

NILMFormer

Non-Intrusive Load Monitoring that Accounts for Non-Stationarity



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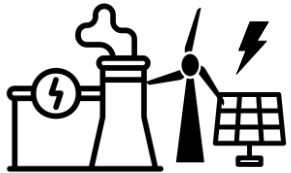
August 6th, 2025



Energy markets are undergoing significant change



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



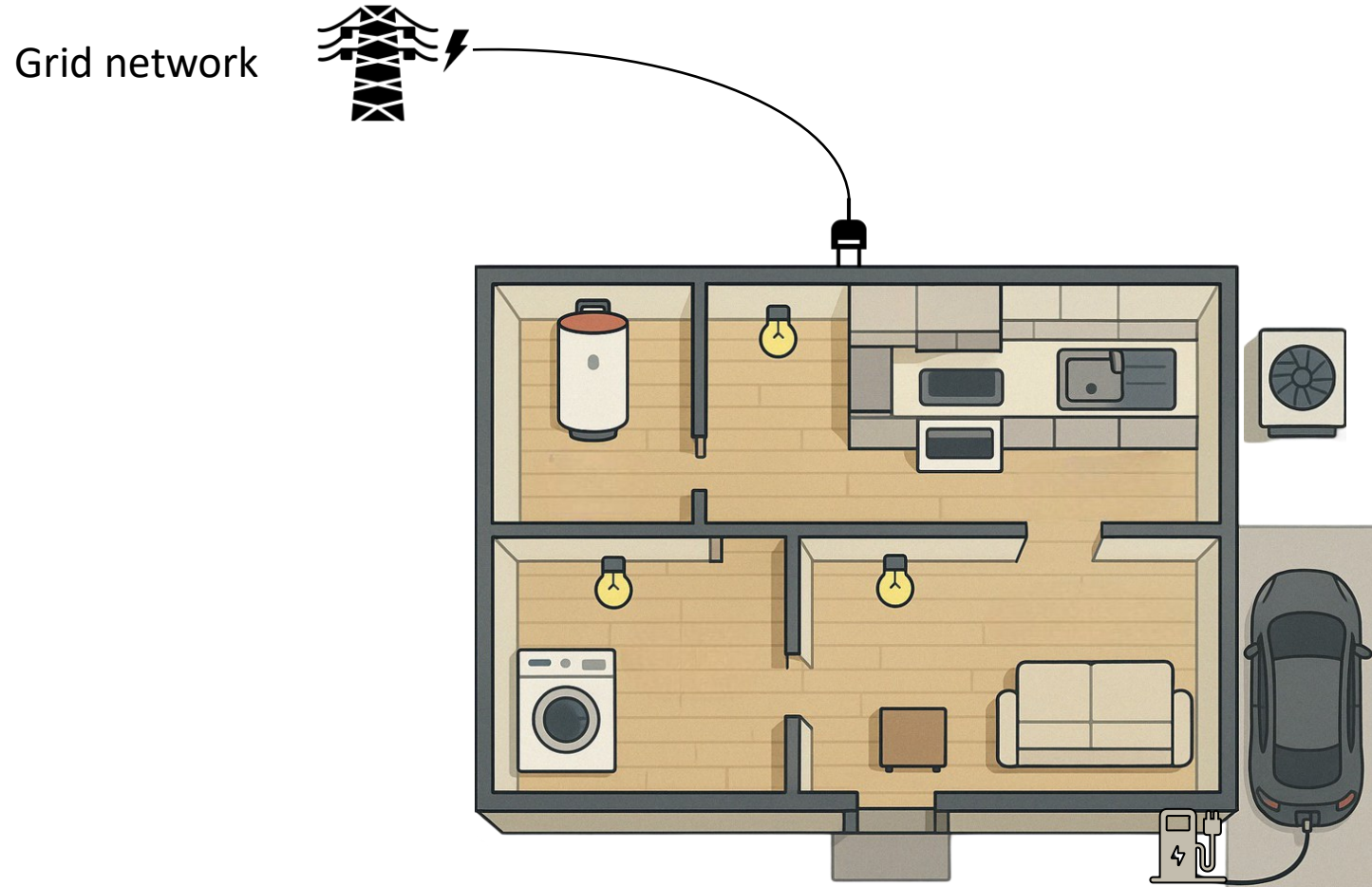
Massive integration of **new** (renewable) **energy sources**



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

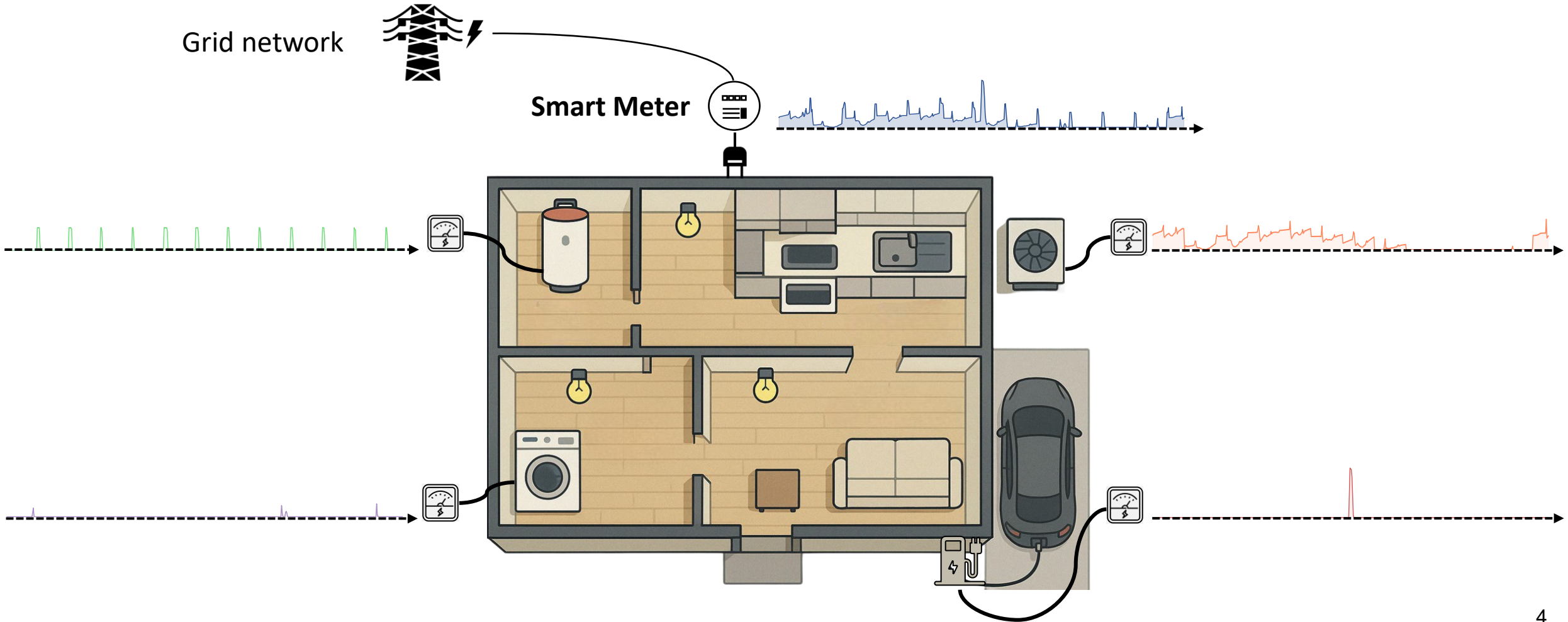
Context: Smart Meter Deployment

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



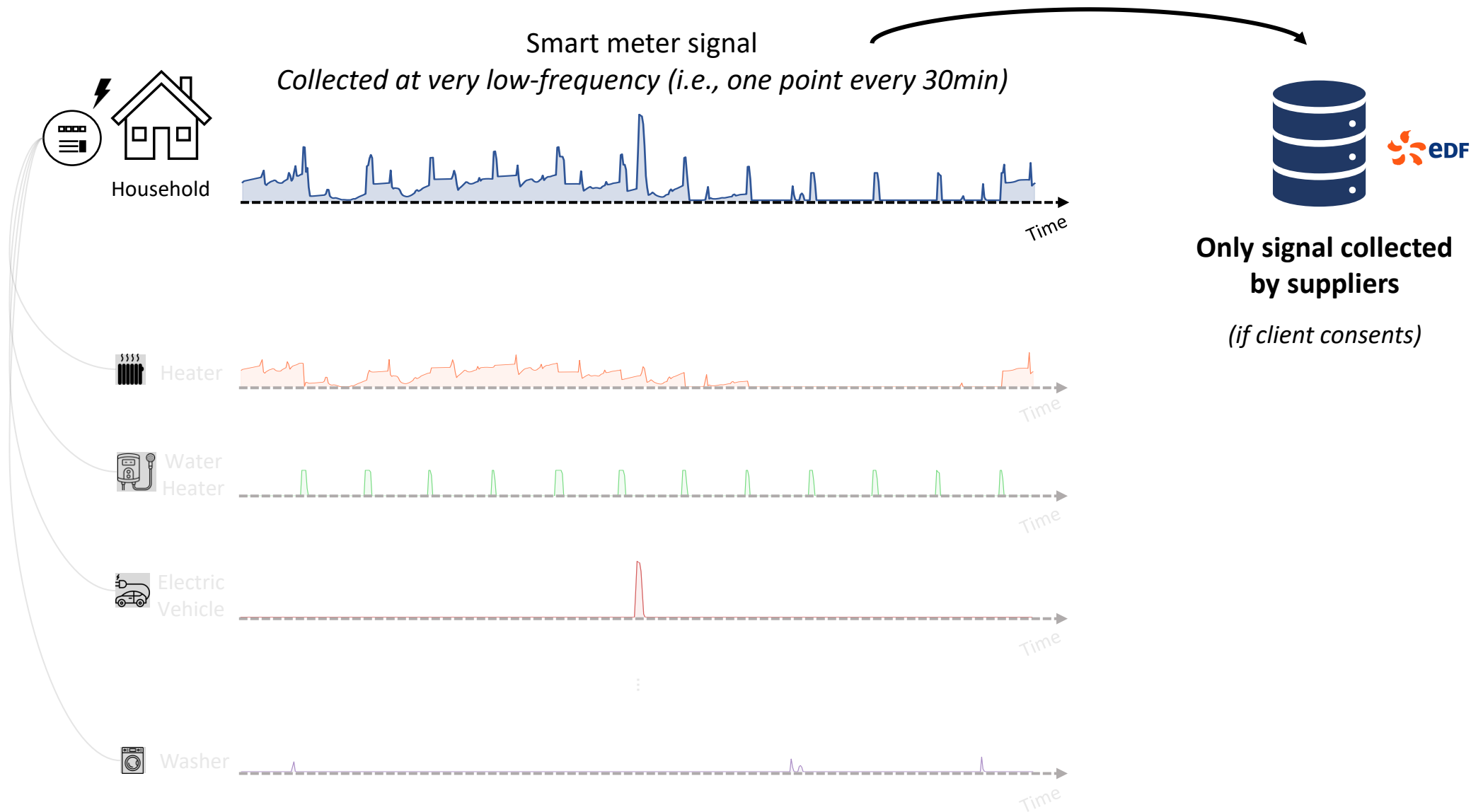
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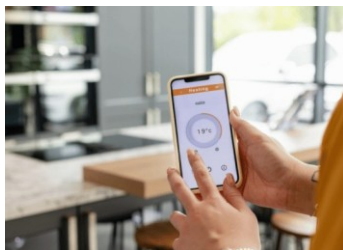
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Context: From Passive Energy Consumers to Active Players

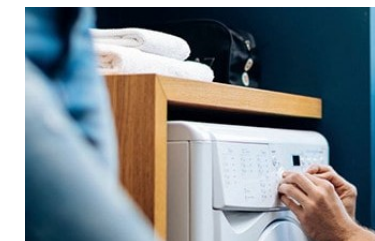
Consumers are **shifting** from **passive users** to **active participants**, increasingly willing to engage in the energy transition.



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

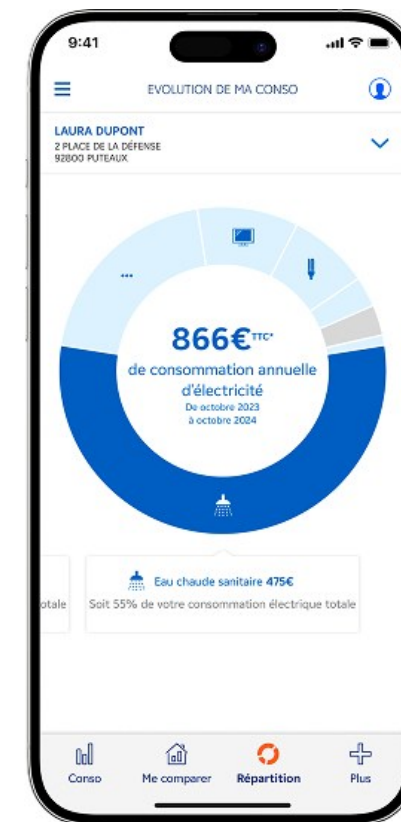
Background: EDF's monitoring solution (*Mon Suivi Conso*)

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 $\approx -70\%$**



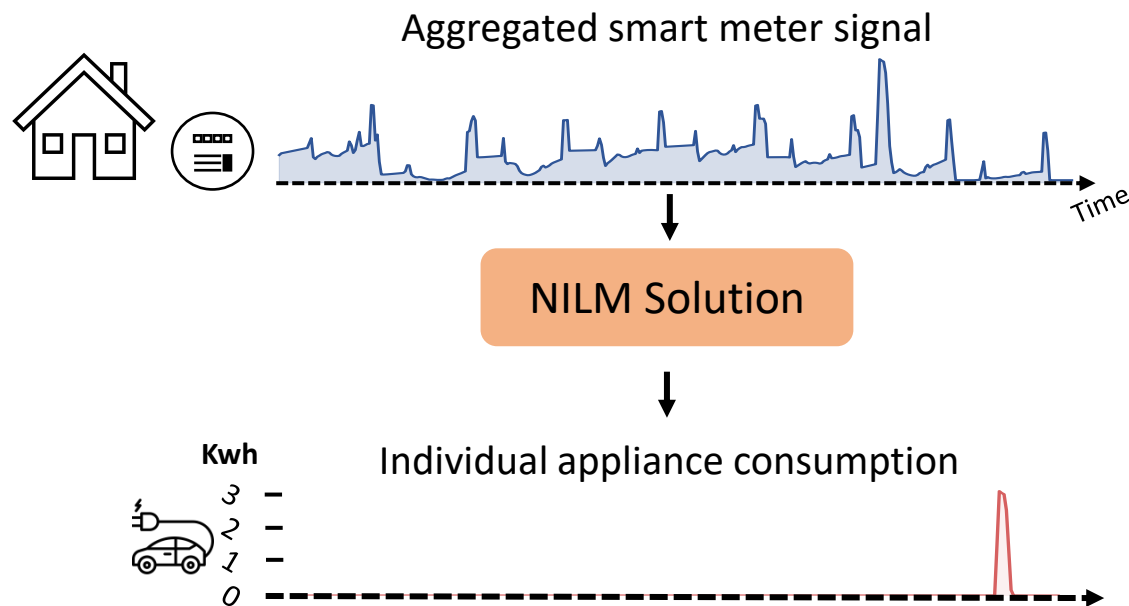
Room for improvement: Monthly estimation is **still coarse**, and users recently requested daily appliance-level insights



[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 Load Monitoring (NILM): estimates power consumption, operational patterns, and on/off state of individual appliances using only the total aggregated signal



Early research (1992)

Combinatorial Optimization
G. W. Hart ^[1]

ML Area (2010's)

Sparse Coding, HMM
Andrew Ng ^[2]

DL Area (2015-now)

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

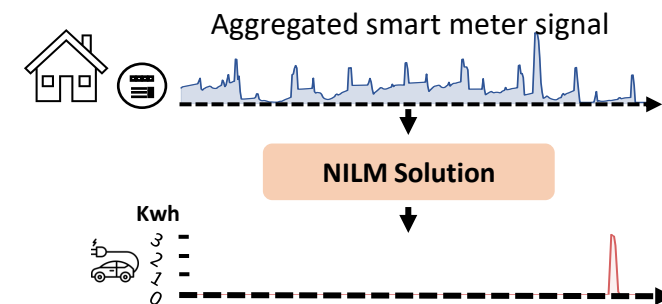
[3] Jack Kelly, Neural NILM, ACM BuildSys', 2015

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*

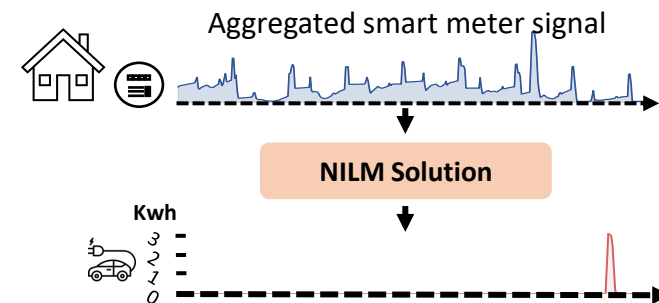


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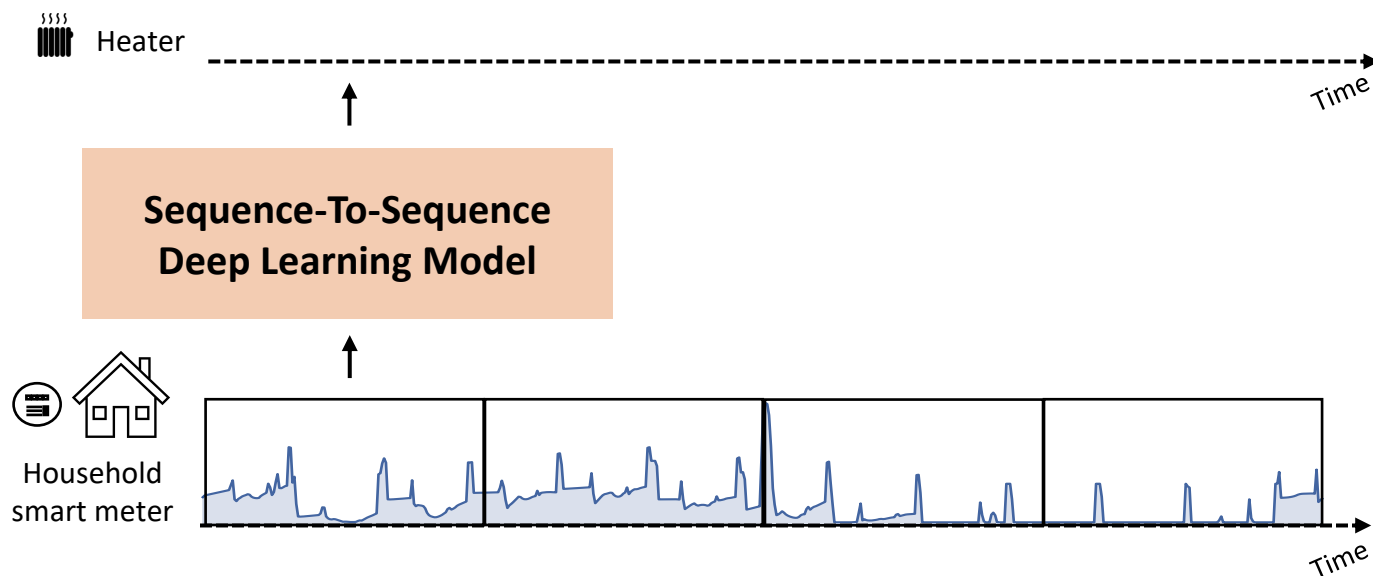
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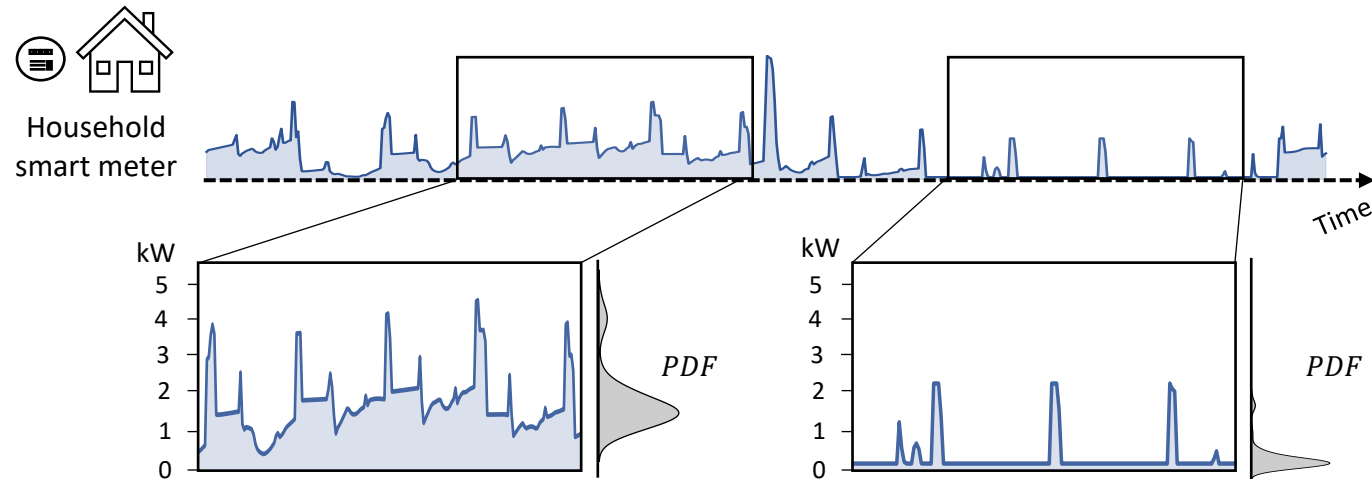


The *Sequence-To-Sequence* paradigm



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

*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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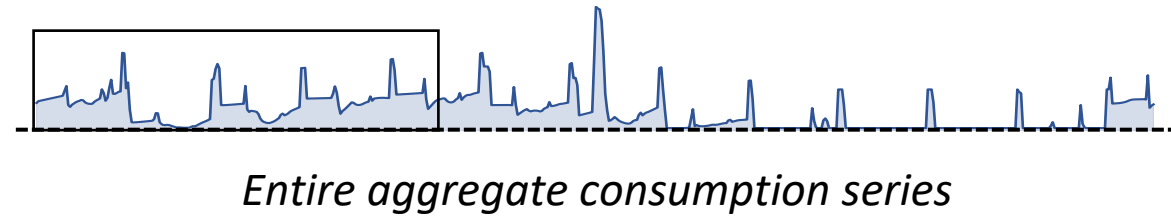
Solutions

✓ **NILMFormer**

✓ **Deployment in “*Mon Suivi Conso*”**

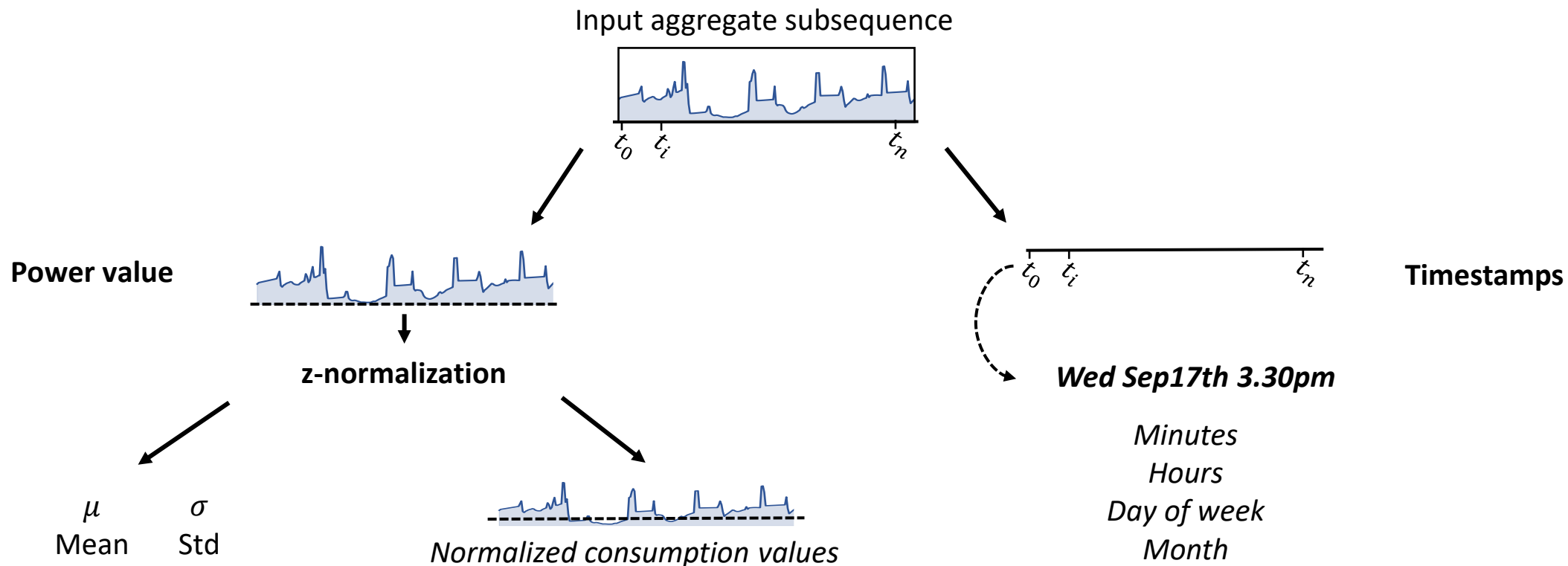
Proposed Approach: NILMFormer

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



Proposed Approach: NILMFormer

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1. *Intrinsic statistics*



2. *Shape*



3. *Timestamps information*

Proposed Approach: NILMFormer

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

I. Distinct encoding modules (*tokenization*)



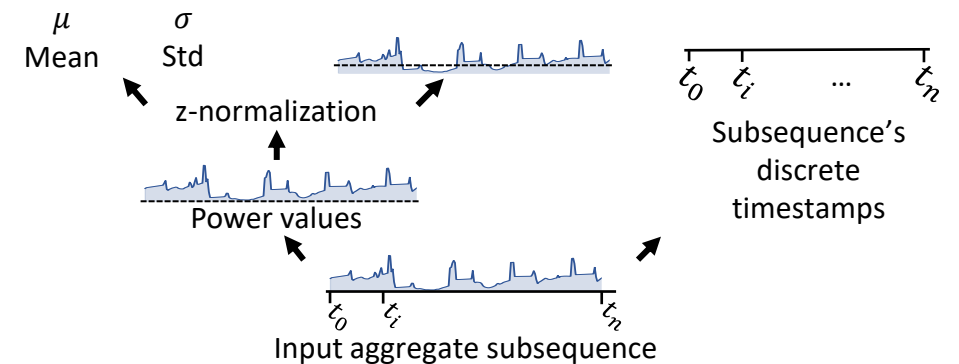
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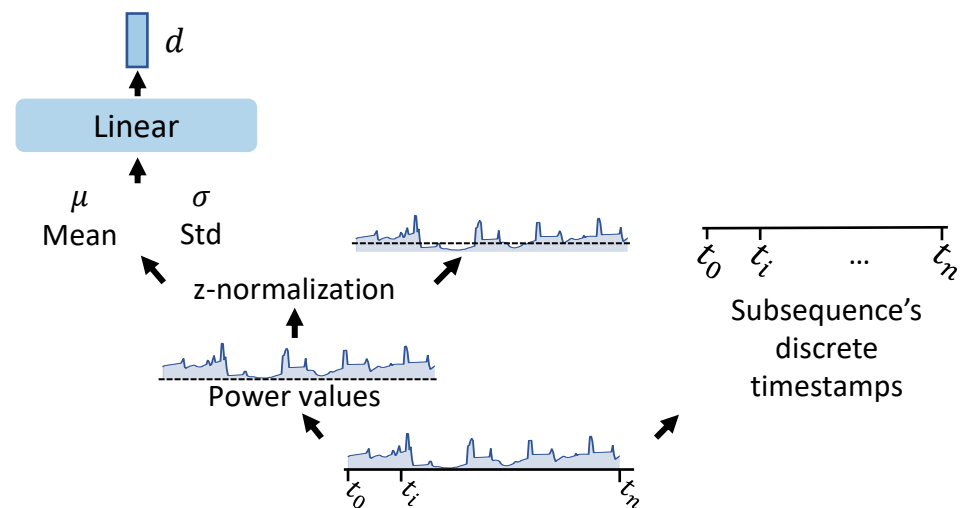
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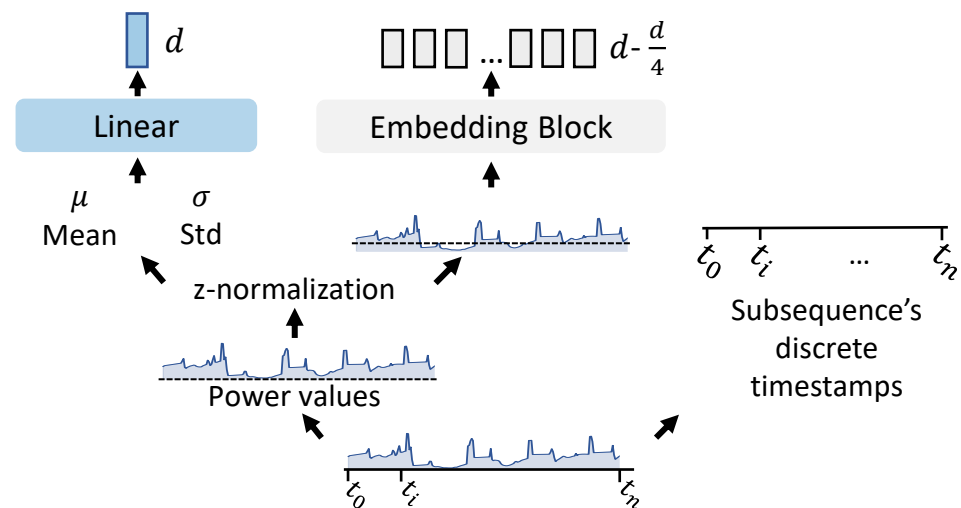
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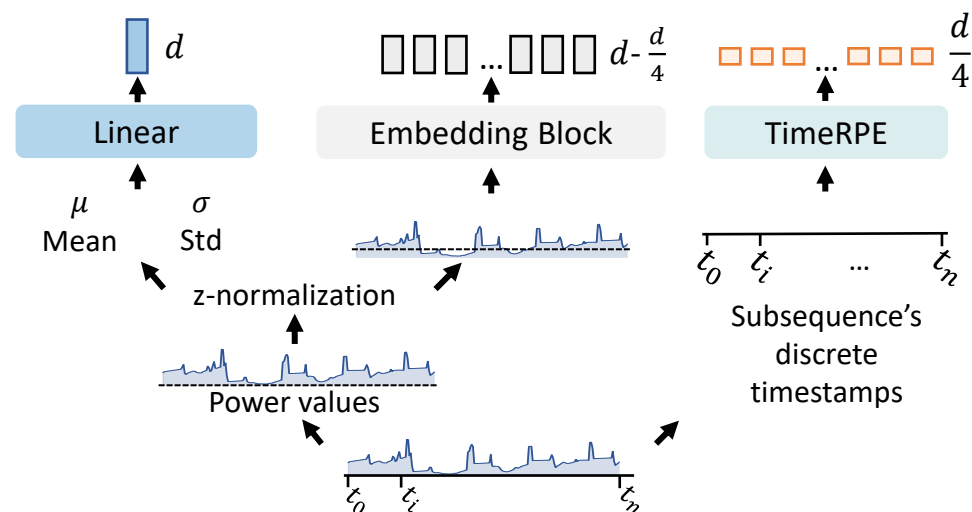
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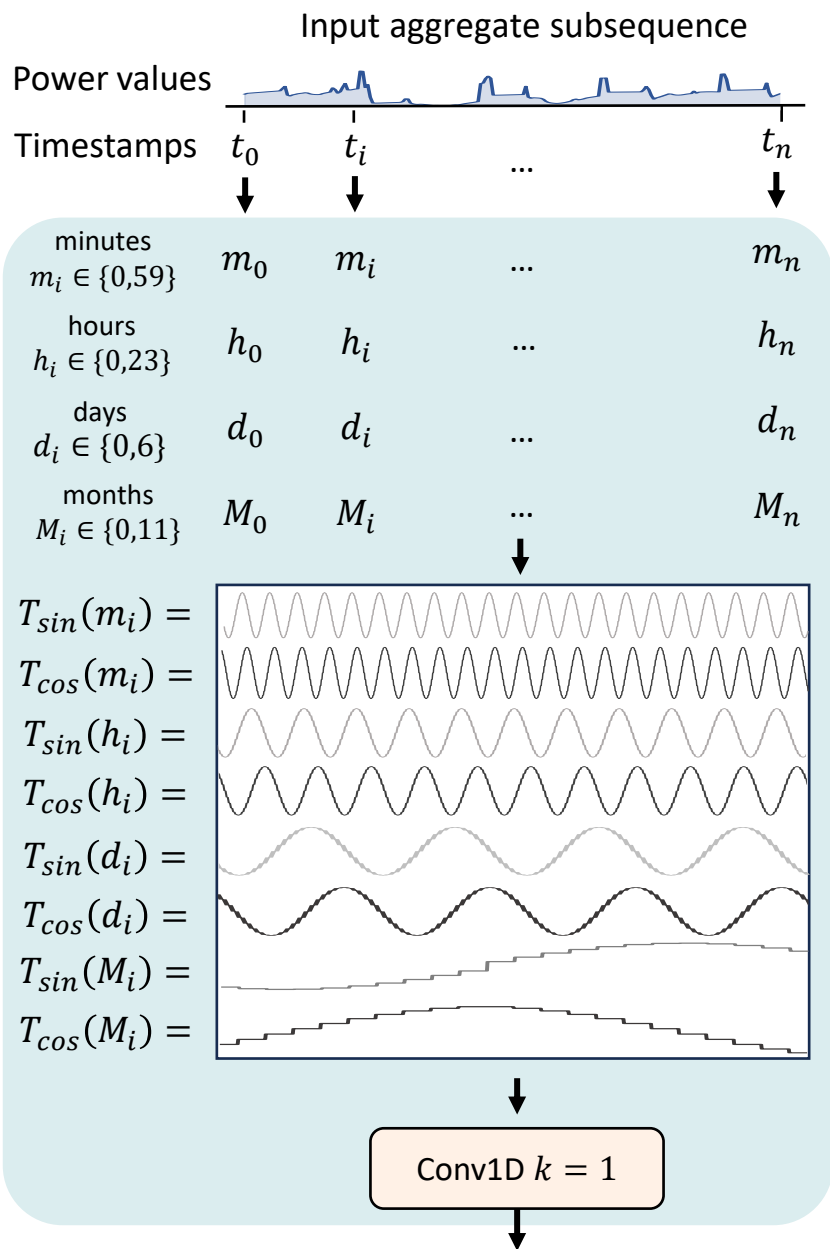
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NILMFormer
Non-Intrusive

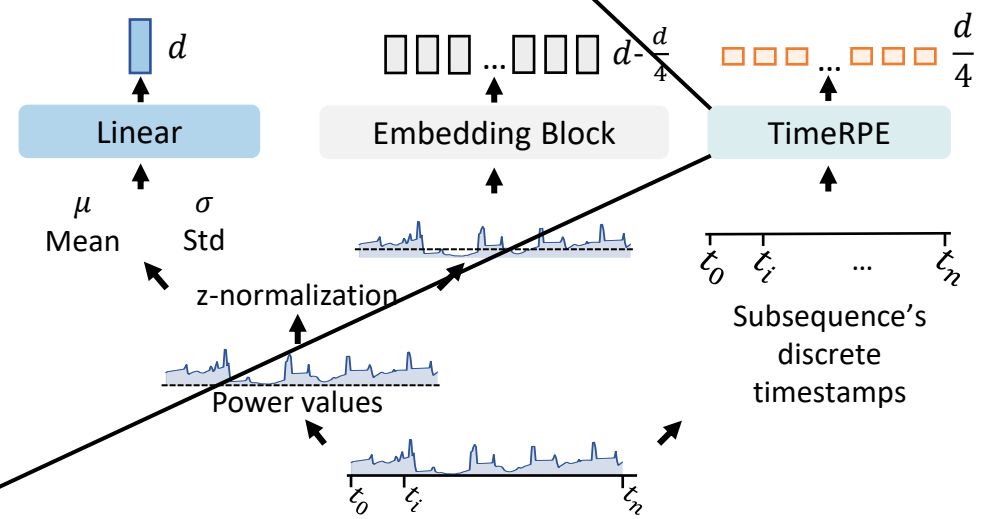
I. Distinct er



Time Related Positional Encoding



for



Proposed Approach: NILMFormer

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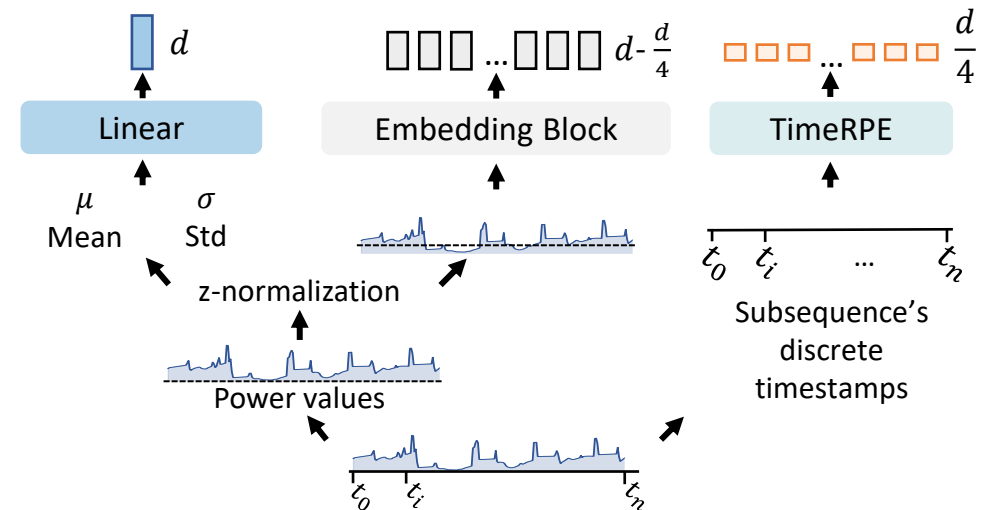
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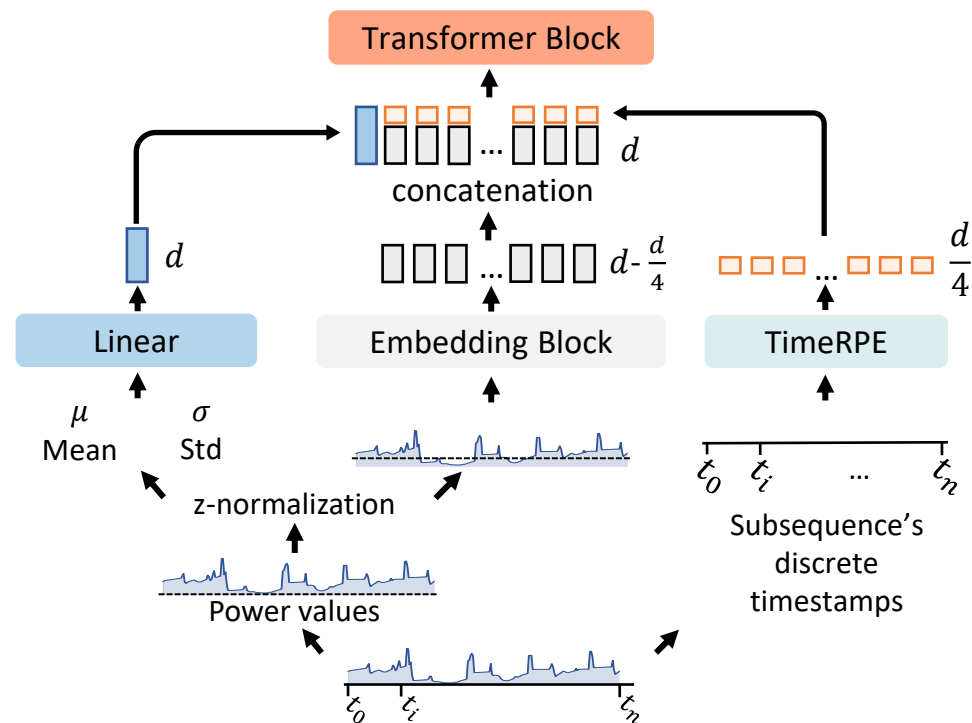


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II. Embedding parts concatenation



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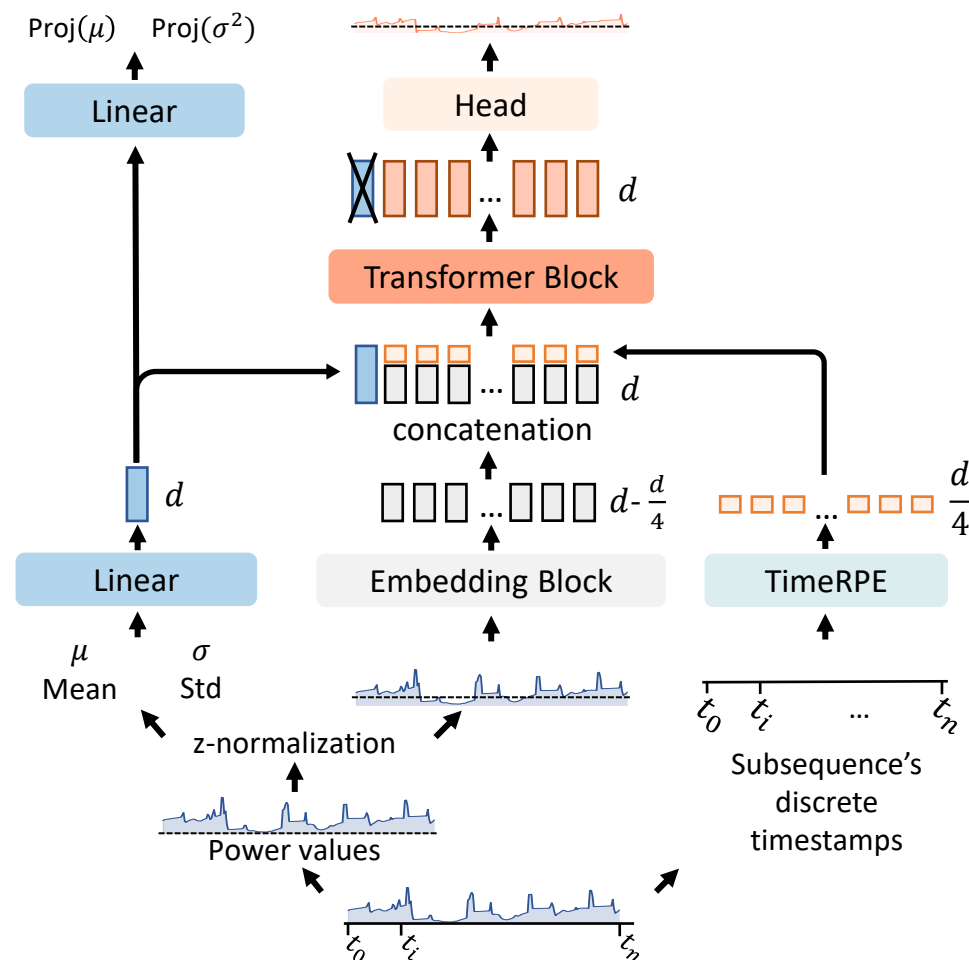
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II. Embedding parts concatenation

III. Subsequence's individual appliance power and statistics prediction



Proposed Approach: NILMFormer

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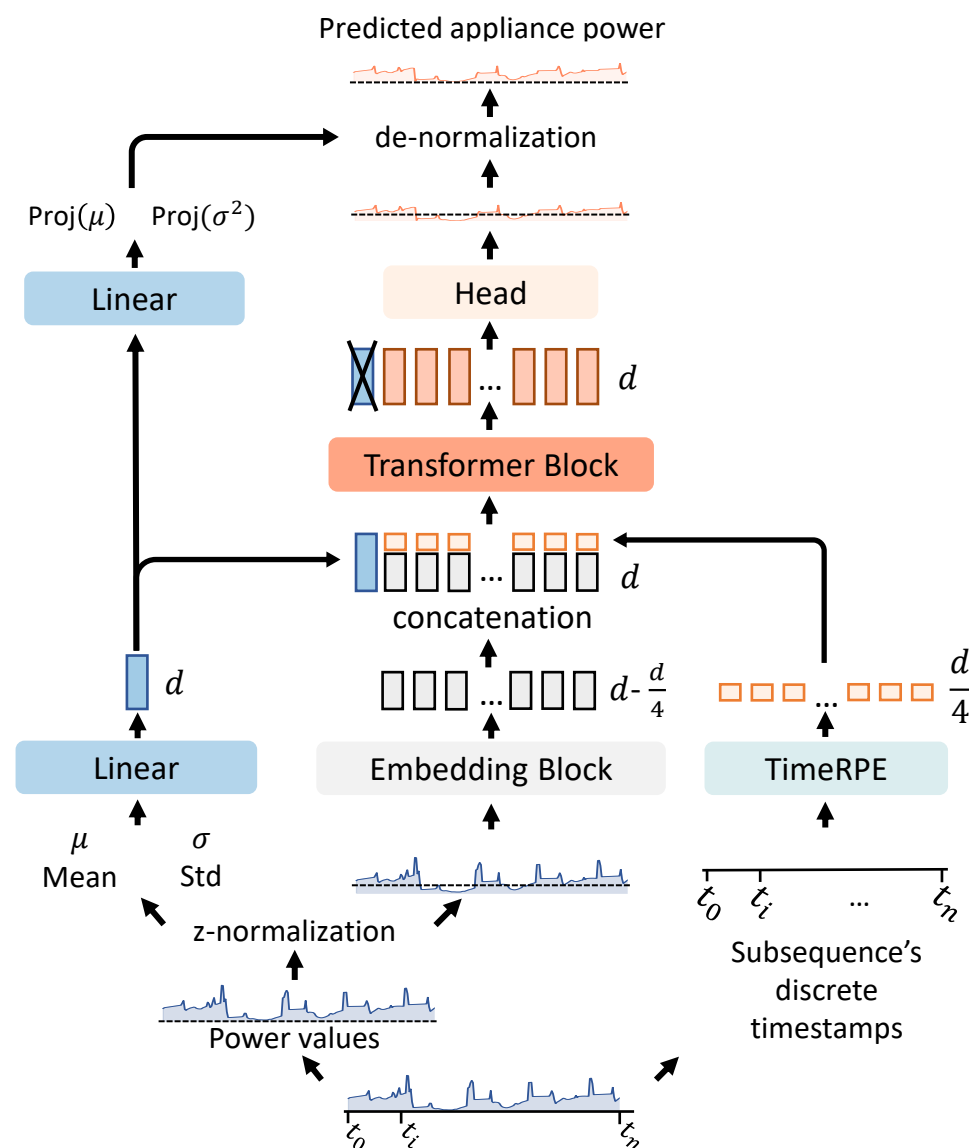


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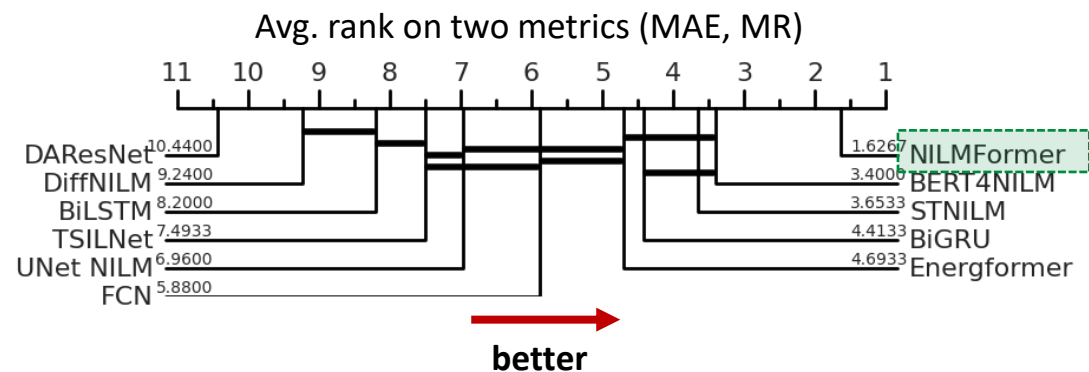
IV. Output de-normalization



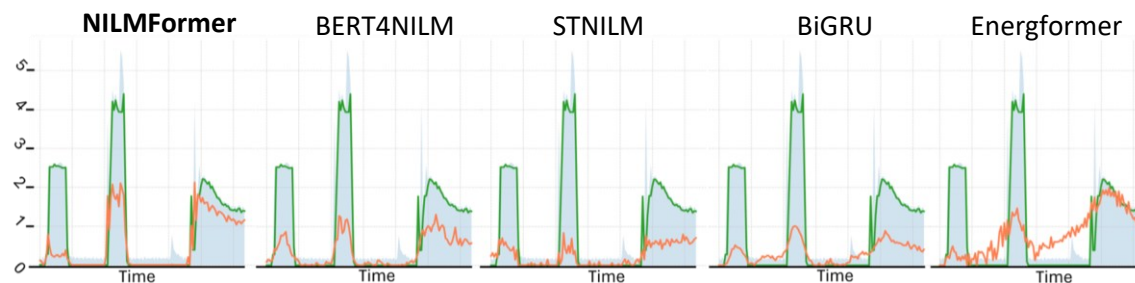
Results: Per-timestamp Energy Disaggregation

Performance comparison with 10 SotA deep-learning NILM baselines

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



≈ 20% increase

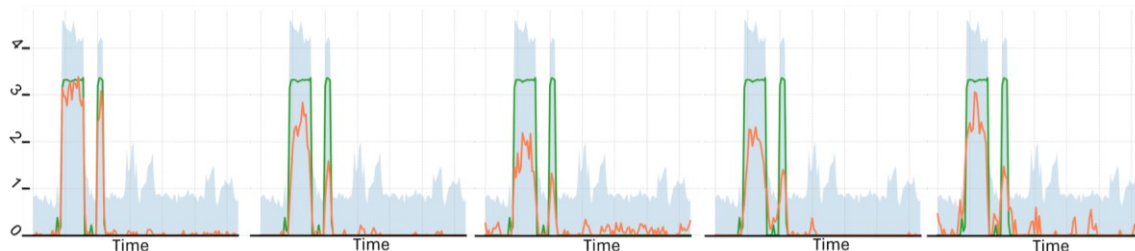


⊖ Household meter reading

— True appliance power

— Models prediction

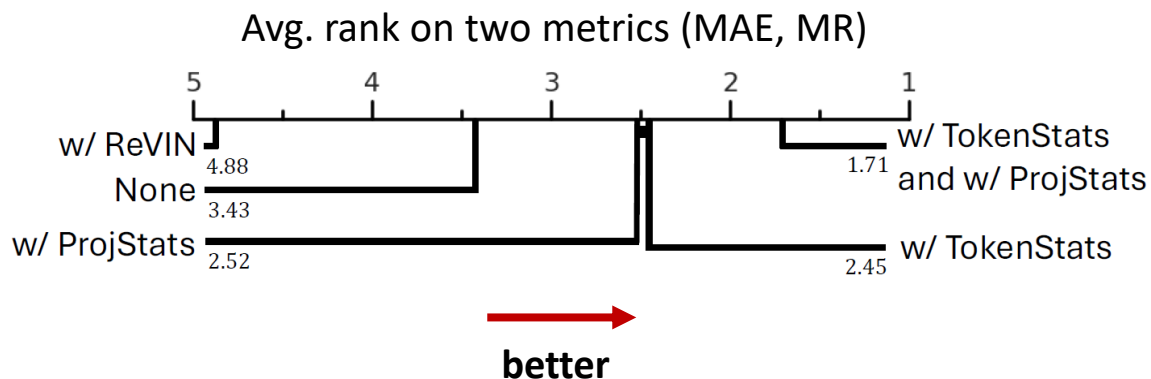
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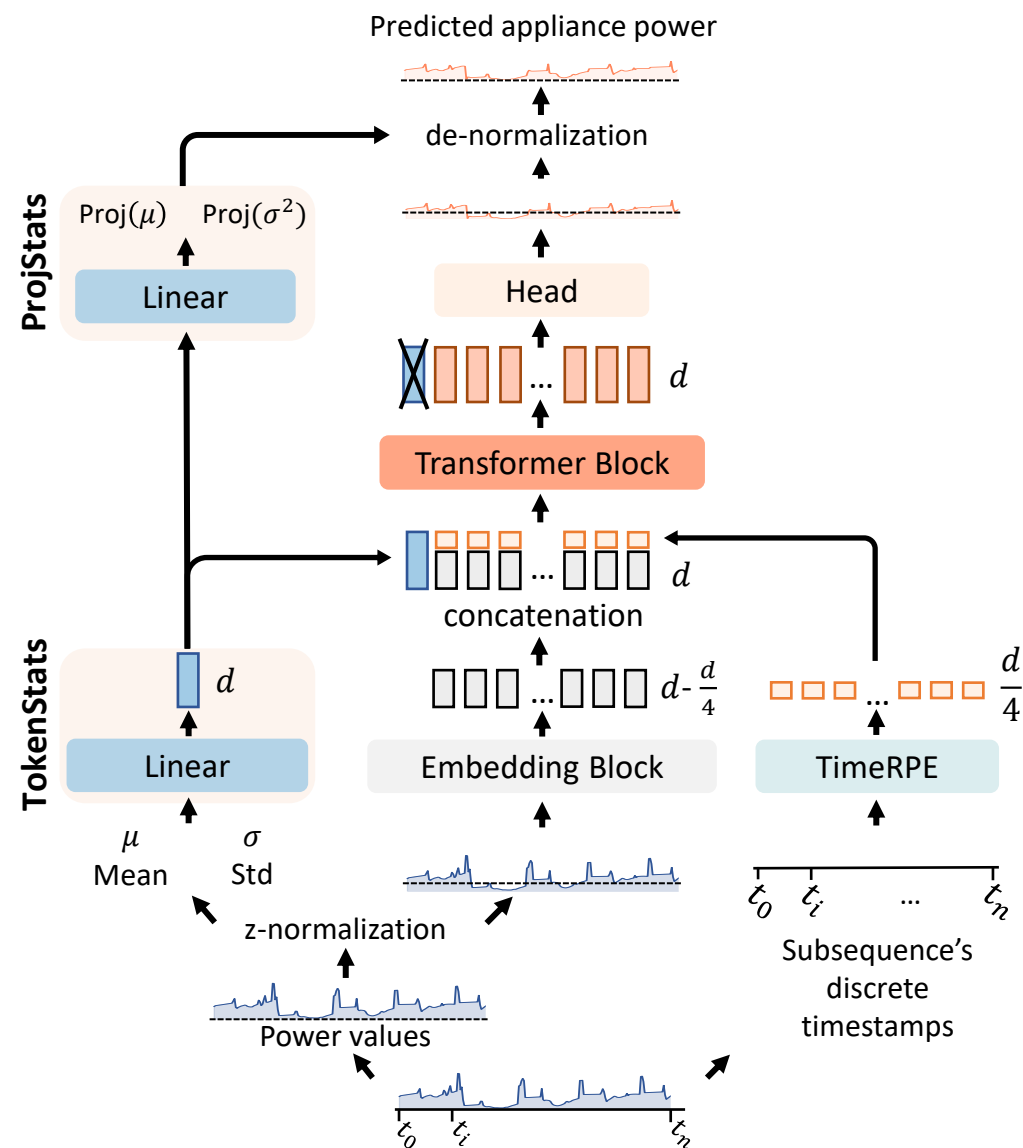
EDF datasets

Ablation Study

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

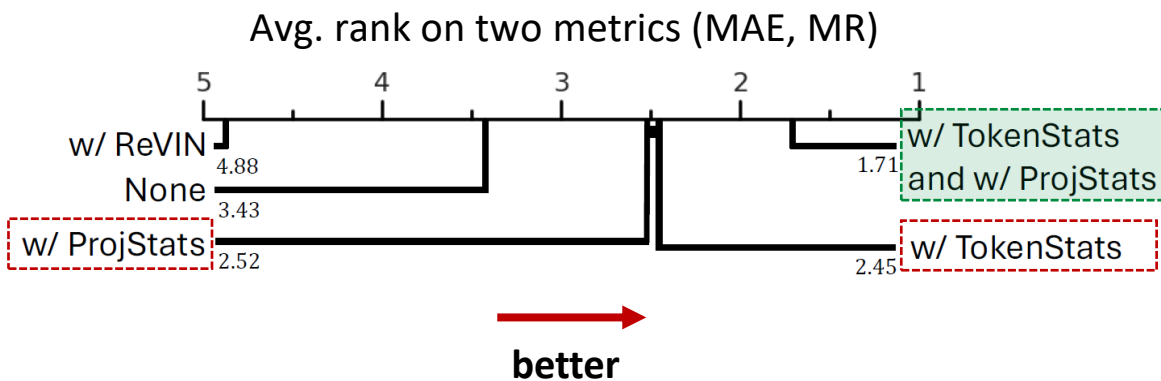


Averaged results over 4 datasets and 14 appliances disaggregation scenarios

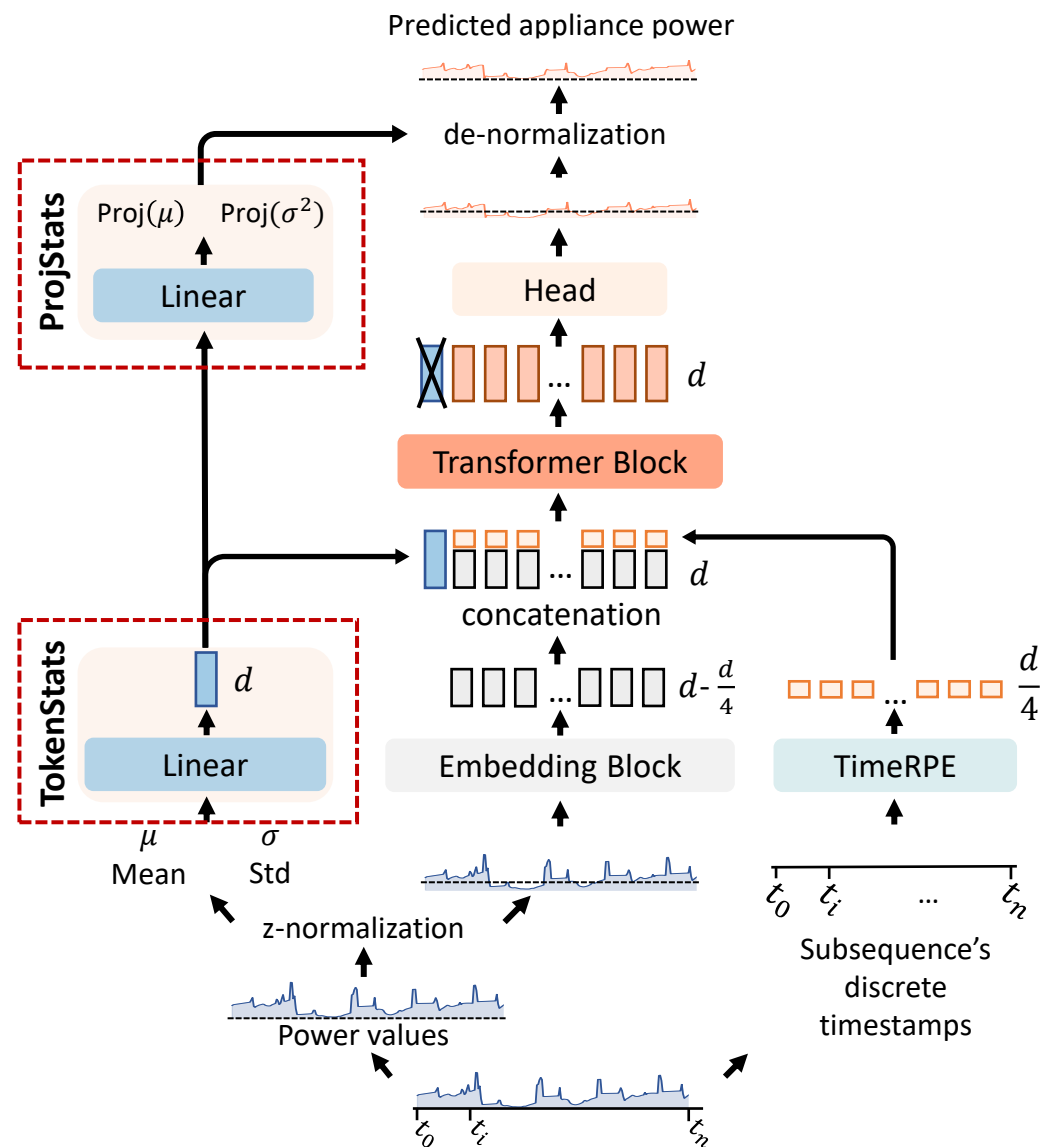


Ablation Study

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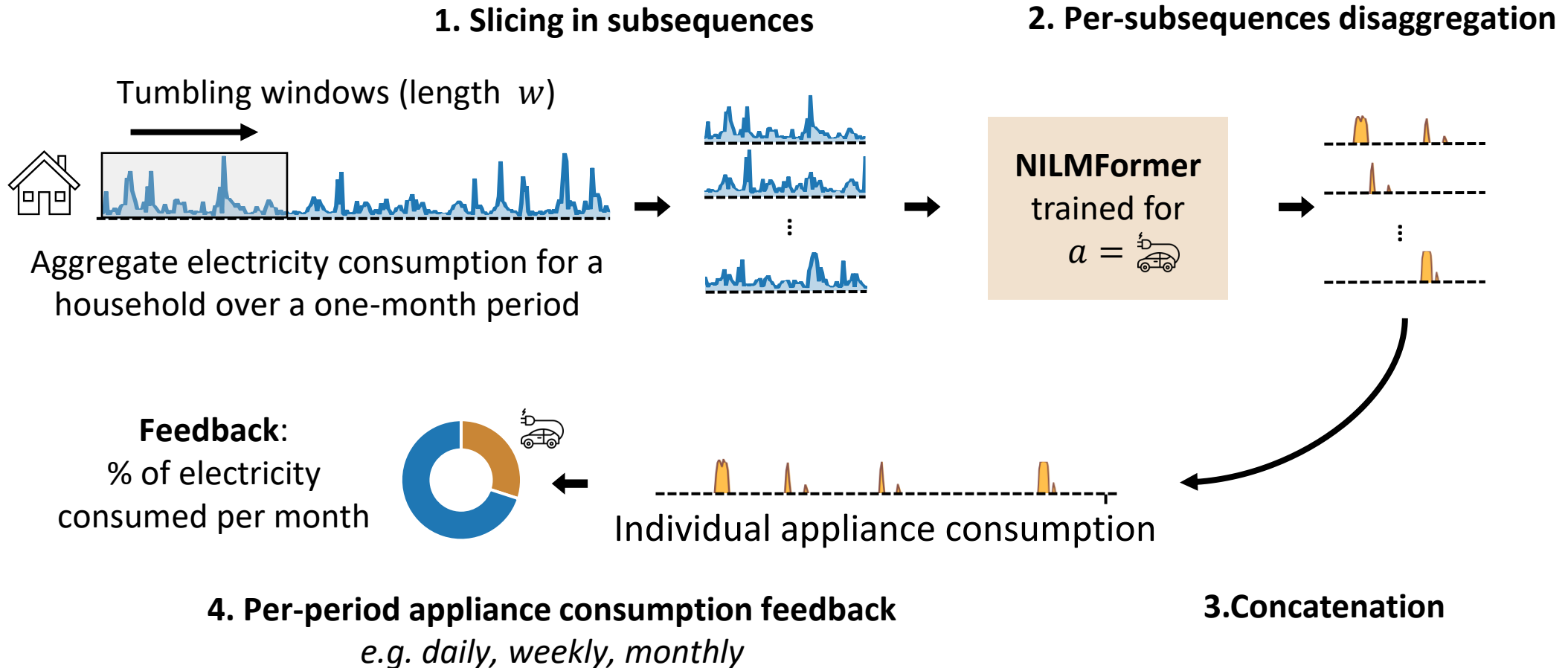


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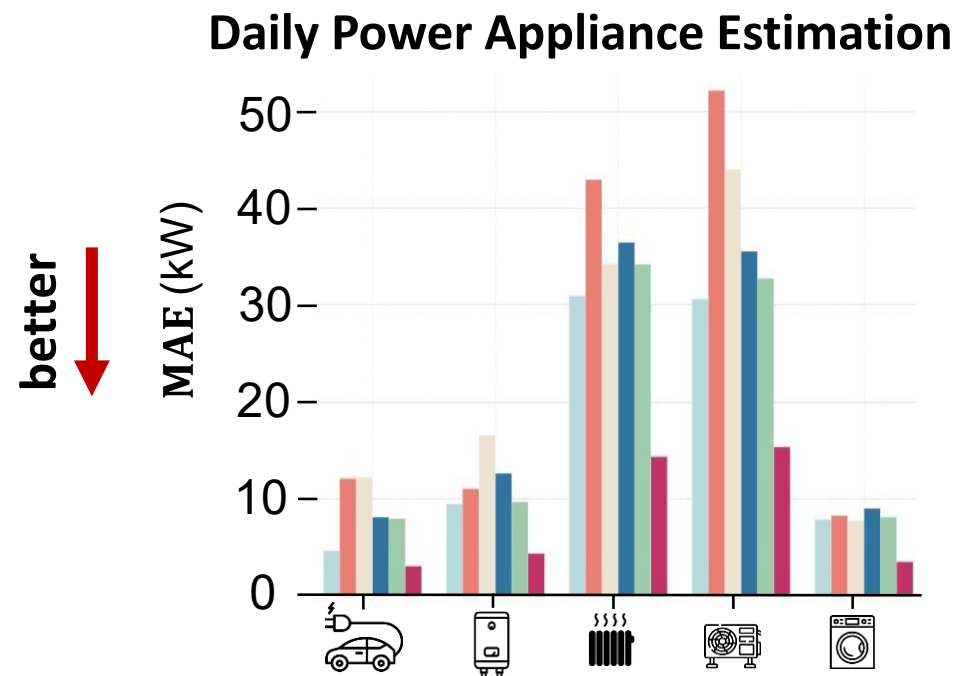
Deployed Solution: NILMFormer for Detailed Appliance Feedback

A Straightforward Framework for delivering Per-Period Energy Estimation

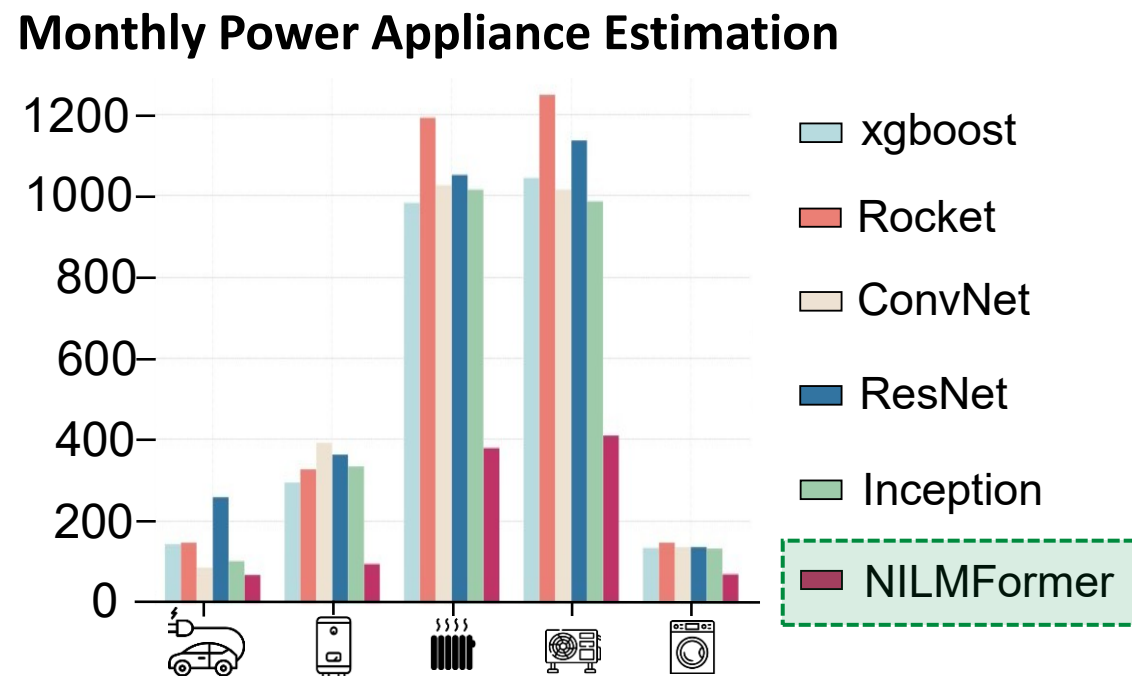


Deployed Solution: NILMFormer for Detailed Appliance Feedback

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



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

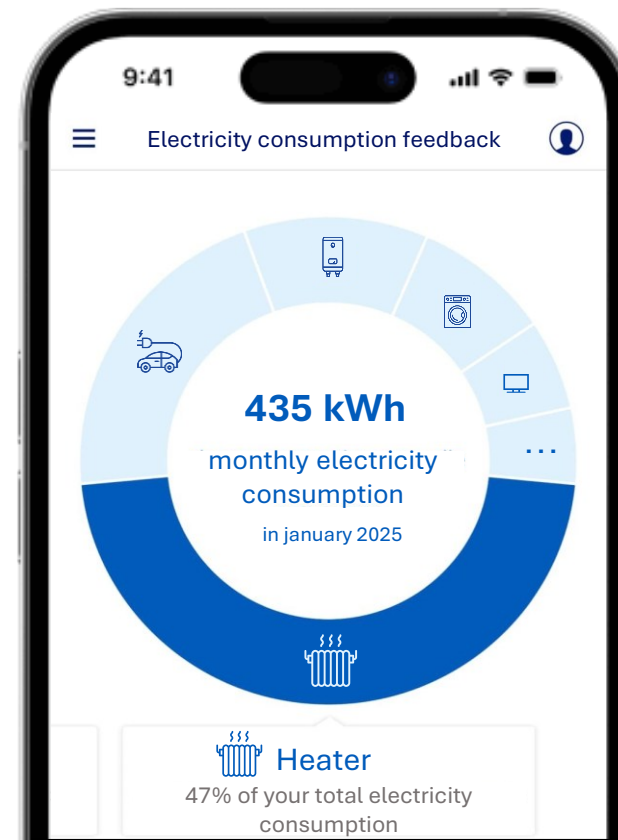


Achieves up to **151% lower error** than the 2nd-best baseline (Inception)

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?

