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A Parallel AI Framework for Autonomous Microgrid Control in Aerospace Systems Application Potential for NASA and the Canadian Space Agency for Deep Neural Control Module (DNCM)

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Abstract

Recent advancements in space exploration platforms, such as NASA's Artemis lunar base program and the Canadian Space Agency's Gateway power systems, demand resilient, autonomous, and intelligent energy control solutions. These systems operate in dynamic, resource-constrained, and fault-prone environments where traditional SCADA or PLC-based controls lack adaptability and predictive capability.

This paper presents **HIRACLE**—*Hybrid Intelligent Resilient Adaptive Control and Learning Engine*—a novel parallel AI framework specifically designed for microgrid systems in extraterrestrial habitats and highaltitude UAV missions. HIRACLE features a modular, edge-deployable architecture combining transformer-based forecasting, deep reinforcement learning, spiking neural fault detection, and graph-based rerouting, all supported by meta-learning for continuous mission adaptation.

The software implementation utilizes containerized deep learning models (TensorFlow/PyTorch) optimized for edge inference using platforms such as NVIDIA Jetson AGX Orin and Xilinx Versal AI Edge SoCs. These models are deployed as distributed agents capable of parallel operation via high-speed buses (CAN-FD, SpaceWire), ensuring real-time coordination across subsystems. Fault classification, ripple anticipation, load optimization, and health-aware scheduling are executed concurrently without centralized computation.

On the hardware front, HIRACLE integrates reconfigurable logic (FPGAs), neuromorphic processors (Intel Loihi 2), SiC-based power conditioning units, and secure telemetry interfaces into a ruggedized control environment. A new chip-level proposal—**HIRACLE-IC**—is introduced, consolidating all AI, logic, sensing, and secure communication into a single embedded platform ready for deployment in lunar, Martian, or stratospheric UAV energy systems.

This approach not only surpasses existing state-of-the-art autonomous energy controls but also positions HIRACLE as a foundational control paradigm for future NASA and CSA missions requiring scalable, intelligent, and mission-adaptive microgrid autonomy.

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I. Introduction

We present a comprehensive and uniquely conceptualized model that combines deep learning, artificial intelligence algorithms, and advanced optimization techniques for the control, stability, error detection, and power optimization of Islanded DC Microgrids used in space habitats and UAVs, as discussed in previous research paper by the same author ,Tiled as " Deep Neural Control Module (DNCM) AI-Driven Adaptive Deep Learning Control Framework for Islanded DC Microgrids in Space Habitats and UAVs"

Mathematical Equations used in Deep Neural Control Module (DNCM)

AI-Driven Adaptive Deep Learning Control Framework for Islanded

DC Microgrids in Space Habitats and UAVs

1. Data Normalization

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (1)$$

2. Transformer Attention Mechanism

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (2)$$

3. Mean Squared Error Loss

$$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2 \quad (3)$$

4. Online Gradient Descent Update

$$\theta_{t+1} \leftarrow \theta_t - \eta \nabla_\theta L_{newbatch} \quad (4)$$

5. State of Charge Dynamics

$$SOC(t+1) = SOC(t) + \eta_c P_{charge}(t) - \frac{P_{discharge}(t)}{\eta_d} \quad (5)$$

6. Load Prioritization Rule

$$L_{served}(t) = \sum_i w_i \cdot \mathbf{1}\{L_i(t) \le E_{available}(t)\} \quad (6)$$

7. Reinforcement Learning Reward Function

$$R_t = \alpha_1 R_{util} + \alpha_2 R_{priority} - \alpha_3 R_{loss} - \alpha_4 R_{batterystrain} \quad (7)$$

8. Bellman Equation (DQN Update)

$$\theta \leftarrow \theta - \eta \nabla_\theta \left(R_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-) - Q(s_t, a_t; \theta)\right)^2 \quad (8)$$

9. CNN Output with Softmax

$$\hat{y} = softmax(f_\theta(x)) \quad (9)$$

10. Categorical Cross-Entropy Loss

$$L(\theta) = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} \log \hat{y}_{i,c} \quad (10)$$

11. Real-Time Fault Classification

$$diagnosis(t) = \mathrm{argmax} f_\theta(S(t)) \quad (11)$$

12. Fault Path Optimization

$$P_{alt} = \arg\min_{P \in \mathcal{P}} cost(P), \quad P \cap v_f = \emptyset \quad (12)$$

13. Health Degradation Forecasting

$$H(t) = H_0 - \alpha t + \beta \log(t+1) \quad (13)$$

14.
Classification Metrics

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \quad FPR = \frac{FP}{FP+TN}$$

$$SuccessRate = \frac{SuccessfulReroutes}{TotalFaultEvents}$$

15. GNN Message Passing Rule

$$x_i^{(t+1)} = \sigma\left(\sum_{j \in N(i)} W x_j^{(t)} + b\right) \quad (16)$$

16. Voltage Forecasting Loss

$$L = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(\hat{V}_i^{t+1} - V_i^{t+1}\right)^2 \quad (17)$$

17. Droop Control Equation

$$R_i(t) = \frac{V_i(t) - V_{ref}}{P_i(t)} \quad (18)$$

18. Proportional Voltage Controller

$u_t = K_p(V_{setpoint} - V_t)$ (19) **19. SoC Forecasting via LSTM**

$\hat{SOC}_{t+1} = LSTM(SOC_t, Load_t)$ (20) **20. Q-Learning Policy**

$$Q(s_t, a_t) = R_t + \gamma \max_a Q(s_{t+1}, a) \quad (21)$$

Novel Parallel Algorithm: HIRACLE

HIRACLE: Hybrid Intelligent Resilient Adaptive Control & Learning Engine is a new, mathematically integrated algorithm designed for **parallelized processing** of control, forecasting, optimization, and fault healing in microgrids. It unifies five AI layers under one resilient, self-learning architecture.

1. Temporal-Spatial Forecast Embedding (GAT-LSTM Transformer)

Step 1: Temporal-Spatial Forecast Embedding What it does: This step uses a combination of deep learning techniques (LSTM and Graph Attention Networks) to predict the future state of the microgrid. It takes into account voltage, power, battery charge levels, and system health.

Why it matters: By anticipating future changes, the system can make better control decisions ahead of time. It acts like the "foresight" or "early warning system" of the algorithm.

$$\mathbf{Z}_{t+1} = GAT\,LSTM(V_{t-k:t}, P_{t-k:t}, SOC_{t-k:t}, H_{t-k:t}) \quad (22)$$

This equation embeds graph-based attention and LSTM forecasting to predict multi-modal state vectors for future action synthesis.

2. Resilience-Aware Deep Q Policy Optimization

Step 2: Resilience-Aware Policy Optimization What it does: This is the core decision-making engine. It chooses the best action at any moment (like charging, discharging, or switching loads) based not just on immediate reward but also on long-term impacts such as battery health and fault risks.

Why it matters: This step makes HIRACLE smarter than traditional algorithms—it cares about both current performance and future resilience, reducing wear and avoiding dangerous states.

$Q^*(s_t,a_t) = R_t + \gamma \max Q(s_{t+1},a) - \lambda_1 \cdot \Delta H(t) - \lambda_2 \cdot 1_{fault}$ (23) a

This modifies classical Bellman formulation to penalize battery health deterioration and fault triggers using a hybrid loss-reward structure.

3. Predictive Droop Stabilization Layer (Advanced Forecast Control)

Step 3: Predictive Droop Stabilization What it does: Using the forecasted values from Step 1, this component adjusts electrical resistance settings in advance to prevent voltage instability. It works like a stabilizer that reacts before a disturbance happens.

Why it matters: In space or aerial microgrids, stability is crucial. This proactive behavior ensures smooth operation even under sudden load changes or power dips.

$$R_i^{next} = \frac{Z_{V_i} - V_{ref}}{Z_{P_i}} \quad if Z_{ripple} > \epsilon \qquad (24)$$

The forecasted ripple from layer 1 is used to preemptively adjust the control droop resistance.

4. Multi-Criteria Fault Rerouting

Step 4: Multi-Criteria Fault Rerouting What it does: If a fault (like a short circuit or component failure) is detected or predicted, this step finds a new way to route electricity through the system. It does so based on not just cost, but how stable and redundant the new route is.

Why it matters: This ensures that the microgrid continues operating even when part of it fails, without depending on human intervention. It mimics biological self-healing.

P^*_{alt}= arg min $[cost(P) - \mu \cdot stability(P) + \kappa \cdot redundancy(P)]$ (25) $P \in \mathrm{P}$

This path optimization extends Dijkstra's algorithm with resilience-aware cost augmentation.

5. Meta-Learning Fine-Tuner

Step5 : Meta−LearningFine−TunerWhatitdoes : Thisisaself−improvementloop.Thealgorithmperiodically

Why it matters: It allows the system to adapt to new environments, like going from a lunar base to a Martian base, or from one UAV mission to another, without retraining from scratch. L

$$_{meta} = \sum_{j=1}^{M} \left(\nabla_\theta Q_{\theta_j}(s_j,a_j) - \nabla_\theta Q_\theta(s_j,a_j)\right)^2 \quad (26)$$

The algorithm periodically retrains using meta-gradient updates from mission variation sets to enhance domain adaptability.

Parallel Execution Pipeline

Each submodule (control, forecasting, optimization, fault healing, droop correction) executes as a distributed agent on an edge-processing core.

Step 6: Parallel Execution Pipeline What it does: All of the above components are designed to work in parallel—meaning they run simultaneously on different edge processors or AI chips in the system.

Why it matters: This greatly speeds up computation and decision-making, which is essential in space or aerial missions where time and resources are limited. [H] HIRACLE Parallelized Agent Loop [1] Initialize: GAT-LSTM, DQN, GNN, CNN, Droop & MetaLearner each time window t in parallel $\mathbf{Z}_{t+1} \leftarrow$ *ForecaststatesusingGAT − LSTM* $a_t \leftarrow \text{argmax}_a$ $Q^*(s_t,a_t)$ from Equation

(2) Execute a_t & monitor ripple $Z_{ripple} > \epsilon$ Adjust R_i^{next} from Equation (3)

Fault detected by CNN Compute reroute P_{alt}^* from Equation (4) Update Qvalues & fine-tune with L_{meta} Innovation HIRACLE doesn't just control a power system — it thinks ahead, protects itself, adapts continuously, and heals itself. These qualities are crucial for mission-critical environments like space habitats, military UAVs, and remote autonomous microgrids.

Mathematical Modules Used Previously (Summarized)

- MinMax Scaling
- Transformer Attention (Eq. 2)
- MSE Loss (Eq. 3)
- Gradient Descent (Eq. 4)
- State of Charge Dynamics (Eq. 5)
- CNN + Softmax Classification (Eq. 9)
- Graph Neural Network Message Passing (Eq. 15)

- Droop Control Formulation (Eq. 17)
- Q-Learning Policy (Eq. 20)

Designing an Innovative Hardware Architecture for HIRACLE Implementation

Space and UAV-Based Deployment of AI-Controlled Microgrid Systems

1. Edge AI Processing Units (EAPUs)

Procedure: Each HIRACLE submodule (forecasting, optimization, self-healing) runs on an independent container deployed on an embedded SoC.

Connections: Interconnected via high-speed serial links (PCIe or I2C) with CAN/SpaceWire backhaul.

Hardware Embedding: Modules like NVIDIA Jetson AGX Orin or Xilinx Versal AI Edge are mounted onto a thermally shielded control board.

Specifications:

Parameter	Range/Value
Operating Power	15–30W
GPU/TPU Cores	512–1024 CUDA/AI cores
Memory	32–64 GB LPDDR5
Inference Latency	< 20 ms per frame
Radiation Tolerance	> 100 krad (space-grade variant)

2. FPGA Acceleration Layer

Procedure: Implements real-time logic for droop control, ripple suppression, and redundancy management.

Connections: FPGA links to EAPUs via AXI interface and configures I/O to battery, load, and bus modules.

Hardware Embedding: Xilinx Kintex UltraScale or Microsemi RTG4 placed on reprogrammable daughterboards.

Specifications:

Parameter	Range/Value
Logic Cells	1M–2.5M
I/O Voltage Levels	1.2V, 1.8V, 3.3V
Response Time	$< 10\mu s$
Clock Speed	300–500 MHz

3. Photonic AI Interconnect (Optional)

Procedure: Optical matrix multiplication units accelerate transformer computations.

Connections: Interfaces with transformer engines inside the EAPUs using PCIe-to-photonic bridges.

Hardware Embedding: Lightmatter Envise photonic processor installed in testbed environment.

Specifications:

Parameter	Range/Value
Compute Throughput	> 1 PFLOP/s photonic ops
Optical Delay	< 1 ns
Thermal Dissipation	Passive or water-cooled
Form Factor	≤ 6U rackmount

4. Neuromorphic Sensor Grid

Procedure: Edge sensors detect faults and ripple patterns using SNNs.

Connections: Neuromorphic ICs connected directly to current/voltage sense lines via ADC front-ends.

Hardware Embedding: Intel Loihi 2 or SynSense DYNAP cores distributed near power buses.

Specifications:

Parameter	Range/Value
Spiking Core Count	128–1024
Latency to Detection	<1 ms
Power Consumption	< 50 mW per chip
Data Output Rate	500–1000 events/sec

5. Backplane Bus Communication

Procedure: All intelligent agents communicate via deterministic protocols like CAN-FD and SpaceWire.

Connections: Wired serial interfaces with error correction and priority queues.

Hardware Embedding: Onboard bus transceivers integrated into custom backplane.

Specifications:

Parameter	Range/Value
Data Rate	100 kbps–400 Mbps
Protocol Layers	CAN-FD ISO 11898-7, ECSS-E-ST-50-12C
Bus Redundancy	Dual-loop supported
Jitter Tolerance	<10 ns

6. Redundant Power Conditioning Units (PCUs)

Procedure: Receive control signals to manage charge/discharge of BESS and handle rerouting.

Connections: Linked to FPGA for pulse-width modulation and digital switching.

Hardware Embedding: Based on SiC MOSFETs with AI-enabled controllers (TI C2000).

Specifications:

Parameter	Range/Value
Switching Frequency	20–100 kHz
Thermal Limits	< 80°C continuous
MOSFET Type	SiC 650V–1200V
Control Accuracy	±1%

7. Secure Control Interface

Procedure: Maintains telemetry and override control via secure middleware.

Connections: Connected via Ethernet or radio uplinks to ground/mission control.

Hardware Embedding: Uses cryptographic processors and blockchain timestamping.

Specifications:

Parameter	Range/Value
Security Protocol	TLS 1.3 + Blockchain
Telemetry Rate	Logs 1–10 Hz
Authentication Delay	< 50 ms
Interface Type	SpaceWire + RS485 Ethernet

HIRACLE Hardware Implementation Goals

This proposed hardware system enables a fully parallel, resilient, and adaptive realization of the HIRACLE algorithm in high-risk aerospace environments. Leveraging the latest edge AI, neuromorphic processors, FPGAs, and photonics, it enables unmatched intelligence, speed, and autonomy in DC microgrid control.

Implementation Pathway for HIRACLE Algorithm: Software to Hardware
Deployment
Including Proposal for a Novel Integrated Control Device (HIRACLE-
IC)

Step-by-Step HIRACLE Implementation from Software to Hardware

Step 1: Software Architecture Design

The HIRACLE algorithm is structured as modular AI agents, each handling tasks like forecasting, optimization, and fault recovery. These modules are developed using Python frameworks like TensorFlow and PyTorch, trained using synthetic and real-world power system data, and validated in MATLAB Simulink or PLECS simulation environments.

Outcome: Self-contained, containerized AI agents capable of edge execution via ONNX Runtime or TensorRT.

Step 2: Firmware Deployment on Edge Processors

The AI modules are deployed on embedded hardware platforms:

- **NVIDIA Jetson AGX Orin** for Transformer inference.
- **Xilinx Versal AI Edge SoC** for real-time deterministic tasks.
- **TI C2000 Microcontroller** for charge/discharge switching.

Each AI agent is containerized and deployed with hardware abstraction for mission-specific reuse.

Step 3: Sensor Interfacing and Signal Routing

Edge sensors (voltage, current, temperature) are connected to the EAPUs through high-resolution ADCs (e.g., ADS8688). Fault patterns and ripple metrics are extracted by neuromorphic coprocessors (e.g., Intel Loihi 2), enabling localized AI response.

Connection: All processors communicate using CAN-FD or SpaceWire with timestamping for synchronization.

Step 4: Closed-Loop Simulation and Learning

The system is validated using digital twin simulations of lunar, Martian, and aerial microgrids. These environments inject faults, demand fluctuations, and irradiance variations to test adaptability.

Self-Improvement: The meta-learning module dynamically adapts control strategies across environments without retraining.

Step 5: Proposal for HIRACLE-IC – A Dedicated Control Device

We propose the development of a specialized SoC named **HIRACLE-IC** integrating all AI logic, neuromorphic processing, reconfigurable logic, and secure telemetry.

Key Features:

- AI Inference Core (Transformer + LSTM)
- FPGA/FPAA-style reconfigurable logic for droop control
- Spiking Neural Detection for ripple/fault response
- Analog interfacing for sensors and SiC switching
- Blockchain telemetry + Zero Trust command access

Step 6: Fabrication and Deployment

Prototype fabrication can be initiated using open-access foundries like SkyWater (130nm node) with embedded flash memory and radiation tolerance. Device deployment spans:

- Autonomous microgrids for lunar habitats
- Mars rovers and remote exploration outposts
- UAV energy pods and airborne microgrid control
- Remote military microgrids in off-grid zones

Conclusion: Uniqueness and Global Relevance

The HIRACLE architecture and its proposed integrated chip represent a disruptive advancement in intelligent microgrid control:

- No previous architecture unifies Transformer forecasting, fault graph rerouting, meta-learning, and predictive droop control into a parallelized edgecapable AI system.
- The HIRACLE-IC chip concept is the first proposal for integrating AI inference, neuromorphic sensing, FPGA logic, and secure telemetry into one mission-rugged chip.
- Designed from inception for harsh aerospace environments, HIRACLE surpasses traditional PLC, SCADA, and remote telemetry systems. • NASA can adopt HIRACLE for resilient energy management in lunar or Martian habitats.
- The **Canadian Space Agency** can leverage HIRACLE for Arctic, polar, and orbital platform

energy control where intelligent autonomy is essential.

HIRACLE is not just an algorithm—it is a next-generation control paradigm for intelligent, autonomous, and adaptive power systems.

Mapped Bibliography

Each reference below is aligned with a specific section of the HIRACLE research paper to demonstrate direct relevance to our software, hardware, control, and parallelization frameworks.

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Note

All references listed above are peer-reviewed or government-verified technical sources, chosen to directly support and contextualize the innovation behind HIRACLE. The URLs provide permanent access to the complete documents.