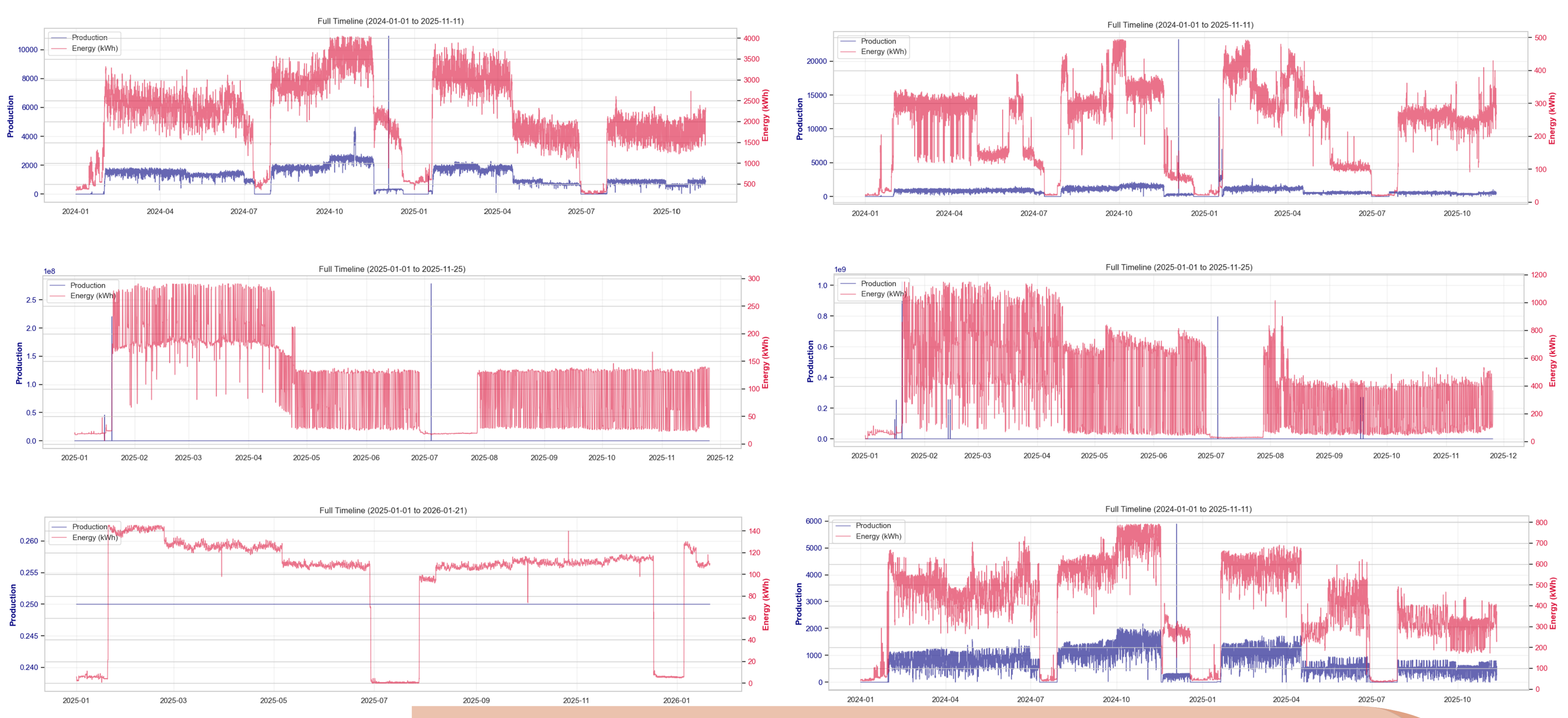
Data-Driven Inefficiency Analysis and AI-Based Predictions for Real-World Industrial Plant Data

VSB TECHNICAL UNIVERSITY OF OSTRAVA | IT4INNOVATIONS NATIONAL SUPERCOMPUTING CENTER
Kristina Motyčková
Marcel Smolík
kristina.motyckova@vsb.cz

Motivation: Industrial energy systems generate vast amounts of data, yet energy management is still often based on manual analysis and passive monitoring. As a result, hidden inefficiencies and waste patterns remain undetected. We propose a next-generation approach to energy analytics, where autonomous AI agents and agile microservices replace traditional methods. This concept aims to enable real-time identification of inefficiencies that are not visible to the human eye. The ultimate goal is to transform energy management from a cost center into a fully optimized ecosystem, where predictive analytics and rapid system response minimize energy waste — ensuring that not a single kilowatt-hour is wasted.

Industrial Data

Consumption (kWh) as the target variable (E_i), reference variables (kg, m^2, number of pieces) (Q_i), downtime, and product types



Noisy data, outliers, missing values, non-stationarity, and sudden changes

Inefficiency Analysis | WHITE BOX model

$$E_i = \alpha + \beta Q_i + \gamma W_i + \delta T_i + \varepsilon_i$$

- E_i: energy consumption, Q_i: production
- W_i: weather conditions, T_i: time effects
- ε_i: error

Quantile regression

Interpretability requirement

Model formulation:

$$Q_\tau(E_i \mid X_i) = X_i^\top \beta^{(\tau)}$$

$$\rho_\tau(u_i) = \begin{cases} \tau u_i & \text{if } u_i \geq 0 \\ (\tau - 1) u_i & \text{if } u_i < 0 \end{cases}$$

Optimization problem:

$$\hat{\beta}^{(\tau)} = \arg\min_{\beta} \sum_{i=1}^{n} \rho_\tau(E_i - X_i^\top \beta)$$

- $u_i = E_i - \hat{E}_i$ (residual), E_i: real value
- $\hat{E}_i = X_i^\top \beta^{(\tau)}$: predicted value
- X_i: input features, β: model coefficients

Model evaluation metrics

MAE (average absolute error)

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

MAPE (error in %)

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

RMSE (penalizes large errors)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

Pinball Loss (quantile error)

$$L_\tau(y_i, \hat{y}_i) = \begin{cases} \tau(y_i - \hat{y}_i), & y_i \geq \hat{y}_i \\ (1-\tau)(\hat{y}_i - y_i), & y_i < \hat{y}_i \end{cases}$$

$$PL_\tau = \frac{1}{n}\sum_{i=1}^{n} L_\tau(y_i, \hat{y}_i)$$

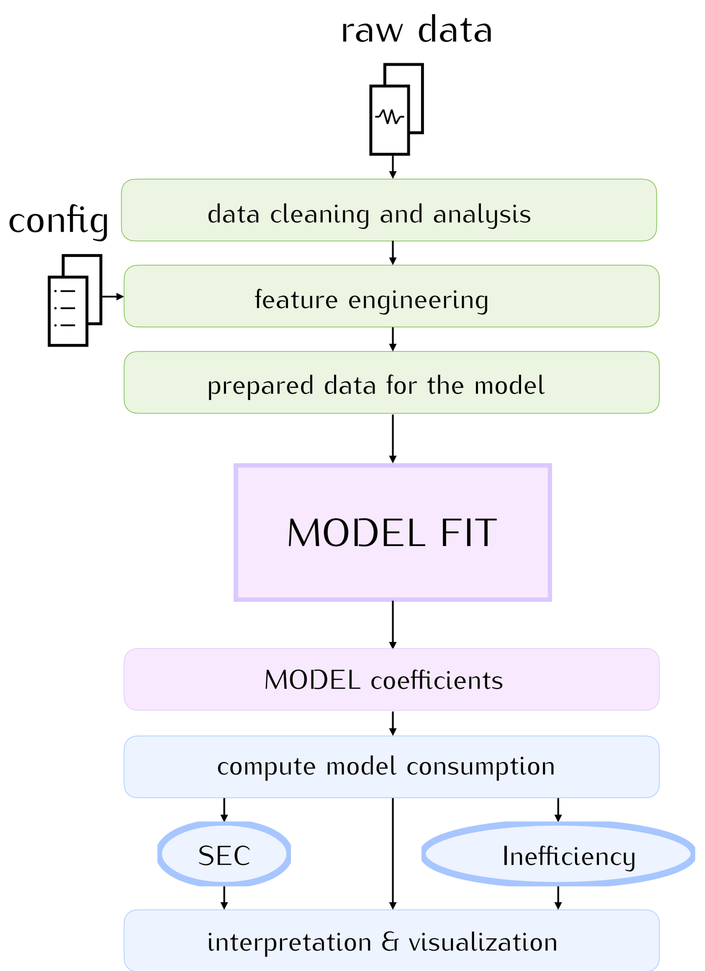
SEC

(specific energy consumption)

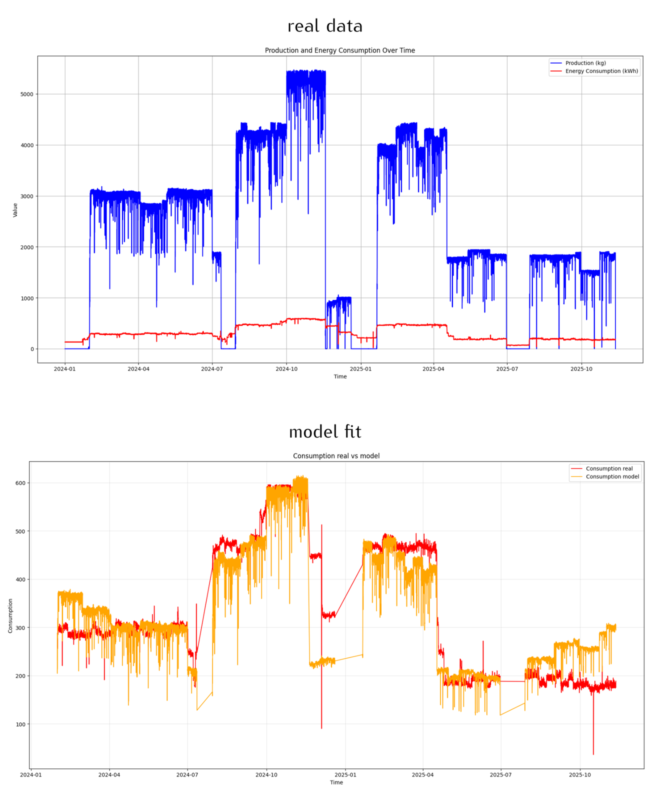
$$SEC_i = \frac{E_i}{Q_i}$$

= energy required per unit of production output

Workflow



Results



Model	MAE	RMSE	MAPE	Pinball Loss
QuantReg	48.03	70.42	19.02	24.02

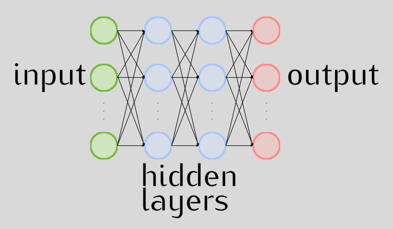
Research Question: "What criteria can be used to evaluate whether a fitted model is suitable for identifying inefficiencies?"

Future Work

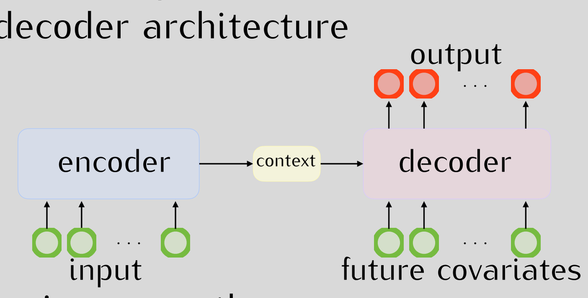
- work still in progress, we are at the beginning
- get more data, more information
- focus on long-term prediction horizons

Predictions | BLACK BOX models

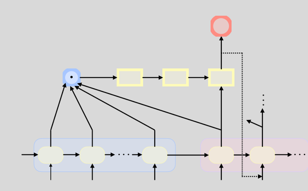
DNN-MLP: despite its simplicity, it remains effective for prediction; typically, only two hidden layers are recommended



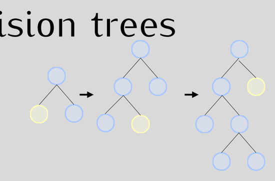
Sequence models: RNN, LSTM, GRU: sequence-to-sequence framework based on encoder–decoder architecture



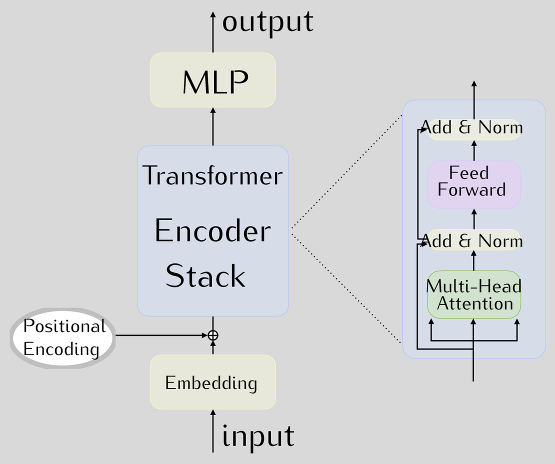
⇒ to improve the performance, we use teacher forcing and Luong attention ⟶



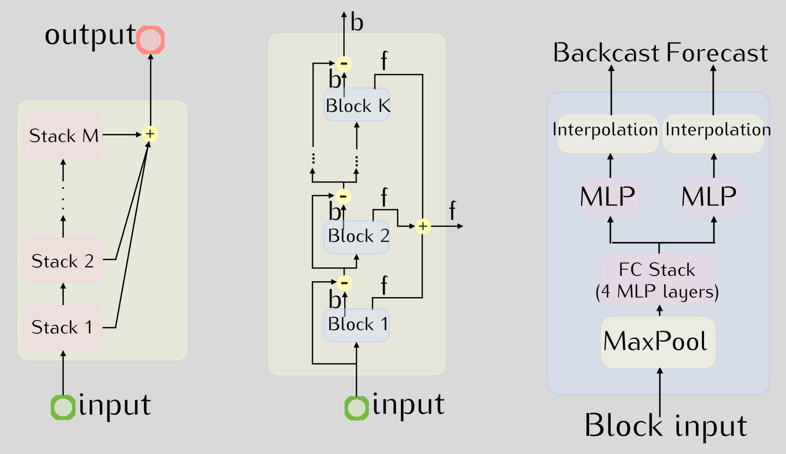
LightGBM: prediction is the sum of sequentially built decision trees



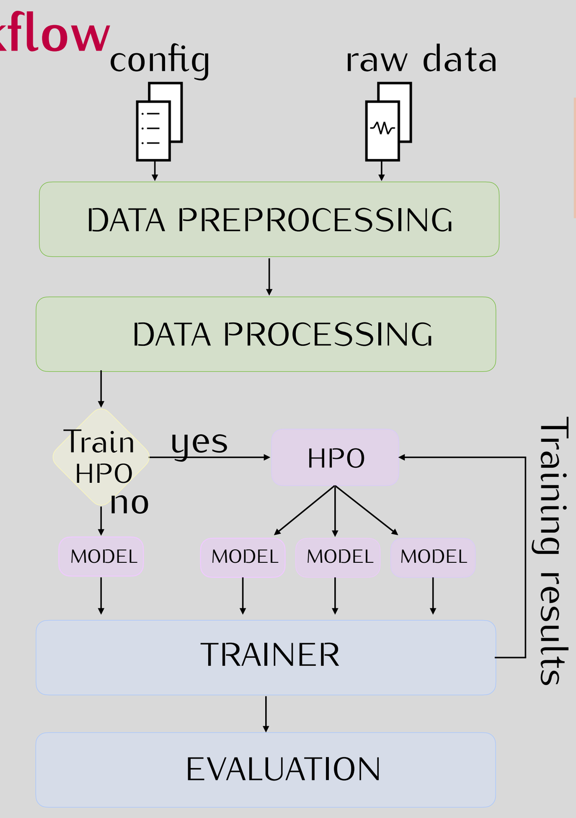
Transformer - Encoder Only: simpler and more stable variant of the Transformer architecture, while still effective for accurate prediction



NHiTS: based on stacked blocks with pooling and interpolation, and can also be configured in a partially interpretable variant

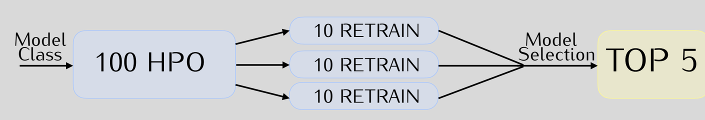


Workflow



High-quality production plan → accurate predictions

Model training



- Hourly data granularity
- Hourly predictions with a 72-hour lookback window and a 24-hour forecast horizon
- Due to limited data availability, we used 10 days for validation and 7 days for testing
- $rMAE = MAE_{\text{model}}/MAE_{\text{naive}}$ (24 h back)
- $CRPS = \mathbb{E}|X - y| - \frac{1}{2}\mathbb{E}|X - X'|$

Deterministic | Point forecast

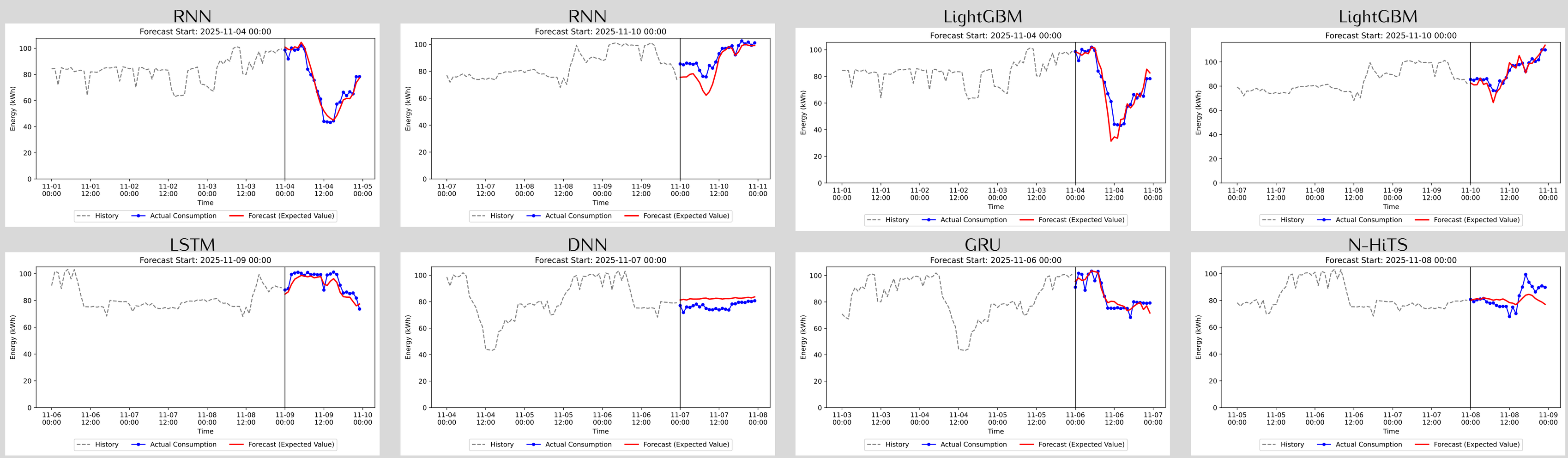
$$\hat{y}_{t+k} = \mathbb{E}[Y_{t+k} \mid \Omega_t; m, \theta]$$

- $\hat{y}_{t+k}$ prediction at horizon $t+k$, Y_{t+k} random future value,
- Ω_t information set at time t, m model,
- θ model parameters, $\mathbb{E}[\cdot]$ conditional expectation.

Model	MAE	MAPE	rMAE
DNN	10.29	12.37	12.27
LightGBM	5.85	6.57	6.81
NHiTS	6.13	7.58	7.31
GRU	4.69	5.81	5.6
RNN	5.26	6.41	6.28
LSTM	5.95	7.23	7.11

MAE of the naive model is 12.04

Results



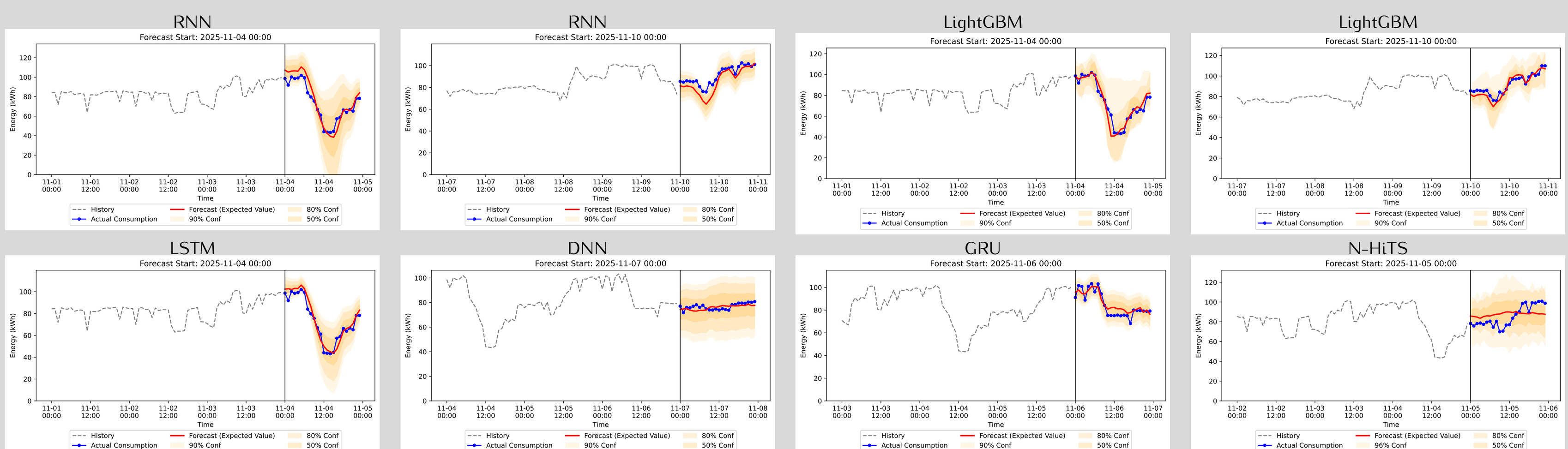
Probabilistic

$$p(Y_{t+k} \mid \Omega_t; m, \theta)$$

- $p(\cdot)$ predictive distribution
- model provides parameters that describe the full predictive distribution

Model	MAE	MAPE	rMAE	CRPS
DNN	12.09	14.06	14.42	7.30
LightGBM	5.48	6.09	6.38	3.98
NHiTS	7.71	9.96	9.2	4.28
GRU	5.00	6.26	5.97	2.88
RNN	5.20	6.35	6.2	3.20
LSTM	5.04	6.11	6.01	2.83

Results



InnovAIte SLOVAKIA
Funded by the European Union NextGenerationEU
RECOVERY AND RESILIENCE PLAN
DEPUTY PRIME MINISTER'S OFFICE FOR THE RECOVERY PLAN AND THE KNOWLEDGE ECONOMY
VAIA RESEARCH AND INNOVATION AUTHORITY