

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

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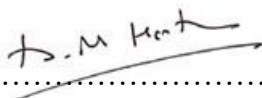
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Declaration

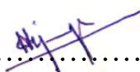
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Abstract

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

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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.
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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.

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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 Linear 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 – Sequence to Multi Point Multi Bin
Seq-M-Point - Sequence to Multi Point
Seq-M-Seq – Sequence to Multi Sequence
Seq-Point – Sequence to Point
Seq-Seq – Sequence to Sequence
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