Optimization of Artificial Neural Network Parameters for Modeling Flue Gas Composition from Woodstove Combustion of Beech Wood and Briquettes

Katarzyna Szramowiat-Sala[1*], Jiří Ryšavý[2], Kamil Krpec[2], Norbert Kowalczyk[1], Jerzy Górecki[1]

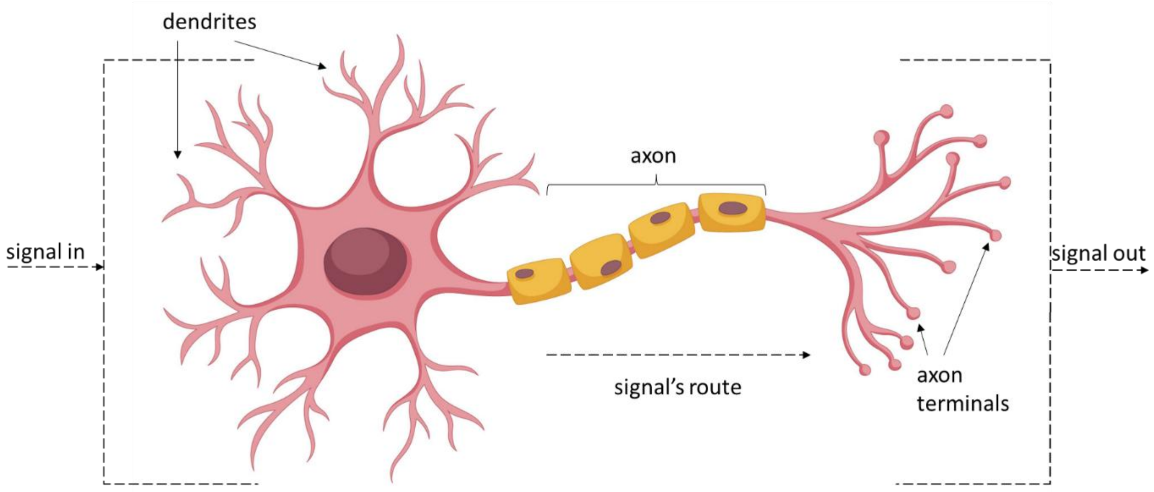
[1]Department of Fuel Technology, Faculty of Energy and Fuels, AGH University of Kraków, Poland

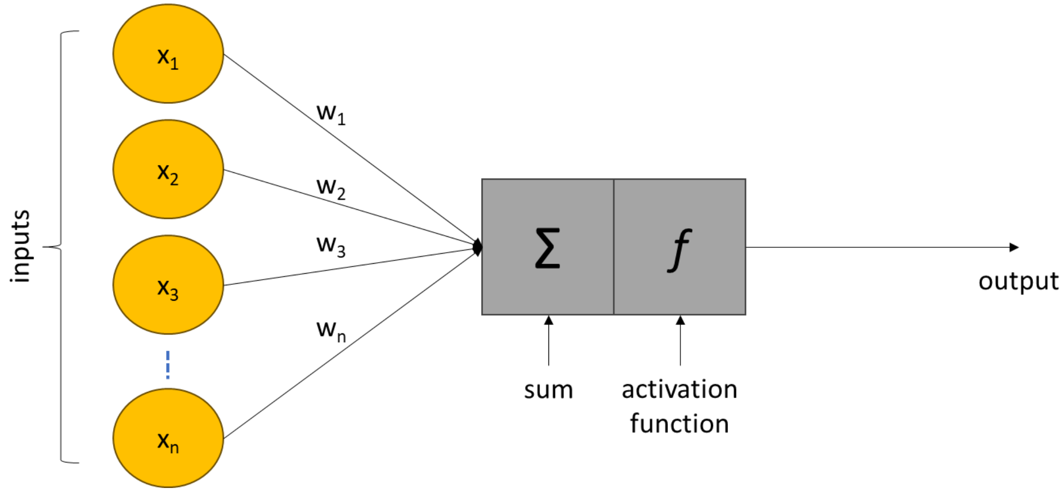
[2]Energy Research Centre, VŠB-Technical University of Ostrava, Czech Republic

International Energy and Environment Conference 2025

8. – 10. 9. 2025
Resort Sepetná, Ostravice, Czechia

Artificial neural networks



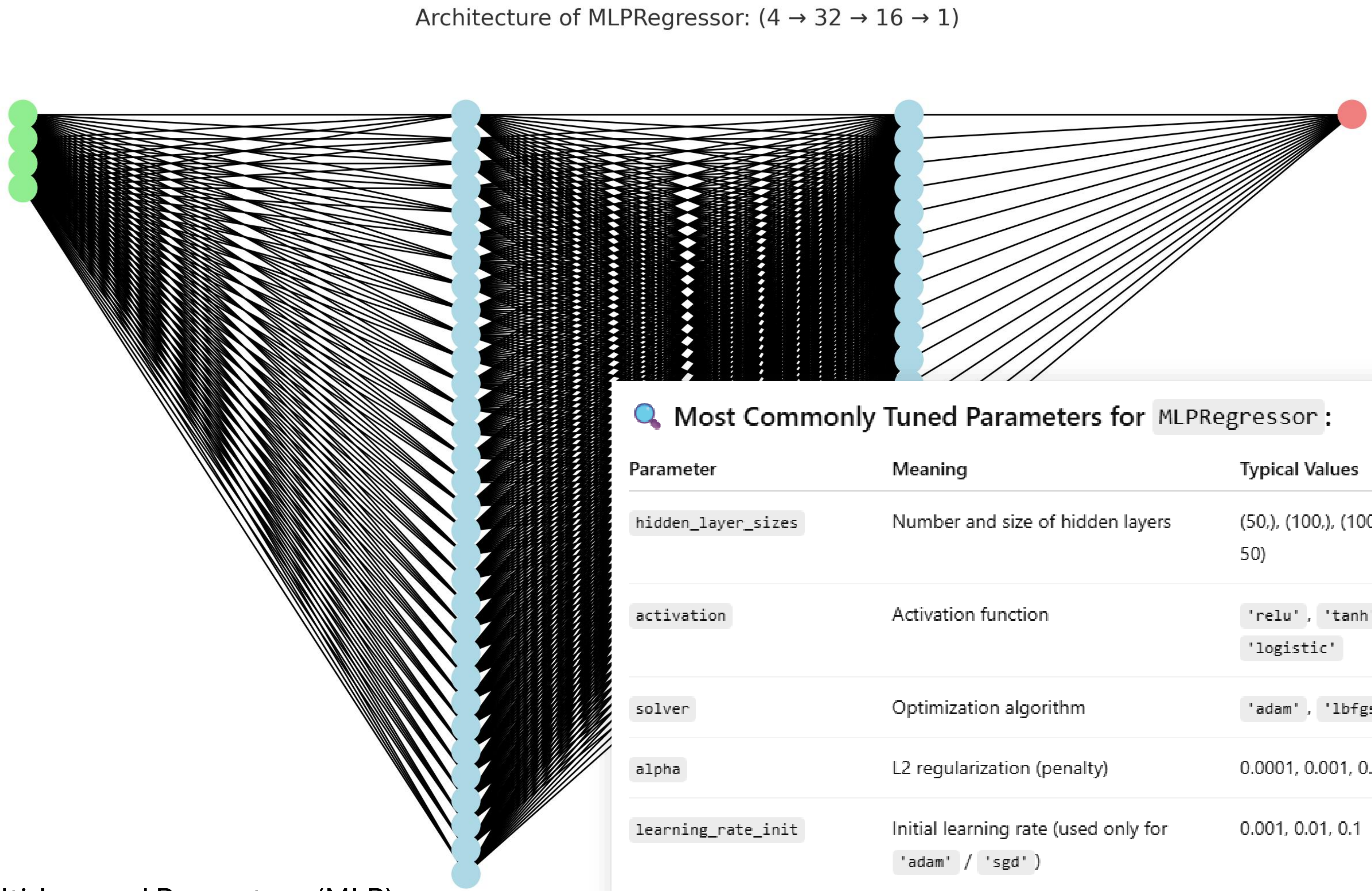


Modeling, data analysis, and process optimization supported by deep learning are based on the functioning of the human brain, which learns primarily from mistakes.

An artificial neural network works similarly. Before being input into the control system, the network is trained until it achieves a minimal error (to a set value—supervised learning—or until it determines that it is satisfactory on its own—unsupervised learning).

Once trained, the network becomes a "regular" algorithm that is integrated into the control system of a given device or system of devices.

In a nutshell and with significant simplification



🔍 Most Commonly Tuned Parameters for `MLPRegressor`:

Parameter	Meaning	Typical Values
`hidden_layer_sizes`	Number and size of hidden layers	(50,), (100,), (100, 50), (50, 50, 50)
`activation`	Activation function	`'relu'`, `'tanh'`, `'logistic'`
`solver`	Optimization algorithm	`'adam'`, `'lbfgs'`, `'sgd'`
`alpha`	L2 regularization (penalty)	0.0001, 0.001, 0.01, 0.1
`learning_rate_init`	Initial learning rate (used only for `'adam'` / `'sgd'`)	0.001, 0.01, 0.1

Multi-Layered Perceptron (MLP)

Research motivation

Efficient and clean wood combustion remains a challenge

→ Strong variability depending on fuel (beech wood vs. briquettes) and operating conditions.

Flue gas composition is critical

→ CO → indicator of incomplete combustion

→ NO_x → environmental impact

→ CO_2, O_2 → combustion efficiency & process control

Current models are insufficient

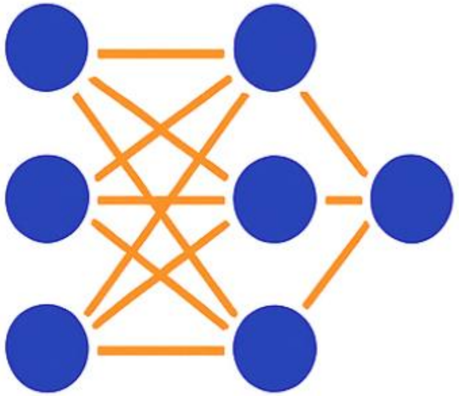
→ Classical approaches (e.g. ARIMA) fail during transient phases.

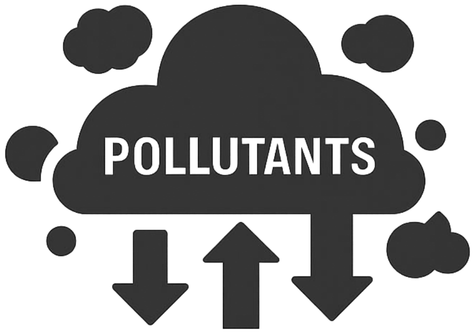
→ Need robust, data-driven prediction methods.

OUR GOAL

→ Develop and optimize **Artificial Neural Network models** for emission prediction,

→ Provide a step toward **intelligent, low-emission woodstoves**.





Experimental setup

STOVE

Romotop Lugo N stove

COMBUSTED FUELS

Beech Wood

Wood Briquettes

TESTING PROCEDURE

PRE-HEATING PHASE

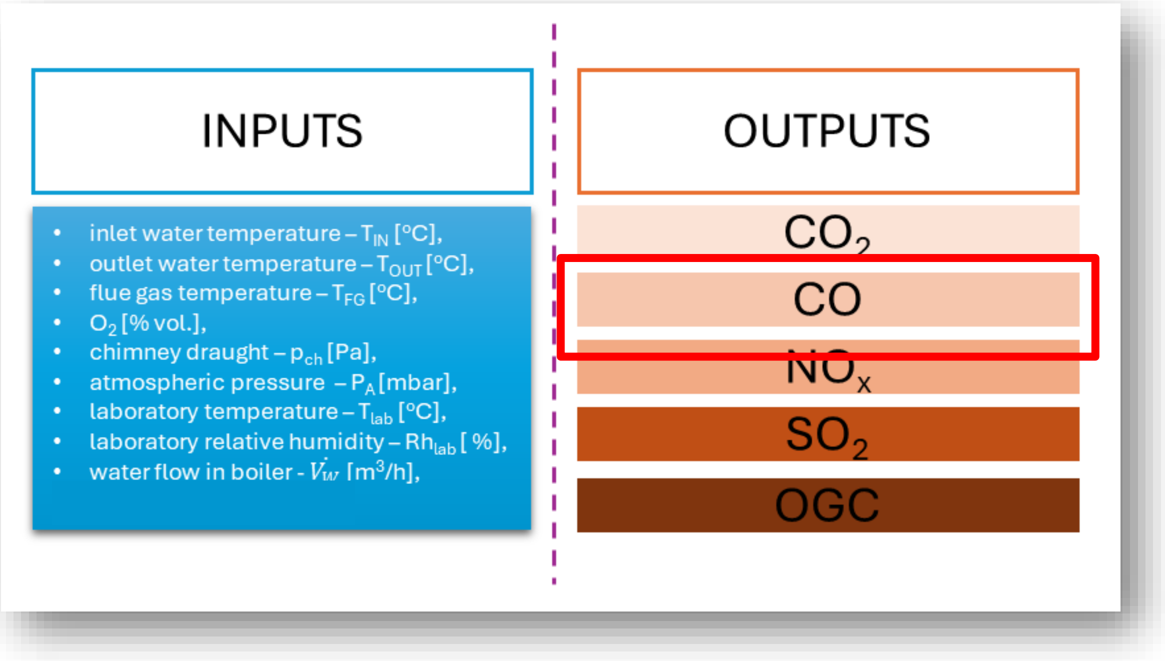
TESTING PHASE
Beech wood

- about 4-5 hours;
- testing phase consists of 5 combustion periods (0,75 h – 1 h each),
- 1 wood log was used (about 1.7 kg) for each combustion period

TESTING PHASE
Briquetts

- about 4-5 hours,
- testing phase consists of 4 combustion periods (0,75 h – 1 h each),
- 1 briquette was used (about 1.8 kg) for each combustion period

Data

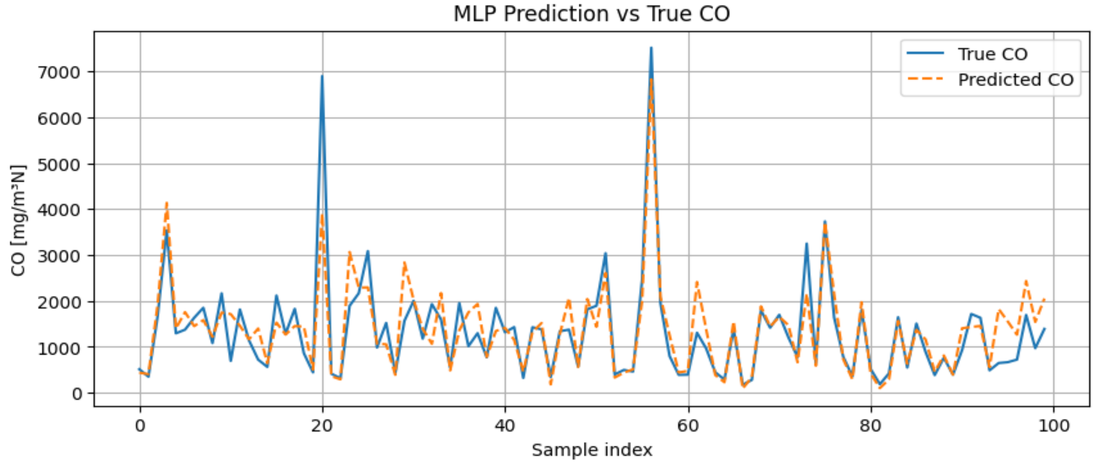


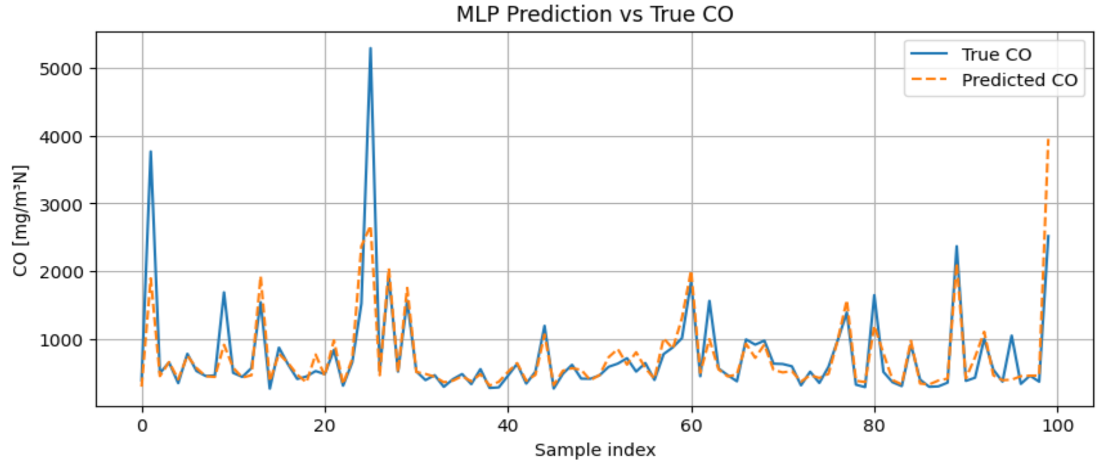
Models

- MLP (different topologies)
- LightGBM
- XGBoost
- Hybrid model: MLP+LightGBM
- Hybrid model: MLP+XGBoost
- ARIMA (includes factor of „time”)
- LSTM (reflects variations in time during the modelled process)

CO prediction: Models' fit evaluation

Model	RMSE [mg/m³N]	R^2
BEECH WOOD		
MLP(16, 1)	1645.97	-1.538
MLP(64, 32, 1)	740.44	0.486
MLP(128, 64, 32, 1)	740.44	0.819
MLP(256, 64, 16, 1)	391.11	0.857
BRIQUETTS		
MLP(16, 1)	927.60	-0.813
MLP(64, 32, 1)	343.02	0.752
MLP(128, 64, 32, 1)	329.27	0.772
MLP(256, 64, 16, 1)	334.99	0.764





CO prediction: Models' fit evaluation

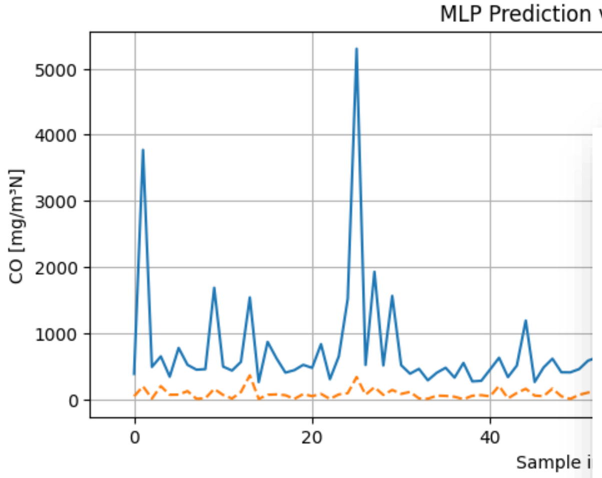
BEECH WOOD

Model	RMSE [mg/m³N]	R^2
XGBoost	276.364	0.928
LightGBM	392.927	0.855
MLP + XGB (50/50)	292.895	0.920
MLP + LightGBM (50/50)	328.369	0.899

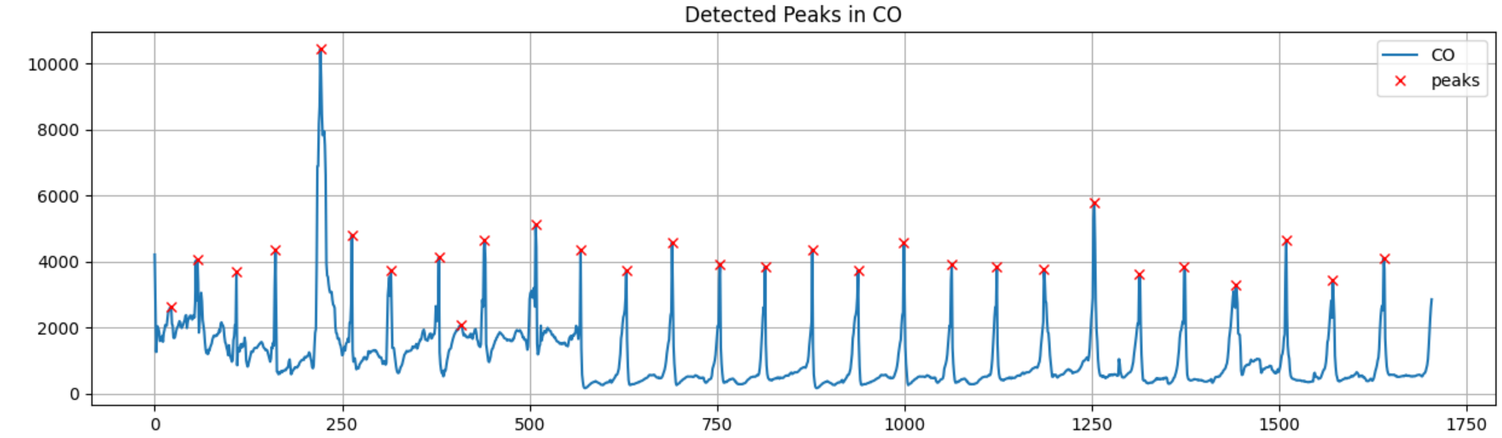
BRIQUETTS

Model	RMSE [mg/m³N]	R^2
XGBoost	251.569	0.867
LightGBM	215.945	0.902
MLP + XGB (50/50)	285.359	0.828
MLP + LightGBM (50/50)	264.452	0.853

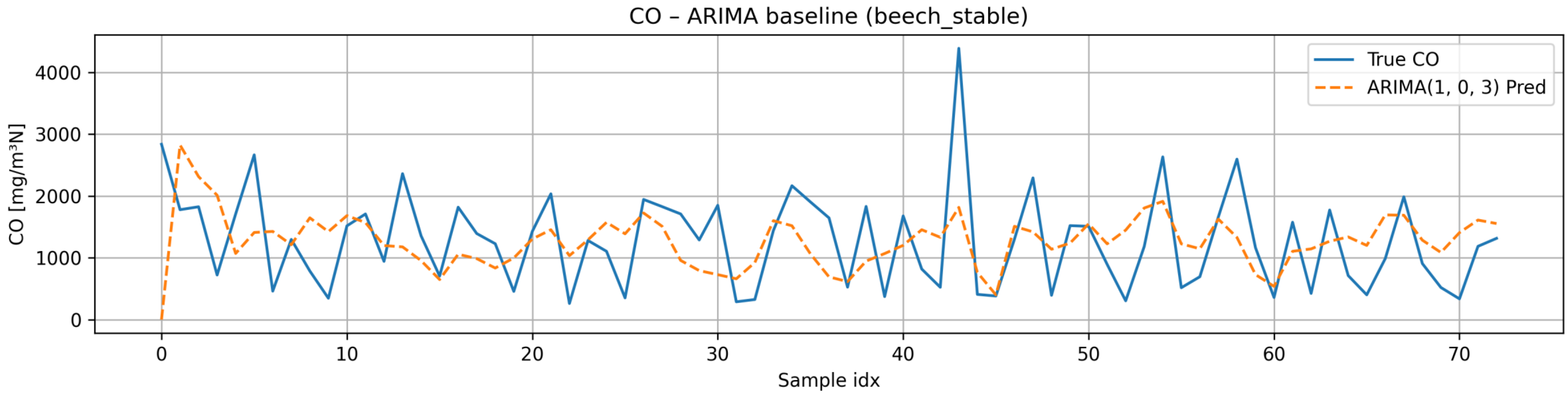
Why MLPRegressor is not „good”?



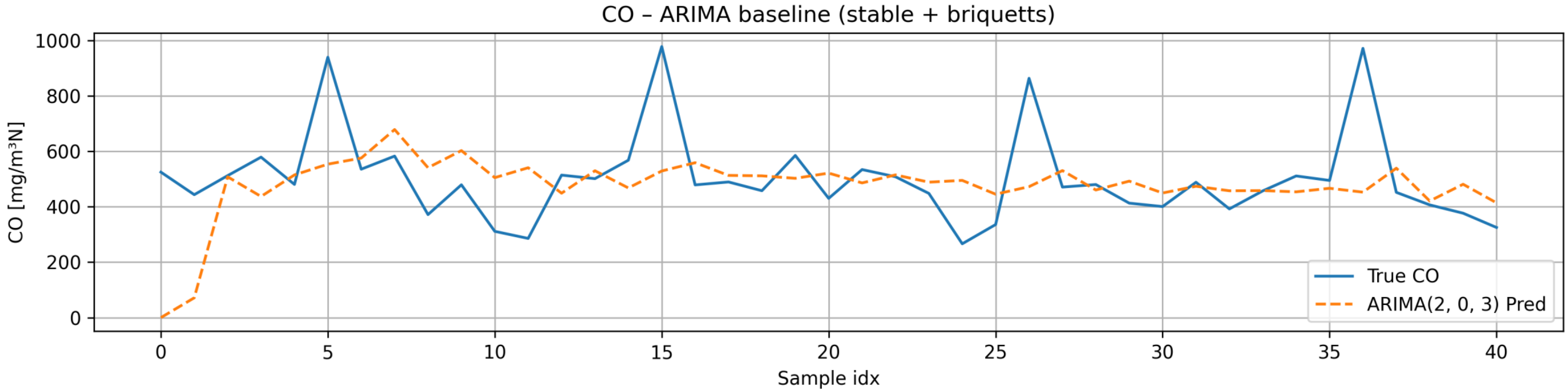
phase	fuel	RMSE	R2
ignition	beech wood	762.263112	0.336973
ignition	briquetts	506.044704	0.857882
stable	beech wood	487.237974	0.604322
stable	briquetts	66.453064	0.833254
burnout	beech wood	720.116419	0.557608
burnout	briquetts	243.334776	0.804779



ARIMA



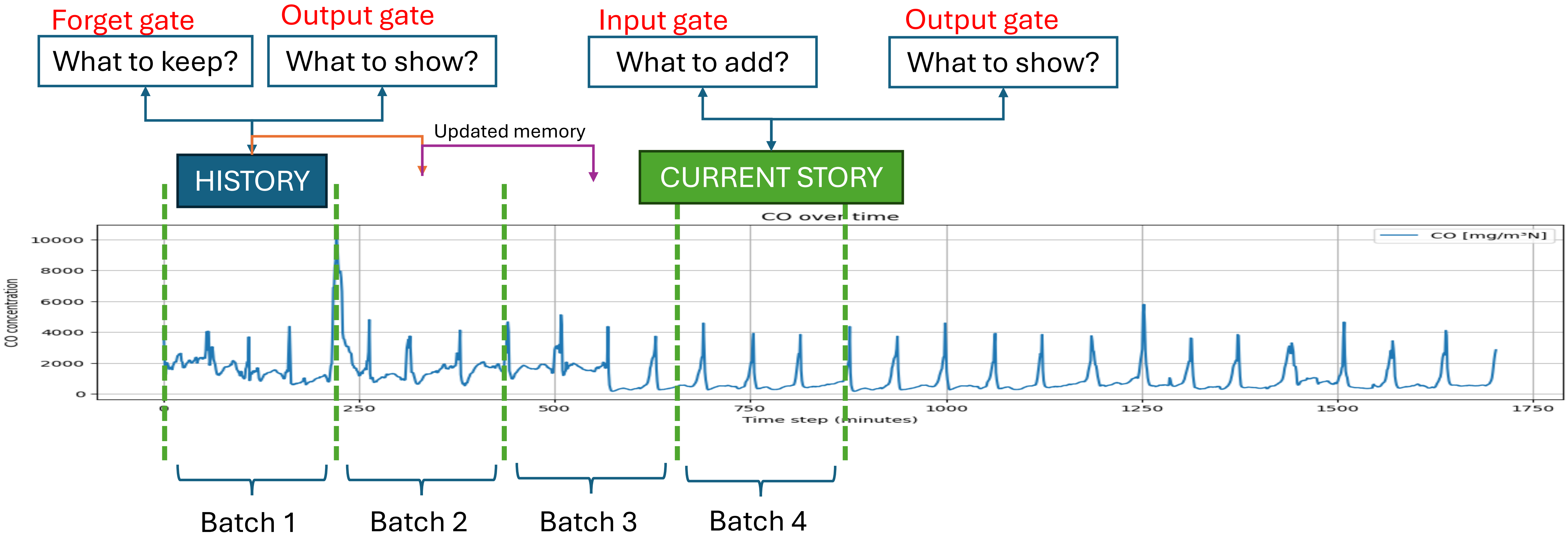
CO – ARIMA baseline (beech_stable)
True CO
ARIMA(1, 0, 3) Pred
CO [mg/m³N]
Sample idx



CO – ARIMA baseline (stable + briquetts)
True CO
ARIMA(2, 0, 3) Pred
CO [mg/m³N]
Sample idx

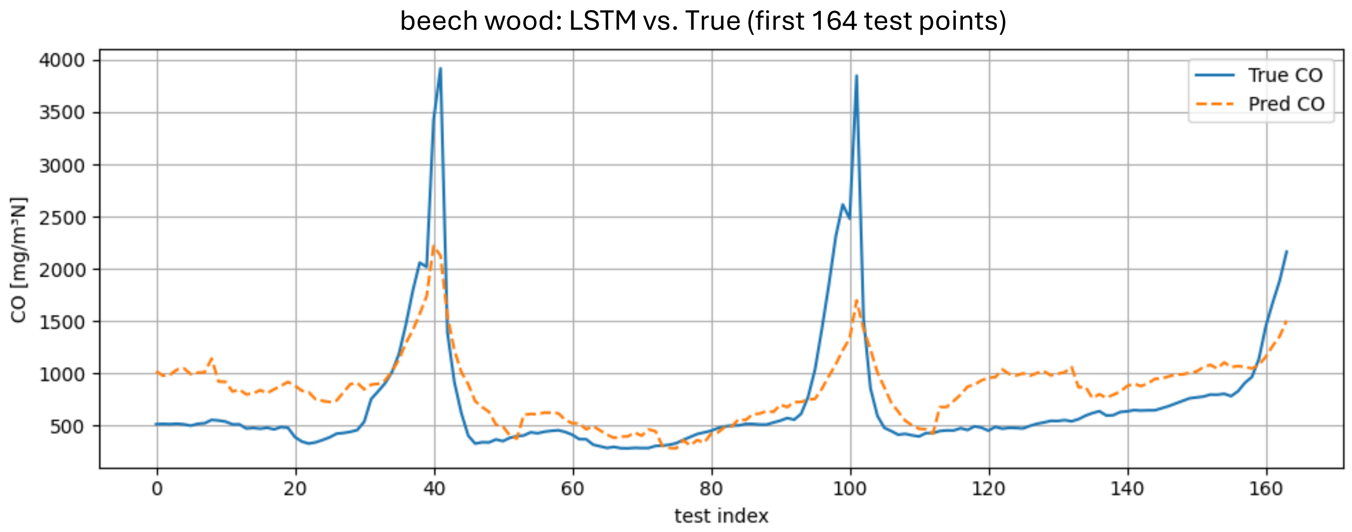
Long Short-Term Memory neural networks (LSTM)

→ „catches" the temporal dynamic variations in a process

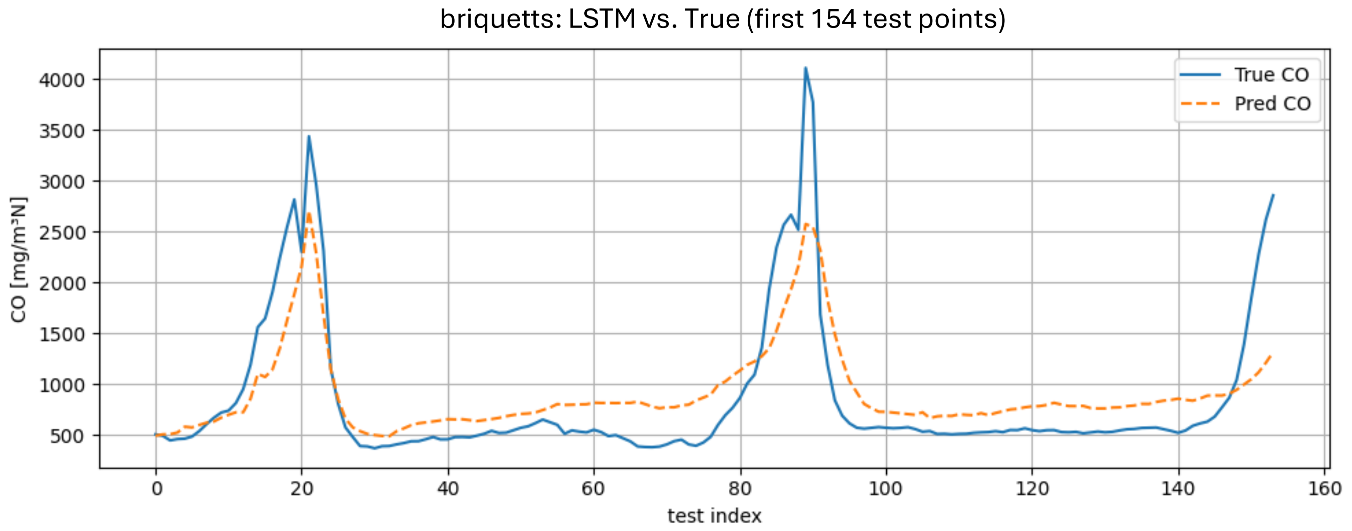


Long Short-Term Memory neural networks (LSTM)

Beech wood combustion:
RMSE: 427.815 mg/m³N
R^2=0.495



Briquetts combustion:
RMSE: 410.747 mg/m³N
R^2=0.686



Conclusions

- Different fuels require different models.
- Beech wood, with unstable combustion, benefits most from deep networks and hybrid models.
- Briquettes, with stable combustion, can be modeled effectively with boosting methods.
- Classical models like ARIMA are insufficient, while LSTM networks can capture important temporal features.

Optimization of Artificial Neural Network Parameters for Modeling Flue Gas Composition from Woodstove Combustion of Beech Wood and Briquettes

Katarzyna Szramowiat-Sala[1]*, Jiří Ryšavý[2], Kamil Krpec[2], Norbert Kowalczyk[1], Jerzy Górecki[1]

Email to: Katarzyna.Szramowiat@agh.edu.pl

AGH Research University Excellence Initiative

Faculty of Energy and Fuels

VSB Technical University of Ostrava

International Energy and Environment Conference 2025
8. – 10. 9. 2025
Resort Sepetná, Ostravice, Czechia