Hydropower Climate Optimisation Challenge

Capstone Project

WattsUp team

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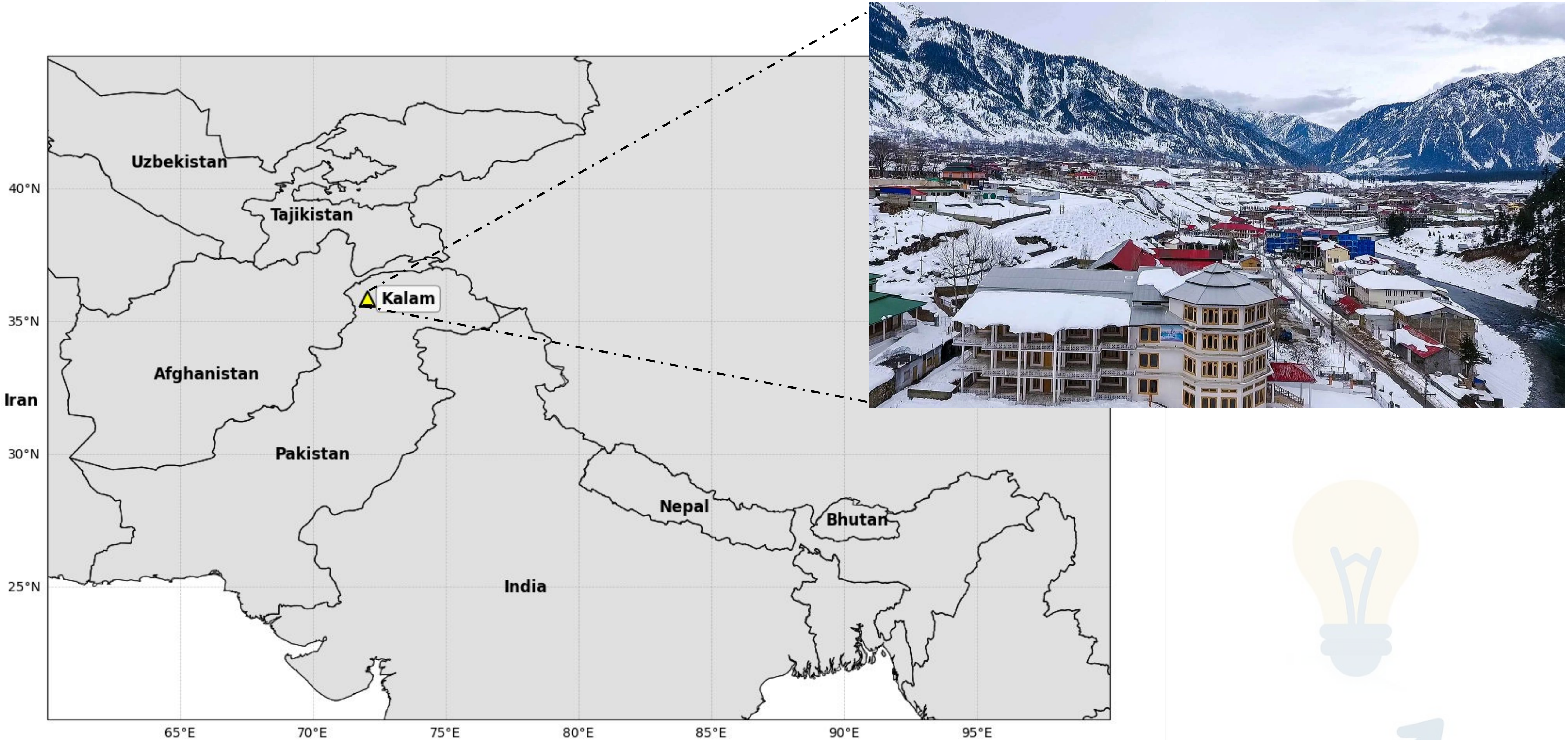
Gozal Jabrayilova
Patrick Kuntze
Florencia Perachia

ABOUT THE CHALLENGE



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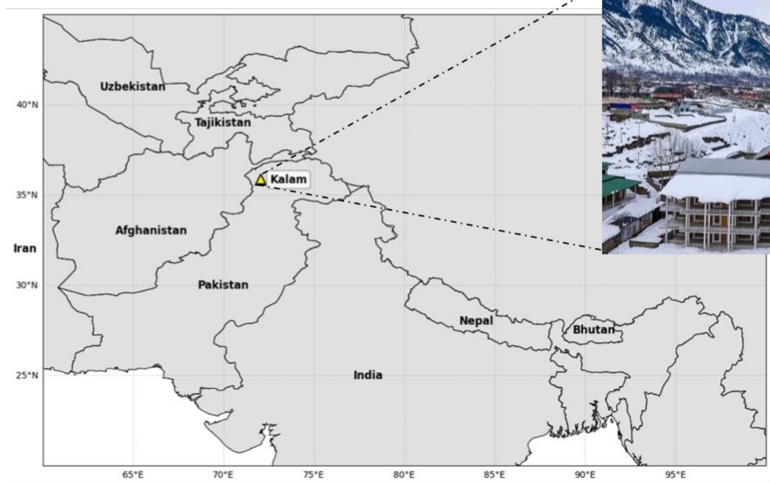


Generation point (Micro-Hydropower plant)

GENERAL OBJECTIVE

Develop a robust predictive model that can accurately forecast the daily hydropower supply (measured in kWh) per user of these Micro-hydropower plants (MHPs)

- predict one month in the future using climate data and previous history of hydropower supply

ABOUT THE DATA

TWO DATASETS

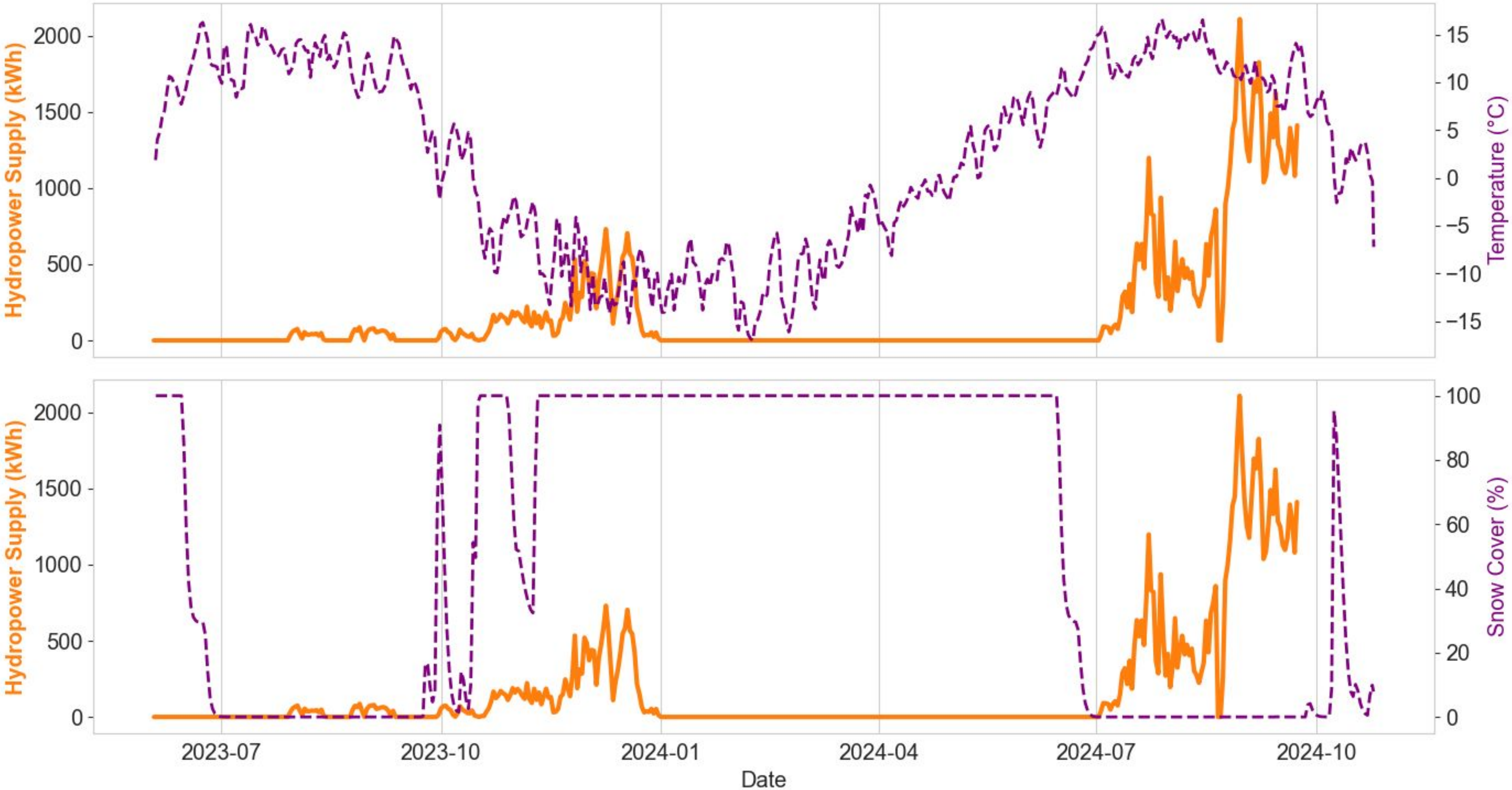
HYDRO-POWER DATA

Operational data including history of hydropower supply (kWh), per day and user

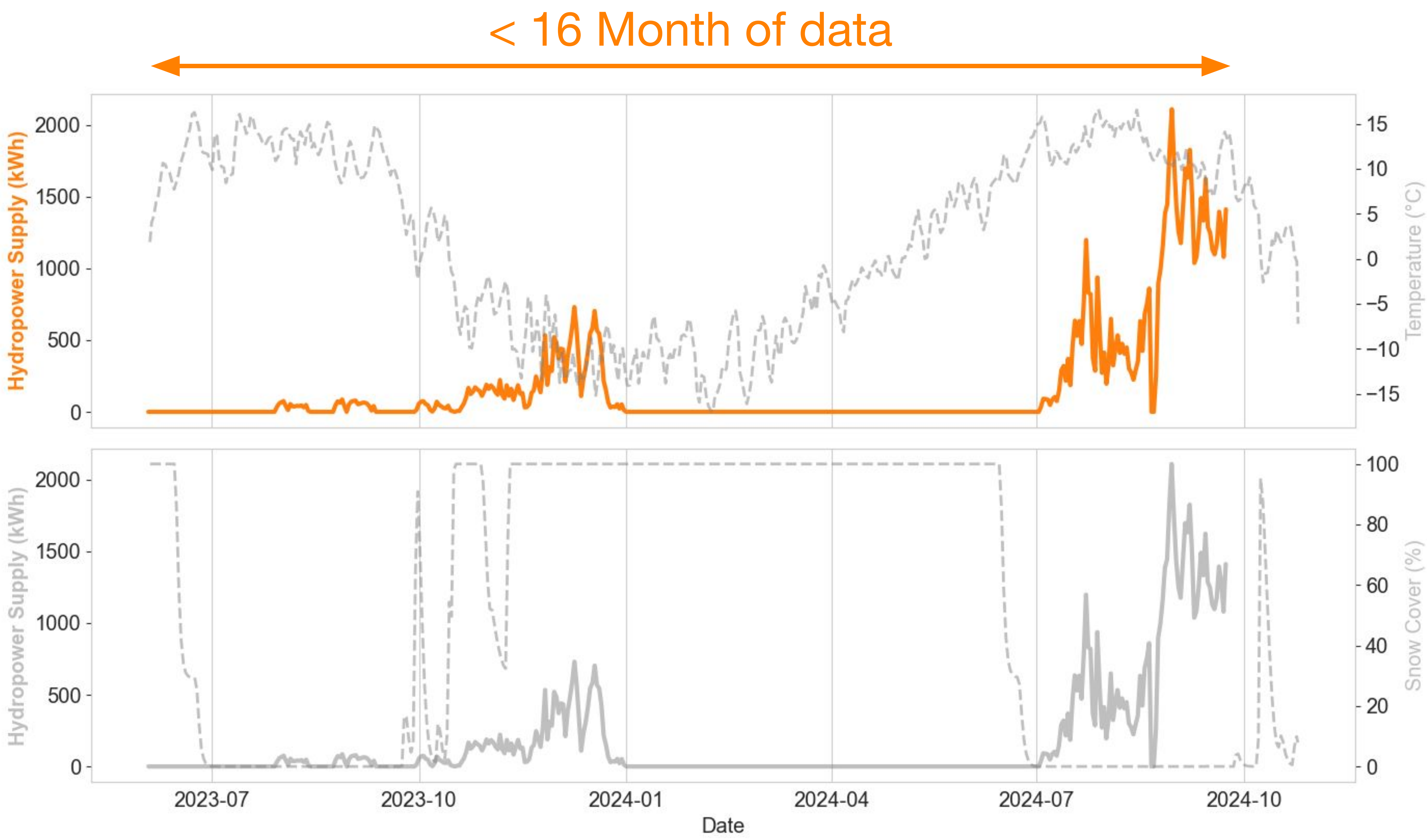
WEATHER DATA

Historical (+ additional month) data including environmental conditions that can influence water flow and energy demand/generation, such as temperature, dew point, wind, and precipitation.

Hydropower Supply & Weather variables



Hydropower Supply & Weather variables



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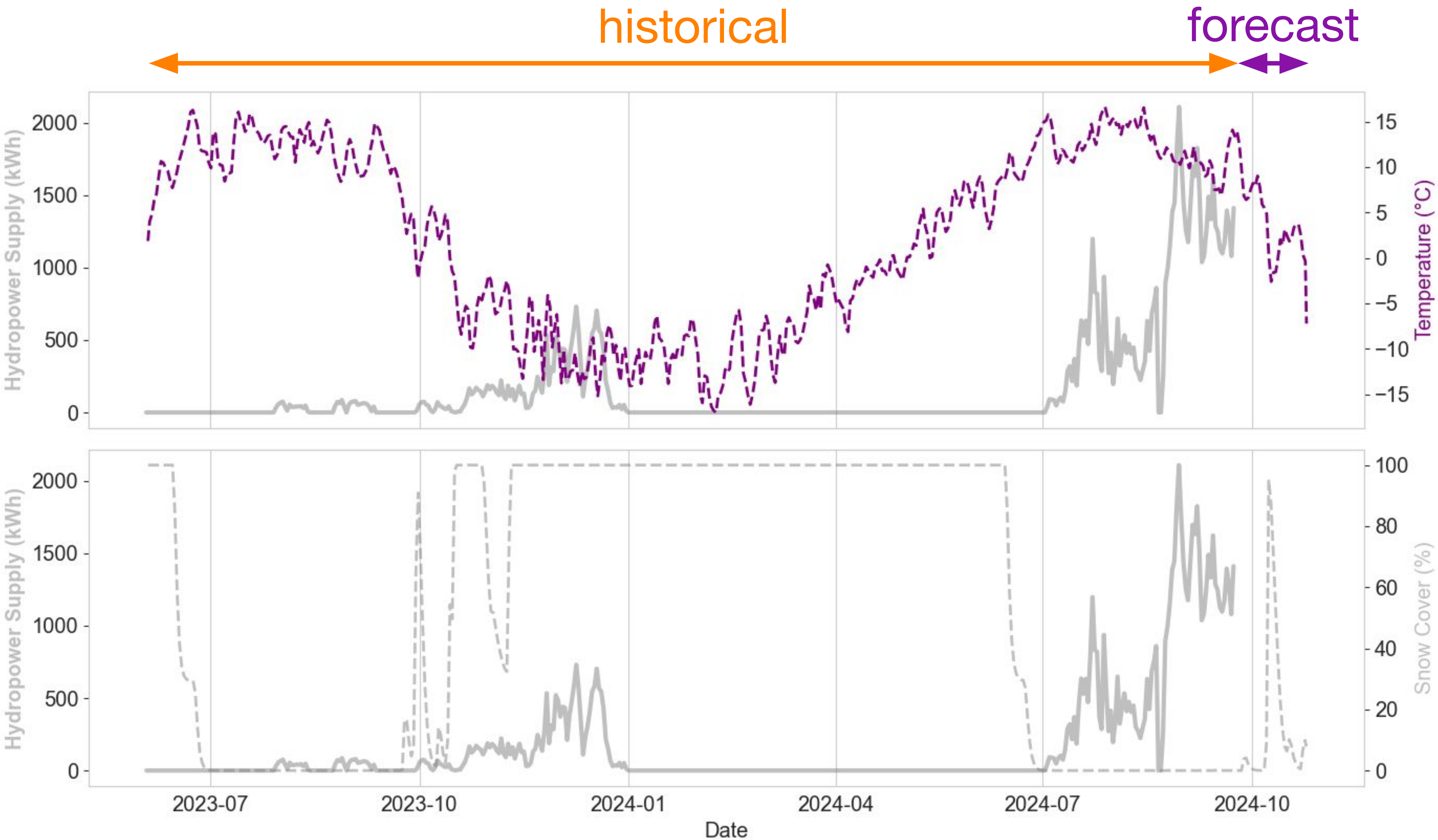

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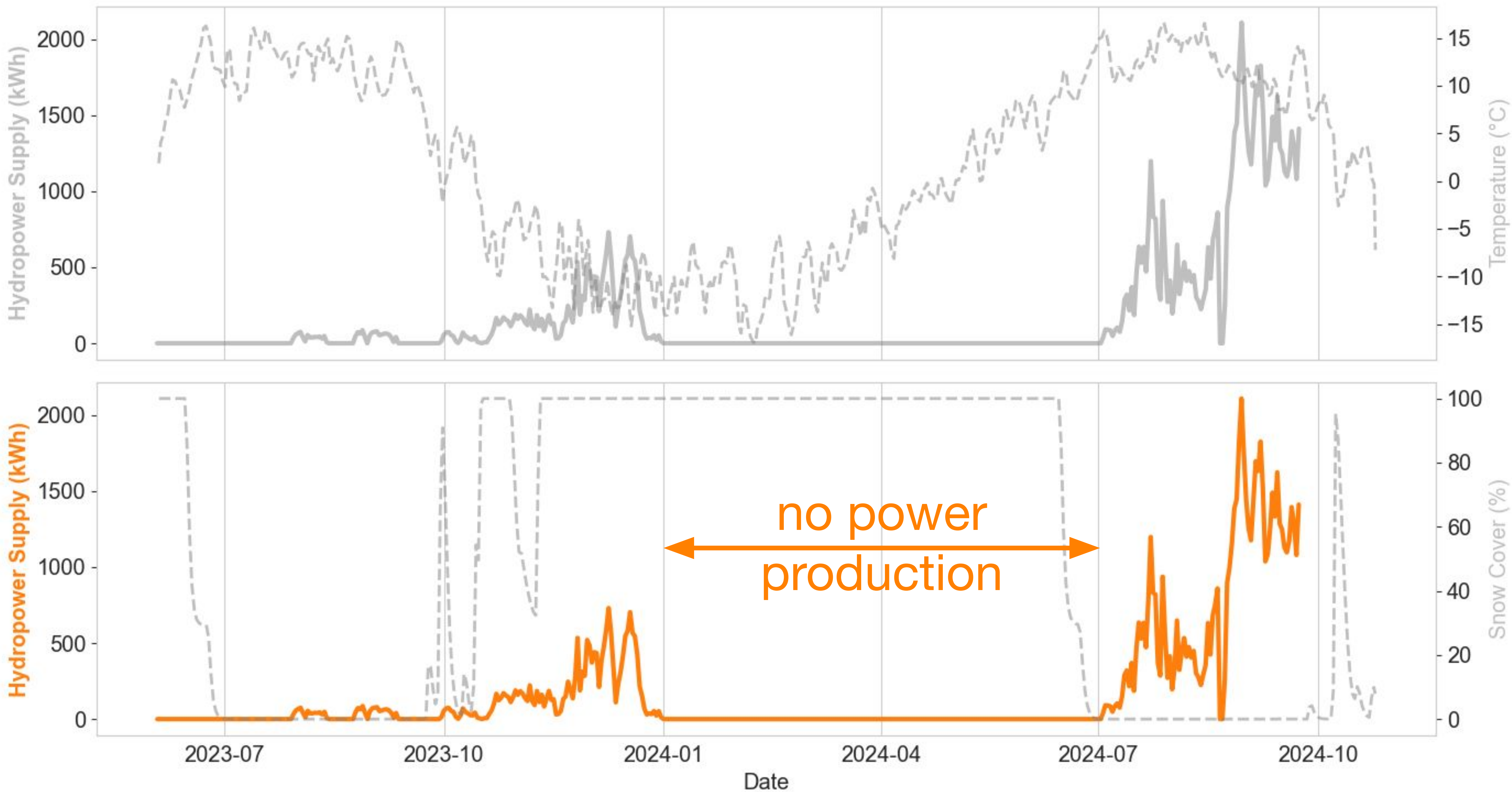

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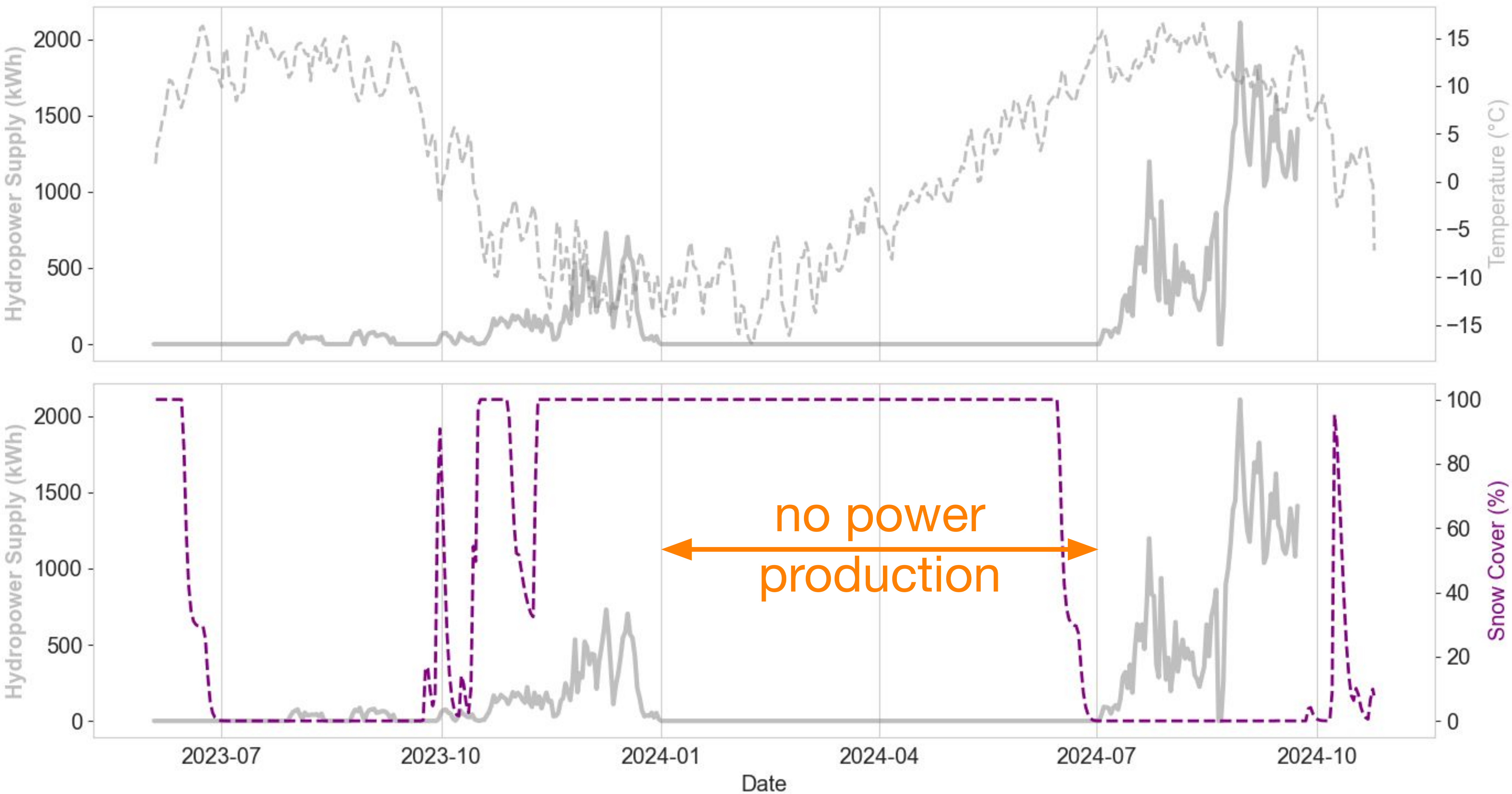


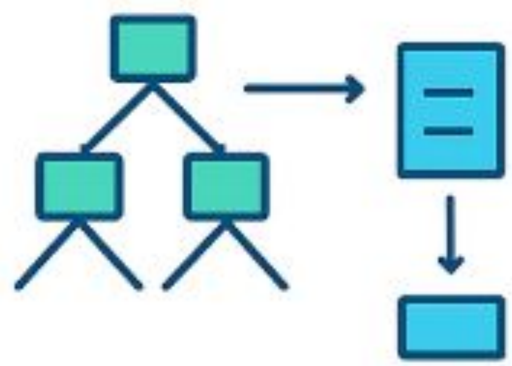
MODELS

1. Prophet

- Time series approach
- Decomposition into:

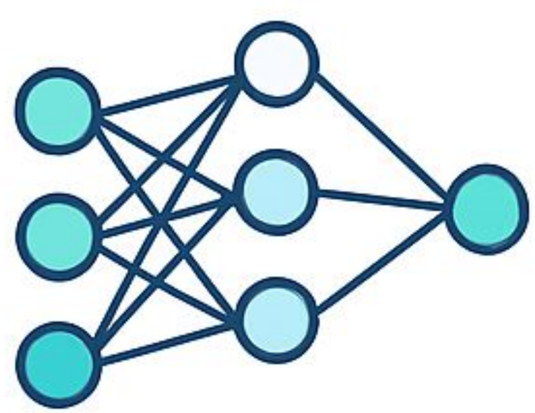
Trend + Seasonality + Events

2. LightGBM



- Ensemble of decision trees
- Trees grow in a leaf wise way
- Gradient boosting model

3. Artificial Neural Network



- Deep learning model
- Dense layers
- Learns complex, non-linear patterns in the data

Evaluation metric chosen: RMSE

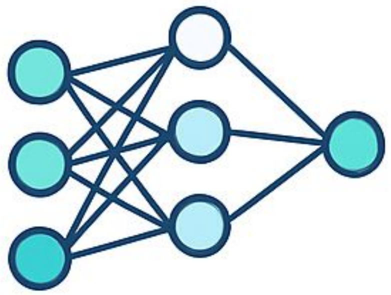
MODELS

Info Data Chat **Leaderboard** Team Submissions | Certificate | Get a score

RANK	USER	PUBLIC SCORE	PRIVATE SCORE	# SUBM
1. WattsUp: Artificial Neural Network			**RMSE= 4.390272303 kWh**	
1	data_style_bender	5.243738863	4.436570142	39
2	Belal_Emad Cairo university	6.093821536	4.48655936	300
17	CodeJoe	6.362519843	4.738247345	208
18. WattsUp: Prophet			**RMSE= 4.75648505 kWh**	
111	thiha_naing	8.076067497	5.712531642	11
112. WattsUp: LightGBM			**RMSE= 5.716274126 kWh**	
	Benchmark	8.410761100	8.794315210	

More about our winning model: ANN

What made our winning model better?



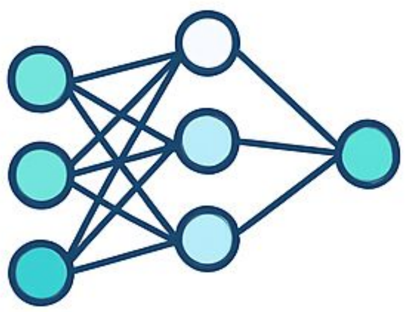
- Feature engineering
  - wind speed
  - ratio snowfall/precipitation
  - temperature - dew point

- Lag + rolling averages of past energy supply

Allowed the model to learn memory/seasonality.

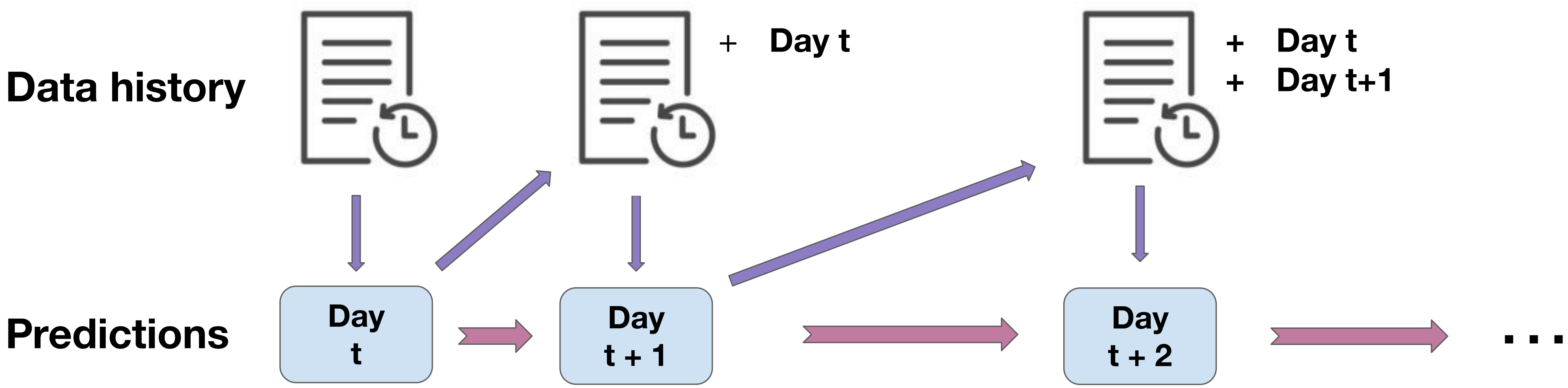
More about our winning model: ANN

What made our winning model better?



- Recursive prediction

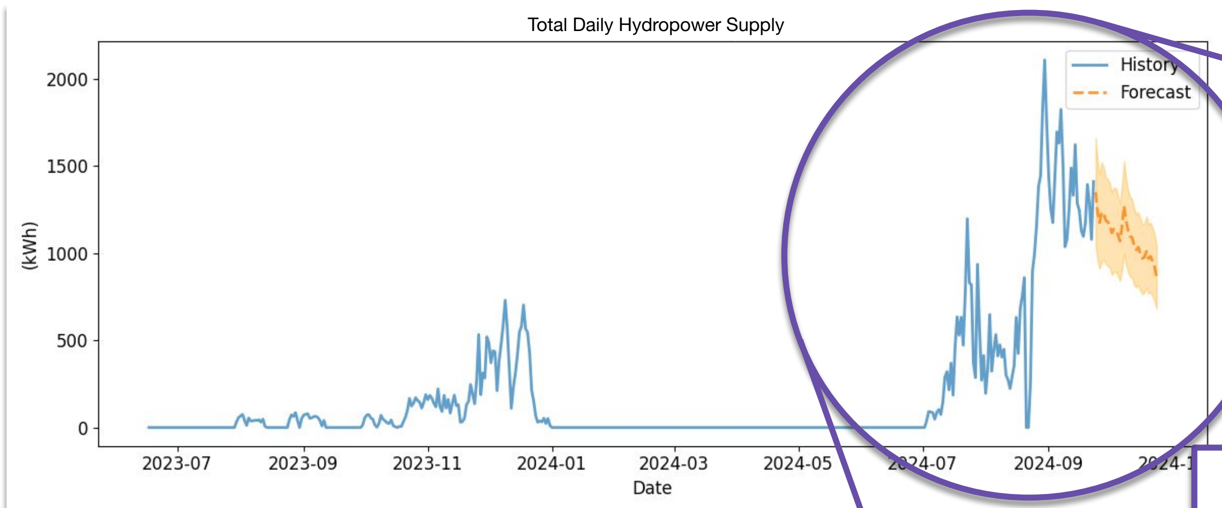
Method: Update the lagged features step by step, and build the forecast day by day

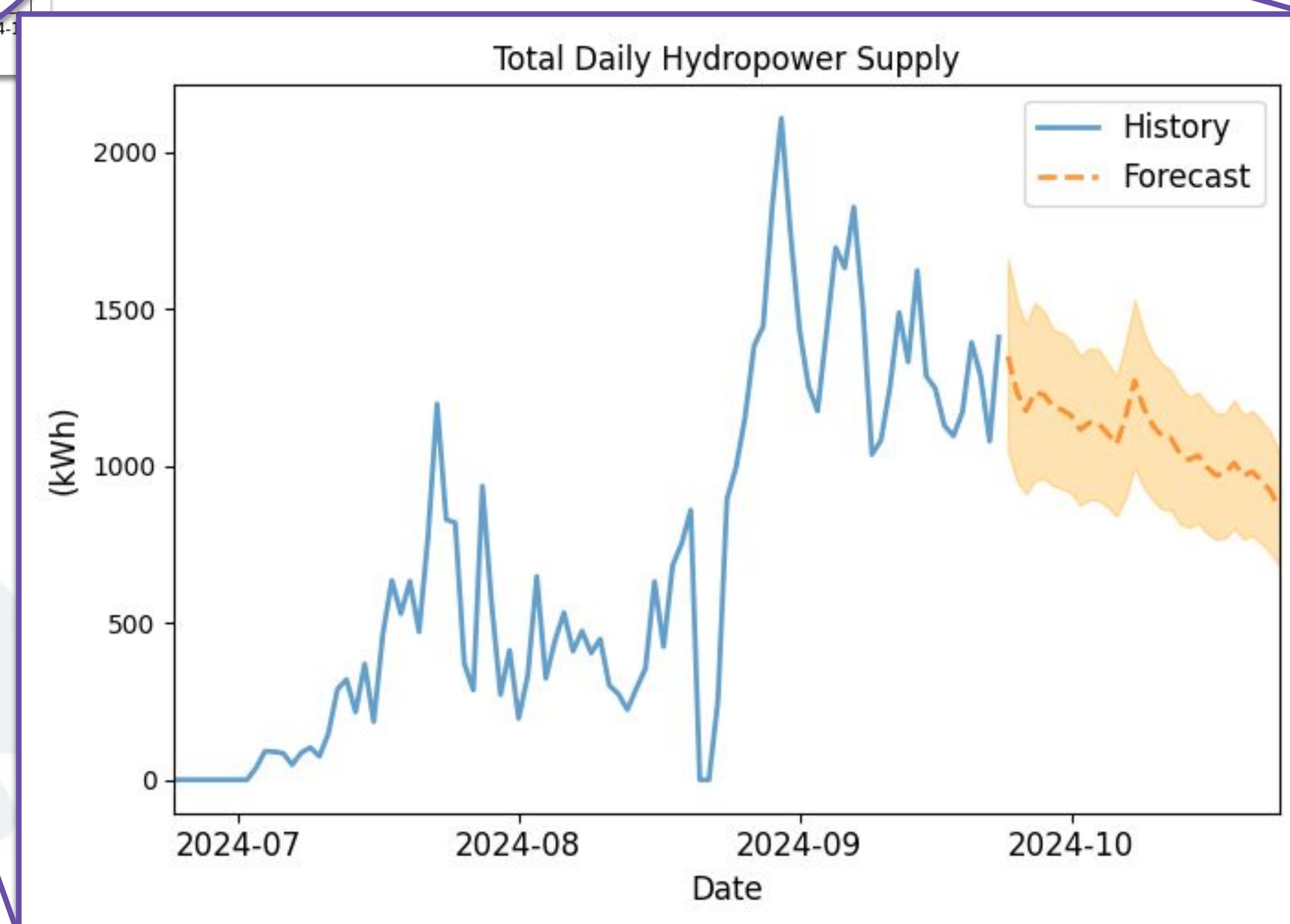


More about our winning model: ANN

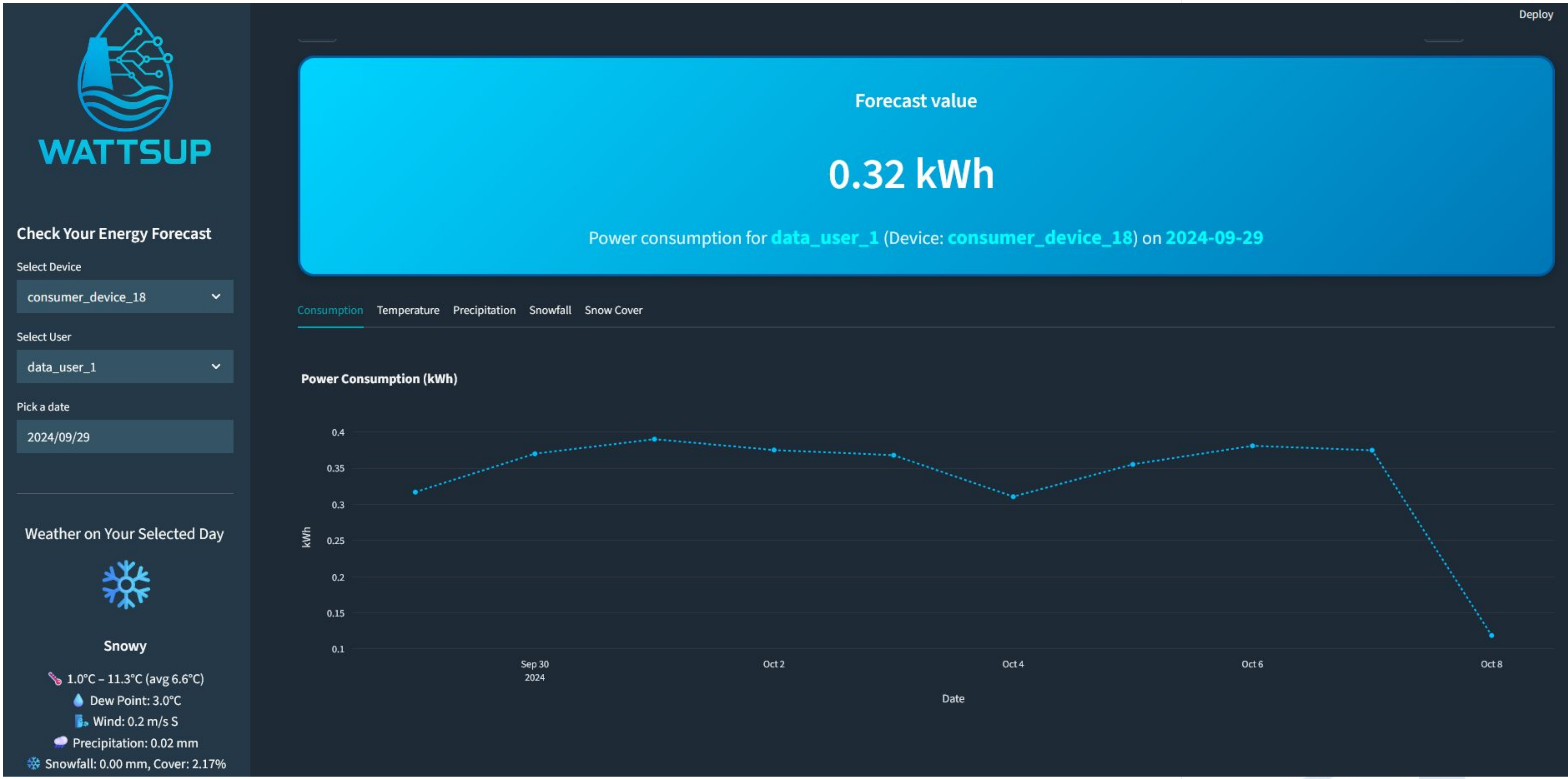
- Uncertainty Estimation (Monte Carlo Dropout):

Introduction of randomness





OUR PRODUCT



WATTSUP
Check Your Energy Forecast
Select Device
consumer_device_18
Select User
data_user_1
Pick a date
2024/09/29
Weather on Your Selected Day
Snowy
1.0°C – 11.3°C (avg 6.6°C)
Dew Point: 3.0°C
Wind: 0.2 m/s S
Precipitation: 0.02 mm
Snowfall: 0.00 mm, Cover: 2.17%
Deploy
Forecast value
0.32 kWh
Power consumption for data_user_1 (Device: consumer_device_18) on 2024-09-29
Consumption
Temperature
Precipitation
Snowfall
Snow Cover
Power Consumption (kWh)
kWh
0.4
0.35
0.3
0.25
0.2
0.15
0.1
Sep 30 2024
Oct 2
Oct 4
Oct 6
Oct 8
Date

OUR PRODUCT

Deploy
WATTSUP
Check Your Energy Forecast
Select Device
consumer_device_18
Select User
data_user_1
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Product Improvement

- Prediction capabilities
- Automated processes

OUTLOOK

Product Improvement

- Prediction capabilities
- Automated processes

Data

- Still a new project = more data to come
- Longer time series: other models performance?
- Geographical data

Acknowledgements

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- Neue fische
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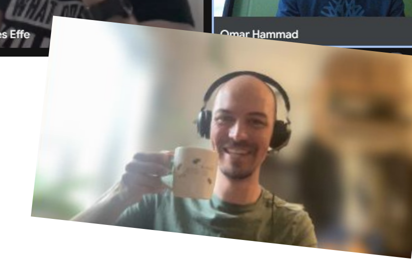

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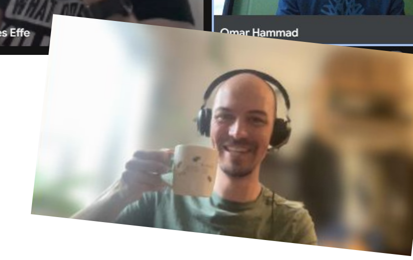

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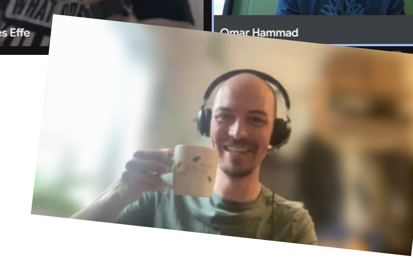
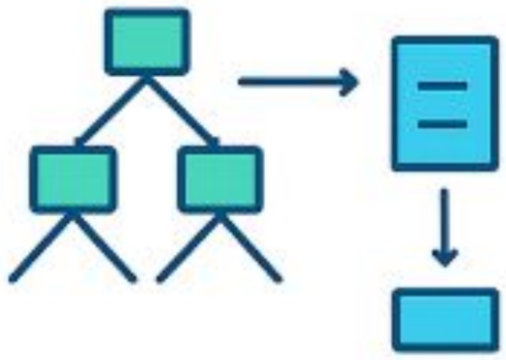


Questions?

EXTRA SLIDES

1) LightGBM



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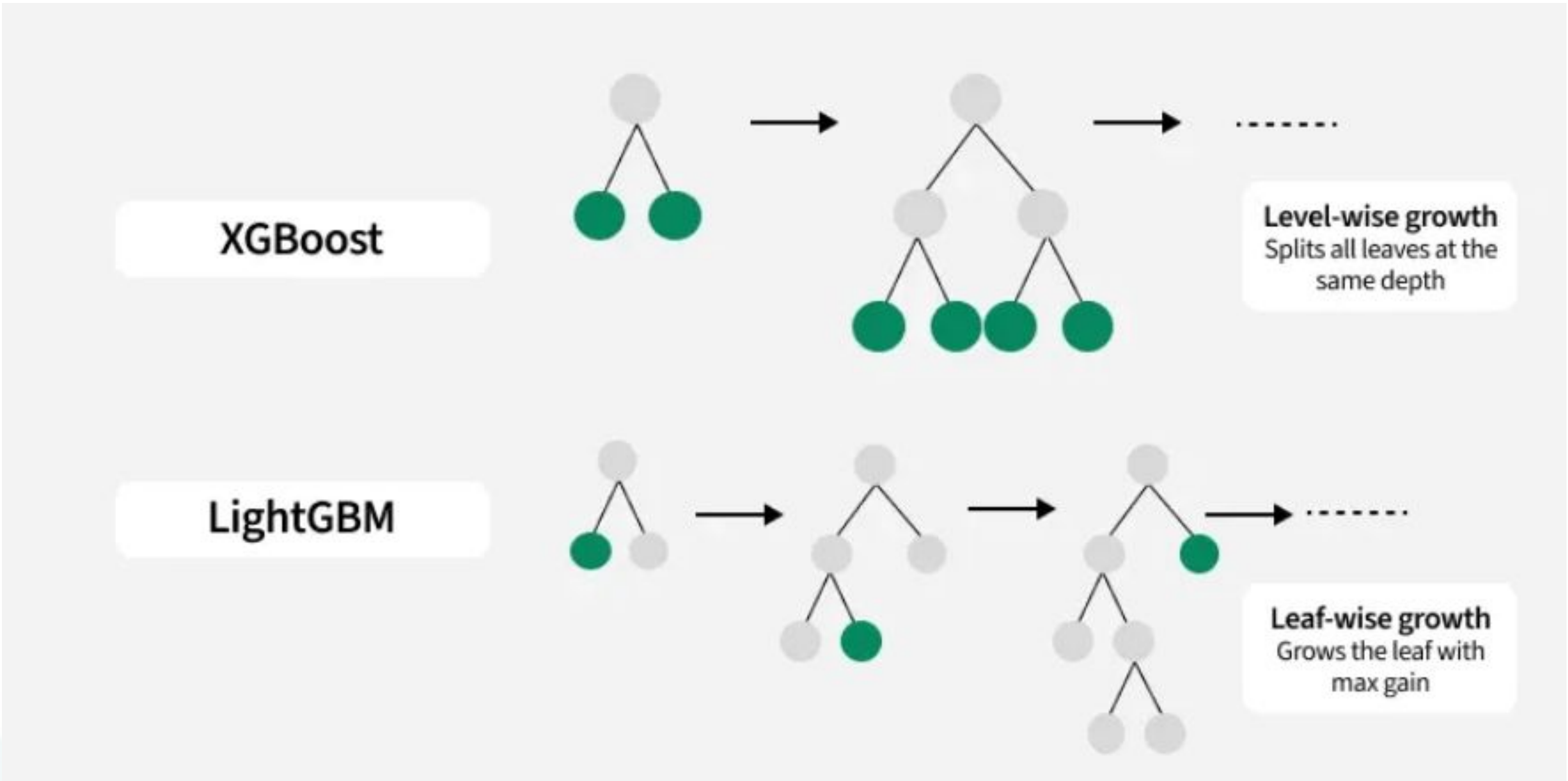


https://www.geeksforgeeks.org/machine-learning/lightgbm-light-gradient-boosting-machine/

MODELS

2) Prophet

- Time series approach
- Decomposable model:

Trend + Seasonality + Events

Type: Additive time series forecasting model (developed by Facebook/Meta).

Core idea: Decomposes a time series into **trend + seasonality + holidays/events + error**.

Trend: Can model linear or logistic growth.

Seasonality: Captured using **Fourier series terms** (weekly, yearly, or daily cycles).

Events/holidays: Special indicators can be added to handle unusual spikes or drops.

Error term: Accounts for noise and unpredictable fluctuations.

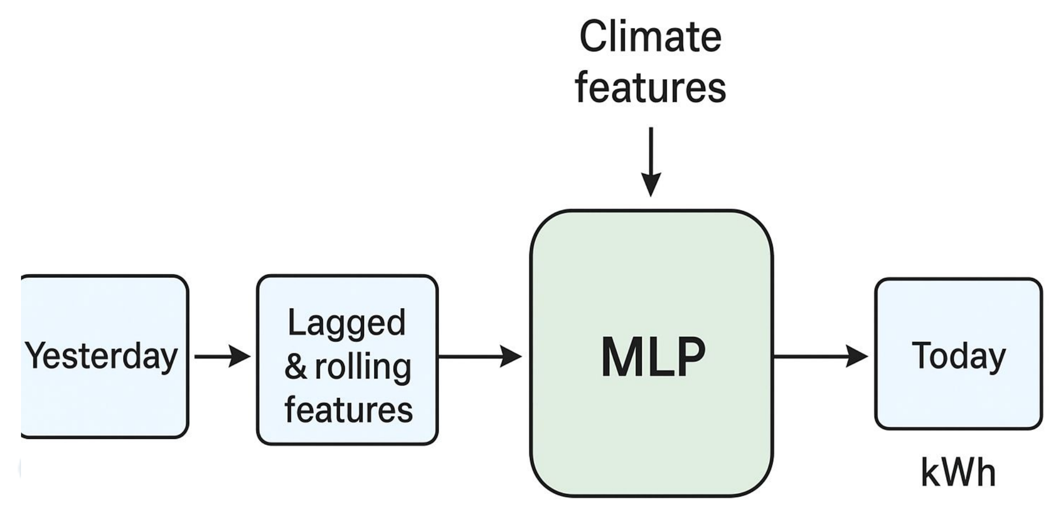
Difference from ML models: Instead of learning from random samples, Prophet **follows the chronological order** and explicitly models the underlying temporal components.

Output: Forecasted values for chosen future dates, with confidence intervals.

Strengths: Easy to use, interpretable, handles missing data and outliers well.

Limitations: Needs longer time series to fully capture seasonality; less flexible than ML models for feature interactions. **How to apply**: Fit the model on historical data (ds, y), specify forecast horizon, optionally add custom events or seasonality, then generate predictions.

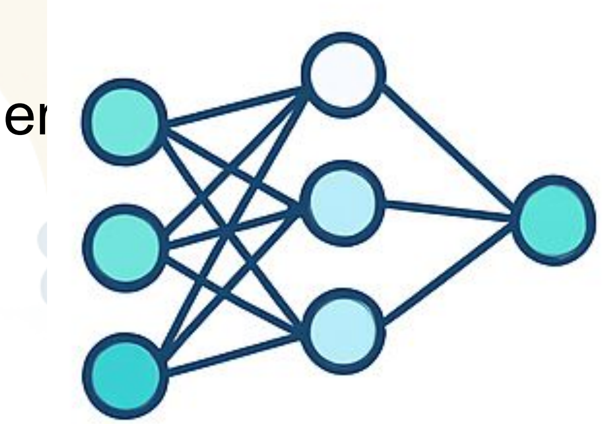
3) ANN



More details about the Neural Network:

Extra month

- **Fully connected** feedforward neural network with **3 hidden layers**.
- Architecture: **128 → 64 → 32 neurons**, all using **ReLU activations**.
- Regularization: **Dropout (20%)** applied after the first two hidden layers
- Final output layer: **1 neuron (ReLU)** to predict daily ener
- Loss function: **Huber**
- Optimizer: **Adam**, with early stopping and learning rate scheduling.



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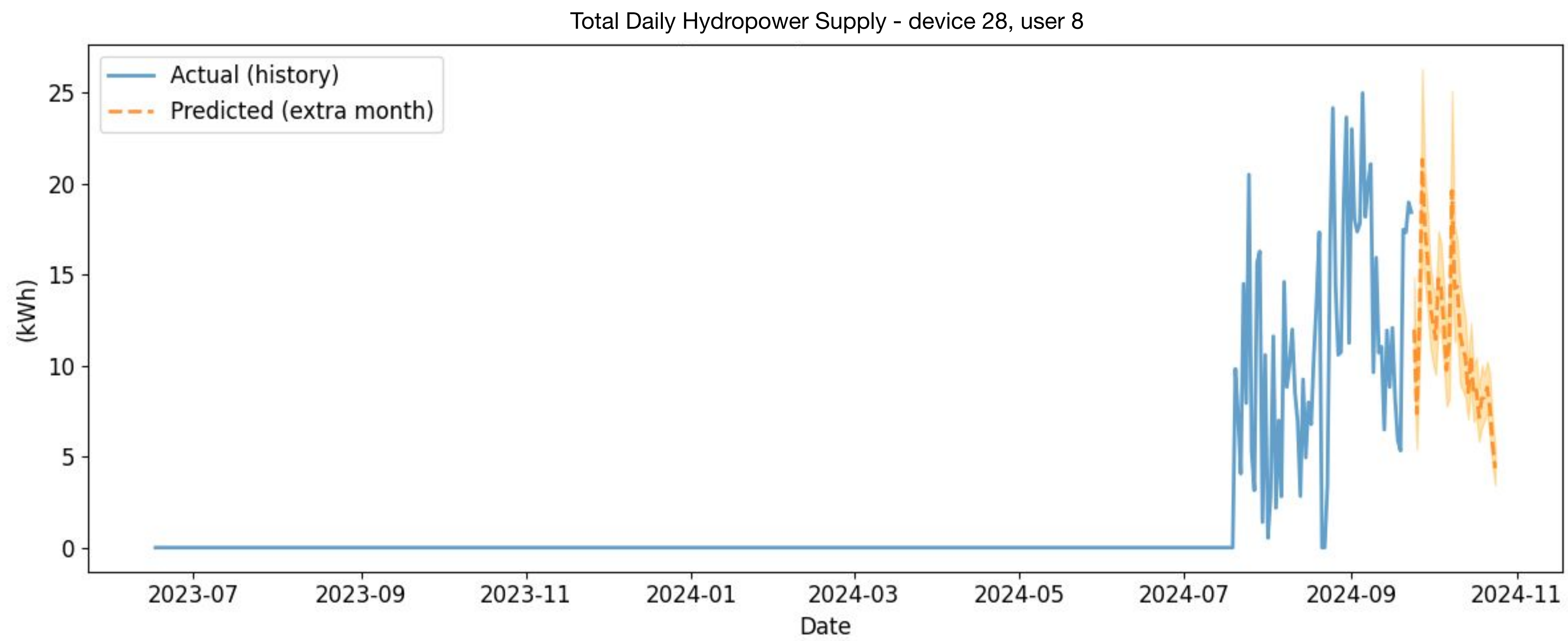

EXTRA SLIDES