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Research Paper

ANN based selective power control in grid connected AC microgrids

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ABSTRACT

Non-linear loads and inverter-interfaced distributed energy resources (DERs) have made harmonic distortion and limited grid hosting capacity two of the most pressing power-quality problems of low-voltage distribution networks. A recently proposed generalized power-based control (GPBC) coordinates the DERs of a grid-connected microgrid from a central controller and offers sinusoidal current synthesis (SCS), resistive load synthesis (RLS) and a decentralized voltage-detection-based harmonic current compensation (VDB-HCC) mode. In the base strategy every controlled power term at the point of common coupling (PCC) is regulated by a proportional-integral (PI) feedback controller that must be detuned to tolerate sampling and communication delays, so the loops settle slowly. This paper replaces the PI controllers with a compact 3-10-1 artificial neural network (ANN) in velocity form, which preserves integral action and zero steady-state error by construction. The network is first trained to imitate the PI law and is then refined in closed loop with a natural evolution strategy over randomised load, reference, communication and plant-uncertainty scenarios. MATLAB/Simulink

results show that all steady-state THD values of the base strategy are preserved, while the integral absolute error of PCC active and reactive power falls from 550 to 253 W-s and from 558 to 250 VAR-s, harmonic loops settle in 0.17–0.33 s instead of more than 0.5 s, the settling time stays at 0.28–0.30 s from a 4 MVA to a 54 kVA grid, and the median Monte-Carlo tracking error drops by 34 %.

Keywords—Advanced microgrid, artificial neural network, generalized power-based control, harmonic power, selective power control, sinusoidal current synthesis, resistive load synthesis, MATLAB/Simulink.

1. INTRODUCTION

Distribution networks were once passive, radial systems feeding mostly linear loads. Today rooftop photovoltaic systems, small wind turbines, battery storage and electric-vehicle chargers are connected directly to low-voltage (LV) feeders through power converters [1], [2], while the load side is dominated by switched-mode supplies, LED lighting and variable-speed drives that draw highly non-linear currents. The resulting harmonic currents create harmonic voltage drops along the feeder, increase losses, overheat transformers and

neutral conductors, trip protection devices and reduce the grid hosting capacity (GHC) of the network [3], [4]. Standards such as IEEE Std 519-2022 and IEEE Std 1547-2018 therefore limit distortion at the point of common coupling (PCC) [5], [6].

Passive and active filters installed near large harmonic loads are costly and act only locally. A more economical option is to use the spare capacity of the inverters that already connect DERs, which can inject harmonic currents that cancel those of nearby non-linear loads, provided that the units are coordinated [4], [7]. An advanced microgrid, i.e. a cluster of DERs, storage and loads that can regulate its power exchange at the PCC on request of the network operator, is a natural platform for this purpose. Its control is organised hierarchically into primary (local converter loops), secondary (central coordination) and tertiary (operator interface) levels [8], [9]. Fig. 1 illustrates such a microgrid.

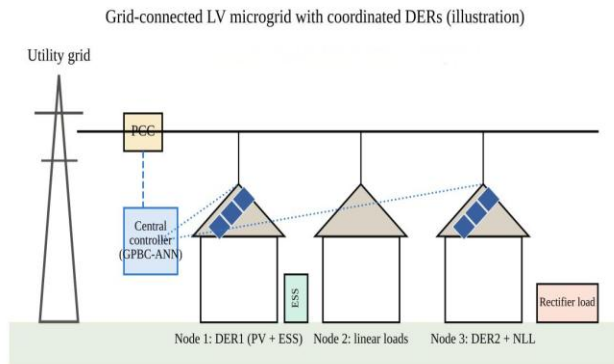


Fig. 1. Grid-connected LV microgrid with coordinated DERs, linear loads and a non-linear (rectifier) load.

The generalized power-based control (GPBC) of Callegari et al. [10] extends power-based control [11], [12] so that a central controller (CC) regulates not only active and reactive power but also in-phase and quadrature harmonic or distortion power terms up to the 11th order. Its feedback action is realised with PI controllers whose bandwidth is limited to about 1 Hz by the one-cycle processing delay, the CAN-link delays and the filters of the secondary loop. As a result,

reference changes, mode transitions and communication disturbances are corrected only after several hundred milliseconds.

A. Objectives

The objectives of this work are: (i) to study the GPBC strategy and reproduce its PI-based results in MATLAB/Simulink; (ii) to design a velocity-form ANN feedback controller and a two-stage training procedure; (iii) to replace the PI blocks of the CC with the ANN without changing the communication protocol, the FfD structure or the mode logic; and (iv) to compare both controllers through RMSE, integral absolute error (IAE), settling time, total harmonic distortion (THD) and Monte-Carlo robustness indices.

B. Contributions

The main contributions are a velocity-form 3-10-1 network that can be dropped into the GPBC in place of each PI block; a two-stage training method in which the network first becomes an exact copy of the base PI and is then refined in closed loop by a natural evolution strategy against randomised delays and uncertainties; and a complete simulation comparison, including an extended grid-strength sweep and a Monte-Carlo robustness study. The remainder of the paper is organised as follows: Section 2 surveys the literature, Section 3 describes the existing system, Section 4 presents the methodology, Section 5 discusses the results and Section 6 concludes.

2. LITERATURE SURVEY

A. Harmonic mitigation with DER inverters

Passive LC filters and active power filters have long been the standard answer to harmonic problems, but both act only at the node where they are installed [3]. Li and He classified harmonic compensation methods for DG-interfacing inverters into current-controlled methods, which inject currents opposite to those of the load, and voltage-controlled methods, which shape the inverter output impedance at harmonic frequencies [4]. Partial compensation within the inverter current rating and multi-

resonant controllers under distorted grid voltage are representative of the former family, and Munir and Li showed that a PV inverter can emulate a resistor at harmonic frequencies to damp propagation along a residential feeder [7].

B. Coordinated compensation in microgrids

For islanded microgrids, Wang et al. added variable harmonic-impedance loops to droop-controlled inverters so that harmonics are shared and resonances damped without communication [13], and Sreekumar and Khadkikar controlled the inverter impedance directly to obtain controllable harmonic sharing [14]. Centralized solutions include the two-level architecture that coordinates DERs and active filters [15] and the enhanced droop scheme with online virtual-impedance adjustment [16]. In grid-connected operation the literature is smaller: virtual admittances attenuate current harmonics [17], and multifunctional inverters combine voltage support with selective compensation [18], but neither provides dispatchability of active, reactive and harmonic power at the PCC. Current-based control makes harmonic current at the PCC dispatchable [19], [20], yet it needs the transformer ratio and loses all compensation when the communication link fails. Voltage support has also been combined with decentralized harmonic mitigation but without harmonic-flow control at the PCC [21]. Table I compares these strategies.

TABLE I

Comparison of Coordinated HCC Strategies for Microgrids

Ref.	Power dispatch	HCC architecture	HCC lost on comm. failure
[13], [14]	No	Decentralized	No
[15], [16], [18]	No	Centralized	No
[17]	No	Decentralized	No
[19], [20]	Yes	Centralized	Yes
[21]	Yes	Decentralized	No
GPBC [10]	Yes	Central. & decentr.	No
This work	Yes	Central. & decentr.	No

C. Evolution of power-based control

Power-based control was introduced by Caldognetto and Tenti as a master-slave scheme in which a master unit at the PCC computes scaling coefficients for active and reactive power and sends them to all DERs, so that sharing is proportional to ratings and no network model is needed [22], [11]. It was extended to single-phase inverters in three-phase four-wire microgrids [12], and a feedback action was later added to form the FfD structure that improves tracking and disturbance rejection [23]. The GPBC generalised the formulation to multiple frequency orders and added the decentralized VDB-HCC mode [10], [24]. The power terms are obtained with conservative power theory, which splits current into active, reactive and void parts using time-domain inner products [25].

D. Neural networks in power-electronic control

Feed-forward networks with one hidden layer are universal approximators [26] and were formalised as identifiers and controllers of dynamic systems by Narendra and Parthasarathy [27]. Bose surveyed neural applications in power electronics and drives [28], Li et al. showed that a neural current controller outperforms vector PI control under disturbances and parameter changes [29], and Zhao et al. identified training data, stability guarantees and computational burden as the practical barriers [30]. Networks can be trained by back-propagation [31], by Levenberg-Marquardt optimisation [32], or, when the cost comes from a non-differentiable simulation, by evolution strategies [33], [34].

E. Research gap

The survey shows that the GPBC is the only strategy that combines model-free coordination, simultaneous dispatch of fundamental and harmonic power terms and continued compensation under communication failure; that its feedback action is a linear PI limited by loop delays; and that no work has applied a neural feedback controller to the selective harmonic and

distortion power loops of a power-based microgrid controller. This paper fills that gap.

3. EXISTING SYSTEM

The existing system is the GPBC of [10] applied to the single-phase LV microgrid of Fig. 1. It contains four linear loads, a rectifier-type non-linear load (NLL) and two 6 kVA dispatchable DERs, each an H-bridge inverter with a storage unit on the DC side and an LC filter. The microgrid is connected to a Thevenin-equivalent feeder through a line impedance and a breaker. TABLE II lists the simulated parameters.

TABLE II

Parameters of the Simulated Microgrid

Parameter	Value
DER rating (each)	6 kVA
Switching/sampling frequency	15 kHz
LC filter L, r, C	1 mH, 77.1 mΩ, 3.3 μF
DC link	400 V, 1.17 mF
Grid voltage, frequency	220 V, 60 Hz
CC feedback PI gains	$K_p=0.071$, $K_i=6.26 \text{ s}^{-1}$
CC processing frequency	60 Hz (6 kHz sampling)
Grid impedance range	$0.0094+j0.0076$ to $0.70+j0.56 \Omega$
NLL	$0.5 \Omega + 2 \text{ mH}$, 2 mF, 25 Ω
Communication	CAN, 125 kbps
Number of DERs	2

A. Structure of the GPBC

Each cycle the CC measures the PCC voltage and current, decomposes the current with conservative power theory and projects it on synchronised sine and cosine signals of orders $h = 3, 5, 7, 9$ and 11 to obtain the in-phase and quadrature harmonic power terms H_{hl} , $H_{h\perp}$ (or distortion power terms D_{hl} , $D_{h\perp}$). For each controlled term X the total power that the DERs must process is the sum of a feedback (F) action, a disturbance-decoupling (D) action that estimates the power drained by internal nodes, and a feedforward (f) action. The result is converted into scaling coefficients in $[-1, 1]$ and broadcast over the CAN link; every DER multiplies them by its own available capacity, so sharing is proportional to rating.

Three modes are available (Fig. 2). In SCS ($\beta = 1$) the harmonic power at the PCC is driven to zero so the grid supplies a sinusoidal current. In RLS ($\beta = 2$) the distortion power is driven to zero so the microgrid looks like a resistor and damps harmonic propagation. In VDB-HCC ($\beta = 3$) resonant controllers add low-impedance paths at the selected harmonics; this mode needs no communication and is activated automatically when voltage THD exceeds 10 % or when no packet has arrived for 18 CC cycles (0.3 s).

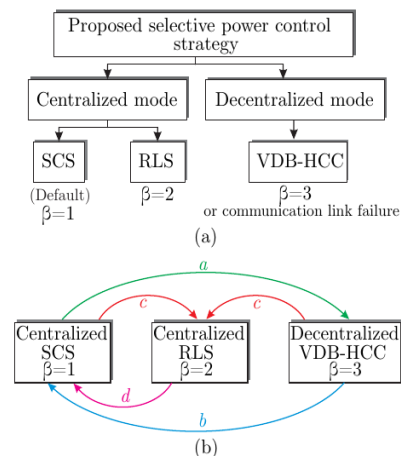


Fig. 2. Operating modes of the selective power control strategy and the state diagram of the transitions.

B. Limitations of the PI feedback action

In the base design all feedback controllers are identical PI blocks with $K_p = 0.071$ and $K_i = 6.26 \text{ s}^{-1}$, tuned for a 1 Hz crossover and 90° phase margin. Their limitations are:

Delay-limited bandwidth: the loop contains a one-cycle (16.7 ms) CC delay, CAN delays in both directions, the moving-average filter of the PCC meter and the DER power dynamics, which forces a conservative gain.

Gain uncertainty: the share of injected harmonic current that reaches the PCC depends on grid impedance and internal loads, so the PI must be robust for the worst case.

Slow recovery: after reference changes, mode transitions and communication disturbances the loops need several hundred milliseconds to settle, and the fD structure without feedback cannot reject link disturbances at all.

Linear law: a PI cannot adapt its aggressiveness to the size of the error.

4. RESEARCH METHODOLOGY

A. Overview

The methodology has five steps: (i) study the GPBC and model the microgrid of Table II in MATLAB/Simulink; (ii) reproduce the PI-based reference results; (iii) log the PI error/increment data; (iv) train the ANN in two stages; and (v) replace the PI blocks with the ANN and repeat identical tests, comparing RMSE, settling time, THD and robustness.

B. Placement of the ANN in the GPBC

The ANN replaces only the feedback controller C_X of each power term (Fig. 3). Feedforward, disturbance decoupling, scaling coefficients, communication, DER local control and mode logic are unchanged, so any improvement can be attributed solely to the controller. One trained network serves all twelve terms (P, Q and the in-phase and quadrature terms of five orders), because the terms have similar loop dynamics and are orthogonal.

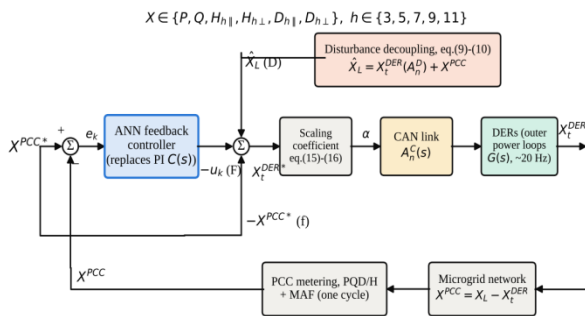


Fig. 3. GPBC loop of one power term with the ANN feedback controller replacing the PI.

C. Velocity-form ANN controller

A digital PI controller at the CC period T_s can be written in incremental form:

$$\Delta u_k = K_p(e_k - e_{k-1}) + K_i T_s e_k \quad (1)$$

The proposed controller keeps the incremental structure but replaces the linear increment by a learned non-linear function of the present and two previous errors:

$$u_k = u_{k-1} + B \cdot [NN(\mathbf{x}_k) - NN(\mathbf{0})] \quad (2)$$

$$NN(\mathbf{x}) = \mathbf{W}_2 \tanh(\mathbf{W}_1 \mathbf{x} + \mathbf{b}_1) + b_2 \quad (3)$$

where $\mathbf{x}_k = [e_k, e_{k-1}, e_{k-2}]^T / B$ and $B = 500$ VA is a normalisation base. Subtracting $NN(\mathbf{0})$ makes the increment exactly zero at zero error, so the output stops changing only when $e_k = 0$ and the zero steady-state error of the PI is retained. The extra input e_{k-2} exposes the error curvature, a derivative-like phase lead that the PI lacks. Anti-windup saturation and the reset on every mode transition are applied exactly as for the PI.

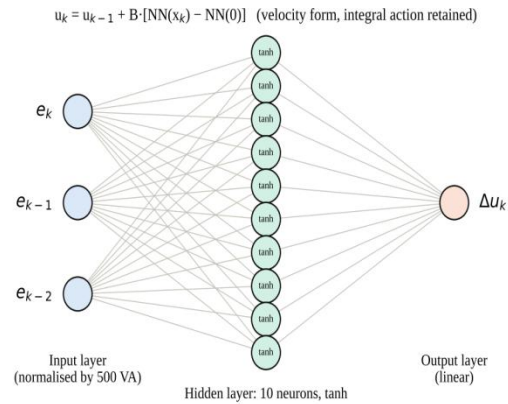


Fig. 4. Architecture of the proposed 3-10-1 ANN controller (tanh hidden layer, linear output).

TABLE III

Specification of the Proposed ANN Controller

Item	Value
Network type	Feed-forward MLP, 1 hidden layer
Inputs	e_k, e_{k-1}, e_{k-2} ($\div 500$ VA)
Hidden / output layer	10 tanh neurons / 1 linear neuron
Parameters	51 (30+10 in layer 1, 10+1 in layer 2)
Execution rate	60 Hz (once per CC cycle)
Stage-1 training	Imitation of PI, 20 000 samples
Stage-2 training	NES, 220 generations, population 2×24

D. Training data and scenarios

For the closed-loop stage a reduced model of one GPBC loop reproduces, cycle by cycle, the timing of the full Simulink model: the PCC term is averaged over the last fundamental cycle, DER reports are one cycle old, commands are applied one cycle later and the DER power loop is a first-order lag with time constant τ . The PCC term is $X^{PCC} = X_L - g \cdot X^{DER}$, where g is the fraction of DER injection that reaches the PCC. A training set of 24 and a validation set of 12 random scenarios, each 6 s long, contain three reference

steps (up to ± 1200 VA), two load steps (up to ± 1500 VA), a DER-to-CC report disturbance (up to ± 400 VA, 0.5 s), a CC-to-DER command disturbance (up to ± 500 VA, 0.5 s) and measurement noise. The gain g is drawn from 0.6 to 1.1 and τ from 5 to 12 ms, and every scenario is run with both the F-only and the full FfD structure.

E. Two-stage training

Stage 1 (supervised initialisation): 20 000 random normalised error triplets in $[-3, 3]$ were generated, the target increment was computed with (1) and the network was trained with Levenberg–Marquardt-type optimisation [32] until the mean squared error was below 10^{-5} p.u.², so that the ANN starts as an exact copy of the PI.

Stage 2 (closed-loop refinement): the weights $\mathbf{w}$ are tuned directly for closed-loop performance with the cost

$$J = \text{mean}(e^2) + \lambda \cdot \text{mean}(\Delta u^2), \lambda = 0.02 \quad (4)$$

summed over the F and FfD structures, using a natural evolution strategy with antithetic sampling [33], [34]. In each generation $P = 24$ perturbations $\varepsilon_i \sim N(0, I)$ are drawn, the cost is evaluated at $\mathbf{w} \pm \sigma \varepsilon_i$, and the weights move along the estimated descent direction

$$\mathbf{w} \leftarrow \mathbf{w} - (\eta/2P) \sum_i A_i \varepsilon_i, A_i = (J_i^+ - J_i^-)/\text{std}(J) \quad (5)$$

with $\sigma = 0.04$ – 0.05 and $\eta = 0.03$ – 0.06 . The weights with the lowest training cost are kept and the validation cost is logged after each generation. Because only cost evaluations are needed, the method copes with delays, saturations and logical resets without differentiation.

F. Safety and implementation

Three properties make the ANN safe to deploy: the velocity form guarantees zero steady-state error; the tanh layer bounds the increment, so a corrupted sample cannot create an unbounded action; and the training set covers plant gains from 0.6 to 1.1 and time constants up to 12 ms. The model uses MATLAB/Simulink with Simscape Electrical (fixed step 0.83 μ s, DER control at 15 kHz, CC triggered at 60 Hz) and a

MATLAB Function block for the network, with a switch that selects the original PI or the ANN so that both are tested on the same model. A quasi-steady harmonic-phasor model of the same network (orders 1–15) was used for training and sweeps. Three test groups were defined: power tracking with disturbance rejection (7 s, stiff grid), an eleven-event mode-transition sequence (8.5 s), and a grid-strength sweep with a Monte-Carlo robustness study.

5. RESULTS AND DISCUSSIONS

A. ANN training

Stage 1 reduces the mean squared error between the network and the PI increment by four orders of magnitude, so the ANN is initially a faithful copy of the PI. In stage 2 (Fig. 5) the closed-loop cost on the training set falls from 2.58 (equal to the PI value of 2.57) to 1.93, a 25 % reduction, and the cost on the independent validation set falls from 3.73 to 3.14 (16 %), confirming generalisation. Most of the gain is obtained in the first 40 generations.

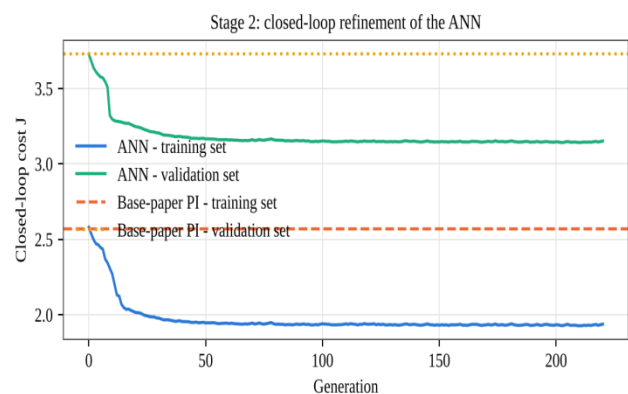


Fig. 5. Stage-2 training: closed-loop cost of the ANN on training and validation scenarios compared with the base PI.

Because the network is small, the learned law can be inspected. For a constant error the equivalent integral gain is 18.3 s^{-1} for small errors and rises to about 30 s^{-1} for errors of 500–1000 VA, against 6.26 s^{-1} for the PI, while the equivalent proportional gain is 0.14 for small errors and becomes slightly negative for large ones. The ANN therefore integrates more strongly while avoiding the proportional kick that,

combined with the two-cycle loop delay, would cause overshoot after large steps.

B. Power tracking and disturbance rejection

In SCS mode on a stiff grid, P/Q dispatch is applied at 1 s, harmonic control from 1.5 s, report and command disturbances at 2.5–4 s, a Q ramp from 4.5 s and a second NLL at 6 s. The P and Q steps settle within ± 50 W in 0.40 s with the ANN, whereas the PI has not settled within 0.5 s. The harmonic terms settle within ± 25 VA in 0.36 s with ANN-FfD against more than 1 s with PI-FfD. After the 7th-order report disturbance the peak deviation is 277 VA with the ANN and 330 VA with the PI, with recovery in 0.70 s instead of 0.99 s, and the IAE of Q during the ramp falls from 37.4 to 16.4 VAR·s. TABLE IV and Fig. 6 give the RMSE over 1.5–7 s.

TABLE IV

RMSE of PCC Power Terms, FfD Structure (P in W, Q in VAR, Harmonic Terms in VA)

Term	PI-FfD	ANN-FfD	Impr. [%]
P	222.1	127.8	42.5
Q	103.1	53.8	47.8
H _{3l}	167.7	160.2	4.5
H _{3⊥}	57.2	31.8	44.4
H _{5l}	131.8	109.7	16.8
H _{5⊥}	57.2	31.8	44.4
H _{7l}	100.8	86.0	14.7
H _{7⊥}	68.2	38.1	44.1
H _{9l}	67.4	46.1	31.6
H _{9⊥}	57.1	31.8	44.3
H _{11l}	72.2	42.5	41.1
H _{11⊥}	69.8	38.1	45.4

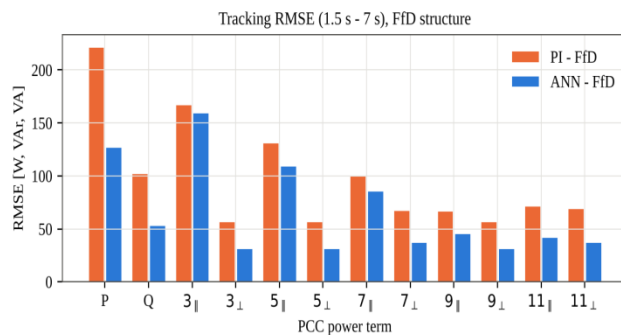


Fig. 6. RMSE of the PCC power terms with PI-FfD and ANN-FfD (1.5–7 s).

With the FfD structure the ANN lowers the RMSE of P by 42.5 %, of Q by 47.8 %, of every

quadrature harmonic term by 44–46 % and of the in-phase harmonic terms by 4.5 % (3rd order) to 41.1 % (11th order); with the F-only structure the reductions lie between 25 % and 46 %. The smallest gain is for the 3rd-order in-phase term, which carries the largest NLL component and is dominated by the unavoidable deviation in the first cycles after each event. The final PCC current THD is 5.7 % for all four cases, because the uncontrolled 13th and 15th harmonics remain: the ANN changes how fast the references are reached, not where the loops settle.

C. Transitions between operating modes

The eleven-event sequence (standby, P/Q dispatch, SCS, distorted grid voltage with 15 % 5th and 10 % 7th harmonic, RLS, return to SCS, VDB-HCC, communication failure and a second NLL) was simulated with both controllers. The ANN brings P to 2.5 kW and Q to 0 VAR in 0.42 s and 0.39 s, whereas the PI needs more than 0.5 s and approaches more slowly (Fig. 7). Over 1–6.5 s the IAE of P falls from 550 to 253 W·s (54 %) and that of Q from 558 to 250 VAR·s (55 %). The harmonic loops settle in 0.30 s after SCS is enabled, 0.24 s after RLS is enabled, 0.17 s after SCS is restored and 0.33 s after SCS is resumed.

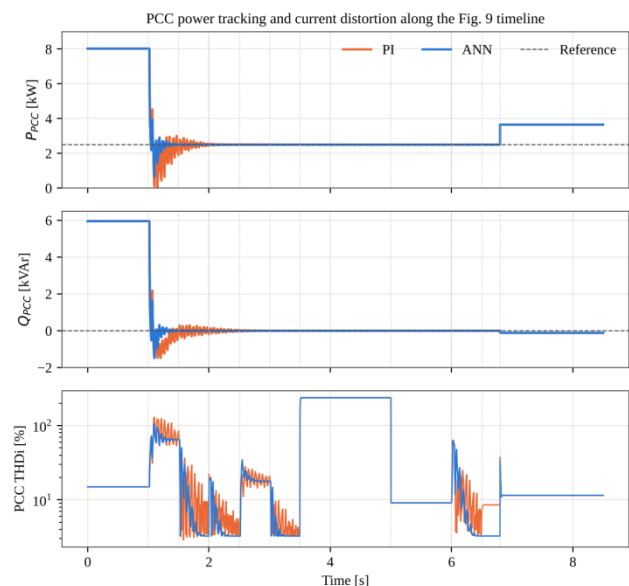


Fig. 7. PCC active power, reactive power and current THD along the eleven-event sequence, PI versus ANN.

Fig. 8 gives the THD at the end of each interval. Where both controllers have settled (standby, VDB-HCC, VDB-HCC with clean grid, second NLL) the values are identical, confirming that the ANN does not alter the steady state. In the remaining intervals the PI is still converging: at the end of the interval in which SCS is resumed its THD_i is 7.09 % against 3.26 % for the ANN. The difference persists during the communication failure, because the DERs freeze the last coefficients received; the ANN had already reached the SCS steady state ($\text{THD}_i = 3.26$ %), whereas the PI froze an unfinished transient (8.56 %). Faster secondary loops thus leave less of the operation in transients, so a link failure is more likely to find the system in a good state. With distorted grid voltage SCS keeps the current sinusoidal although THD_v is about 18 %, RLS makes the current proportional to the voltage so THD_i rises to 17–18 %, and VDB-HCC lowers THD_v to 2.3 % at the price of a large harmonic current drawn from the grid.

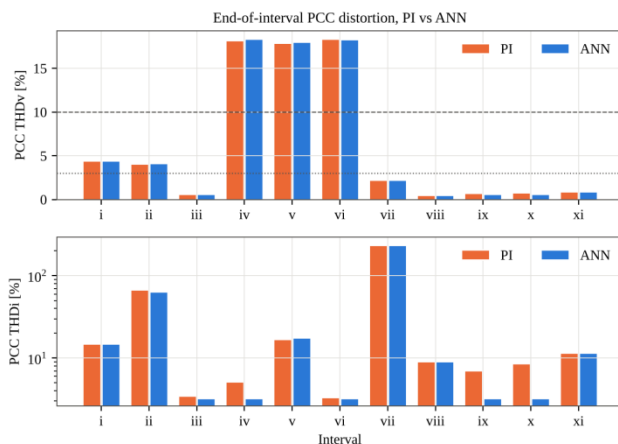


Fig. 8. End-of-interval PCC THD_v and THD_i (log scale for THD_i), PI versus ANN.

D. Effect of the grid short-circuit level

The grid impedance was varied from $0.0094+j0.0076 \Omega$ ($\text{SCC} \approx 4$ MVA, stiff) to $0.70+j0.56 \Omega$ ($\text{SCC} \approx 54$ kVA, weak) and each mode was evaluated 2 s after activation (Fig. 9). Without selective control THD_v grows from 0.13 % to 8.6 % as the grid weakens and THD_i is 57–71 %. Both centralized modes reduce THD_v to

0.02–1.24 % and THD_i to about 3 %, the residual being the uncontrolled orders above the 11th. VDB-HCC gives the lowest THD_v in the weakest grid (0.51 %) but cannot control the PCC current, whose THD_i rises to about 50 % in stiff grids.

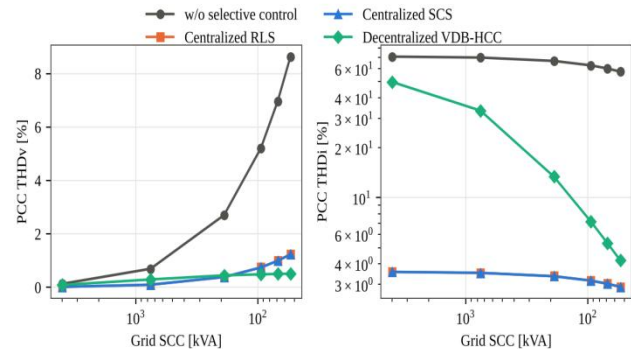


Fig. 9. PCC THD_v and THD_i versus grid SCC for the four modes, NLL as distortion source (ANN controller).

Grid strength strongly affects the PI loops, since the gain from DER injection to PCC current changes with the share of harmonic current absorbed by internal loads. Fig. 10 shows that the 5 % settling time of the 3rd-order term varies between 0.72 s and 1.13 s with the PI but stays between 0.28 s and 0.30 s with the ANN over the whole range. In RLS mode the PI loop is poorly damped in weak grids: 2 s after activation THD_v is 2.74 % at 69 kVA and 12.34 % at 54 kVA with the PI, against 1.00 % and 1.24 % with the ANN, and THD_i is 10.7 % and 37.0 % (PI) against 3.0 % and 2.9 % (ANN).

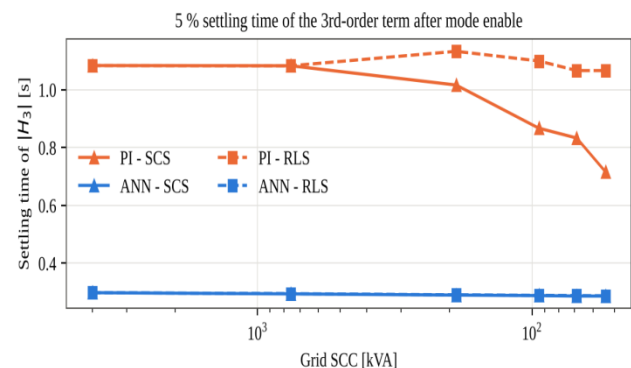


Fig. 10. Settling time of the 3rd-order term versus grid SCC for SCS and RLS modes, PI versus ANN.

E. Robustness analysis

To test the controllers beyond the training range, 80 random scenarios with wider plant-gain

(0.5–1.2) and time-constant (4–16 ms) ranges were generated. The median RMSE falls from 358 VA with the PI to 238 VA with the ANN (34 %) and the interquartile range is narrower (Fig. 11). The 90th percentile is practically equal (1196 VA and 1198 VA) because the worst cases are dominated by the unavoidable error of the first cycles after large simultaneous steps, which no feedback controller can remove with a two-cycle loop delay. No scenario became unstable with either controller.

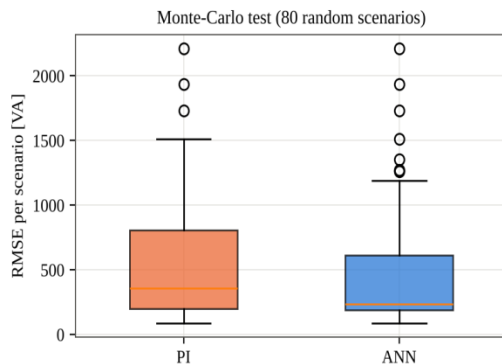


Fig. 11. Distribution of tracking RMSE over 80 random scenarios outside the training range, PI versus ANN.

F. Overall comparison and discussion

TABLE V

Overall Comparison of the Base PI and the Proposed ANN

Performance index	Base PI	ANN	Improvement
Training cost J (train / val.)	2.57 / 3.73	1.93 / 3.14	25 % / 16 %
RMSE of P, FfD [W]	222.1	127.8	42.5 %
RMSE of Q, FfD [VAr]	103.1	53.8	47.8 %
IAE of P / Q, 1–6.5 s [W·s / VAr·s]	550 / 558	253 / 250	54 % / 55 %
Harmonic-loop settling [s]	> 0.5	0.24–0.33	> 40 %
Settling vs SCC [s]	0.72–1.13	0.28–0.30	60–74 %
THD _i frozen at comm. failure [%]	8.56	3.26	62 %
Median Monte-Carlo RMSE [VA]	358	238	34 %
Steady-state PCC THD	Same	Same	Unchanged
Parameters / operations per cycle	2 / 3	51 / ~70	Trivial for a DSP

TABLE V summarises the comparison. Three conclusions follow. First, the limitation of the base strategy lies in the dynamics of its feedback loops, not in its formulation, because changing only the feedback law improves performance. Second, the gain comes from training against the actual loop delays and uncertainties: the network learned a higher equivalent integral gain with reduced proportional action for large errors, which a fixed linear PI cannot provide. Third, the velocity form makes the improvement free of steady-state risk. Limitations are that training used a reduced single-term loop, that the worst-case Monte-Carlo errors are set by the loop delay rather than the controller, and that a PI retuned by the same closed-loop optimisation would narrow part of the gap.

6. CONCLUSION

This paper replaced the PI feedback controllers of the generalized power-based control of a grid-connected AC microgrid with a compact velocity-form 3-10-1 artificial neural network, initialised as an exact copy of the PI and refined in closed loop by a natural evolution strategy. MATLAB/Simulink results show that all steady-state power-quality results are preserved, while the RMSE of PCC active and reactive power drops by 42.5 % and 47.8 %, the IAE of power tracking falls by 54–55 %, harmonic loops settle in 0.17–0.33 s instead of more than 0.5 s, the settling time stays at 0.28–0.30 s from a 4 MVA to a 54 kVA grid, and the median Monte-Carlo error falls by 34 % with no instability. With only 51 parameters and about 70 operations per term per 60 Hz cycle, the network is an effective and low-risk upgrade of the secondary control of power-based microgrids.

Future work includes implementation on the central-controller DSP and hardware-in-the-loop validation, a multi-input network that sees all power terms together, on-line adaptation of the weights, learning-based controllers for the DER outer loops, extension to three-phase four-wire

microgrids, and formal stability certification of the neural closed loop.

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