



Tokyo Tech

The Real-world Emissions Prediction with Deep Learning Based on the SEMS Measurement Data

Susumu (Mu) SATO, Ryo HIMENO, Seiya ABE, Tsuyoshi NAGASAWA
and Hidenori KOSAKA (Tokyo Institute of Technology)
Takeshi TANGE (NGK Spark Plug Co., Ltd)
Kotaro TANAKA (Ibaraki University)



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Research Background



- ✓ Local roadside emission → “Hot spot”
- ✓ RDE regulations using PEMS



PEMS measurement

On-road measurement data; NOx mass ≥ 0.08 g/km

- ✓ “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 in real time without direct measurement of emissions.



For the real-world emissions evaluation,

1. Analysis of emission behavior by on-road measurement on general roads and highways using diesel passenger vehicle
2. Construction and verification of emission prediction model by deep learning using vehicle information obtained by measurement

Test Vehicle

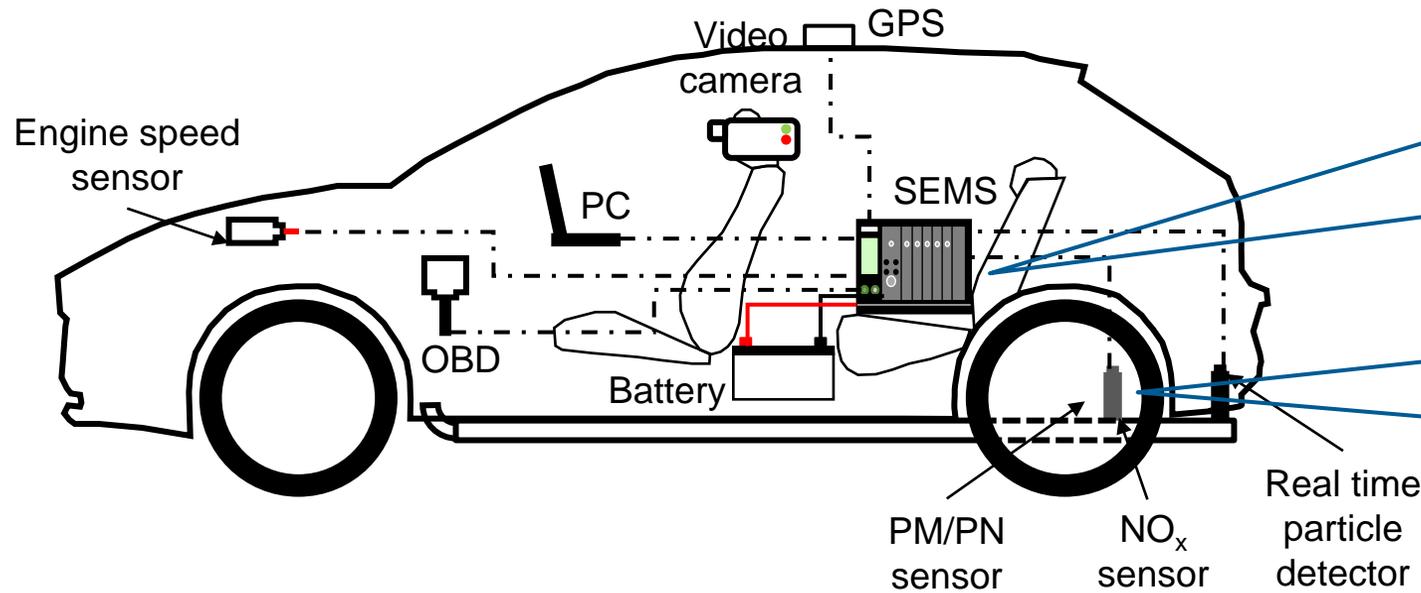
Type	Station Wagon
Riding capacity [people]	5
Length [m]	4.06
Width [m]	1.69
Height [m]	1.50
Wight [kg]	1220
Engine type	L-4 DOHC Diesel Engine
Displacement [L]	1.49
Compression ratio	14.8
Fuel supply system	Common-rail Fuel Injection
Aftertreatment system	DOC, DPF
Adapted emission regulation	Japan 2009 Regulation: NOx < 0.08 g/km
Fuel consumption saving	Stop idling system



On-road Driving Test Setup



✓ Sensor-based Emissions Measurement System



SEMS
(NCEM, NGK Spark Plug)



NOx Sensor
(NOx, O₂)

✓ Measurement Items

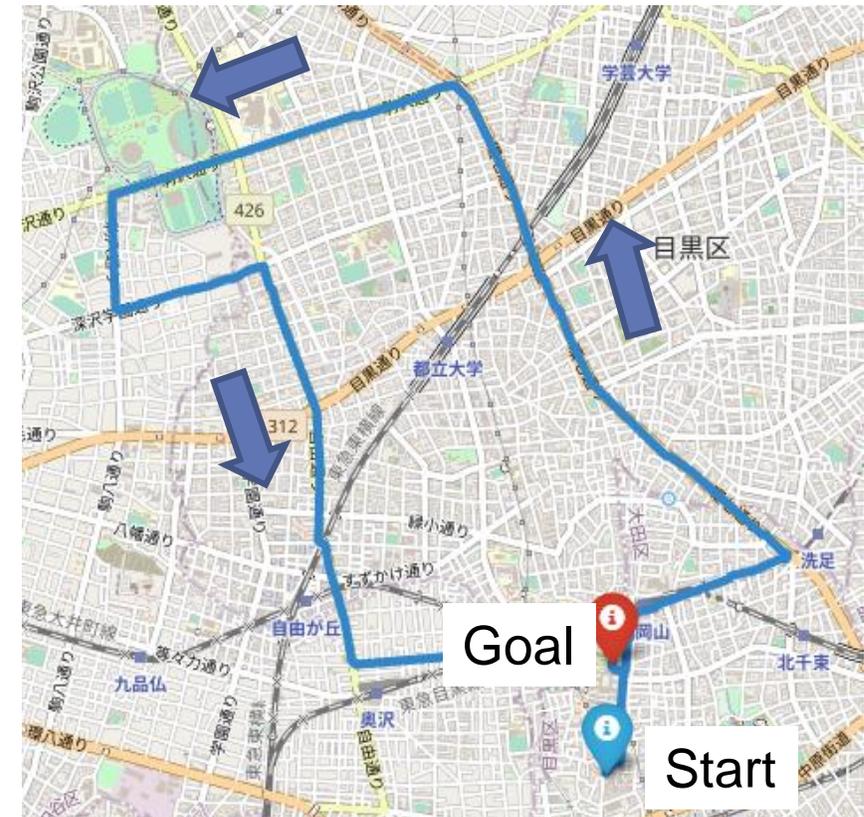
NOx conc., O₂ conc. (→ CO₂ conc. Calculation)*, OBD information, GPS, traffic situation

* S. Sato, et al, "Real-World Emission Analysis Methods Using Sensor-Based Emission Measurement System", SAE paper 2020-01-0381 (2020)

On-road Driving Test Routes

On-road driving tests: 79 times, general road & highway

	Route Number	Number of runs	Distance [km]
General road	Route 1	45	9.664
	Route 2	4	8.935
	Route 3	15	9.761
	Route 4	1	3.209
	Route 5	1	2.244
General road & Highway	Route 6	3	30.063
	Route 7	3	23.464
	Route 8	2	40.931
	Route 9	3	30.289
	Route 10	1	37.081
	Route 11	1	13.133

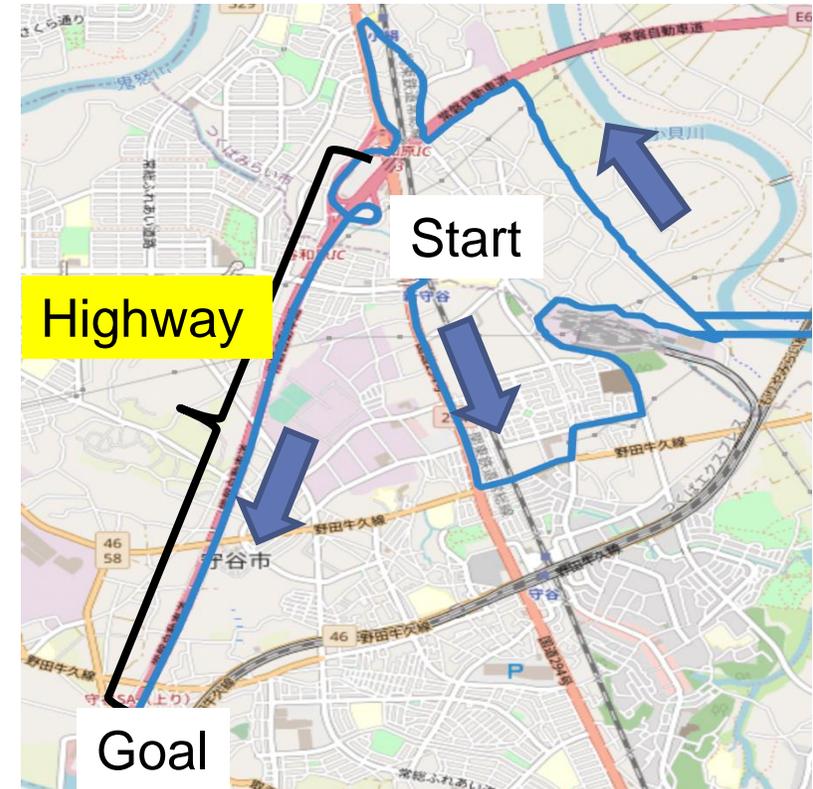


Route 1

On-road Test Routes



	Route Number	Number of runs	Distance [km]
General road	Route 1	45	9.664
	Route 2	4	8.935
	Route 3	15	9.761
	Route 4	1	3.209
	Route 5	1	2.244
General road & Highway	Route 6	3	30.063
	Route 7	3	23.464
	Route 8	2	40.931
	Route 9	3	30.289
	Route 10	1	37.081
	Route 11	1	13.133



Route 11

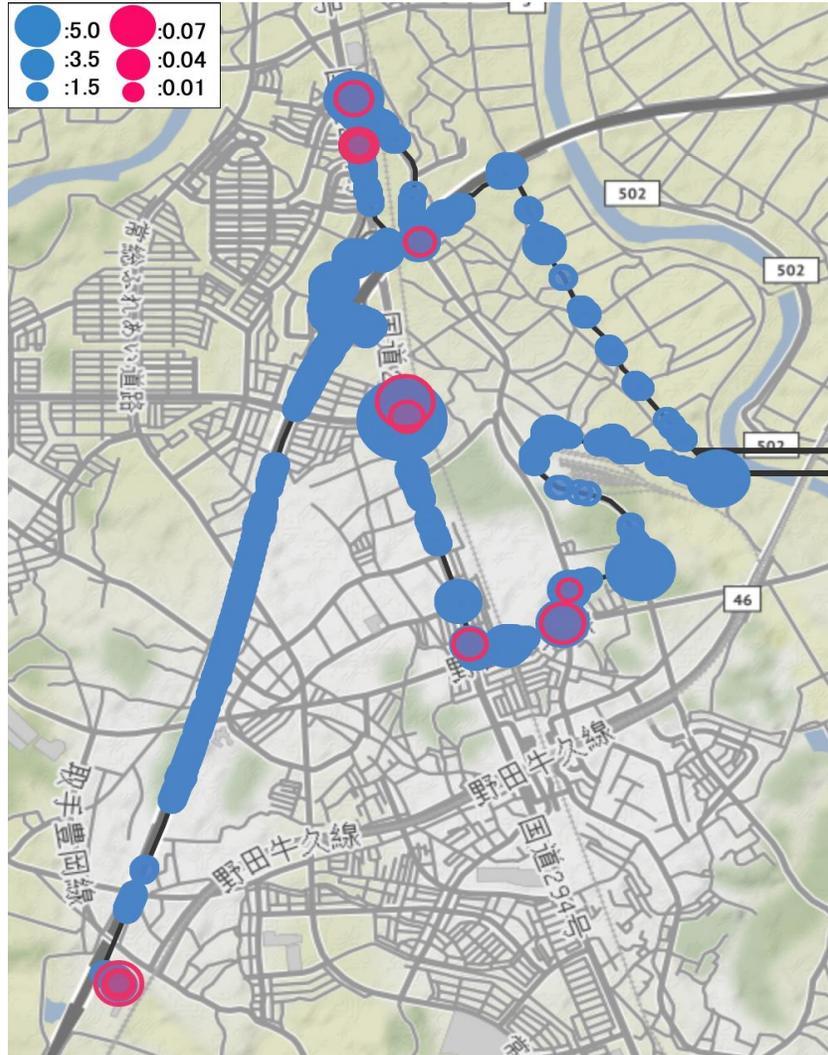
For deep learning, the measurement data of Route 1 – 10 were used for the learning, the data of Route 11 was used for the validation.

Hot Spot Analysis

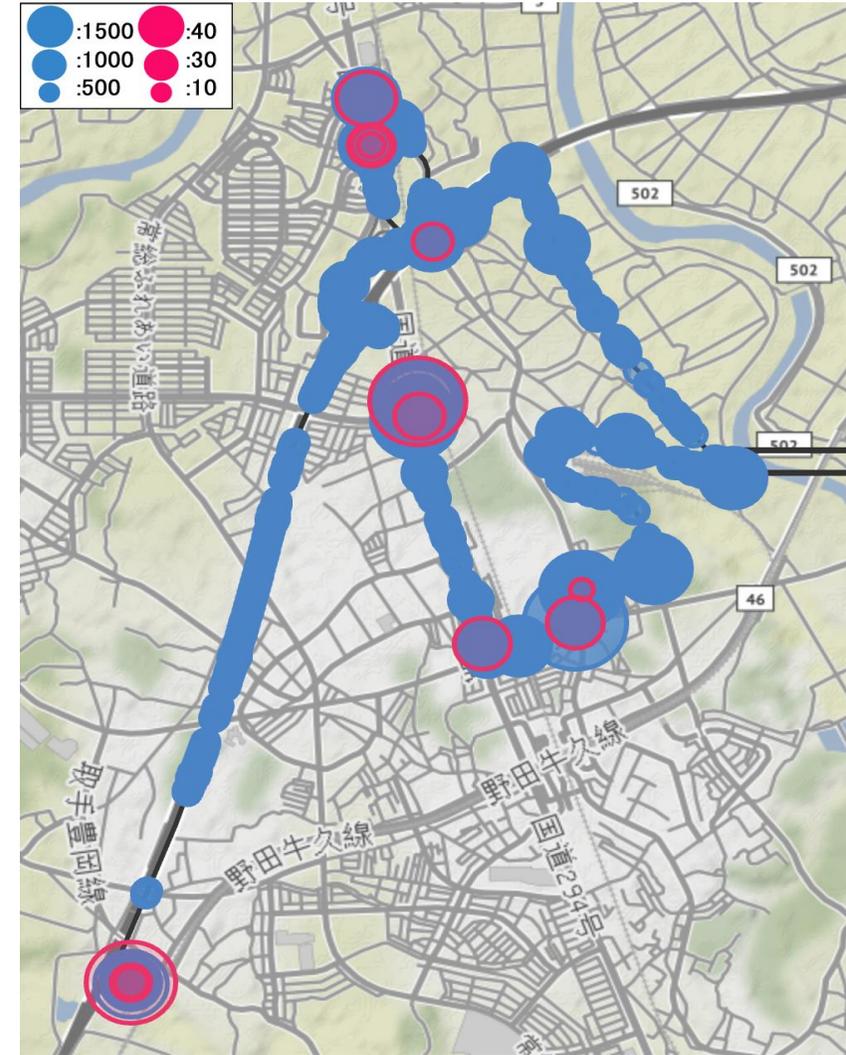
✓ $E_{NOx,x} \geq 0.05$ g/km, $E_{CO2,x} \geq 100$ g/km

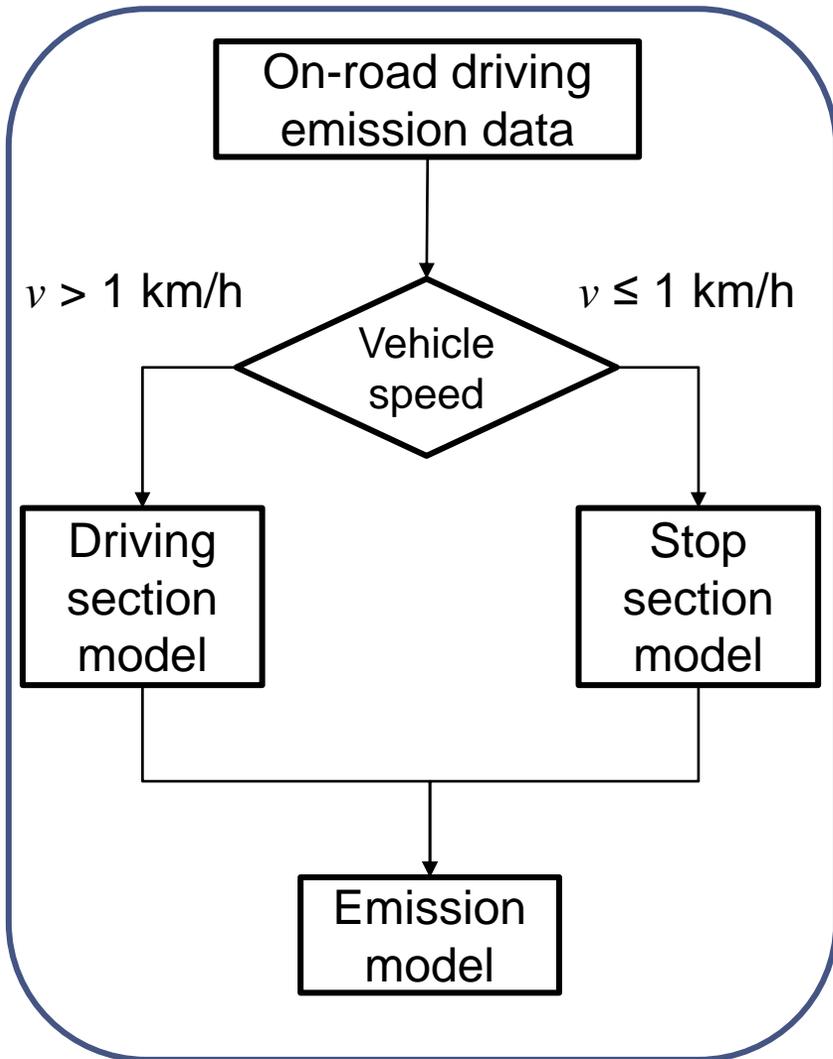
	Driving [g/km]
	Stop [g]

NO_x



CO₂



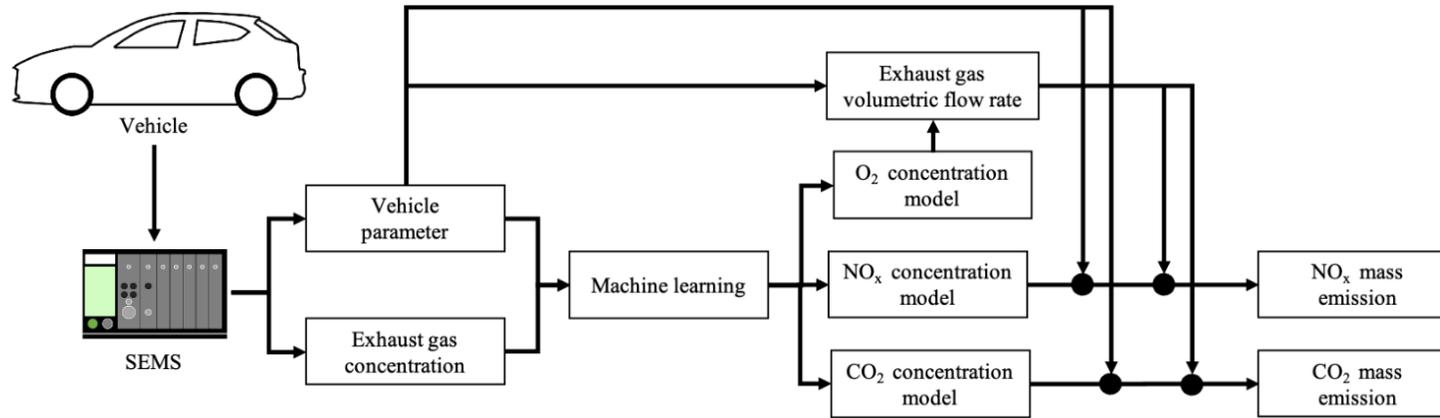


- ✓ Stop section model
Prediction using non-linear regression equation for each engine speed classification
 - Clustering by Dynamic Time Warping (DTW) & k-means methods
 - Support Vector Regression (SVR)
- ✓ Driving section model
Prediction using a time series prediction model by deep learning
- ✓ Prediction models for NO_x and CO₂ emissions

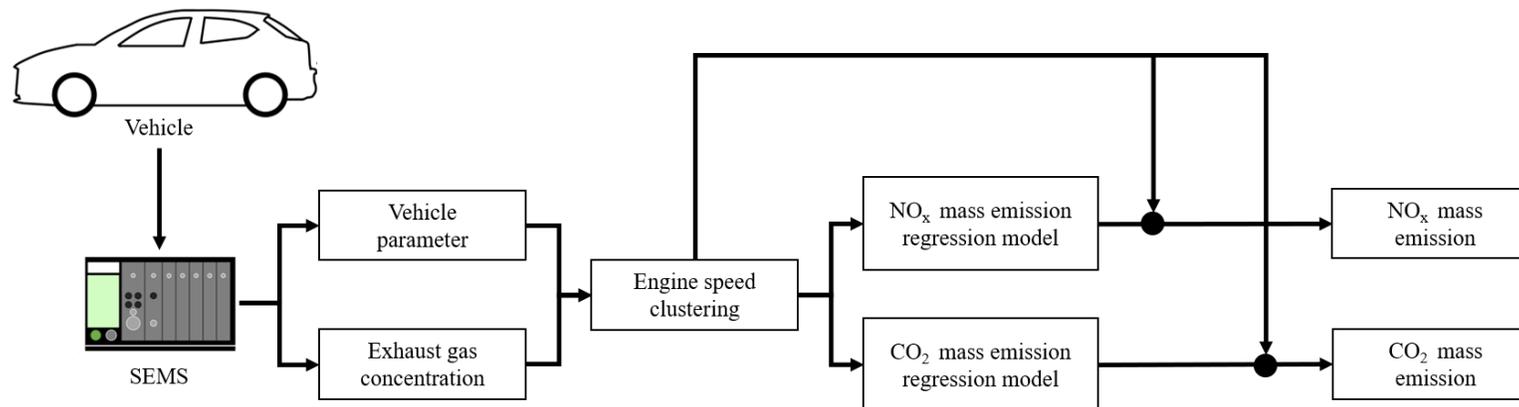
Emission Prediction Flow



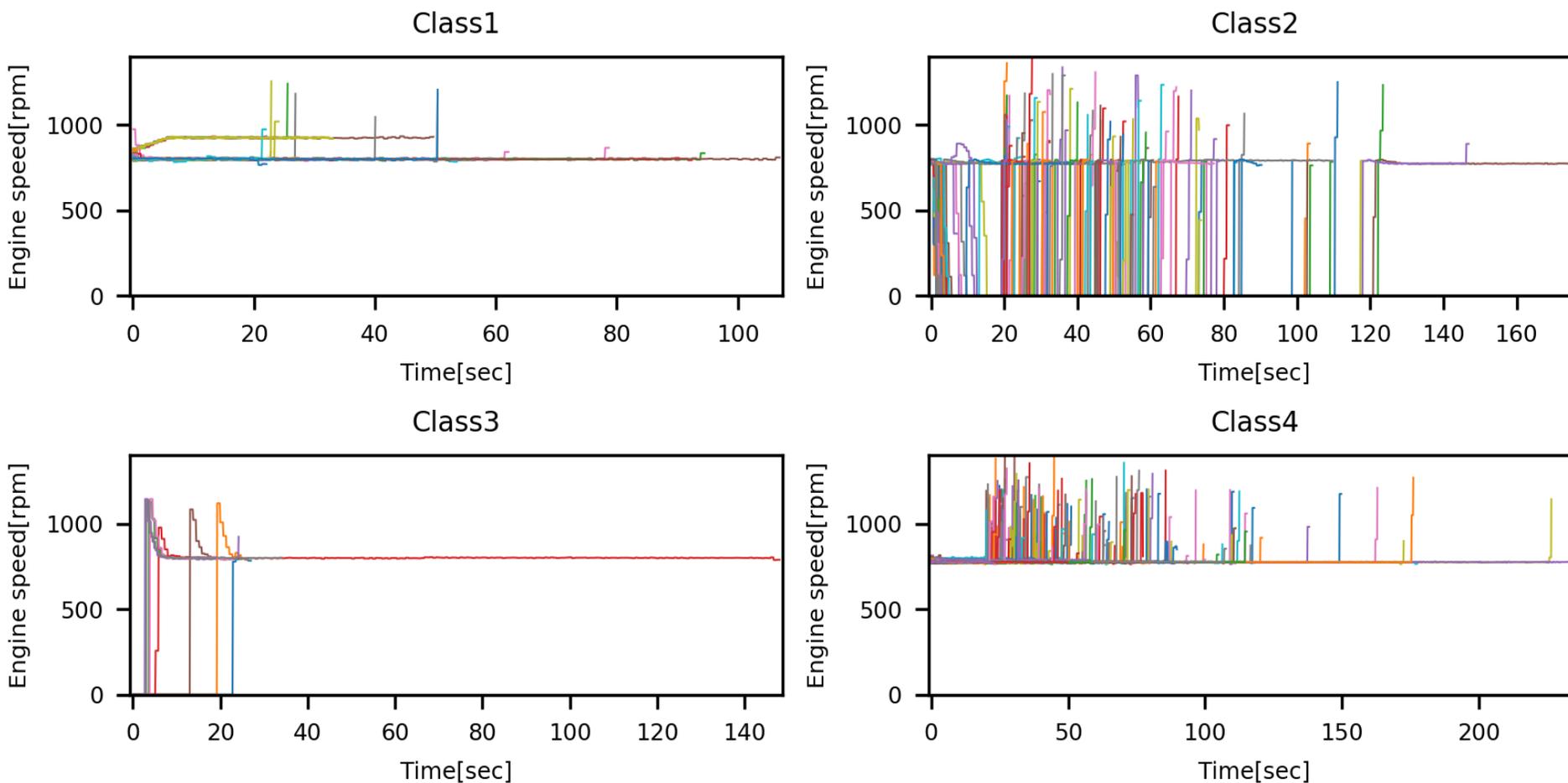
✓ Driving section prediction



✓ Stop section prediction



Stop Section Model

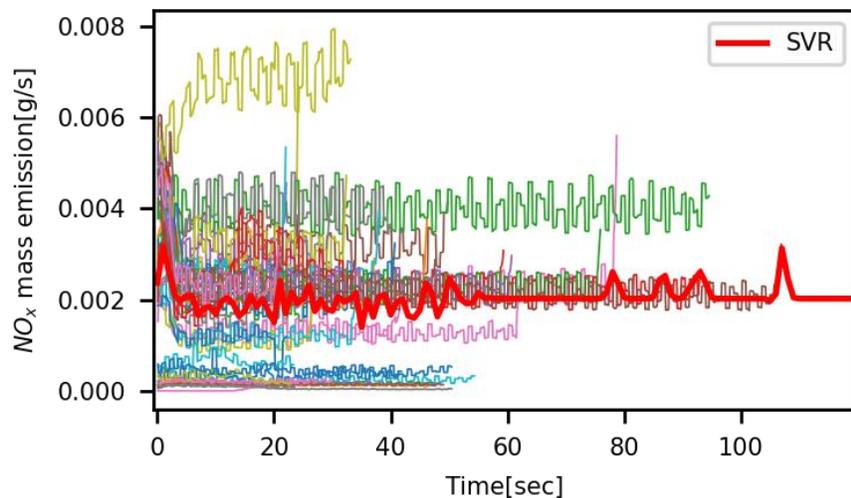


- ✓ Class 1 & 4: Mass emission calculation with non-linear regression
- ✓ Class 2 & 3: Calculated as no idling and mass emissions of 0 g/s

Stop Section Model

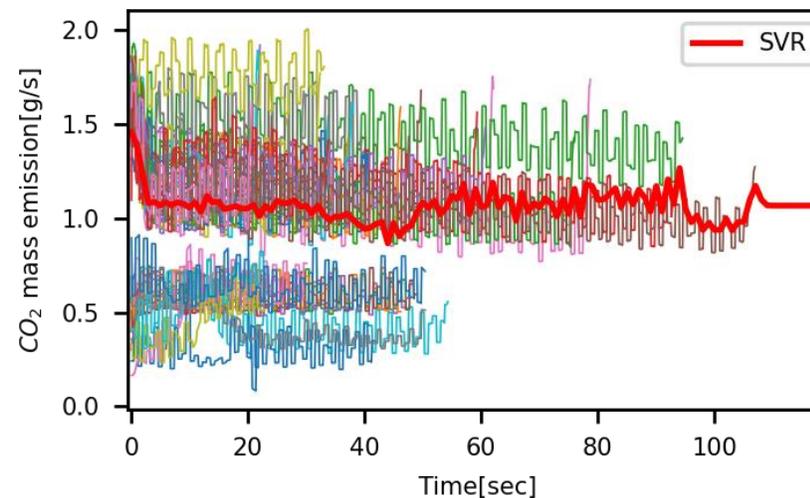
NO_x

Class1 NO_xmodel

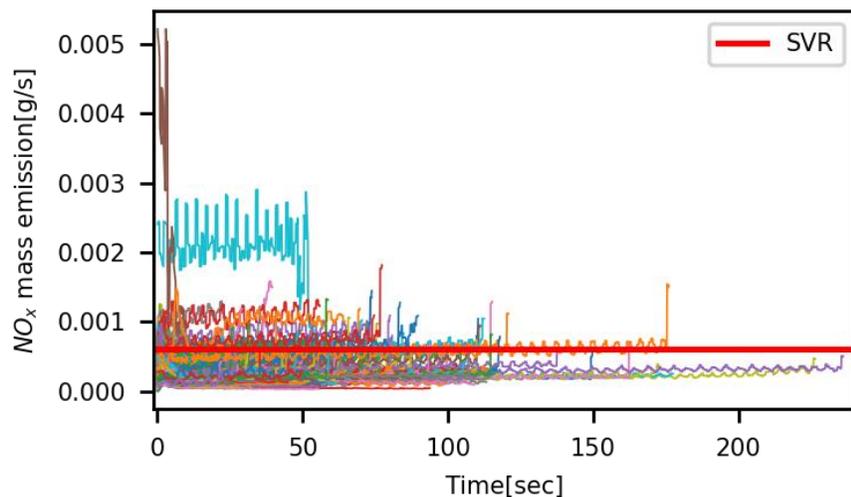


CO₂

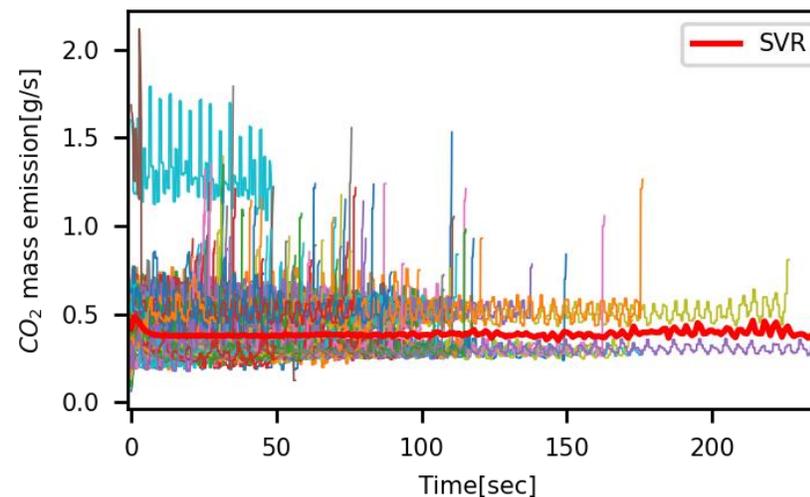
Class1 CO₂model



Class4 NO_xmodel



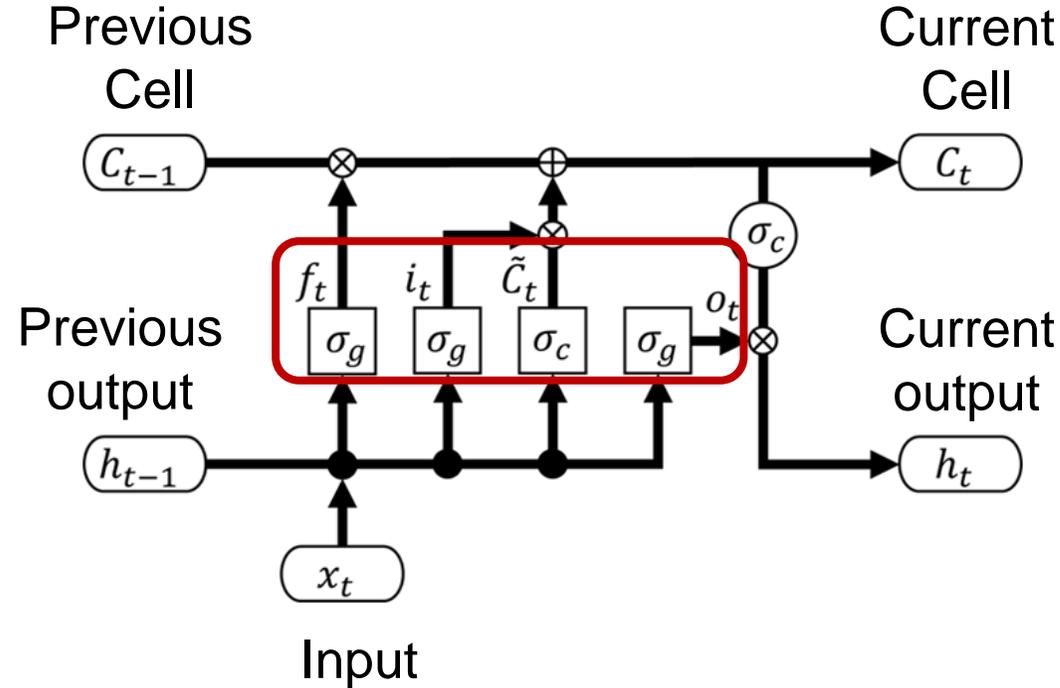
Class4 CO₂model



Driving Section Model: LSTM



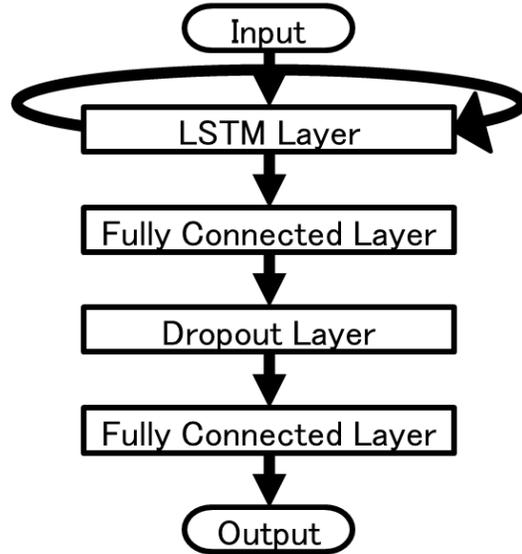
Deep learning with “Long Short-Term Memory” [Hochreiter, S. et al., 1997]



- ✓ Predictable in long-term time series by selecting information used for learning

LSTM Network, Learning Parameters

- Deep learning network



Layer	Option
Sequence Input Layer	12 Parameter Input
LSTM Layer	500 Hidden Unit
1st Full Connected Layer	400 Output Size
Dropout Layer	0.5 Dropout Ratio
2nd Full Connected Layer	1 Output Size

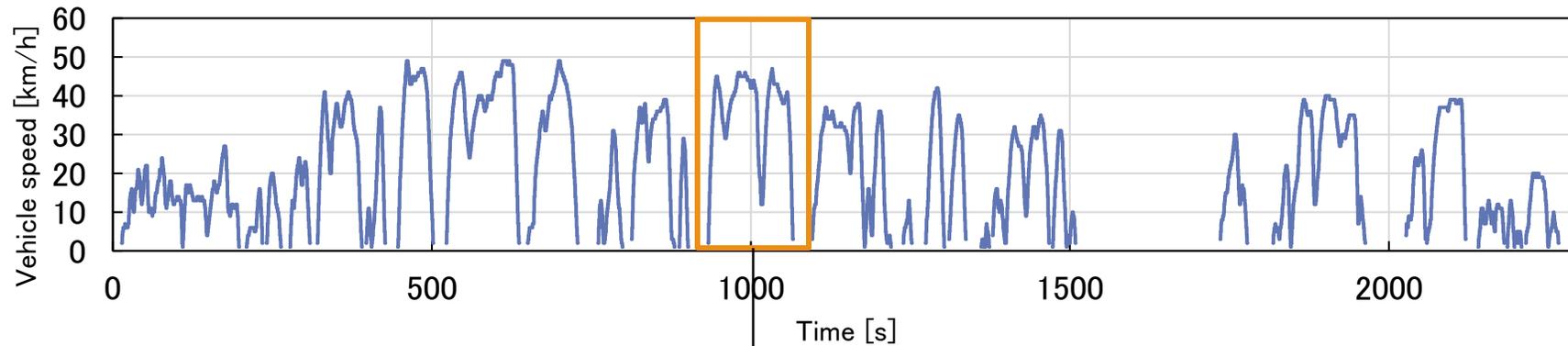
- Learning parameters

Behavior	Parameter
Engine	Engine Speed [rpm]
	Mass Air Flow Rate [g/s]
	Engine Load Value [%]
	Throttle Position [%]
	Fuel Rail Pressure [kPa]
	Intake Manifold Absolute Pressure [kPa]
	Fuel Injection Timing [rad]
	Engine Coolant Temperature [°C]
Vehicle	Intake Air Temperature [°C]
	Vehicle Speed [km/h]
	Acceleration [m/s]
Driver	Pedal Position [%]

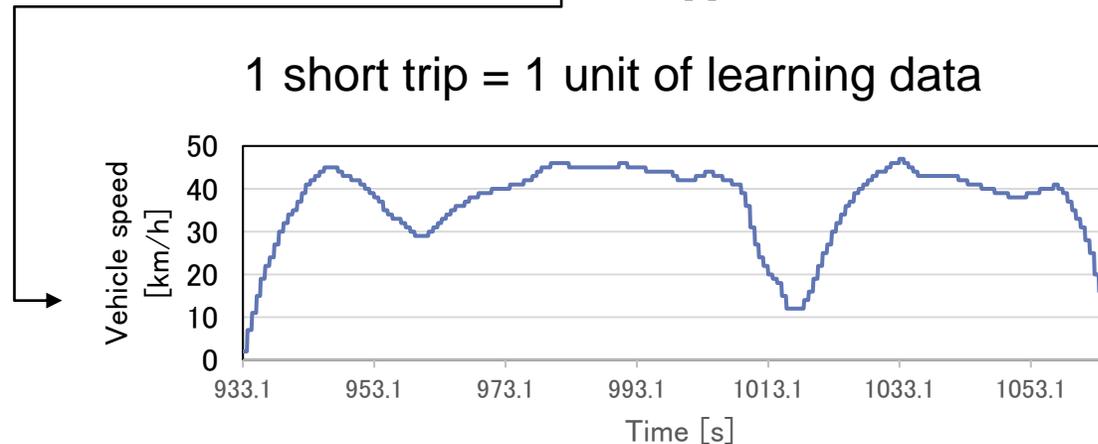
Driving Section Model: Short Trips

- ✓ 2041 short trips data obtained from 77 on-road driving data

1 on-road driving test data ($v \geq 1$ km/h)



1 short trip = 1 unit of learning data



- ✓ In the section where the short trip is long (300 sec or more), the data is divided into 20 (highway driving data).

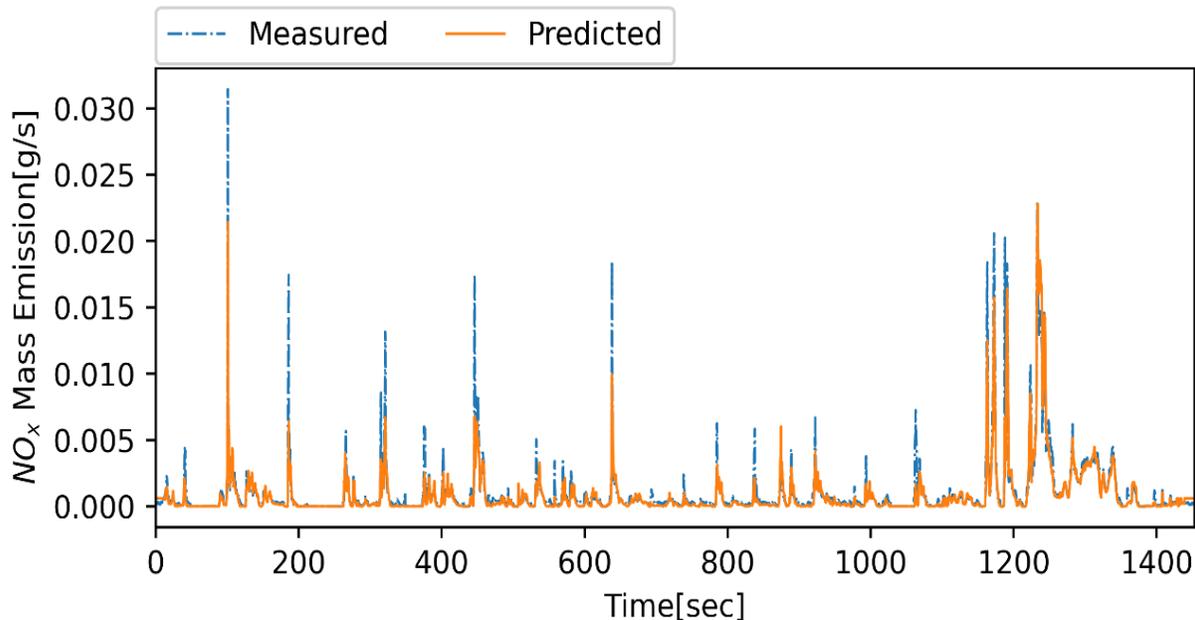
Prediction Results

NO_x

- Route-averaged mass emission

Measured: 15.0 g/s
Predicted: 12.4 g/s } Error 17.1%

- Time series

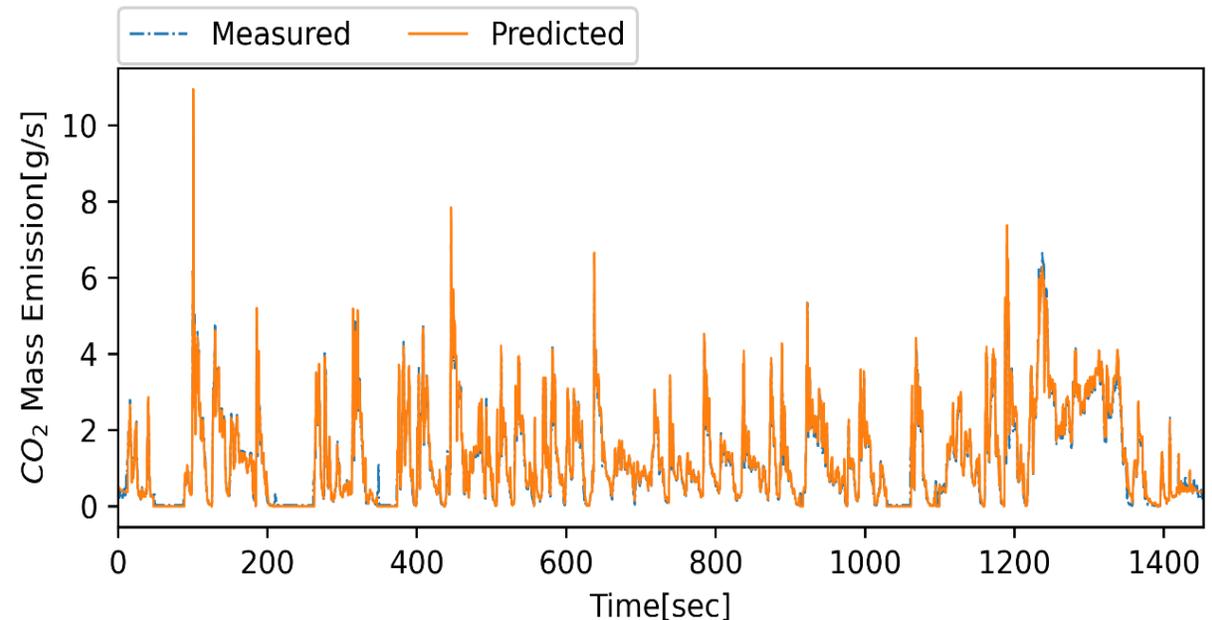


CO₂

- Route-averaged mass emission

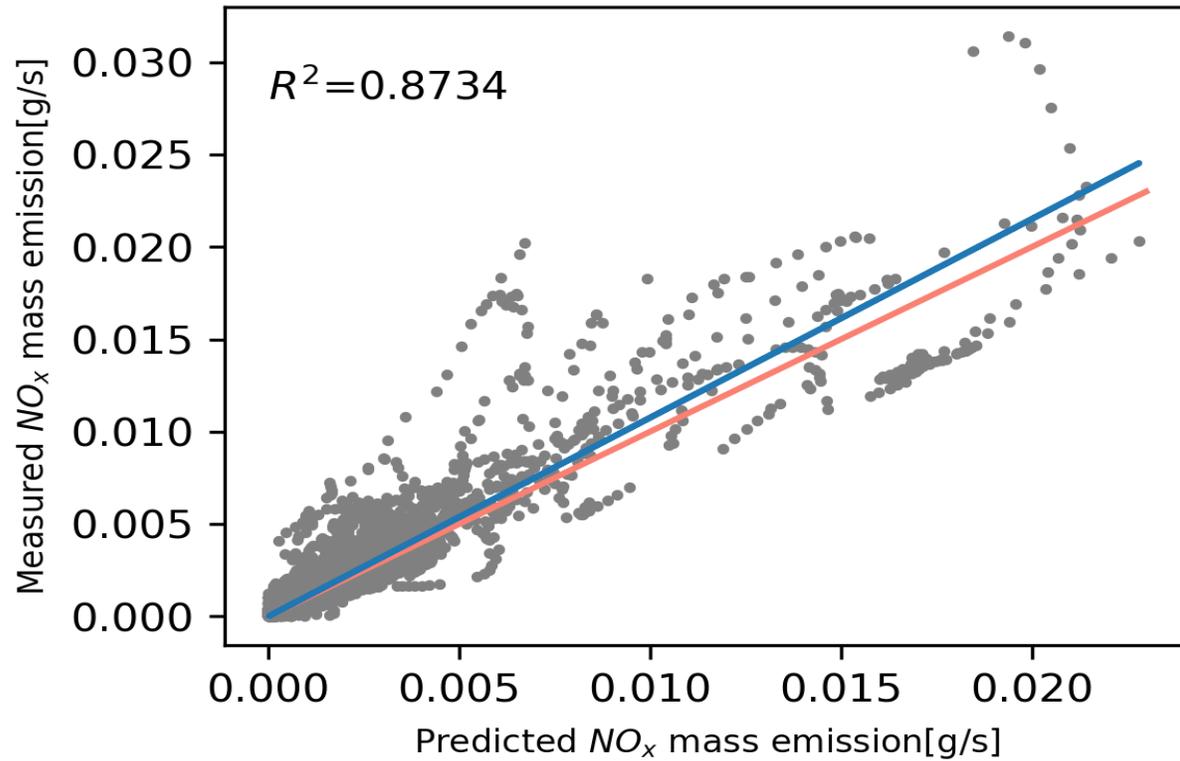
Measured: 17908.9 g/s
Predicted: 18518.6 g/s } Error 3.4%

- Time series

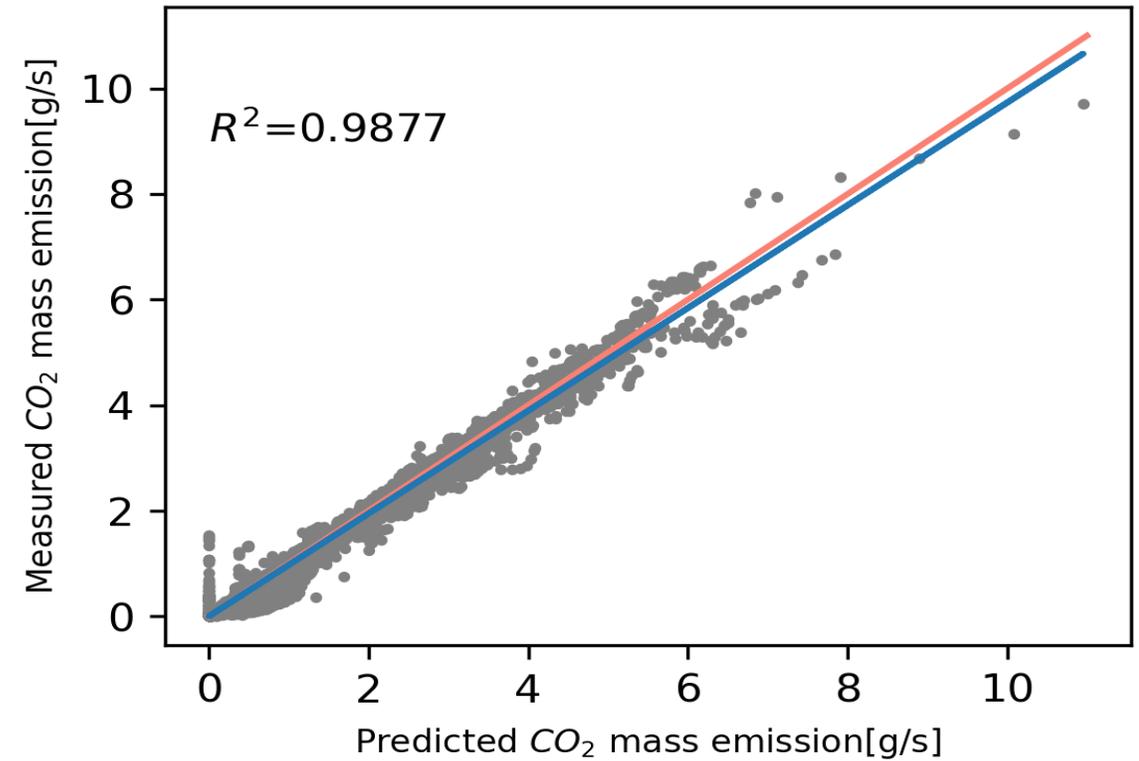


Prediction Results

NO_x



CO₂



1. Large amount of NO_x and CO₂ were emitted when the speed fluctuation of the vehicle becomes large and the acceleration / deceleration changes.
2. A prediction model of real-world emissions using deep learning was constructed.
3. When a verification route consisting of general roads and highways was predicted, the relative error due to the total value of the mass emission for the entire route was 17.1% for NO_x and 3.4% for CO₂. While the CO₂ emission prediction model can predict with high accuracy, the NO_x emission prediction model shows a deviation from the measured value when NO_x emission largely emitted.
4. We are conducting real-world emission analysis of direct-injection gasoline vehicle. A model is constructed to predict the emission behavior of NO_x, NH₃, CO₂, and PM / PN.



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Thank You for Your Listening

Susumu (Mu) Sato
Tokyo Institute of Technology
sato.s.ay@m.titech.ac.jp

