MathWorks
AUTOMOTIVE CONFERENCE 2023
India

AI Use Cases in Powertrain Development

Padmavathi R, Mahindra & Mahindra

MathWorks

AI Use Cases in Powertrain Development

Contents

1. A statistical approach : Worst case emissions cycle for on road emissions robustness enhancement

2. Machine Learning approach : Virtual NOx sensor for onboard NOx monitoring/ Physical sensor replacement

Worst Case Emission Cycle development for BS6.2

Methodology to Build Confidence in Meeting IRDE Emissions

steps

1. Introduction- Overall Process
2. Random IRDE Cycle Generation
3. Worst Case Cycle Generation
4. Statistical analysis : Confidence level in meeting CF

Overall Process

- A Process to Establish confidence & robustness on meeting Emission criteria IRDE .

Confidence on meeting RDE

Vehicle on road

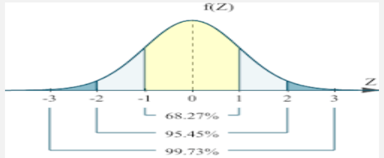
On road data collection 1000 Km

Simulation

WCC Generation

30 Random IRDE cycles generation GT Tool

Chassis Dyno



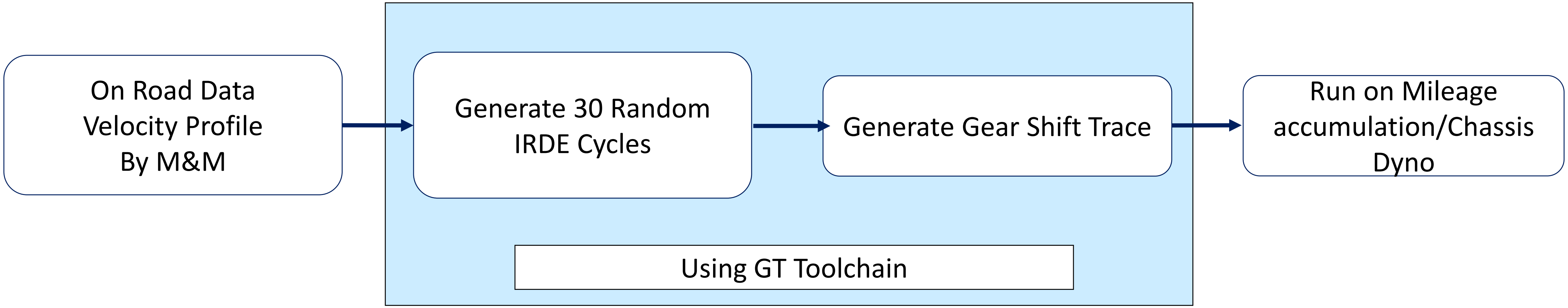
Probability analysis

Correlation Test WCC & 30 IRDE cycles

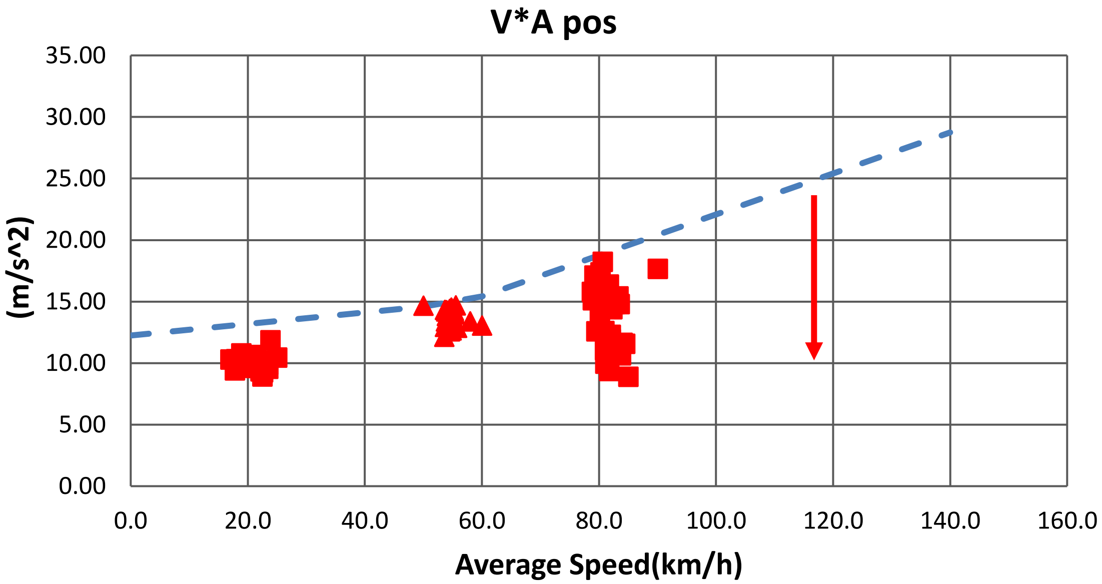
Statistical analysis

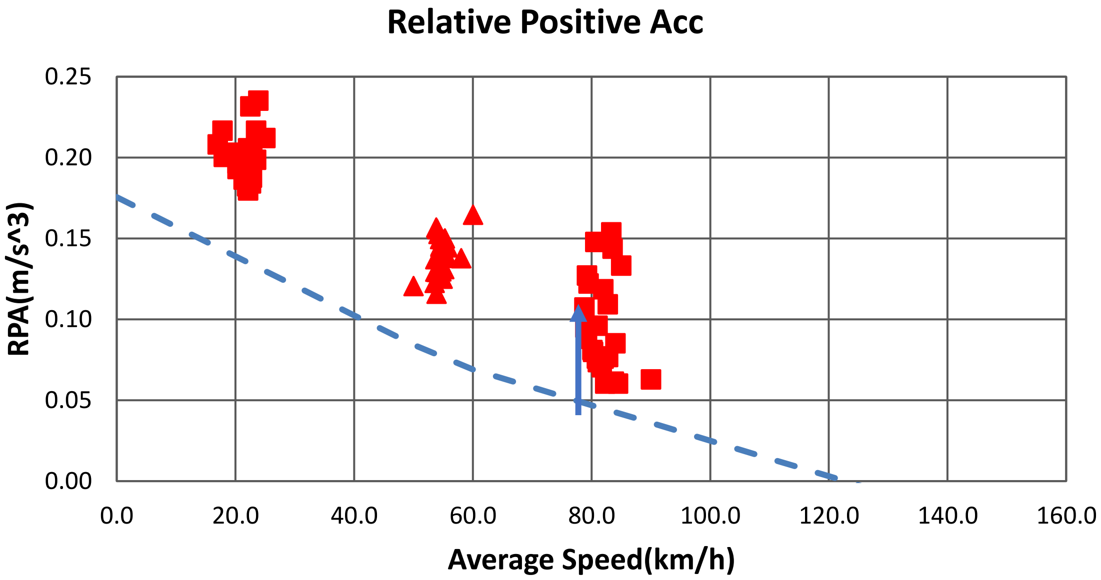
- Finalise WCC cycle to Test & optimise further

35 Random Cycles Generation



All Random RDE cycles meeting the IRDE Boundary conditions

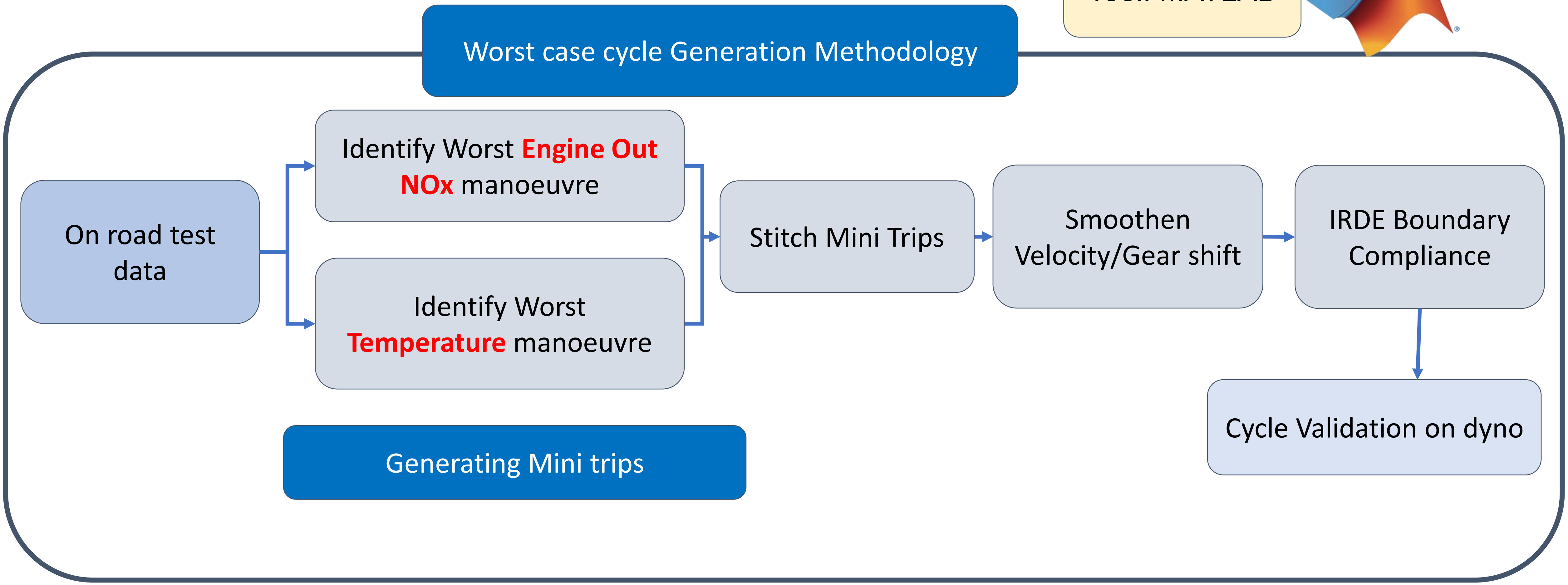




Process

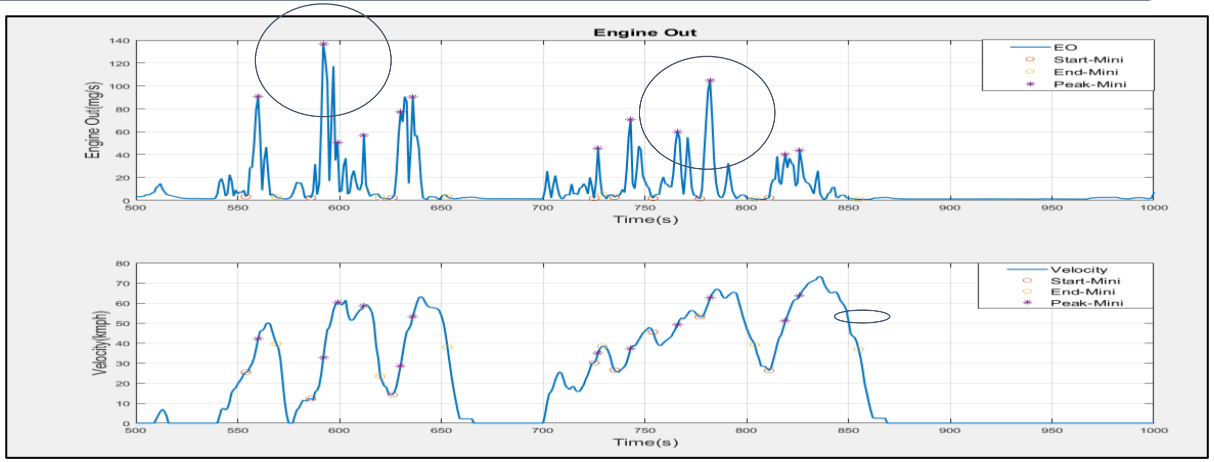
- To Generate “Worst Case RDE” drive Cycles suitable for use on Dynamometer.
- Worse case cycle contains the Highest Engine out Nox Emissions & Lowest after treatment Efficiency/ AFT temperature ,Hence the combination is Highest tail pipe Emission.

Tool: MATLAB

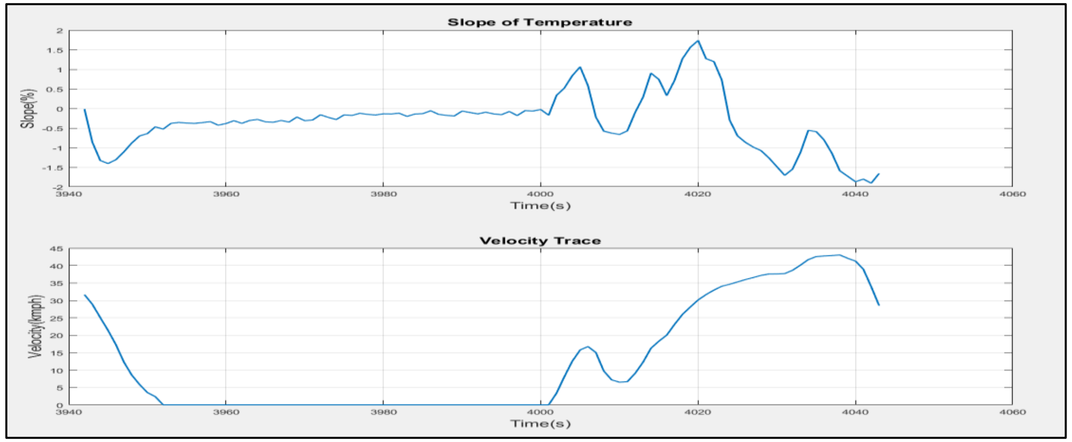


Mini Trip Generation

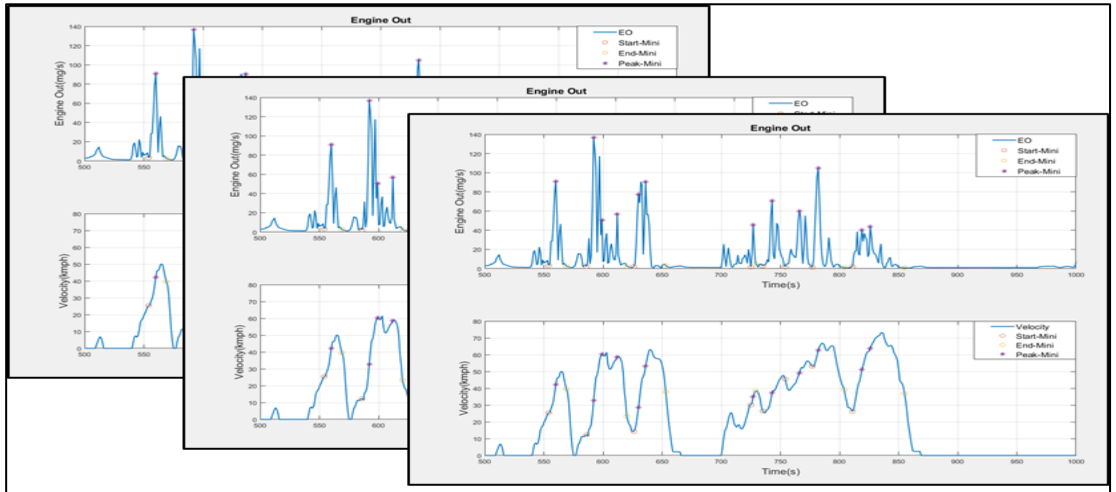
Identify NOx peaks at Engine Out



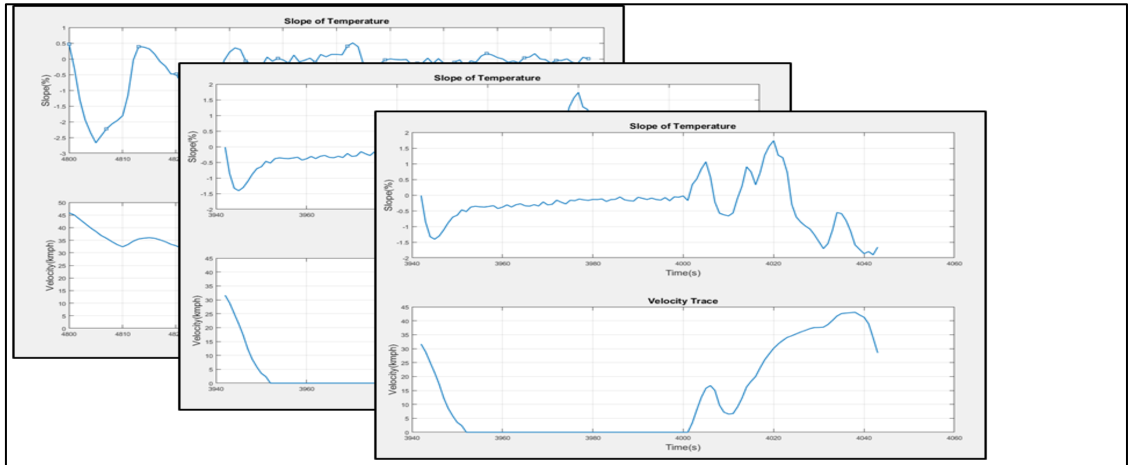
Identify Temperature mini Trip



Stitch Mini Trips ,Smoothen gearshift and acceleration to meet IRDE BC



Identify NOx peaks at Engine Out

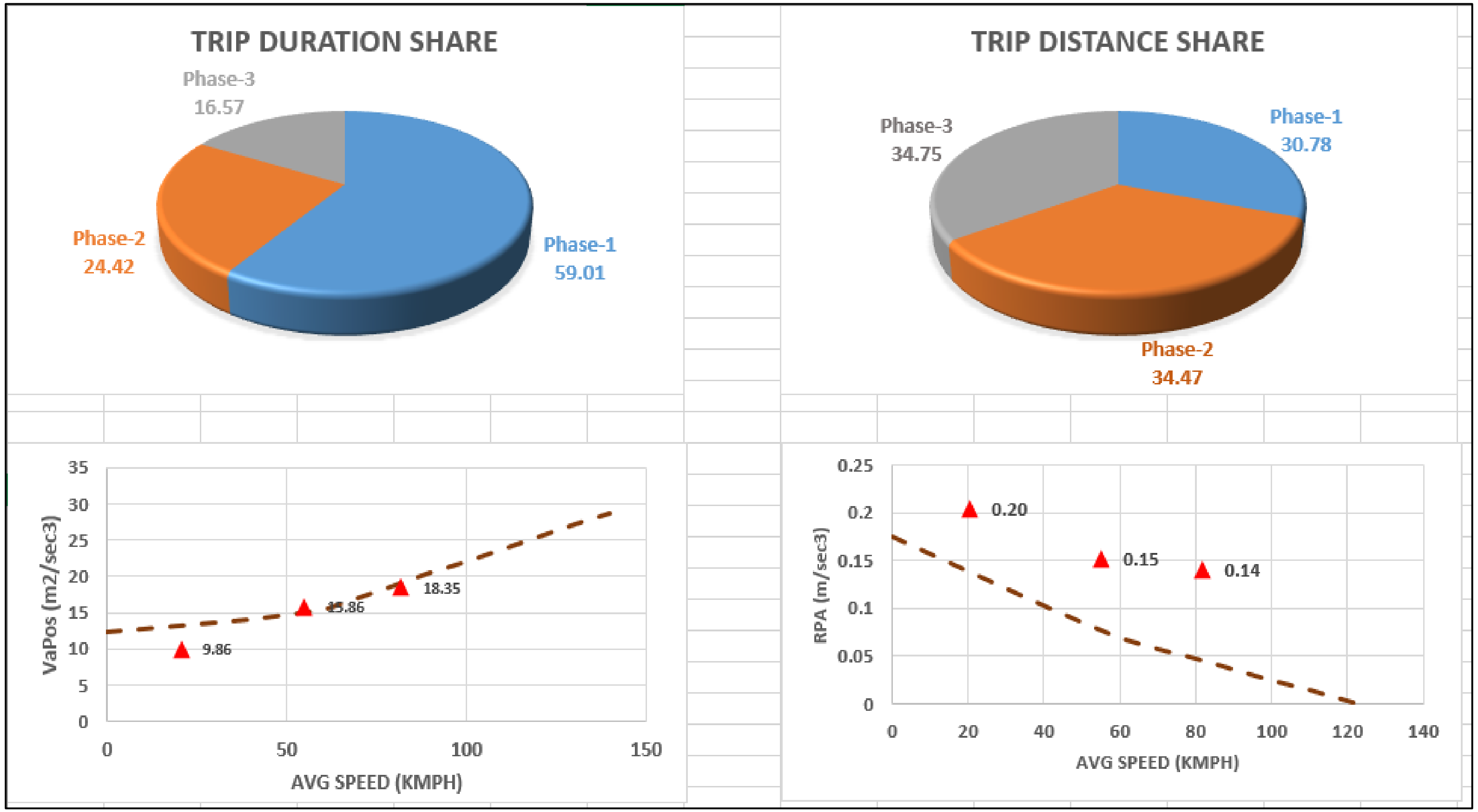


Pre Maneuver with Velocity end same as EO-Mini start

Worst Case Cycle(WCC): Validation IRDE Boundary Conditions

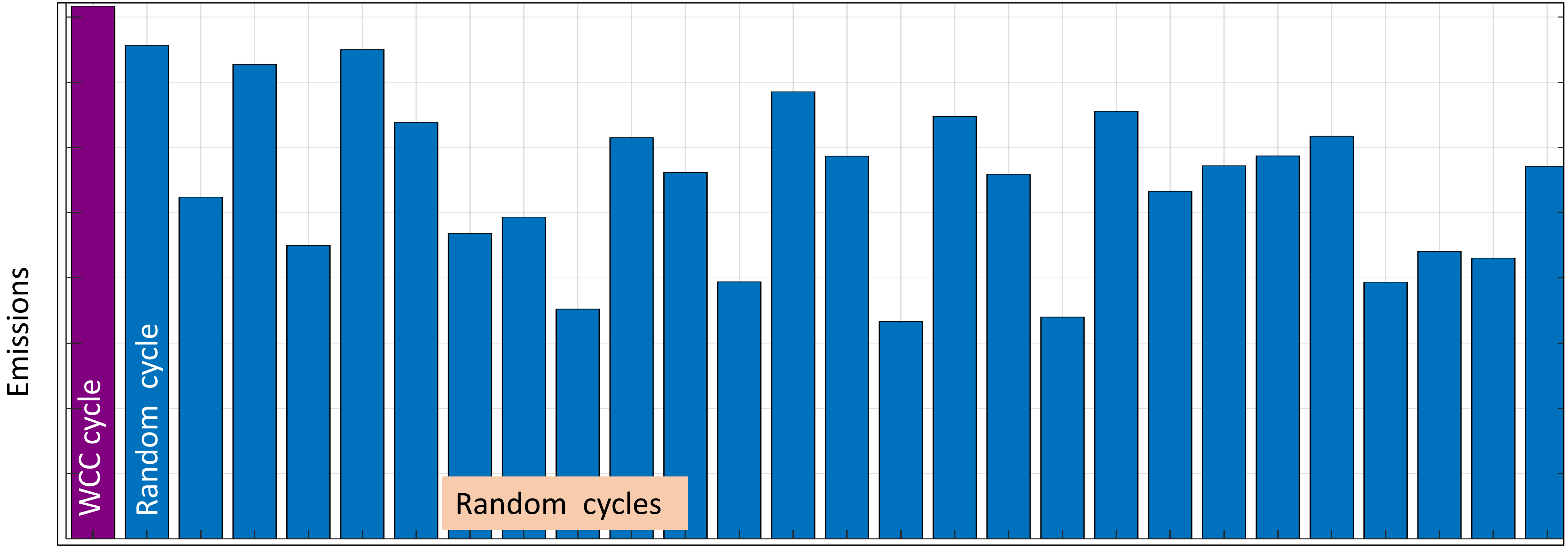
BOUNDARY CONDITIONS		LIMIT	TEST RESULTS
TOTAL TEST DURATION		90 - 120min	111.6
TRIP DURATION SHARE	Phase-1		57.1
	Phase-2		31.3
	Phase-3		23.3
TOTAL DISTANCE			80
TRIP DISTANCE SHARE	Phase-1	24% - 44% (Min 16km)	19.3
	Phase-2	23% - 43% (Min 16km)	28.0
	Phase-3	23% - 43% (Min 16km)	32.2
Time for V>75 KMPH		At least 5min	18.4
MAX SPEED			118.8
% TIME FOR MORE THAN ALLOWED MAX SPEED		3%	2.6
AVERAGE SPEED			42.8
Average Speed Phase Wise	Phase-1	15 - 30kmph	20.3
	Phase-2		53.8
	Phase-3		82.7
DURATION OF SPEED > 75 KMPH		At least 5min	18.4
NO. OF ACCLN POINTS	Phase-1	150	1474
	Phase-2	150	1060
	Phase-3	100	755
NO. OF VEH STOPS >10 SEC			17
DURATIO OF LONGEST STOP		5min	1.72
TOTAL STOP DURATION % of PHASE 1		6% - 30%	19.40
TIME FOR VEH SPEED BELOW 20 KMPH		20min	2.25
ALTITUDE GAIN FOR URBAN, m		1200m/100km	165.9
ALTITUDE GAIN IN TOTAL, m		1200m/100km	246.9
DELTA /END ALTITUDE, m		100m	29

- Worst case Cycle meeting the all trip dynamics & Boundary conditions of Indian real drive cycle (IRDE)



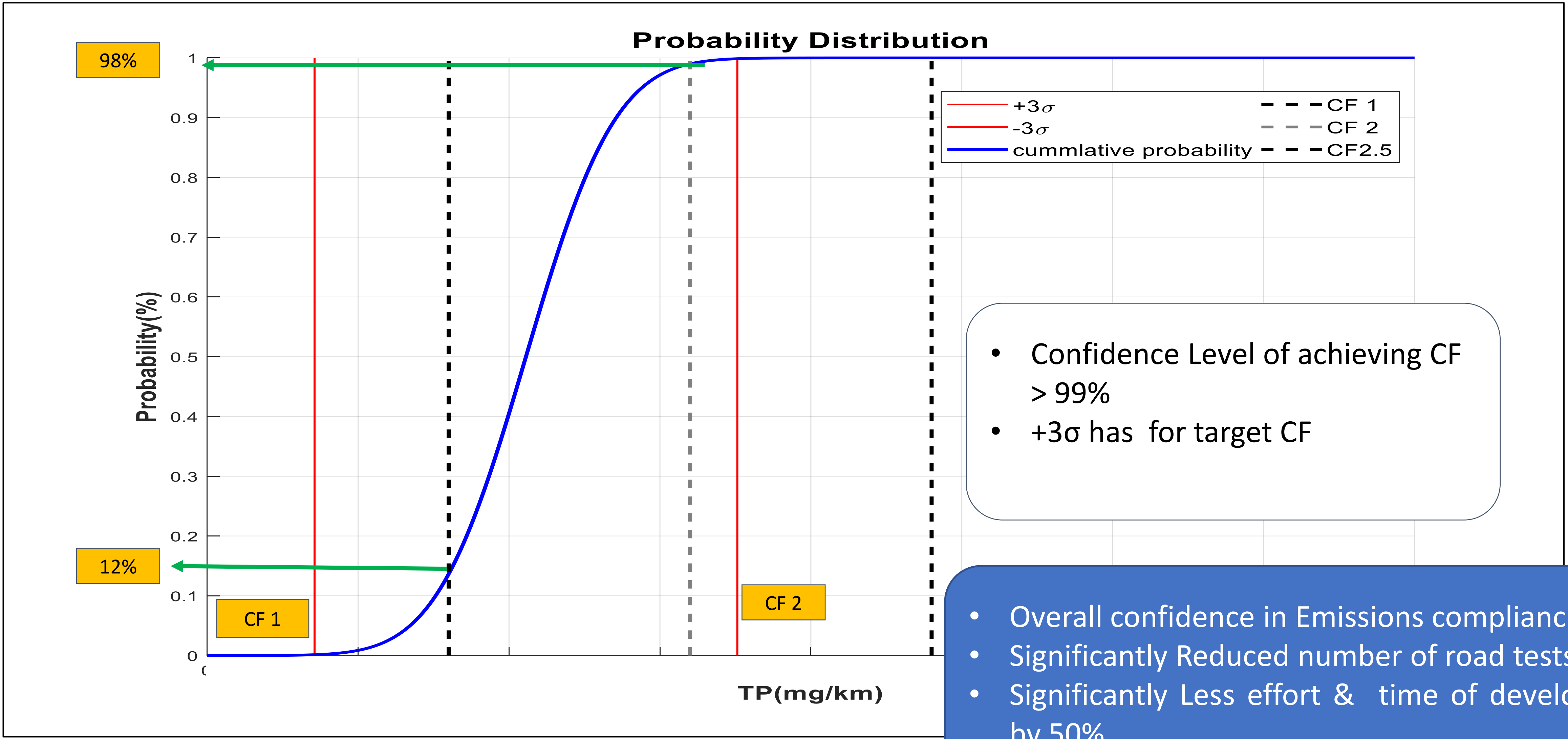
Cycle Statistics-Overall

Tailpipe Emissions WCC cycle Vs Random cycles



WC Cycle Emissions shows higher cycles Nox compared to all random cycles.

Cycle Statistics-Overall



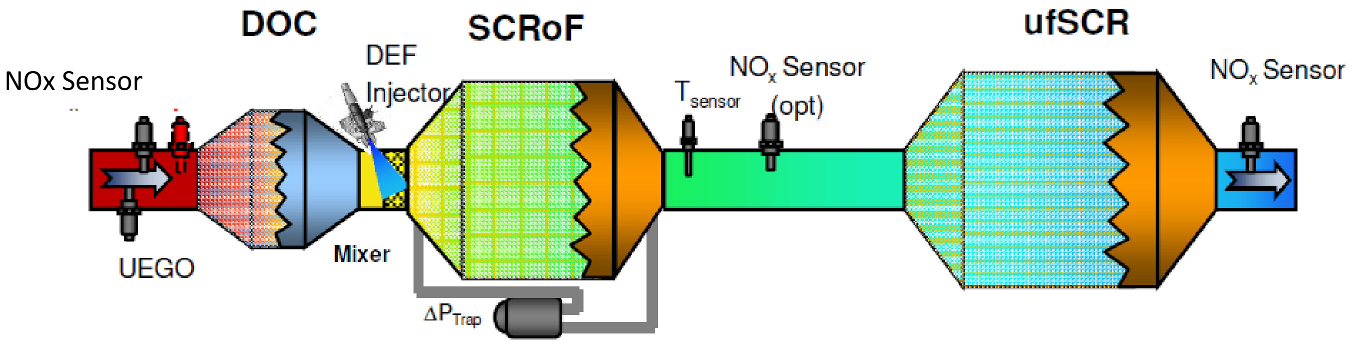
- Confidence Level of achieving CF > 99%
- +3σ has for target CF

- Overall confidence in Emissions compliance
- Significantly Reduced number of road tests 50%
- Significantly Less effort & time of development by 50%

Machine Learning : Virtual Nox Modelling

NOx Sensor

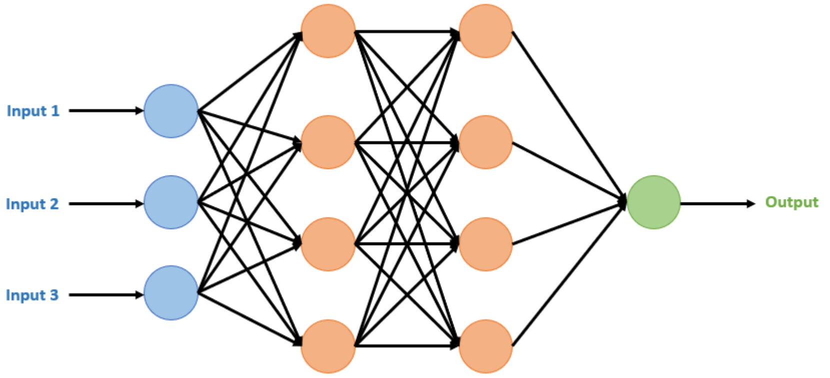
- Purpose
  - After-Treatment Device Management (LNT, SCR etc.)
  - Diagnosis After-Treatment Systems:
    - Plausibility check and functional diagnosis



Problem statement

Zirconia NOx Sensor

- Physical sensor
- Overtime measurement degradation
- Light-off temp requirement
- Cost
- Maintenance

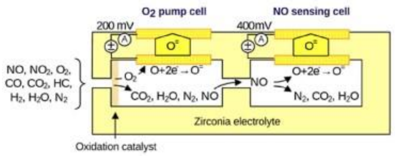


Virtual NOx sensor

- Accurate measurement over time
- Cost effective
- Real time predictions
- Adaptable with varied driving conditions

Virtual NOx sensor modelling strategies

Theoretical modelling- Derived from physics

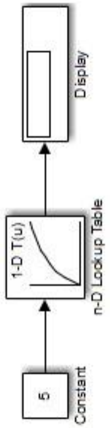


Electrical systems
- Ohm's Law
- Kirchhoff's Law

Hydrodynamics
- Bernoulli's Law
- Conservation law

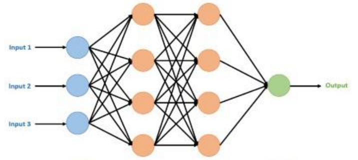
Thermodynamics
- Ideal gas Law
- Entropy

Map Based modelling



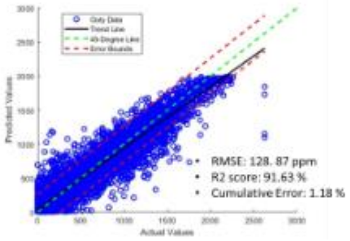
- Map based calibration (EGR on, EGR off)
- Correction coefficients are calibration dependent

Artificial Intelligence modelling



- Machine learning
  Deep learning
  Artificial NN

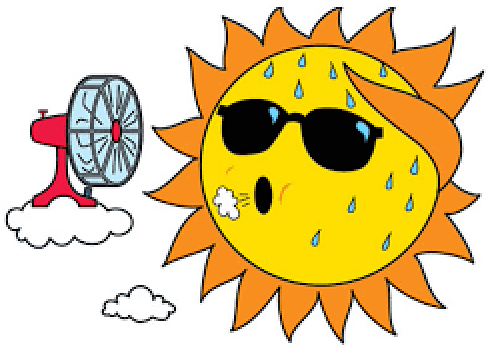
Training based modelling
- Corelating I/O of data to find relation



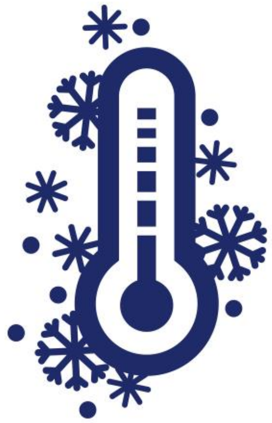
	Theoretical	Map Based	AI
Calibration/testing effort			
Modelling complexity			
Accuracy			
Computational effort → Real time applicability			

Methodology

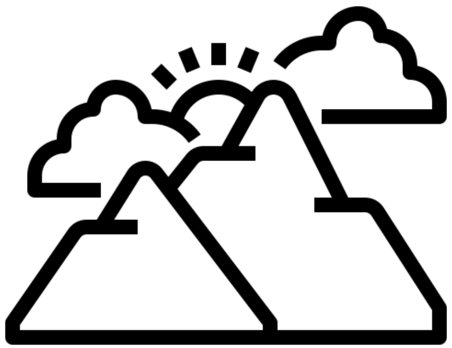
- Extensive data collection and model training
  - Dedicated data collection at different Temperature, altitude and driving conditions



Hot data



Cold data



Altitude data

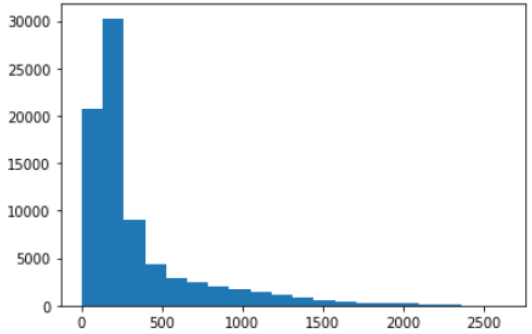
Methodology

Data Processing

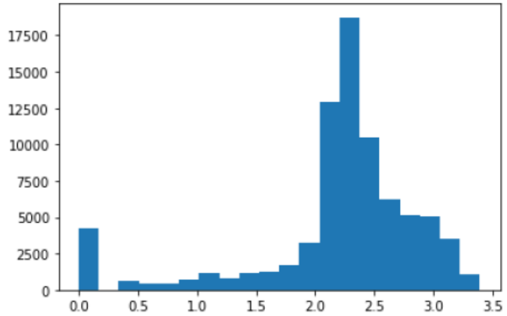
Data Cleaning and preprocessing and transformation

Feature selection
- Engine expert's insight

Model selection and training

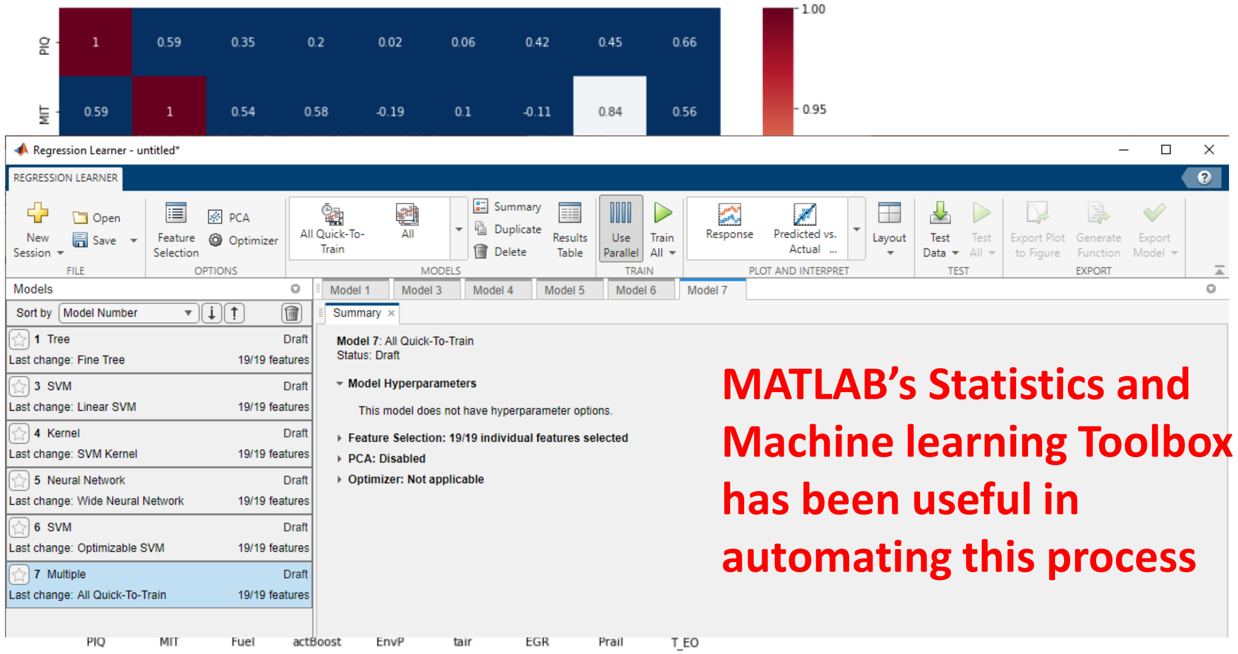


Histogram: engine out NOx g/hr for train-test



Histogram: Log transformed engine out NOx

Heat map for Feature correlation



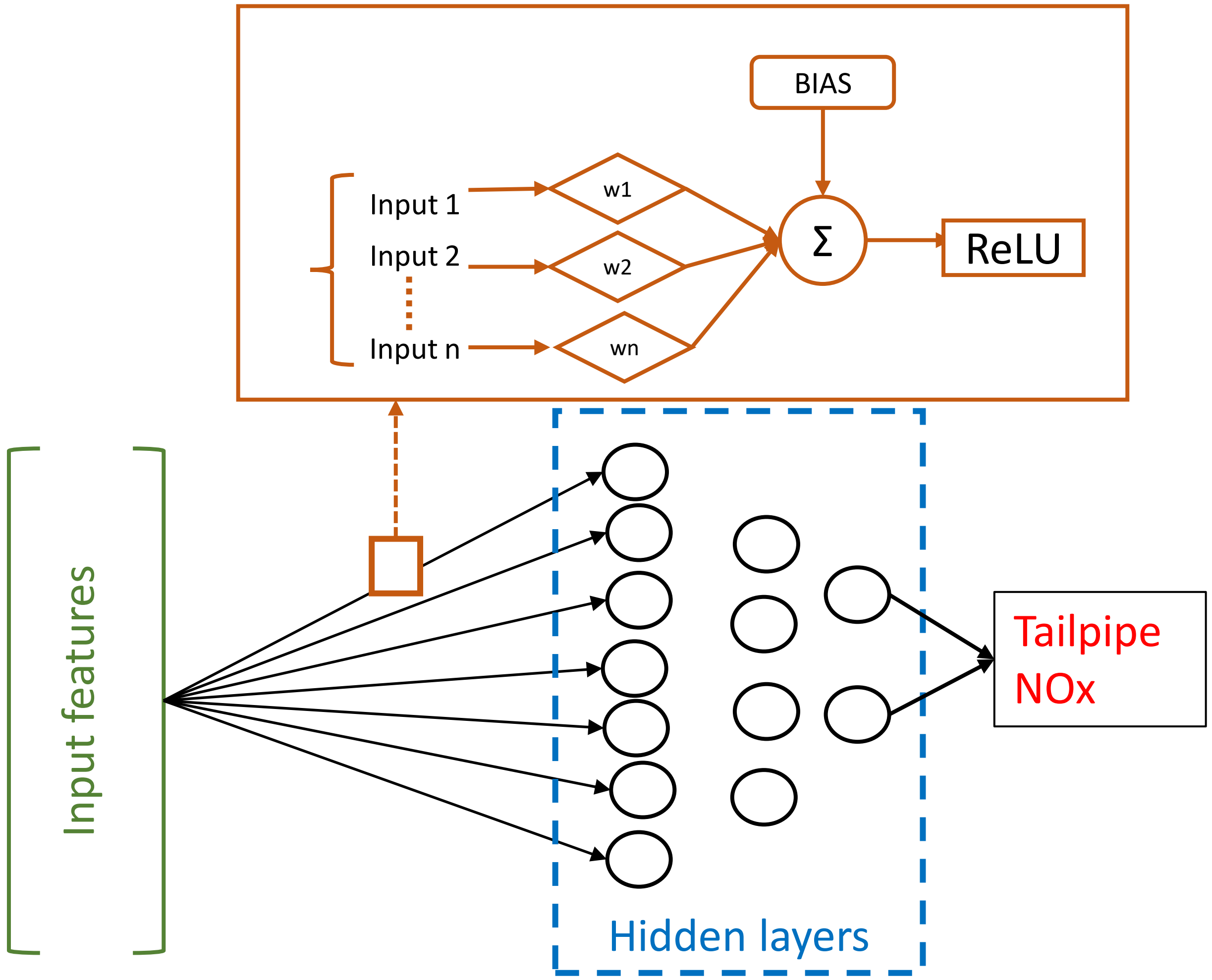
MATLAB's Statistics and Machine learning Toolbox has been useful in automating this process

ML model and optimization

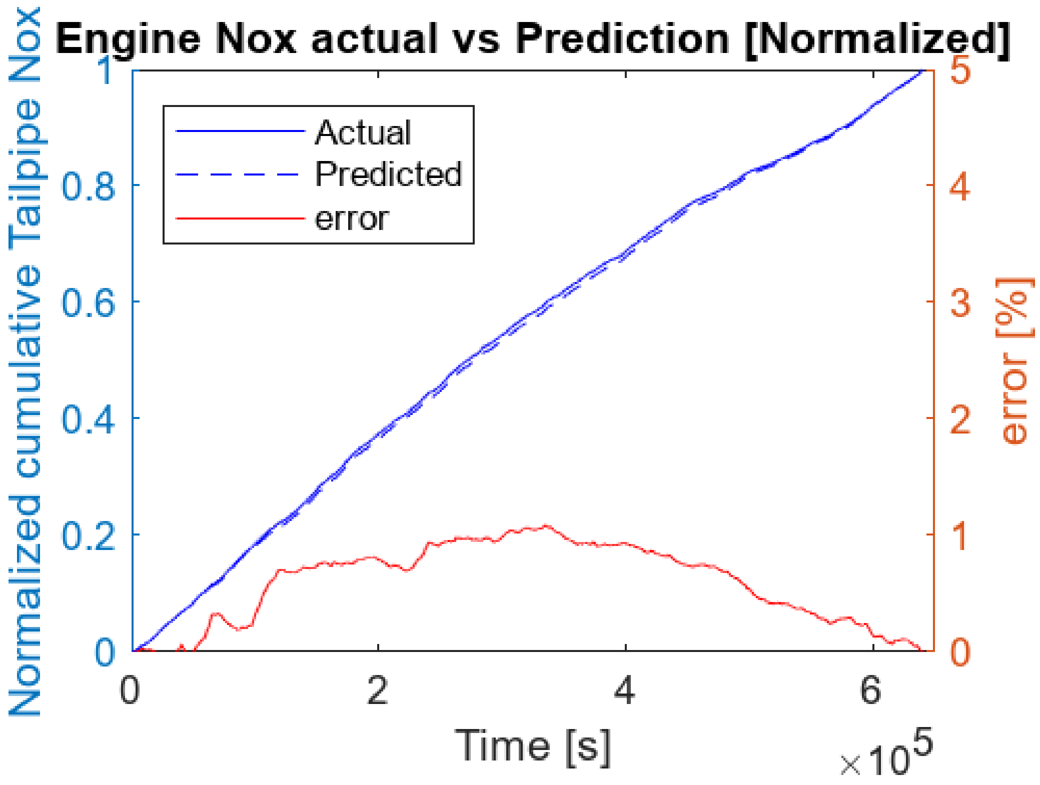
- Model:
  - Neural network (NN)

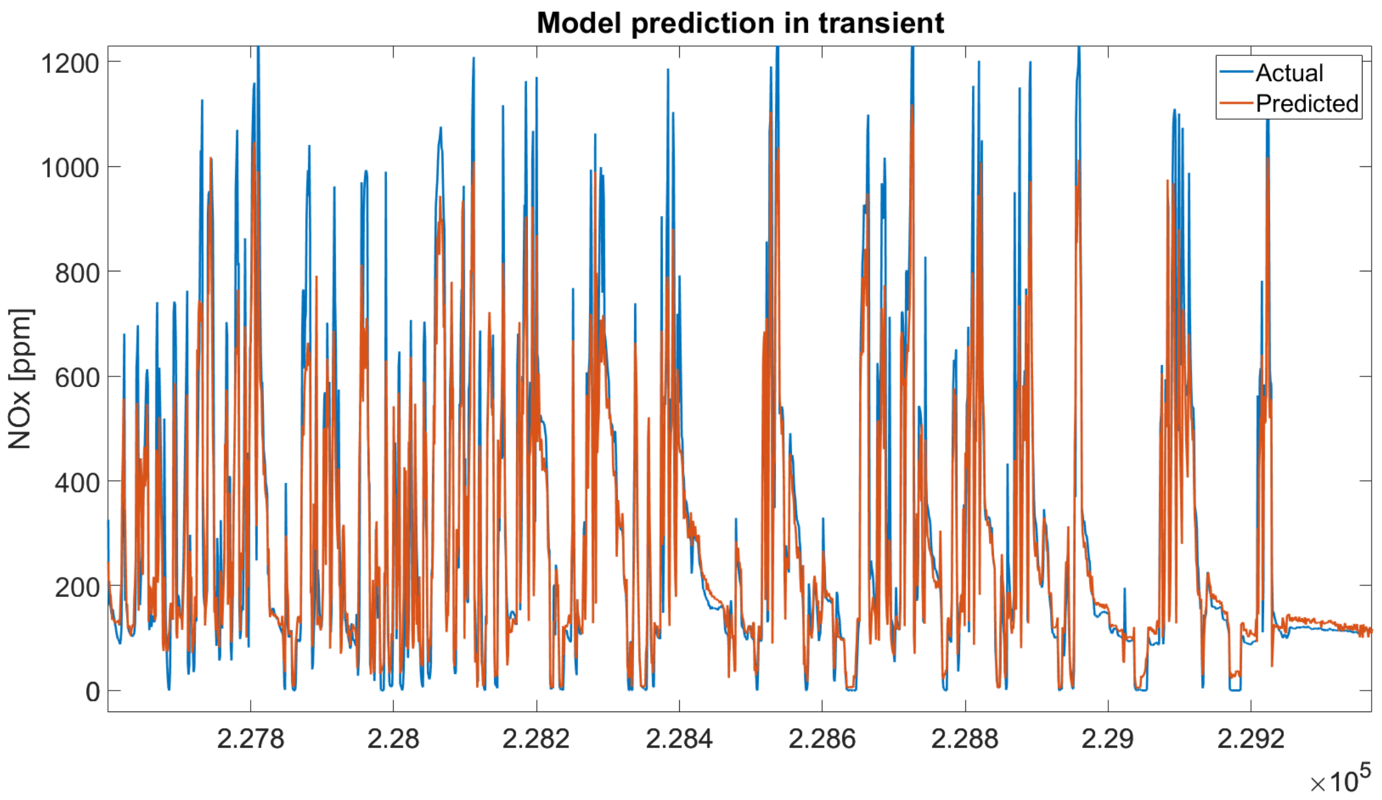
- Optimizer:
  - ASHA (Asynchronous Successive Halving Algorithm)

- Advantages of using ASHA
  - Automated & Efficient Hyperparameter Optimization
  - Better Model performance compared to Bayesian optimization



Model validation

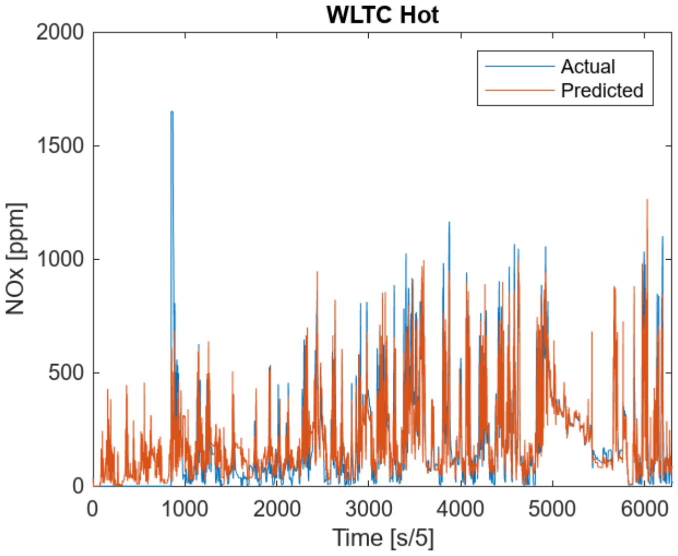


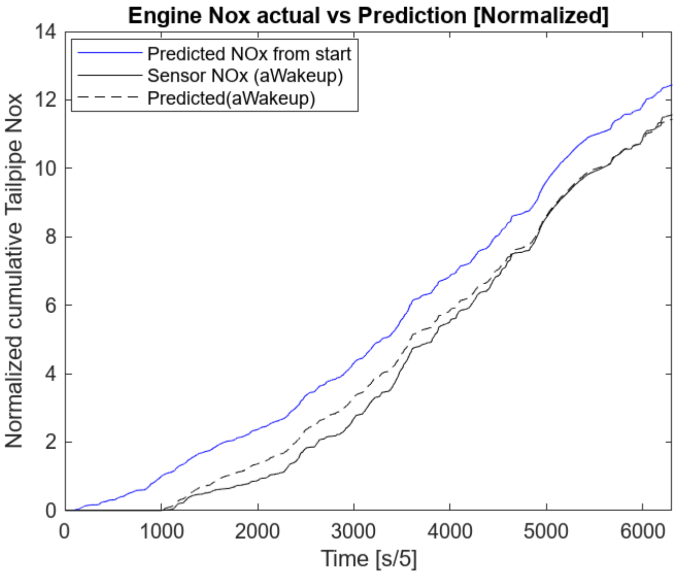


- Normalized Cumulative data is within 1% error range
- Model prediction in transient is good compared to actual NOx

Model performance on untrained cycles

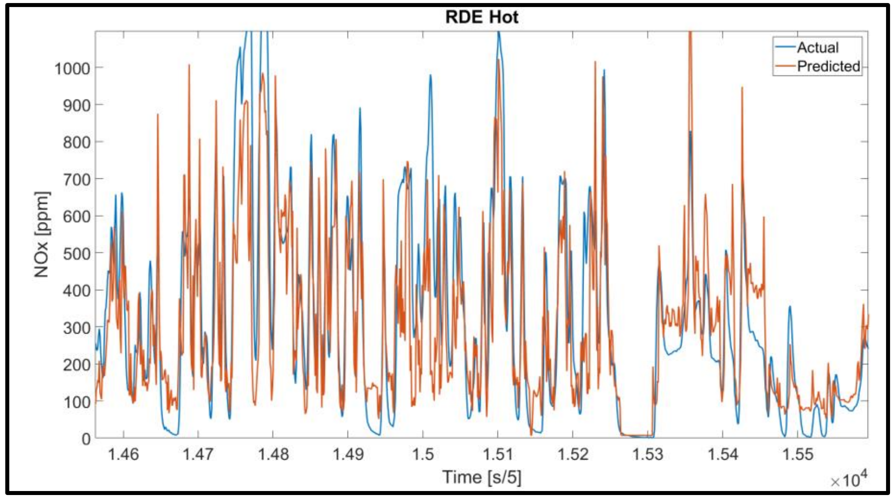
WLTC

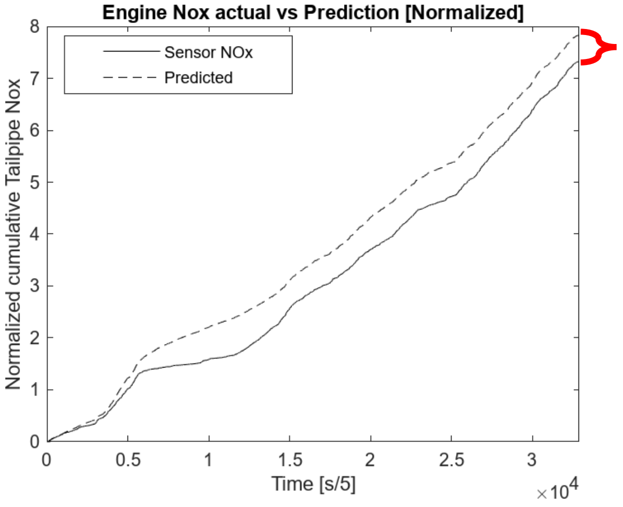




- In cumulative terms, Actual and Predicted NOx is comparable
- However, instantaneous Virtual NOx model is over predicting at lower speeds whereas underpredicting at higher speeds
- This is due to the dataset used for training. More extensive testing data is required for better model predictions

RDE





Process so far

NOx modelling using Python

- Sea Level Validation

Achieved:
- Good accuracy on the test data

Next step?
- Add more driving condition in the test data

Modelling using Python Deep learning

- Altitude data added

Achieved:
- Good accuracy on the test data
- Model was heavy for real time prediction

Next step?
- Shallow NN

Modelling using MATLAB (Shallow NN)

- Code size compatible with ECU

Next step?
- Implementation on the ECU
- More detailed training dataset
- Impact of Humidity on NOx
- Cold start and high speed conditions

Thank you for your attention!

Q&A