



Time Series Challenge (Summer 2024) **Heat and water Demand forecasting**

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Agenda

Pattern Recognition Lab



- **01** Motivation
- **02** Introduction
- 03 Dataset Overview
- 04 Data Preprocessing
- **05** Architecture
- 06 Model Evaluation
- 06 Conclusion

Motivation











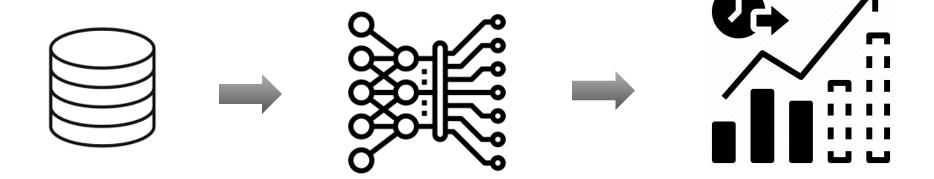
Introduction

Time Series Challenge





Downstream Task:



Historical Heat and Water data

Forecasting model

Prediction for next 24 hours

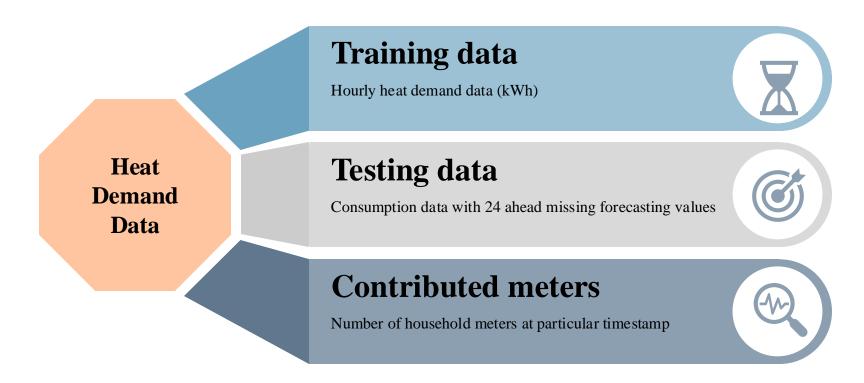
Dataset Overview

Time Series Challenge





Heat Demand Data for urban population



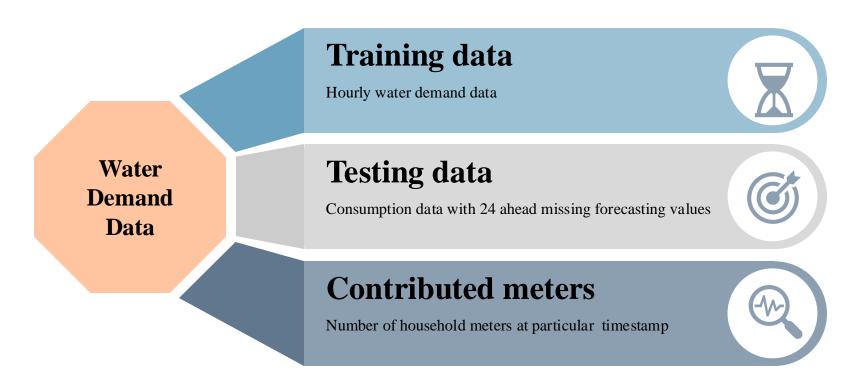
Dataset Overview

Time Series Challenge





Water Demand Data for urban and rural population



Dataset Overview





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Weather Data:

• Timestamp, Temperature, Feels like, Weather Description, Latitude, Longitude..... etc.



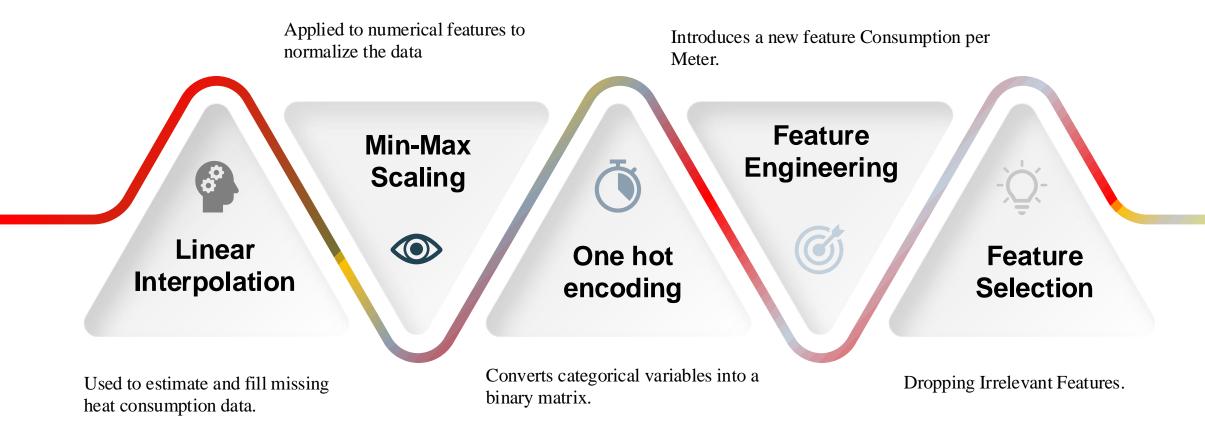
Data Pre-Processing

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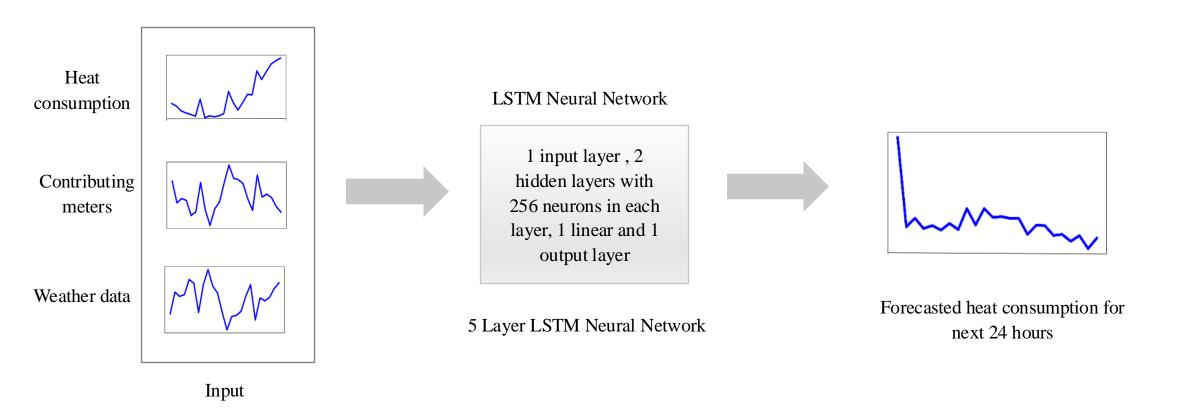
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Architecture: Heat Demand Forecasting



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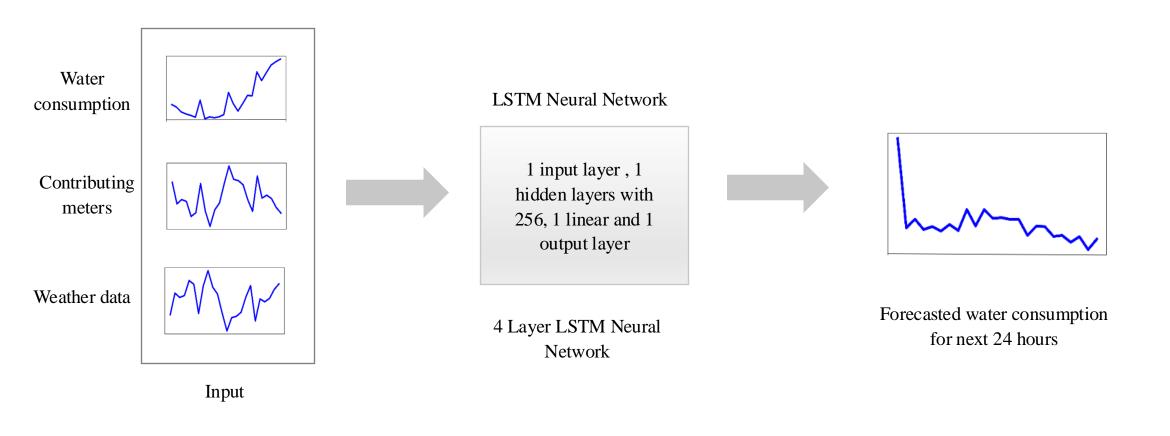
Optimizer: Adam Loss: MSE Batch size: 32 Learning rate: 0.001

Architecture: Water Demand Forecasting (Urban)





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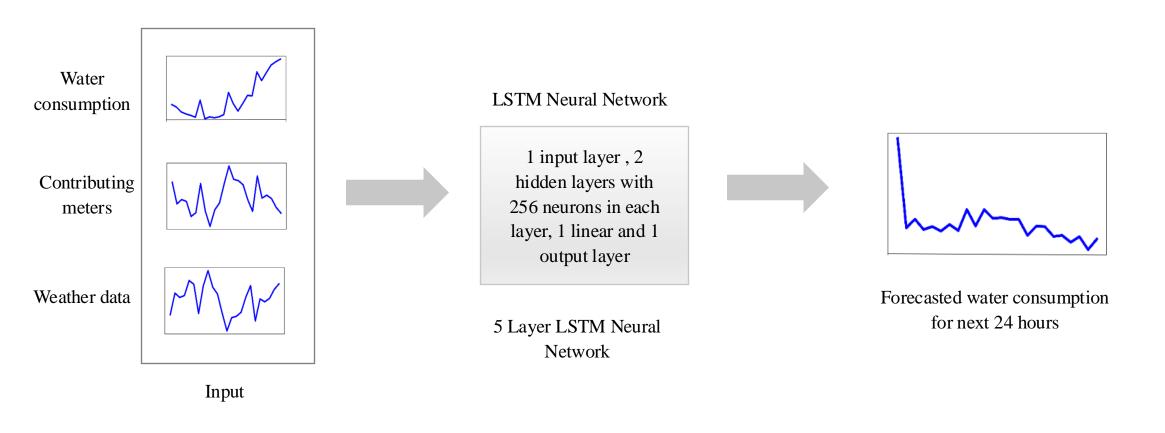
Optimizer: RMS Loss: MSE Batch size: 32 Learning rate: 0.0006

Architecture: Water Demand Forecasting (Rural)





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Optimizer: Adam Loss: MSE Batch size: 32 Learning rate: 0.01





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Evaluation Metrics:

• Mean Absolute Error (MAE) and MAPE were used to evaluate model performance.

Data/Metrics	MAE	MAPE (%)
Heat DMA	177.739	0.0653
Water DMA 1	1.604	0.137
Water DMA 2	0.489	0.221

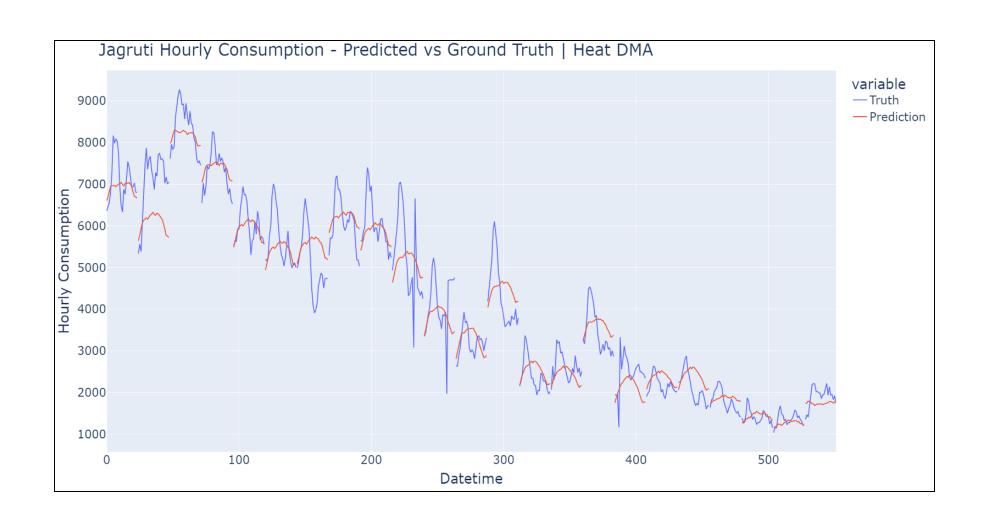
Data/Metrics	MAE	MAPE
Heat DMA	425.9	0.112
Water DMA 1	11.529	1.151
Water DMA 2	0.501	0.191

Deep Learning Based Forecasting Model from the lab

Deep Learning Based Forecasting Model obtained by me

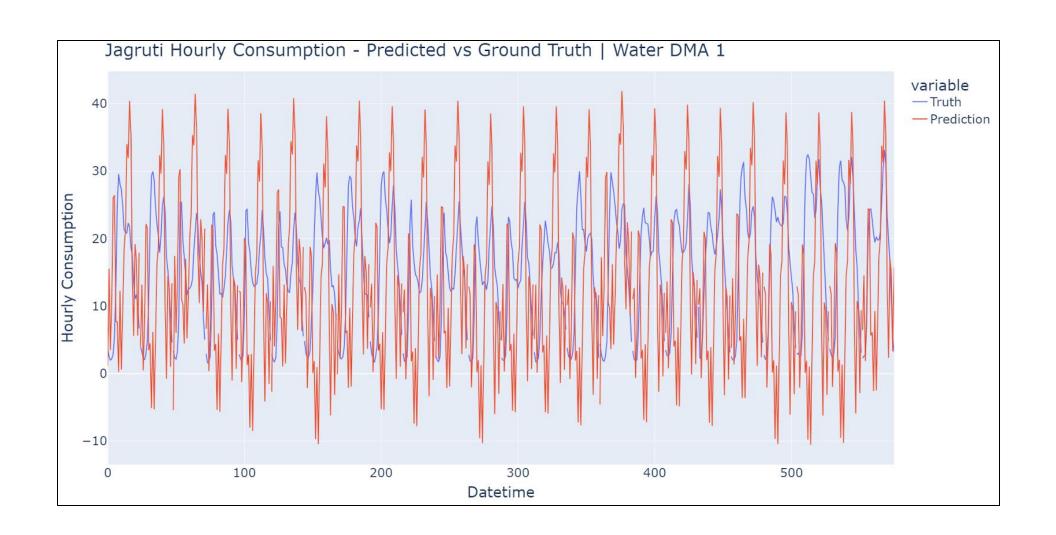






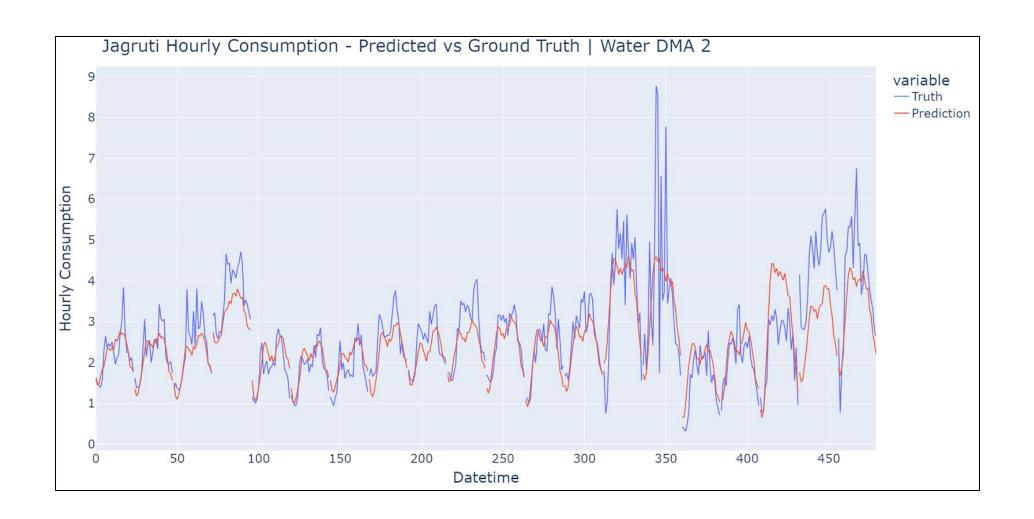












Conclusion

Heat and Water Demand Forecasting

• LSTM models are highly effective for forecasting heat and water demand due to their ability to capture temporal and non-linear patterns in time series data.

• I STM outperform traditional methods but require more data, computational power, and careful tuning.

Data/Metrics	MAE	MAPE (%)
Heat DMA	177.739	0.0653
Water DMA 1	1.604	0.137
Water DMA 2	0.489	0.221





DMA	RMSE	MAPE	MAE
Heat	219.406	0.0653	177.739
Water 1	2.013	0.137	1.604
Water 2	0.641	0.221	0.489

Table: Deep Learning Based Forecasting Model from the lab

Data/Metrics	MAE	MAPE (%)	RMSE
Heat DMA	368.01	9.43	535.12
Water DMA 1	11.52	115.17	14.27
Water DMA 2	0.50	19.19	0.73

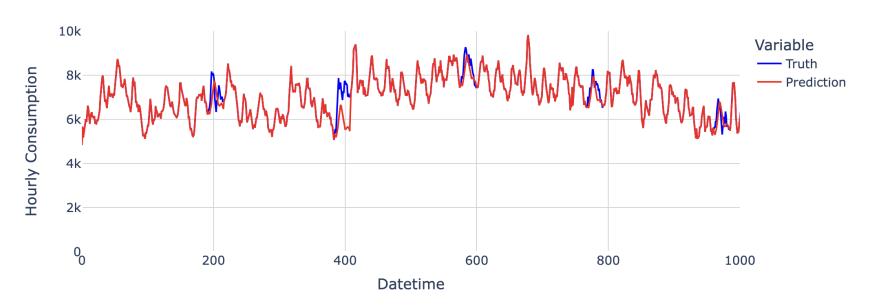
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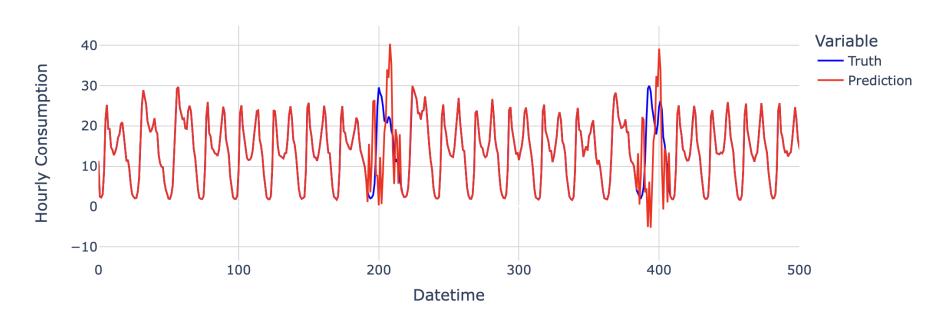
Predicted vs Ground Truth | Heat DMA







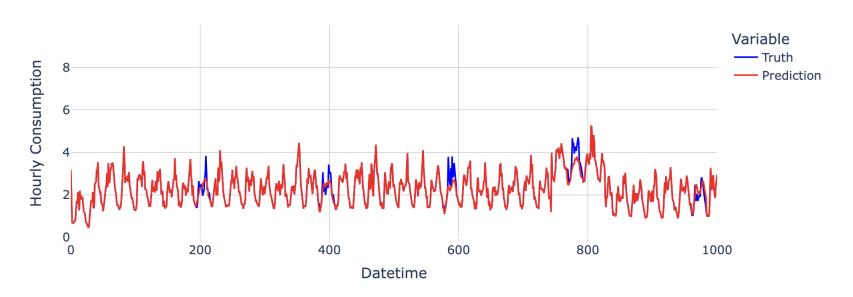
Predicted vs Ground Truth | Water DMA 1







Predicted vs Ground Truth | Water DMA 2







Thank you!

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