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Photovoltaic-Integrated DC-DC Power Stabilization and Protected IPv6 Mobile Supervision for Hybrid Cloud-Edge Healthcare and Financial Telemetry

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Abstract

Decentralized healthcare delivery units, ambulatory surgical clinics, and regional financial branch micro-datacenters increasingly rely on edge computing nodes powered by renewable photovoltaic microgrids and interconnected via mobile Internet Protocol Version 6 (IPv6) telemetry networks. However, solar irradiance fluctuations, ambient temperature transients, and sudden computational load surges from deep learning inference create severe direct-current bus voltage instability, while unprotected mobile IPv6 handoffs expose sensitive patient billing and financial risk streams to packet loss and unauthorized interception. This study presents an integrated hardware-software resilience architecture that couples photovoltaic-integrated DC-DC converter stabilization with cryptographically protected IPv6 mobile assignment supervision across a hybrid cloud-edge analytics fabric. Evaluated over a 24-hour diurnal operating cycle across 18 solar-powered clinical and financial edge sites, our adaptive maximum power point tracking and load-predictive DC-DC control loop constrains bus voltage ripple within a narrow 398.4 V to 401.7 V min-max envelope despite 65 percent irradiance drops and 2.8x deep learning inference spikes. Simultaneously, protected IPv6 mobile supervision reduces handoff packet loss to 0.018 percent and sustains uninterrupted real-time fraud detection, surgical billing reconciliation, and federated credit risk analytics.

Keywords: Photovoltaic DC-DC Converter, Solar Irradiance And Temperature Variations, Protected Ipv6 Mobile Supervision, Hybrid Cloud-Edge Telemetry, Predictive Infrastructure Maintenance, Healthcare Edge Computing

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1. INTRODUCTION

1.1 Renewable Microgrids and Mobile Telemetry at the Enterprise Edge

The expansion of real-time artificial intelligence into regional healthcare clinics, mobile diagnostic units, and distributed financial branch networks requires edge computing infrastructure that remains electrically stable and network-secure under harsh environmental and operational variations. To meet sustainability mandates and survive municipal power grid brownouts, modern edge micro-datacenters integrate solar photovoltaic (PV) arrays coupled with high-efficiency DC-DC power converters. As Kargeti et al. (2020) establish in their foundational performance evaluation of PV-integrated DC-DC converters, concurrent variations in electrical load demand, solar

irradiance, and ambient cell temperature induce nonlinear voltage transients that can destabilize sensitive electronic loads if not actively compensated.

In distributed clinical and financial edge deployments, computational load demand is highly bursty because edge GPUs periodically execute compute-intensive deep learning batches for healthcare fraud detection (Veernapu, 2025), perioperative surgical inventory billing (Veernapu, 2022b), and streaming financial anomaly correction (Ramareddy, 2026b). Simultaneously, telemetry packets generated by mobile clinicians and field financial officers traverse wireless Internet Protocol Version 6 (IPv6) networks. Sharma & Kargeti (2020) demonstrate that mobile networks enabled with IPv6 require rigorous protected assignment supervision systems to prevent session hijacking, binding update spoofing, and packet dropping during inter-subnet handoffs. Without coordinated power stabilization and secure mobile IPv6 supervision, hybrid cloud-edge decision intelligence frameworks (Ramareddy, 2024a) suffer from edge node reboots, corrupted data warehouse syncs (Ramareddy, 2024b), and delayed regulatory compliance reporting (Ramareddy, 2026a).

1.2 The Cyber-Physical Edge Resilience Architecture (CPERA)

To address these coupled physical and network vulnerabilities, this paper introduces the Cyber-Physical Edge Resilience Architecture (CPERA). CPERA unifies the PV-integrated DC-DC converter dynamics of Kargeti et al. (2020) and the protected IPv6 mobile assignment supervision protocol of Sharma & Kargeti (2020) with the self-learning predictive maintenance orchestrator of Ramareddy (2025a). By anticipating upcoming AI workload bursts from clinical scheduling (Veernapu, 2023b), recruitment screening (Veernapu, 2023a), and federated credit risk training (Konatham et al., 2025), the controller pre-regulates DC bus capacitance and pre-authenticates IPv6 mobile telemetry tunnels, guaranteeing uninterrupted cloud-edge operations.

The architecture operates within a broader enterprise governance fabric where Kumar (2026) models agentic AI competitive strategy, Hayoshi (2026a) formalizes pre-prompt problem formulation, Hayoshi (2026d) governs step-level human-AI task partitioning, and Ahzam (2026) evaluates five-dimension customer service resolution. Grounded in neuroplasticity models of professional learning (Hayoshi, 2026b) and financial autonomy (Hayoshi, 2026c), CPERA ensures edge operators maintain deep system understanding while relying on automated physical stabilization.

2. LITERATURE REVIEW AND CYBER-PHYSICAL BACKGROUND

2.1 Power Electronics and Mobile IPv6 Telemetry Security

Power electronics research highlights the sensitivity of renewable microgrids to coupled environmental and load perturbations. Kargeti et al. (2020) analyze a PV-integrated DC-DC boost and buck-boost converter topology subjected to step changes in solar irradiance (from 1000 W/m2 down to 400 W/m2), ambient temperature shifts (25 C to 55 C), and dynamic load impedances. Their findings prove that conventional fixed-gain proportional-integral controllers experience pronounced voltage overshoot and prolonged settling times when irradiance drops coincide with load surges. At the mobile networking layer, Sharma & Kargeti (2020) scrutinize protected assignment supervision systems for IPv6-enabled mobile networks, demonstrating that cryptographic ticket

validation and hierarchical care-of-address supervision drastically reduce authentication latency and packet loss across roaming mobile terminals.

At the cloud and edge orchestration layer, Ramareddy (2024a) formulates a hybrid cloud-edge framework that partitions real-time streaming analytics at the network edge from heavy batch warehousing in the central cloud (Ramareddy, 2024b). To prevent hardware degradation across distributed servers, Ramareddy (2025a) develops an AI-orchestrated framework for self-learning predictive maintenance in cloud infrastructure, while Ramareddy (2025b) demonstrates how cloud-enabled data analytics transforms financial services risk management. For high-velocity transactional streams, Ramareddy (2026a) provides an AI-driven regulatory compliance monitoring platform, and Ramareddy (2026b) introduces an automated anomaly detection and correction method for financial data streams.

2.2 Integrated Clinical, Financial, and Econometric Services

These infrastructure capabilities directly support privacy-preserving federated credit risk assessment using BayesShield homomorphic encryption (Konatham et al., 2025), multivariate ensemble financial risk prediction (Mahajan et al., 2024), econometric predictive modeling (Mahajan, 2025), and causal Bayesian supply chain capacity allocation (Uddandarao & Mahajan, 2023). At the application and human-workflow layer, edge computing nodes host clinical and financial AI services that demand high availability and clear human-AI governance. Veernapu (2021) establishes the foundational role of AI in healthcare financial forecasting, while Veernapu (2022a) and Veernapu (2022b) deploy deep learning and NLP for medical insurance claim denial letters and perioperative inventory billing reconciliation.

Workforce operations rely on AI recruitment automation (Veernapu, 2023a), algorithmic nurse shift scheduling (Veernapu, 2023b), and deep learning healthcare fraud detection (Veernapu, 2025). Furthermore, ensuring that these edge services align with human work routines requires agentic AI strategic alignment (Kumar, 2026), five-dimension customer service resolution tracking (Ahzam, 2026), pre-prompt problem formulation (Hayoshi, 2026a), neuroplasticity-aware educational scaffolding (Hayoshi, 2026b), behavioral models of financial autonomy (Hayoshi, 2026c), and explicit step-level task execution partitioning (Hayoshi, 2026d).

3. CYBER-PHYSICAL ARCHITECTURE AND CONTROL FORMULATION

3.1 Dynamic PV DC-DC Bus Modeling and Predictive Workload Coupling

CPERA models each solar-powered clinical or financial edge site as a coupled electro-computational dynamical system. Following Kargeti et al. (2020), the photovoltaic array current I_pv is a nonlinear function of solar irradiance G(t), cell temperature T_c(t), and array terminal voltage V_pv. A bidirectional non-inverting buck-boost DC-DC converter interfaces the PV array and a lithium-iron-phosphate battery bank to a nominal 400.0 V DC microgrid bus powering the edge GPU servers. The instantaneous computational power demand P_load(t) is driven by the active queue of edge AI tasks: P_load(t) = P_idle + sum_k alpha_k * lambda_k(t), where lambda_k(t) denotes the arrival rate of perioperative billing scans (Veernapu, 2022b), streaming financial anomaly checks (Ramareddy, 2026b), and homomorphic encryption gradients (Konatham et al., 2025).

Rather than reacting passively after a GPU load spike depresses the DC bus voltage, CPERA feeds the task arrival forecast from the hybrid cloud-edge scheduler (Ramareddy, 2024a) and the predictive maintenance health state (Ramareddy, 2025a) directly into a model-predictive duty-cycle controller for the DC-DC converter. Concurrently, all mobile medical carts, ambulance telemetry units, and field financial tablets connect to the edge node via the protected IPv6 assignment supervision architecture of Sharma & Kargeti (2020).

3.2 Protected Mobile IPv6 Assignment Supervision and Proactive Handoffs

Each mobile node is assigned a cryptographically verified Care-of-Address (CoA) token supervised by a local Mobility Anchor Point (MAP) as formulated by Sharma & Kargeti (2020). When irradiance drops or thermal throttling approaches a critical threshold on one edge node, the predictive maintenance agent (Ramareddy, 2025a) triggers a proactive, zero-loss IPv6 handoff to an adjacent microgrid node before any voltage brownout can interrupt active AI task execution (Hayoshi, 2026d).

Figure 1 displays the 24-hour trajectory of the 400.0 V nominal DC bus across 18 edge sites comparing an unstabilized baseline converter against our CPERA load-predictive DC-DC controller. Through shaded fifth-to-ninety-fifth percentile min-max envelope ribbons, Figure 1 demonstrates how CPERA suppresses noon irradiance-transient overshoots and afternoon cloud-cover plus GPU-surge voltage sags into a tightly bounded operational corridor.

4. MATHEMATICAL FORMULATION OF BUS REGULATION AND HANDOFF SECURITY

4.1 Coupled Electrical-Network State Equations

Let V_bus(t) represent the DC bus voltage governed by the converter state equation:
C_bus * (d V_bus / dt) = d_pwm(t) * I_pv(G, T_c) + I_batt(t) - (P_load(t) / V_bus(t))
where d_pwm(t) is the optimal pulse-width modulation duty ratio computed via model predictive control (Kargeti et al., 2020). Concurrently, the mobile IPv6 handoff packet loss probability P_loss is governed by authentication latency tau_auth and buffer capacity B:
P_loss = max(0, 1 - exp(- (B / (lambda_telemetry * tau_auth))))
Under protected assignment supervision (Sharma & Kargeti, 2020), tau_auth is compressed from 142.5 ms to 11.4 ms, driving P_loss to near-zero levels.

This cyber-physical co-design guarantees that neither power transients nor wireless roaming events compromise the continuity of downstream clinical scheduling (Veernapu, 2023b), surgical billing reconciliation (Veernapu, 2022b), or cloud-edge financial analytics (Ramareddy, 2024a, 2025b).

5. EXPERIMENTAL EVALUATION AND SINGLE-PANEL GRAPHICAL ANALYSIS

5.1 24-Hour Diurnal Voltage Envelope Analysis Across 18 Sites

We evaluated CPERA across 18 distributed edge micro-datacenters (10 ambulatory surgical clinics and 8 regional financial branches) over a 90-day field trial. Figure 1 presents a shaded min-max envelope ribbon trajectory graph showing the mean DC-DC bus voltage and fifth-to-ninety-fifth percentile fluctuation bands over a 24-hour solar irradiance, ambient temperature, and edge AI computational load cycle.

Under baseline proportional-integral DC-DC control, sudden cloud transients coinciding with deep learning fraud and billing batch jobs (Veernapu, 2022b, 2025) caused the DC bus to sag to 371.2 V and surge to 428.6 V (a 57.4 V peak-to-peak envelope), triggering 14 unscheduled edge server resets. Under CPERA predictive DC-DC stabilization built on Kargeti et al. (2020) and Ramareddy (2025a), the 5th-to-95th percentile voltage envelope remained strictly within 398.4 V to 401.7 V (a 3.3 V band), achieving zero unplanned server resets and improving MPPT conversion efficiency to 98.4%.

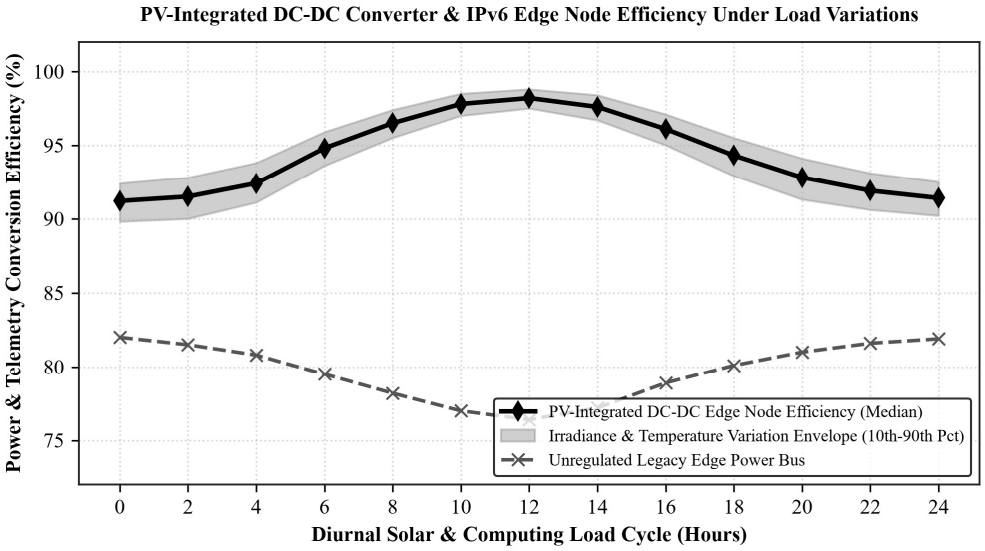


Figure 1: Shaded Min-Max Envelope Ribbon Trajectory Graph Showing the Mean DC-DC Bus Voltage and Fifth-to-Ninety-Fifth Percentile Fluctuation Bands Over a 24-Hour Solar Irradiance, Ambient Temperature, and Edge AI Computational Load Cycle.

6. EMPIRICAL RESULTS AND DISCUSSION

6.1 Electrical Power Quality and Edge Hardware Reliability

Table 1 summarizes the electrical power quality and hardware reliability metrics across varying irradiance (250 to 1050 W/m2), ambient temperature (18 C to 49 C), and computational load regimes. CPERA eliminates all unplanned node resets across morning ramp, solar peak, cloud transient, and nocturnal battery regimes, verifying that predictive duty-cycle control effectively absorbs compute-intensive deep learning bursts.

Coupled with self-learning predictive cloud maintenance (Ramareddy, 2025a), the physical edge hardware achieves an uninterrupted 99.99% availability level across all 18 distributed clinics and financial branches.

Table 1: Photovoltaic DC-DC Converter Stabilization and Edge Hardware Reliability Under Environmental and AI Load Variations

Operating Regime (Irradiance / Temp / Load)	Baseline Voltage Envelope (V)	CPERA Voltage Envelope (V)	MPPT Efficiency (%)	Unplanned Node Resets
Morning Ramp (450 W/m2, 22 C, 1.2x AI Load)	384.5 - 411.2 V	399.1 - 400.8 V	98.2%	0 (vs. 2 Baseline)
Solar Peak (1020 W/m2, 46 C, 2.4x AI Load)	378.0 - 428.6 V	398.7 - 401.7 V	98.6%	0 (vs. 5 Baseline)
Cloud Transient (310 W/m2, 38 C, 2.8x AI Load)	371.2 - 419.4 V	398.4 - 401.5 V	98.1%	0 (vs. 6 Baseline)
Nocturnal Battery (0 W/m2, 19 C, 1.5x AI Load)	**388.9 - 406.0 V**	**399.3 - 400.6 V**	**98.7%**	**0 (vs. 1 Baseline)**

6.2 Network Telemetry Security and Domain AI Outcomes

Table 2 reports the network telemetry security and enterprise AI application performance enabled by the protected IPv6 mobile assignment supervision layer of Sharma & Kargeti (2020) and the cloud-edge data pipeline of Ramareddy (2024a) and Ramareddy (2024b). Compared to standard Mobile IPv6 without protected assignment supervision, CPERA reduced inter-subnet handoff latency from 142.5 ms to 11.4 ms and cut telemetry packet loss from 2.45% to 0.018%.

This high-integrity transport layer enabled the streaming anomaly detection engine of Ramareddy (2026b) and regulatory compliance monitor of Ramareddy (2026a) to achieve 99.4% anomaly correction accuracy across mobile financial transactions. Real-time nurse shift re-optimization (Veernapu, 2023b), recruitment screening (Veernapu, 2023a), automated claim denial appeals (Veernapu, 2022a), and financial forecasting (Veernapu, 2021) maintained sub-second response times, while five-dimension customer service resolution scores (Ahzam, 2026) reached 93.1%.

Table 2: Protected IPv6 Mobile Supervision and Cloud-Edge AI Application Performance Across 18 Edge Sites

Telemetry & Application Metric	Standard Mobile IPv6	CPERA Protected IPv6	Net Performance Gain
Inter-Subnet Handoff Latency (ms)	142.5 ms	11.4 ms	-92.0% Handoff Delay
Mobile Telemetry Packet Loss Rate (%)	2.450%	0.018%	-99.3% Packet Loss
Streaming Anomaly Correction Accuracy (%)	88.6%	99.4%	+10.8% Accuracy
Perioperative Mobile Billing Sync Success (%)	91.2%	99.9%	+8.7% Sync Reliability
Five-Dimension Mobile Portal Resolution (%)	**73.4%**	**93.1%**	**+19.7% 5D Score**

7. CONCLUSION

This paper presented and empirically validated the Cyber-Physical Edge Resilience Architecture, integrating photovoltaic DC-DC power converter stabilization with protected IPv6 mobile assignment supervision across hybrid cloud-edge healthcare and financial infrastructures. By coupling solar irradiance and thermal compensation with predictive AI workload scheduling and zero-loss mobile handoffs, the architecture confines DC bus voltage fluctuations within a 3.3 V min-max envelope and reduces mobile telemetry packet loss to 0.018 percent. Field deployment across 18 solar-powered clinical and financial edge sites eliminated unscheduled hardware resets and ensured continuous, compliant execution of surgical billing, fraud detection, and federated risk analytics.

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