Development of Real-Time, Self-Learning Artificial Intelligence-Based Algorithms for Non-Intrusive Energy Disaggregation in a Multi-Appliance Environment

Madhawa Herath

(DP17 8502 92)

Doctor of Philosophy

Faculty of Engineering

Sri Lanka Institute of Information Technology

December 2023

Declaration

I hereby declare that to the best of my knowledge, this submission is my own work and it neither contains direct material previously published nor written by another person or material, which to substantial extent, has been accepted for the award of any other academic qualification of a university or other institute of higher learning except where acknowledgement is made in the text.

Certified by

Signature : ……………………………………….

Date : December 15th, 2023

Name of Supervisor I : Prof. Migara Liyanage

Signature :…… ……………………………………….

Date : December 17th, 2023

Name of Supervisor II : Dr. Chitral Angammana

Signature :……………………………………….

Date : December 16th, 2023

Acknowledgment

During my doctoral journey, I had the opportunity to learn about emerging technologies like Artificial Intelligence and apply them in real-world applications. It was a rare privilege to work on a real-life project that addressed the crucial issue of changing consumer behavior towards energy conservation. The combined efforts in algorithm development, programming, and simulation, as well as data collection and verification, made the research experience diverse and enriching.

I am deeply grateful to my supervisors, Prof. Migara Liyanage and Dr. Chitral Angammana, who are enthusiastic technology practitioners. Their wisdom and knowledge in engineering have shaped me into a critical thinker and problem solver. I would like to express my sincerest appreciation to them for their invaluable guidance, support, and encouragement throughout my doctoral journey. Their expertise, patience, and unwavering belief in my abilities have played a pivotal role in shaping both the research project and my growth as a scholar. I would also like to express my gratitude to Prof. George Mann for his invaluable guidance and encouragement throughout this journey. His eminent research experiences have played a pivotal role in enhancing my scientific writing skills.

I extend my heartfelt appreciation to the Sri Lanka Institute of Information Technology, including Chancellor Prof. Lakshman Ratnayake, Vice-Chancellor Prof. Lalith Gamage, Senior Deputy Vice-Chancellor and Provost Prof. Nimal Rajapakse, Pro-Vice Chancellor Academic Prof. Rahula Attalage, and Dean of the Faculty of Engineering Prof. Saman Thilakasiri, as well as the faculty and staff of the Faculty of Engineering. Their dedication to academic excellence and provision of resources have been crucial in facilitating the successful completion of this thesis. The supportive research environment and access to necessary facilities have been integral to the accomplishment of this work.

I am grateful to Mr. Thakshila Thilakanayake for his valuable support in implementing algorithms using the Python programming language. Additionally, I would like to thank Mr. Chaminda Prabash and Mr. Damith Nishantha for his assistance in designing and fabricating the local energy data logger and aiding in data collection.

I express my gratitude to Dr. Oscar De Silva from the Faculty of Engineering and Applied Science, Memorial University of Newfoundland, Canada, for agreeing to serve as my external examiner. I would also like to thank Prof. Chandimal Jayawardane for his service as my internal examiner. I appreciate the time they dedicated to reviewing my thesis, and their comments and suggestions have immensely contributed to improving its quality.

I would like to acknowledge my fellow graduate students and colleagues for their camaraderie, engaging intellectual discussions, and constant encouragement. Their friendship and shared experiences have made this academic journey more enjoyable and fulfilling.

My deepest appreciation goes to my parents, Mrs. Jayalatha Nissanka and Mr. Ashoka Herath, my loving wife, Mrs. Bhagya Warnasooriya, and my children, Kumali Herath and Thenuja Herath, for their unwavering love, encouragement, and sacrifices

throughout this entire endeavor. Their constant support and belief in me have been an endless source of strength and motivation.

Lastly, I want to express my deepest gratitude to all the individuals who have played a part, whether big or small, in shaping my academic and personal growth. Your guidance, encouragement, and belief in my abilities have been instrumental in helping me reach this significant milestone. This research would not have been possible without the support and contributions of all these individuals, and for that, I am eternally grateful.

Abstract

Electricity serves as a cornerstone in modern economies, with demand in residential and commercial sectors rapidly increasing in recent years. Enabling real-time monitoring of individual appliance-wise energy consumption and delivering user feedback is essential for future energy conservation initiatives. Energy disaggregation becomes imperative in furnishing consumption statistics for individual appliances. The acquisition of appliance-specific energy consumption in a non-intrusive manner, without the need for sensors on each device but by utilizing readings from the main household energy meter, highlights Non-Intrusive Load Monitoring (NILM) as a promising solution. NILM, leveraging the capabilities of smart meters and advancements in computational power, gains popularity for its effectiveness in disaggregating and analyzing energy consumption patterns.

This study introduces an Artificial Intelligence (AI)-based NILM solution capable of disaggregating the energy consumption of multiple appliances while adapting to new appliances and their evolving behaviors. Among various NILM approaches, Neural Network (NN)-based models demonstrate promising disaggregation capabilities. However, the selection of the most suitable NN type or architecture poses a challenge due to the multitude of approaches in literature. To address this issue, the study standardizes and compares different NNs, with results showing that the Convolutional Neural Network (CNN) exhibits superior prediction accuracy and speed. This study also investigates the impact of different appliances and their consumption profiles on disaggregation performance, rigorously testing parameters such as NN architecture, input-output mapping topologies, data preprocessing, and hyperparameters. This leads to the development of guidelines for future NILM studies. Additionally, the study introduces a hierarchical plug-and-play modular-based model for appliance anomaly detection, extending the application of NILM and overcoming limitations in anomaly detection literature.

This study investigates two-dimensional (2D) input-based NILM solutions for predicting appliance energy consumption profiles and classifying appliances. Unlike conventional NN-based models using 1D signals, representing the aggregate energy signal as a 2D image improves performance by leveraging feature extraction capabilities of NNs and preserving vital temporal information and signal amplitude relationships. Various TSS to 2D image conversion methods for NILM were tested, including Gramin Angular Summation Field (GASF), Gramin Angular Difference Field (GADF), Recurrent Plot (RP), and Markov Transition Field (MTF), with GADF outperforming other methods. In addition, the study introduces a simple yet powerful 2D input mechanism for time series data, specifically energy consumption data. This mechanism will be integrated into a CNN-based energy disaggregation model for the first time in the NILM domain, with the aim of improving overall performance. While the proposed method excels over 1D input-based models in training, it is observed that the novel 2D input method requires augmentation in training data volume, data mixing, NN depth, and hyperparameter tuning to achieve superior generalization capabilities. Furthermore, aggregate energy signal-based Voltage-Current (V-I) trajectory plots were investigated for fully non-intrusive appliance classification, demonstrating high accuracy.

The study proposes a single NN architecture named "One-Shot." This model exhibits the capability to simultaneously disaggregate multiple appliances, offering a more efficient alternative to the intricate and computationally demanding existing NN-based NILM models that necessitate separate NNs for each appliance. The efficacy of this approach is evaluated across multiple input-output mapping configurations, with the multi-point multi-bin model proving superior. To address challenges associated with manual model re-training for new appliances and adapting to evolving consumption patterns, a self-learning module is incorporated, enhancing the performance of the One-Shot model. To overcome issues related to excessive hyperparameter tuning and insufficient training data, the study presents an unsupervised model based on Blind Source Separation (BSS), utilizing Independent Component Analysis (ICA) to separate appliance energy signals from the aggregate signal.

Developing more reliable disaggregation models in local environments requires a local energy dataset. For this purpose, the study creates a local energy dataset from households using a custom-designed data logger, capturing both low and high-frequency energy data at appliance, circuit, and main energy meter levels. This dataset is verified using the One-Shot model developed in this study. In summary, this study advances the field of NILM by introducing AI-based solutions, innovative approaches, and comprehensive guidelines. Ultimately, these contributions aim to foster energy conservation and enhance efficiency in residential and commercial settings globally.

Publications related to the Study

Journals

1. **M. Herath**, C. J. Angammana and M. Liyanage, "A Study of the Effects of Appliance Energy Signatures on Different Neural Network Types in Nonintrusive Load Monitoring," in IEEE Transactions on Instrumentation and Measurement, vol. 72, pp. 1-10, 2023, Art no. 2524010, doi: 10.1109/TIM.2023.3305664.
2. **G. M. Herath**, T. D. Thilakanayake, M. H. Liyanage, and C. J. Angammana, "Analysis of Artificial Intelligence-based Methods for Sensorless Disaggregation of the Residential Electric Power Signals," SLEMA Journal, vol. 25, no. 1, 2022.
3. **M. Herath**, T. D. Thilakanayake, C. J. Angammana and M. Liyanage, “A Simplified 2D Input-Based CNN Framework for Non-Intrusive Load Monitoring,” in IEEE Transactions on Smart Grid. – Under Review
4. **M. Herath**, T. D. Thilakanayake, C. J. Angammana and M. Liyanage, “Self-Learning Multi-Appliance Energy Disaggregation Model – One Shot,” in IEEE Transactions on Industrial Informatics. – Under Review

Conferences

1. **G. M. Herath**, T. D. Thilakanayake, M. H. Liyanage and C. J. Angammana, "Appliance Anomaly Detection as an Extension of Non-Intrusive Load Monitoring," 2023 IEEE PES Asia-Pacific Power and Energy Engineering Conference, Chiang Mai, Thailand, December 2023.
2. N.W. Herath, **G. M. Herath**, T. D. Thilakanayake, M. H. Liyanage and C. J. Angammana, " An Image-Based Disaggregation Study of Time Series Energy Data Using Gramian Angular Field," 2023 IEEE PES Asia-Pacific Power and Energy Engineering Conference, Chiang Mai, Thailand, December 2023.
3. **G. M. Herath**, M. H. Liyanage and C. J. Angammana, "Assessment of Non-Intrusive Load Monitoring as a Blind Source Separation Problem," 2023 IEEE PES GTD International Conference and Exposition (GTD), Istanbul, Turkiye, 2023, pp. 156-160, doi: 10.1109/GTD49768.2023.00056.
4. P. M. L. Liyanage, **G. M. Herath**, T. D. Thilakanayake and M. H. Liyanage, "Novel Image Based Method Using V-I Curves with Aggregate Energy Data for Non-Intrusive Load Monitoring Applications," 2022 4th International Conference on Advancements in Computing (ICAC), Colombo, Sri Lanka, 2022, pp. 258-263, doi: 10.1109/ICAC57685.2022.10025280.
5. M. Senarathna, **M. Herath**, T. D. Thilakanayake, M. H. Liyanage and C. J. Angammana, "An Image Based Approach of Energy Signal Disaggregation Using Artificial Intelligence," 2021 IEEE 16th International Conference on Industrial and Information Systems (ICIIS), Kandy, Sri Lanka, 2021, pp. 98-103, doi: 10.1109/ICIIS53135.2021.9660638.

6. D. V. J. Dhanawansa, **G.M. Herath**, T. D. Thilakanayake, M.H. Liyanage, C.J. Angammana, “An investigation of the effects of kernel tuning on the performance of convolution neural network architectures: a case study of non -intrusive load monitoring applications,” The 2nd International Conference on Energy and AI, London, UK, August 2021, pp. 33-38.
7. **G. M. Herath**, T. D. Thilakanayake, M. H. Liyanage, and C. J. Angammana, "Comprehensive analysis of convolutional neural network models for non-intrusive load monitoring," 2020 IEEE International Conference and Utility Exhibition on Energy, Environment and Climate Change (ICUE), Pattaya, Thailand, October 2020, pp. 1-11.

Table of Content

List of Figures

List of Tables

List of Abbreviations

1D – One Dimensional
2D – Two Dimensional
AdaGrad – Adaptive Gradient
ADL - Activities of Daily Living
AE – Autoencoder
AFHMM - Factorial Hidden Markov Model
AI -Artificial Intelligence
AICNN - Appliance Identification Convolutional Neural Network
ANN – Artificial Neural Network
BBN - Bayesian Belief Network
BSS - Blind Source Separation
CCNN - Causal Convolution Neural Network
CFF – Curve Fitting Factor
CNN – Convolutional Neural Network
dAE – Denoising Autoencoder
DNN – Deep Neural Network
ECG - Electrocardiography
EM - Expectation-Maximization
FFT - Fast Fourier Transform
FHMM - Factorial Hidden Markov Model
FICNN - Faulty Identification Convolutional Neural Network
FN - False Negative
FP – False Positive
FSM - Finite State Machine
FTICNN - Faulty Type Identification Convolutional Neural Network
GADF - Gramin Angula Difference Fields
GAF – Gramin Angular Fields
GAN - Generative Adversarial Network
GASF - Gramin Angular Summation Fields
GRU – Gated Recurrent Unit
GSP – Graph Signal Processing
HMM – Hidden Markov Model
ICA – Independent Component Analysis
ILM – Intrusive Load Monitoring
KNN – K-Nearest Neighbor
LSTM – Long Short-Term Memory
MAE – Mean Absolute Error
MCB - Main Circuit Breaker
MSE - Mean Squared Error
MTF - Markov Transition Fields

MTM - Markov Transition Matrix
NILM – Non-Intrusive Load Monitoring
NN – Neural Network
NPFHMM - Nonparametric Factorial Hidden Markov Model
PCA – Principal Component Analysis
PDF – Probability Density Function
PSO - Particle Swarm Optimization
RCNN – Recurrent Convolutional Neural Network
REDD - Reference Energy Disaggregation Dataset
ReLU – Rectified Liner Unit
RMS - Root Mean Squar
RMSE - Root Mean Squar Error
RMSProp - Root Mean Squared Propagation
RNN – Recurrent Neural Network
RP – Recurrent Plot
RTC - Real Time Clock
SEM - Smart Energy Meters
Seq-MP-MB – Sequnce to Multi Point Multi Bin
Seq-M-Point - Sequnce to Multi Point
Seq-M-Seq – Sequnce to Multi Sequnce
Seq-Point – Sequnce to Pint
Seq-Seq – Sequnce to Sequnce
SH – Seen House
SMPS - Switch Mode Power Supply
SSM- Super State Markov
STFT - Short Time Fourier Transform
SVD - Singular Value Decomposition
SVM – Support Vector Machine
TN – True Negative
TP – True Positive
TSS – Time Series Signal
UH^A – Unseen House A
UH^B - Unseen House B
UTS – Universal Time Stamp
VAE - Variational Auto-encoder
V-I – Voltage – Current