

**OPTIMIZATION OF MULTI AGENT BASED ENERGY
MANAGEMENT SYSTEMS USING REINFORCEMENT
LEARNING FOR MICROGRIDS**

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Degree of Master of Science

Department of Electrical Engineering

University of Moratuwa

Sri Lanka

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Thesis/Dissertation submitted in partial fulfillment of the requirements for the degree
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DECLARATION

I declare that this is my own work and this thesis/dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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ABSTRACT

People's concerns about environmentally friendly power generation have given rise to a new concept known as distributed generation. The integration of renewable-based distributed generation resources into the main power grid, on the other hand, is difficult due to their constant monitoring and control requirements. As a result, microgrids have been identified as appropriate platforms for integrating distributed generation resources and loads. Instead of using traditional centralized control architecture, these microgrids use distributed control systems like multi-agent-based systems as a novel approach. Social, reactive, proactive, and autonomous are the common features of these control agents. These agents can be improved by using machine learning-based technologies to introduce intelligence. As a result, the focus of this research is on using Reinforcement Learning as an experimental machine learning method to optimize the energy generation function of a grid-connected microgrid so that the microgrid's grid dependency is minimized as the agent learns. To determine the best technique for system optimization, the proposed microgrid's performance is tested using single and multi-agent reinforcement learning models in Python. A hardware testbed is developed for the selected high-performance model to demonstrate the practical applicability of reinforcement learning.

Keywords: Distributed Generation, Energy management, Microgrid, Multi-Agent, Neural network, python programming, Q learning, Reinforcement learning

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LIST OF ABBREVIATIONS

AGC	Automatic Generation Control
ANN	Artificial Neural Network
CN	Convolutional Neural
DER	Distributed Energy Resource
DG	Distributed Generation
DoD	Depth of Discharge
DQL	Deep Q Learning
IDLE	Integrated Development Environment
LCD	Liquid Crystal Display
MAE	Mean Absolute Error
MARL	Multi-Agent Reinforcement Learning
MAS	Multi-Agent System
MC	Monte Carlo
MCU	Micro Controller Unit
MDP	Markov Decision Process
MLP	Multi-Layer Perceptron
NCRE	Non-Conventional Renewable Energy
PCC	Point of Common Coupling
PV	Photovoltaic
RER	Renewable Energy Resource
ReLu	Rectified Linear Unit

RL	Reinforcement Learning
RMSE	Root Mean Square Error
RN	Recurrent Neural
RSE	Residual Standard Error
SARL	Single Agent Reinforcement Learning
TD	Temporal Difference
TOU	Time of Use
UCB	Upper Confidence Bound

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