



**OPTIMISED HYBRID DEEP LEARNING MODELS FOR
INTEGRATED ENERGY MODELLING AND ANOMALY
DETECTION UNDER IPMVP COMPLIANCE**

اویونسیتی تیکنیکال ملیسیا ملاک
SUZIEE BINTI SUKARTI

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

DOCTOR OF PHILOSOPHY

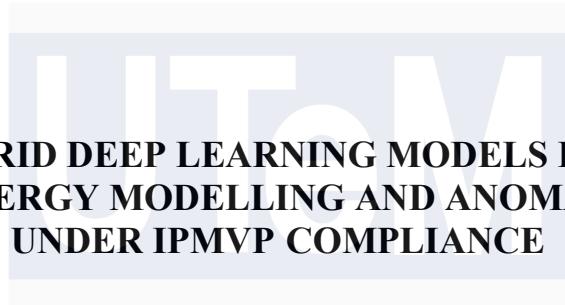
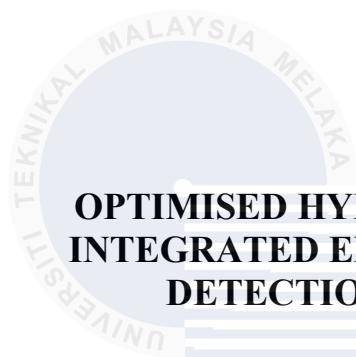
2025



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UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Faculty of Electrical Technology and Engineering



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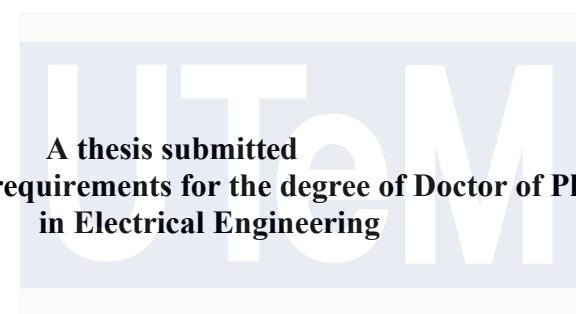
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COMPLIANCE**

SUZIEE BINTI SUKARTI



A thesis submitted
in fulfillment of the requirements for the degree of Doctor of Philosophy
in Electrical Engineering

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UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Faculty of Electrical Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2025

DECLARATION

I declare that this thesis entitled “Optimised Hybrid Deep Learning Models for Integrated Energy Modelling and Anomaly Detection under IPMVP Compliance “ is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



Signature :

Name : Suziee Binti Sukarti

Date : 03 / 9 / 2025

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APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Doctor of Philosophy



Signature :
Supervisor Name : Assoc. Prof. Ts. Dr. Mohamad Fani Bin Sulaiman
Date : 05 / 9 / 2025

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DEDICATION

To my beloved parents, Siti Masrah Binti Yusoff and Sukarti bin Sukimi, whose endless sacrifices, unwavering prayers, and unconditional love have carried me through every challenge. Your strength and resilience have been the foundation of my journey, and I am forever grateful for everything you have endured for my sake.

This achievement is a reflection of your love, patience, and belief in me. With all my heart, I dedicate this work to you



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ABSTRACT

Global decarbonisation efforts have intensified the demand for credible verification of energy performance in industrial facilities. Yet, conventional regression-based and other existing Measurement and Verification (M&V) methods under the International Performance Measurement and Verification Protocol (IPMVP) struggle to address baseline uncertainty, residual fluctuations, and non-routine events (NREs) in dynamic industrial systems. This study proposes an optimised IPMVP-compliant framework that integrates energy baseline prediction, anomaly detection, and energy savings verification. Baseline modelling was developed using deterministic deep learning models, namely deep neural networks (DNN), convolutional neural networks (CNN), and recurrent neural networks (RNN), with the DNN showing the most reliable performance. For anomaly detection, hybrid deep learning models combining DNN with stochastic architectures, specifically the Factorised Conditional Restricted Boltzmann Machine (FCRBM) and the Generative Adversarial Network (GAN), were introduced to detect NREs and support adjusted baseline calculations. The hybrid DNN-FCRBM model achieved the best balance between accuracy and reliability, consistently identifying downtime-related anomalies and producing realistic savings estimates of about 10%. Bayesian optimisation was further applied to refine detection thresholds and improve robustness. Overall, the framework enhances the transparency and scalability of industrial M&V, providing a practical solution for post-retrofit performance verification and supporting future adaptive energy analytics.

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**MODEL PEMBELAJARAN MENDALAM HIBRID DIOPTIMUMKAN UNTUK
PEMODELAN TENAGA BERSEPADU DAN PENGESANAN ANOMALI DI BAWAH
PEMATUHAN IPMVP**

ABSTRAK

Usaha dekarbonisasi global telah meningkatkan keperluan terhadap pengesahan yang boleh dipercayai bagi prestasi tenaga di fasiliti industri. Walau bagaimanapun, kaedah Pengukuran dan Pengesahan (M&V) regresi konvensional serta kaedah lain di bawah International Performance Measurement and Verification Protocol (IPMVP) masih bergelut untuk menangani ketidakpastian garis dasar, turun naik baki, dan kejadian bukan rutin (NRE) dalam sistem tenaga industri yang dinamik. Kajian ini mencadangkan satu kerangka IPMVP yang dioptimumkan dan berasaskan data, yang menggabungkan ramalan garis dasar tenaga, pengesahan anomali, serta pengesahan penjimatan tenaga. Pemodelan garis dasar dibangunkan menggunakan model pembelajaran mendalam deterministik iaitu deep neural network (DNN), convolutional neural network (CNN), dan recurrent neural network (RNN), dengan DNN menunjukkan prestasi yang paling boleh dipercayai. Bagi pengesahan anomali, model pembelajaran mendalam hibrid yang menggabungkan DNN dengan seni bina stokastik, khususnya Factorised Conditional Restricted Boltzmann Machine (FCRBM) dan Generative Adversarial Network (GAN), digunakan untuk mengesan NRE dan menyokong pelarasaran garis dasar. Model hibrid DNN-FCRBM mencapai keseimbangan terbaik antara ketepatan dan kebolehpercayaan, dengan konsisten mengenal pasti anomali berkaitan henti operasi serta menghasilkan anggaran penjimatan tenaga sekitar 10%. Pengoptimuman Bayesian turut diaplikasikan untuk menambah baik nilai ambang pengesahan dan meningkatkan kekuahan. Secara keseluruhannya, kerangka ini meningkatkan ketelusan dan kebolehskalaan M&V industri, menyediakan penyelesaian praktikal untuk pengesahan prestasi selepas pelaksanaan EEM serta menyokong analitik tenaga adaptif pada masa hadapan.

ACKNOWLEDGEMENT

Alhamdulillah, all praises be to Allah, the Most Gracious and the Most Merciful, for granting me the strength, patience, and perseverance to complete this research journey.

I extend my sincere appreciation to my main supervisor, Ts. Dr. Mohamad Fani Sulaima, for his dedicated supervision, expert guidance, and continuous support throughout this research. I am also grateful to my co-supervisor, Assoc. Prof. Ir. Dr. Aida Fazliana Abdul Kadir, for her valuable advice and encouragement.

My sincere appreciation extends to the team at Top Glove Factory No. F40, whose collaboration, support, and commitment were integral to the success of this research. I am particularly indebted to Ts. Muhamad Hafizul Shamsor, Nurain Masran, Christopher Siaw Wei Yao and Mansor Daud for their exceptional assistance throughout the study. Their willingness to facilitate data access, provide operational insights, and offer practical guidance was invaluable in shaping the quality and comprehensiveness of this work. Their continuous cooperation, responsiveness, and technical support significantly contributed to overcoming challenges and ensuring the smooth progression of this research.

I am profoundly grateful to my beloved parents, Siti Masrah Binti Yusoff and Sukarti Bin Sukimi, for their unconditional love, prayers, and unwavering support. Their belief in me has been a constant source of motivation and strength. I also wish to express my heartfelt appreciation to my siblings, Mohd Hairul, Diana, Jamaliah, Junaidah and Suryani, whose encouragement and steadfast presence have been a continual source of comfort and inspiration.

To my extended family and friends, thank you for your companionship, encouragement, and the moments of respite that have helped me navigate the challenges of this academic journey.



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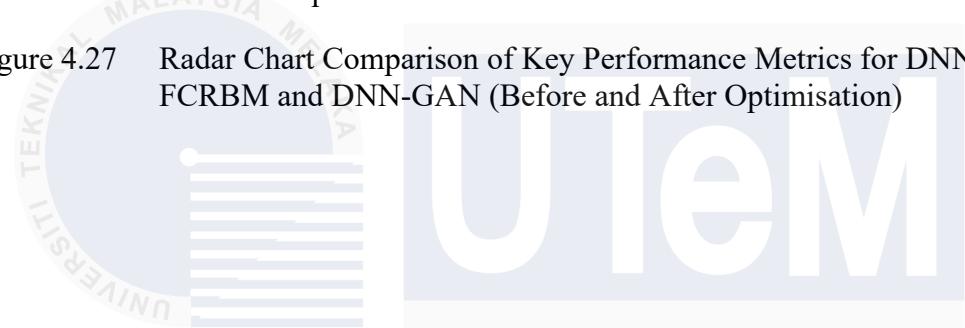
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LIST OF ABBREVIATIONS

AM&V	- Advanced Measurement and Verification
AMI	- Automated Metering Infrastructure
ASHRAE	- American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BMS	- Building Management Systems
CNN	- Convolutional Neural Networks
CUSUM	- Cumulative Sum Control Chart
DL	- Deep Learning
DT	- Decision Tree model
DNN	- Deep Neural Network
EDA	- Exploratory Data Analysis
EEM	- Energy Efficiency Measures
EEU	- Energy Use Intensity
ECCA	- Energy Efficiency and Conservation Act
EMEER	- Efficient Management of Electrical Energy Regulation
EPC	- Energy Performance Contracting
EVO	- Efficiency Valuation Organization
FCRBM	- Factored Conditional Restricted Boltzmann Machine
FFNN	- Feed Forward Neural Network
FSU	- Fractional Savings Uncertainty
HVAC	- Heating, Ventilation, and Air Conditioning
GP	- Genetic Programming

GAP	- Generative Adversarial Networks
GDP	- Gross Domestic Product
HL	- Hidden Layer
IEA	- International Energy Agency
IPCC	- Intergovernmental Panel on Climate Change
IMPVP	- International Performance Measurement and Verification Protocol
KNN	- K-Nearest Neighbors
LR	- Linear Regression
LBNL	- Lawrence Berkeley National Laboratory
ML	- Machine Learning
MV	- Measurement and Verification
MLP	- Multi-Layer Perceptron
MLR	- Multiple Linear Regression
MEPS	- Minimum Energy Performance Standards

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NRA	- Non-Routine Adjustment
NRE	- Non-Routine Events
NEEAP	- National Energy Efficiency Action Plan
ReLU	- Rectified Linear Unit
RNN	- Recurrent Neural Networks
SDGs	- Sustainable Development Goals
SeLU	- Scaled Exponential Linear Unit
SLP	- Single Layer Perceptron
SVM	- Support Vector Machines

TMY	- Typical Meteorological Year
UNEP	United Nations Environment Programme
UNFCCC	United Nations Framework Convention on Climate Change



LIST OF SYMBOLS

y	- Actual observed value
\bar{Y}_t	- Mean of observed values
\hat{y}_t	- Predicted output at time step t for RNN
h^l	- Output of layer l in DNN or CNN
h_t	- Hidden state at time step t in RNN
ϵ_{adj}	- Adjusted residual after excluding non-routine events
ϵ_i	- Residual between baseline prediction and measured energy for observation i
$\mu_{RE_{GAN}}$	- Mean of reconstruction errors from GAN model
$\sigma_{RE_{GAN}}$	- Standard deviation of reconstruction errors from GAN model
<i>Adjusted Baseline</i> _{i}	- Adjusted baseline prediction for instance i
<i>Anomaly Flag</i> _{i}	- Binary flag indicating whether instance i is anomalous
<i>Baseline</i> _{i}	- Original baseline prediction for instance i
<i>Breakdown</i> _{i}	- Breakdown data value for instance i
<i>Energy Savings</i> _{i}	- Energy savings for instance i
$HT_{DNN-FCRBM}$	- Hybrid threshold for DNN-FCRBM combination
RE_{DNN}	- Reconstruction error from DNN model
$RE_{DNN-FCRBM}$	- Hybrid reconstruction error from DNN-FCRBM combination
$RE_{DNN-GAN}$	- Hybrid reconstruction error from DNN-GAN combination
RE_{FCRBM}	- Reconstruction error from FCRBM model
RE_{GAN}	- Reconstruction error from GAN model
W_{hh}	- Weight matrix from hidden state to hidden state in RNN
W_{hy}	- Weight matrix from hidden state to output in RNN
W^l	- Weight matrix for layer l in DNN or CNN
W_{xh}	- Weight matrix from input to hidden state in RNN
b_h	- Bias vector for hidden state in RNN