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EnerGAN: A Generative Adversarial Network for Energy Disaggregation

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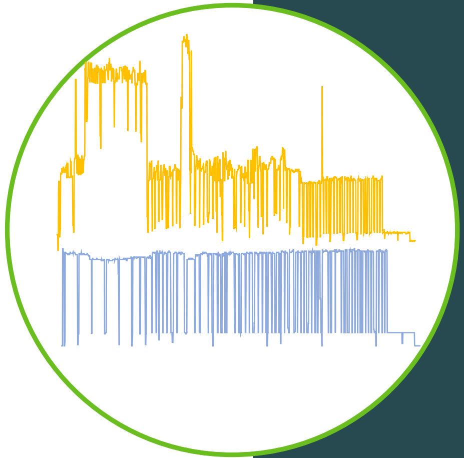
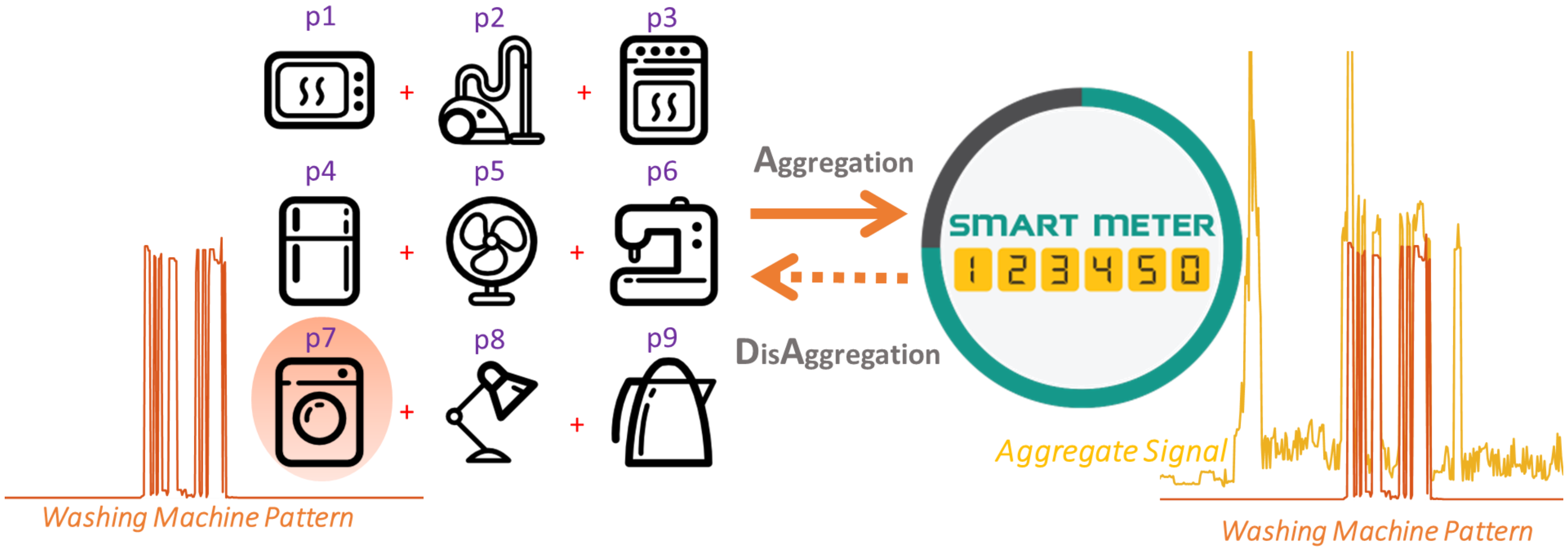
Presentation Outline

- The NILM Problem
- NILM Problem Formulation
- The Proposed Solution: EnerGAN Model
- EnerGAN Network Configuration
- Performance Evaluation and Comparisons





THE NILM PROBLEM

Non-Intrusive Load Monitoring (NILM), or **Energy Disaggregation** *(Hart, 1992)* is known as the determination of appliance-specific load consumption, using the aggregate power signal of a household as input.

THE NILM PROBLEM

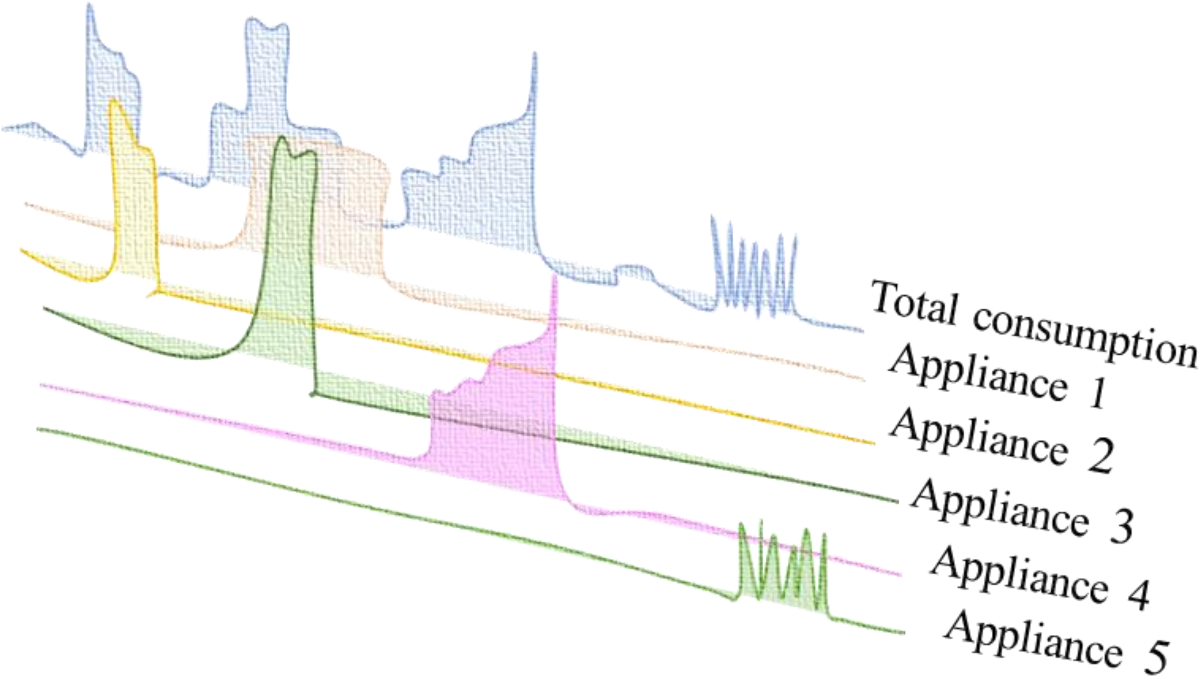
Energy disaggregation entails to

a **blind source separation problem**;

it could be described as an Independent Component Analysis (ICA) case, whereby the aim is to separate the aggregate power signal into additive subcomponents (individual appliances' signals).

Goal:

To recover the original component (appliance) signals from a mixture (total) signal.



NILM PROBLEM FORMULATION

Let *p(t)* be the aggregate measured energy signal for the whole household under study. We assume $p_j(t)$ the active power load of the *j*-th appliance, where $j=1,\ldots M$. We can express the total power consumption *p(t):*

$$p(t) = \sum_{j=1}^{M} p_j(t) + e(t) \tag{1}$$

where $e(t)$ is the additive noise of the measurements. NILM is the separation of the total power *p(t)* into the individual appliance source signals $p_j(t)$, which are not available a priori, assuming the absence of installed smart plugs. Instead, only *p(t)* is given. Therefore, the problem is to estimate $\hat{p}_j(t)$, given *p(t)*.

Generative Models for NILM

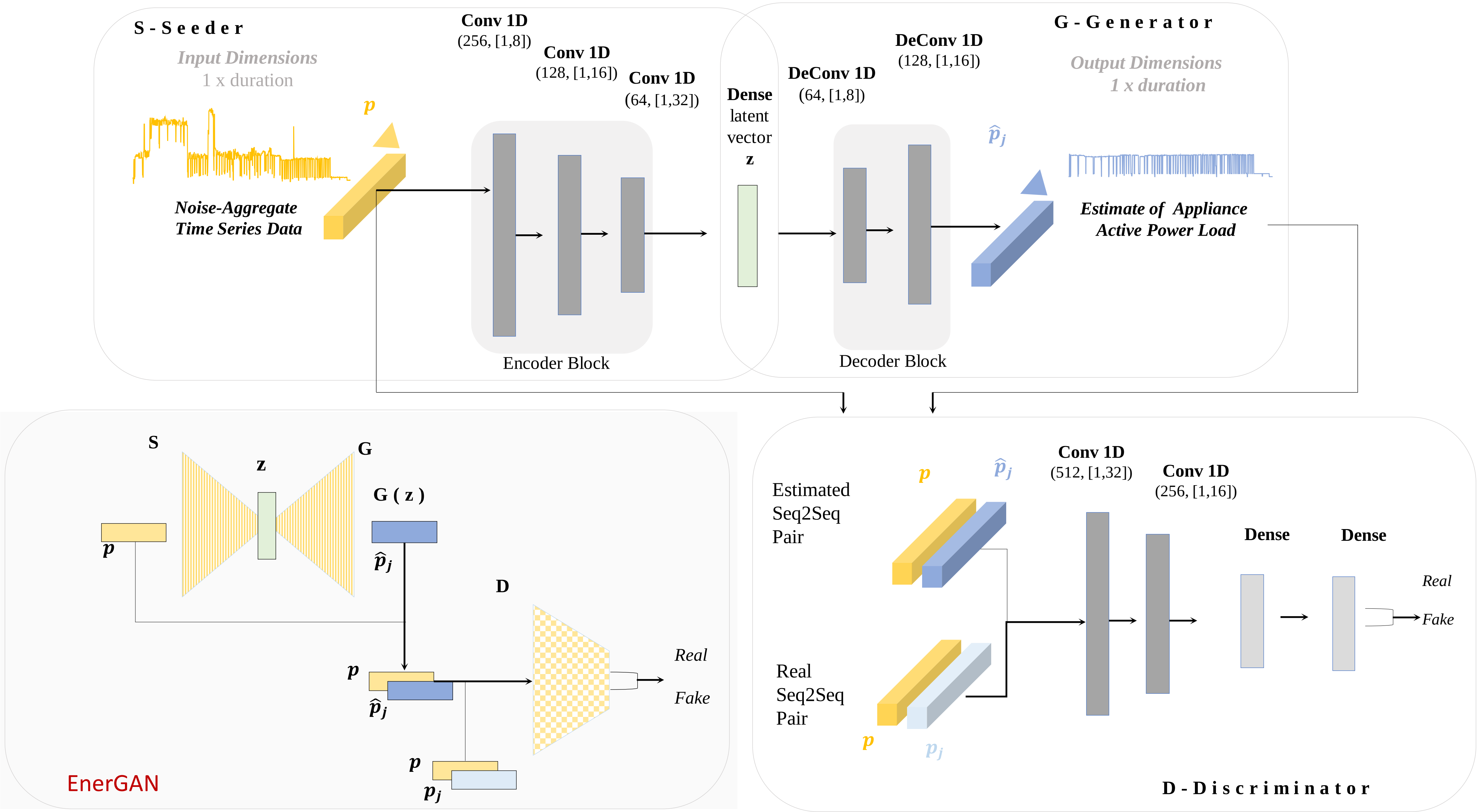
Generative models:

- encode probability distributions and specify how to generate data that fit such distributions. Independent Component Analysis (ICA) is a generative model, which calculates the source signals and the mixing coefficients that give the measured mixed signals. ICA is a special case of blind source separation, similar to NILM problem. Thus, applying generative models for NILM could be a solution to the problem.
- Hidden Markov Models (*Rabiner, 1989*), that are also widely applied for NILM, are generative models, however they fail to: *(i)* describe physical systems with long range correlations, and *(ii)* approximate the long-distance dependencies. Long Short-term memory networks (*Hochreiter, 1997*) have significant advantages over ones constrained by fixed-order Markov assumptions.

THE PROPOSED APPROACH: EnerGAN MODEL

- Generative adversarial networks (GANs) are neural networks that learn data distributions through adversarial training (*Goodfellow, 2014*).
- Given the aggregate (noisy) signal, EnerGAN (a robust to noise GAN) can successfully extract appliance signal (clean signal).
- EnerGAN model consists of three core-components:
    - the **seeder S**, a “noisy” load consumption signal (1D) is the model’s input. The encoder is responsible for non-linear dimensionality reduction, mapping the input signal to a compact and informative subspace (latent vector),
    - the **generator G**, (i.e. a decoder) maps the seeder’s provided values to a higher feature space, which describes accurately the appliances waveform, and
    - the **discriminator D**, takes as input paired sequences of the aggregate signal and the respective appliance power load and decides if each pair is real, based on ground truth values, or a generated construction of the generator (fake).

EnerGAN
Network Configuration



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Performance Evaluation and Comparisons

- ***Datasets:*** AMPds and REFIT

- ***Metrics:***

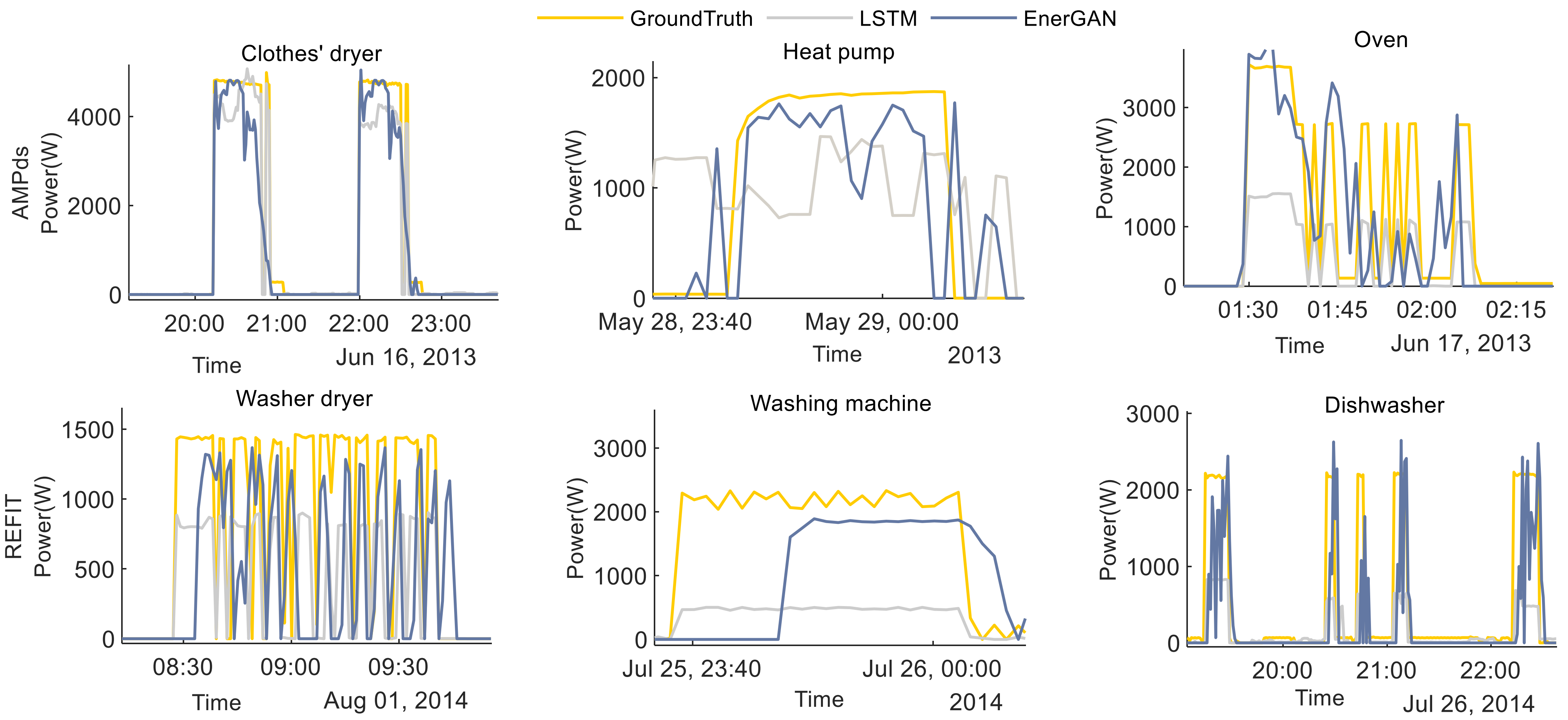
$$MAE = \frac{\sum_{t=1}^{N} \left| \hat{p}_j(t) - p_j(t) \right|}{N} \qquad RMSE = \sqrt{\frac{\sum_{t=1}^{N} (\hat{p}_j(t) - p_j(t))^2}{N}}$$

- ***Comparison Methods:***
  (i) Convolutional Neural Network based method (*Kaselimi*, *2019a*),
  (ii) Long Short Term Memory method (*Kaselimi*, *2019b*, *2020*),
  (iii) denoising Autoencoders (DAE),
  (iv) combinatorial optimization (CO) (*Batra*, *2014*) and
  (v) Factorial Hidden Markov Model (FHMM) (*Batra*, *2014*).

Performance Evaluation and Comparisons

Dataset	Appliance	Metric	Method					
			EnerGAN	**LSTM**	**TDLCNN**	**DAE**	**FHMM**	**CO**
AMPds	Dryer	*MAE*	18.7	25.4	34.4	20.0	129.6	117.5
		RMSE	219.3	180.9	202.5	213.8	323.2	453.3
	Heat Pump	*MAE*	84.9	161.7	158.7	56.1	121.7	249.1
		RMSE	244.7	369.8	305.4	219.5	426.6	458.7
	Oven	*MAE*	8.9	15.8	42.2	10.6	49.4	267.0
		RMSE	135.6	141.2	201.3	119.7	360.8	432.8
REFIT	Washer Dryer	*MAE*	39.0	44.3	75.8	93.8	229.4	204.3
		RMSE	196.9	223.1	194.4	245.0	523.3	480.2
	Washing Machine	*MAE*	27.9	29.5	85.8	72.6	177.0	219.1
		RMSE	194.6	186.3	208.3	228.1	493.5	593.5
	Dishwasher	*MAE*	38.8	66.8	94.1	102.2	147.7	188.9
		RMSE	242.3	244.5	237.4	322.3	535.2	477.2

Performance Evaluation and Comparisons



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Thank you for your attention

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