NILMFormer
Non-Intrusive Load Monitoring that Accounts for Non-Stationarity

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Context: Efficient Energy Management

Energy markets are **undergoing significant change**

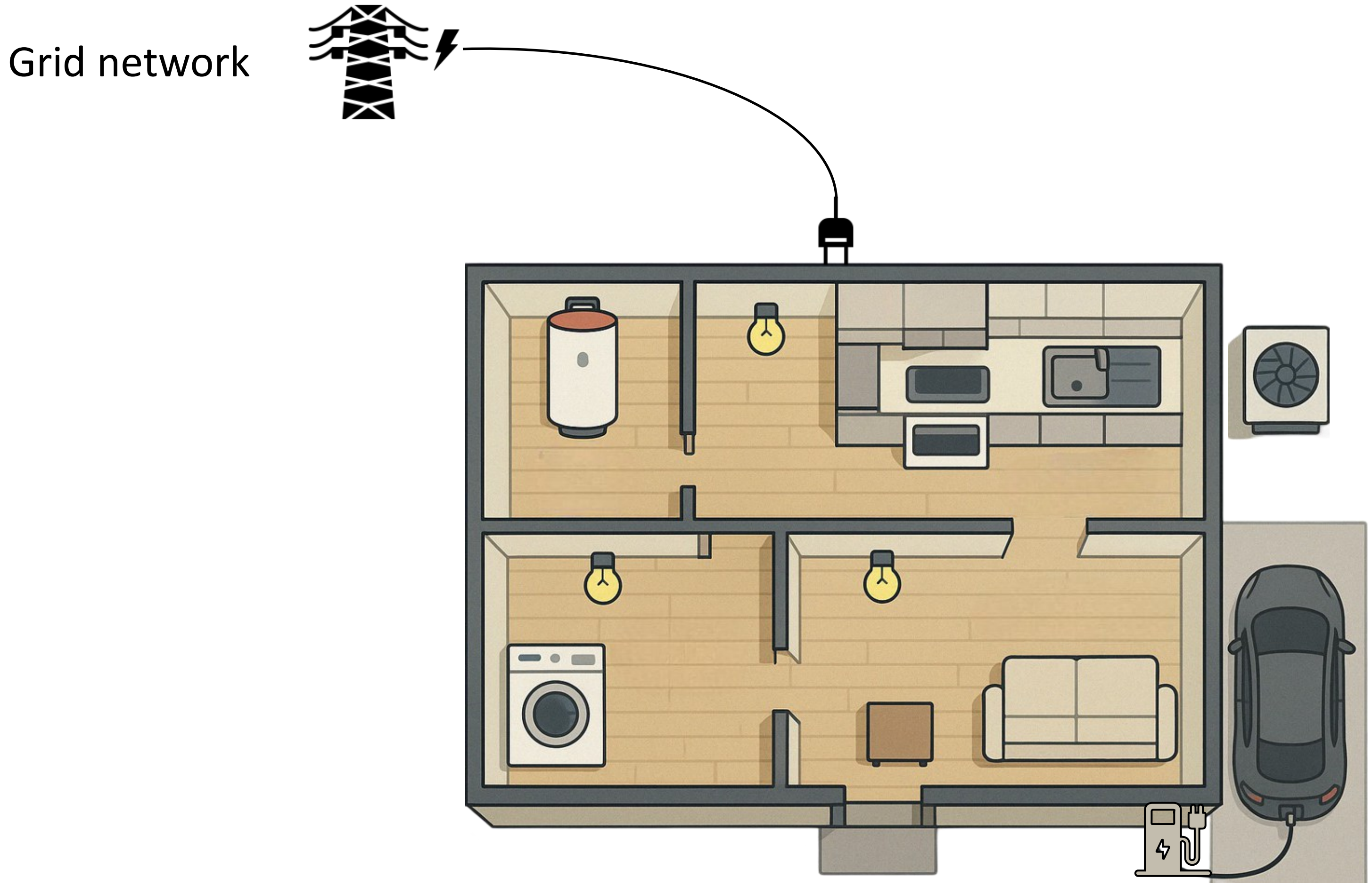
Decarbonation: COP28 (2023) → "beginning of the end of fossil fuels"

Massive integration of **new** (renewable) **energy sources**

Large-scale end-use **electrification** *(Electric Vehicle, Heater, AC)*

Context: Smart Meter Deployment

Millions of **Smart Meters** deployed in **individual households**



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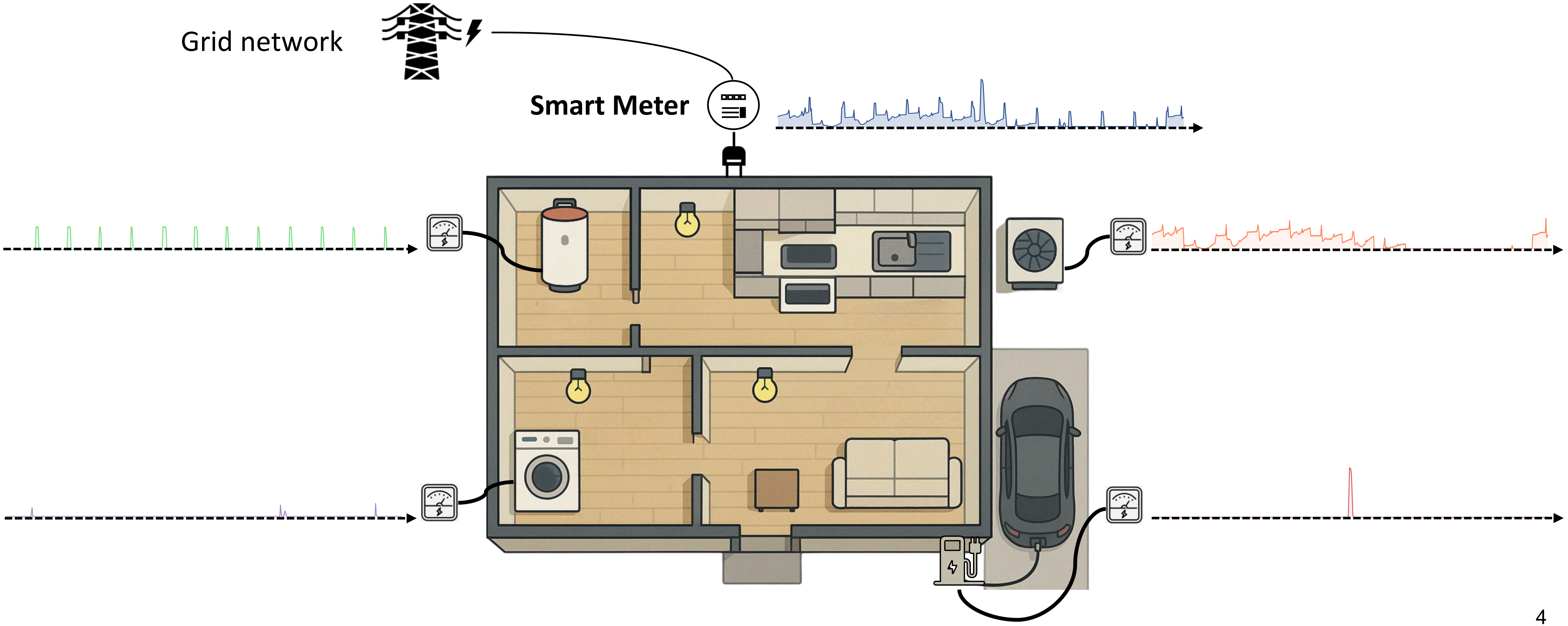

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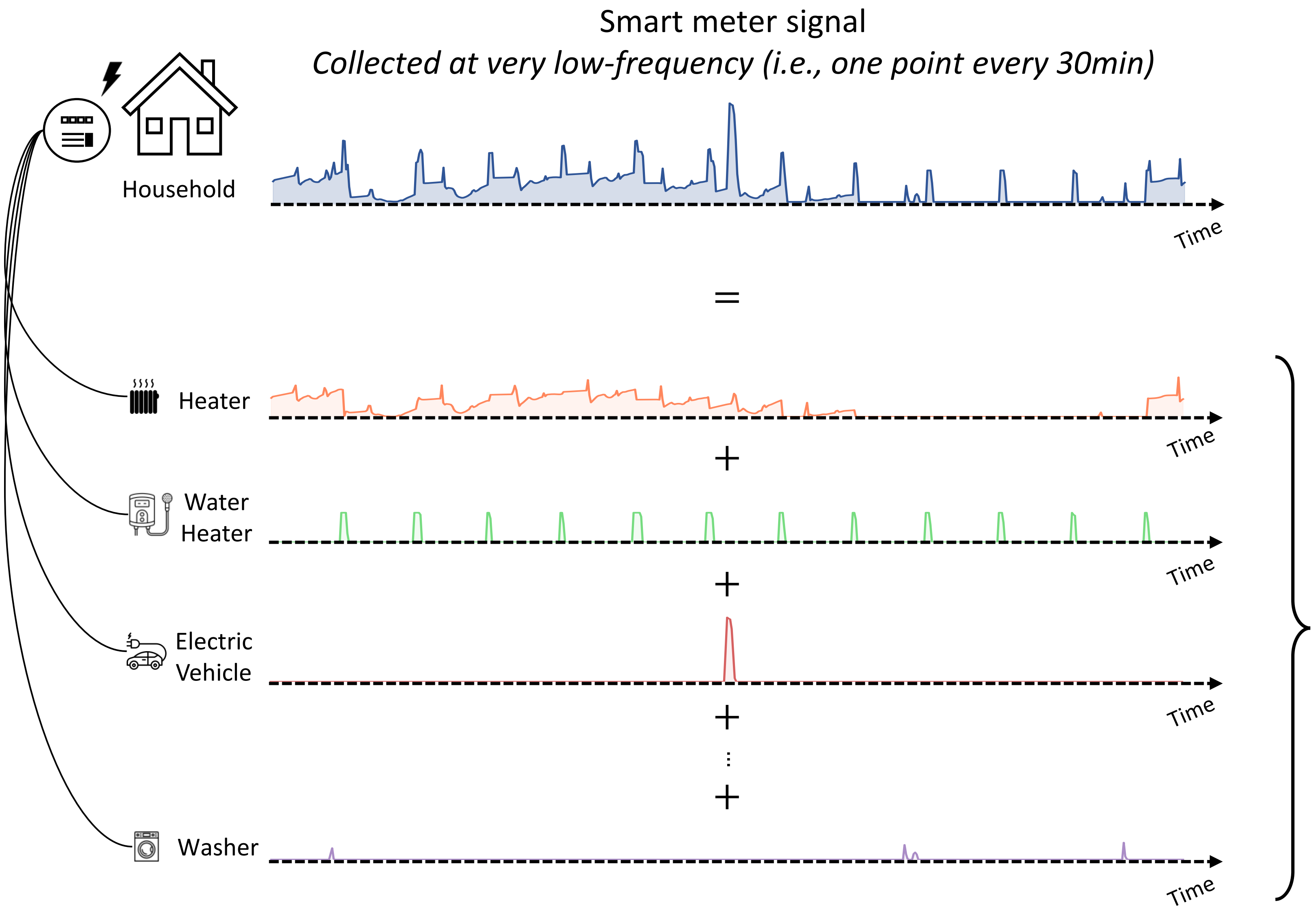

Sum of all individual **appliances'** power **consumption**

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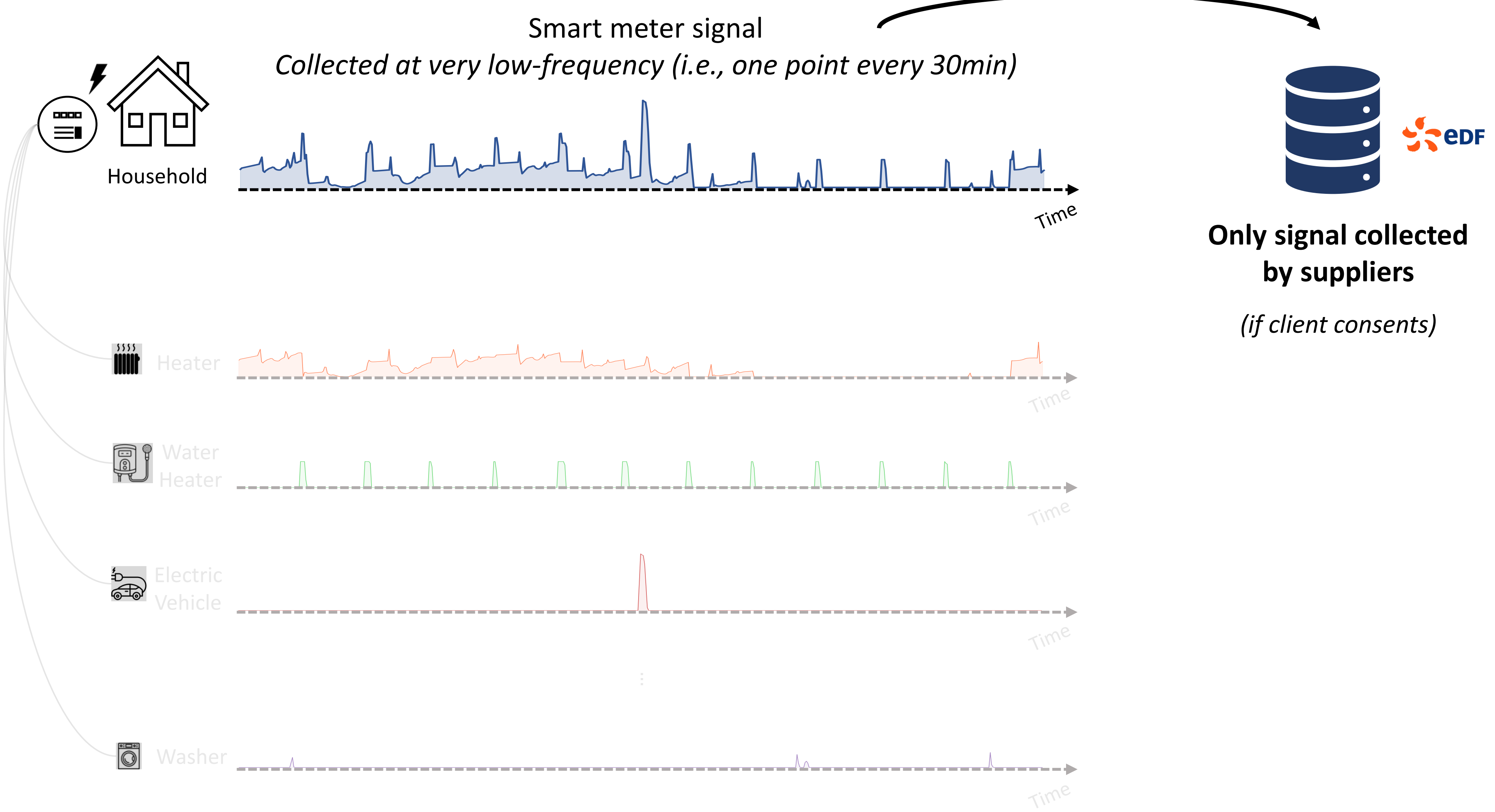
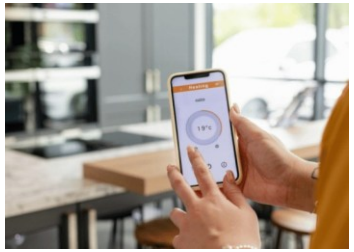


Only signal collected by suppliers

(if client consents)

Context: From Passive Energy Consumers to Active Players

Consumers are **shifting** from **passive users** to **active participants,** increasingly willing to engage in the energy transition.



Consumption feedback

empowering awareness

Active consumption

shifting usage based on grid needs

Help **customers reduce** their **bill** *(up to -12 %)* [1, 2]

[1] Martinez et al., Advanced Metering Initiatives and Residential Feedback Programs, 2010

[2] Allcott et al., Social norms and energy conservation, Journal of Public Economics, 2011

EDF’s Appliance-Level Feedback Solution

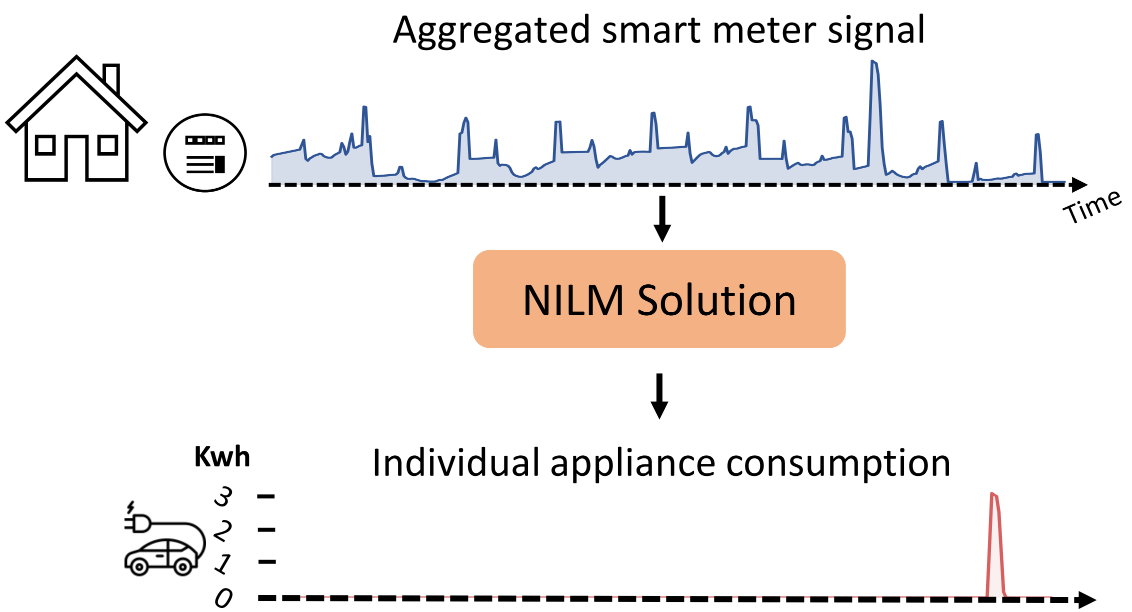
- **2015** - Launch of *Mon Suivi Conso* (web + app)
- **2018** - **Annual appliances estimate** using a **semi-supervised** statistics approach[1]
- **2023** - **Deep-Learning based** approach → monthly estimation reduced error **by $\approx -70\ \%$**

Room for improvement: Monthly estimation is **still coarse, and users recently requested** daily appliance-level **insights**

[1] L. Bozzi et al., Individual electricity consumption of a given appliance from a set of electrical equipment, French Patent, 2014.

Background: Non-Intrusive Load Monitoring

Non-Intrusive **L**oad **M**onitoring (NILM): estimates **power consumption**, operational **patterns**, and **on/off state** of individual appliances using **only the total aggregated signal**



a Time Series Regression task

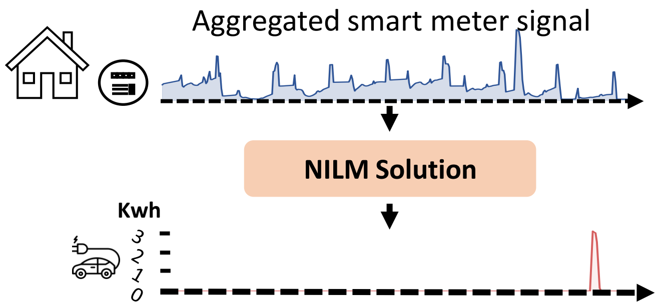
Early research (1992)	ML Area (2010's)	DL Area (2015-now)
Combinatorial Optimization G. W. Hart [1]	Sparse Coding, HMM Andrew Ng [2]	RNN, CNN, Transformer Jack Kelly [3]

[1] G. Hart, Nonintrusive appliance load monitoring, 1992 [2] Andrew Ng, Energy Disaggregation via Discriminative Sparse Coding, NIPS, 2011 [3] Jack Kelly, Neural NILM, ACM BuildSys', 2015

Background: Non-Intrusive Load Monitoring

SotA NILM methods are based on **deep-learning**

- **Operates** on **subsequences** of an entire electricity consumption series: *scalability* and *performance*



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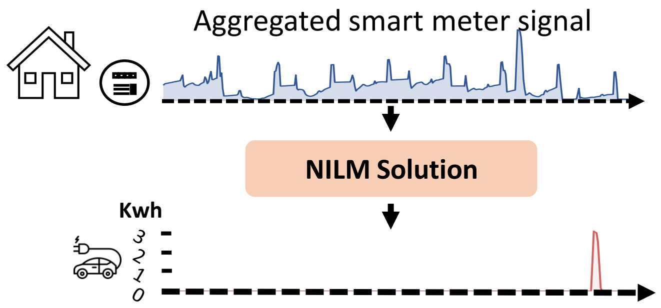

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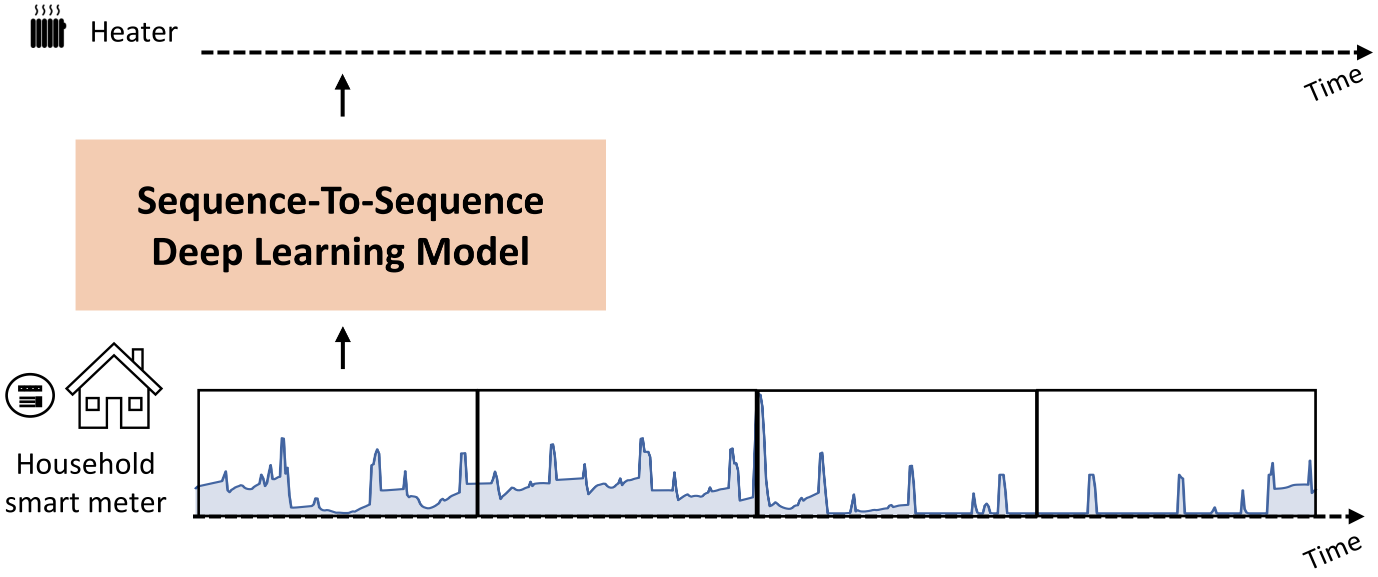
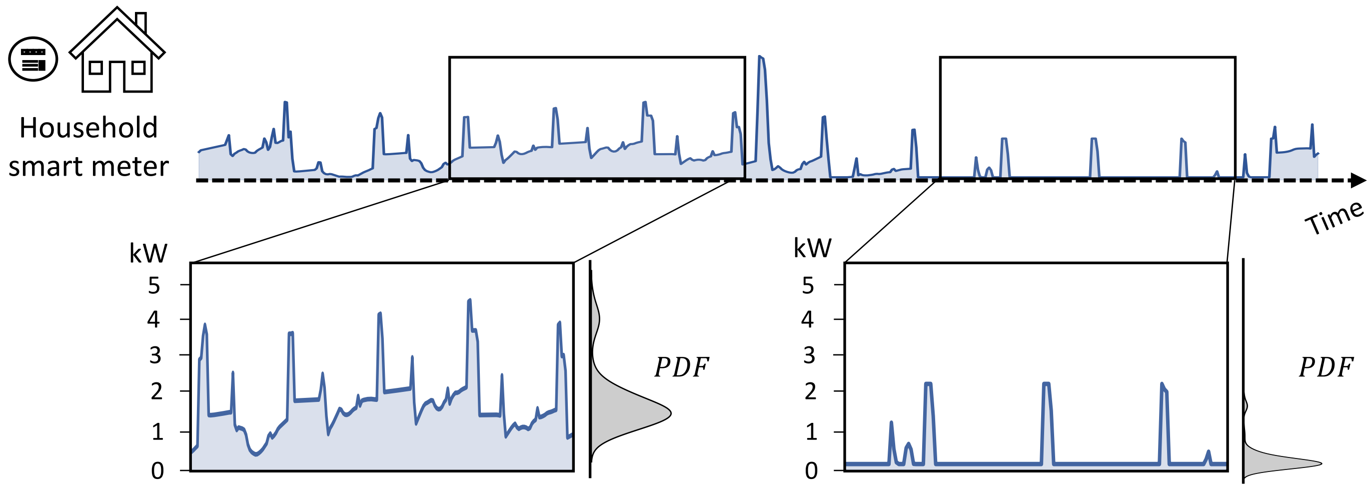
The *Sequence-To-Sequence* paradigm



Problem

Non-Stationarity Nature of Electricity Consumption Data



Accounting for **non-stationarity** in deep learning **significantly improves** time series **forecasting accuracy** ! [1, 2]

[1] T. Kim et al., Reversible Instance Normalization for Accurate Time-Series Forecasting against Distribution Shift, ICLR, 2021
[2] Y. Liu et al., Non-stationary Transformers: Exploring the Stationarity in Time Series Forecasting, NIPS, 2022

Challenges

*How to provide detailed and accurate **fine-grained** appliance consumption **feedback** to customers?*

Challenges

1. **Considering non-stationary**
   Mitigating the data distribution nature of smart meter data

2. **Delivering granular, actionable feedback to customers**
   Per-timestamp, daily, weekly and monthly

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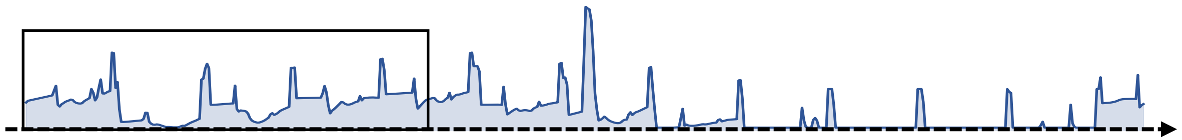
Solutions

✓ **NILMFormer**

✓ **Deployment** in *"Mon Suivi Conso"*

Proposed Approach: NILMFormer

How to **mitigate** the subsequence **data drift aspect?**



Entire aggregate consumption series

Proposed Approach: NILMFormer

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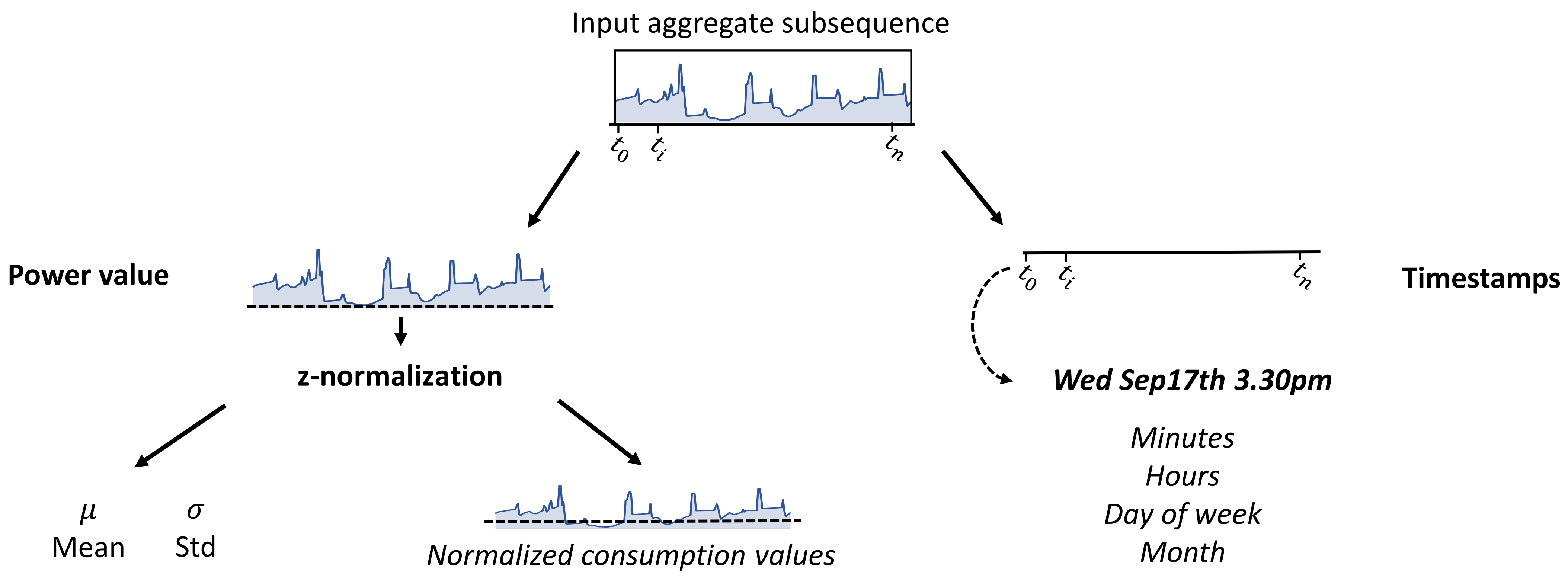

1. Intrinsic statistics

2. Shape

3. Timestamps information

NILMFormer: A Non-Stationarity Aware Transformer for Non-Intrusive Load Monitoring

I. Distinct encoding modules (*tokenization*)

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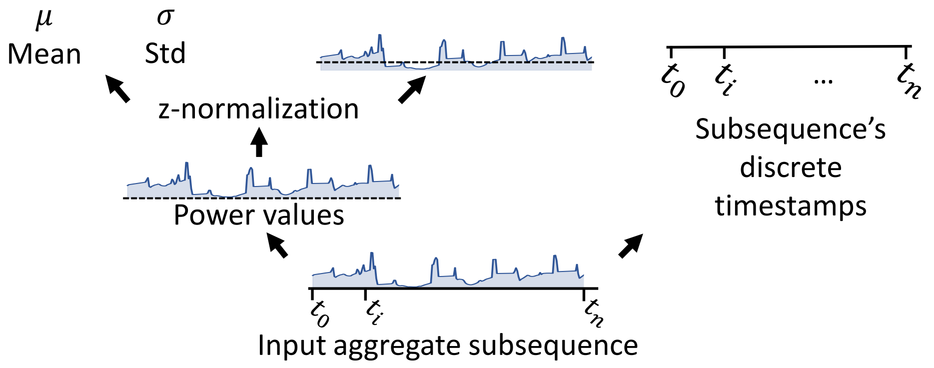

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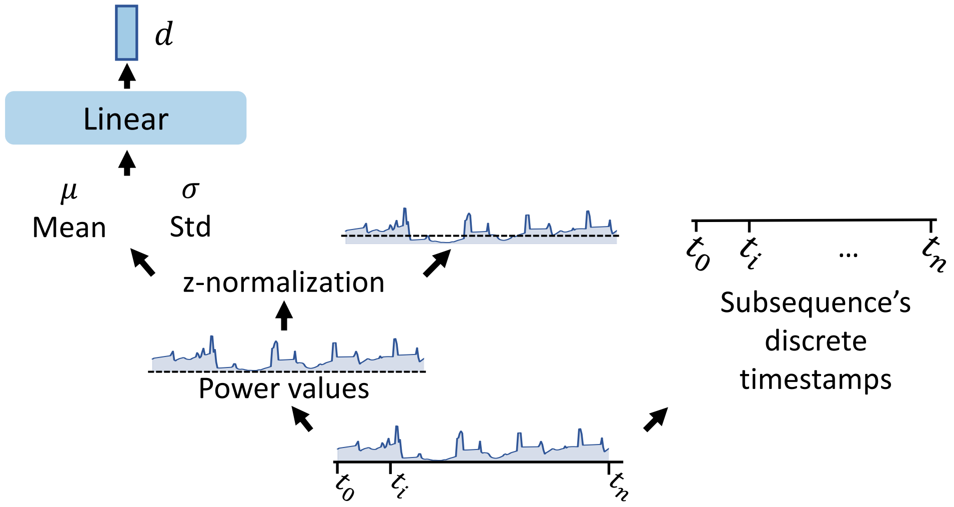

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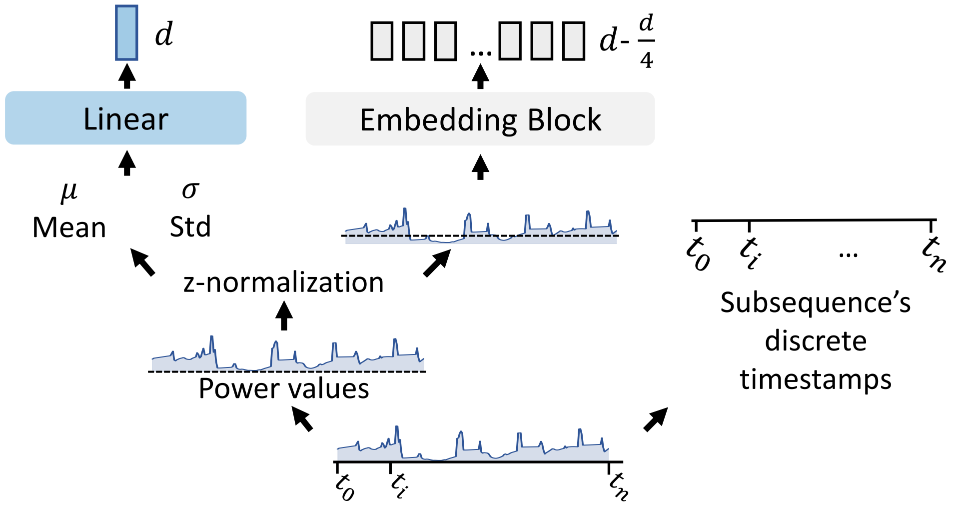

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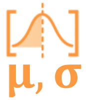

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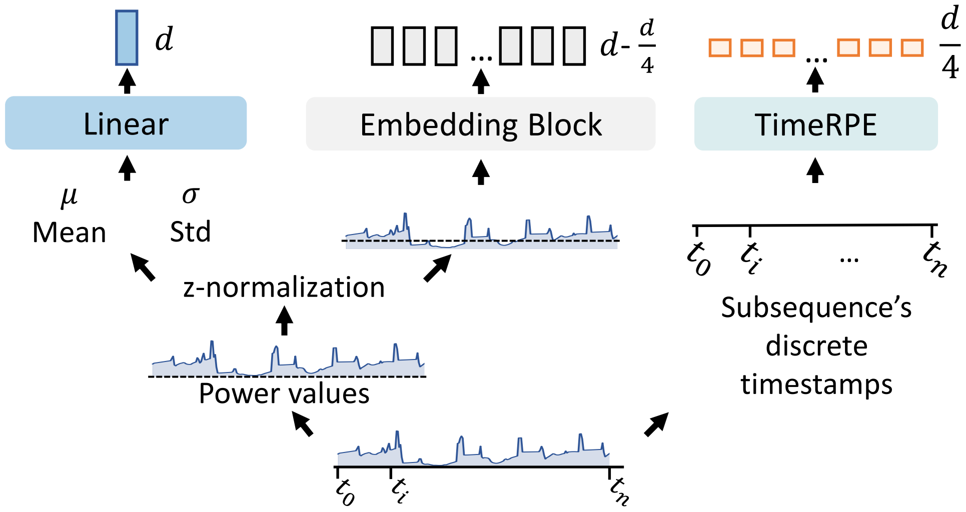

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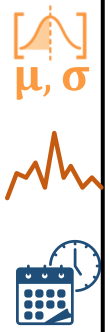
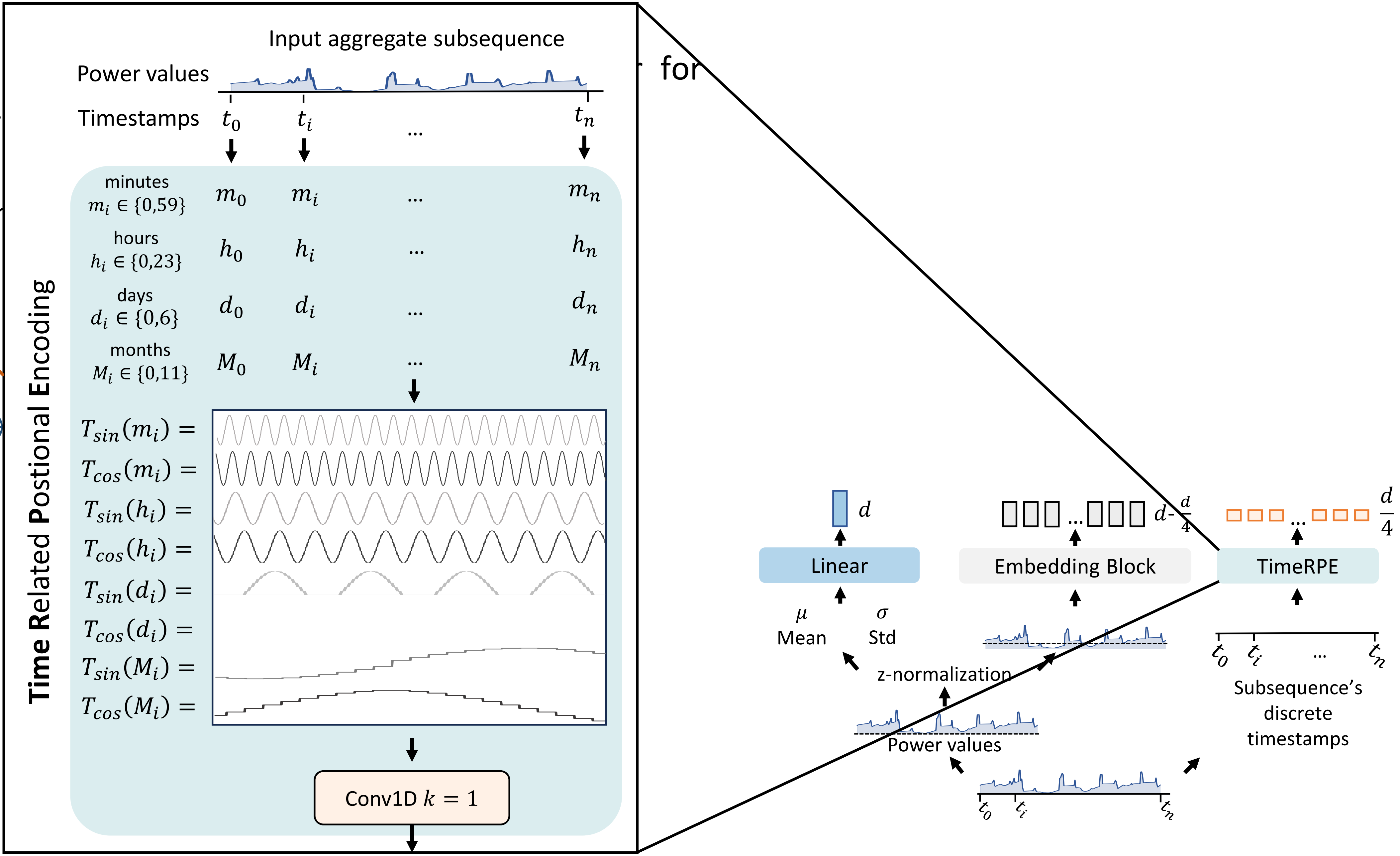
NILMForm for

Non-Intrus

I. Distinct en





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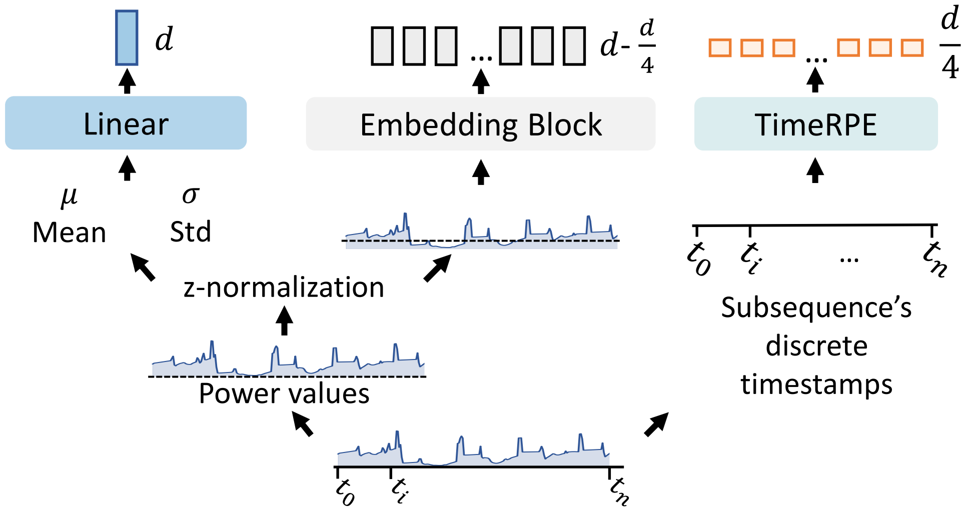

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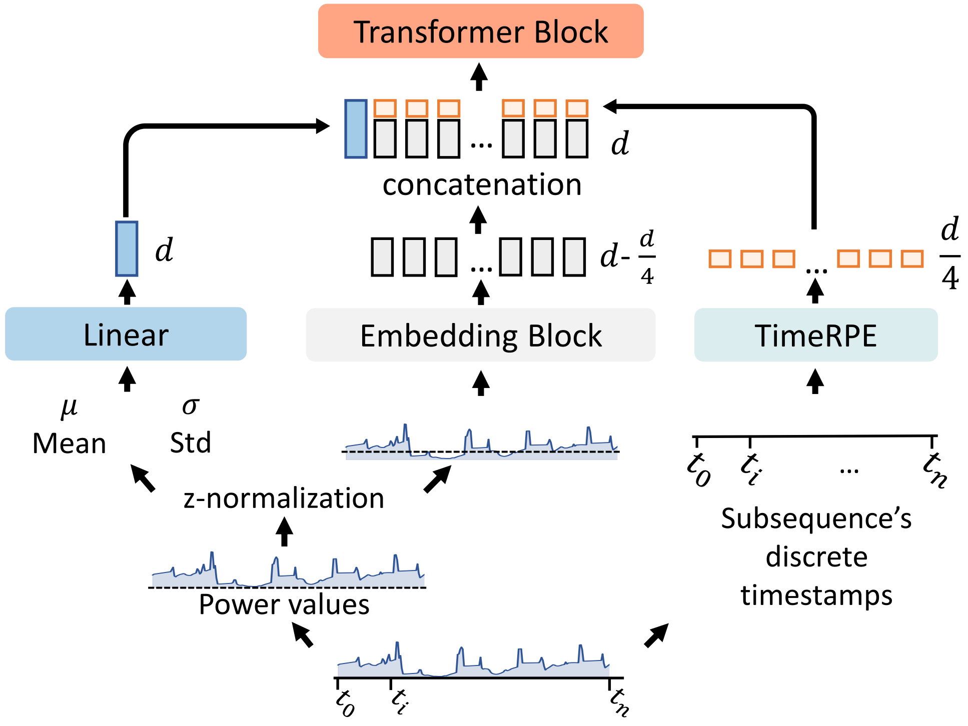

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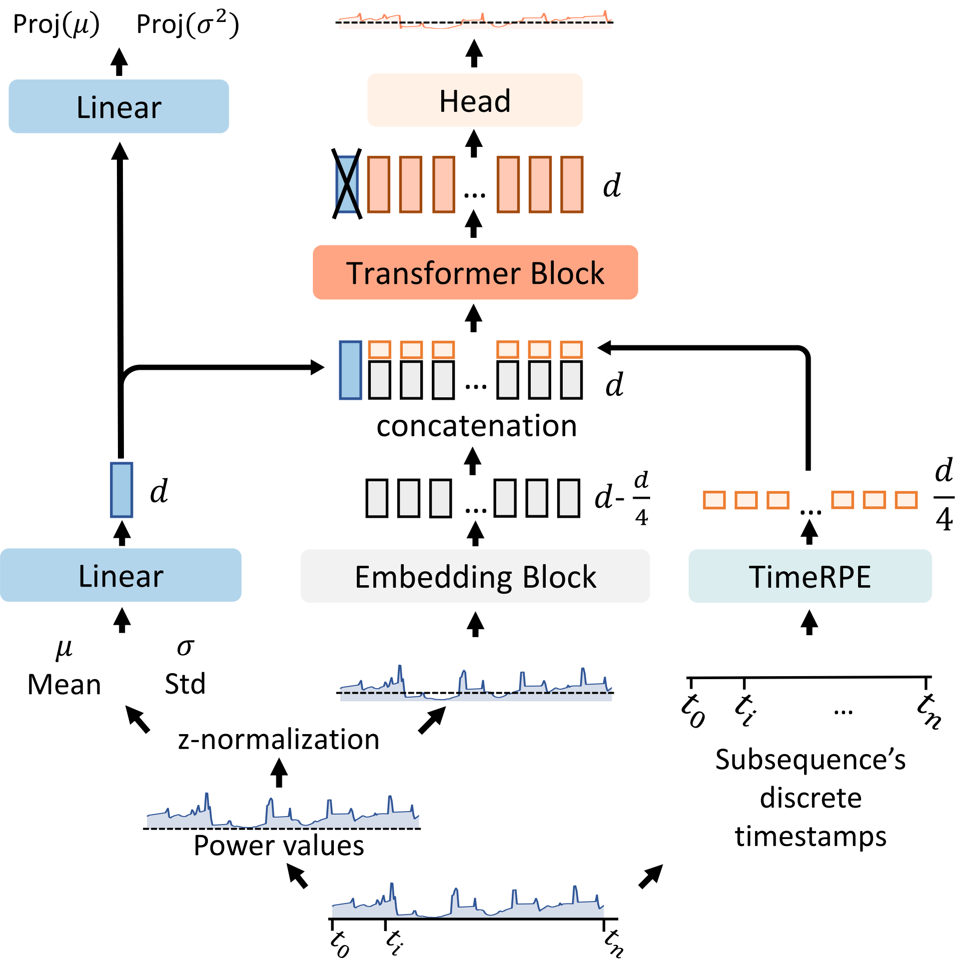

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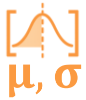

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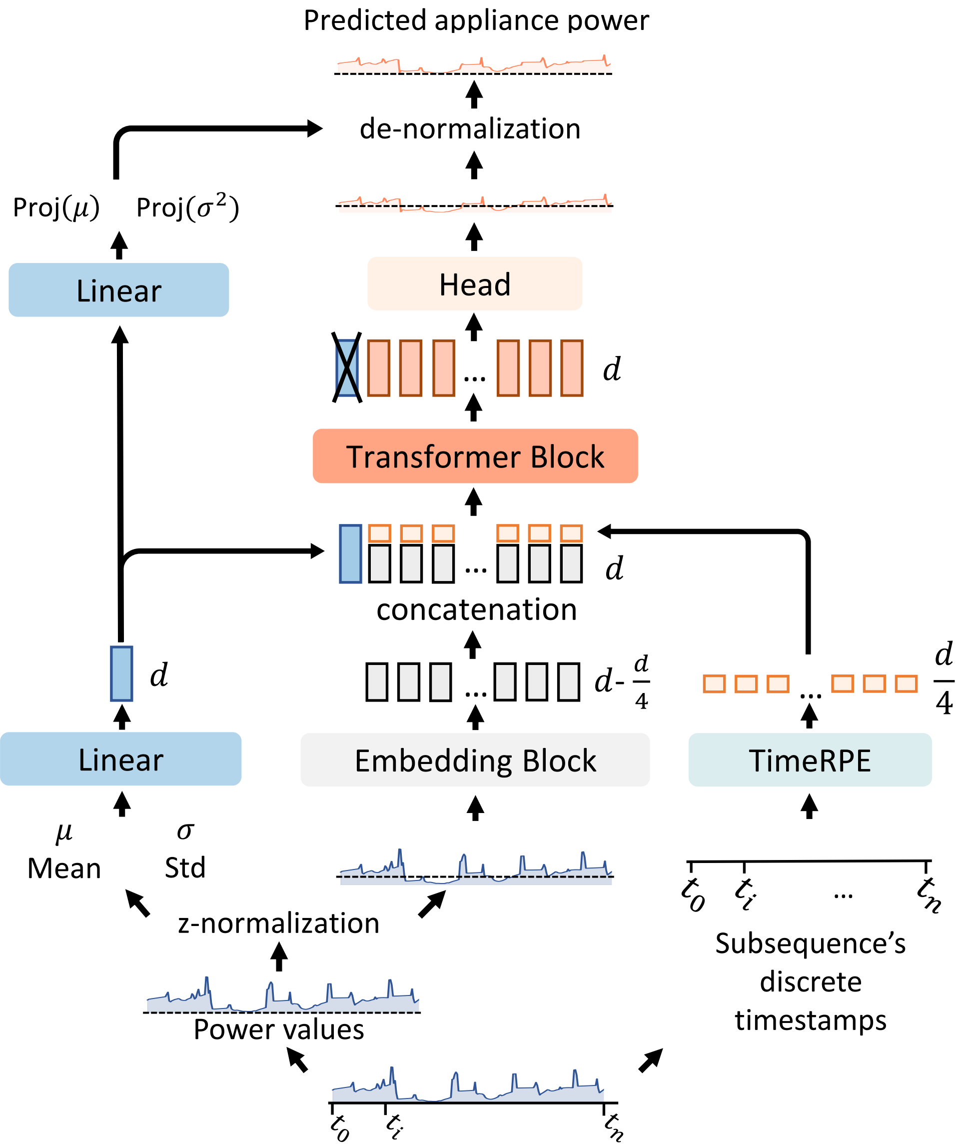
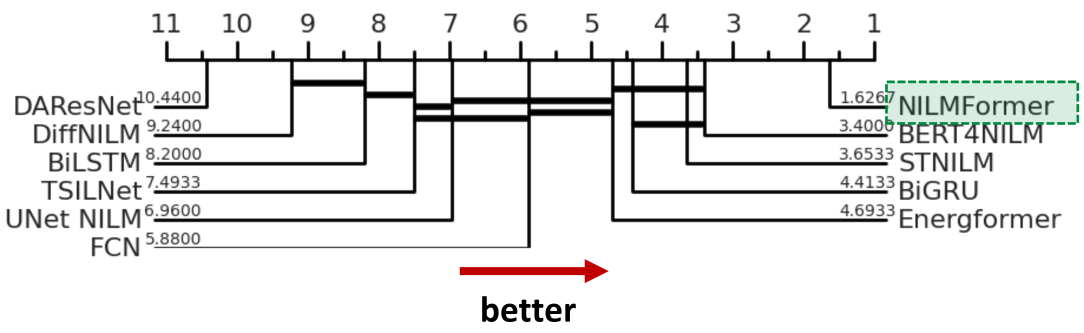
IV. Output **de-normalization**



Results: Per-timestamp Energy Disaggregation

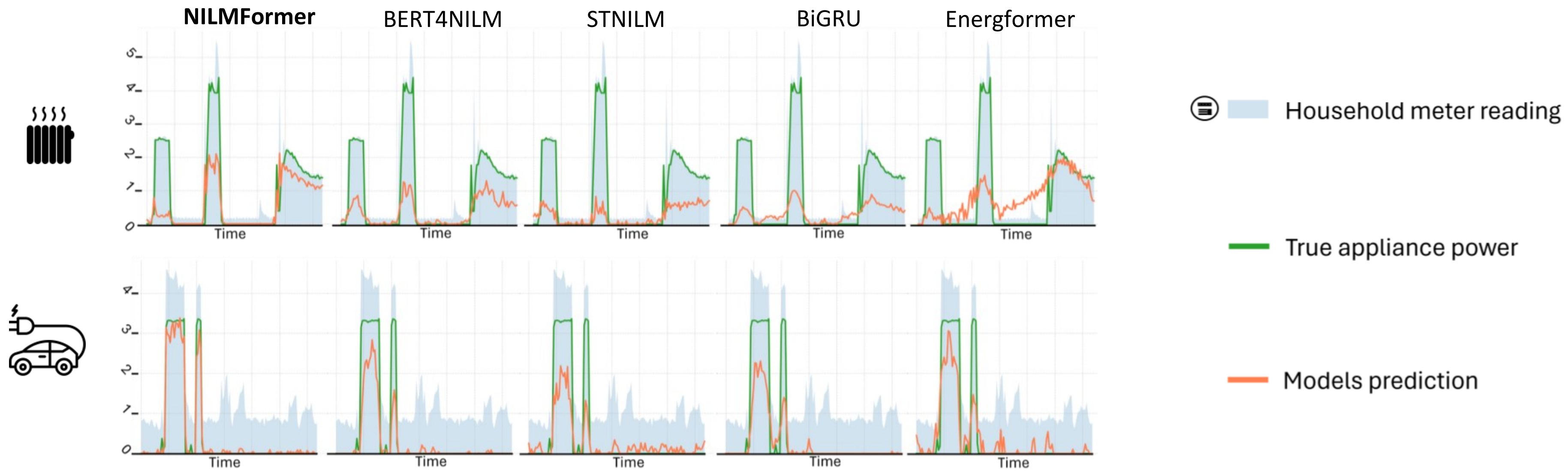
Performance comparison with **10 SotA** deep-learning **NILM baselines**

Averaged across 4 datasets (including 2 public benchmarks) and 14 appliance disaggregation scenarios



≈**20% increase**

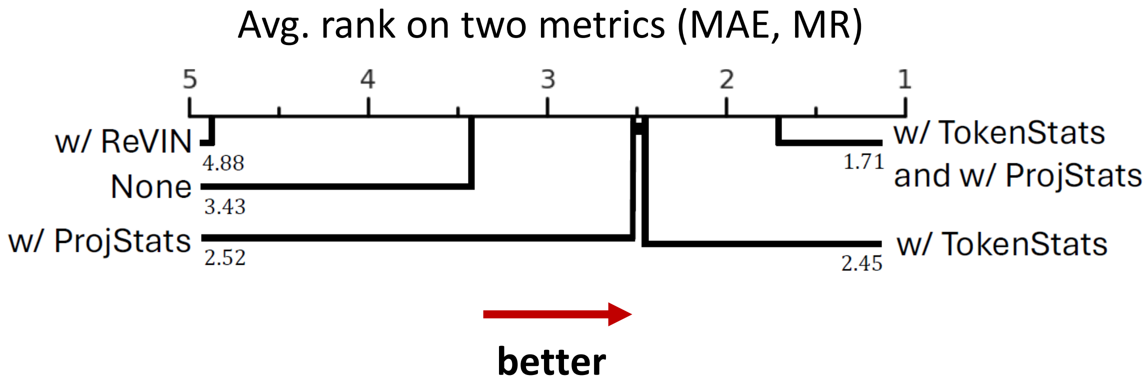
≈ **10% increase**



EDF datasets

Ablation Study

Effects of proposed **Non-Stationary Mechanisms** on **NILMFormer Performance**



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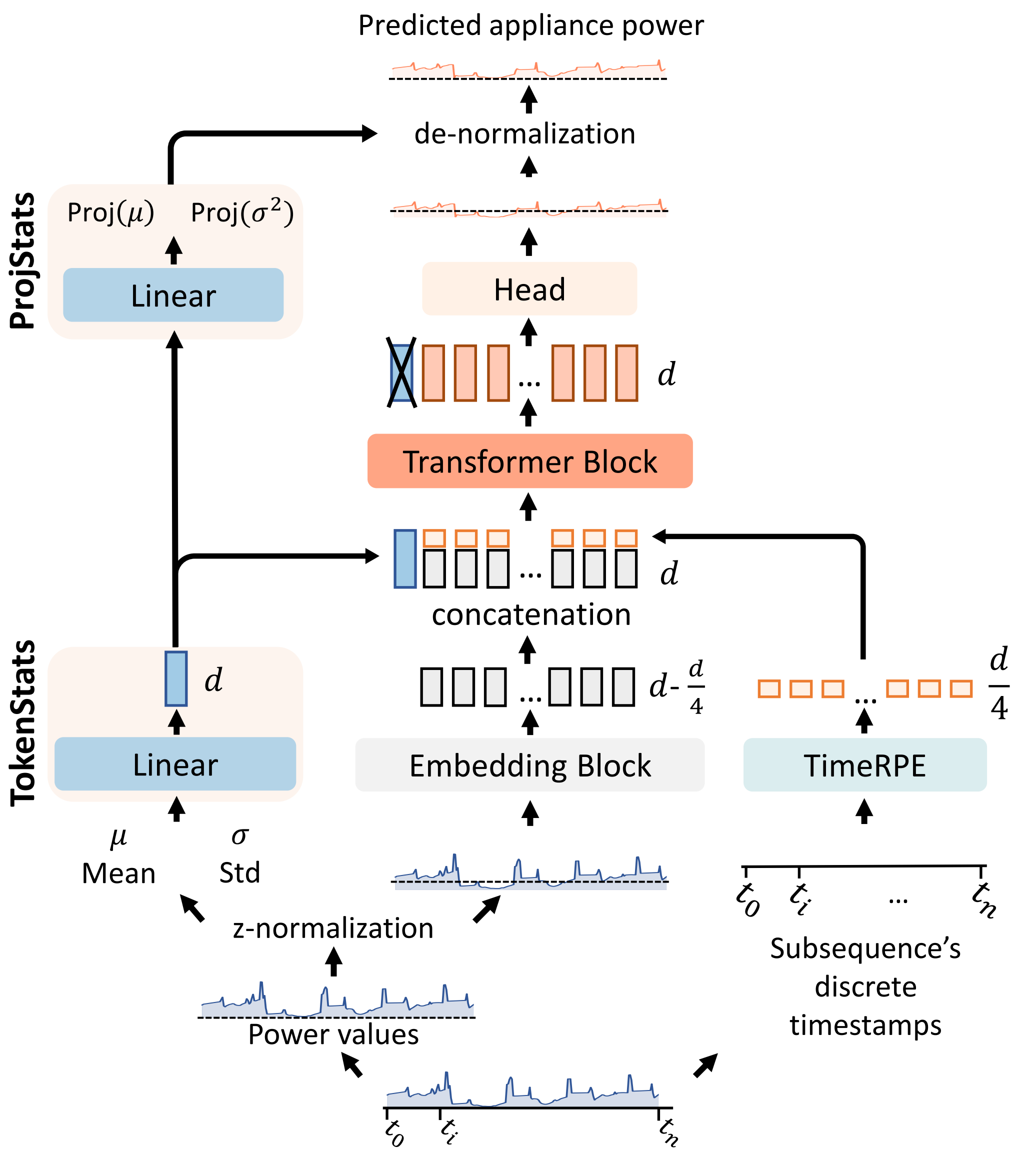

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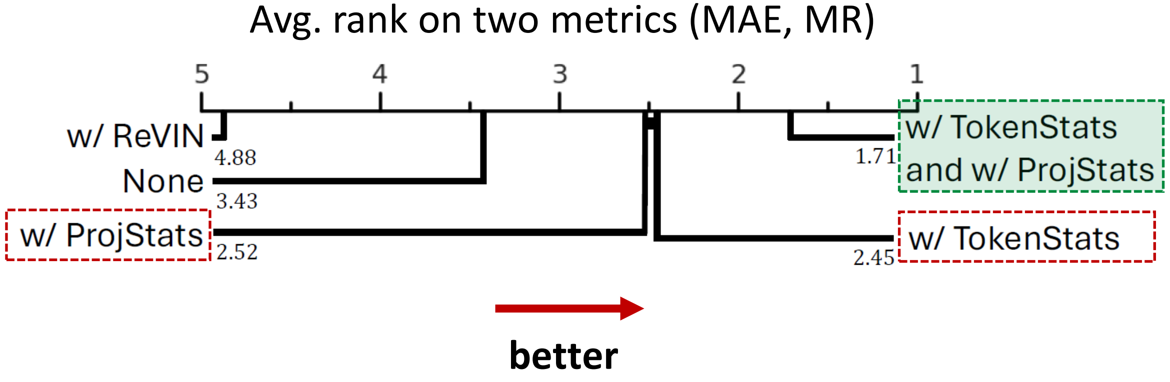

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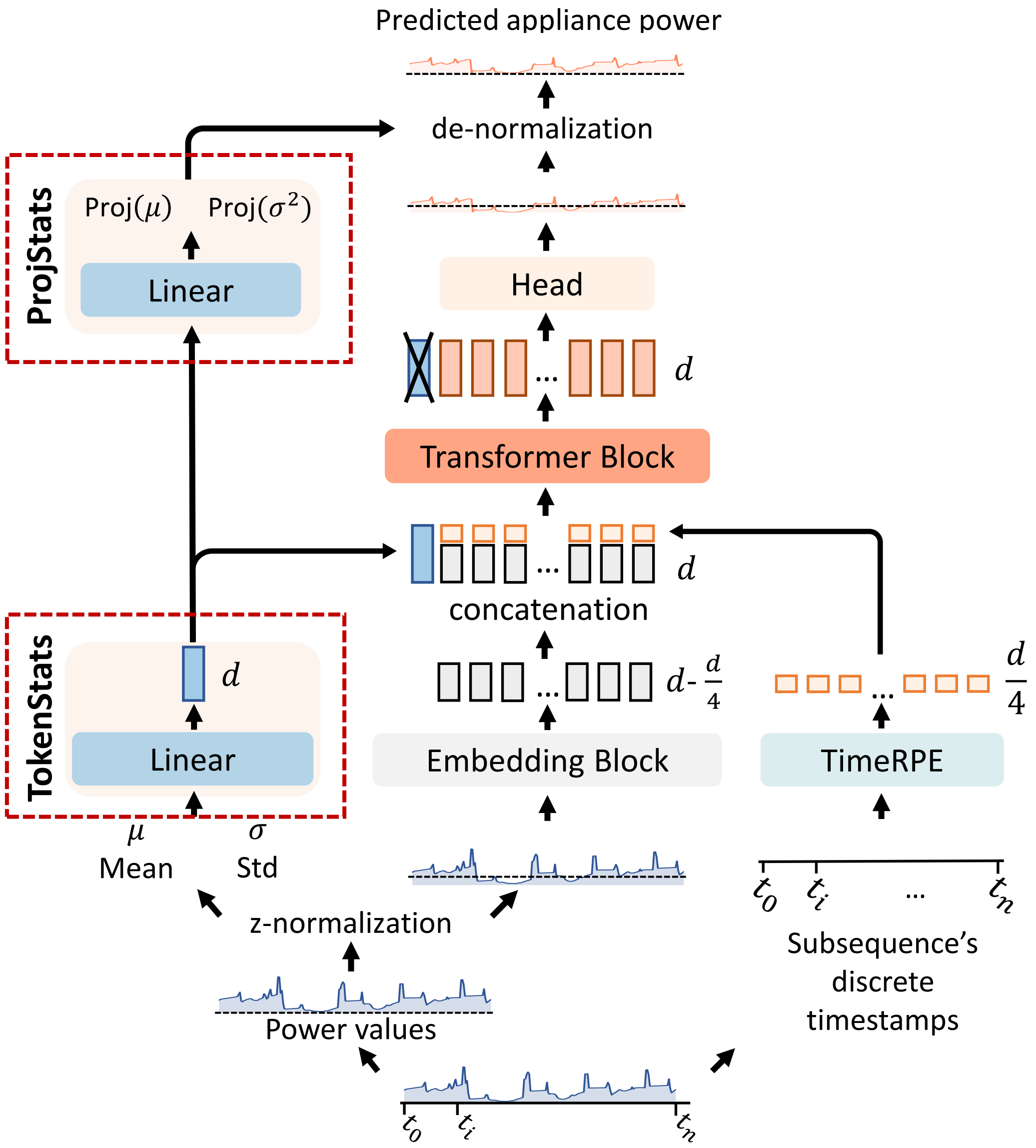
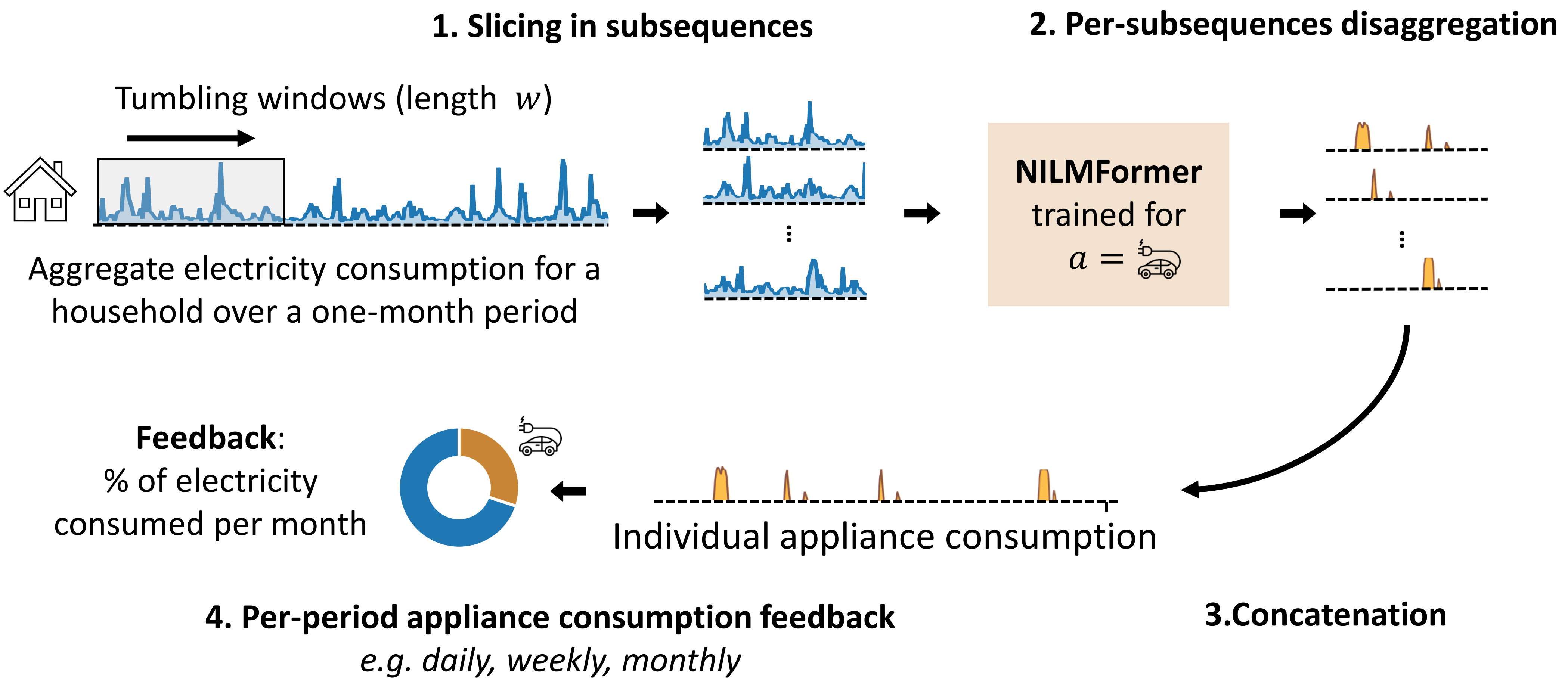


Deployed Solution: NILMFormer for Detailed Appliance Feedback

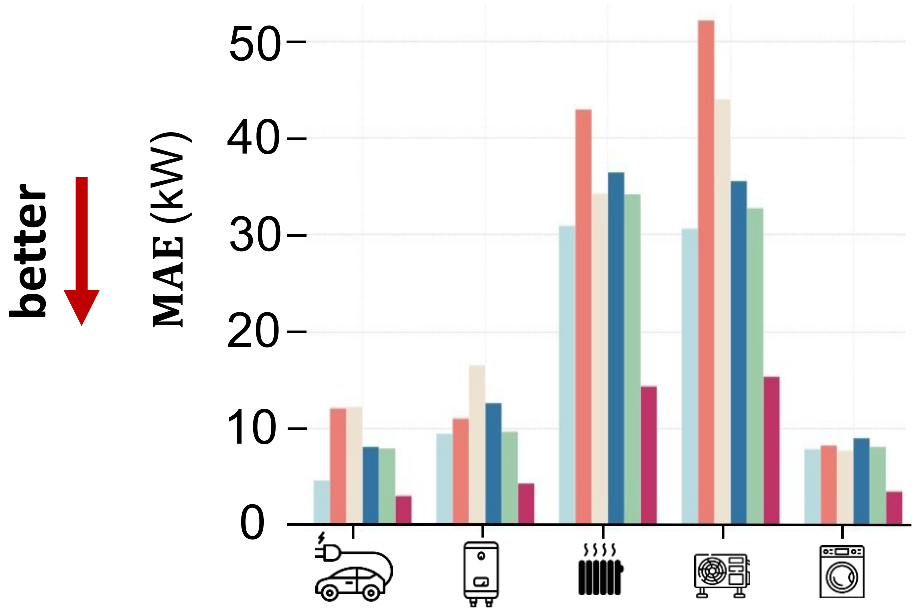
A Straightforward **Framework** for delivering **Per-Period Energy Estimation**



Deployed Solution: NILMFormer for Detailed Appliance Feedback

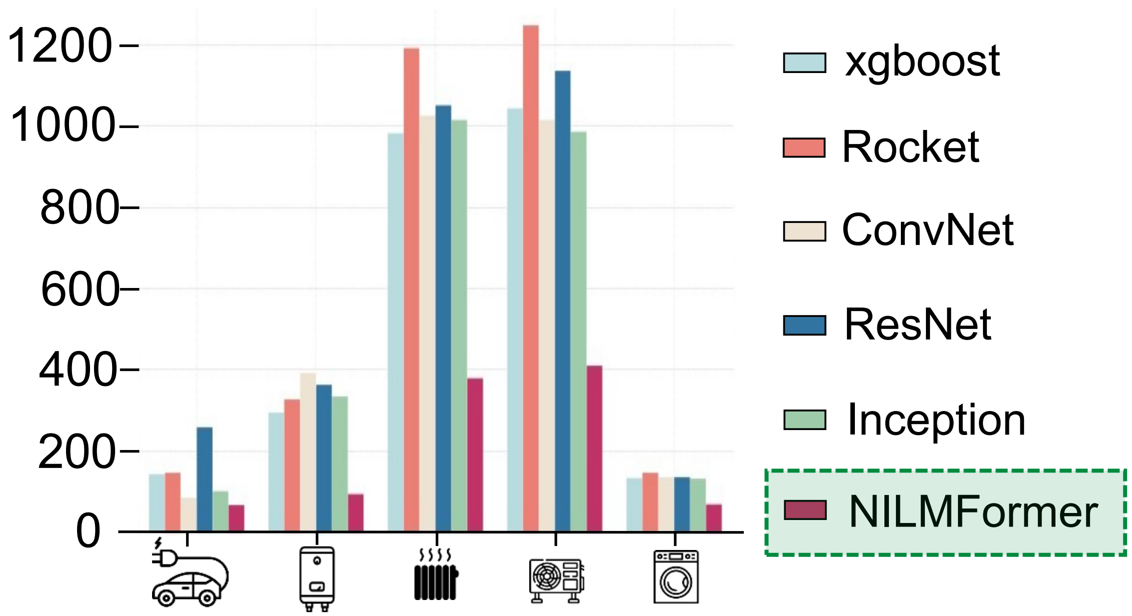
Performance comparison with **TSER approaches** (previous **EDF**’s Investigated Solution in *Mon Suivi Conso*)

Daily Power Appliance Estimation



Achieves up to 52% lower error
than the 2nd-best baseline(XGBoost)

Monthly Power Appliance Estimation



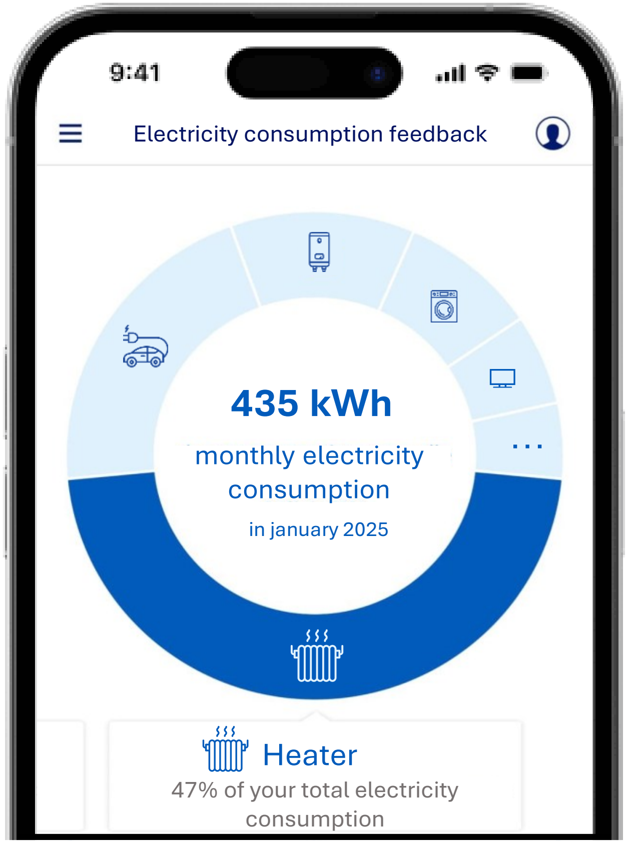
Achieves up to 151% lower error
than the 2nd-best baseline (Inception)

EV · WaterHeater · Heater · Heatpump · White Appliances

Deployed Solution: NILMFormer for Detailed Appliance Feedback

Deployment of **NILMFormer** in *Mon Suivi Conso*

- **Scale**: Appliance-level insights at **daily, weekly, and monthly** granularity for more than **4 million** customers.
- **Throughput**: Runs on the entire customer base (~4 M meters) **in ≈11 hours**, demonstrating **industrial-grade scalability**.
- **Adoption: 8.4 million reported visits** on the appliance-feedback feature in *Mon Suivi Conso* **during Q4 2024 (60% of the total feed).**



Conclusion

- **NILMFormer:** a **state-of-the-art deep-learning approach** that explicitly handles the **non-stationary nature of smart-meter data.**

- **Results:** achieves **significantly better performance than prior NILM methods** across diverse datasets and appliances.

- **Impact:** deployed in EDF's *Mon Suivi Conso*, **delivering actionable appliance-level feedback at scale** to **millions of customers**.

- **Other application (Internal Decisions Making at EDF)**: recently used to identify the impact of different off-peak EV charging systems on client's consumption.

Thank you!

Contact: adrien.petralia@edf.fr

Want to learn more about our work?

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