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VI SEMESTER INTERDISCIPLINARY PROJECT

Artificial Intelligence based efficiency optimization for the DAB DC–DC Converter with Triple Pulse Shift Modulation

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Abstract

Conventional modulation techniques like Single-Phase-Shift (SPS) lead to poor efficiency in DAB DC–DC converters under varying load and voltage conditions. Furthermore, existing optimization approaches are computationally intensive and model-dependent, making them unsuitable for real-time implementation in dynamic environments where fast and adaptive control strategies are essential.

Problem Statement

This project applies Q-learning, a reinforcement learning technique, to optimize the Triple Phase Shift (TPS) control strategy in Dual Active Bridge (DAB) DC–DC converters for improved bidirectional energy transfer efficiency under varying load and voltage conditions. By modeling three independent phase-shift parameters (D1, D2, D3) as a reinforcement learning problem, the Q-learning agent minimizes a custom objective function based on power loss and output error.

Objectives

1. To design and develop two H-Bridges modules required for the Dual Active Bridge (DAB) DC–DC converter architecture.
2. To develop an efficiency optimization scheme for a Dual Active Bridge (DAB) DC-DC Converter.
3. To implement reinforcement learning specially Q-learning to identify optimal triple phase shift angles (D1,D2,D3) D1:Shift between primary & secondary voltages, D2-D3:Shift within each bridges.
4. To visualize the training progress and optimization results using matplotlib.

Methodology

- **System Initialization**: The simulation begins with system setup and input of operating conditions like voltage, current and load.
- **State Definition**: The current state is defined by TPS values (D1, D2, D3).
- **Q-Learning Action Selection**: Based on the state, the agent selects an action (new TPS values) using the Q-learning policy.
- **Simulation and Q-Table Update**: The converter operates with new values, and the Q-table is updated based on the reward.
- **Termination or Deployment**: If the learning is complete, the trained agent is deployed for real-time control; else, the cycle repeats.

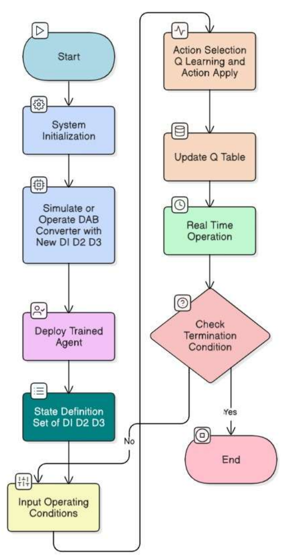

Figure:1 Flowchart

Hardware model

Figure:2 Hardware Test Bench

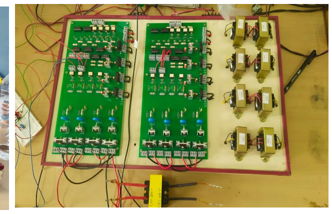

Figure:3 DAB Control Board

Results

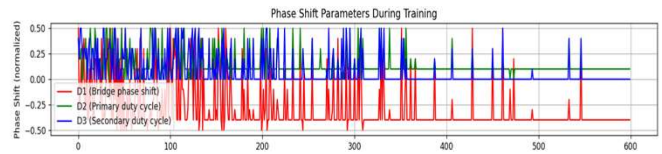

Figure:4 Phase Shift Parameters

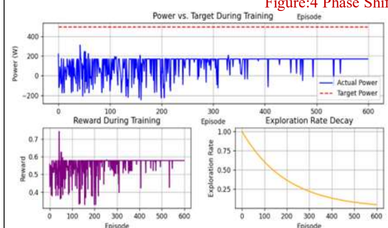

Figure:5 Training Stability Trend

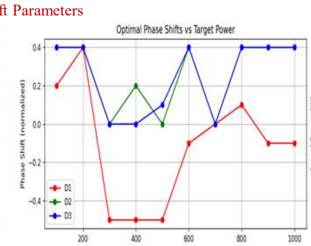

Figure:6 Phase Shift Optimization

Figure:7 Performance Drop-Off

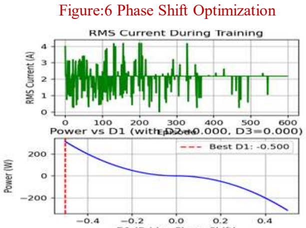

Figure:8 D1 Impact Analysis

Outcome

- **High Power Accuracy**: Achieved >99.6% power tracking using Q-learning across wide load ranges.
- **Efficiency Boost**: Average 2.2% efficiency improvement and 15.2% RMS current reduction over SPS.
- **Fast, Adaptive Control**: Converges in under 1000 episodes and adapts to changing conditions without retraining.
- **Hardware Readiness**: Suitable for real-time deployment on microcontrollers with low memory and timing overhead.
- **Scalable & Extendable**: Methodology is scalable to other converters and supports future upgrades like Deep Q-Learning and online adaptation.

References

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