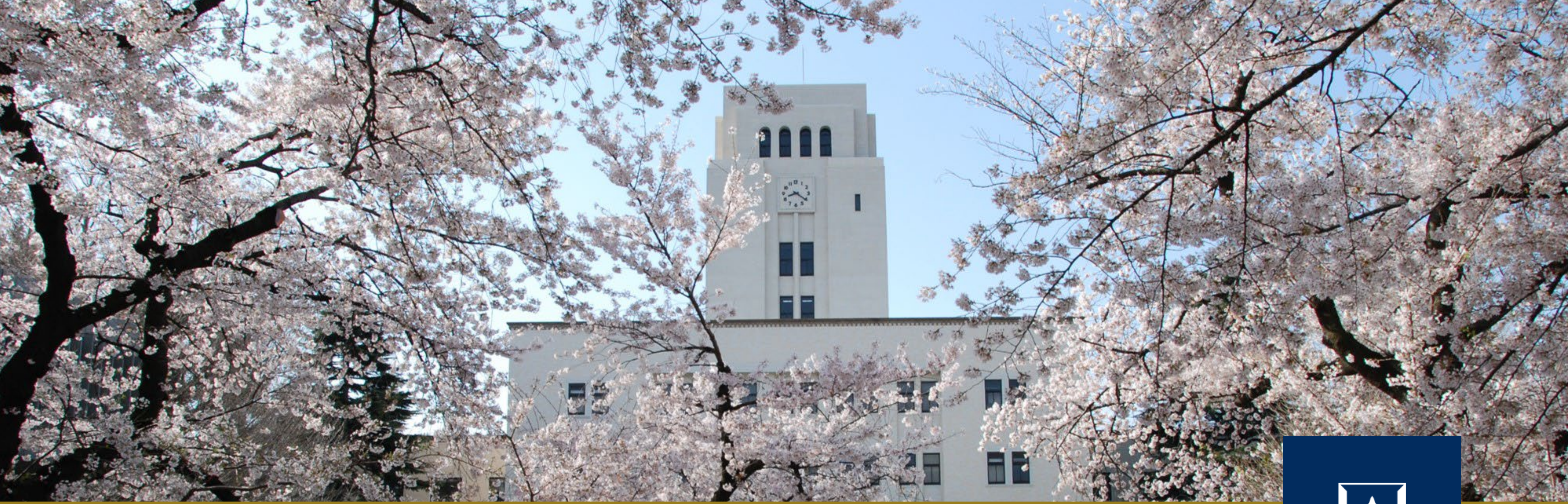

Study on Analysis and Prediction of Real-world Emissions from Direct Injection Gasoline Vehicle Using On-road Driving Emission Measurement Data

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@ CE-CERT, UC Riverside

Tokyo Tech

NGK SPARK PLUG CO.,LTD

Research Background

✓ "How much" and "Where" air pollutant are emitted?
= "Hot Spot" or not?

✓ Evaluation of the roadside real-world emission using on-board emission measurement system

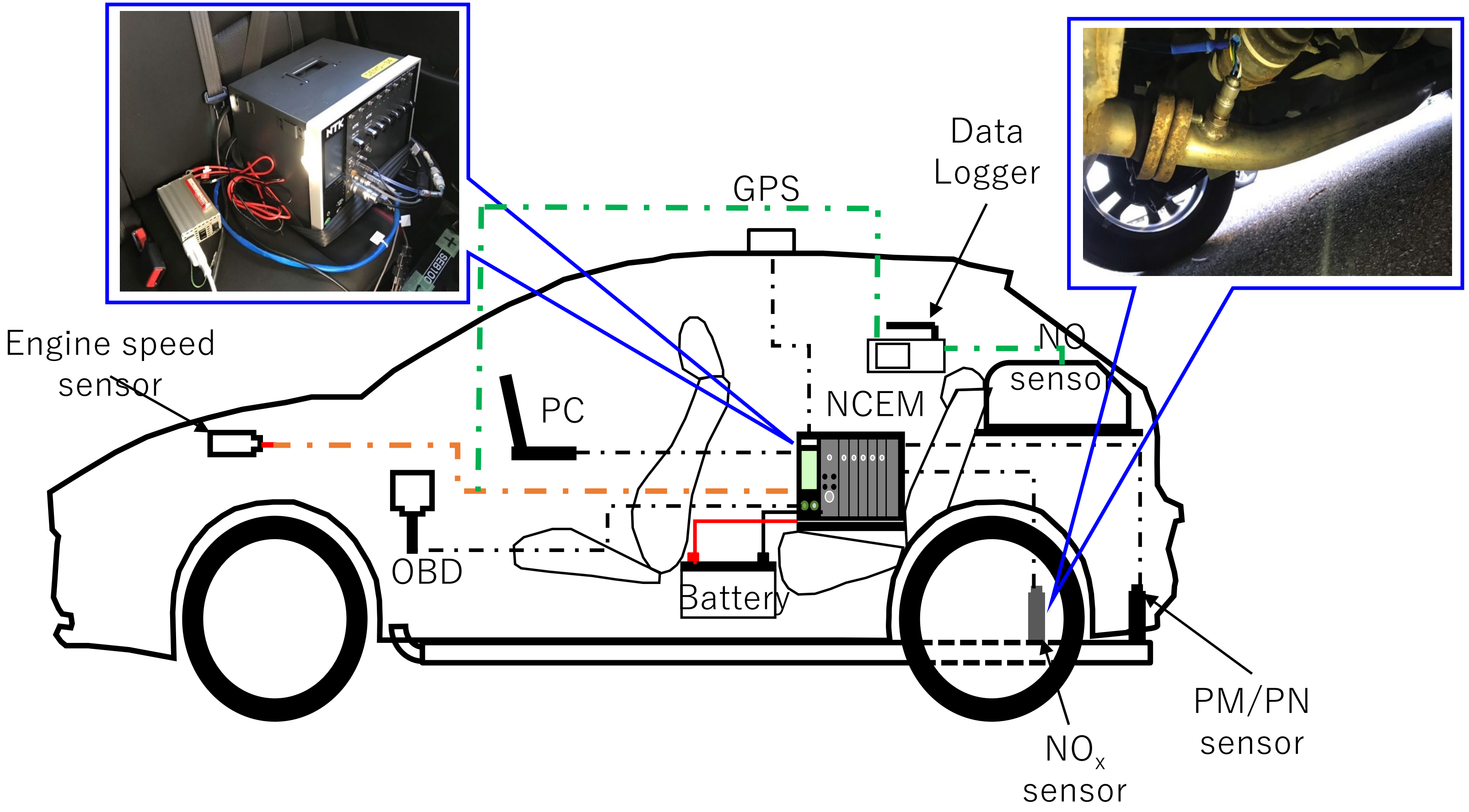
✓ In the future, there will be a need for a method of grasping the real-world emissions using only vehicle information obtained through OBD port in real time without direct measurement of emissions.

For the real-world emissions evaluation for GDI vehicle,

1. Analysis of NO and NH_3 emission behavior by on-road measurement on general roads using gasoline passenger vehicle
2. Construction and verification of emission prediction model by deep learning using vehicle OBD information obtained

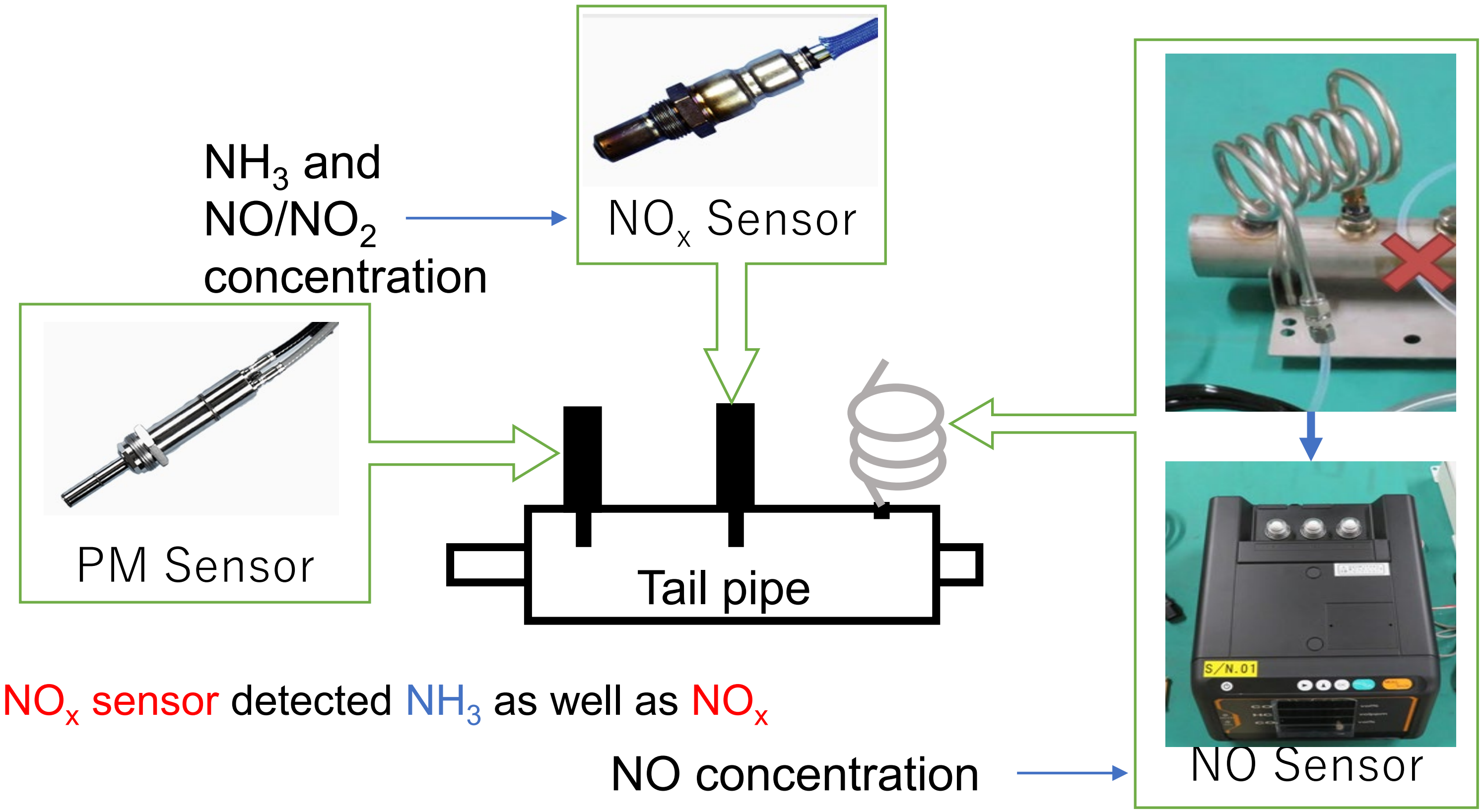
Test Vehicle and Sensor-based Emission Measurement System

Injection	DI
Engine type	In line 4 cylinder turbo
Displacement (cc)	1618
Max. power output (kW per rev / min)	140 / 5600
After treatment device	TWC
Vehicle mass (t)	1.565
Emission standard	2005
Model year	2014



Ref: Yang et al., Science of the Total Environment, Vol. 640-641, p. 364-376, 2018

Emissions Measurement Sensors

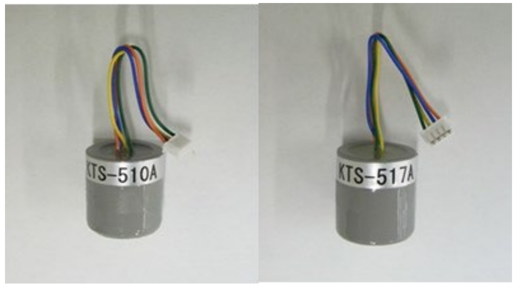


NO_x sensor detected NH_3 as well as NO_x

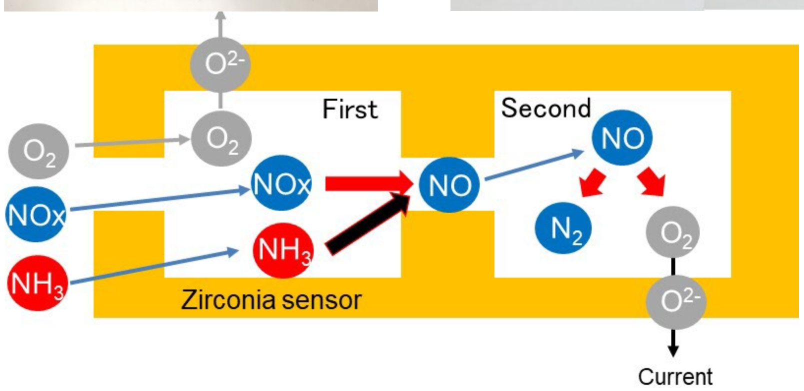
NH_3 Concentration Calculation

NOx sensor (NCEM)

Potential sensor for NO,NH_3



NH3 sensor for diesel



- Signals obtained from NOx sensor include those derived from NO and NH_3.
- Potential sensor for NO can measure the NO concentration.

When NOx sensor and potential sensor for NO are used, ammonia emitted from gasoline vehicles will be measured.

[NOx sensor] – [Potential sensor for NOx] ≈ NH_3

➡ Sensor signals were compared with those obtained by FT-IR and laser-based measurement system.

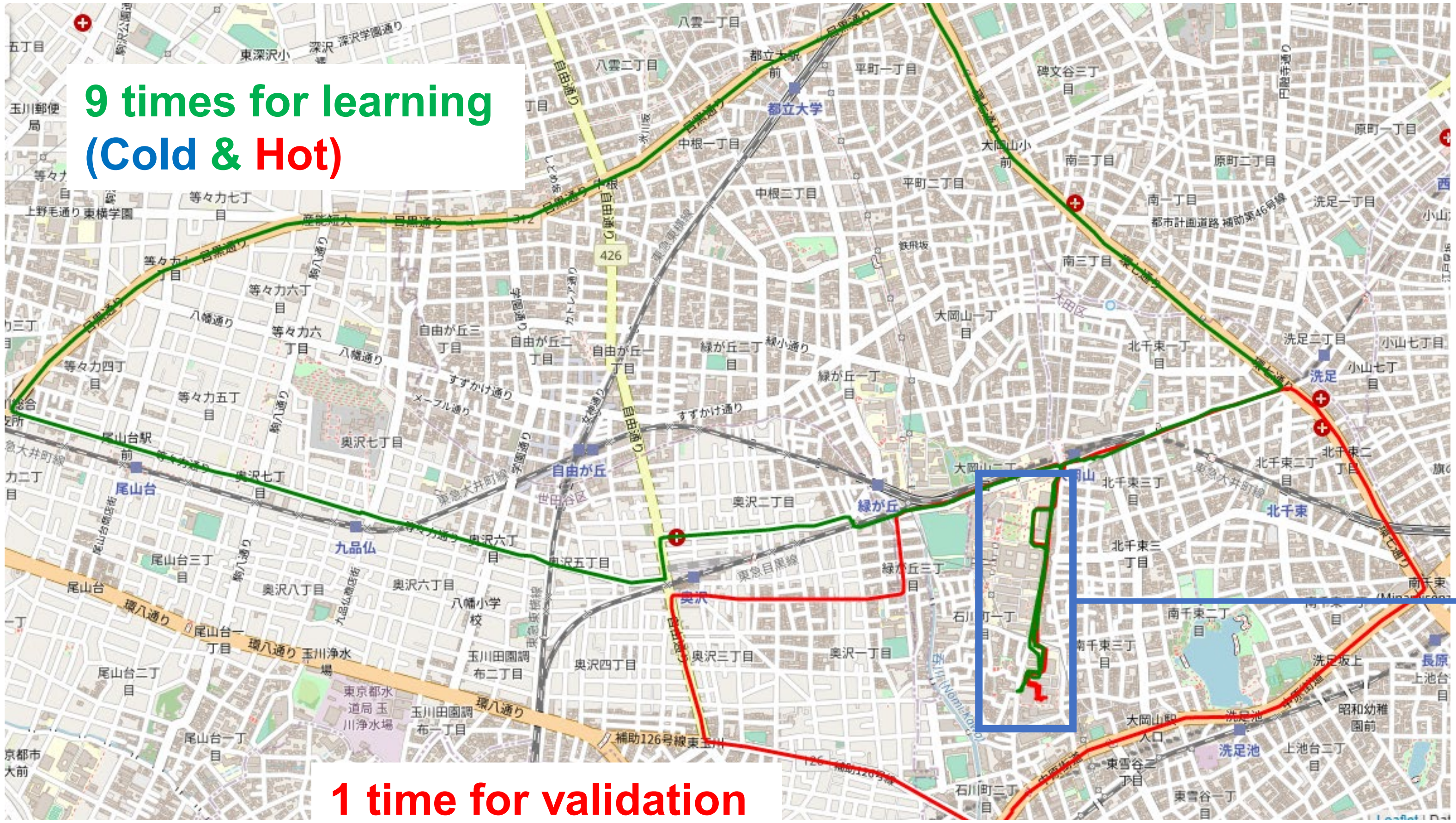
$$C_{NH3} = \frac{C_{NOx} - C_{NO}}{0.9}$$

Division by 0.9 is used to calibrate the sensor sensitivity.

Ref: K. Tanaka et al., the 10th Annual International PEMS Conference (2021)

Ref: K. Tanaka et al., Society of Automotive Engineers of Japan, 2020 Annual Autumn Conference Proceedings, No. 232 (in Japanese)

Test Routes, Experimental Conditions

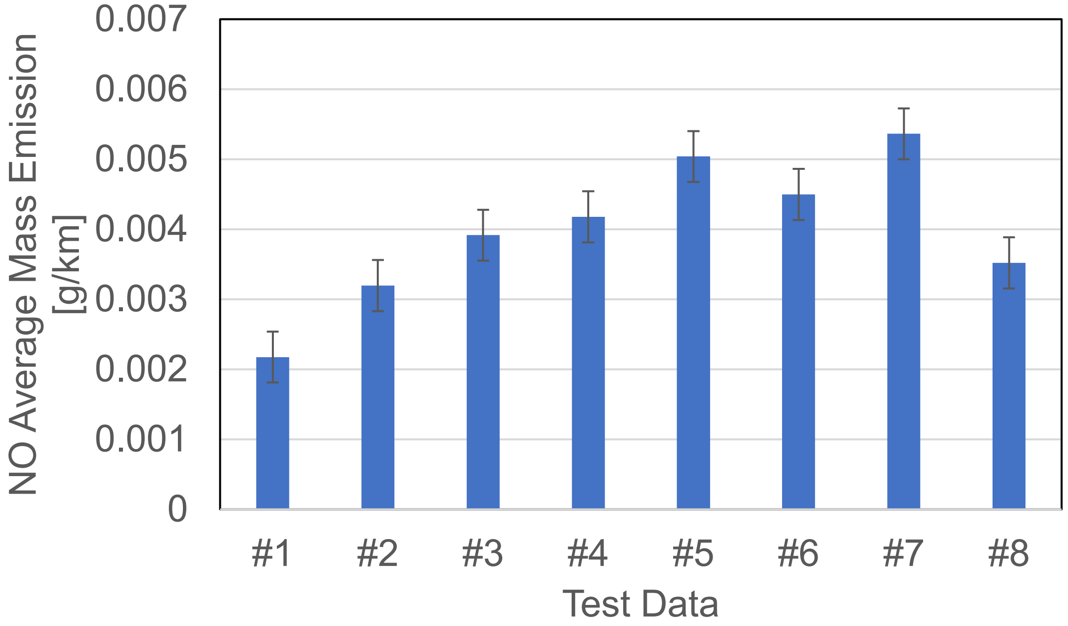


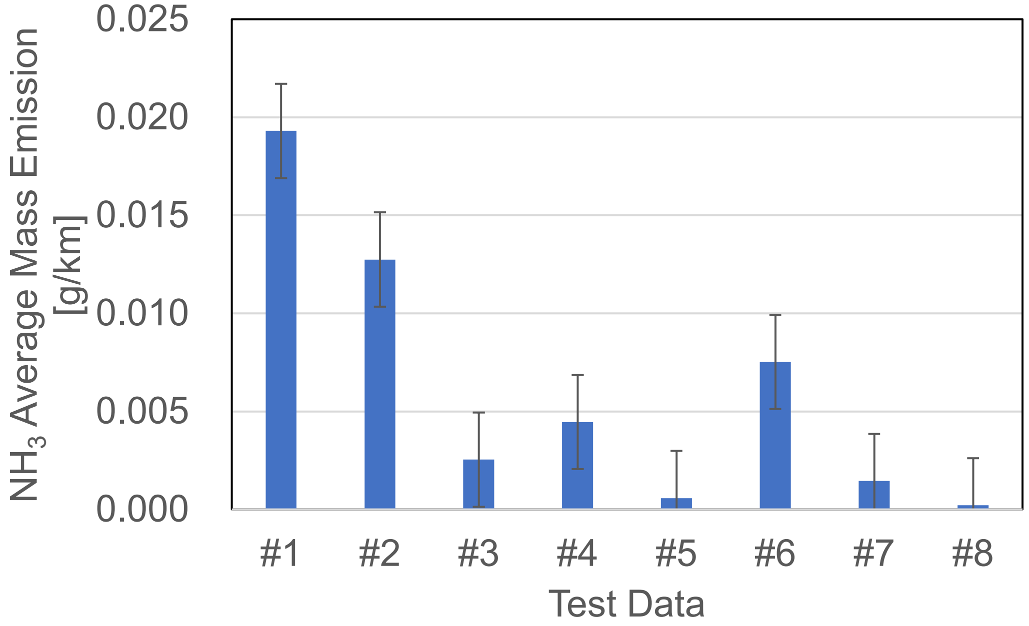
Analyzed emission
NO, NH_3

Samling frequency	10 Hz
Number of tests	10 times
Fuel	Gasoline (H/C = 1.8)

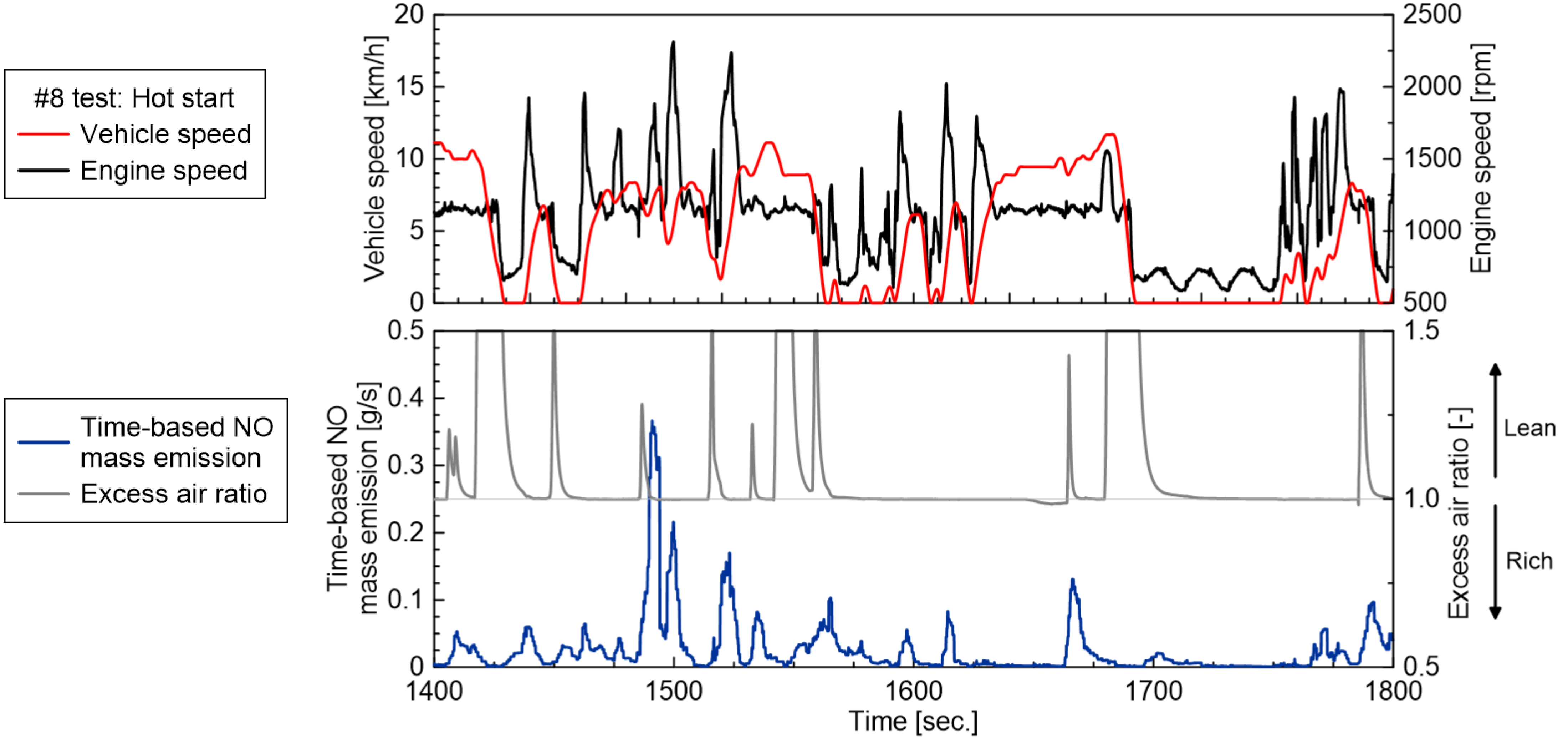
Average Emission

Test Data	Hot/Cold
#1	Cold
#2	Cold
#3	Hot
#4	Cold
#5	Hot
#6	Cold
#7	Hot
#8	Hot



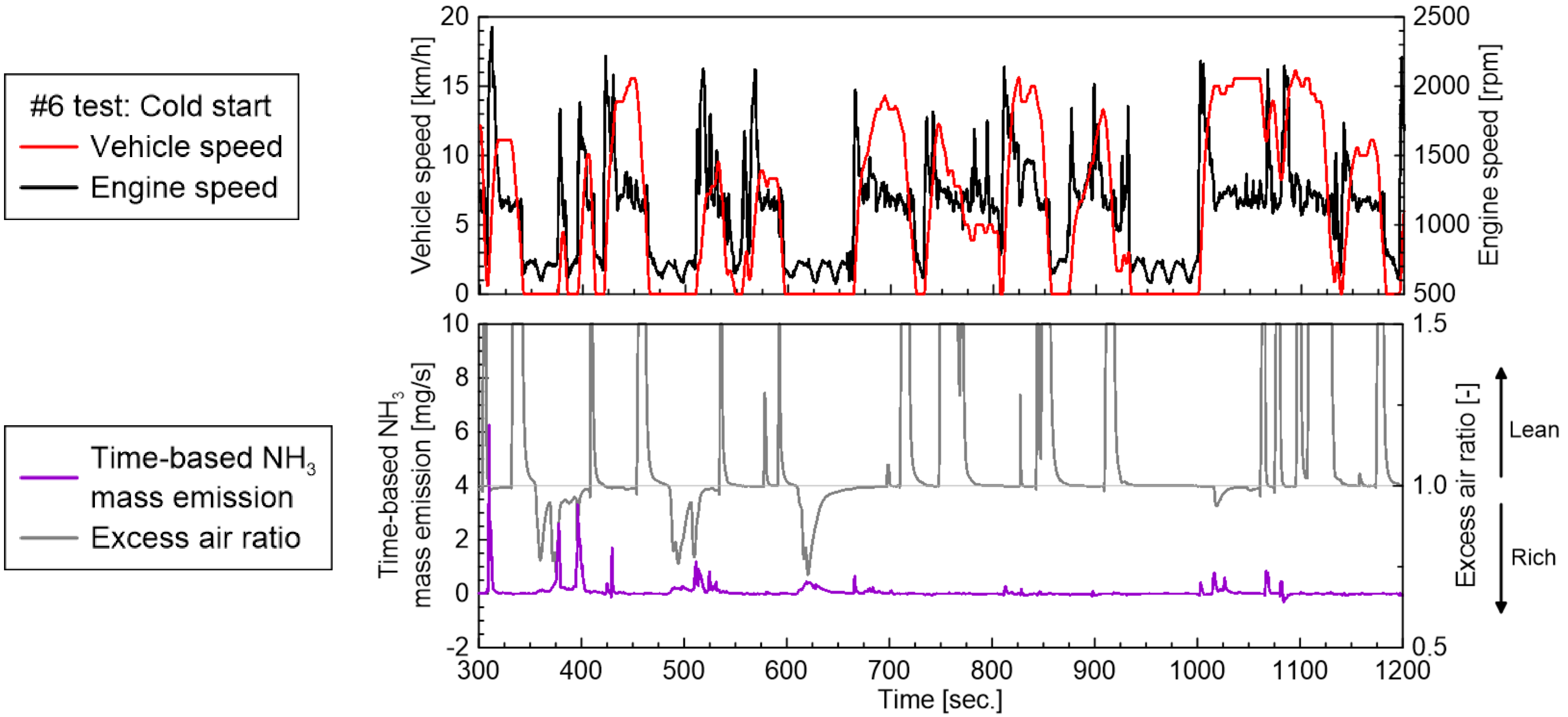


NO Emission Analysis



Ref: Sato et al., 2022 PEMS Conference

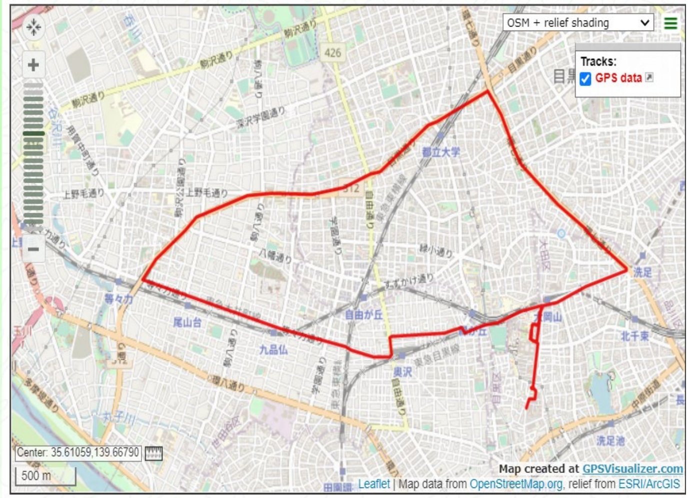
NH_3 Emission Analysis



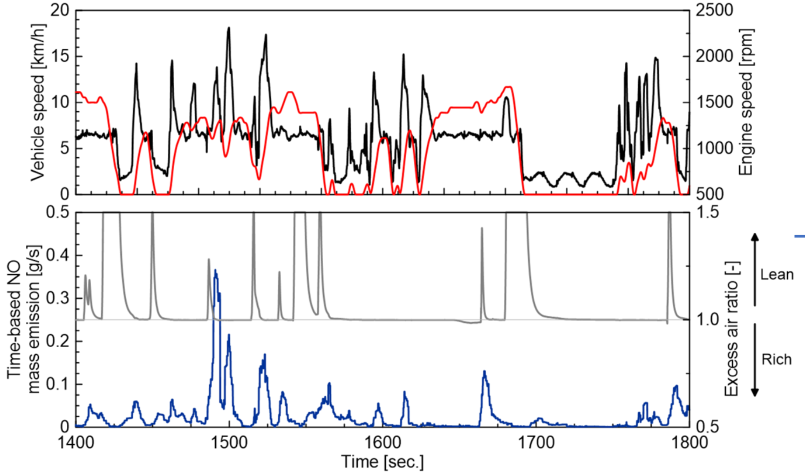
$$CO + H_2O \rightarrow CO_2 + H_2$$
$$2NO + 2CO + 3H_2 \rightarrow 2NH_3 + 2CO_2$$
$$2NO + 5H_2 \rightarrow 2NH_3 + H_2O$$

Ref: Barbier et al., Applied Catalysis B Environmental, Vol. 4, p. 105-140, 1994
Ref: Sato et al., 2022 PEMS Conference

Flowchart of Emissions Prediction



Analysis of NO, NH3



LSTM-based prediction model

Input

LSTM layer

Dense

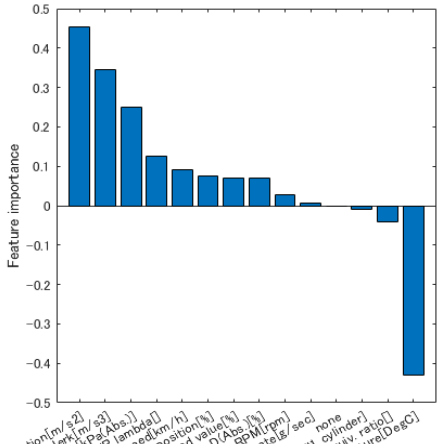
Dropout layer

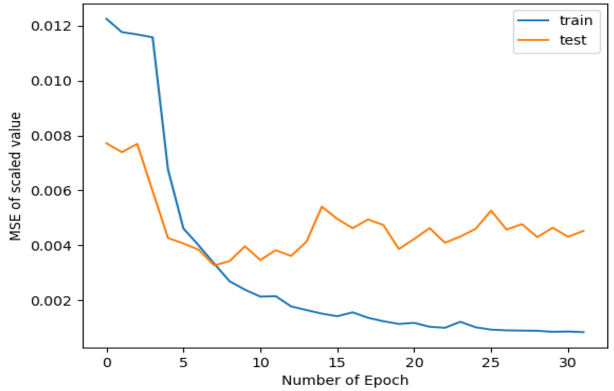
Dense

Dense

Output

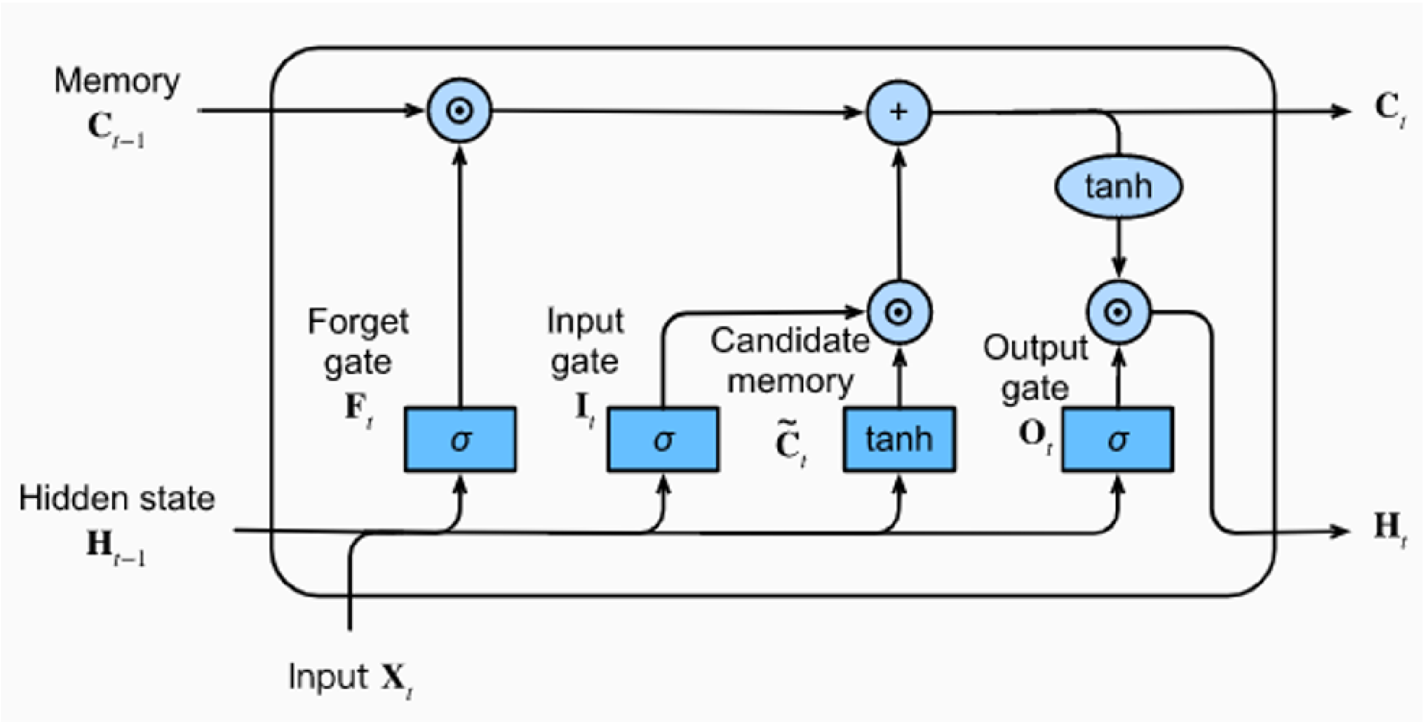
Validation and improvement of model





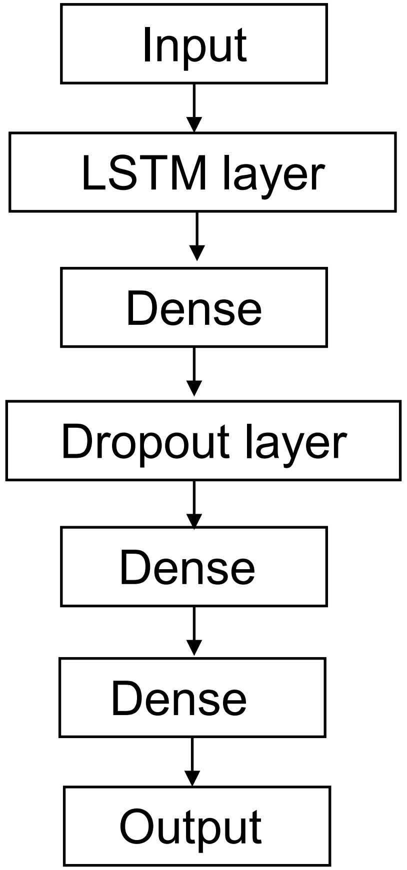
Change of learning conditions

LSTM (Long-Short Term Memory)



Configuration of LSTM
https://medium.com/@ottaviocalzone/an-intuitive-explanation-of-lstm-a035eb6ab42c

Prediction model



Input Parameters for NO Prediction

Behavior	Parameter
Engine	Engine load [%]
	Engine speed [rpm]
	Engine coolant temperature [^{o}C]
	Intake Manifold Abs. Pressure [kPa]
	Timing advance [deg relative to #1 cylinder]
	MAF air flow rate [g/s]
	Throttle position [%]
	OBD Fuel/Air equivalence ratio [-]
	O2S1WR Lambda [-]
Vehicle	Vehicle speed [m/s]
	Acceleration [m/s^2]
	Jerk [m/s^3]
Driver	Pedal position D [%]
Road condition	Road gradient [-]

Feature Importance and Learning Conditions

Feature importance

$$Feature\ Importance(x_n) = RMSE_{without\ x_n} - RMSE_{with\ x_n}$$

Where,

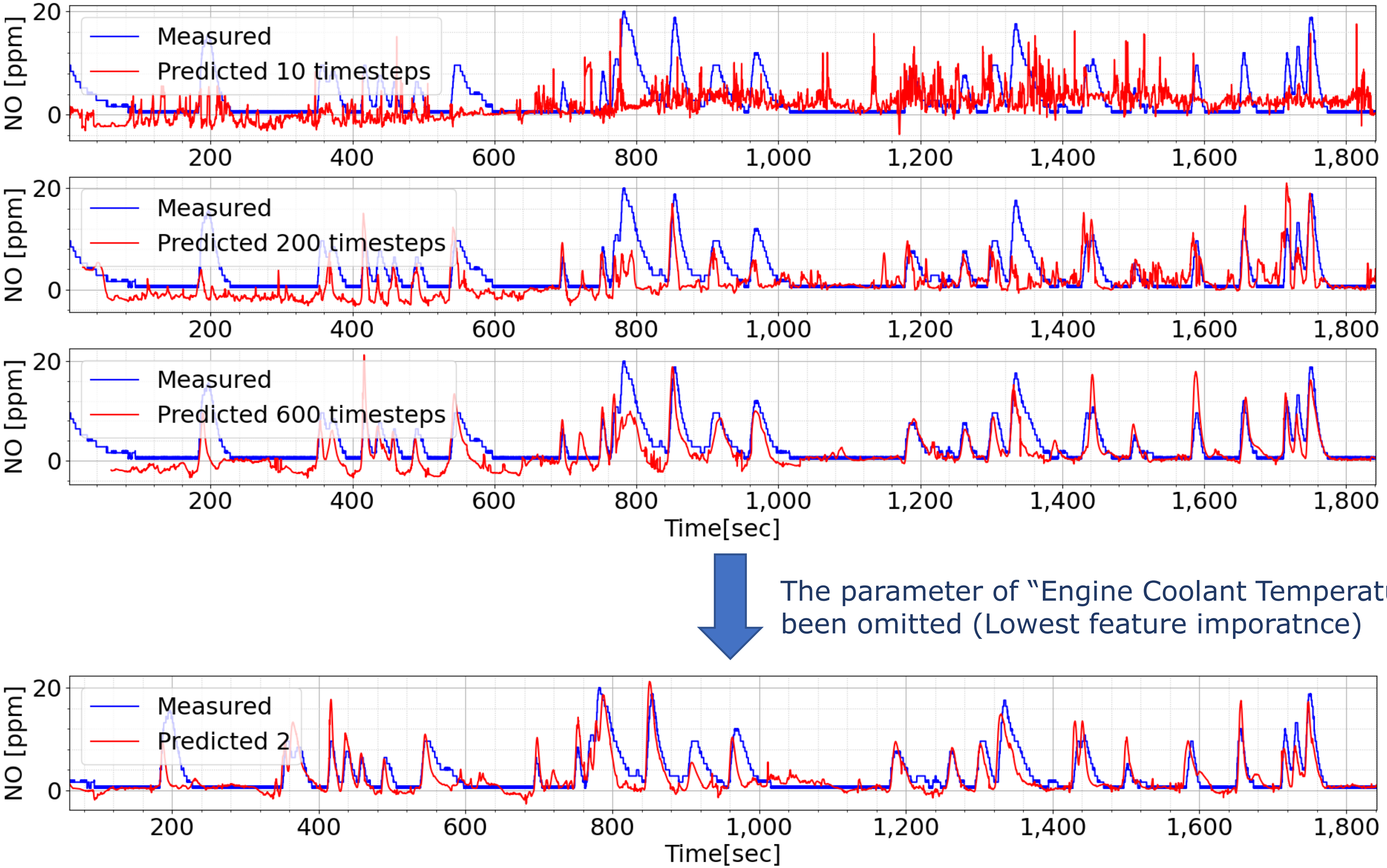
$RMSE_{without\ x_n}$: Root mean squared of the model when the parameter is omitted from training

$RMSE_{with\ x_n}$: Root mean squared of the model when all parameters are trained

Learning Conditions

Number of epochs	32
Number of timesteps	10, 25, 50, 100, 200, 400, 600 (1.0, 2.5, 5.0, 10, 20, 40, 60 sec)
Batch size	20
Learning rate	0.001
Optimizer	Adam
Verbose	2
Loss function	Mean squared error (MSE) and Root mean squared error (RMSE)

Results of NO Prediction



10 timesteps
RMSE=4.605

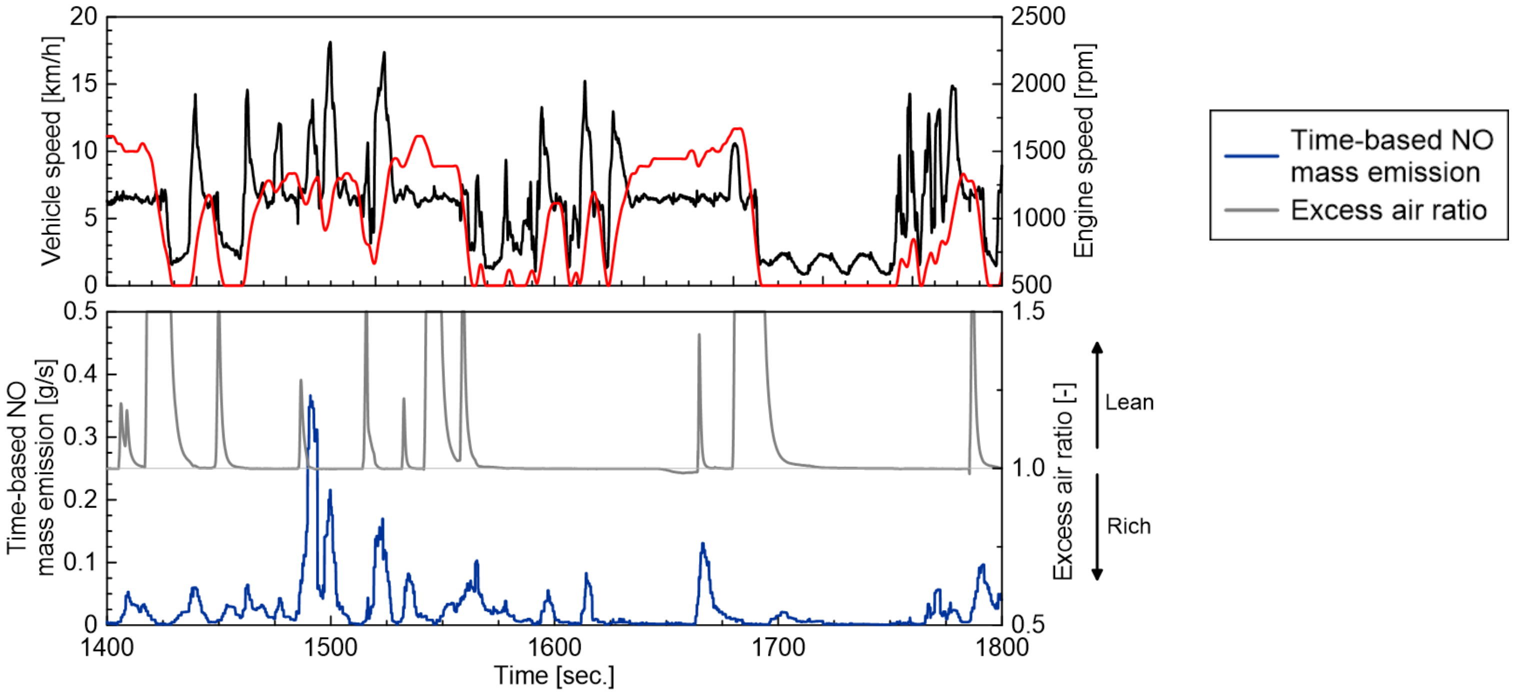
200 timesteps
RMSE=4.117

600 timesteps
RMSE=3.097

The parameter of “Engine Coolant Temperature” has been omitted (Lowest feature imporatnce)

600 timesteps
Model 2
RMSE=2.697

Importance of Longer Timestep for the LSTM Learning



- ✓ NOx emission mechanism for gasoline vehicle equipped with TWC

  Fuel cut → Lean condition → Change of TWC state → Fuel injection → NOx emission

- ✓ Longer timestep is required for the prediction of long-time phenomenon

Results of NH_3 Prediction

10 timesteps
RMSE=13.31

200 timesteps
RMSE=20.85

600 timesteps
RMSE=12.01

Summary

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1. NO emission was found especially in lean condition where the excess air ratio is close to 1.

2. NH_3 emission increased in rich condition. In rich condition, there is not enough oxygen for complete combustion and CO was formed. NH_3 was generated from this CO.

3. For the emission prediction with LSTM method, by using different timesteps samples, it was found that after 200 to 600 timesteps, the prediction accuracy increased for both NO and NH_3 prediction. By testing different timesteps, the suitable length of the inputs can be verified. Longer timesteps tend to provide more information for prediction model to learn from.

4. In addition, feature importance was also calculated. Some parameters yielded negative importance. It can be said that those parameters should be omitted from the inputs to avoid overfitting. This method has proven effective in improving the model accuracy.

Thank You for Your Listening

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