Deep Learning Based Non-Intrusive Load Monitoring for Smart Energy Management in Households

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About the Speaker: Basirah Noor

- PhD Researcher in Advanced Information Technology
- Research Focus: Deep Learning, NILM, Gen AI and cybersecurity
- Education
  - MS in Information Security (2023)
  - Bachelors in Electrical Engineering (2017)
- Interest: IoT-enabled optimization

Presentation Overview

Motivation

Background and NILM Concept

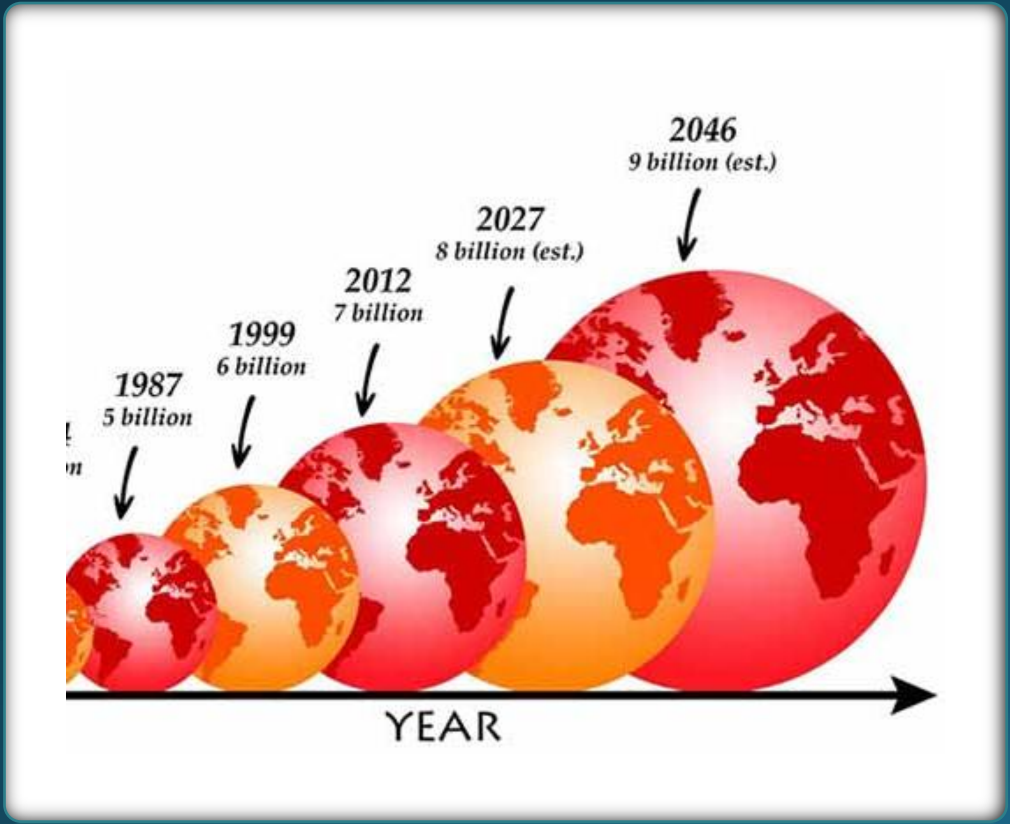
Methodology

Seq2Seq vs Seq2Point Models

Experimental Results

Conclusion and Future Work

Motivation



- Global electricity demand is rapidly increasing
- Aggregate smart meter data provides limited insight
- Need appliance-level monitoring without intrusive sensors
- Enable energy optimization and demand-side management

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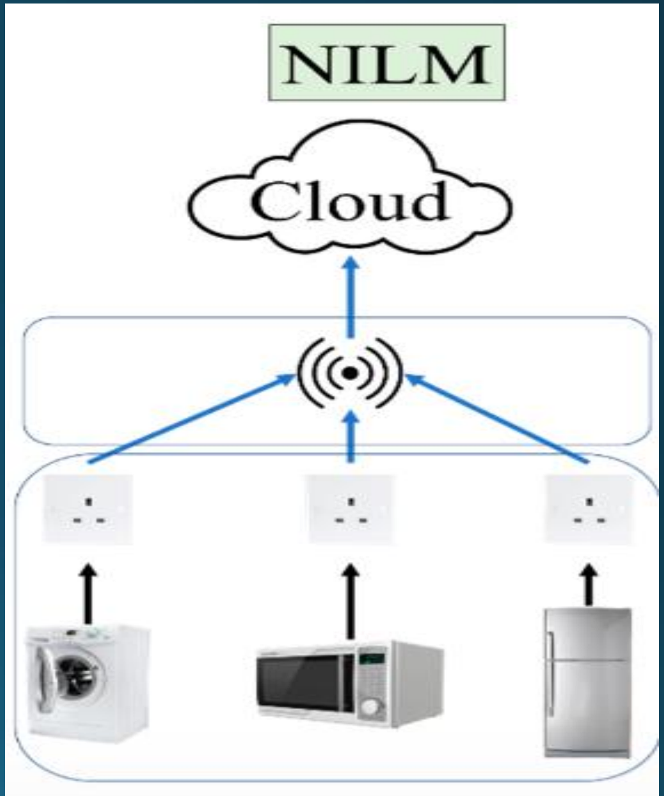
What is NILM?

- Non-Intrusive Load Monitoring (NILM)
- Disaggregates total household power into appliance-level consumption
- Based on Hart's Energy Decomposition Theory
- Can be modeled as regression and classification problem



Why Deep Learning for NILM?

- Traditional models rely on manual feature engineering
- CNNs automatically extract temporal patterns
- Better generalization and performance
- More computationally efficient than RNN/LSTM in long signals

Research Objectives

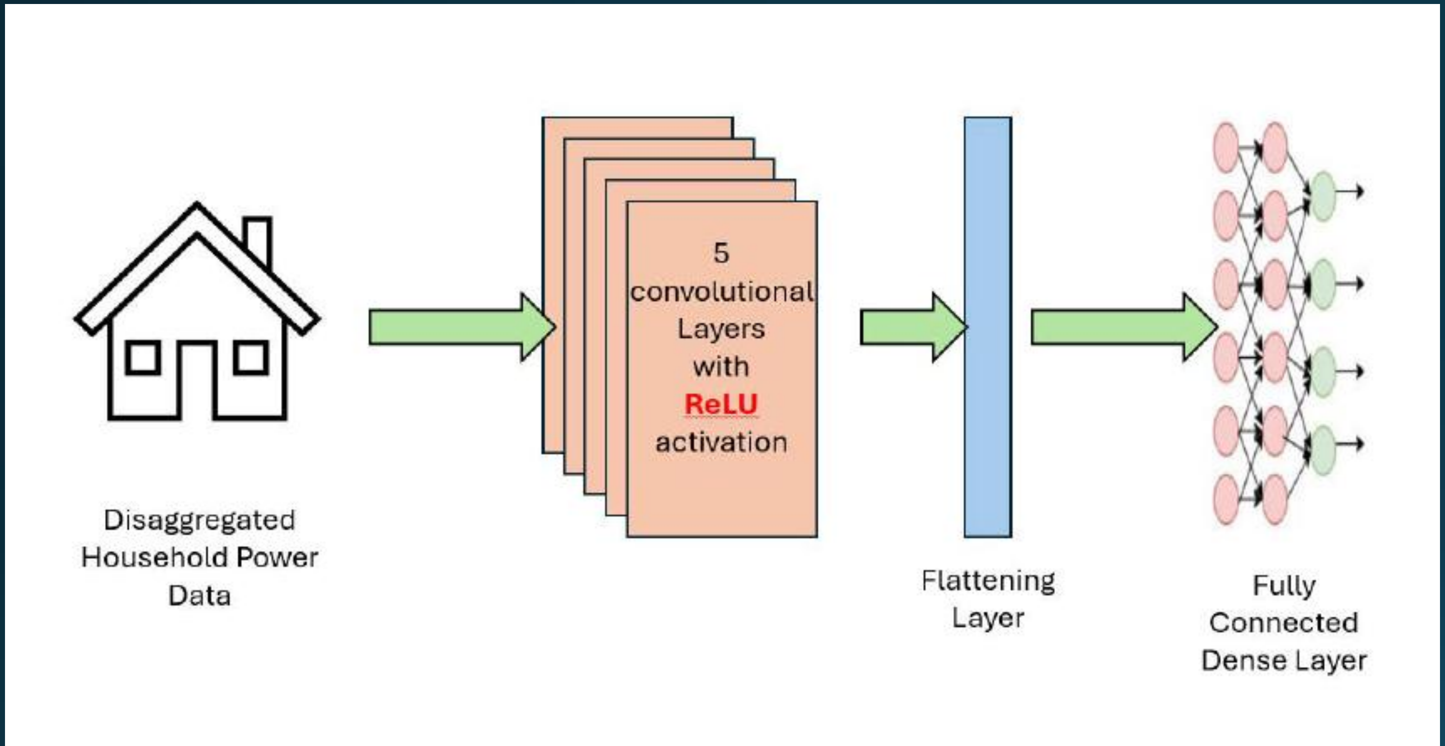
- Optimize CNN-based NILM models
- Compare Seq2Seq and Seq2Point architectures
- Improve ON/OFF state detection
- Evaluate cross-dataset generalization

Datasets

- UK-DALE (5 households) – Training & Validation
- REFIT (20 households) – External Testing
- Appliances: Kettle, Microwave, Dishwasher, Washer-Dryer, Fridge-Freezer

Data Preprocessing

- Cleaning and gap filling
- Resampling (30–60 seconds)
- Normalization (Min-Max, Z-score)
- Threshold-based ON/OFF labeling
- Exploratory Data Analysis



CNN Architecture

- 5 Convolutional layers
- ReLU activation
- Dense layer (256 neurons)
- Regression output → Threshold → ON/OFF classification
- Batch size: 1024

Seq2Seq vs Seq2Point Model

Seq2Seq Model

- Input: Sequence
- Output: Sequence (same length)
- Captures long-term dependencies
- Better for cyclic and long-duration appliances

Seq2Point

- Input: Sliding window
- Output: Single midpoint prediction
- High precision for sharp transitions
- Better for short-duration high-power appliances

Experimental Results

TABLE I. RESULTS OF MAE FOR SEQ2SEQ AND SEQ2POINT MODELS UNDER DIFFERENT PARAMETER SETTINGS.

	Window Duration		Batch Size		Dropout Ratio		Learning Ratio		Resampling	
	23 min	45 min	128	1024	0	0.25	0.0001	0.001	30s	45s
Seq2seq										
Kettle	14.14	13.33	14.09	13.65	13.59	14.08	14.14	13.59	13.41	13.50
Fridge-Freezer	26.55	26.30	26.57	26.17	25.81	27.39	25.36	25.81	26.87	26.54
Dish Washer	23.63	23.66	24.48	25.46	24.36	24.36	24.46	24.36	23.77	24.09
Microwave	9.62	10.26	10.33	11.00	11.41	11.27	10.80	11.41	9.56	8.56
Washer Dryer	20.97	19.09	18.24	17.00	17.91	17.81	15.15	17.91	12.69	14.49
Seq2point										
Kettle	13.52	13.93	12.80	13.82	13.44	13.90	14.36	13.44	13.11	13.30
Fridge-Freezer	27.11	25.64	24.63	25.05	25.68	25.14	25.93	25.68	26.66	26.61
Dish Washer	24.75	22.95	23.43	25.10	25.04	25.11	24.54	25.04	24.41	23.91
Microwave	10.44	11.91	10.97	9.96	12.07	11.50	14.15	12.07	9.42	10.81
Washer Dryer	23.20	18.67	17.77	18.89	15.60	18.01	20.40	15.60	13.45	13.68

Training Parameter Influence

Model Performance Across Different Appliance Load Patterns

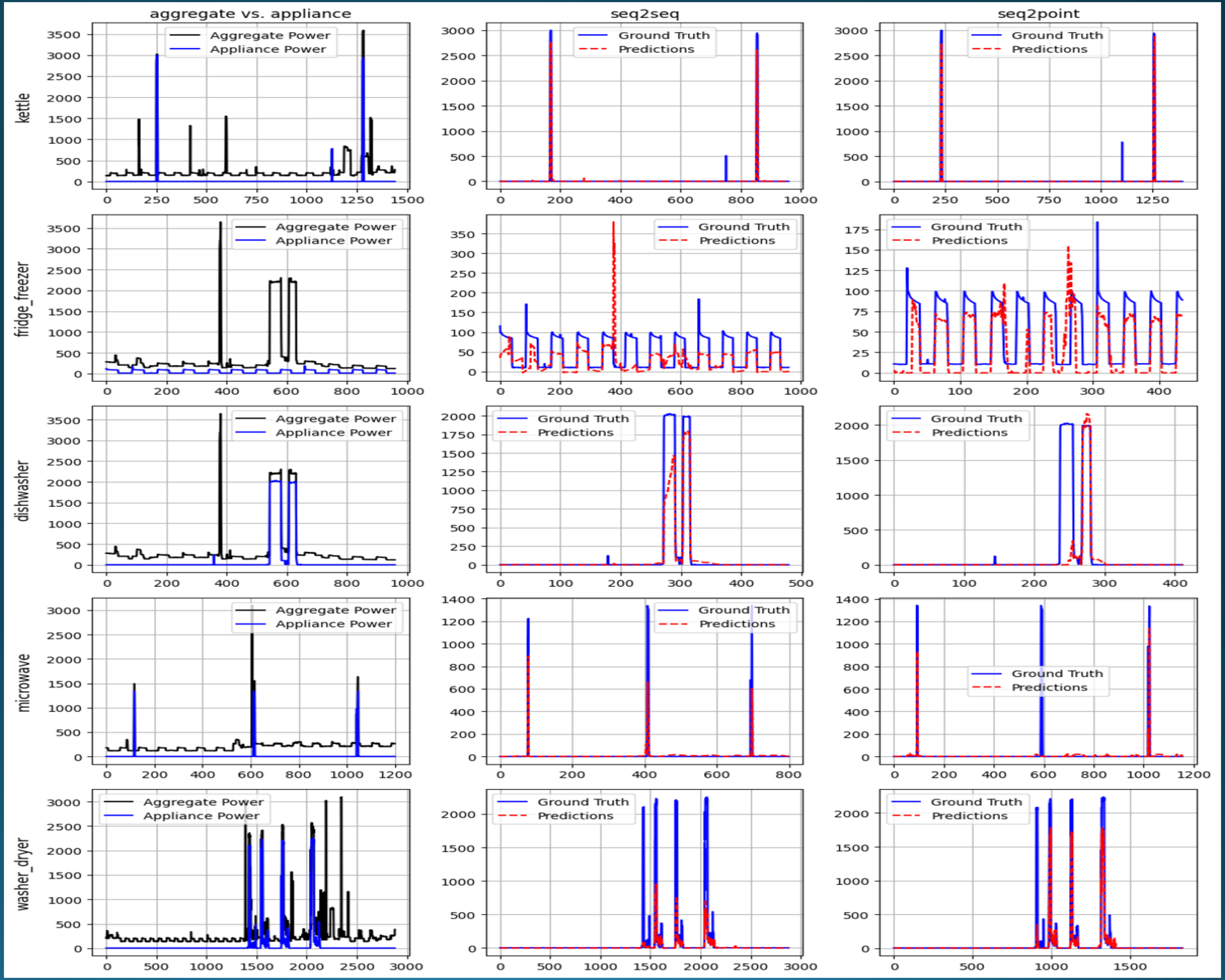


TABLE II. RESULTS OF REGRESSION AND CLASSIFICATION METRICS FOR SEQ2SEQ AND SEQ2POINT MODELS APPLIED ON UK-DALE DATASET

Appliance	Seq2Seq						Seq2Point					
	Acc	Prec	F1	Rec	MAE	SAE	Acc	Prec	F1	Rec	MAE	SAE
Kettle	0.99	0.74	0.74	0.75	13.25	0.04	0.99	0.72	0.79	0.85	11.12	0.05
Fridge-Freezer	0.78	0.63	0.52	0.44	25.16	0.01	0.80	0.63	0.63	0.63	23.69	0.07
Dishwasher	0.98	0.57	0.52	0.51	23.68	0.15	0.98	0.56	0.57	0.59	23.49	0.01
Microwave	0.99	0.40	0.27	0.20	9.57	0.92	0.99	0.74	0.27	0.20	8.04	0.45
Washer-Dryer	0.99	0.51	0.52	0.52	8.43	0.18	0.99	0.21	0.33	0.73	13.22	0.81

Comparison between Seq2Seq and Seq2Point

Performance on the Holdout Set

TABLE III. Combined Results of Regression and Classification Metrics for Seq2Seq and Seq2Point Models on REFIT

Appliance	Seq2Seq						Seq2Point					
	Acc	Prec	F1	Rec	MAE	SAE	Acc	Prec	F1	Rec	MAE	SAE
Kettle	0.99	0.55	0.27	0.21	21.18	0.42	0.99	0.59	0.37	0.33	17.08	0.49
Fridge-Freezer	0.66	0.56	0.44	0.41	37.75	0.61	0.67	0.56	0.41	0.36	35.75	0.49
Dishwasher	0.98	0.59	0.24	0.18	39.17	0.68	0.98	0.57	0.32	0.26	39.01	0.63
Microwave	0.99	0.20	0.11	0.09	17.95	2.51	0.99	0.19	0.09	0.07	14.92	1.54
Washer-Dryer	0.98	0.26	0.19	0.17	29.22	0.80	0.99	0.31	0.34	0.41	29.52	0.94

Conclusion

- CNN-based NILM effectively disaggregates power
- Seq2Point best for short high-power events
- Seq2Seq better for continuous loads
- Hyperparameter tuning is critical
- Appliance-specific model selection is important

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