WHAT IS A GOOD LOAD FORECAST?

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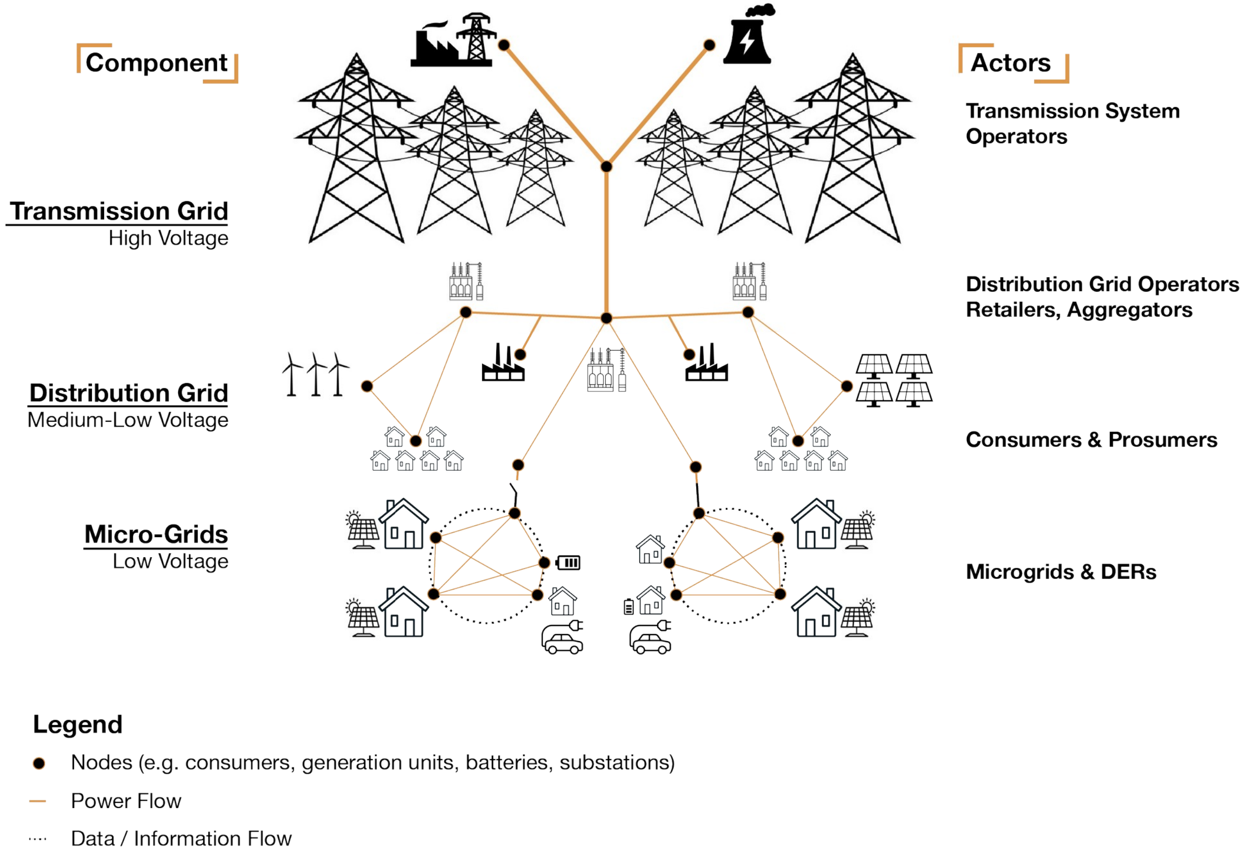
MOTIVATION – LOAD FORECASTING INTRO

- Energy forecasting is an important task for various actors in the energy system:
  - **Grid Operators** need load forecasts to ensure power quality and safety
  - **Retailers** need load forecasts to efficiently bid in energy markets
  - **Microgrids** and Energy Communities need load forecasts to economically dispatch flexibilities, to provide ancillary services
  - **Households** need load forecasts for their Energy Management Systems
- There is a plethora of methods to forecast load
- Many works compare methods for a single data set or use case



MOTIVATION – HOW ARE METHODS TYPICALLY COMPARED?

- Euclidian Error Metrics are widely spread.
- Common error metrics are:
  - Root mean squared error (RMSE)
  - Mean Absolute Percentage Error (MAPE)
  - Mean Bias Error
- The Problem:
  - These statistical metrics are sometimes not relevant for real system applications
  - *“Forecasts possess no intrinsic value, they acquire value through their ability to influence decisions made by users of the forecasts”* – A.H. Murphy

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N} | y_t - \hat{y}_t |$$

$$MBE = \frac{1}{N}\sum_{t=1}^{N} y_t - \hat{y}_t$$

where,

N = number of samples
y_t = ground truth based on measurement data
$\hat{y}_t$ = prediction of the forecasting model

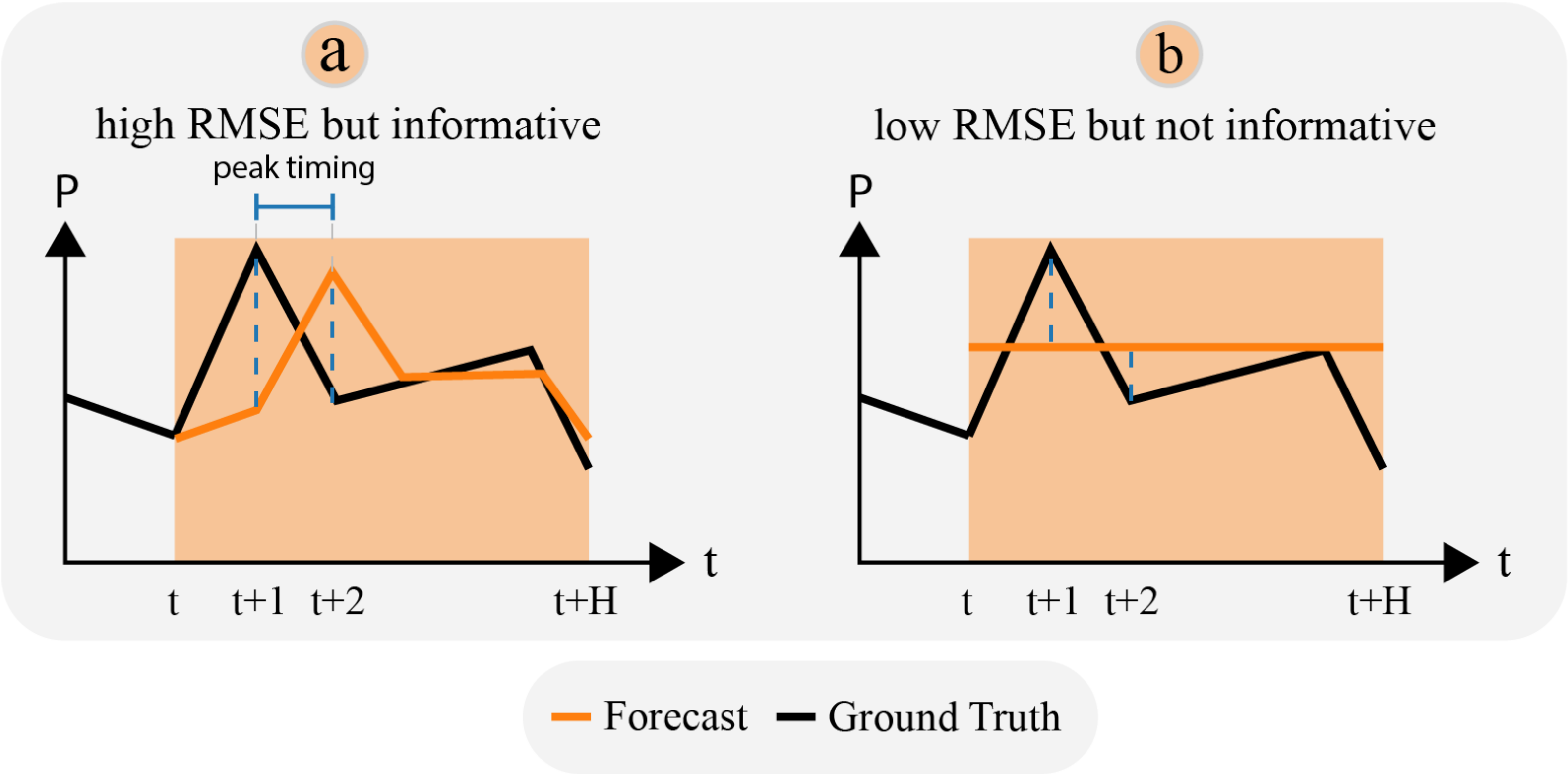
WHEN DO EUCLIDIAN METRICS FAIL?

Double Penalty Effect

Setting: model correctly learns to predict a peak, but misses the exact timestep

Effect: one penalty for underestimating the peak at timestep t+1 and then another penalty for overestimating the peak at t+2

(see Haben et al., 2021)

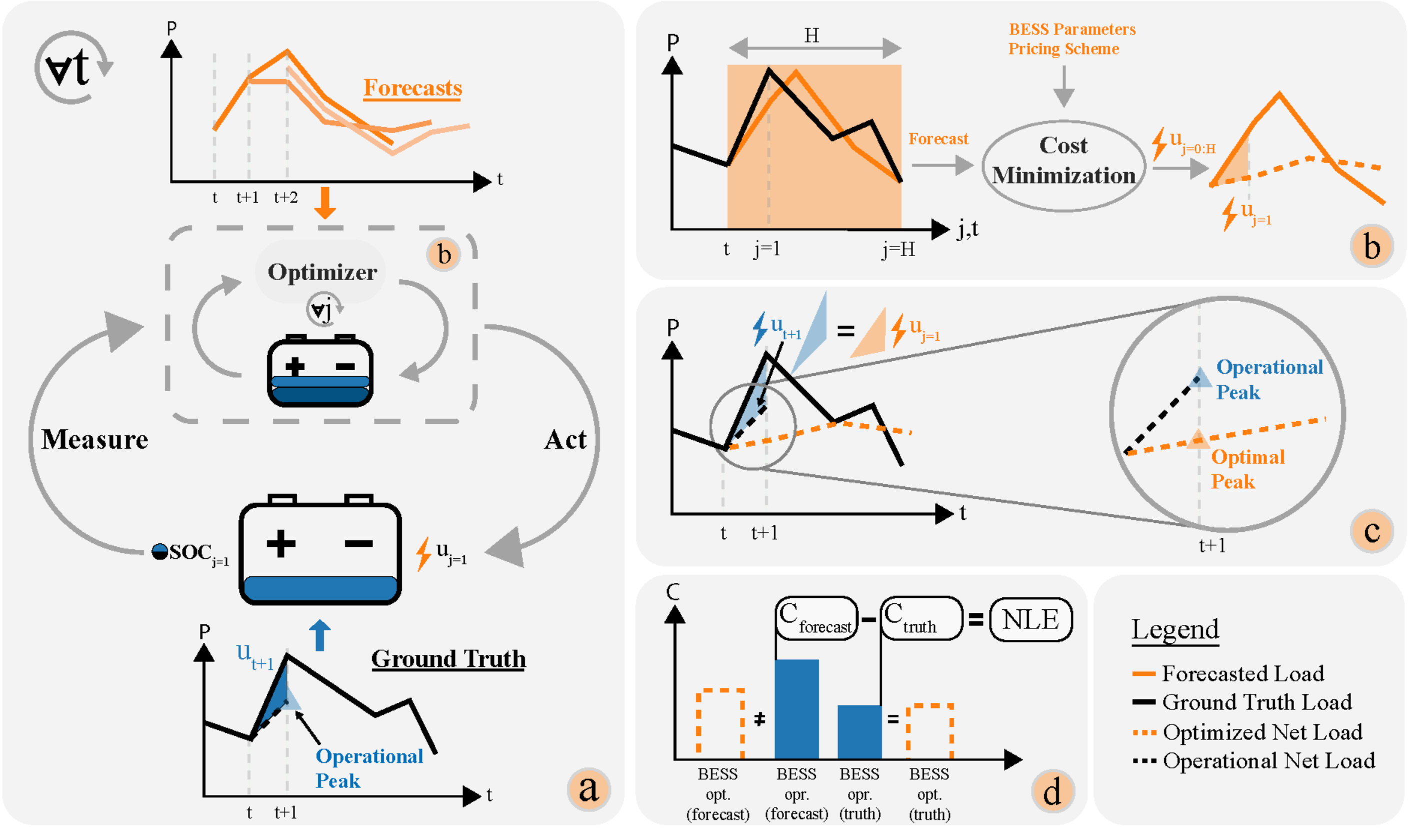


EXISTING WORK – ECONOMIC EVALUATION OF FORECASTS

- **Ranaweera et al. (1997)**
  - Assessed the economic implications of improved peak load forecasts.
  - Implemented forecast errors as a random variable in Monte Carlo simulations.
- **Voss et al. (2020)**
  - Analyzed forecasts in a Model Predictive Control (MPC) framework for peak load reduction.
  - Demonstrated improved results with Local Permutation Invariant k-Nearest Neighbors.
- **Putz et al. (2023) & Houben et al. (2023)**
  - Focused on the monetary value of forecasts in an MPC setup for complex energy systems.
  - Compared multiple forecasting algorithms; detailed cost savings analysis under various conditions.
- **Gokhale et al. (2023)**
  - Evaluated transfer learning with Temporal Fusion Transformer for household load forecasting.
  - Investigated both mean absolute error and operational costs in an MPC framework.

METHODS – NET LOAD ERROR (1)

- **Goal.** Devise an application-driven forecast metric for grid operators to assess load forecasts
- **Background.** Grid Operators use load forecasts to anticipate daily peak load, to procure balancing service providers (BSPs)
- **Idea.**
  - Stylized Energy System of a Battery Electrical Storage System (BESS) + Load + Load Forecast + Daily Demand Charge
  - Operated with Model Predictive Control in the resolution of the forecast
  - Executed once based on the load forecast, and once on the ground truth
  - The difference is the Net Load Error



METHODS – NET LOAD ERROR (2)

Control Step: Operational Load

$$l_{t+1}^{opr} = y_{t+1} + u_{j=1}$$

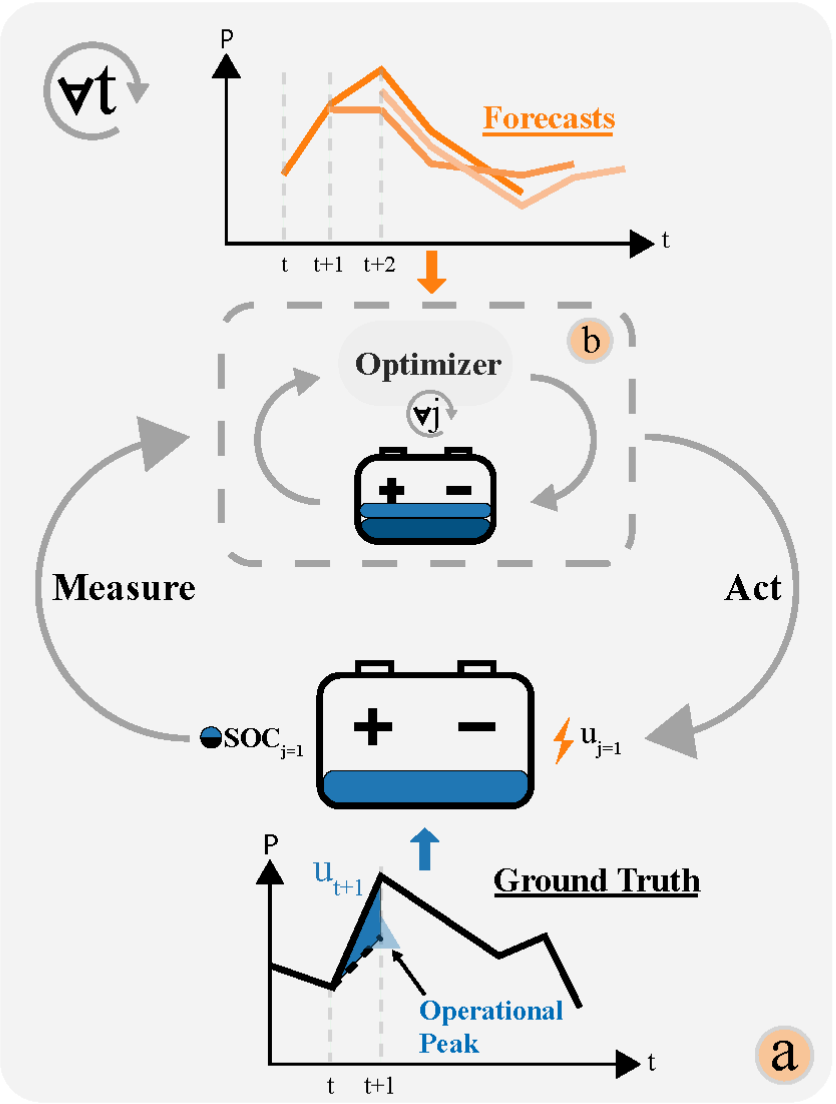
Closed-Loop: State of charge (SOC) is passed to the next optimization

$$SOC_{j=0,t+1} = SOC_{j=1,t}$$

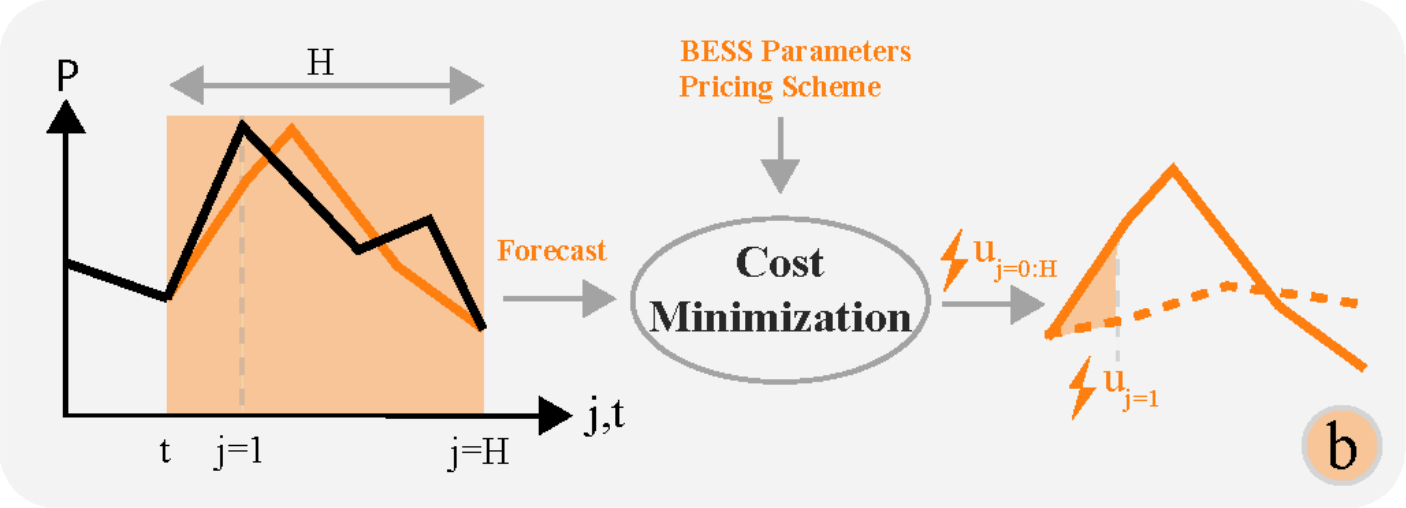
Repeated for all t in T

Ex-post Daily Demand Charge Pricing Scheme

$$C_{DC} = \sum_{d} max\ y_{t;d} * P_{DC}$$



METHODS – NET LOAD ERROR (3)



$$\min_{u} C^{opt}(l^{opt}, P_{DC}) + V(SOC_{j=H}) \quad \text{s.t.} \quad g(l^{opt}, P_{DC}, \theta) \geq 0, \quad h(l^{opt}, P_{DC}, \theta) = 0.$$

where,

C^{opt} = demand charge proxy cost for horizon H
u = charging actions $u_{j=0:H}$
l^{opt} = optimized net load $l^{opt}_{j=0:H}$
V = terminal costs, avoiding complete discharge at the final optimization timestep
SOC = state-of-charge of the BESS
P_{DC} = daily demand charge
θ = BESS parameters

Strategy:
Modify the load to reduce peak

$$l_j^{opt} = \hat{y}_j + u_j$$

Optimization Problem:
find optimal charging schedule

METHODS – NET LOAD ERROR (4)

Objective Function

	Total Costs
	Horizon peak
	Terminal Costs (~Value of Energy)

Important Constraints

	Horizon Peak
	Energy Balance
	Energy Storage

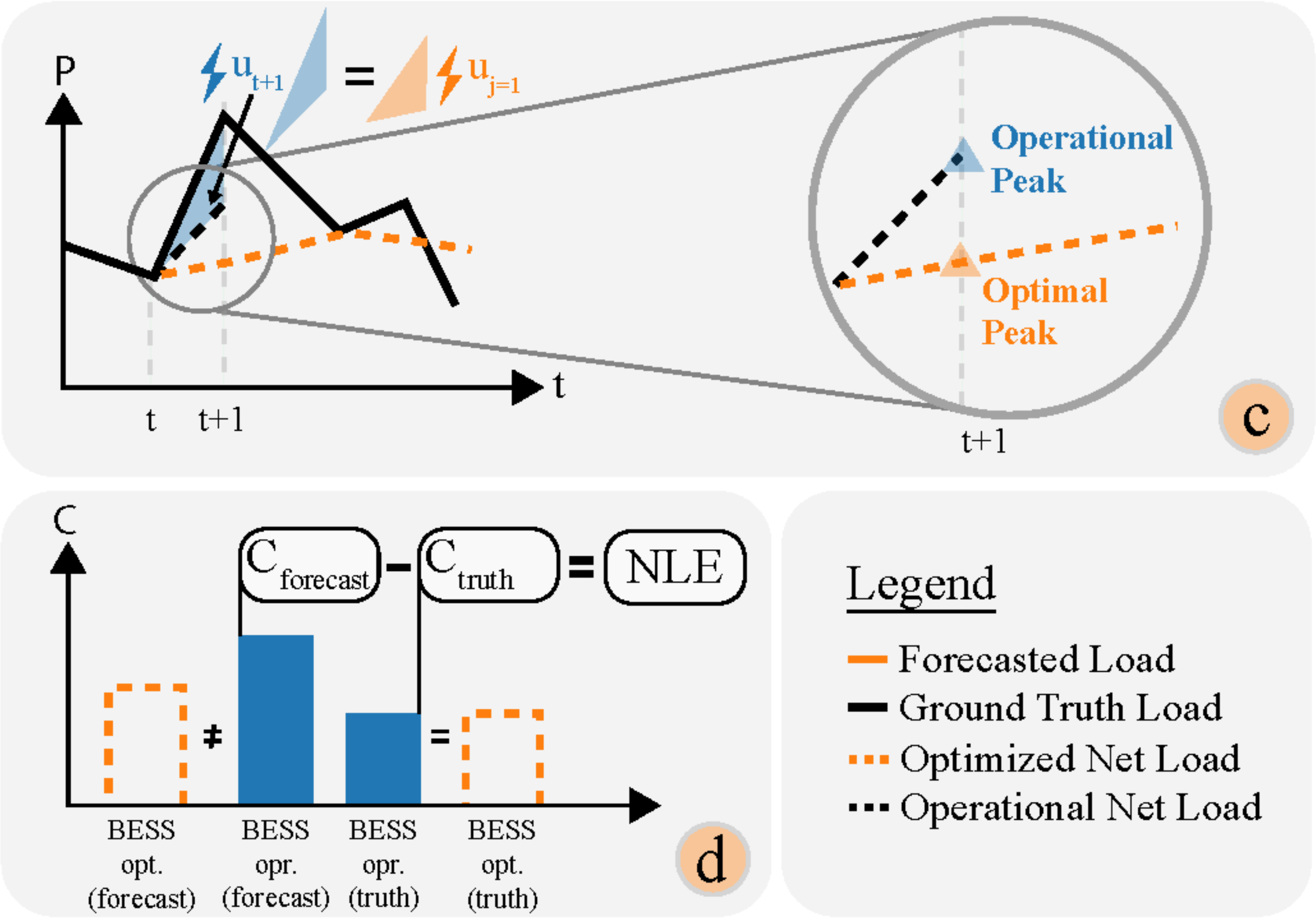
METHODS – NET LOAD ERROR (5)

Control Step:
Operational Load

$$l_{t+1}^{opr} = y_{t+1} + u_{j=1}$$

Deviation:
Operational Load
and Optimal Load differ
if load forecast has errors

$$l_j^{opt} \neq l_{t+1}^{opr}$$

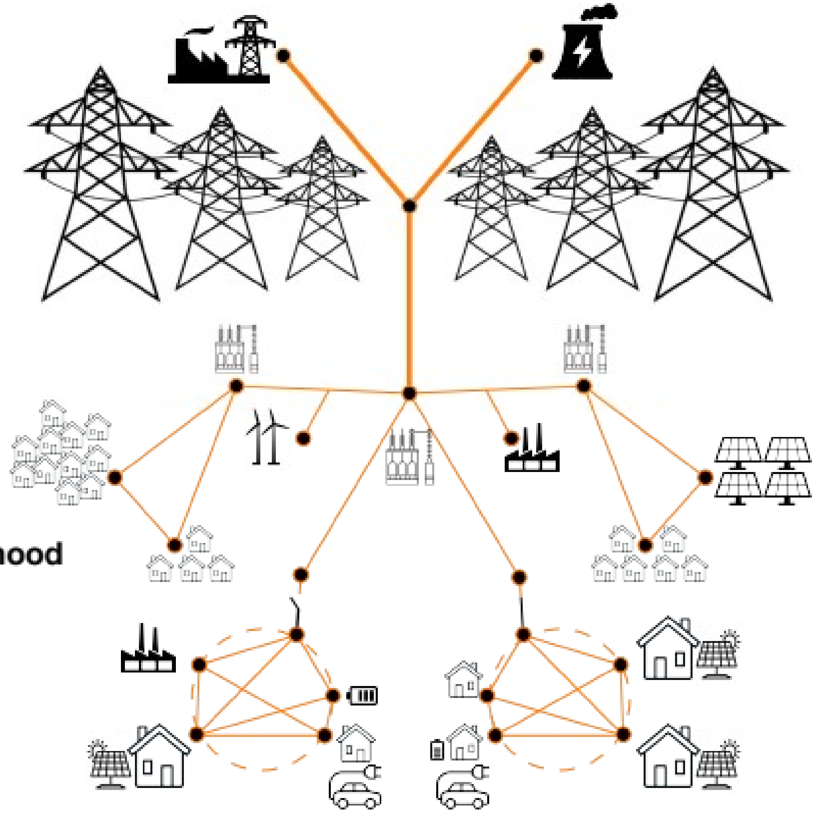


CASE STUDY – DATA & PREPROCESSING

- Open-source load datasets
- 5 Scales to cover full spectrum of consumers
- Cleaned NaNs & Resampled to 1h
- BoxCoxTransform for each dataset
- Encoded datetime:
  - Day of week (one-hot)
  - hour of the day (trigonometric)
  - Month of the year
- Corresponding (measured) outdoor air temperature data for each dataset

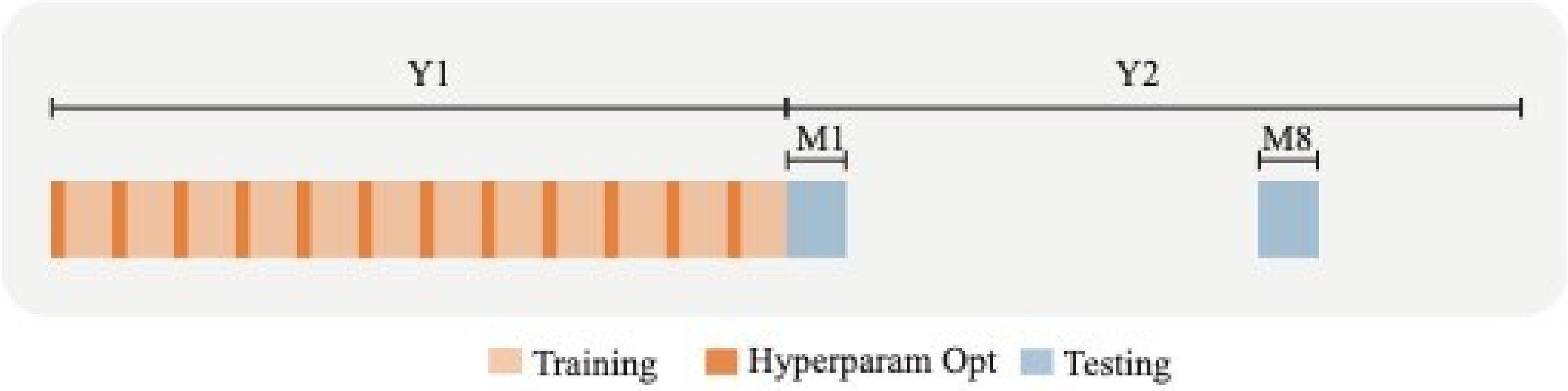
Dataset per Spatial Scale

Location	Resolution	Scale	
USA	60 min	1-50 GW	**County**
Portugal	15 min	5-50 MW	**Town**
Portugal	15 min	50-200 kW	**Village**
USA	60 min	5-20 kW	**Neighborhood**
USA	60 min	0-2000 W	**Building**

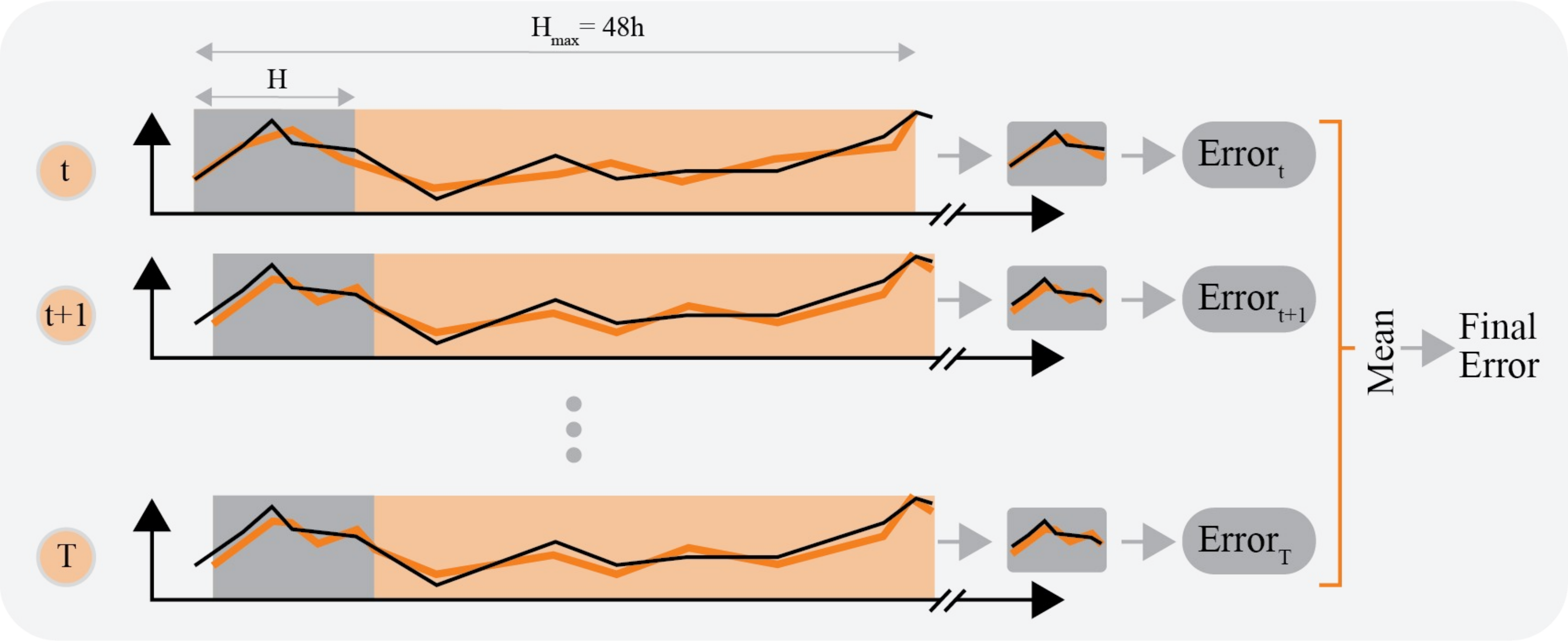


CASE STUDY – TRAIN TEST SPLIT

- Training Set was one year for all datasets
- Testing Set in another year, manually selected to include extreme weather conditions
- Hyperparameters were optimized on the set of first weeks of each month in the training set



CASE STUDY – FORECAST EVALUATION



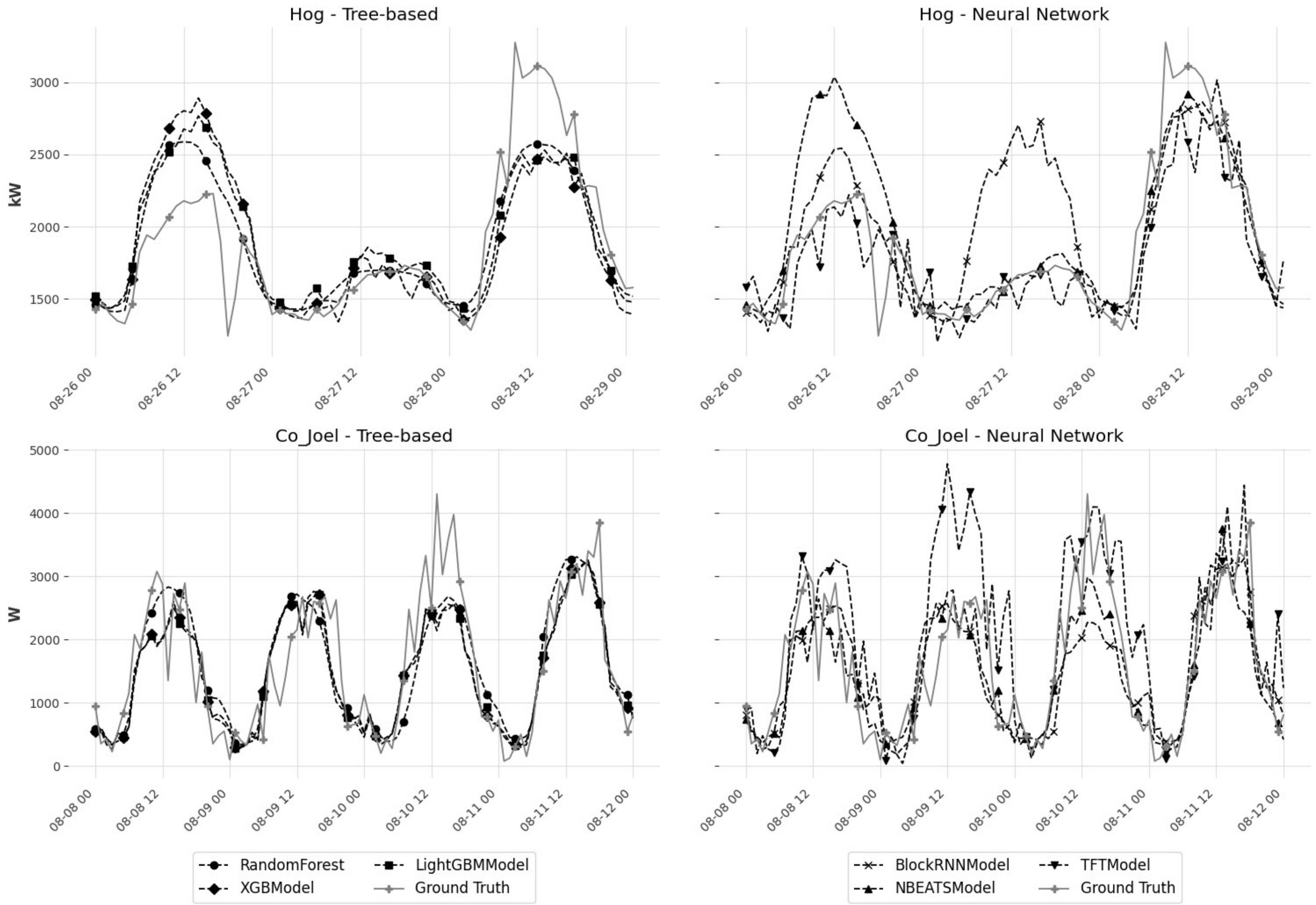
CASE STUDY – ALGORITHMS

Algorithm	Type	Mechanism	Implementation
RF	Decision Tree Ensemble	Bagging	Direct
XGBoost	Decision Tree Ensemble	Gradient Boosting	Direct
LightGBM	Decision Tree Ensemble	Gradient Boosting	Direct
GRU	Deep Neural Network	Memory Gates	MIMO
N-BEATS	Deep Neural Network	Basis Expansion	MIMO
TFT	Deep Neural Network	Attention	MIMO

\+ Multi-variate Linear Regression as a **Benchmark Algorithm**

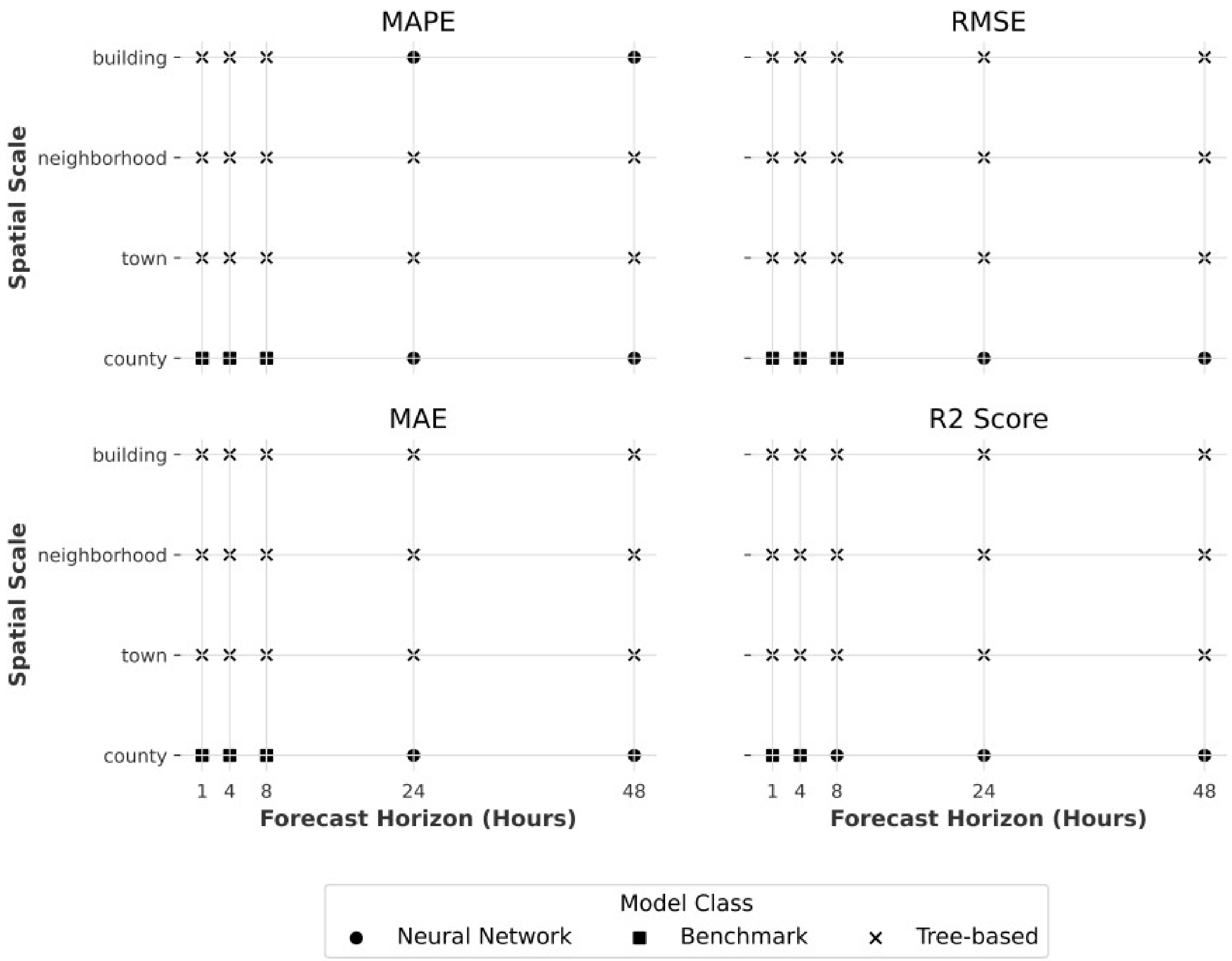
RESULTS – QUALITATIVE ASSESSMENT

- All methods model unseen data well
- Tree-based methods better able to follow trends
- Neural Networks more erratic trajectory
- Neural networks higher peaks, but over-predict



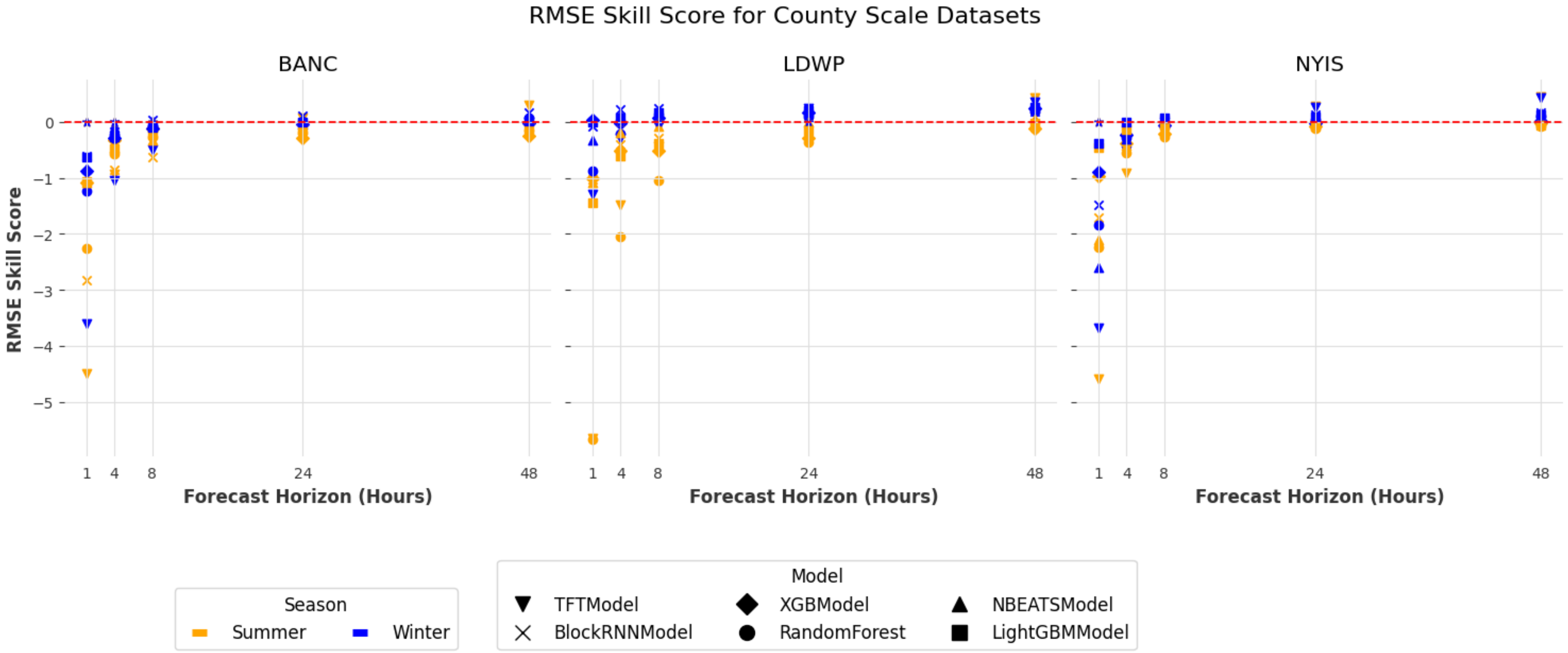
RESULTS – EUCLIDIAN METRICS

- Tree-based Models outperform Neural Networks on a majority of datasets
- Linear Regression Benchmark work on short horizons on easy datasets



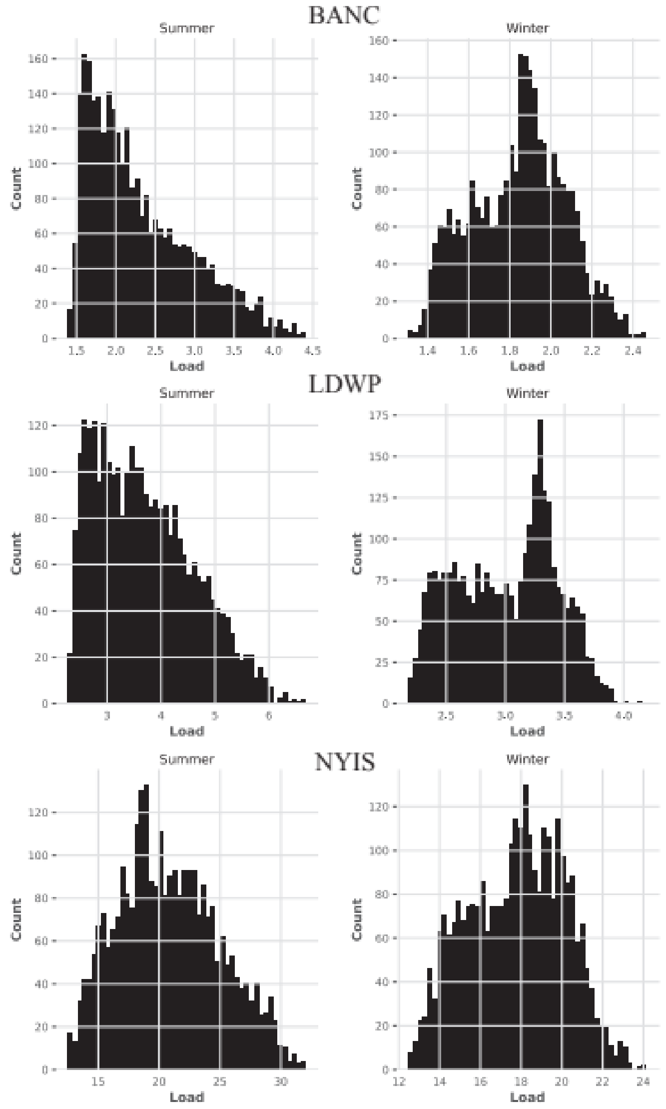
RESULTS – SEASONAL DIFFERENCES

- Summers are harder to forecast than winters
- Forecast Skill improves with increasing horizon
- Neural Networks overtake Tree-based methods for long horizons



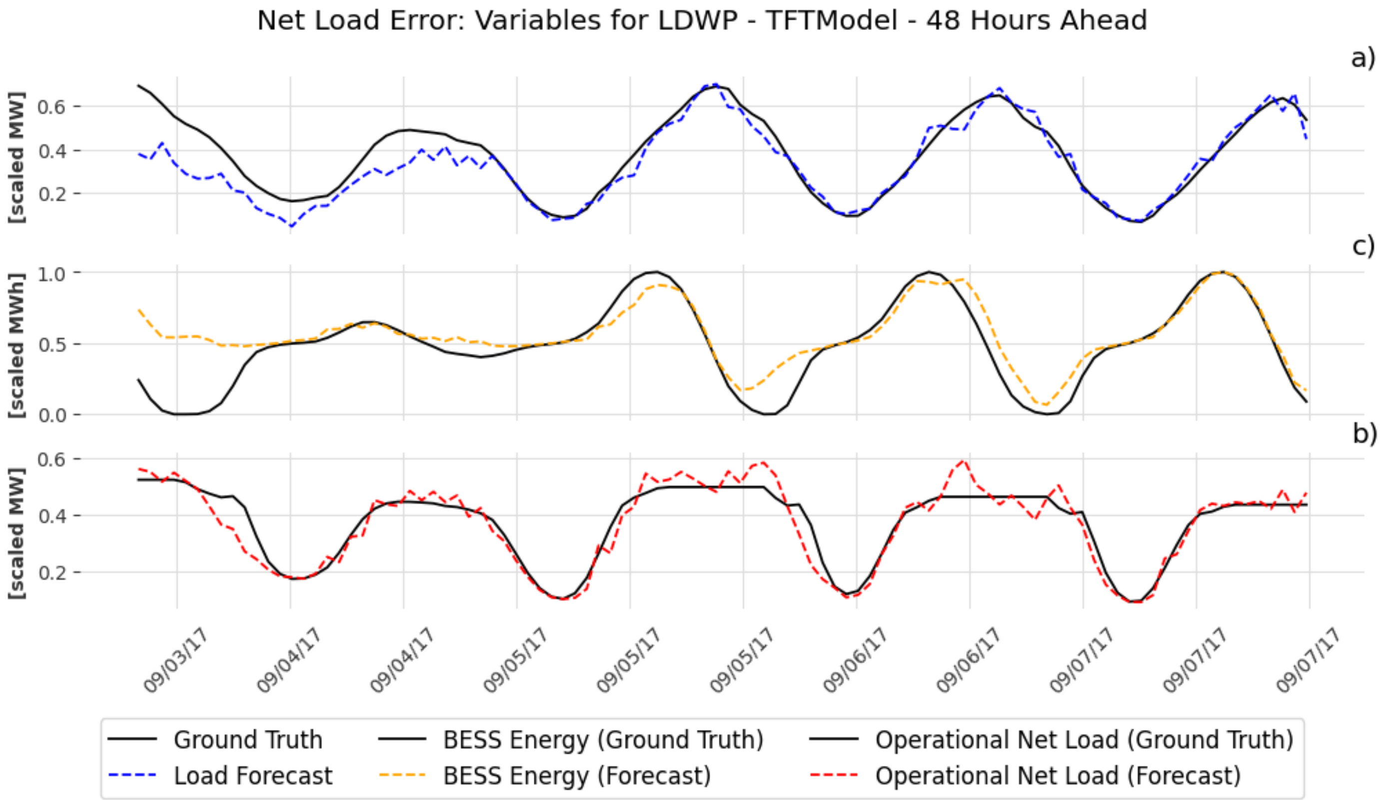
RESULTS – SEASONAL DISTRIBUTIONS

- Explanation of relative low performance in summer:
- Distribution shift:
  - Winter = Quasi Normal
  - Summer = Asymmetric, long tail
- Problematic use of BoxCox transform on the whole dataset
- Possible solutions:
  - Train a separate model for each season
  - Use different BoxCox Transforms for sub-datasets



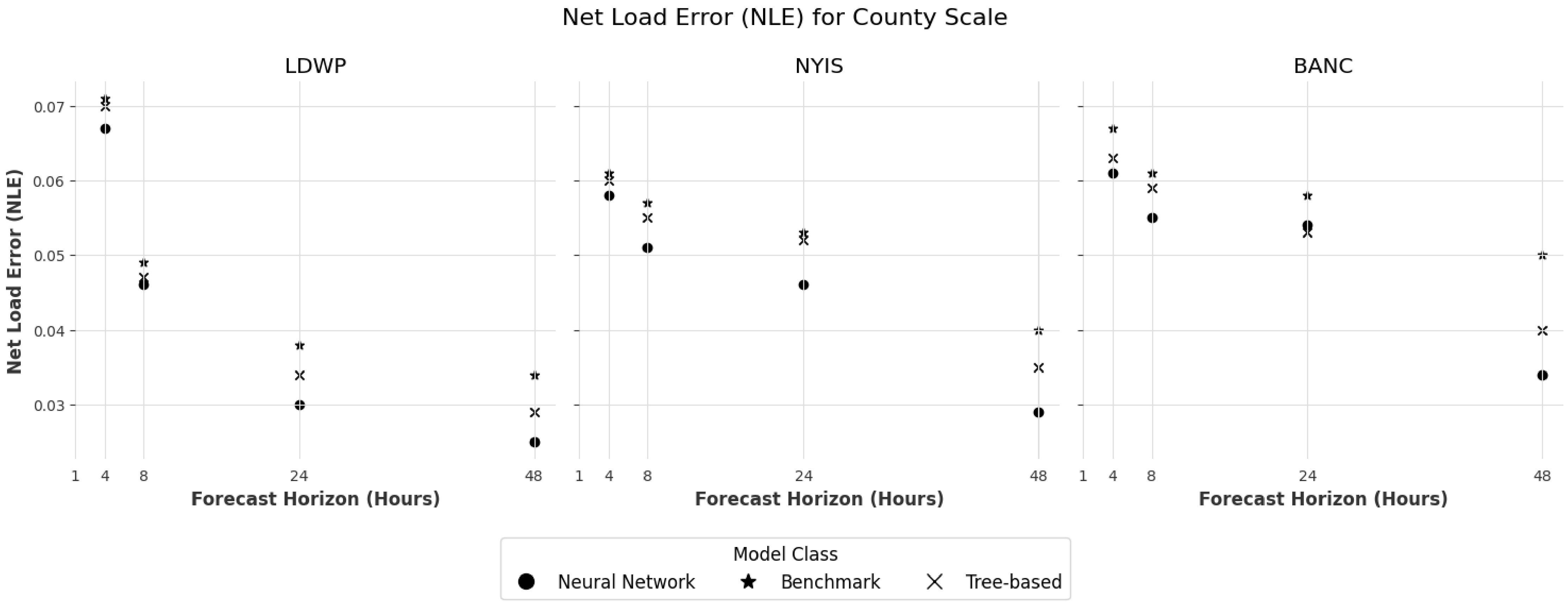
RESULTS – NET LOAD ERROR

- Top subfigure shows the concatenation of j=1 forecasts vs ground truth
- Mid subfigure shows SOC based on MPC
- Bottom subfigure shows the resulting net load



Empirical Validation: Under-predictions lead to increased peak in net load

RESULTS – NET LOAD ERROR SCORES



Decreasing Scores, for longer horizons

Neural Networks lower scores

CONCLUSION

- Introduced Net Load Error as an Application-Driven Forecast Metric
- Supplement Euclidian metrics to improve model selection process for real-life applications
- Empirical results on 15 datasets
- Euclidian metrics favor tree-based methods
- NLE results show that neural networks may outperform tree-based methods for peak prediction
- NLE is lower for longer forecasting horizons

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