref} + S_{nom} \text{ANN}_3\left(\frac{Q_{ref} - Q_{meas}}{S_{nom}}, \frac{\hat{Q} - Q_{meas}}{S_{nom}}\right)$$

(12)

limited to $|u_Q| \leq Q_{av}$. Training minimises the mean squared error with Adam [36] (learning rate 0.003, mini-batch 256, 70/15/15 % split, early stopping after 40 epochs without improvement); Levenberg–Marquardt [37] is the usual MATLAB alternative. The networks are converted to Simulink blocks with gensim, and the adaptive-reference logic is implemented in a MATLAB Function block. Fig. 6 shows the architectures, and Table IV the training results.

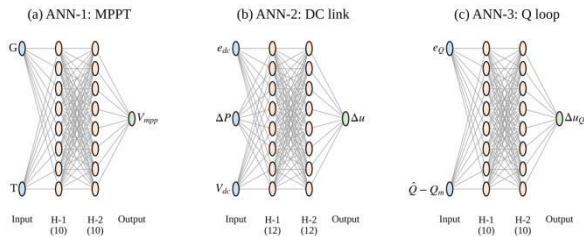


Fig. 6. Architectures of the three ANN controllers.

TABLE IV. TRAINING CONFIGURATION AND RESULTS OF THE ANNS

Item	ANN-1	ANN-2	ANN-3
Replaces	P&O search	DC-link PI	Q-loop PI
Structure	2-10-10-1	3-12-12-1	2-10-10-1
Samples	4000	30 000	30 000
Teacher	Exact MPP	Predictive, 25 ms	Predictive, 60 ms
Best epoch	400	314	42
Test MSE	0.218 V ²	4.08e-4 p.u. ²	9.07e-6 p.u. ²
Regression R	0.99997	0.97431	0.99806

D. Case Studies and Performance Indices

Nine case studies are run with PI and ANN controllers under identical irradiance and load: irradiance steps, PVDG and load impact, clear sky, cloud shading, SVR coordination, large disturbances (a 0.2 s short circuit and a 135 kW load rejection), SVR reference change, margin validation and nominal irradiance. The indices are the DC-link overshoot and 5 V settling time, the MPPT efficiency $\eta = \int P_{PV} dt / \int P_{mpp} dt$, the

fluctuation index FI (RMS of the node-840 voltage after removing its 30 s moving average), the regulation error, the saturation time ($|Q_{PV}| \geq 0.99 Q_{av}$), the tap count and the number of reference adaptations.

5. RESULTS AND DISCUSSIONS

A. MPPT and DC-Link Controllers

Irradiance on one PVDG was stepped from 1000 to 600 W/m² at 1 s, to 850 at 2 s and to 350 at 3 s (Fig. 7). With P&O + PI, a sudden drop lets the inverter keep exporting the old power until the integrator catches up, so the DC-link voltage collapses by 113 V and 135 V on the two downward steps and the PV power falls to 87.0 % of P_{mpp} . ANN-2, using PV power feed-forward, limits the deviation to 26 V and 33 V, keeps power above 99 % of P_{mpp} , and cuts the settling time from about 100 ms to 34 ms. ANN-1 gives a constant reference, removing the 7.7 V P&O ripple (Table V, Fig. 8).

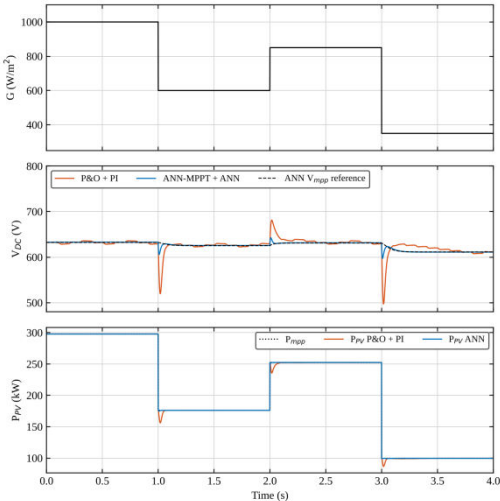


Fig. 7. Irradiance steps, DC-link voltage and PV power.

TABLE V. PI VERSUS ANN DC-LINK AND MPPT CONTROLLERS

Index (step)	P&O + PI	ANN-1 + 2	Improv.
Max. dev., 1000→600 (V)	112.9	26.4	76.6 %
Max. dev., 600→850 (V)	49.0	16.0	67.4 %
Max. dev., 850→350 (V)	135.2	32.7	75.8 %
Settling, 1000→600 (ms)	97.8	33.6	65.6 %
Settling, 850→350 (ms)	100.0	34.0	66.0 %
Min. P _{PV} /P _{mpp} (%)	87.0	99.5	—
Steady V _{dc} ripple (V p-p)	7.7	0.0	100 %
MPPT efficiency (%)	99.78	99.99	+0.21

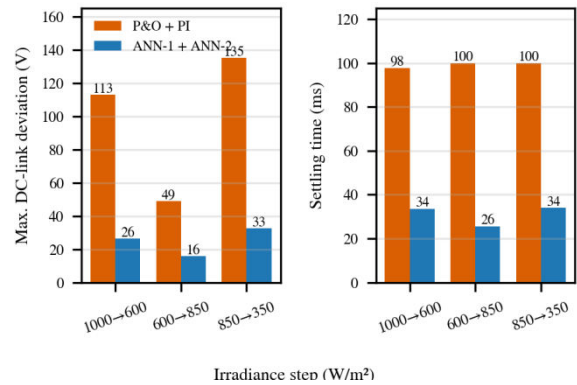


Fig. 8. DC-link deviation and settling time for the three steps.

B. Impact of PVDGs and Fixed versus Adaptive Reference

With PVDGs on MPPT and no voltage support, the voltage at node 840 is higher and more variable (FI rises from 1.37×10^{-3} to 1.72×10^{-3} p.u., range 0.976–1.039 p.u.), and the SVRs cannot remove the fluctuations. Under clear sky, a fixed reference leaves PVDG-840 saturated for 45.7 % of the period after the load pick-up at about 590 s, whereas the adaptive reference reduces this to 0.05 % (PI) and 0.14 % (ANN). The ANN reduces FI from 0.406×10^{-3} to 0.308×10^{-3} p.u. (24.1 %) because it removes the P&O ripple and applies the reactive correction faster.

Under cloud shading (Fig. 9, Table VI), a fixed reference saturates for 45.4 % of the time and FI is 1.040×10^{-3} p.u. The adaptive reference restores the margin 13–14 times, reduces saturation to about 0.2 % and halves FI. Replacing the PI by an ANN with a fixed reference does not remove the saturation (45.4 %), so the adaptive reference and the ANN address different problems and are complementary. With the adaptive reference, the ANN lowers FI by 3.8 % and the largest 1 s voltage change by 6.7 %, and removes the fast oscillation inherited from P&O.

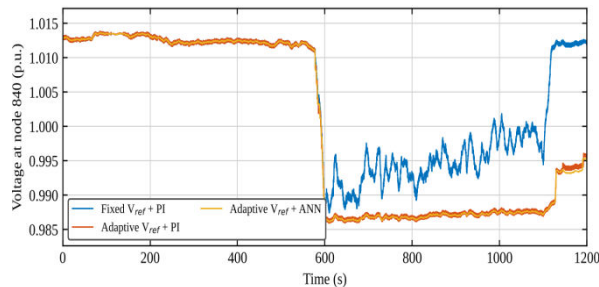


Fig. 9. Voltage at node 840 under cloud shading.

TABLE VI. CLOUD SHADING CONDITIONS (NODE 840)

Index	Fixed + PI	Adaptive + PI	Adaptive + ANN
Fluct. index (10^{-3} p.u.)	1.040	0.520	0.500
Mean $ V - V_{ref} $ (10^{-3} p.u.)	8.286	0.715	0.709
Max. 1 s change (10^{-3} p.u.)	2.58	3.41	3.19
No-regulation time (%)	45.36	0.10	0.18
Reference adaptations	0	14	13
Mean reactive margin (%)	35.4	56.8	56.8

C. Coordination with SVRs and Large Disturbances

With all PVDGs adaptive and SVRs active, the uncoordinated case shows an antagonistic interaction: RG11 raises its tap after 590 s, the PVDGs oppose each voltage step, lose margin and adapt repeatedly, giving 6 tap operations and 57 (PI) or 48 (ANN) reference adaptations. With coordination (Fig. 10, Table VII), each PVDG shifts its reference by ΔV_{tap} , so the reactive power is barely affected by taps, and tap operations fall to 2 and adaptations to 16. The mean margin is lower because the PVDGs handle fast fluctuations and the SVRs handle slow changes, as intended. With coordination the ANN lowers FI by 7.7 % relative to PI. A faster inner controller without coordination cannot remove the antagonistic interaction.

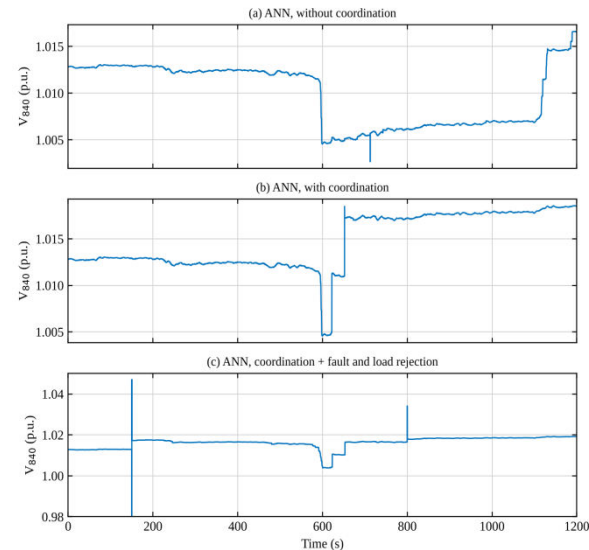


Fig. 10. Voltage at node 840 with ANN controllers: (a) no coordination, (b) coordination, (c) coordination with disturbances.

TABLE VII. EFFECT OF SVR COORDINATION

Index	PI, no coord.	ANN, no coord.	PI, coord.	ANN, coord.
SVR tap operations	6	6	2	2

Ref. adaptations	57	48	16	16
Saturation, PVDG-840 (%)	0.09	0.23	0.01	0.02
Fluct. index (10^{-3} p.u.)	0.401	0.325	0.543	0.502
Voltage range (p.u.)	1.003–1.018	1.003–1.017	1.003–1.018	1.005–1.019

For large disturbances, a 0.2 s short circuit near node 832 drops the node-840 voltage to 0.909 p.u. for both controllers, and a 135 kW load rejection raises it to 1.034 p.u. with regulation recovered within about 0.1 s. These events are not mistaken for tap steps. After a 2.5 % reduction of the RG11 reference, the PVDGs follow the new level after each tap with 3 tap operations and 16 (PI) or 12 (ANN) adaptations.

D. Margin Validation and Nominal Irradiance

The margin formula was evaluated online for PVDG-840. Before the test, the computed feasible range is 0.9991–1.0235 p.u. in MPPT mode and widens to 0.9910–1.0229 p.u. with 50 % FPPT curtailment, as Q_{av} rises from 217 to 282 kvar. With the reference at the computed limits, the PVDG runs at 71–91 % of Q_{av} and the voltage stays within 3×10^{-3} p.u. of the reference, so the formula is a useful, slightly conservative estimate.

The worst case is nominal irradiance (1000 W/m²), when the inverter has almost no reactive capability. With P&O + PI, the oscillating active power makes Q_{av} oscillate around the inverter limit and triggers 2520 adaptations in 20 minutes; the ANN gives a constant reference and reduces this to 210, but FI stays high (0.715×10^{-3} p.u.) because capability is absent. Oversizing the inverter by 50 % lowers FI to 0.314×10^{-3} p.u. and eliminates saturation without energy loss, while 25 % curtailment gives 0.423×10^{-3} p.u. at the cost of 25 % of the energy (242 to 181 kWh in 20 minutes). Since nominal irradiance is rare, either option is acceptable, with oversizing preferable when inverter cost is a small part of the plant cost.

E. Overall Comparison

Table VIII and Fig. 11 compare the controllers. The largest ANN gains are on the DC side, where the PI must rebuild its reference through the integrator and P&O adds ripple; these gains carry over to the feeder as lower fluctuation indices and fewer reference adaptations. Gains in regulation error are small because it is dominated by the droop

characteristic and reactive limits shared by both controllers. The adaptive reference and SVR coordination remain essential, since no improvement of the inner loops can solve loss of regulation capability or antagonistic interaction.

TABLE VIII. OVERALL COMPARISON OF PI AND ANN CONTROLLERS

Index	Case	PI	ANN	Improv.
Max. DC-link dev. (V)	Steps	135.2	32.7	75.8 %
Settling time (ms)	Steps	97.8	33.6	65.6 %
Fluct. index (10^{-3} p.u.)	Clear sky	0.406	0.308	24.1 %
Fluct. index (10^{-3} p.u.)	Cloud	0.520	0.500	3.8 %
Max. 1 s change (10^{-3} p.u.)	Cloud	3.41	3.19	6.7 %
Fluct. index (10^{-3} p.u.)	SVR coord.	0.543	0.502	7.7 %
Ref. adaptations	Nominal G	2520	210	91.7 %

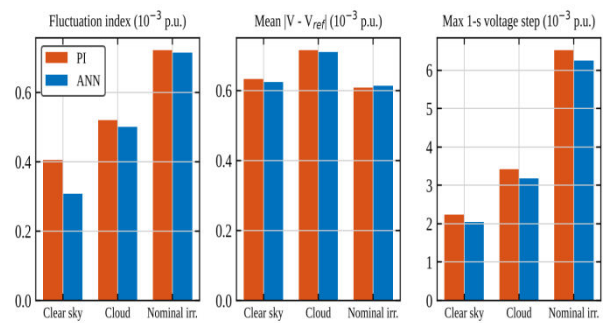


Fig. 11. Fluctuation index, regulation error and largest 1 s voltage change (PI versus ANN).

6. CONCLUSION

This paper extended the adaptive voltage control with dynamic voltage reference for PVDG by replacing the PI controllers of the MPPT controller and the voltage regulator with ANN controllers, and evaluated it on a reduced IEEE 34-node feeder with three 300 kW PVDGs, two SVRs, fractal cloud shading and a variable load. The ANN-based MPPT controller cut the largest DC-link deviation by 75.8 %, reduced the settling time from about 100 ms to about 30 ms, kept the PV power above 99 % of the maximum during transients and removed the P&O oscillation. The networks reached regression coefficients of 0.99997, 0.974 and 0.998 without over-fitting. The adaptive reference remained essential: a fixed reference lost regulation capability for about 45 % of the cloudy period against less than 0.2 % with the adaptive reference. With the adaptive reference, the ANNs reduced the fluctuation index by 24.1 % (clear sky), 3.8 % (clouds) and 7.7 % (SVR coordination), and the adaptations at nominal irradiance from 2520 to 210. Local SVR coordination reduced tap operations from 6 to 2,

and at nominal irradiance 50 % inverter oversizing or 25 % curtailment restored regulation capability. Future work includes hardware-in-the-loop implementation on a real-time simulator or DSP, online or reinforcement-learning adaptation of the ANN weights, an adaptive droop gain, unbalanced switching-level models of the full IEEE 34-node feeder, and coordination with battery storage and a centralised secondary layer.

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