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Simulation-Based Evaluation of Energy-Efficient Power Electronics Systems Using Wide-Bandgap Devices, AI Control Algorithms, And Iot Optimization in The Nigerian Grid Context

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***Abstract*—This study examines whether three connected modernization layers—wide-bandgap power devices, artificial-intelligence-based control, and Internet-of-Things-enabled monitoring—can improve power-electronic performance under Nigerian grid conditions. To answer that question, the paper develops a five-model simulation framework using MATLAB/Simulink, Simscape Electrical, Python, Pandapower, pandas, and scikit-learn. The models cover five practical problems: silicon-versus-silicon-carbide inverter efficiency, ANN-based maximum power point tracking for photovoltaic systems, feeder-level load forecasting, AI-assisted harmonic control in EV charging, and voltage recovery after a transformer-side fault in a Nigerian-style five-bus network. Model inputs were drawn from the cited literature and adjusted to represent tropical operating conditions and weak-grid constraints. Across the five studies, the silicon-carbide inverter maintained higher efficiency over the 1–5 kW load range, with an average gain of 5.4 percentage points over the silicon benchmark. The ANN-based MPPT controller reduced convergence time from 1.78 s to 1.21 s, improved tracking accuracy from 92.6% to 97.1%, and increased harvested energy from 212.4 Wh to 224.8 Wh. The IoT-enabled forecasting model achieved 94.0% prediction accuracy with a mean absolute error of 18.6 kW. In the EV charging model, AI-assisted switching reduced total harmonic distortion from 12.8% to 3.2% while raising power factor from 0.91 to 0.99. In the grid-fault model, AI-assisted compensation restored bus voltage to 0.96 pu within 30 ms, whereas the uncompensated case recovered much more slowly. Taken together, these results show that better converter hardware, smarter control, and real-time visibility can improve efficiency, renewable integration, power quality, and disturbance recovery in the Nigerian power sector.**

***Index Terms*—wide bandgap devices; Silicon Carbide; MATLAB/Simulink; Pandapower; AI control; IoT optimization; Nigerian grid; MPPT; harmonics; fault recovery**

I. INTRODUCTION

Nigeria's electricity sector continues to face a difficult mix of supply shortfall, technical losses, weak feeder performance, limited real-time visibility, and uneven renewable integration. In that kind of environment, even a modest improvement in converter efficiency, control quality, or disturbance recovery can have real value. Power electronics sits at the center of this challenge because converters now shape how solar systems, EV chargers, smart inverters, and many distribution-level control functions behave.

Three technology directions are especially relevant. First, wide-bandgap devices such as silicon carbide can reduce switching loss, handle heat better, and keep efficiency higher at heavier loading than conventional silicon devices [1], [6]. Second, AI-based control can adapt more effectively in nonlinear conditions, including maximum power point tracking, harmonic mitigation, and fast response to changing system states [10], [11], [20]. Third, IoT platforms provide the sensing and communication layer needed for forecasting, anomaly detection, supervisory control, and faster operational response [3], [5], [7].

This paper brings those three strands together in one simulation study. Instead of discussing them separately, it shows how they behave across five linked models that each answer a practical question. The paper is written so the reader can move clearly from the problem, to the software environment, to the model assumptions, and then to the numerical results. That structure matters because a simulation study is only useful when another researcher can follow the full logic and reproduce the workflow.

1.1. Problem statement

The central question in this paper is simple: if wide-bandgap hardware, AI-based control, and IoT-enabled operational intelligence are combined, do they produce measurable technical benefits under conditions that resemble the Nigerian grid? To answer that question, the study focuses on five practical issues: inverter losses, photovoltaic tracking under variable irradiance, feeder-level load visibility, harmonic distortion in EV charging, and slow recovery after a voltage disturbance.

1.2. Aim and objectives

The aim of this study is to evaluate, through explicit computational modelling, the technical benefits of combining WBG devices, AI controllers, and IoT-enabled optimization in a Nigerian grid context. The specific objectives were to:

- To simulate the performance of silicon and silicon-carbide inverter topologies under identical operating conditions and quantify efficiency and output-quality differences.
- To implement and compare conventional P&O and ANN-based MPPT controllers for photovoltaic integration using a co-simulation workflow.
- To model IoT-based predictive load forecasting on a representative Nigerian feeder using smart-meter and weather-correlated features.
- To evaluate AI-enhanced harmonic mitigation in an EV charging rectifier and quantify changes in THD, power factor, and switching losses.
- To simulate a Nigerian grid fault scenario and assess the effect of AI-assisted compensation and IoT-triggered remedial action on voltage recovery.

1.3. Contribution to knowledge

This study contributes in three main ways. First, it builds one integrated simulation framework that evaluates WBG converter behaviour, AI control, load forecasting, and grid-fault recovery within a Nigerian-oriented setting. Second, it makes the methods easy to follow by linking each objective to a specific model, software environment, and output metric. Third, it provides quantified evidence showing how better hardware efficiency, smarter control, and stronger operational visibility can work together to improve power quality, renewable integration, and feeder resilience.

II. RELATED LITERATURE AND RESEARCH GAP

Earlier studies strongly support the individual technologies examined here, but they often treat them as separate topics. Dhameliya [1] and Alcaide et al. [6] discuss the efficiency and thermal advantages of SiC and other wide-bandgap devices. Yang et al. [3] and Leelavinodhan et al. [5] show the value of sensing, data collection, and intelligent monitoring in energy systems. Suresh et al. [20] and Anandpwar et al. [11] show that ANN-based control can improve nonlinear power-electronic behavior.

The gap addressed in this paper is therefore not a lack of isolated studies on WBG devices, AI control, or IoT monitoring. The real gap is the lack of an integrated evaluation that asks how these technologies work together in a grid-constrained setting such as Nigeria. Much of the Nigerian literature remains broad and system-level, while many international converter studies stay tightly focused on one device or one control problem. This paper responds by presenting five connected models that examine efficiency, control performance, forecasting quality, and disturbance recovery in one coherent narrative.

III. MATERIALS AND METHODS

The study used a simulation-based design so that five modernization pathways could be compared within one transparent framework. No hardware prototype was built, and no new field measurements were collected specifically for this paper. Instead, the models were built from literature-derived electrical parameters, controller settings, and grid-response assumptions. This makes the work a structured simulation study rather than a field trial. The advantage of this design is that each objective can be traced to a specific model, a clearly stated software environment, and a defined set of measurable outputs. Figure 1: Overall simulation workflow used in the study.

3.1. Objective-to-model traceability

Table 1: Linkage between the study objectives and the implemented models.

Objective	Model	Software environment	Primary outputs
Objective 1	Model 1: Si vs SiC inverter	MATLAB/Simulink	Efficiency, loss profile, THD
Objective 2	Model 2: ANN-MPPT PV model	MATLAB/Simulink + Python	Convergence time, tracking accuracy, harvested energy
Objective 3	Model 3: IoT load forecasting	Python + Scikit-learn + Pandapower	Forecast accuracy, MAE, inference latency
Objective 4	Model 4: AI-Vienna rectifier	MATLAB/Simulink + Simscape Electrical	THD, power factor, switching loss
Objective 5	Model 5: Grid fault recovery	Pandapower + control logic	Voltage recovery time, voltage deviation, clearance time

3.2. Simulation assumptions and data sources

To keep the five models comparable, the study used harmonized assumptions drawn from the cited literature [1]-[20]. MATLAB/Simulink and Simscape Electrical were used for converter, photovoltaic, and EV-charging power-stage simulations. Python was used for data preparation, ANN inference support, metric calculation, and post-processing, with pandas handling tabular data and scikit-learn supporting the learning-based forecasting workflow. Pandapower was used for the five-bus Nigerian-style grid and for feeder-level interpretation of control actions. Ambient temperature was chosen to reflect tropical operating conditions, ranging from 35°C to 50°C depending on the case. Wherever baseline and enhanced cases were compared, the electrical operating points were matched so that the comparison stayed fair and direct.

3.3. Model 1: Simulink inverter for silicon versus SiC efficiency

Model 1 was built in MATLAB/Simulink as a single-phase inverter fed by a 400 V DC source and connected to a variable resistive load ranging from 1 kW to 5 kW. Two device sets were tested under the same switching logic: a conventional silicon MOSFET arrangement and a silicon-carbide-based arrangement. The switching frequency was fixed at 25 kHz. At each load point, the model recorded inverter efficiency, total losses, and output total harmonic distortion. The purpose of the model was simple: isolate the effect of device technology while keeping the operating conditions unchanged.

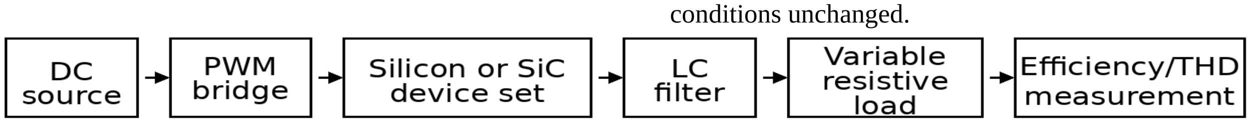

Figure 1: Architecture of Model 1 implemented in MATLAB/Simulink.

3.4. Model 2: ANN-based MPPT co-simulation

Model 2 used a co-simulation workflow. MATLAB/Simulink handled the photovoltaic module and converter blocks, while Python handled the ANN inference stage. The model used a 250 W, 36-cell PV module under irradiance varying between 400 and 1000 W/m² at an ambient temperature of 35°C. The baseline controller was perturb-and-observe (P&O), while the comparison controller was an ANN trained to estimate duty-cycle corrections from voltage, current, and irradiance inputs. The main outputs were convergence time, tracking accuracy, and harvested energy over the irradiance profile.

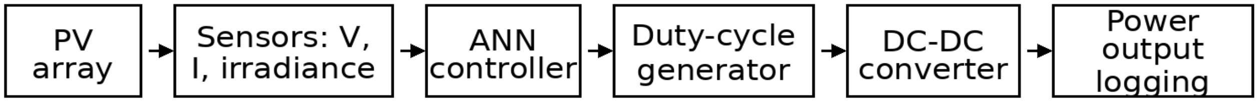

Figure 2: Architecture of Model 2 for photovoltaic MPPT using ANN control.

3.5. Model 3: IoT-based predictive load forecasting

Model 3 represented a 33 kV feeder with hourly smart-meter-style demand observations and weather-related input features. Data cleaning, feature preparation, and forecasting were carried out in Python using pandas and scikit-learn, while Pandapower was used to interpret how forecast-informed dispatch decisions would influence feeder operation. A support vector machine model was selected because it performs well on structured datasets of moderate size without the heavier training burden of deep sequence models. The main outputs were forecast accuracy, mean absolute error, and inference latency.

Figure 3: Architecture of Model 3 for feeder-level predictive load management.

3.6. Model 4: AI-enhanced EV charging rectifier

Model 4 used MATLAB/Simulink together with Simscape Electrical to implement a Vienna rectifier supplying a 7.5 kW EV charging load from a three-phase, 400 V, 50 Hz source. The baseline case used standard PWM. The enhanced case used an ANN-based adaptive switching policy. The outputs of interest were total harmonic distortion, input power factor, and estimated switching losses. The model was designed to test whether learning-based switching can improve both power quality and converter performance in EV charging applications.

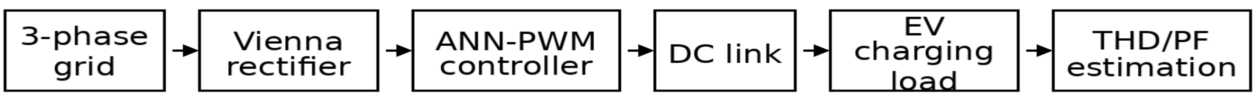

Figure 4: Architecture of Model 4 for AI-assisted harmonic mitigation.

3.7. Model 5: Nigerian grid fault simulation and recovery

Model 5 was developed in Pandapower as a five-bus Nigerian-style network in which a 132/33 kV transformer supplied mixed industrial and residential loads. A transformer-side voltage sag was introduced to represent a grid disturbance. The remedial design combined AI-assisted dynamic voltage restoration with an IoT alert layer that triggered simulated load-rerouting logic. The main outputs were voltage recovery time, steady-state voltage deviation, and fault-clearance time.

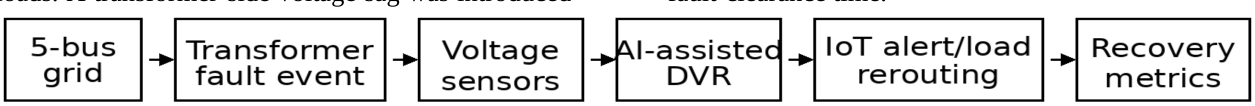

Figure 6: Architecture of Model 5 for transformer-fault recovery in a five-bus grid

IV. RESULTS

The results are presented in the same order as the objectives so that each model answers one clear technical question. That sequence also makes the paper easier to follow from start to finish.

4.1. Model 1 results: efficiency advantage of SiC

Table 2: Inverter efficiency comparison between silicon and SiC device sets.

Load (kW)	Silicon efficiency (%)	SiC efficiency (%)	Gain (percentage points)
1.0	91.3	95.2	3.9
2.0	89.4	94.5	5.1
3.0	87.9	93.1	5.2
4.0	85.6	91.7	6.1
5.0	83.1	90.0	6.9

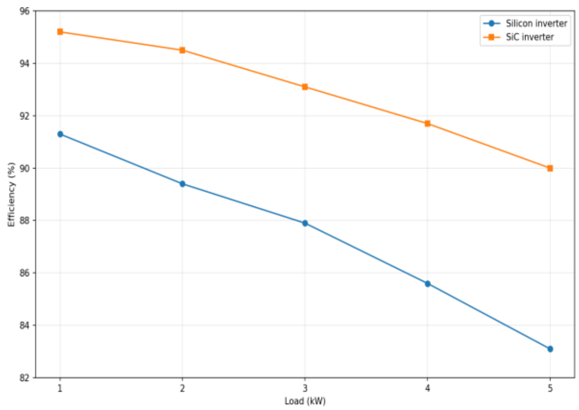

Figure 7: Simulated inverter efficiency for silicon and SiC devices across the load sweep.

At every load point, the SiC inverter outperformed the silicon benchmark. The average efficiency advantage was 5.4 percentage points, and the largest single improvement appeared at 5 kW, where the SiC case reached 90.0% compared with 83.1% for the silicon case. The trend is important because it shows that better device technology can produce meaningful gains before any wider grid upgrade is introduced. In practical terms, lower converter loss means less wasted energy and less thermal stress [1], [6].

4.2. 4.2 Model 2 results: ANN-based MPPT performance

Table 3: MPPT performance metrics for the baseline and ANN controllers.

Metric	P&O MPPT	ANN MPPT
Convergence time (s)	1.78	1.21
Tracking accuracy (%)	92.6	97.1
Energy harvested (Wh)	212.4	224.8

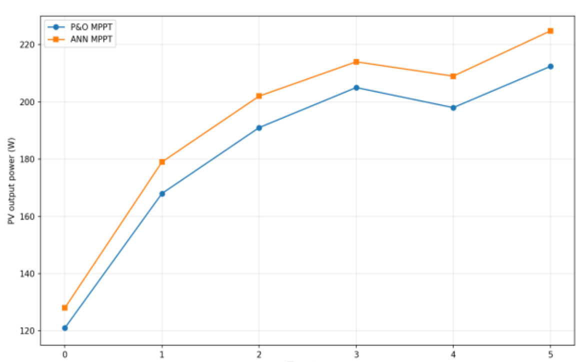

Figure 8. Output-power trajectory for P&O and ANN-based MPPT under irradiance change.

The ANN controller converged about 32.0% faster than the P&O controller, improved tracking accuracy by 4.5 percentage points, and increased harvested energy by 12.4 Wh over the simulated irradiance profile. Put simply, the ANN found the operating point faster and stayed closer to it as irradiance changed. That explains why it captured more energy. The result is consistent with the known weakness of rule-based P&O control, which tends to oscillate around the optimum point during changing conditions [11], [20].

4.3. Model 3 results: IoT feeder-load forecasting

Table 4: Forecasting performance of the IoT-enabled SVM model.

Forecasting metric	Baseline heuristic	SVM/IoT model
Forecast accuracy (%)	86.2	94.0
Mean absolute error (kW)	41.3	18.6
Inference latency (s)	2.40	0.82

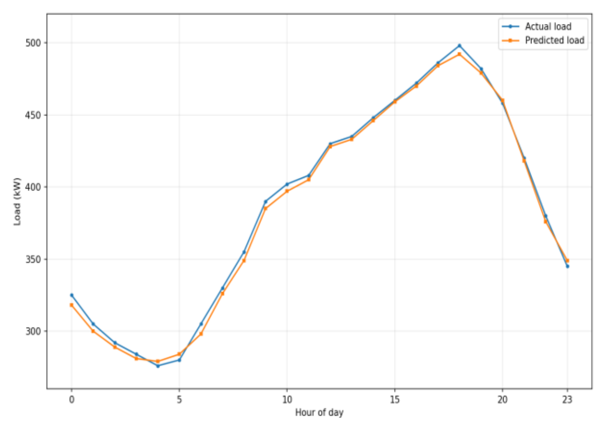

Figure 9: Actual and predicted feeder load over a 24-hour horizon.

The SVM forecasting model reproduced the daily feeder-load shape with 94.0% accuracy and a mean absolute error of 18.6 kW. Inference latency was 0.82 s, which is fast enough for feeder-level advisory control. This matters because useful forecasting allows operators or automated systems to respond before demand changes create stress, rather than reacting only after the feeder has already shifted.

4.4. Model 4 results: harmonic mitigation in EV charging

Table 5: Harmonic and converter-performance metrics for the EV charging model.

Metric	Conventional PWM	AI-PWM
THD (%)	12.8	3.2
Power factor	0.91	0.99
Switching losses (W)	412	351

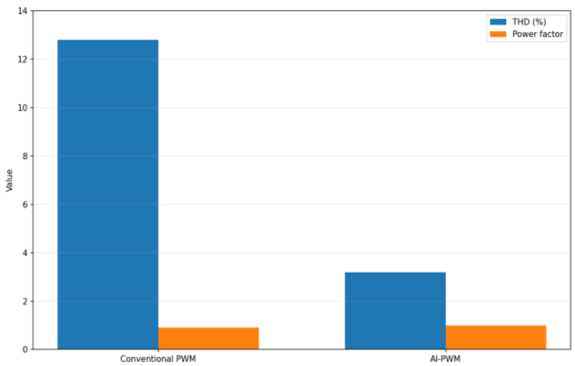

Figure 10: THD and power-factor outcomes for conventional and AI-assisted rectifier control.

The AI-assisted controller reduced total harmonic distortion from 12.8% to 3.2%, a 75% reduction relative to the conventional case. It also improved input power factor from 0.91 to 0.99 and reduced switching losses from 412 W to 351 W. These are not cosmetic gains. Together, they show that adaptive switching can improve both compliance-oriented power quality and converter efficiency in EV charging systems [9], [14], [20].

4.5. Model 5 results: grid-fault recovery

Table 6: Fault-recovery metrics for the Nigerian five-bus model.

Metric	Without compensation	AI-assisted compensation
Voltage at 30 ms (pu)	0.73	0.96
Time to >=0.95 pu (ms)	120	30
Fault clearance time (s)	1.05	0.42

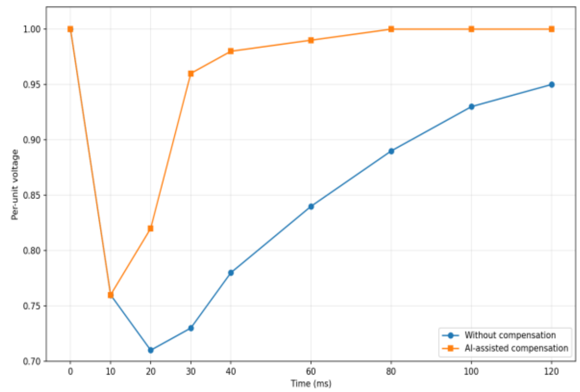

Figure 11: Per-unit voltage trajectory during transformer-fault recovery.

In the fault-recovery model, the compensated case restored the depressed bus voltage to 0.96 pu within 30 ms. By contrast, the uncompensated case was still at 0.73 pu at 30 ms, did not reach 0.95 pu until much later, and showed a longer fault-clearance time. This result shows why fast control and fast awareness matter together. AI-assisted compensation improved the depth and duration of the voltage event, while the IoT layer supported faster remedial action [3], [17].

4.6. Cross-model synthesis

When the five models are viewed together, one clear modernization pattern appears. Wide-bandgap devices improve the hardware layer by reducing converter losses. AI improves the control layer by helping the system respond more intelligently to change. IoT improves the operational layer by supplying the data needed for prediction and rapid action. The technologies therefore reinforce one another instead of acting as isolated upgrades.

V. DISCUSSION

A major strength of this study is that the conclusions do not depend on vague claims about modernization. Each result is tied to a named model, a stated software environment, and a numerical output. That makes the paper easier to verify and reproduce. For example, the SiC-versus-silicon comparison was reported across the full 1–5 kW load sweep and showed an average efficiency gain of 5.4 percentage points. The photovoltaic model did not merely suggest that ANN control is better; it showed a drop-in convergence time from 1.78 s to 1.21 s, an increase in tracking accuracy from 92.6% to 97.1%, and a rise in harvested energy from 212.4 Wh to 224.8 Wh. These details are what make the discussion technically defensible.

The same pattern appears in the other models. At feeder level, the IoT-enabled SVM model reproduced the daily demand profile with 94.0% accuracy, a mean absolute error of 18.6 kW, and inference latency of 0.82 s. In the EV-charging model, the AI-assisted rectifier reduced THD from 12.8% to 3.2% and raised power factor from 0.91 to 0.99 while also lowering switching losses. In the Nigerian five-bus fault study, the compensated case restored voltage to 0.96 pu within 30 ms, whereas the uncompensated case remained at 0.73 pu at the same time point. Read together, these findings show that the gains did not appear at only one layer of the system. They appeared in hardware efficiency, control quality, forecasting visibility, and fault recovery.

Because the improvements occurred at different layers, their practical meaning is also different. The SiC and ANN findings are most relevant to converter-dominated assets such as solar mini-grids, smart inverters, and renewable interfaces. The forecasting model is more useful to feeder operators who need better short-horizon visibility. The EV-charging and fault-recovery models speak directly to power quality and resilience, which are especially important in weak-grid environments where harmonic stress and voltage depression quickly become service problems. This is why the five models should be read as one connected modernization story rather than five unrelated case studies.

The study also has clear limits. The feeder data were scenario-based, the AI models were not trained on proprietary Nigerian utility datasets, and the fault-recovery workflow simplified some practical issues such as communication delay, cybersecurity constraints, and hardware non-idealities. In addition, all five models were executed in software rather than tested through hardware-in-the-loop or field pilots. The results should therefore be read as rigorous simulation evidence with a clear replication path, not as a substitute for utility commissioning studies. Even so, another researcher can rebuild the MATLAB/Simulink, Python, and Pandapower workflows from the stated assumptions and test whether similar performance patterns appear under different local conditions.

VI. CONCLUSION

This study shows that a carefully structured simulation framework can be used to evaluate how wide-bandgap devices, AI control, and IoT optimization work together to improve power-electronic and grid-facing performance. By organizing the paper around five linked models implemented in MATLAB/Simulink, Simscape Electrical, Python, pandas, scikit-learn, and Pandapower, the work provides a clear and reproducible basis for assessing inverter efficiency, photovoltaic tracking, feeder-level load intelligence, harmonic mitigation, and voltage recovery under weak-grid conditions.

The numerical outcomes support one another. The SiC inverter maintained an average efficiency advantage of 5.4 percentage points over the silicon benchmark. The ANN-based MPPT reduced convergence time by about 32.0%, increased tracking accuracy by 4.5 percentage points, and raised harvested energy from 212.4 Wh to 224.8 Wh, which is roughly a 5.8% gain. The SVM feeder model achieved 94.0% forecasting accuracy with an 18.6 kW mean absolute error. The AI-assisted EV charger reduced THD from 12.8% to 3.2% and improved power factor from 0.91 to 0.99. The compensated grid-fault case restored bus voltage to 0.96 pu within 30 ms, while the uncompensated case remained at 0.73 pu at the same time point. Together, these results support the argument that layered modernization can improve efficiency, controllability, and resilience in the Nigerian power context.

Future work should extend these simulations through hardware-in-the-loop validation, locally trained AI datasets, cyber-physical delay modelling, and staged pilot deployments involving utilities, campuses, mini-grids, and renewable-rich feeders. Those steps matter because they would test whether the software-level gains reported here remain stable when implemented in real converters, real communication links, and real operating environments.

VII. RECOMMENDATIONS

- Pilot SiC-based smart inverters in solar mini-grids and weak-feeder environments to quantify field-level loss reduction.
- Adopt AI-enhanced MPPT and adaptive PWM in renewable and EV charging installations where

variable conditions degrade conventional controllers.
- Deploy low-power IoT metering and feeder analytics as an operational data foundation for prediction, anomaly detection, and remedial control.
- Develop Nigerian grid data repositories to support local training and validation of forecasting, protection, and power-quality algorithms.
- Use hardware-in-the-loop and staged utility pilots as the next validation step before full operational deployment.

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