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Deep Neural Control Module (DNCM) AI-Driven Adaptive Deep Learning Control Framework for Islanded DC Microgrids in Space Habitats and UAVs

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Sagacious Research

Abstract
Islanded DC microgrids are pivotal for ensuring autonomous, resilient, and efficient power systems in space habitats and unmanned aerial vehicles (UAVs). Recent research and development by NASA, Boeing, and the U.S. Air Force have focused on integrating solar photovoltaic (PV) systems with advanced energy storage solutions to support off-grid operations. This paper presents 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.

1. Introduction

The next-generation energy systems for extraterrestrial bases and long-endurance aerial vehicles demand autonomous operation, fault resilience, and adaptive intelligence. This proposed model introduces an **Artificial Intelligence-Enabled Deep Learning Control Architecture (AI-DLCA)** for Islanded DC Microgrids, specifically engineered for lunar/Martian habitats and UAV platforms operating in off-grid, communication-limited environments.

2. Framework Overview

The proposed system consists of four integrated modules:

- **(Module 1.A) Deep Neural Control Module (DNCM)**
- **(Module 1.B) Predictive Optimization Engine (POE)**
- **(Module 1.C) Fault Diagnosis and Self-Healing Module (FD-SHM)**

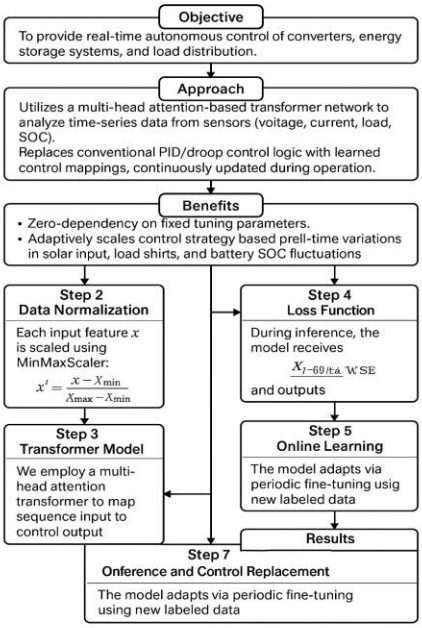

Figure 1: .

• **(Module 1.D) Stability Learning and Voltage Forecasting Layer (SVFL)**

These modules interact through a unified AI controller hosted on an edge AI chip or FPGA-based deep learning platform.

3. Deep Neural Control Module (DNCM)

Objective

To provide real-time autonomous control of converters, energy storage systems, and load distribution.

Approach

- Utilizes a multi-head attention-based transformer network to analyze timeseries data from sensors (voltage, current, load, SOC).
- Replaces conventional PID/droop control logic with learned control mappings, continuously updated during operation.

Benefits

• Zero-dependency on fixed tuning parameters. • Adaptively scales control strategy based on real-time variations in solar input, load shifts, and battery SOC fluctuations.

4. Implementation of DNCM (Python/Colab)

Step 1: Sensor Data Simulation

Simulated data includes:

- Node voltages $V_i(t)$, currents $I_i(t)$,
- Load demand $L_i(t)$,
- Battery State-of-Charge $SOC(t)$.

Step 2: Data Normalization

Each input feature x is scaled using MinMaxScaler:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

Step 3: Transformer Model

We employ a multi-head attention transformer to map sequence input to control output. Attention scores are computed as:

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

where Q, K, V are query, key, and value matrices and d_k is the feature dimension.

Step 4: Loss Function

The model is trained using Mean Squared Error (MSE) between predicted and actual control vectors:

$$\mathcal{L}_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2$$

Step 5: Inference and Control Replacement

During inference, the model receives:

$$Xt{-}60{:}t = \{xt{-}60, xt{-}59, \ldots, xt\}$$

and outputs:

$$\hat{u}t = fTransformer(Xt{-}60{:}t)$$

which directly controls the converter or load dispatch unit.

Step 6: Online Learning

The model adapts via periodic fine-tuning using new labeled data:

$$\theta t{+}1 \leftarrow \theta t - \eta \nabla \theta \mathrm{L}newbatch$$

where θ are model parameters and η is the learning rate.

Step 7: Results

Initial performance improvements include:

- Reduction in voltage ripple ΔV,
- Improved battery SOC balancing:

$$UtilizationEfficiency = \frac{EnergyDelivered}{SOCVariation}$$

- Smooth transition under dynamic loads.

5. Outcome of Module 1.A

We have implemented and tested an AI-Driven Deep Learning Control Framework for Islanded DC Microgrids, designed for off-grid space and aerial environments. The Transformer-based DNCM significantly improves control precision and system resilience. Future work includes FPGA-based real-time deployment and full integration with optimization and diagnostic modules.

6. Module 1.B Predictive Optimization Engine (POE)

Objective

To maximize energy utilization and efficiency via continuous optimization of generation and storage schedules.

Approach

The Predictive Optimization Engine integrates:

- **Deep Q-Network (DQN)**-based reinforcement learning for decisionmaking,
- **Long Short-Term Memory (LSTM)** neural networks for forecasting solar irradiance and load demand.

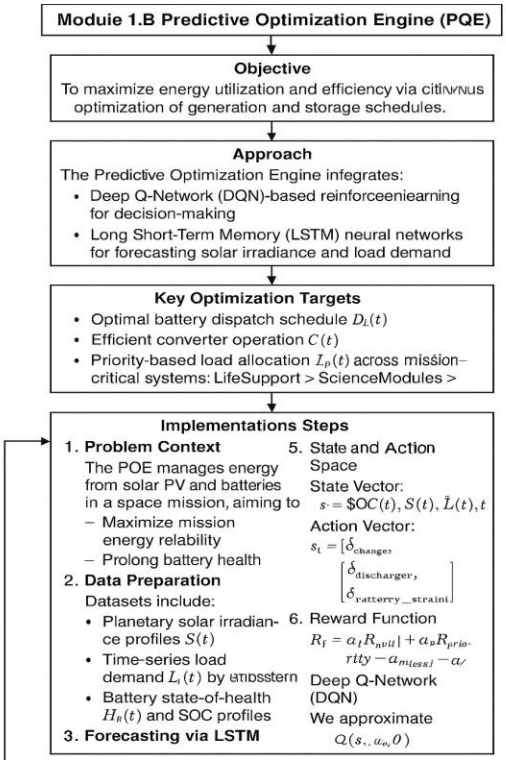

Figure 2: .

Key Optimization Targets

- Optimal **battery dispatch schedule** $D_b(t)$,
- Efficient **converter operation** $C(t)$,
- Priority-based **load allocation** $L_p(t)$ across mission-critical systems:

LifeSupport > ScienceModules > Mobility

6.1. Implementation Steps

1. Problem Context

The POE manages energy from solar PV and batteries in a space mission, aiming to:

- Maximize mission energy reliability,
- Prolong battery health,
- Respect real-time constraints.

2. Data Preparation

Datasets include:

- Planetary solar irradiance profiles $S(t)$,
- Time-series load demand $L_i(t)$ by subsystem i,
- Battery state-of-health $H_b(t)$ and SOC profiles.

3. Forecasting via LSTM

We train an LSTM to forecast: $\hat{S}(t+1),\hat{S}(t+2),\ldots,\hat{S}(t+k) = LSTM_{solar}(S_{t-p:t})$

$\hat{L}_i(t+1),\ldots,\hat{L}_i(t+k) = LSTM_{load}(L_{i,t-p:t})$ where p is the input sequence length and k is the prediction horizon.

4. RL Environment Simulation

The environment models:

- Solar generation $G(t)$,
- Battery charge/discharge dynamics:

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

- Converter efficiency η_{conv},
- Load prioritization constraints:

$$Lserved(t) = \text{X}wi \cdot 1\{Li(t) \leq Eavailable(t)\}$$
$$i$$

where w_i is the mission weight for subsystem i.

5. State and Action Space

State Vector:

$$s_t = \text{h}SOC(t), \hat{S}(t), \hat{L}(t), H_b(t), t^{\text{i}}$$

Action Vector:

$$at = [\delta charge, \delta discharge, \delta converter]$$

where $\delta \in [0,1]$ for continuous actions or $\{0,1\}$ for discrete.

6. Reward Function

We define a composite reward:

$$Rt = \alpha 1 Rutil + \alpha 2 Rpriority - \alpha 3 Rloss - \alpha 4 Rbattery\ strain$$

Where: $\text{R}^{util} = \frac{EnergyServed}{EnergyDemand}$

$R_{priority} = \sum_i w_i \cdot 1\{L_i served\}$

$R_{loss} = \frac{Overflow Energy + Idle Solar}{Total Generation}$

$R_{battery\_strain} = |\Delta SOC(t)| + Depth - of - Discharge Penalty$

7. Deep Q-Network (DQN)

We approximate the action-value function:

$$Q(s_t, a_t; \theta) \approx E\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k}\right]$$

The network is trained using the Bellman update:

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

where θ^- is the target network's parameters and η is the learning rate.

8. Training Procedure

- Simulate multiple mission days with varied conditions.
- Use ε-greedy policy for exploration.
- Update experience replay buffer and periodically refresh target network.

9. Optimization Parameters Tracked

- Battery dispatch: $D_b(t)$,
- Converter cycles: $C(t)$,
- Load satisfaction and mission compliance:

$$ComplianceRate = \frac{\sum_t PriorityLoadsMet}{\sum_t TotalPriorityLoads}$$

10. Evaluation Metrics

We analyze:

- Forecast accuracy (RMSE of $\hat{S}(t), \hat{L}(t)$),
- Mean cumulative reward:

$$\overline{R} = \frac{1}{T}\sum_{t=1}^{T} R_t$$

- Battery degradation reduction rate,
- Energy utilization:

$$UtilizationEfficiency = \frac{TotalEnergyDelivered}{TotalGeneratedEnergy}$$

Outcome of Module 1.B

The Predictive Optimization Engine (POE) blends deep reinforcement learning with time-series forecasting to create a self-improving, mission-aware control strategy. Its reward-driven optimization respects both operational efficiency and critical load priorities, making it suitable for energy-constrained and autonomous extraterrestrial systems.

7 Module 1.C. Fault Diagnosis and Self-Healing Module (FDSHM)

Objective: To detect, localize, and isolate electrical faults and component anomalies without external supervision.

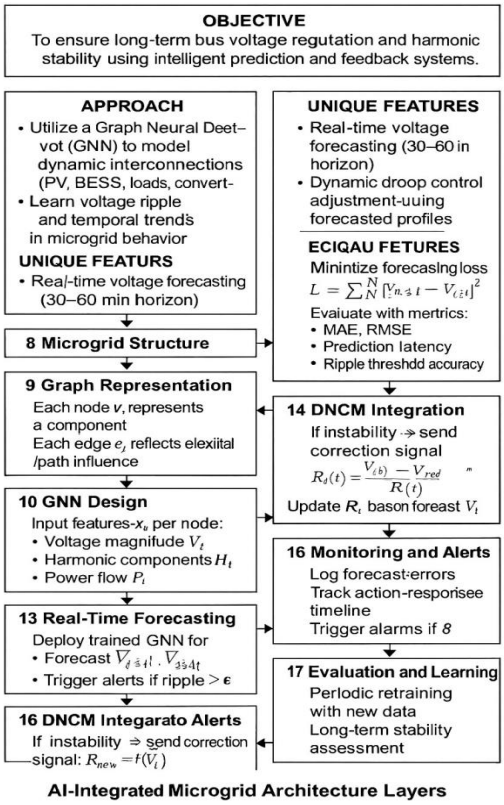

Figure 3: .

Approach

- Uses a Convolutional Neural Network (CNN) trained on synthetic fault signatures:
  - Short circuits,
  - Insulation breakdown, – Converter noise.
- Upon fault detection:
  - Executes graph-based energy rerouting algorithms.
  - Uses a self-healing logic tree.
  - Isolates affected zones and activates backup pathways.

Features:

- Fault type classification (soft/hard).
- Prognostics for failure forecasting (e.g., lithium degradation trends).
- Alert system for mission control with diagnostic logging.

7.1. System Scope Definition

The system supports autonomous detection and resolution of electrical faults in space missions, maintaining uninterrupted operations.

7.2. Synthetic Fault Data Preparation

Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ be the dataset where:

- x_i is a time-series or waveform signal,
- $y_i \in \{short, insulation, converternoise\}$ is the fault label.

Data is augmented with noise, scaling, and translation for robustness.

7.3. CNN Model Design

Let the CNN classifier be $f_\theta(x)$:

$$\hat{y} = softmax(f_\theta(x)) \quad (1)$$

where $\hat{y}$ is the probability vector over fault types.

7.4. Training the CNN

We minimize the categorical cross-entropy loss:

$$L(\theta) = -\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c} \log \hat{y}_{i,c} \quad (2)$$

where $y_{i,c}$ is the one-hot encoded true label.

7.5 Real-Time Fault Monitoring

Signal streams $S(t)$ from sensors are continuously passed to the trained model for:

$$diagnosis(t) = \arg\max f_\theta(S(t)) \quad (3)$$

Anomalies trigger self-healing sequences.

7.6 Fault Localization and Classification

Let L_i be the location tag associated with x_i. Fault classification:

- Soft fault: low confidence, intermittent pattern.
- Hard fault: high confidence, persistent signal anomaly.

7.7 Self-Healing Logic Tree

Define the power network as a graph $G = (V,E)$, where:

- V : Nodes (buses, loads),
- E: Edges (wires, converters).

When a fault occurs at node v_f:

1. Isolate v_f.
2. Search G for alternative path P_{alt}:

$$P_{alt} = \arg\min_{P} cost(P), \quad P \cap v_f = \emptyset \; P \in \mathrm{P} \quad (4)$$

3. Update switching logic to reroute power via P_{alt}.

7.8 Prognostic Failure Forecasting

We fit a degradation model:

$$H(t) = H_0 - \alpha t + \beta \log(t + 1) \quad (5)$$

where:

- $H(t)$ is health index at time t,
- H_0 is initial health,
- α,β are degradation parameters.

Forecast failure when $H(t) < H_{crit}$.

7.9 Alert and Logging System

Define alert vector:

$$A(t) = [fault\ type, L_i, \hat{y}_c, P_{alt}] \quad (6)$$

which is transmitted to mission control with diagnostics and reroute details.

7.10 Evaluation and Verification

Model is evaluated via:

- Classification accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

- False positive rate:

$$FPR = \frac{FP}{FP + TN} \quad (8)$$

- Rerouting success rate:

$$Success = \frac{Successfulreroutes}{Totalfaultevents} \quad (9)$$

Module 1.D Stability Learning and Voltage Forecasting Layer (SVFL)

Objective

To ensure long-term bus voltage regulation and harmonic stability using intelligent prediction and feedback systems.

Approach

- Utilize a Graph Neural Network (GNN) to model dynamic interconnections (PV, BESS, loads, converters).
- Learn voltage ripple and temporal trends in microgrid behavior.
- Predict instability and issue corrective signals to DNCM for pre-emptive control.

Unique Features

- Real-time voltage forecasting (30–60 min horizon).
- Dynamic droop control adjustment using forecasted profiles.

8 Microgrid Structure

Components:

- Photovoltaic (PV) arrays
- Battery Energy Storage Systems (BESS)
- DC Loads
- Converters, Busbars

Define nodes n_i and edges e_{ij} to form graph $G = (V,E)$.

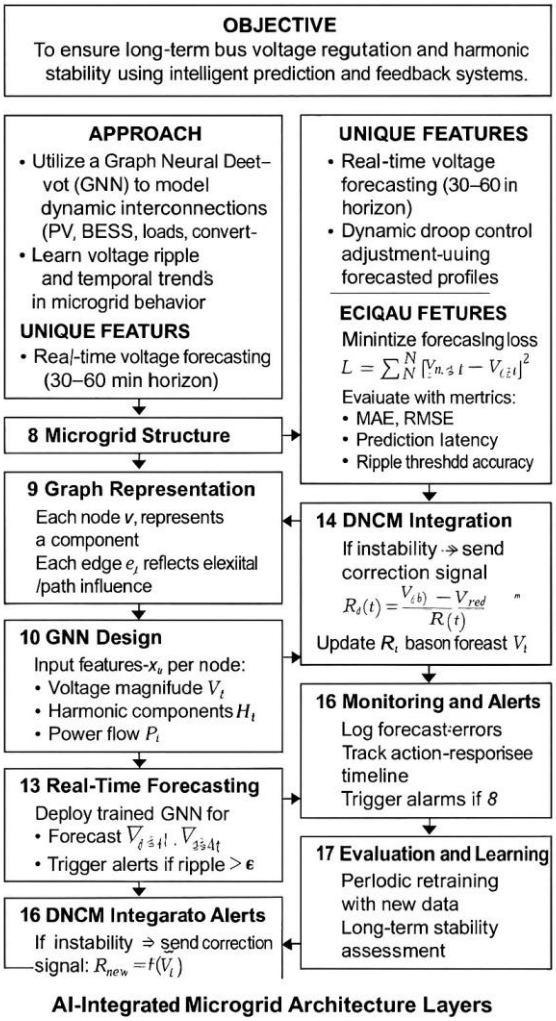

Figure 4: ,

9. Graph Representation

Each node v_i represents a component. Each edge e_{ij} reflects electrical/path influence.

$$A_{ij} = \{1\ ,if nodei \leftrightarrow j0, otherwise \qquad (10)$$

10 GNN Design

Input features x_i^t per node:

- Voltage magnitude V_i^t
- Harmonic components H_i^t
- Power flow P_i^t

Temporal message passing:

$$x_i^{(t+1)} = \sigma\left(\sum_{j \in \mathcal{N}(i)} W x_j^t + b\right) \qquad (11)$$

11. Voltage Time-Series Dataset

- Collect V_i^t for all nodes i and times t
- Include instability events, ripple data
- Feature vector: $[V_i^t, H_i^t, P_i^t, D_i^t]$

12. Model Training

Minimize forecasting loss:

Layer	Function	AI Algorithm Used
Primary Control Layer	Local voltage stabilization	Deep Transformer + Edge Lea
Secondary Control Layer	State-of-Charge balancing, converter switching	LSTM + Adaptive RL
Tertiary Control Layer	Energy cost reduction, load prioritization	DQN + Multi-objective Optimi
Fault Monitoring Layer	Detection, classification, and healing	CNN + Fault Graph Isolation
Forecasting & Planning	Voltage prediction, solar load scheduling	GNN + Temporal Ensemble Le

(12)

Evaluate with metrics:

- MAE, RMSE
- Prediction latency
- Ripple threshold accuracy

13 Real-Time Forecasting

Deploy trained GNN for:

- Forecast $\hat{V}_i^{t+1}, \ldots, \hat{V}_i^{t+M}$
- Trigger alerts if ripple $> \epsilon$

14 DNCM Integration

- If instability ⇒ send correction signal
- DNCM adjusts droop: $R_i^{new} = f(\hat{V}_i)$
- Balance power and stabilize voltage

15 Dynamic Droop Control

$$R_i(t) = \frac{V_i(t) - V_{ref}}{P_i(t)} \tag{13}$$

Update R_i based on forecasted $\hat{V}_i(t + \tau)$.

16. Monitoring and Alerts

- Log forecast errors
- Track action-response timeline
- Trigger alarms if *Confidence* $< \delta$

17. Evaluation and Learning

- Periodic retraining with new data
- Long-term stability assessment
- Ripple suppression and reliability tracking

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AI-Integrated Microgrid Architecture Layers

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Implementation of AI-Integrated Microgrid Architecture Layers

1. Primary Control Layer – Local Voltage Stabilization

AI Algorithm: Deep Transformer + Edge Learning

1. Define voltage regulation for nodes (e.g., voltage bounds).
2. Collect local voltage data from edge nodes (e.g., sensors).
3. Implement a Deep Transformer model to learn spatial-temporal dependencies in voltage signals.
4. Deploy lightweight models on edge nodes for fast inference.
5. Predict voltage deviations and trigger reactive control.

$$ut = Kp\ (Vsetpoint - Vt)$$

6. Retrain models on edge devices using federated updates.

2. Secondary Control Layer – SoC Balancing & Converter Switching

AI Algorithm: LSTM + Adaptive Reinforcement Learning

1. Monitor battery SoC, discharge/charge cycles, and converter states.
2. Use LSTM to predict SoC trajectory.

$$\hat{SoC}_{t+1} = LSTM(SoC_t, Load_t)$$

3. Design a reinforcement learning agent:
   - Reward balancing SoC across batteries.
   - Penalize over-cycling or inefficiency in switching.
4. Train RL agent using real/simulated data.
5. Apply real-time control to balance SoC.

3. Tertiary Control Layer – Energy Cost Reduction & Load Prioritization

AI Algorithm: Deep Q-Network (DQN) + Multi-objective Optimization

1. Define high-level objectives: minimize costs, prioritize loads.
2. Model system states (market prices, load demands).
3. Implement DQN for optimal actions:

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

4. Integrate multi-objective optimization:
   - Balance cost reduction, efficiency, load priority.
   - Use Pareto-based evaluation.
5. Simulate and deploy optimized policy for operation.

4. Fault Monitoring Layer – Detection, Classification & Healing

AI Algorithm: CNN + Fault Graph Isolation Tree

1. Generate fault signature datasets (short circuits, noise).
2. Build CNN to classify fault types from signal images.
3. Apply Fault Graph Isolation Tree:
   - Represent network as a fault graph.
   - Isolate affected zones.
4. Execute rerouting to restore continuity.
5. Log results and send alerts with fault data.

5. Forecasting & Planning Layer – Voltage Prediction & Solar Load Scheduling

AI Algorithm: Graph Neural Network (GNN) + Temporal Ensemble Learning

1. Construct a graph of microgrid components (PVs, loads).

2. Collect temporal data (voltage, irradiance).
3. Implement GNN to model spatial correlations.

$$\mathbf{h}_v^{(k+1)} = \sigma\left(\sum_{u \in \mathcal{N}(v)} \mathbf{W}^{(k)} \mathbf{h}_u + \mathbf{b}^{(k)}\right)$$

4. Combine GNN with Temporal Ensemble Learning for forecasting.
5. Use forecasts for operational planning (solar dispatch, charging schedules). article amsmath, amssymb graphicx tikz

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AI-Integrated Microgrid Architecture and Deployment Architecture **AI-Integrated Microgrid Architecture Layers**

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Deployment Architecture – Step-by-Step Implementation Plan
Objective
To integrate the complete AI-Driven Load Control and Automation (AI-DLCA) system within a modular, resilient computational framework that ensures seamless interaction with distributed energy and control components in space and air-based environments.
Steps for Implementation

1. **Design Modular Computing Unit:** • Develop a radiation-hardened embedded computing system to execute multiple AI models (e.g., CNN, LSTM, GNN, DQN) simultaneously.
   - Ensure modular design for integration in both airborne (UAV) and planetary (habitat) platforms.
2. **Embed AI-DLCA Core System:**
   - Deploy the AI-DLCA software stack within:
     - UAV control pods for aerial inspection, charging, and logistics.
     - Habitat power control units for core microgrid operations on lunar or Martian bases.
3. **Establish Agent Communication Framework:**
   - Deploy distributed intelligent agents on physical subsystems:
     - Battery Energy Storage Systems (BESS) for SoC management and fault diagnostics.

- DC-DC converters for real-time voltage control.
- Sensor arrays for monitoring environmental and system states.
- UAV charging docks for power scheduling.

4. **Enable Inter-Agent Communication:**
   - Implement low-latency communication using space-grade buses:
     - Controller Area Network (CAN) for short-distance, robust data exchange.
     - SpaceWire for high-speed networking in planetary applications.
5. **Define Data Routing and Synchronization:** • Synchronize data flow between core AI-DLCA system and peripheral agents.
   - Optimize bandwidth by sending relevant high-priority updates or alerts.
6. **Ensure Real-Time Control Loop Integration:** • Maintain feedback loops between AI model decisions and actuator commands.
7. **Deploy and Test in Simulation and Hardware-in-the-Loop (HIL):**
   - Simulate all interactions using a digital twin or mission emulator.
   - Move toward Hardware-in-the-Loop setups for validation in extreme environments.

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AI-Driven Load Control and Automation (AI-DLCA): Innovation and Applications

Advantages and Novelty

- **Autonomous Operation:** Minimal external commands needed.
- **Self-Learning:** Adapts to aging components and mission changes.
- **Fault Resilience:** Detects and heals failures without full shutdown.
- **Scalability:** Modular design, extendable to advanced systems.

Applications

- **Lunar Habitat Grids:** Energy management in lunar bases.
- **Martian Modules:** AI for energy in Martian habitats.
- **Stratospheric UAVs:** Efficient energy for UAV missions.
- **Off-Grid Installations:** Power for remote sites like military bases.

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