Pattern Recognition Lab
DIEHL Metering
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Heat Demand Forecasting with Multi-Resolutional Representation of Heterogeneous Temporal Ensemble

Neurips 2022 - Tackling Climate Change with Machine Learning

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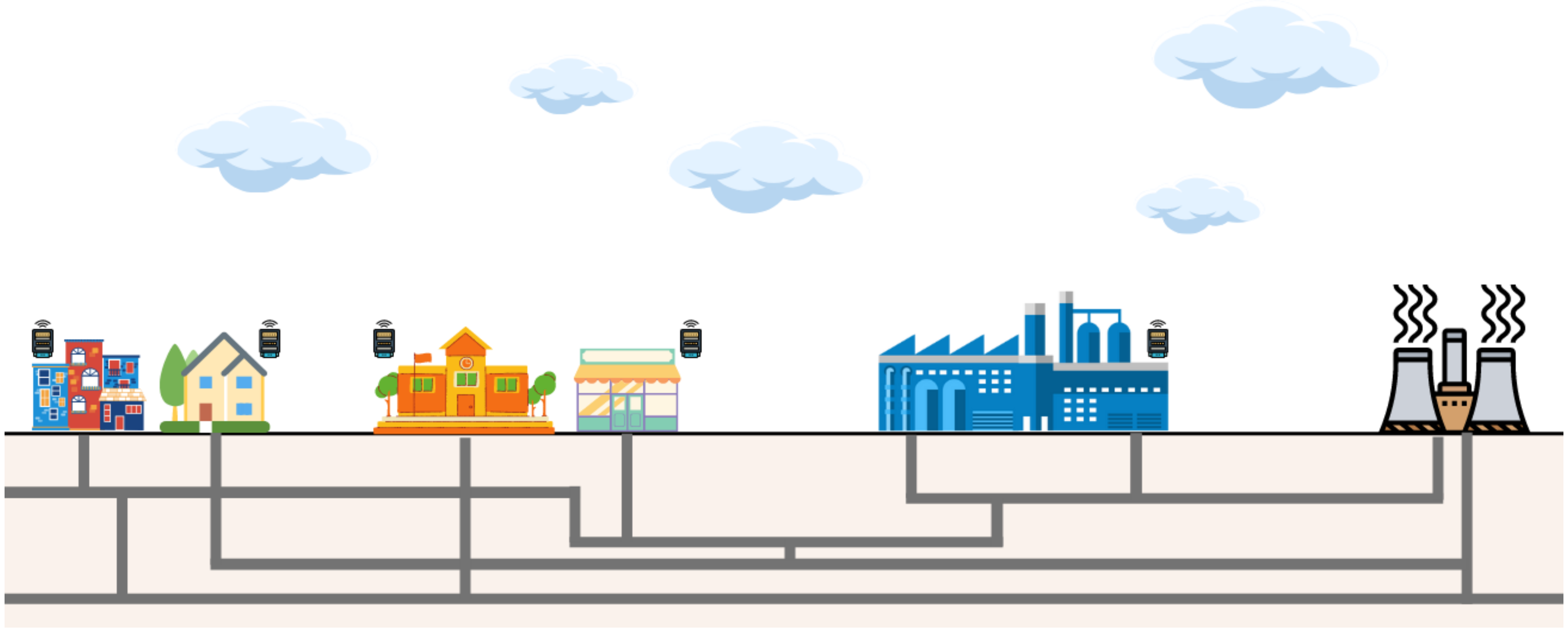
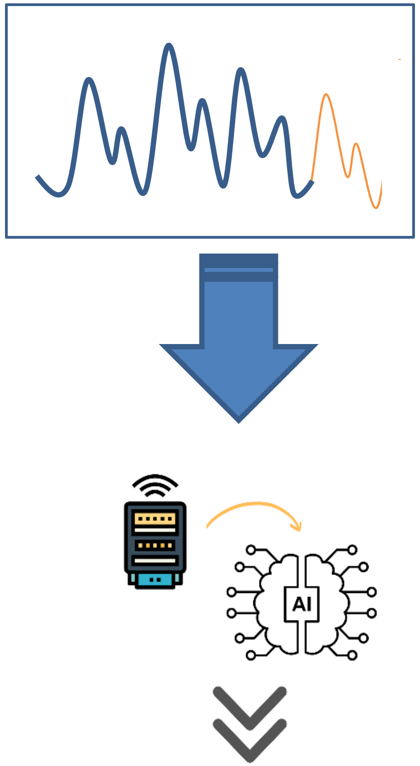
Outline

- Motivation
- Introduction
- Methodology
- Experimental setup
- Results and discussion
- Conclusion

Motivation



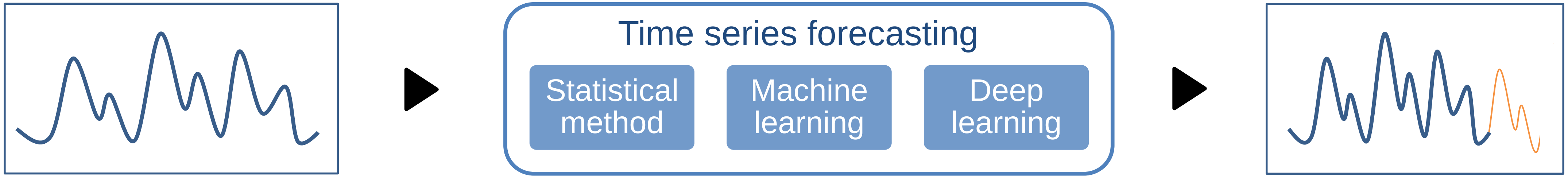


optimized heat supply

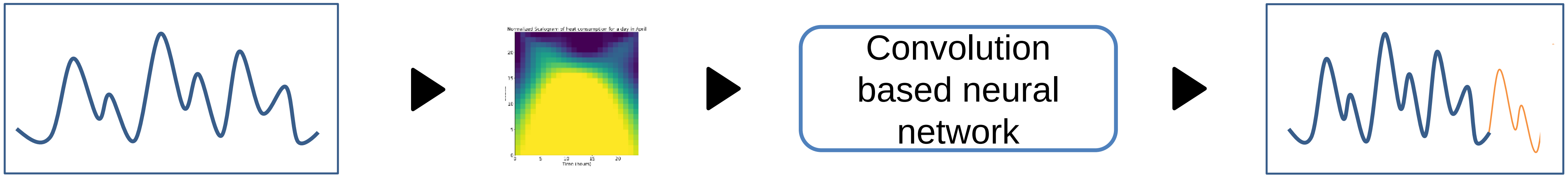
Reduce carbon footprint through supply demand optimization
Heat demand forecasting

Introduction

Heat Demand Forecasting



Proposed framework:



Methodology

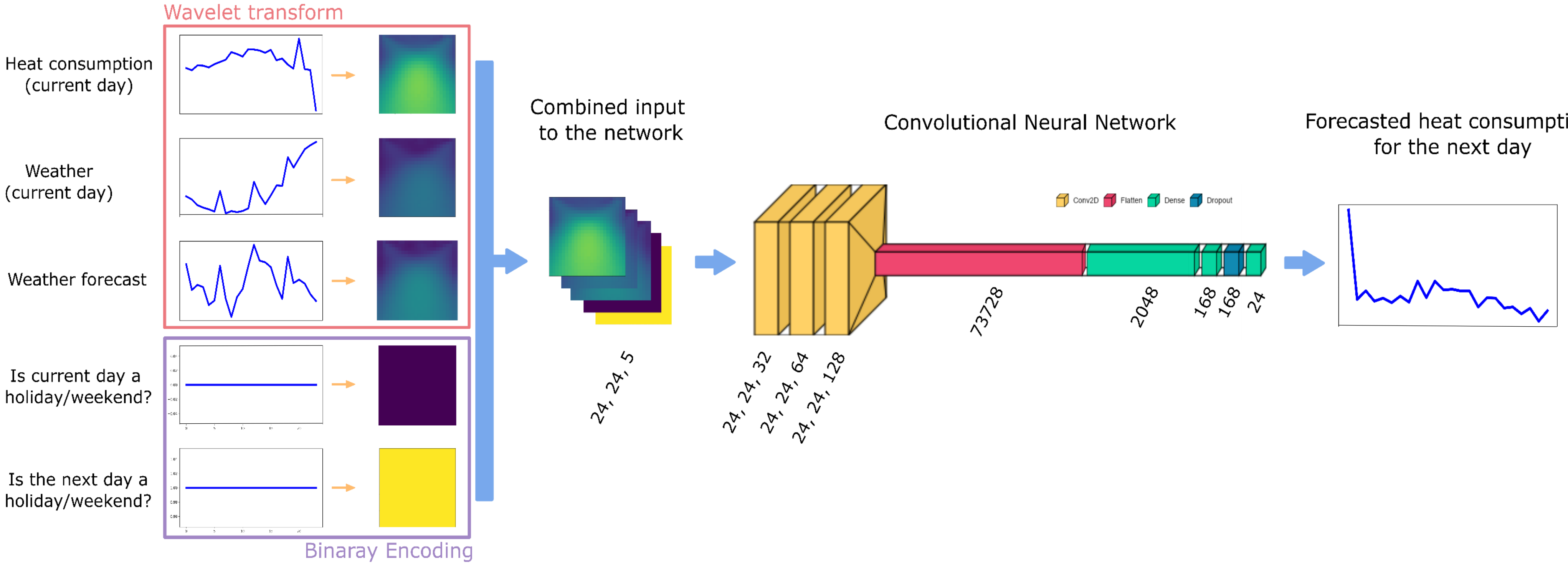


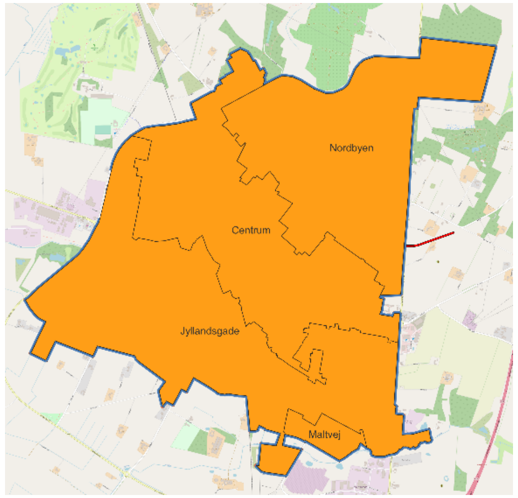
Illustration of the framework architecture

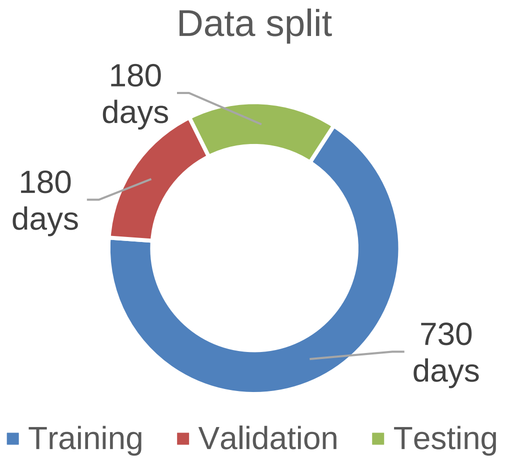
Non-linearity: ReLU, Leaky-ReLU

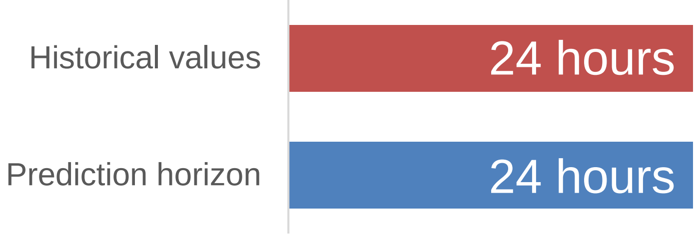
Optimizer: ADAM

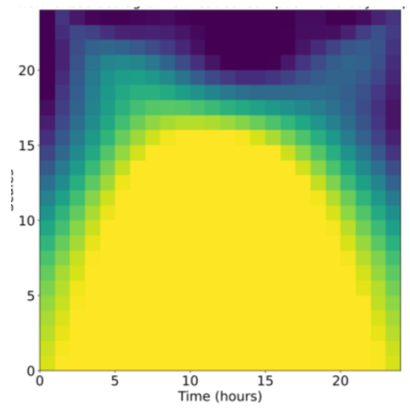
Loss: MSE

Experimental Setup







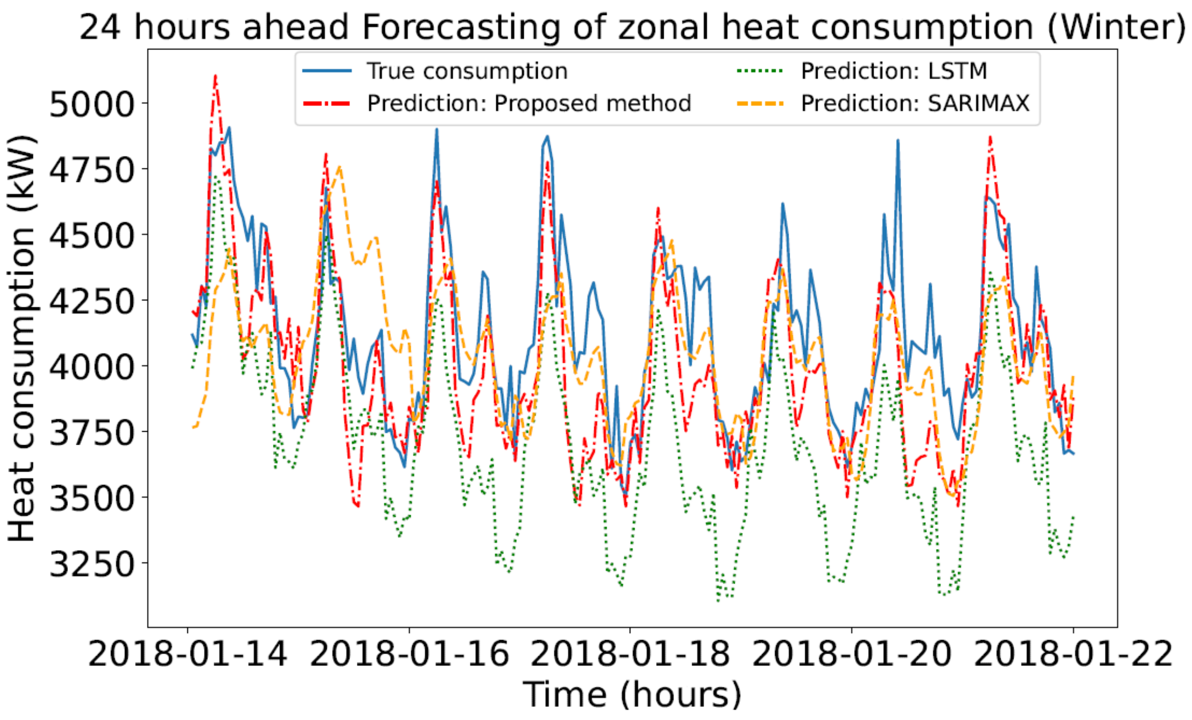


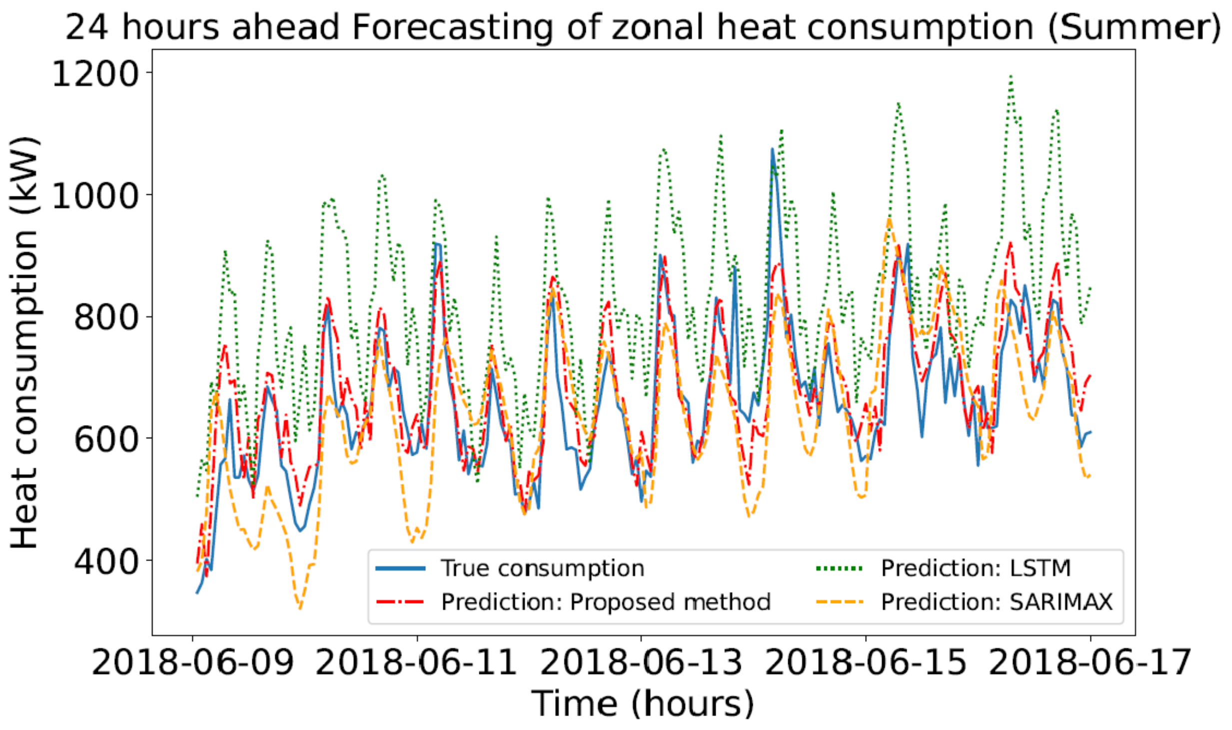
- 5-channel input
- Number of scales: 24
- Batch size: 7

Inputs	Historical heat consumption
	Historical weather data
	Forecasted weather data
	Holiday information of current day
	Holiday information for forecasting day

Results

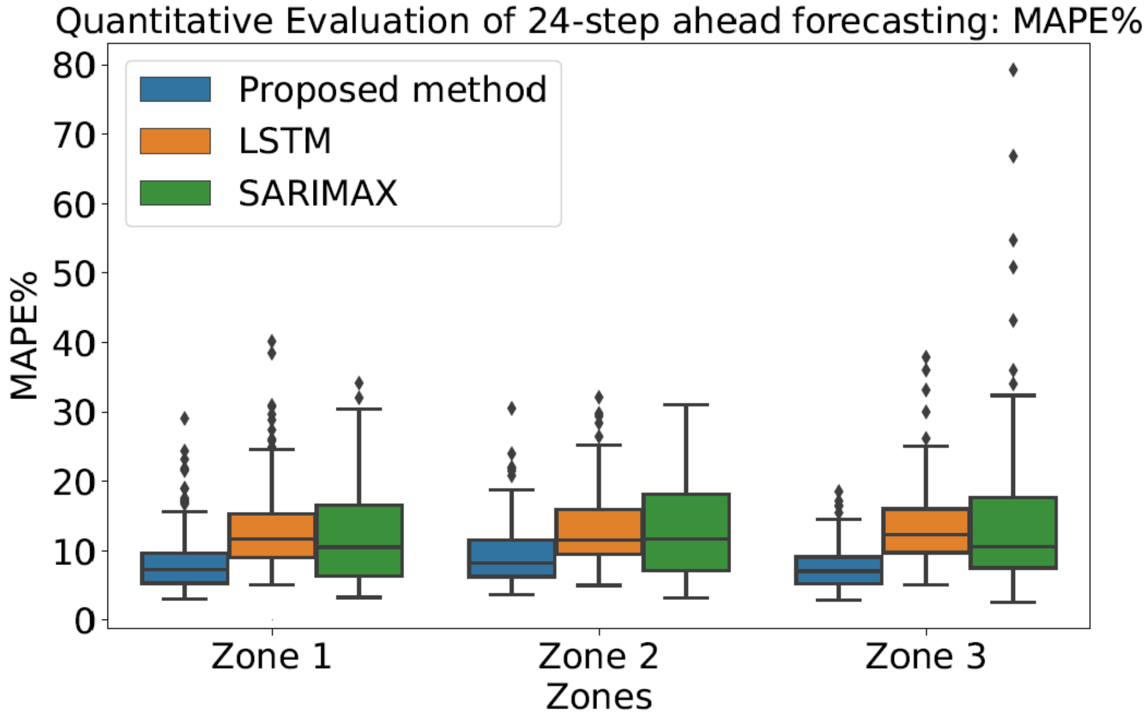
- Comparison with LSTM, SARIMAX

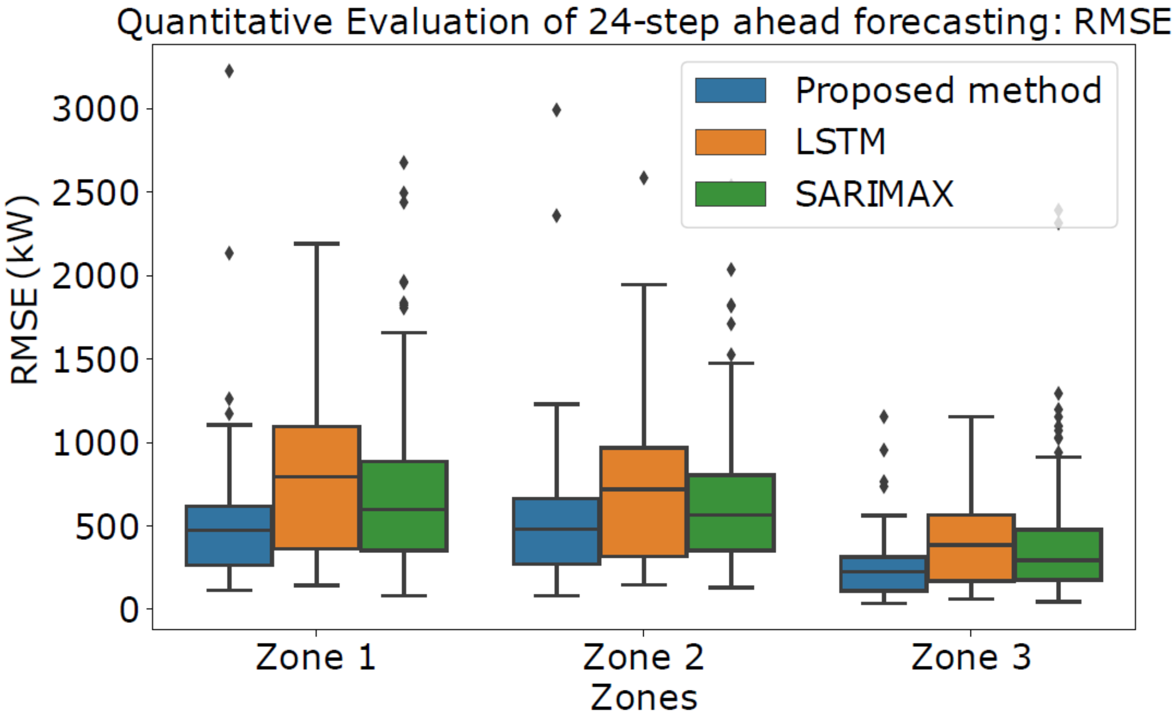




Results

- Comparison with LSTM, SARIMAX





Conclusion

- A multi-resolution analysis-based framework for multi-step ahead forecasting
- Leverage information from the time and frequency domain
- Capability to combine Image-like representations of endogenous data (consumption) and exogenous factors
- Better performance in comparison with baseline LSTM and SARIMAX method with lower forecasting error metrics
- Robustness across climatic seasons and geographic zones.

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