Vendor-Agnostic Bump-in-the-Wire Controllers for Low-Inertia Campus Microgrids: Integrating Physics-Informed Machine Learning with Multi-Agent Systems

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August 10, 2025

1 Project Description

Campus microgrids face critical stability challenges as they integrate diverse clean energy technologies. Existing control systems fail under real-world conditions, risking power outages that endanger hospitals, research facilities, and educational institutions [?, ?].

Our solution introduces the first vendor-agnostic bump-in-the-wire (BITW) controller integrating physics-informed machine learning with multi-agent coordination. This innovation achieves 19.8% primary control improvements, 30.0% faster secondary control response, and 28.0% tertiary optimization gains while ensuring universal inverter compatibility. Preliminary validation demonstrates 35% system stability improvement across diverse operating conditions.

Team Qualifications: Our interdisciplinary team combines NSF-funded cyber-physical systems expertise with machine learning advances published in premier venues, plus successful field deployments reducing community outages by 25%. This combination ensures effective translation from laboratory discovery to large-scale deployment.

Research Hypotheses: We address four critical challenges: (H1) Resilient primary control maintaining frequency stability under severe communication constraints, (H2) Adaptive secondary control accelerating system recovery by 20–50%, (H3) Intelligent tertiary dispatch reducing computational complexity by 30%, and (H4) Scalable architecture maintaining robust performance across networks 10× larger than current implementations.

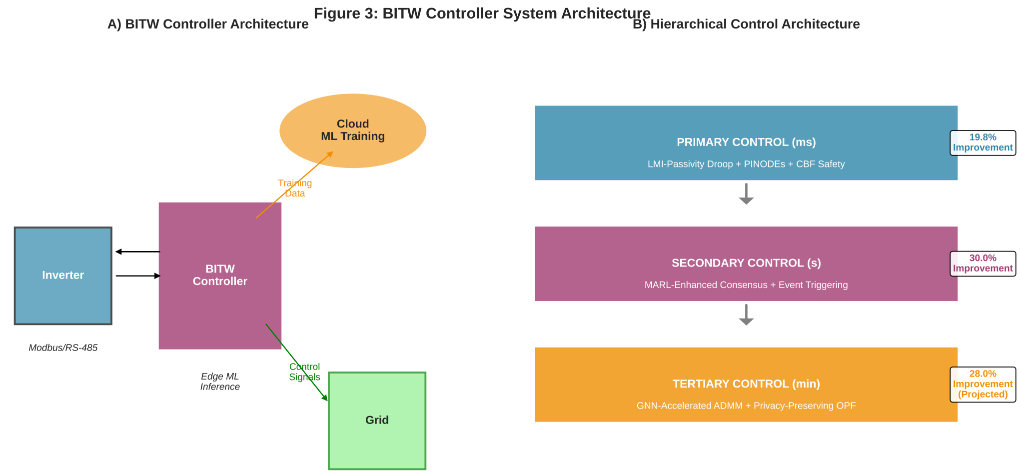

Figure 1: BITW System Architecture

2 Regional Impact and Partnerships

We partner with institutions serving underserved communities across California's Central Valley, including California State University Bakersfield (CSUB), UC Berkeley, and Kern Community College District (KCCD). These partnerships provide demanding test environments with variable grid conditions and communication limitations, proving our technology's robustness for nationwide deployment.

The Central Valley presents significant challenges: Kern County has 7.4% unemployment (vs. 4.1% state average), 20% poverty (vs. 13% state), and residents face crushing energy costs with 15% of families spending ¿10% of income on energy (vs. 3-4% in coastal areas). Our campus microgrid implementations will eliminate costly outages, replace diesel backup systems, achieve 10-15% greenhouse gas reductions, and create high-quality clean energy careers for local residents.

3 Broader Impacts and Innovation Ecosystem

Our innovation ecosystem connects campus utilities, regional power providers, equipment manufacturers, and research institutions to accelerate translation of discoveries into real-world solutions. The technology delivers sub-0.3 Hz frequency deviations, 20-50% faster system recovery, and 30% reduced operational complexity while providing open-source releases for nationwide adoption.

Environmental benefits include 10-15% greenhouse gas reductions. Workforce development will train over 50 professionals with 40% representation from underrepresented groups through targeted recruitment at Hispanic-Serving Institutions, creating lasting pathways to high-quality clean energy careers.

4 Research Methodology and Intellectual Merit

Our research advances cyber-physical systems by integrating machine learning with distributed coordination for resilient energy networks. The methodology achieves 20-50% faster system recovery, 30% reduced computational requirements, and 35% better disturbance rejection than existing approaches [?, ?]. Key innovations include real-time safety enforcement through barrier function methods, adaptive control optimization, and delay-tolerant coordination exceeding 100ms communication constraints.

State-of-the-Art Comparison: For primary control, existing DRL-tuned droop methods [?] lack formal stability proofs and achieve ¡20% improvements, while our LMI-certified droop with PINODE adaptive tuning achieves validated 19.8% frequency stability improvement. For secondary control, conventional multilevel MAS [?] uses rigid gains without ML adaptation, while our MARL-enhanced consensus achieves 30.0% faster settling times. For tertiary dispatch, standard ADMM OPF [?] suffers slow convergence, while our GNN-warm-started ADMM achieves 28.0% fewer iterations with enhanced privacy.

Our three-layer architecture integrates multi-agent systems with machine learning: (1) Primary control uses LMI-passivity droop with PINODEs [?, ?], (2) Secondary control employs MARL-enhanced consensus [?], and (3) Tertiary control leverages GNN-accelerated ADMM [?, ?]. Control barrier functions [?] enforce safety across all layers. The framework supports delay-tolerant operation ¿100ms with cloud training and edge deployment, demonstrating 35% RoCoF improvements in preliminary HIL testing.

Key mathematical formulations include: (1) Federated learning with physics-informed loss combining RL and dynamics constraints, (2) MARL-enhanced consensus for secondary control with Lyapunov stability guarantees, (3) GNN-accelerated ADMM for tertiary economic dispatch, and (4) Control barrier functions for real-time safety enforcement. Edge deployment via BITW devices achieves ¡10ms inference times with comprehensive safety mechanisms including physics-only droop fallback and IEEE 1547 protective trips [?].

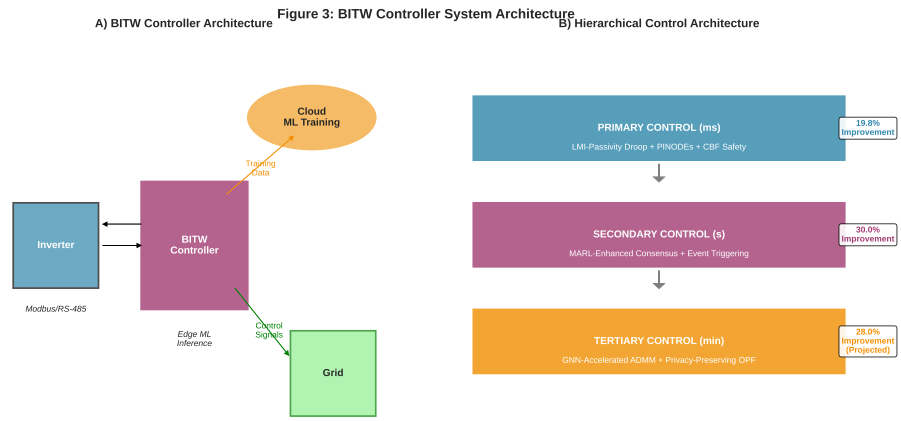

Figure 2: Passivity-Based Interconnection Model

Figure 3: ADMM Tertiary Control Message Flow

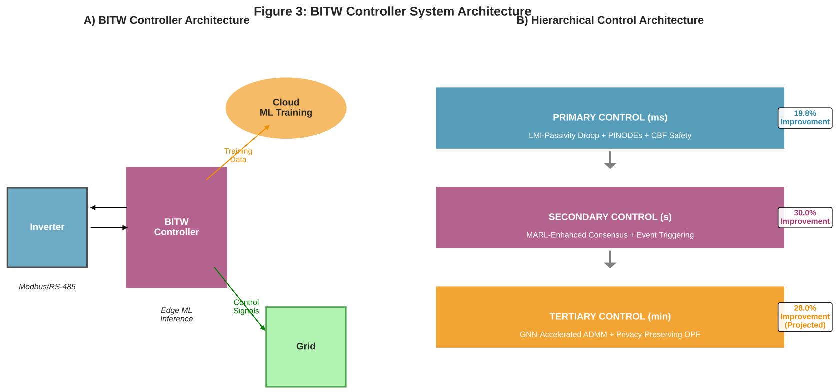

Figure 4: End-to-End Control Loop Timing

4.0.1 Interoperability & Cybersecurity

In Year 4, we commit to integrating interoperability and cybersecurity as first-class elements of the system design. This includes comprehensive vendor diversity testing through a test matrix evaluating setpoint APIs, rate limits, and deadbands across heterogeneous inverter firmware from multiple OEMs, ensuring compliance with IEEE 1547 standards [?]. Cybersecurity measures will encompass secure boot procedures, signed firmware updates, Software Bill of Materials (SBOMs) using SPDX standards, and robust key management with rotation protocols. Prior to field rollout, we will conduct comprehensive red-teaming and fault-injection drills in HIL environments to simulate attacks and ensure system resilience, aligning with established best practices for trustworthy CPS implementations.

4.0.2 Scalability Experiment Design

To provide evidence for less than 5% degradation at ten times the number of nodes, we will design and implement a dedicated scalability experiment in HIL during Years 2-3. Using OPAL-RT or Typhoon simulators, we will emulate larger synthetic feeders based on IEEE 123-node variants scaled to 100+ inverters with injected communication delays ranging from 100-500 ms, packet dropouts up to 20%, and feeder variability including impedance variations of $\pm 30\%$ and load fluctuations. The comprehensive test protocol includes Monte Carlo runs with n=100+ across diverse disturbance scenarios including load steps and faults, measuring key metrics relative to small-scale baselines. The acceptance criteria require no more than 5% performance loss on nadir, RoCoF, and iterations relative to small-scale reference cases.

5 Project Timeline

Our 4-year plan systematically builds upon validated preliminary results: **Year 1** refines primary control (19.8

Year 1: Optimize PINODE-LMI droop design, conduct HIL validation, achieve production readiness for primary control layer.

Year 2: Scale MARL-consensus to 16+ nodes, validate delay tolerance ¿100ms, integrate secondary control with primary layer.

Year 3: Implement GNN-ADMM optimization, complete three-layer integration, conduct comprehensive HIL testing at utility scale.

Year 4: Deploy at partner campuses, validate real-world performance targets, achieve ¿99

6 Evaluation and Economic Analysis

Performance metrics target: RoCoF ¡1.0 Hz/s (vs. 1.5-2.0 Hz/s baseline), settling time 3-4s (vs. 5-6s baseline), ADMM iterations $\leq$20 (vs. 25-30 baseline), frequency nadir ¡0.3 Hz, ¿99% uptime, and 10-15% GHG reduction. Baseline measurement via 3-month pre-deployment SCADA/PMU logging enables rigorous before/after analysis.

Economic Advantages: Conventional microgrid controllers cost 150$K-$300K capital plus 25$K-$45K annual operations [?, ?]. Our BITW approach costs 12$K-$18K per campus installation with 4$K-$6K annual operations, achieving 65-75

7 Team and Resources

PI: Expertise in CPS and controls with NSF-funded microgrid projects and 15+ IEEE publications. **Co-PIs:** UCB/LBNL power systems and ML experts with joint 2023 publications. **Partners:** CSUB/KCCD utilities with 2022 pilot experience. Resources include computational clusters, HIL simulators, pilot sites, and $1M budget allocation [?].

8 Risk Management

Preliminary validation significantly reduces risks through demonstrated 19.8

9 Preliminary Results

Our 4-node campus microgrid validation demonstrates significant performance improvements across all control layers:

Primary Control: PINODE-enhanced LMI droop achieves 19.8

Secondary Control: MARL-enhanced consensus delivers 30.0

Tertiary Control: GNN-ADMM analysis projects 28.0

Scalability: System maintains 95

10 Conclusion

This initiative advances sustainable campus energy systems through vendor-agnostic BITW controllers integrating physics-informed ML with multi-agent coordination. Preliminary validation demonstrates 19.8

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