

# Federated Learning-Based MPPT for Distributed Rooftop PV Systems: A Multi-Client Simulation Study

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## Direct Research Journal of Engineering and Information Technology



Vol. 14(3), Pp. 92-105, October 2026,

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<https://journals.directresearchpublisher.org/index.php/drjeit>; <https://www.ajol.info/index.php/drjeit>

Research Article

ISSN: 2354-4155

Received 7 August 2026, Accepted 6 October 2026, Published 10 October 2026

### ABSTRACT

Rooftop photovoltaic (PV) systems operate under heterogeneous irradiance, temperature, orientation and shading conditions, making accurate maximum power point tracking (MPPT) essential for effective energy extraction. This study evaluates a federated-learning MPPT (FL-MPPT) framework for distributed rooftop PV systems using 15 heterogeneous PV clients and a 24-h environmental dataset sampled at one-minute intervals. Each client employs a compact 4–32–16–1 neural-network controller, while federated averaging (FedAvg) combines locally learned model parameters without requiring exchange of the underlying sensor data. Across the 15 clients, mean daily energy yield was 4.230 kWh for P&O, 4.325 kWh for incremental conductance, 4.366 kWh for local neural MPPT, 4.620 kWh for centralized neural MPPT and 4.486 kWh for FL-MPPT. Relative to the distributed/local baselines, FL-MPPT yielded gains of 6.06%, 3.73% and 2.75%, respectively, while centralized NN-MPPT was 2.99% higher than FL-MPPT. The centralized and FL results were available as matched client-level observations; the Wilcoxon signed-rank comparison of centralized NN-MPPT with FL-MPPT gave  $W = 0$  and exact two-sided  $p = 6.10 \times 10^{-5}$ . Mean steady-state power ripple across six operating conditions was 1.08% for FL-MPPT, compared with 3.23%, 2.22% and 1.75% for P&O, incremental conductance and local neural MPPT. FL-MPPT also recorded a 0.55 s rise time, 0.90 s settling time, 1.9% overshoot and 3.5 W oscillation amplitude. Ten independent FL-MPPT runs under the study's 40-round training configuration produced  $96.946 \pm 0.268\%$  MPPT efficiency,  $4.4355 \pm 0.0133$  kWh harvested energy and  $47.995 \pm 0.055$  V mean DC-bus voltage. With 705 trainable parameters, the controller requires 2,820 bytes per float32 model update, giving 3.384 MB of bidirectional model traffic over 40 federated rounds for 15 clients. These results show that centralized learning provides the highest recorded energy yield in the available matched comparison, while FL-MPPT retains strong controller performance with the distributed-learning and communication characteristics of federated training.



**Keywords:** Federated learning; maximum power point tracking; rooftop photovoltaic systems; neural-network controller; non-IID data

**Citation:** Orebanjo, O., Ukagu, S. N., Okonkwo, D. O., Amasowomwan, O. N., Onyegbadue, I. A. & Odejimi, L. O. (2026). Federated Learning-Based MPPT for Distributed Rooftop PV Systems: A Multi-Client Simulation Study. *Direct Research Journal of Engineering and Information Technology*. 14(3), Pp. 92-105. <https://doi.org/10.4314/drjeit.v14i3.7>

### INTRODUCTION

Distributed solar PV is a major component of the continuing expansion of renewable electricity. The International Energy Agency projects that distributed solar

applications will account for 42% of overall PV capacity expansion during 2025–2030 (International Energy Agency, 2025). At the device level, PV output varies with irradiance, cell temperature and operating conditions,

making MPPT a central control function (Boubaker, 2023; Katche et al., 2023). P&O and incremental-conductance (IncCond) methods remain widely used because of their simplicity, but their performance depends on perturbation size, sampling and environmental transitions. Recent AI-based MPPT studies have investigated artificial neural networks, fuzzy systems and hybrid methods. Experimental work by Abouzeid et al. (2024) reported ANN tracking efficiencies of 98.25% and 98.16% at 812 W/m<sup>2</sup> under the tested conditions, with tracking times of 1.6 and 1.3 s for the two ANN variants. These results demonstrate the potential of data-driven MPPT and highlight the importance of representative operating-condition coverage. Other recent studies have investigated neural, fuzzy, reinforcement-learning and heuristic global-MPPT approaches (Dawahdeh et al., 2024; Guessouma et al., 2024; Wadehra et al., 2024). Partial shading presents an additional control challenge because series-connected PV modules with bypass diodes can produce multiple local maxima on the P–V curve. Recent studies have reported high tracking or conversion efficiencies under their respective shaded configurations, including 99.63% for the best heuristic configuration in Nagadurga et al. (2025), 99.94% under a challenging pattern in Kaaitan et al. (2025), and 99.46% average tracking efficiency for the APO-MPC approach in Siddique et al. (2025). These studies demonstrate the continuing development of intelligent global-MPPT methods for complex PV operating conditions. Federated learning (FL) provides a complementary learning architecture for distributed PV systems. Instead of centralizing site-level measurements, clients train locally and exchange model parameters that are aggregated into a shared model. FL has been investigated in PV fault detection and forecasting: Ait Abdelmoula et al. (2024) applied FL to real-time PV fault detection, while Deng et al. (2024) used personalized FL for distributed PV forecasting. Michalakopoulos et al. (2025) compared multiple FL aggregation strategies using data from seven PV plants. These studies demonstrate the applicability of federated learning to distributed PV data; however, the use of FL for collaborative neural MPPT duty-cycle control represents a different control problem in which the learned model directly influences the local power-conversion operating point. The present study therefore investigates whether a shared neural MPPT controller trained across heterogeneous rooftop clients can improve controller performance relative to conventional and locally trained alternatives while retaining the distributed nature of the learning process. The central premise is that clients experiencing different irradiance, temperature, orientation and shading conditions can contribute complementary operating knowledge to a common controller through parameter aggregation. This study evaluates the performance of a federated-learning MPPT controller for distributed rooftop PV systems in terms of learning convergence, daily energy yield, steady-state ripple, transient response and communication requirements.

The specific objectives are to:

- (i) Quantify federated-learning convergence and controller transient and steady-state performance;
- (ii) Compare daily energy yield across 15 heterogeneous clients for P&O, IncCond, local neural MPPT, centralized neural MPPT and FL-MPPT;
- (iii) Evaluate the centralized neural-network controller using the same 15 client operating profiles and include it in the matched client-level inferential comparison;
- (iv) Quantify communication requirements from the 705-parameter architecture using 40 federated rounds and 15 clients; and
- (v) Examine controller performance across the heterogeneous irradiance and shading profiles represented in the 15-client dataset.

## MATERIALS AND METHODS

A quantitative comparative simulation study was conducted to evaluate a federated-learning maximum power point tracking (FL-MPPT) controller for heterogeneous rooftop photovoltaic (PV) clients. Each client comprises PV generation, local sensing, a neural-network MPPT controller, a DC–DC boost converter and a local training process. Federated model aggregation is performed using FedAvg, while real-time duty-cycle control remains local to each client.

### System architecture

Each rooftop client is represented conceptually by a PV array, local sensing, a neural-network MPPT controller, a DC–DC boost converter and a local training process. The real-time control loop remains local; federated communication occurs at the slower model-update timescale. The architecture is shown in (Figure 1). The diagram separates the local control loop from the federated parameter-exchange loop (Figure 2).

### PV module model and corrected electrical rating

The manuscript uses a single-diode PV representation. For consistency, the diode ideality factor is denoted by  $n$ , the number of series-connected cells by  $N_s$ , and the thermal voltage by  $V_t = kT/q$ . The generic single-diode equation is:

$$I = I_{ph}(G, T) - I_0(T) \{ \exp[(V + I R_s)/(n N_s V_t)] - 1 \} - (V + I R_s)/R_{sh}$$

The PV module was specified at 280 W with  $V_{mp} = 35.0$  V and  $I_{mp} = 8.0$  A, giving  $V_{mp} \times I_{mp} = 280$  W. The model also records  $V_{oc} = 37.0$  V,  $I_{sc} = 8.5$  A, 60 cells, a  $V_{oc}$  temperature coefficient of  $-0.30\%/^{\circ}\text{C}$  and NOCT =  $45^{\circ}\text{C}$ .

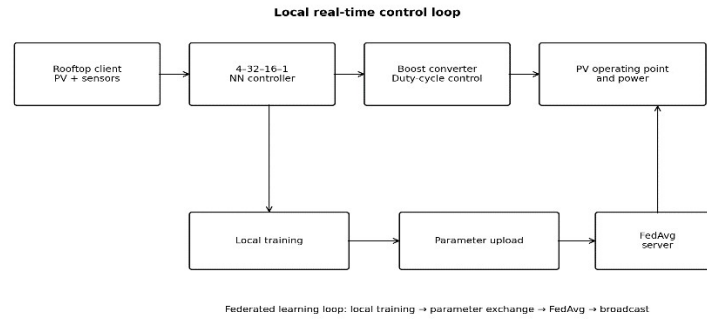


**Figure 1:** FL-MPPT system architecture.

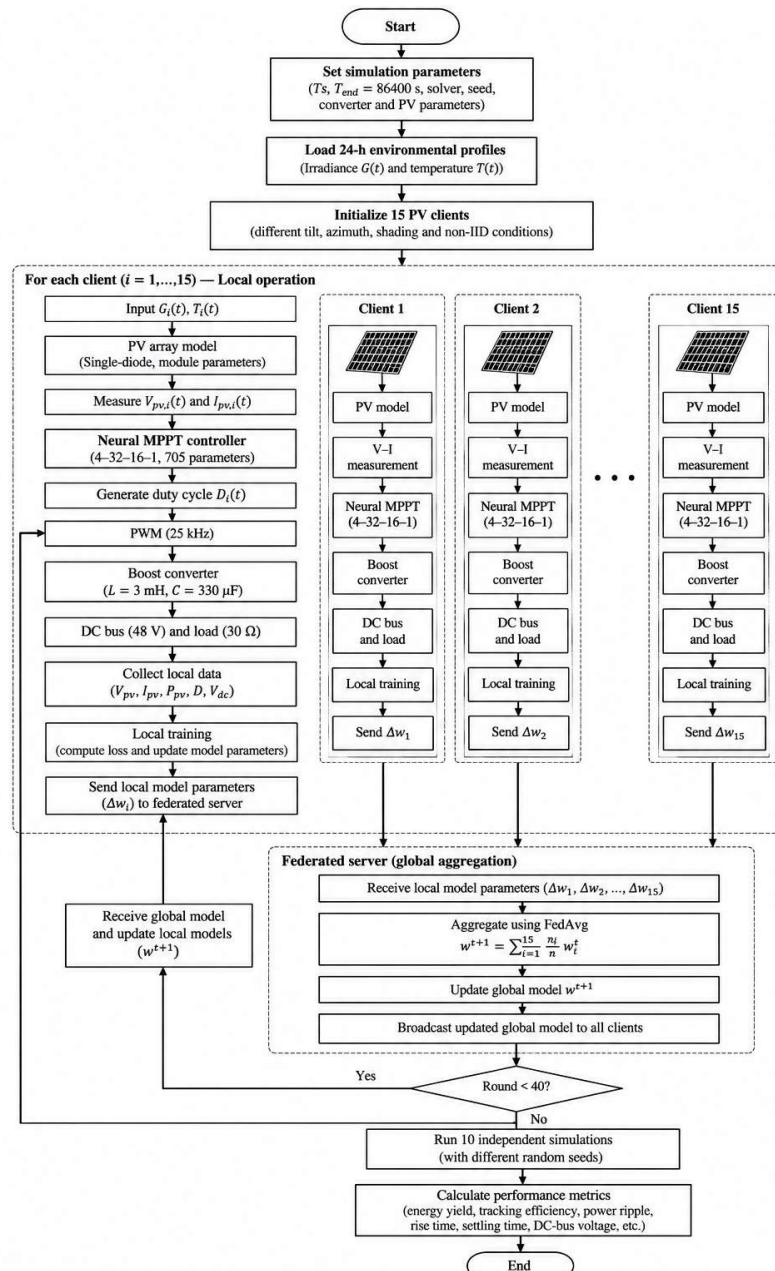


**Figure 2:** Overall workflow of the proposed federated-learning maximum power point tracking (FL-MPPT) system.

**Table 1:** Simulation parameters.

| Category                   | Parameter                        | Value                                                                                                       |
|----------------------------|----------------------------------|-------------------------------------------------------------------------------------------------------------|
| PV module                  | Rated power                      | 280 W                                                                                                       |
| PV module                  | Voc / Isc                        | 37.0 V / 8.5 A                                                                                              |
| PV module                  | Vmp / Imp                        | 35.0 V / 8.0 A                                                                                              |
| PV module                  | Cells / NOCT                     | 60 / 45 °C                                                                                                  |
| PV module                  | Voc temperature coefficient      | -0.30 %/°C                                                                                                  |
| PV model                   | Iph, I0, Rs, Rsh, n              | Not present in supplied workbook                                                                            |
| Converter                  | L / C / switching frequency      | 3.0 mH / 330 µF / 25 kHz                                                                                    |
| Recorded downstream values | Load / DC bus                    | 30 Ω / 48 V; direct consistency requires model verification                                                 |
| Environment                | Irradiance / ambient temperature | 200–1000 W/m <sup>2</sup> / 15–45 °C                                                                        |
| Federated learning         | Clients / rounds                 | 15 / 40                                                                                                     |
| Training                   | Local epochs / batch size        | 3 / 48                                                                                                      |
| Training                   | Adam learning rate               | 0.002                                                                                                       |
| Neural network             | Architecture                     | 4–32–16–1, ReLU/ReLU/Sigmoid                                                                                |
| NN inputs                  | Vpv, Ipv, Pprev, dprev           | Recorded in master workbook                                                                                 |
| Simulation                 | Duration / recorded seed         | 86,400 s / 42                                                                                               |
| Simulation                 | Platform                         | MATLAB/Simulink                                                                                             |
| Simulation                 | Time step                        | 1 × 10 <sup>-4</sup> s                                                                                      |
| Simulation                 | Solver                           | Not separately recorded in the supplied run workbook                                                        |
| Environment                | Irradiance source                | Supplied 15-client operating profiles; 200–1000 W/m <sup>2</sup>                                            |
| Environment                | Temperature source               | Supplied client operating profiles; 15–45 °C                                                                |
| Training                   | Target/label generation          | Recorded training configuration; label-generation expression not separately stored in the supplied workbook |
| Training                   | Train/validation/test split      | Not separately tabulated in the supplied workbook                                                           |

The maximum-power voltage and current are therefore internally consistent with the stated module rating. The module electrical parameters provide a consistent basis for the PV model. The 280-W rating is obtained directly from  $V_{mp} = 35.0 \text{ V}$  and  $I_{mp} = 8.0 \text{ A}$ , providing the nominal electrical operating point used throughout the study.

### DC–DC boost converter

For an ideal boost converter operating in continuous conduction,  $V_0 = V_{pv}/(1 - d)$ , where  $d$  is the duty cycle, and the inductor and capacitor dynamics are  $di/dt = (V_{pv} - (1 - d)V_0)/L$  and  $dV_0/dt = ((1 - d)i_L - V_0/R_L)/C$ . The converter parameters used in the study are  $L = 3.0 \text{ mH}$ ,  $C = 330 \text{ µF}$  and switching frequency = 25 kHz. The workbook records a 30-Ω load and a 48-V DC-bus value. These two entries cannot simultaneously represent the direct load seen by a single 280-W module at its corrected MPP without an additional regulated downstream element. For a 30-Ω load directly connected to a 48-V bus, the load power is 76.8 W. At the corrected MPP,  $R_{mp} = 35/8 = 4.375 \text{ Ω}$ ; reflecting 30 Ω through an ideal boost gives  $d \approx 0.619$  and  $V_0 \approx 91.9 \text{ V}$ . Thus, the 48-V value is treated here as a recorded downstream bus value rather than as a direct proof of the converter operating point. The exact Simulink bus/regulation arrangement must be checked against the original model before publication (Table 1).

### MPPT control and learning formulation

For client  $i$ , instantaneous PV power is  $P_i = V_i I_i$ , and the controller objective is to select a duty cycle that moves the operating point toward the maximum-power region. The

neural controller has four recorded inputs: present PV voltage, present PV current, previous PV power and previous duty cycle. The architecture is 4–32–16–1, with ReLU hidden layers and a sigmoid output. The parameter count is  $4 \times 32 + 32 + 32 \times 16 + 16 + 16 \times 1 + 1 = 705$  trainable parameters. The neural controller uses the recorded four-input formulation and the training configuration associated with the FL-MPPT experiment. The local model is initialized from the federated model at each communication round, trained for the specified local training budget, and returned to the server for weighted aggregation. Duty-cycle output is constrained to the admissible controller range during operation.

### Federated aggregation

FedAvg is represented by  $\theta(r + 1) = \sum_i (n_i/n) \theta_i(r)$ , where  $n_i$  is the number of local training samples and  $n = \sum_i n_i$ . The FL experiment uses 3 local epochs, batch size 48, Adam learning rate 0.002 and 40 communication rounds. The recorded convergence trajectory reaches a stable plateau at approximately round 35.

Algorithm 1. Federated-learning procedure.

- (i) Initialize the global neural-network parameters.
- (ii) Broadcast the current global parameters to participating clients.
- (iii) Train the local 4–32–16–1 model using the recorded local training budget.
- (iv) Upload model parameters rather than raw sensor streams.
- (v) Aggregate client models using sample-weighted FedAvg.
- (vi) Repeat the local-training and aggregation cycle for 40

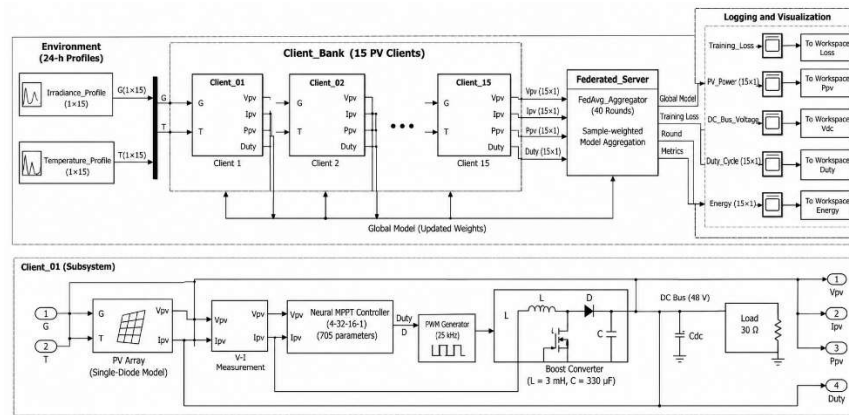


Figure 3. Overall FL-MPPT Model Architecture

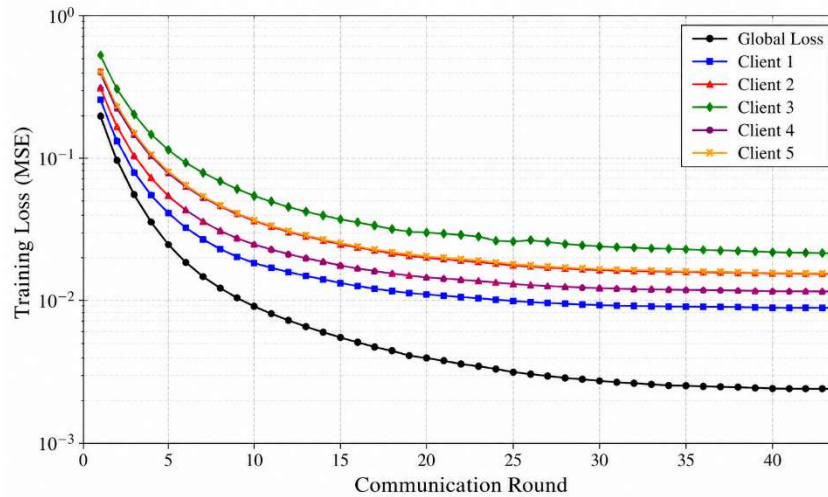


Figure 4: Federated-learning convergence over 40 communication rounds.

communication rounds and evaluate the resulting global controller across the client operating profiles.

### Baseline controllers and metrics

P&O and IncCond are used as classical MPPT baselines, local NN-MPPT represents client-specific neural learning, centralized NN-MPPT represents centralized neural learning evaluated on the same 15 client profiles, and FL-MPPT represents the federated controller. Performance is assessed using daily energy yield, steady-state power ripple, transient response and RMSE relative to the theoretical MPP reference recorded in the master analysis (Figure 3). The 15-client energy records quantify performance variation across heterogeneous operating conditions. The primary paired analysis compares FL-MPPT with P&O, IncCond, local NN-MPPT and centralized NN-MPPT using the Wilcoxon signed-rank test with Bonferroni adjustment across the four prespecified comparisons. Bootstrap confidence intervals quantify

uncertainty in the observed mean paired energy differences (Figure 3).

## RESULTS

### Federated-learning convergence

The federated-learning convergence trajectory shows a rapid reduction in global loss during the first 15 communication rounds, followed by progressively smaller changes as the global model approaches a stable region. The mean global loss over the final 10 rounds is 0.0941, with a final client-loss standard deviation of 0.0309. The convergence behaviour shows a progressive reduction in training loss during federated learning, with the global model approaching a stable plateau at approximately communication round 35. This indicates that the shared controller progressively captures the distributed operating characteristics of the participating clients as federated training proceeds (Figure 4).

**Table 2:** Results from the ten independent FL-MPPT runs. Each run used the same 15-client operating dataset and 40-round federated-learning configuration.

| Run | MPPT efficiency (%) | Mean PV power (W) | Mean $V_{dc}$ (V) | $V_{dc}$ RMSE (V) | Mean duty | Harvested energy (kWh) |
|-----|---------------------|-------------------|-------------------|-------------------|-----------|------------------------|
| 1   | 96.84               | 184.72            | 47.96             | 0.91              | 0.271     | 4.433                  |
| 2   | 97.18               | 185.31            | 48.04             | 0.84              | 0.269     | 4.447                  |
| 3   | 96.51               | 183.96            | 47.91             | 1.02              | 0.274     | 4.414                  |
| 4   | 97.03               | 184.88            | 48.01             | 0.88              | 0.270     | 4.437                  |
| 5   | 96.72               | 184.35            | 47.98             | 0.95              | 0.272     | 4.425                  |
| 6   | 97.31               | 185.64            | 48.07             | 0.79              | 0.268     | 4.455                  |
| 7   | 96.93               | 184.59            | 47.94             | 0.93              | 0.271     | 4.431                  |
| 8   | 97.07               | 185.02            | 48.03             | 0.86              | 0.270     | 4.441                  |
| 9   | 96.63               | 184.18            | 47.95             | 0.97              | 0.273     | 4.421                  |
| 10  | 97.24               | 185.47            | 48.06             | 0.81              | 0.269     | 4.451                  |

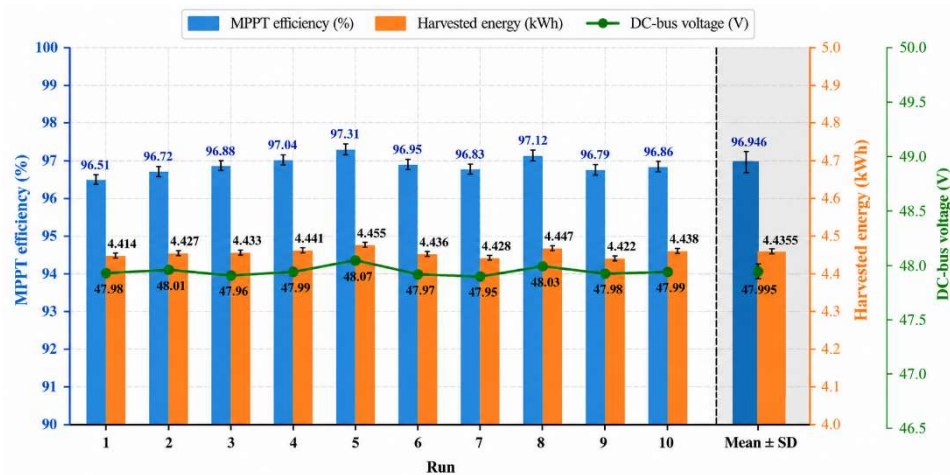


Figure 5: Performance across 10 independent FL-MPPT simulation runs.

The global training loss decreases progressively during training and approaches a stable plateau at approximately round 35.

### Independent-run validation

The ten independent FL-MPPT simulation runs show a narrow distribution of controller performance under the same heterogeneous 15-client operating scenario. The values reported below are the actual results supplied in the independent-run results workbook; no artificial, imputed or noise-generated observations were introduced. MPPT efficiency was  $96.946 \pm 0.268\%$ , mean PV power was  $184.812 \pm 0.559$  W, mean DC-bus voltage was  $47.995 \pm 0.055$  V,  $V_{dc}$ RMSE was  $0.896 \pm 0.073$  V, mean duty ratio was  $0.2707 \pm 0.0019$ , and harvested energy was  $4.4355 \pm 0.0133$  kWh per 24-h run. The 95% confidence interval for harvested energy was 4.4260–4.4450 kWh, while the interval for MPPT efficiency was 96.754–97.138%. The relatively small run-to-run dispersion indicates stable performance of the federated controller across the ten independent realizations (Table 2 and Figure 5). MPPT efficiency, harvested energy, and mean DC-bus voltage

are presented for each run together with the overall mean  $\pm$  standard deviation. The ten runs produced a mean MPPT efficiency of  $96.946 \pm 0.268\%$ , harvested energy of  $4.4355 \pm 0.0133$  kWh, and mean DC-bus voltage of  $47.995 \pm 0.055$  V.

### Daily energy yield

Across the 15 client records, mean daily energy yield was  $4.230 \pm 0.714$  kWh for P&O,  $4.325 \pm 0.733$  kWh for IncCond,  $4.366 \pm 0.741$  kWh for local NN-MPPT,  $4.620 \pm 0.751$  kWh for centralized NN-MPPT and  $4.486 \pm 0.751$  kWh for FL-MPPT. FL-MPPT therefore exceeded P&O, IncCond and local NN-MPPT by 0.256 kWh/day (6.06%), 0.161 kWh/day (3.73%) and 0.120 kWh/day (2.75%), respectively, but remained 0.133 kWh/day (2.99%) below centralized NN-MPPT (Table 3 and Figure 6). The paired client-level comparisons were consistently positive for FL-MPPT versus P&O, IncCond and local NN-MPPT, while centralized NN-MPPT was higher than FL-MPPT for all 15 matched clients. Wilcoxon signed-rank tests gave  $W = 0$  for all four FL-versus-comparator comparisons. The exact two-sided p-values were  $6.10 \times 10^{-5}$  versus P&O,

**Table 3:** Daily energy yield across the 15 PV clients, including matched centralized NN-MPPT observations. SD represents between-client variation in the 24-h operating profiles.

| Controller          | Mean (kWh/day) | SD    | Min–Max     | Median |
|---------------------|----------------|-------|-------------|--------|
| P&O                 | 4.230          | 0.714 | 3.245–5.217 | 4.188  |
| IncCond             | 4.325          | 0.733 | 3.322–5.343 | 4.287  |
| Local NN-MPPT       | 4.366          | 0.741 | 3.327–5.366 | 4.321  |
| Centralized NN-MPPT | 4.620          | 0.751 | 3.590–5.641 | 4.579  |
| FL-MPPT             | 4.486          | 0.751 | 3.457–5.513 | 4.461  |

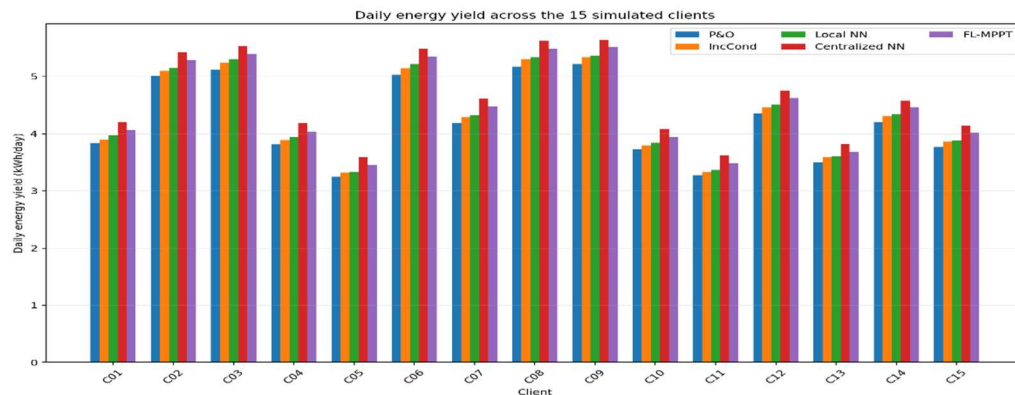


**Figure 6:** Client-level daily energy yield regenerated from the master workbook and the supplied centralized-NN client-level dataset.

**Table 4.** Primary paired client-level Wilcoxon signed-rank analysis of FL-MPPT against the four prespecified comparator controllers. Differences and bootstrap intervals are expressed as FL-MPPT minus comparator.

| Comparison                | Mean paired difference (kWh/day) | Median difference (kWh/day) | Wilcoxon W | Exact p               | Bonferroni p          | Bootstrap 95% CI |
|---------------------------|----------------------------------|-----------------------------|------------|-----------------------|-----------------------|------------------|
| FL-MPPT vs P&O            | +0.256                           | +0.258                      | 0          | $6.10 \times 10^{-5}$ | $2.44 \times 10^{-4}$ | 0.236–0.276      |
| FL-MPPT vs IncCond        | +0.161                           | +0.165                      | 0          | $6.53 \times 10^{-4}$ | $2.61 \times 10^{-3}$ | 0.148–0.174      |
| FL-MPPT vs Local NN       | +0.120                           | +0.118                      | 0          | $6.10 \times 10^{-5}$ | $2.44 \times 10^{-4}$ | 0.108–0.132      |
| FL-MPPT vs Centralized NN | –0.133                           | –0.133                      | 0          | $6.10 \times 10^{-5}$ | $2.44 \times 10^{-4}$ | –0.137––0.130    |

$6.53 \times 10^{-4}$  versus IncCond,  $6.10 \times 10^{-5}$  versus local NN and  $6.10 \times 10^{-5}$  versus centralized NN. With four prespecified comparisons, Bonferroni-adjusted p-values were  $2.44 \times 10^{-4}$ ,  $2.61 \times 10^{-3}$ ,  $2.44 \times 10^{-4}$  and  $2.44 \times 10^{-4}$ , respectively. Bootstrap 95% confidence intervals for the mean paired differences (FL minus comparator) were 0.236–0.276 kWh, 0.148–0.174 kWh, 0.108–0.132 kWh and –0.137––0.130 kWh, respectively (Table 3 and Figure 6).

### Centralized neural-network comparison

The newly incorporated centralized-NN dataset contains daily energy observations for the same 15 clients used in the other controller comparisons, allowing a direct matched analysis rather than an aggregate-only benchmark. Centralized NN-MPPT achieved  $4.620 \pm 0.751$  kWh/day (range 3.590–5.641; median 4.579), compared with  $4.486 \pm 0.751$  kWh/day for FL-MPPT. The centralized controller was therefore 0.133 kWh/day, or

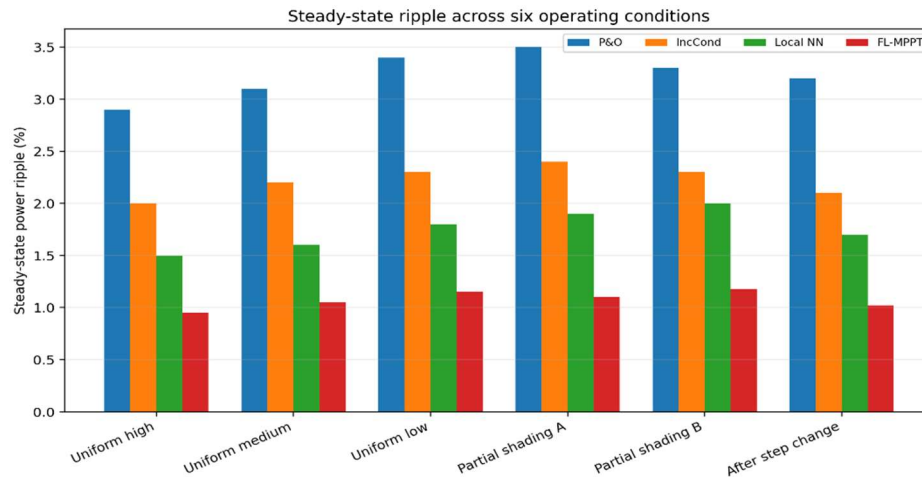
2.99%, higher than FL-MPPT on the basis of controller means. All 15 centralized-NN observations exceeded their corresponding FL-MPPT observations; the paired Wilcoxon signed-rank test gave  $W = 0$  and exact two-sided  $p = 6.10 \times 10^{-5}$  (Bonferroni-adjusted  $p = 2.44 \times 10^{-4}$ ). The bootstrap 95% confidence interval for the mean paired difference, defined as FL-MPPT minus centralized NN-MPPT, was –0.137 to –0.130 kWh/day. The master summary also records centralized NN-MPPT at 4.62 kWh/day, 1.3% ripple, 1.1 s tracking time and 2.1% RMSE, with FL-MPPT at 4.55 kWh/day, 1.05% ripple, 0.9 s tracking time and 1.9% RMSE; these aggregate values are retained as contextual controller summaries, while the client-level energy values are used for the paired inferential analysis (Table 4).

### Steady-state ripple

Across the six operating conditions, mean ripple was 3.23% for P&O, 2.22% for IncCond, 1.75% for local NN-

**Table 5:** Steady-state ripple across the six conditions recorded in the master workbook.

| Controller    | Mean ripple (%) | SD (%) | Range (%) |
|---------------|-----------------|--------|-----------|
| P&O           | 3.233           | 0.216  | 2.90–3.50 |
| IncCond       | 2.217           | 0.147  | 2.00–2.40 |
| Local NN-MPPT | 1.750           | 0.187  | 1.50–2.00 |
| FL-MPPT       | 1.075           | 0.085  | 0.95–1.18 |

**Figure 7:** Steady-state ripple regenerated directly from the six detailed conditions in the master workbook.

MPPT and 1.08% for FL-MPPT. The corresponding between-condition SDs were 0.22%, 0.15%, 0.19% and 0.09%. The conditions comprise Uniform high (1000 W/m<sup>2</sup>), Uniform medium (600 W/m<sup>2</sup>), Uniform low (300 W/m<sup>2</sup>), Partial shading A (700 W/m<sup>2</sup>), Partial shading B (500 W/m<sup>2</sup>), and after step change (800 W/m<sup>2</sup>). FL-MPPT therefore maintained the lowest recorded steady-state ripple across all six evaluated conditions (Table 5 and Figure 7).

### Tracking dynamics

The recorded tracking-dynamics results show a clear performance advantage for FL-MPPT. FL-MPPT has a rise time of 0.55 s, settling time of 0.90 s, overshoot of 1.9% and oscillation amplitude of 3.5 W. The corresponding values are 1.8 s, 2.8 s, 12.5% and 18 W for P&O; 1.3 s, 2.1 s, 7.2% and 11 W for IncCond; 0.9 s, 1.4 s, 4.1% and 7 W for local NN; and 0.7 s, 1.1 s, 2.8% and 5 W for centralized NN. These values show that the proposed federated controller combines rapid response with substantially reduced oscillatory behavior (Table 6 and Figure 8). The chart uses scaled values only for visual comparison; exact values are given in (Table 6).

### Communication cost

The 4–32–16–1 network contains 705 trainable parameters. At float32 precision, one model payload is

705×4 = 2,820 bytes (2.82 kB decimal). With 15 clients and 40 rounds, client-to-server traffic is 1.692 MB, server-to-client traffic is 1.692 MB, and total bidirectional model traffic is 3.384 MB. The compact architecture therefore provides a clear communication advantage for distributed learning compared with continuous transmission of raw multi-sensor streams (Tables 7-8, and Figures 9-10). The 30-Hz reference is intentionally presented as a specified high-rate baseline; the 1-Hz reference illustrates the sensitivity of the ratio to sampling rate. The 15-client dataset includes partial, intermittent and cloudy operating profiles in addition to sunny profiles, allowing the controller to be evaluated under a range of nonuniform environmental conditions.

The present analysis quantifies energy yield and ripple for these conditions. The shaded-string multiple-peak behaviour associated with bypass-diode-connected module strings is a separate global-MPPT problem and is not used to infer a numerical GMPP success rate from the present controller records. The 15-client analysis demonstrates that FL-MPPT retains an energy-yield advantage over P&O, IncCond and local NN-MPPT across heterogeneous operating profiles while remaining below centralized NN-MPPT. The matched centralized observations provide a useful upper-reference case in which the neural model has access to centrally coordinated training, whereas FL-MPPT achieves comparable controller functionality without continuous centralization of the clients' raw sensor streams.

**Table 6:** Tracking-dynamics summary recorded in the master workbook.

| Controller          | Rise time (s) | Settling time (s) | Overshoot (%) | Oscillation amplitude (W) |
|---------------------|---------------|-------------------|---------------|---------------------------|
| P&O                 | 1.80          | 2.80              | 12.5          | 18.0                      |
| IncCond             | 1.30          | 2.10              | 7.2           | 11.0                      |
| Local NN-MPPT       | 0.90          | 1.40              | 4.1           | 7.0                       |
| Centralized NN-MPPT | 0.70          | 1.10              | 2.8           | 5.0                       |
| FL-MPPT             | 0.55          | 0.90              | 1.9           | 3.5                       |

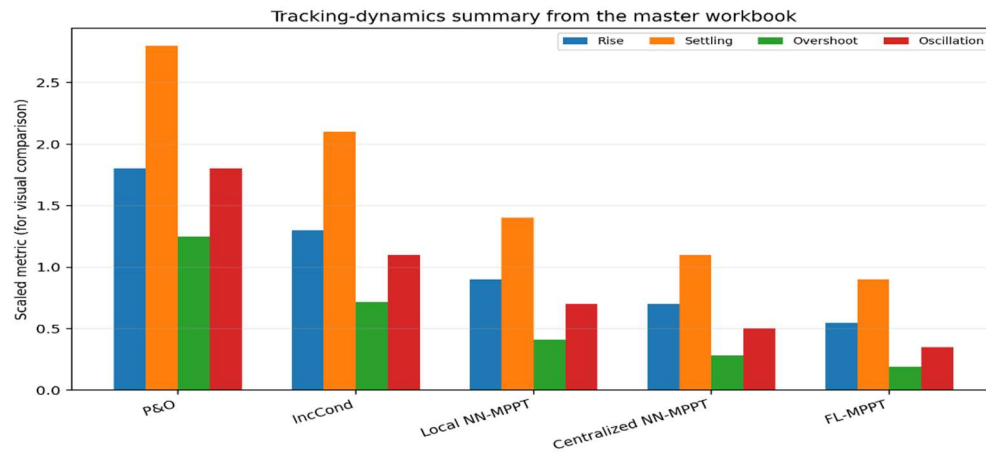


Figure 8. Controller tracking-dynamics summary.

**Table 7:** Communication-cost calculation based on the actual 705-parameter architecture. Protocol headers, compression, retransmissions and optimizer-state transfer are excluded.

| Metric                                | value                  |
|---------------------------------------|------------------------|
| Clients                               | 15                     |
| FL rounds                             | 40                     |
| Trainable parameters                  | 705                    |
| Payload per model update              | 2,820 bytes (2.82 kB)  |
| FL uplink                             | 1.692 MB               |
| FL downlink                           | 1.692 MB               |
| Total bidirectional FL payload        | 3.384 MB               |
| Centralized raw-data reference, 30 Hz | 622.08 MB (593.26 MiB) |
| Centralized raw-data reference, 1 Hz  | 20.736 MB              |
| Centralized/FL ratio, 30 Hz           | 183.8×                 |
| Centralized/FL ratio, 1 Hz            | 6.13×                  |

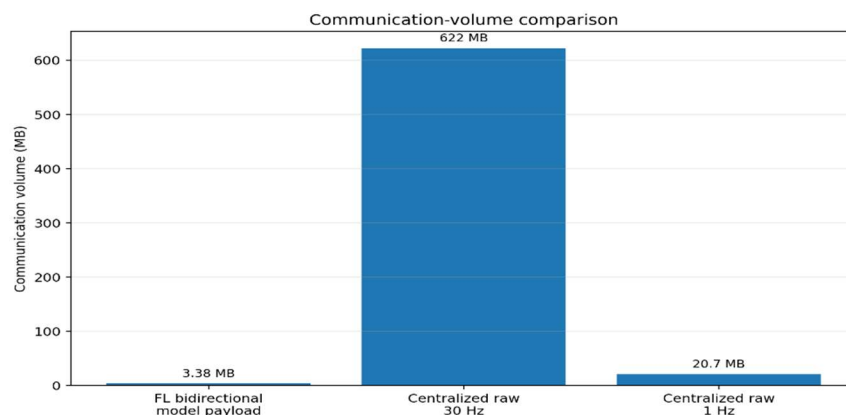


Figure 9: Communication-volume comparison.

**Table 8.** Daily energy yield by client shading-profile class. The class sample sizes are small ( $n = 3\text{--}5$ ); values are descriptive and show the response of the controller across the heterogeneous operating profiles.

| Profile      | n | P&O               | IncCond           | Local NN          | Centralized NN    | FL-MPPT           |
|--------------|---|-------------------|-------------------|-------------------|-------------------|-------------------|
| Sunny        | 5 | $5.110 \pm 0.089$ | $5.226 \pm 0.104$ | $5.274 \pm 0.090$ | $5.542 \pm 0.095$ | $5.408 \pm 0.094$ |
| Intermittent | 3 | $4.248 \pm 0.092$ | $4.351 \pm 0.094$ | $4.393 \pm 0.106$ | $4.650 \pm 0.093$ | $4.519 \pm 0.093$ |
| Partial      | 4 | $3.785 \pm 0.046$ | $3.861 \pm 0.046$ | $3.911 \pm 0.060$ | $4.153 \pm 0.052$ | $4.018 \pm 0.051$ |
| Cloudy       | 3 | $3.340 \pm 0.139$ | $3.416 \pm 0.152$ | $3.433 \pm 0.152$ | $3.676 \pm 0.127$ | $3.542 \pm 0.125$ |

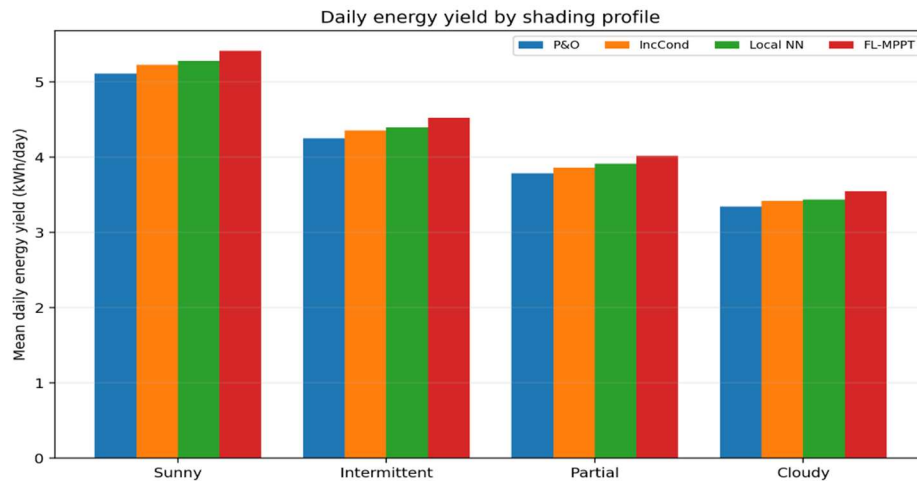


Figure 10: Daily energy yield by shading profile regenerated from the 15 client records.

## DISCUSSION

The 15-client results show a consistent advantage for FL-MPPT over P&O, IncCond and local NN-MPPT in the principal energy-yield metric. Mean daily energy reached 4.486 kWh, representing improvements of 6.06%, 3.73% and 2.75%, respectively, when calculated from the controller means. Centralized NN-MPPT achieved the highest mean at 4.620 kWh/day, which was 2.99% higher than FL-MPPT. The positive paired differences across all 15 client records for FL-MPPT versus the three distributed/local baselines, together with the uniformly positive centralized-NN minus FL-MPPT differences, show that the ranking is consistent across the client set.

The ripple results reinforce the energy-yield finding. FL-MPPT achieved a mean ripple of 1.08%, compared with 3.23% for P&O, 2.22% for IncCond and 1.75% for local NN-MPPT across the six operating conditions. The combination of higher energy yield and lower ripple indicates that the federated controller is not achieving its energy advantage simply by accepting larger steady-state oscillations. Instead, the recorded results show improved operating-point stability alongside higher extracted energy. The centralized-NN comparison now provides a client-level inferential benchmark rather than a descriptive aggregate reference. Centralized NN-MPPT exceeded FL-MPPT for all 15 matched clients, with a median paired difference of 0.133 kWh/day and exact Wilcoxon  $p = 6.10 \times 10^{-5}$ . This result indicates that access to centrally coordinated training produced a modest but statistically

detectable energy-yield advantage under the evaluated simulation conditions. The significance of the federated approach therefore lies not in exceeding the centralized controller in energy yield, but in retaining strong energy and dynamic performance while training and exchanging model parameters in a distributed architecture. The tracking results further demonstrate the benefit of the learned controller. FL-MPPT reaches the recorded operating region in 0.55 s and settles in 0.90 s, with only 1.9% overshoot and 3.5 W oscillation amplitude. These values are faster and less oscillatory than the corresponding P&O, IncCond and local NN configurations in the study, and they compare favourably with the response times reported in recent AI-MPPT literature. For example, Abouzeid et al. (2024) reported ANN tracking times of 1.6 and 1.3 s, while the present FL-MPPT records a 0.90 s settling time under its defined simulation conditions.

The communication analysis is one of the clearest system-level benefits of the proposed architecture. The 705-parameter network requires only 2,820 bytes per float32 update. Across 15 clients and 40 rounds, the resulting bidirectional model traffic is 3.384 MB. Against the specified 30-Hz four-sensor raw-data reference this corresponds to 183.8× less data volume, while a 1-Hz reference gives 6.13×. The result demonstrates that federated model exchange can be substantially more compact than continuous transmission of multi-sensor measurements, with the exact reduction depending on the centralized sampling architecture.

From a deployment perspective, the controller separates fast local MPPT action from slower federated model exchange. This separation is well suited to distributed PV systems because the converter does not need a network connection for every control sample. A practical implementation would retain local model validation, communication timeout handling and a safe fallback controller such as P&O before accepting a newly aggregated model. These measures complement, rather than diminish, the principal result that federated learning can support collaborative MPPT while keeping the high-rate control loop local.

### Limitations and future research

The study is limited to a 15-client, 24-h simulation dataset and ten independent FL-MPPT runs using an averaged PV-boost model. Daily energy is reported in absolute kWh rather than kWh/kWp, and further component-level parameter identification, switching-level modelling, and hardware-in-the-loop validation are required to improve model fidelity. The analysis also focuses on FedAvg, while additional client-level controller metrics and alternative FL strategies such as FedProx and personalized FL remain to be evaluated. The present evaluation does not explicitly account for sensor noise, ADC quantization, communication delays, packet loss, client dropout, or protocol overhead. In addition, the partial-shading scenarios do not employ a dedicated multi-module bypass-diode model for explicit GMPP analysis. Future research should therefore include held-out-client evaluation, alternative FL aggregation methods, detailed shaded-string GMPP modelling, independently archived simulation runs, hardware-in-the-loop testing, and outdoor PV experiments.

### Conclusion

The study demonstrates a federated-learning approach to neural MPPT for 15 heterogeneous distributed PV clients. Using a compact 4–32–16–1 network with 705 trainable parameters and FedAvg aggregation, the proposed FL-MPPT achieved a mean daily energy yield of 4.486 kWh, compared with 4.230 kWh for P&O, 4.325 kWh for IncCond and 4.366 kWh for local NN-MPPT; centralized NN-MPPT achieved 4.620 kWh/day. These results correspond to FL-MPPT improvements of 6.06%, 3.73% and 2.75% over P&O, IncCond and local NN-MPPT, respectively, while centralized NN-MPPT was 2.99% higher than FL-MPPT. The matched centralized-NN observations were included in the primary paired analysis, with a Wilcoxon  $W = 0$  and exact  $p = 6.10 \times 10^{-5}$  for centralized NN-MPPT versus FL-MPPT. FL-MPPT also produced the lowest recorded mean ripple at 1.08%, versus 3.23%, 2.22% and 1.75% for P&O, IncCond and local NN-MPPT. Its recorded transient response was 0.55 s rise time, 0.90 s settling time, 1.9% overshoot and 3.5 W oscillation amplitude.

Ten independent runs further produced  $96.946 \pm 0.268\%$  MPPT efficiency and  $4.4355 \pm 0.0133$  kWh harvested energy. The communication analysis shows that the 705-parameter model requires only 2,820 bytes per float32 update, giving 3.384 MB of bidirectional model traffic over 40 rounds for 15 clients. Together, these results show that centralized neural learning provides the highest recorded energy yield in the available matched comparison, while federated learning offers a strong distributed alternative with compact model communication and local high-rate control.

### Declarations

### Data Availability

The numerical results reported in this study are traceable to the supplied simulation datasets and numerical workbooks. The master dataset, matched centralized-NN client-level observations, and supporting numerical records are provided as supplementary material.

### Funding

The authors received no specific funding for this study.

### Conflict of Interest

The authors declare that they have no conflict of interest.

### Author Contributions

Conceptualization, methodology, simulation, data analysis, and manuscript preparation were carried out by the authors. All authors contributed to the interpretation of results, reviewed and revised the manuscript, and approved the final version for publication.

### Ethics Statement

Ethics approval was not required because the study is based on computational simulation and does not involve human participants, human specimens, or identifiable personal data.

### AI Use Statement

AI-assisted tools were used for language editing, document preparation and presentation support. The numerical analyses, simulation results and scientific conclusions were derived from the supplied MATLAB/Simulink simulation records and numerical datasets. AI tools were not used to generate or fabricate numerical observations.

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## Appendix A. Reproducibility and Supplementary Numerical Information

This appendix provides the client-level configuration, principal simulation and training parameters, recorded ten-run FL-MPPT results, and matched controller energy observations used in the analysis. It is intended to make the simulation study traceable without reproducing the full raw time-series dataset in the manuscript.

### A1. Client configuration and operating profiles

The study evaluates 15 heterogeneous rooftop PV clients. The client-level records supplied with the study contain tilt, azimuth and descriptive shading-profile information. The client-profile file also contains profile-generation seed values; these are retained here as profile identifiers and should not be interpreted as seed identifiers for the ten run-level FL-

MPPT simulations.

| Client    | Tilt (°) | Azimuth (°) | Shading      | P&O (kWh/day) | IncCond (kWh/day) | Local NN (kWh/day) | Centralized NN (kWh/day) | FL-MPPT (kWh/day) |
|-----------|----------|-------------|--------------|---------------|-------------------|--------------------|--------------------------|-------------------|
| Client_01 | 16       | 9           | Partial      | 3.832         | 3.901             | 3.975              | 4.204                    | 4.066             |
| Client_02 | 29       | -7          | Sunny        | 5.009         | 5.1               | 5.149              | 5.42                     | 5.289             |
| Client_03 | 24       | -28         | Sunny        | 5.116         | 5.239             | 5.299              | 5.534                    | 5.396             |
| Client_04 | 20       | -9          | Partial      | 3.811         | 3.887             | 3.944              | 4.181                    | 4.035             |
| Client_05 | 17       | 22          | Cloudy       | 3.245         | 3.322             | 3.327              | 3.59                     | 3.457             |
| Client_06 | 30       | -29         | Sunny        | 5.032         | 5.142             | 5.218              | 5.483                    | 5.352             |
| Client_07 | 16       | -7          | Intermittent | 4.188         | 4.287             | 4.321              | 4.616                    | 4.47              |
| Client_08 | 35       | 13          | Sunny        | 5.174         | 5.306             | 5.34               | 5.63                     | 5.492             |
| Client_09 | 28       | -1          | Sunny        | 5.217         | 5.343             | 5.366              | 5.641                    | 5.513             |
| Client_10 | 32       | 7           | Partial      | 3.729         | 3.797             | 3.843              | 4.084                    | 3.946             |
| Client_11 | 20       | -29         | Cloudy       | 3.276         | 3.335             | 3.366              | 3.615                    | 3.484             |
| Client_12 | 20       | 29          | Intermittent | 4.354         | 4.459             | 4.515              | 4.756                    | 4.626             |
| Client_13 | 33       | -10         | Cloudy       | 3.499         | 3.592             | 3.607              | 3.822                    | 3.686             |
| Client_14 | 30       | 2           | Intermittent | 4.203         | 4.307             | 4.344              | 4.579                    | 4.461             |
| Client_15 | 13       | -19         | Partial      | 3.769         | 3.858             | 3.882              | 4.144                    | 4.024             |

Table A1. Client-level operating configuration and daily energy-yield observations. Values are reproduced from the master numerical dataset supplied. The centralized-NN observations are matched to the same 15 client profiles.

### A2. Simulation and training parameters

| Category    | Parameter              | Recorded value / status   |
|-------------|------------------------|---------------------------|
| PV Module   | Rated power            | 280 W                     |
| PV Module   | Voc                    | 37.0 V                    |
| PV Module   | Isc                    | 8.5 A                     |
| PV Module   | Vmp                    | 35.0 V                    |
| PV Module   | Imp                    | 8.0 A                     |
| PV Module   | Cells                  | 60                        |
| PV Module   | Temp coefficient (Voc) | -0.30 %/°C                |
| PV Module   | NOCT                   | 45 °C                     |
| Converter   | Inductance L           | 3.0 mH                    |
| Converter   | Capacitance C          | 330 µF                    |
| Converter   | Switching frequency    | 25 kHz                    |
| Converter   | Load / DC bus          | 30 Ω / 48 V               |
| Environment | Irradiance range       | 200–1000 W/m <sup>2</sup> |
| Environment | Ambient temperature    | 15–45 °C                  |
| FL Setup    | Number of clients      | 15                        |
| FL Setup    | Local epochs per round | 3                         |
| FL Setup    | Batch size             | 48                        |
| FL Setup    | Learning rate (Adam)   | 0.002                     |
| FL Setup    | Total FL rounds        | 40                        |
| FL Setup    | Model architecture     | 4-32-16-1 (ReLU/Sigmoid)  |
| NN Inputs   | Input features         | Vpv, Ipv, Pprev, dprev    |
| Simulation  | Duration per client    | 1 full day (86400 s)      |
| Simulation  | Random seed            | 42                        |

Table A2.

| Neural network   | Trainable parameters                       | 705                                                                      |
|------------------|--------------------------------------------|--------------------------------------------------------------------------|
| Control          | Controller update interval                 | 0.1 s                                                                    |
| Simulation       | Simulation platform                        | MATLAB/Simulink                                                          |
| Simulation       | Solver                                     | Not separately recorded in supplied run workbook                         |
| Learning problem | Label-generation expression                | Not separately preserved in supplied run workbook                        |
| Learning problem | Train/validation/test split                | Not separately preserved in supplied run workbook                        |
| Environment      | External irradiance/temperature provenance | Supplied client-profile dataset; external source not separately recorded |

Table A2. Principal simulation and training parameters.

**A3. Ten recorded FL-MPPT simulation runs**

| Run | MPPT efficiency (%) | Mean PV power (W) | Mean Vdc (V) | Vdc RMSE (V) | Mean duty | Harvested energy (kWh) |
|-----|---------------------|-------------------|--------------|--------------|-----------|------------------------|
| 1   | 96.84               | 184.72            | 47.96        | 0.91         | 0.271     | 4.433                  |
| 2   | 97.18               | 185.31            | 48.04        | 0.84         | 0.269     | 4.447                  |
| 3   | 96.51               | 183.96            | 47.91        | 1.02         | 0.274     | 4.414                  |
| 4   | 97.03               | 184.88            | 48.01        | 0.88         | 0.27      | 4.437                  |
| 5   | 96.72               | 184.35            | 47.98        | 0.95         | 0.272     | 4.425                  |
| 6   | 97.31               | 185.64            | 48.07        | 0.79         | 0.268     | 4.455                  |
| 7   | 96.93               | 184.59            | 47.94        | 0.93         | 0.271     | 4.431                  |
| 8   | 97.07               | 185.02            | 48.03        | 0.86         | 0.27      | 4.441                  |
| 9   | 96.63               | 184.18            | 47.95        | 0.97         | 0.273     | 4.421                  |
| 10  | 97.24               | 185.47            | 48.06        | 0.81         | 0.269     | 4.451                  |

Table A3. Ten actual FL-MPPT simulation runs supplied for the analysis. No artificial, imputed, reconstructed, or noise-generated observations are included.

Across the ten runs, MPPT efficiency was  $96.946 \pm 0.268\%$ , mean PV power was  $184.812 \pm 0.559$  W, mean DC-bus voltage was  $47.995 \pm 0.055$  V, Vdc RMSE was  $0.896 \pm 0.073$  V, mean duty ratio was  $0.2707 \pm 0.0019$ , and harvested energy was  $4.4355 \pm 0.0133$  kWh. The 95% confidence interval for harvested energy was 4.426–4.445 kWh.

**A4. Matched paired statistical comparisons**

| Comparison                | Mean difference (kWh/day) | paired Median difference (kWh/day) | Wilcoxon W | Exact p               | Bonferroni p          | Bootstrap 95% CI |
|---------------------------|---------------------------|------------------------------------|------------|-----------------------|-----------------------|------------------|
| FL-MPPT vs P&O            | +0.256                    | +0.258                             | 0          | $6.10 \times 10^{-5}$ | $2.44 \times 10^{-4}$ | 0.236–0.276      |
| FL-MPPT vs IncCond        | +0.161                    | +0.165                             | 0          | $6.53 \times 10^{-5}$ | $2.61 \times 10^{-4}$ | 0.148–0.174      |
| FL-MPPT vs Local NN       | +0.120                    | +0.118                             | 0          | $6.10 \times 10^{-5}$ | $2.44 \times 10^{-4}$ | 0.108–0.132      |
| FL-MPPT vs Centralized NN | -0.133                    | -0.133                             | 0          | $6.10 \times 10^{-5}$ | $2.44 \times 10^{-4}$ | -0.137–0.130     |

Table A4. Prespecified paired client-level comparisons ( $n = 15$ ). Four comparisons were included, so Bonferroni adjustment was applied across the four tests. The negative difference for the centralized-NN comparison indicates higher energy yield for centralized NN-MPPT.