

LSTM 24-hour Forecast Report - 西条

$$\begin{aligned}i_t &= \sigma(W_i x_t + U_i h_{t-1} + b_i) \\f_t &= \sigma(W_f x_t + U_f h_{t-1} + b_f) \\o_t &= \sigma(W_o x_t + U_o h_{t-1} + b_o) \\\tilde{c}_t &= \tanh(W_c x_t + U_c h_{t-1} + b_c) \\c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \\h_t &= o_t \odot \tanh(c_t) \\\hat{y}_t &= W_y h_t + b_y\end{aligned}$$

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

i_t, f_t, o_t : input, forget and output gates controlling memory flow
 c_t : cell state storing long-term information
 h_t : hidden state passed to the next time step
 σ : sigmoid activation function
 \tanh : hyperbolic tangent activation for non-linearity
 \mathcal{L} : mean squared error minimized during training

The LSTM (Long Short-Term Memory) model is a type of recurrent neural network (RNN) designed to learn temporal dependencies in sequential data. It introduces a memory cell that can preserve information across long time intervals through a system of gates:

1. The **input gate** decides how much new information enters the memory cell.
2. The **forget gate** controls what information should be discarded from the cell state.
3. The **output gate** determines how much of the internal memory contributes to the output.

This gating mechanism allows the LSTM to model both short-term and long-term dependencies. During training, the model minimizes the mean squared error between predicted and actual values.

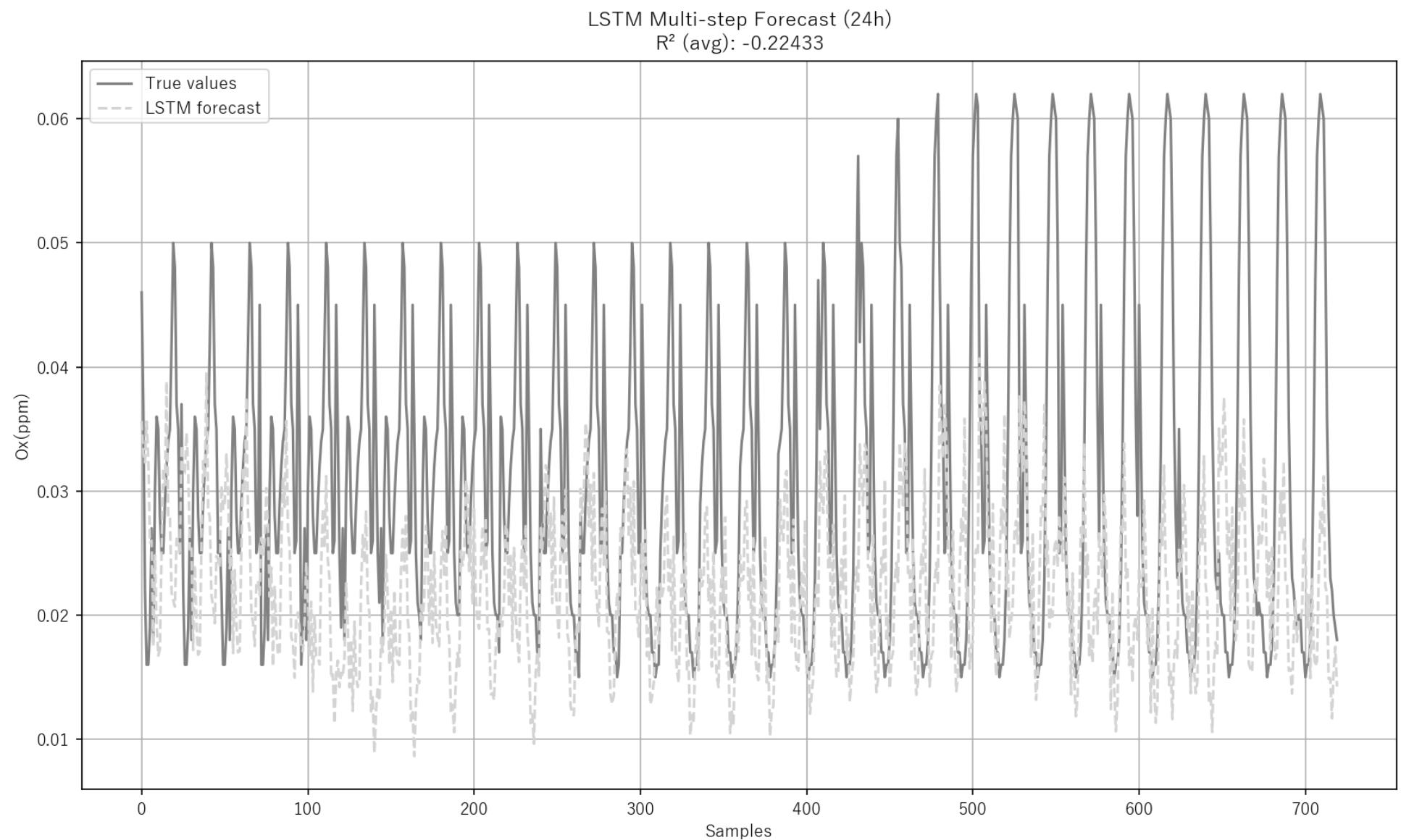
Prefecture code	38
Station code	38206050
Station name	西条
Target item	Ox(ppm)
Number of data points in the train set	15747
Number of data points in the test set	6749
Forecast horizon (hours)	24
Model	LSTM
Elapsed time	0 min 3 sec
Number of features used	25
Residuals mean	0.01094
Residuals median	0.009274
Residuals mode	0.007036

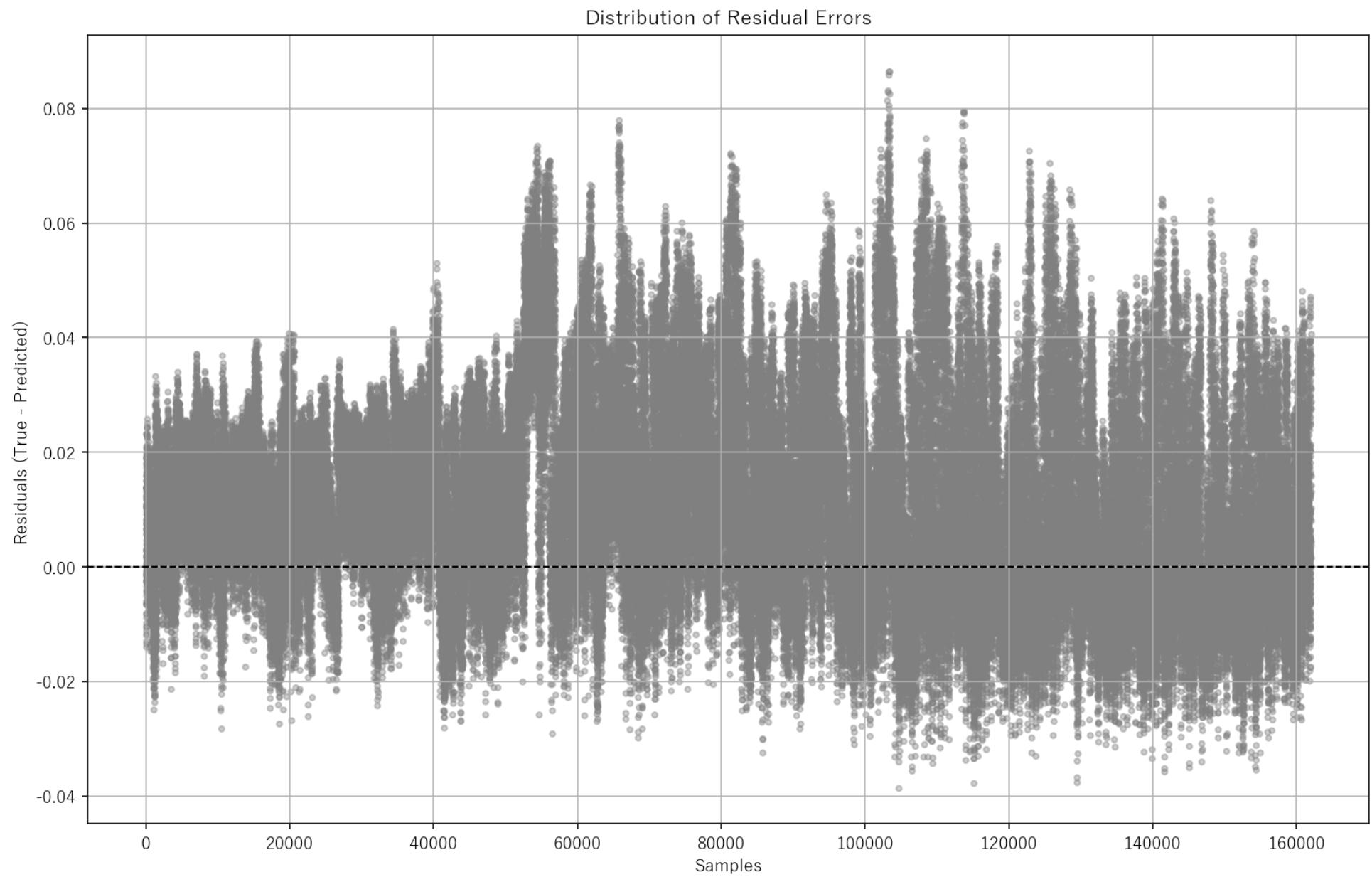
Features used for prediction

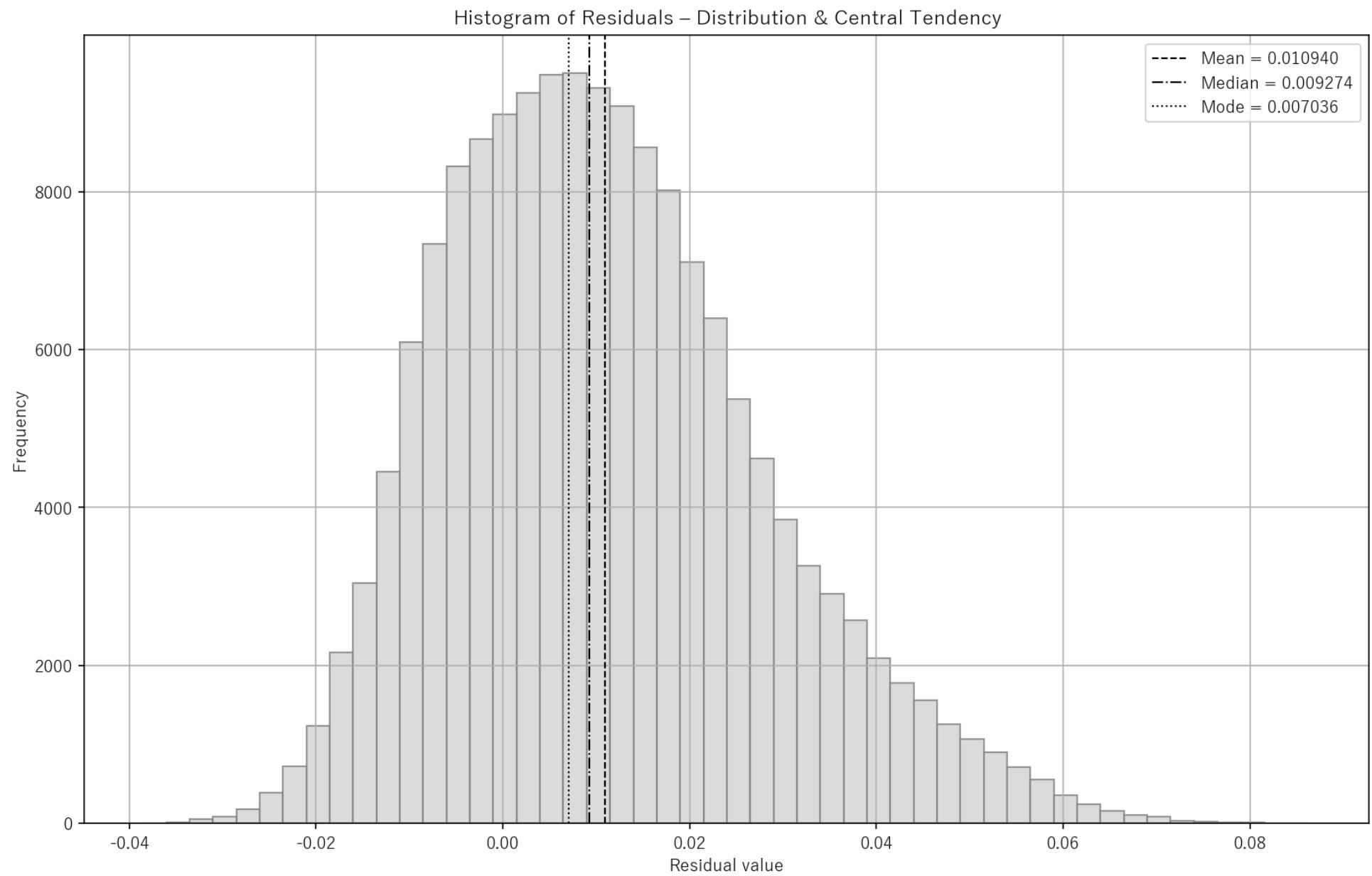
NO(ppm)	NO2(ppm)	U	V	Ox(ppm)_roll_mean_3
Ox(ppm)_roll_std_6	NO(ppm)_roll_mean_3	NO(ppm)_roll_std_6	NO2(ppm)_roll_mean_3	NO2(ppm)_roll_std_6
U_roll_mean_3	U_roll_std_6	V_roll_mean_3	V_roll_std_6	Ox(ppm)_diff_1
Ox(ppm)_diff_2	Ox(ppm)_diff_3	NO(ppm)_diff_3	NO2(ppm)_diff_3	U_diff_3
V_diff_3	hour_sin	hour_cos	dayofweek	is_weekend

Model accuracy

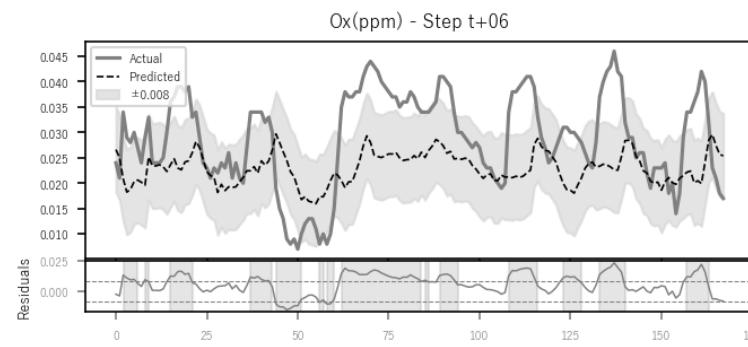
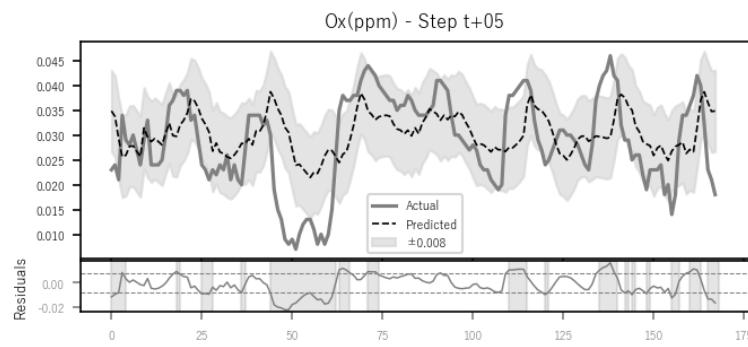
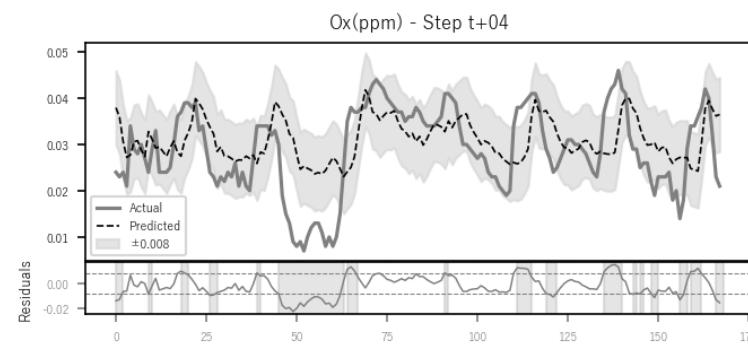
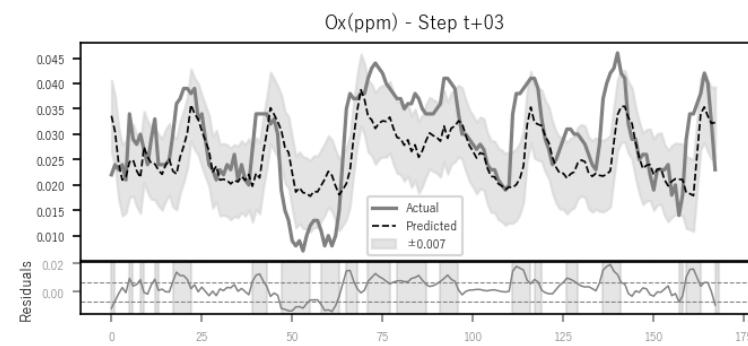
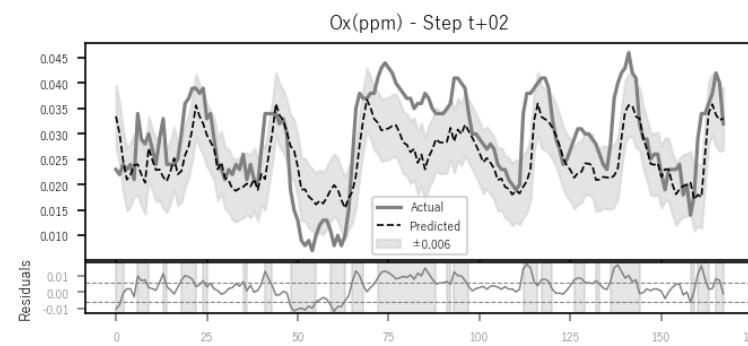
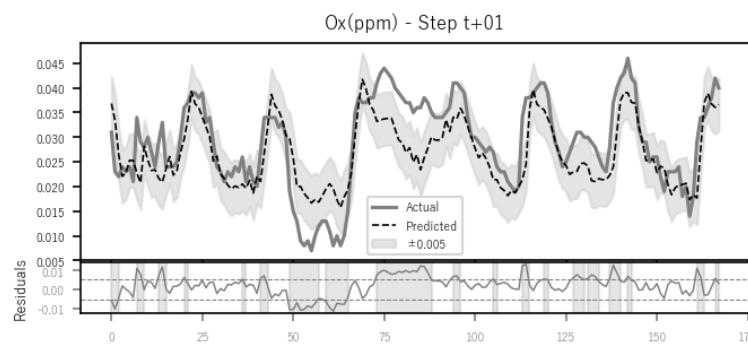
Target	R ²	MAE	RMSE
Ox(ppm)_t+01	0.5840	0.0090	0.0118
Ox(ppm)_t+02	0.4174	0.0107	0.0139
Ox(ppm)_t+03	0.3016	0.0118	0.0152
Ox(ppm)_t+04	0.3145	0.0120	0.0151
Ox(ppm)_t+05	0.2596	0.0123	0.0157
Ox(ppm)_t+06	-0.1180	0.0148	0.0193
Ox(ppm)_t+07	-0.0535	0.0144	0.0187
Ox(ppm)_t+08	-0.6056	0.0179	0.0231
Ox(ppm)_t+09	-0.0668	0.0146	0.0188
Ox(ppm)_t+10	-0.6102	0.0179	0.0231
Ox(ppm)_t+11	-0.7437	0.0188	0.0241
Ox(ppm)_t+12	-0.8013	0.0191	0.0245
Ox(ppm)_t+13	-0.3043	0.0162	0.0208
Ox(ppm)_t+14	-0.0847	0.0150	0.0190
Ox(ppm)_t+15	-0.1736	0.0155	0.0198
Ox(ppm)_t+16	0.0246	0.0144	0.0180
Ox(ppm)_t+17	-0.3217	0.0163	0.0210
Ox(ppm)_t+18	-0.2822	0.0159	0.0207
Ox(ppm)_t+19	-0.8286	0.0195	0.0247
Ox(ppm)_t+20	-0.7955	0.0193	0.0245
Ox(ppm)_t+21	-0.8283	0.0196	0.0247
Ox(ppm)_t+22	-0.2747	0.0159	0.0206
Ox(ppm)_t+23	-0.1505	0.0151	0.0196
Ox(ppm)_t+24	-0.2423	0.0158	0.0204



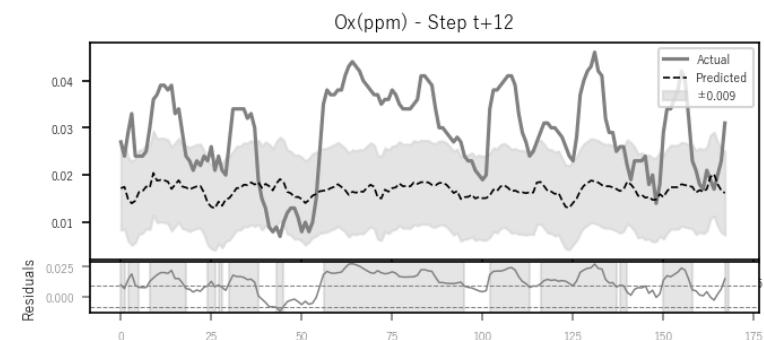
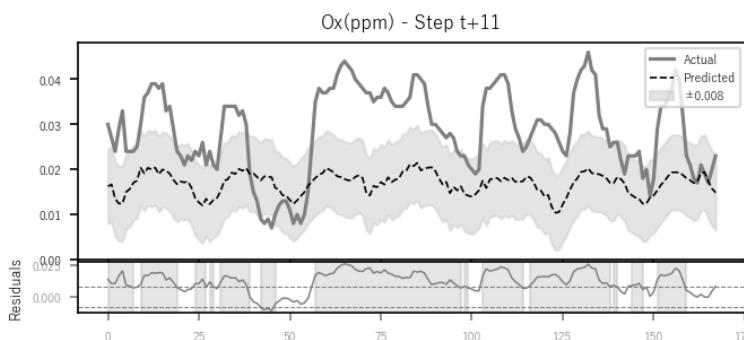
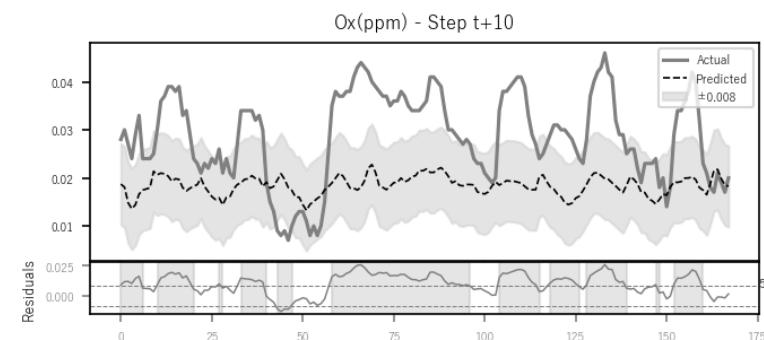
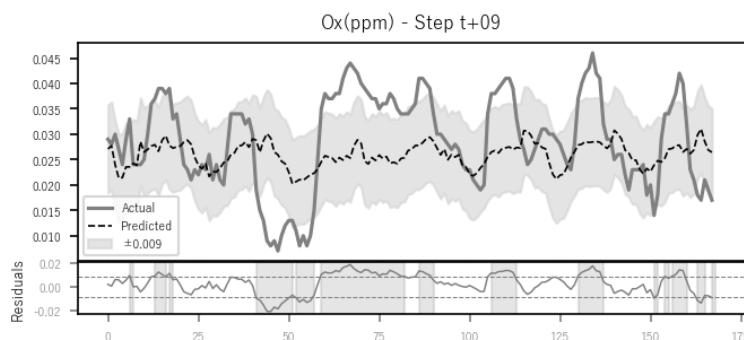
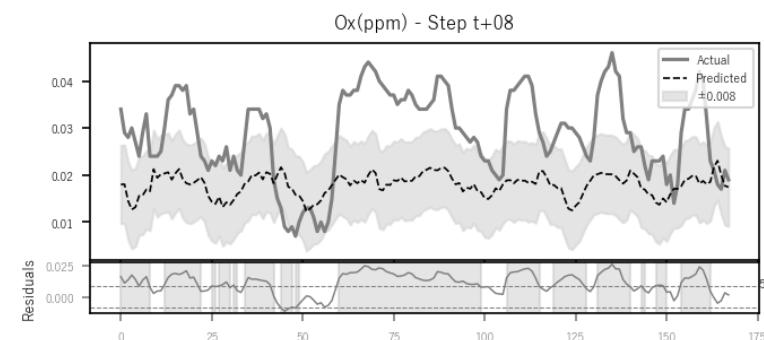
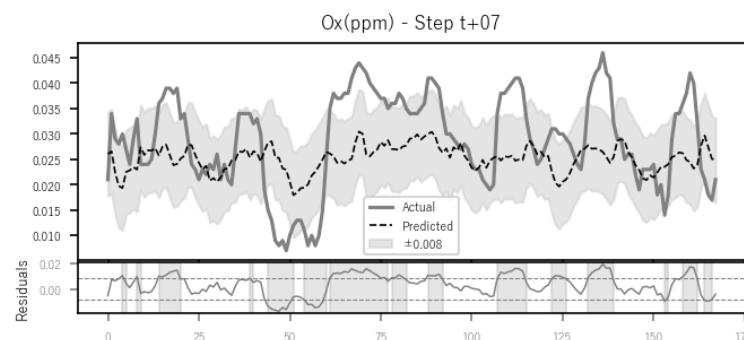




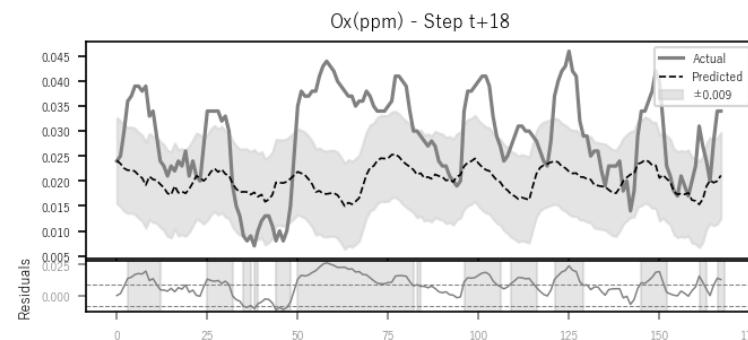
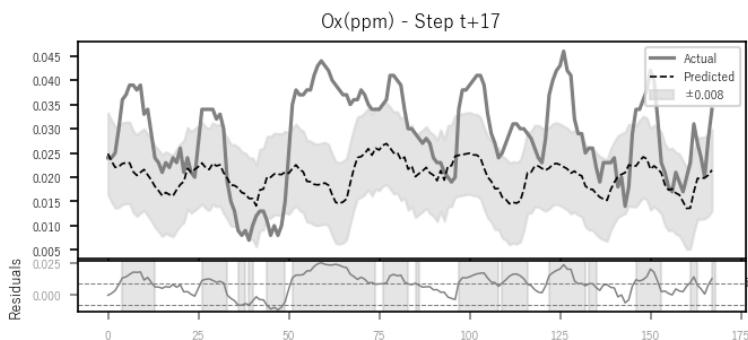
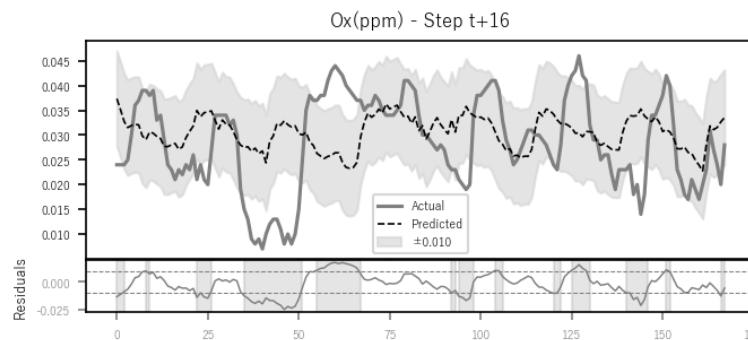
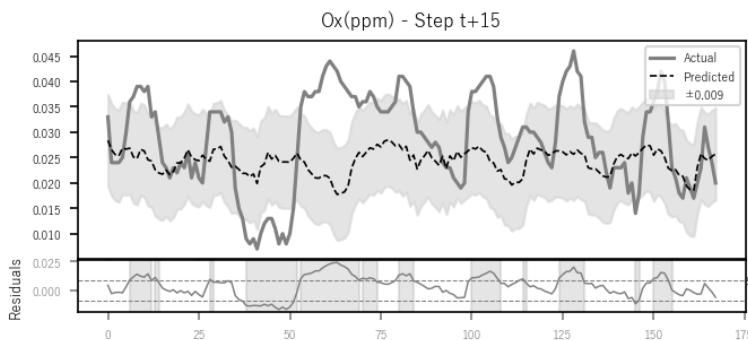
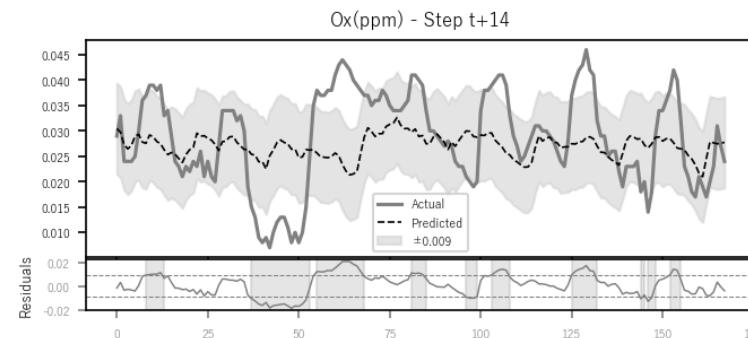
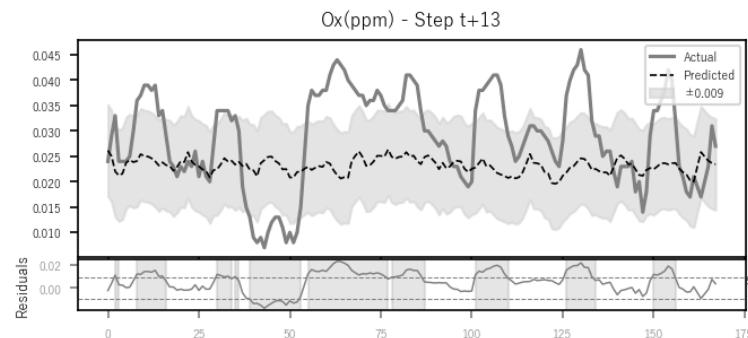
Comparison between actual and predicted values
with \pm Standard Deviation Bands



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