Data-Driven Insights for Heavy Duty Fleet Emissions

Powered by AVL Data Analytics™

Joshua Orlando

Today’s Agenda

1 **The Data Analytics Marathon**
What are you doing with data?

2 **Fleet Monitoring**
Targeted Insights for your customer fleet

3 **Use Case Examples**
Get more out of your data

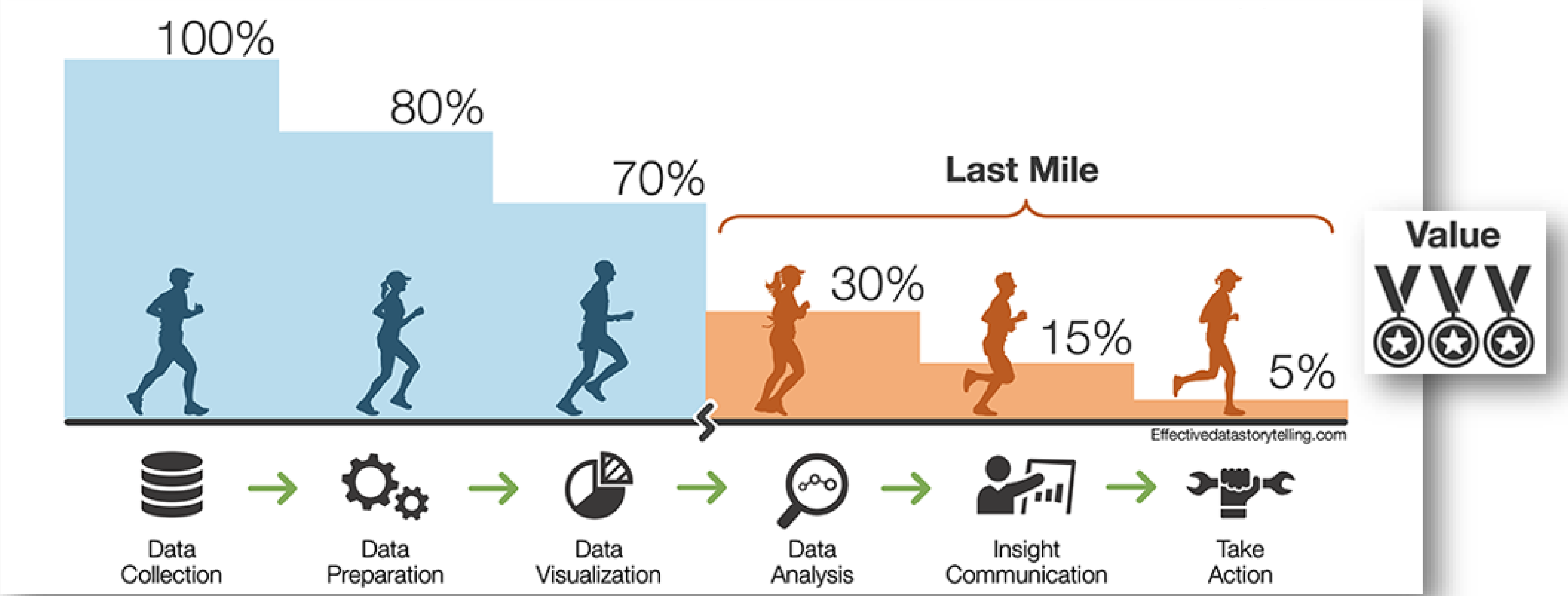
4 **Solution and Benefits**
Proven to increase your efficiency

What is driving the automotive industry?

The Data Analytics Marathon

Public

Where Is Your Position in the Data Analytics Marathon?

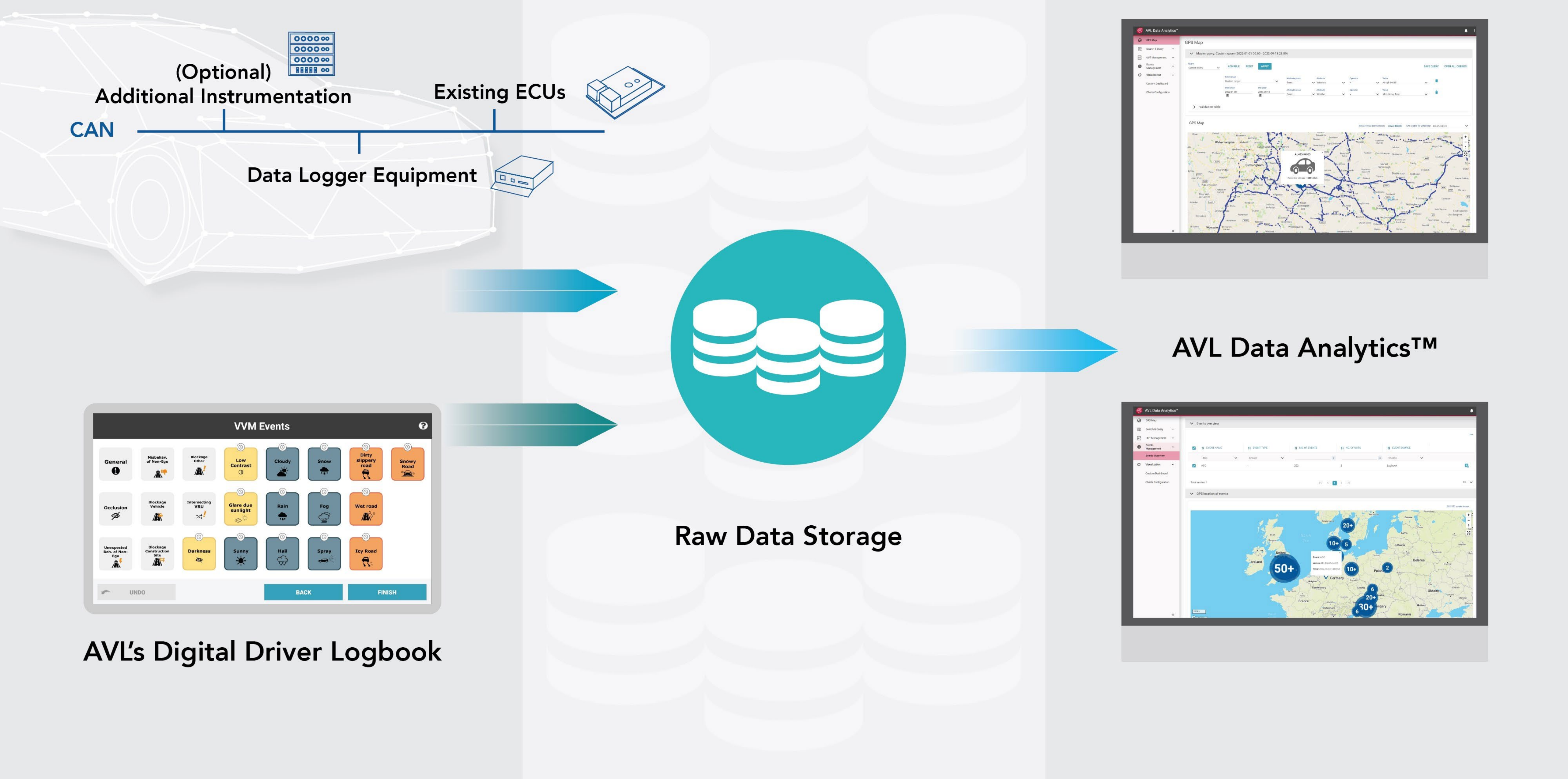


Source: Forbes.com

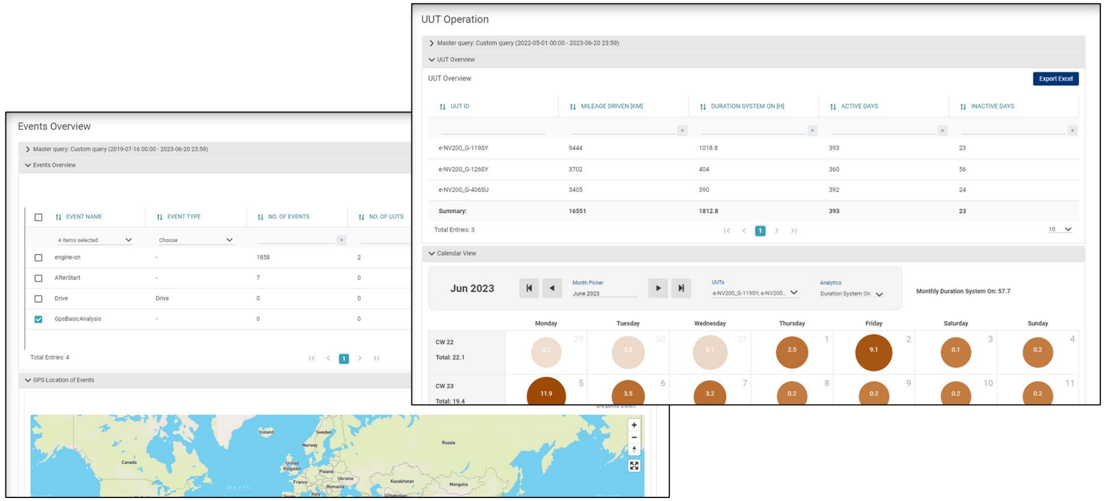
Make more out of your fleet data

Targeted Fleet Data Analytics

Fleet Data Analytics



Fleet Monitoring



- **Overview**
  - Solution for monitoring testing fleets
  - Monitoring different aspects of the vehicle operation and validation project progress

- **Event Detectors**
  - Measurement based events
  - Component based controller events
  - Diagnostic Trouble Codes

- **KPIs**
  - Fault counters
  - Deviations from setpoints/models
  - Start-end-min-max-mean of monitoring signals
  - Mileage / operating hours / down time
  - Testing coverage

- **Charts and Tables**
  - Mileage accumulation charts
  - Operating point heatmaps
  - Speed distribution bar charts
  - Signal monitoring scatter plots
  - Daily operation calender view
  - Location and routing maps

Functional Digital Twins across the Life Cycle

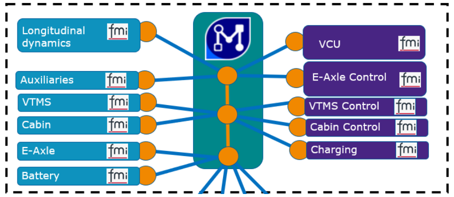
Scalable Digital Twin

Conversion for scalability

Digital Master

Systems Engineering SysML

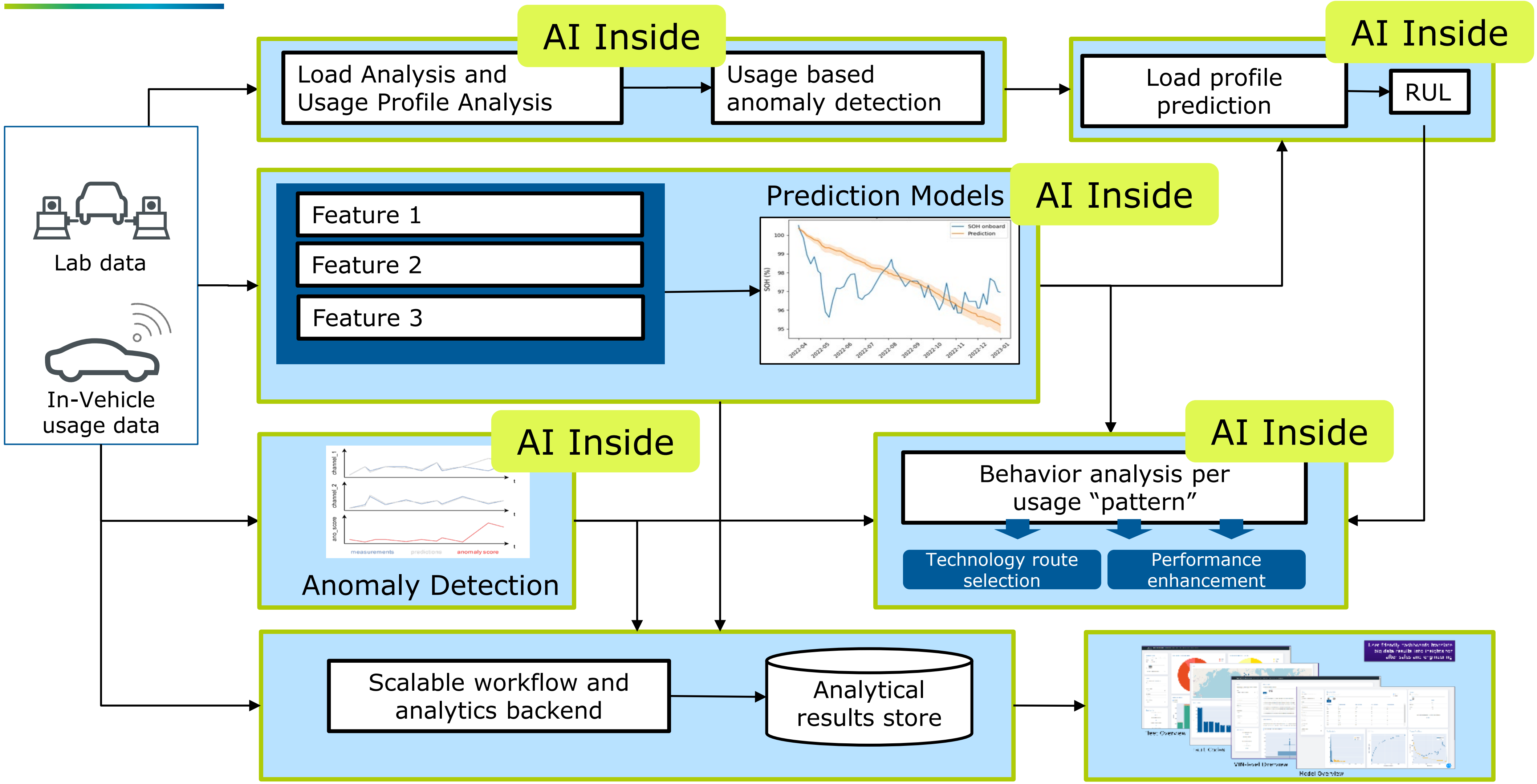
Digital Prototype



Environment:	SysML	SIL/HIL	SIL/HIL	Cloud
Instances:	One according to specs	One Continuously adapted throughout development	For each validation vehicle	Digital twins for every single vehicle in the customer fleet

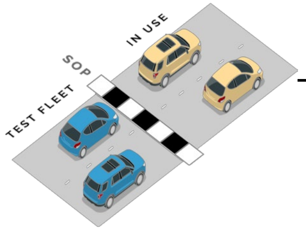
Continuous Re-training

Digital Twin – Reference Architecture

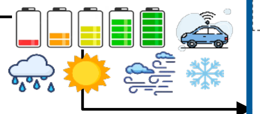


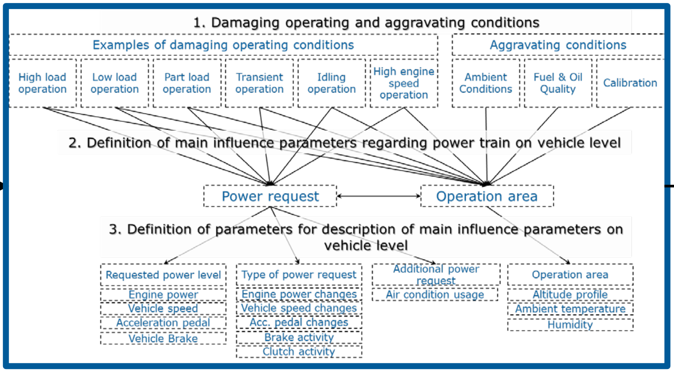
Usage and Load Profile Analysis

From Fleet Data to Requirements to Validation Cycles with unsupervised clustering



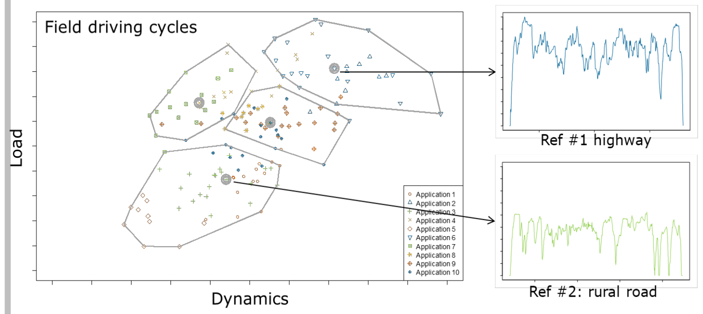
Input: Fleet data



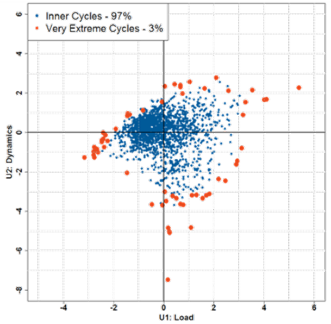


Definition of Target Vehicle Usage Parameters

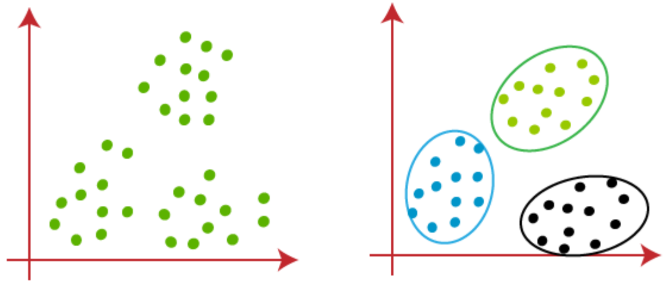
VUP Computation per Duty Cycle



Usage profile differentiation



Standard vs. Extreme Usage



Similarity Analysis

Benefits:

- Understand customer usage and extreme users
- Optimized requirements for quality and costs
- Optimized simulation and test cycles

Analysis of Telemetry Fleet Data

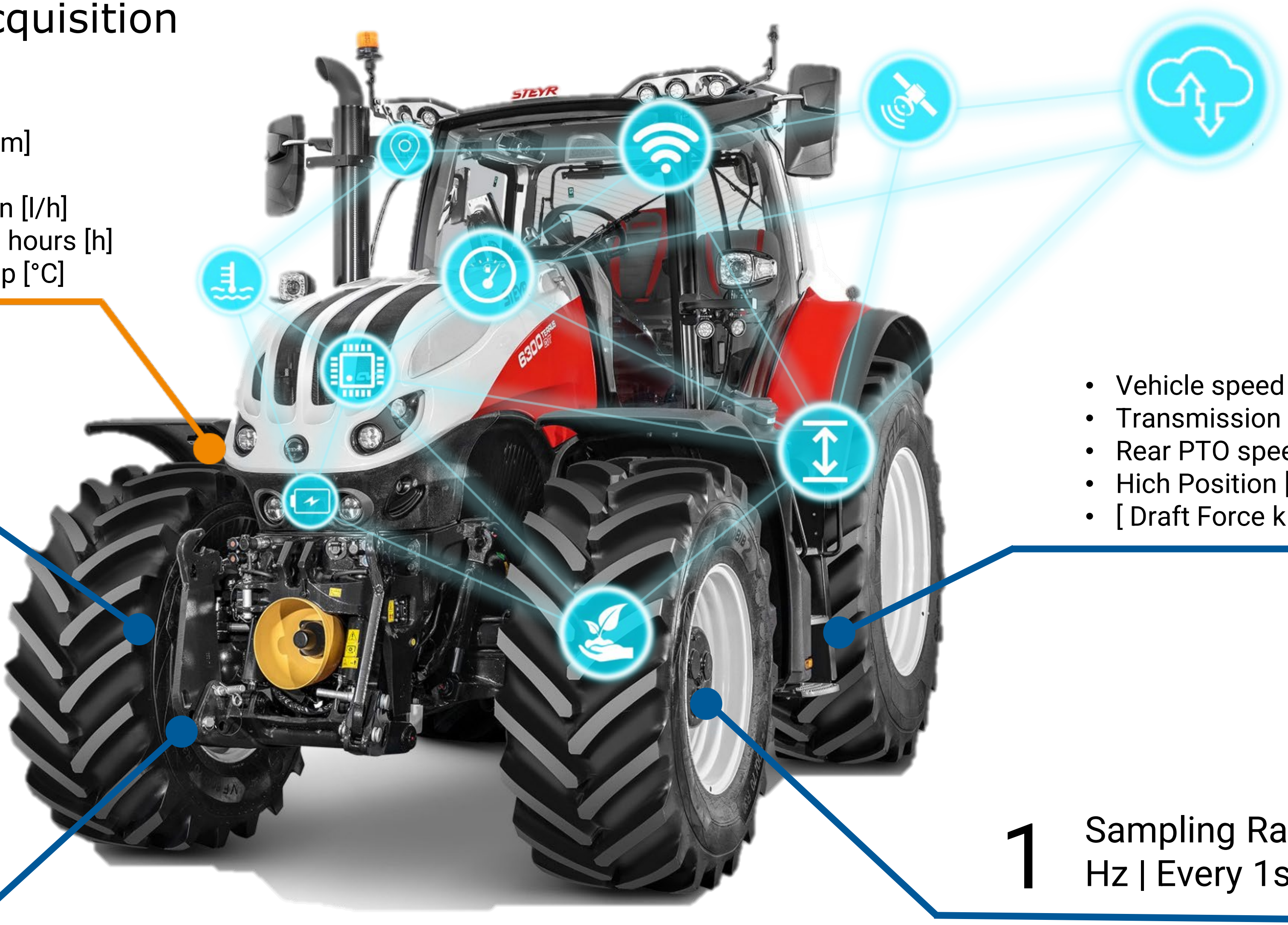
Data Engineering & Geospatial Data Analysis

Operation Profile Analysis

Features | Data Acquisition

- Engine Speed [rpm]
- Engine load [%]
- Fuel consumption [l/h]
- Engine operating hours [h]
- Ambient Air Temp [°C]

- Front PTO Speed [rpm]



- Vehicle speed [kph]
- Transmission Gear [enum]
- Rear PTO speed [rpm]
- Hich Position [%]
- [Draft Force kN]

>50 Features CAN-Signals

1 Sampling Rate Hz | Every 1s

Fleet in numbers

2020 OCT – 2021 OCT

9493 Unique Vehicles

80 %

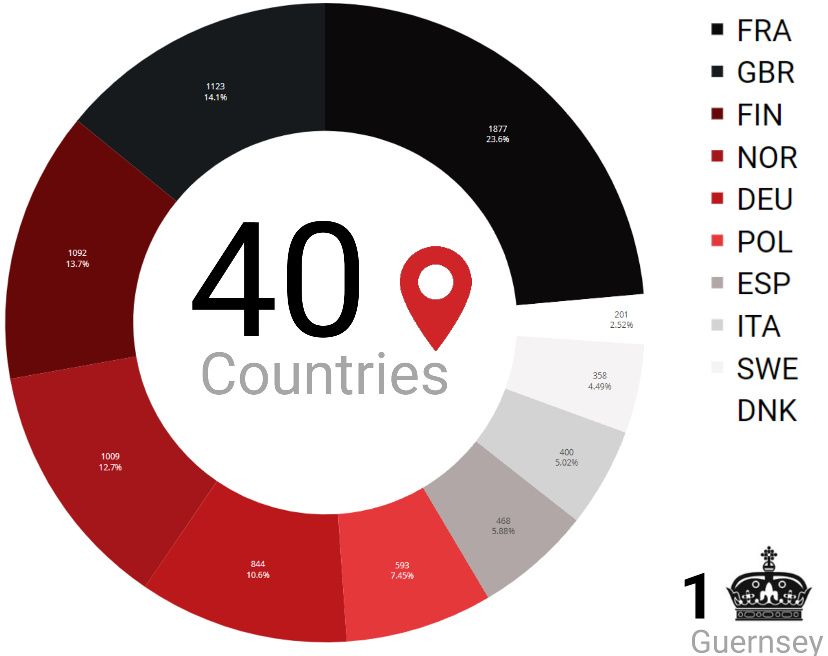
Connected Vehicles Day

3628 | 6544

3.5 Hours | Day

418 p.a.

23 %	TRANSPORT
9 %	STATIONARY WORK
26 %	STANDSTILL IDLE
1 %	PTO ONROAD
14 %	FIELD + PTO
27 %	FIELD



1

Guernsey

3.92 Mio Km **33.21** Km / day

3082

Around Earth

204 to Moon

40121 m^3

Fuel Total

31 liter | Day

Tank Trucks

691

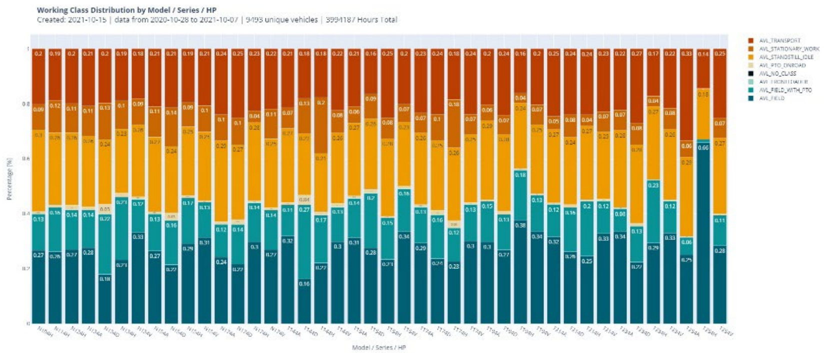
10 liter | hour

Total 4192

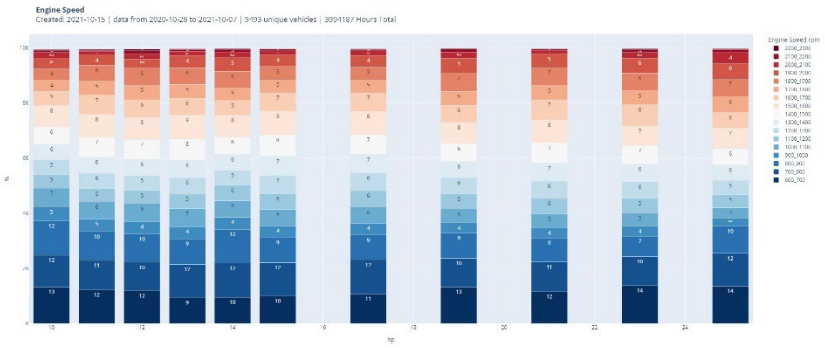
CO_2 Tons

105920

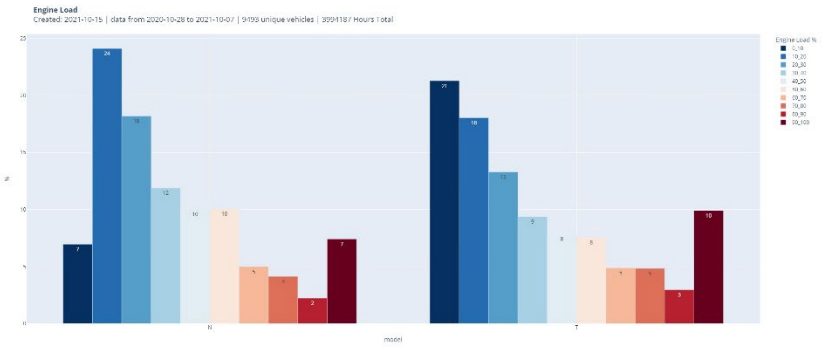
Machine Profiling for Engineering
Grouping Possibilities



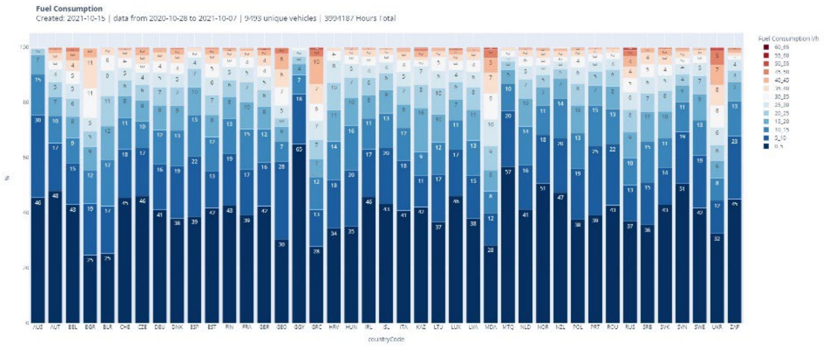
Series | Model | HP



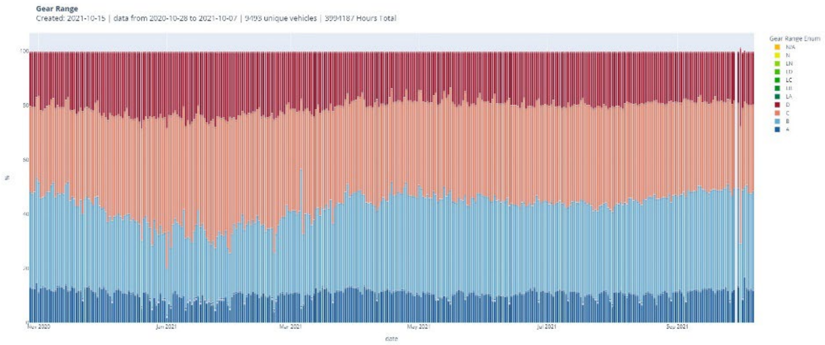
Horsepower (110, 120, 150)



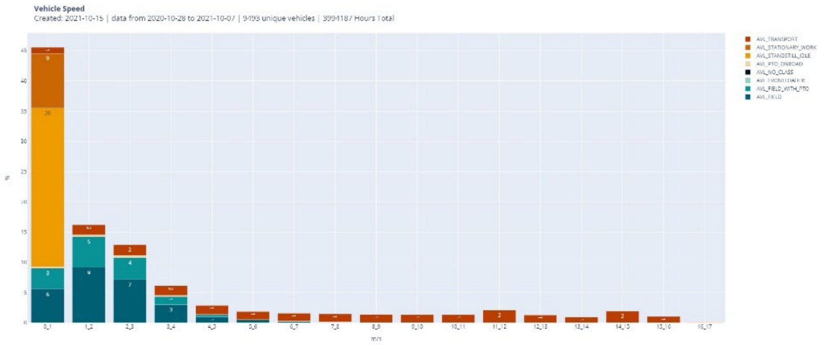
Series (Multi, Profi, TERRUS)



Country (GBR)



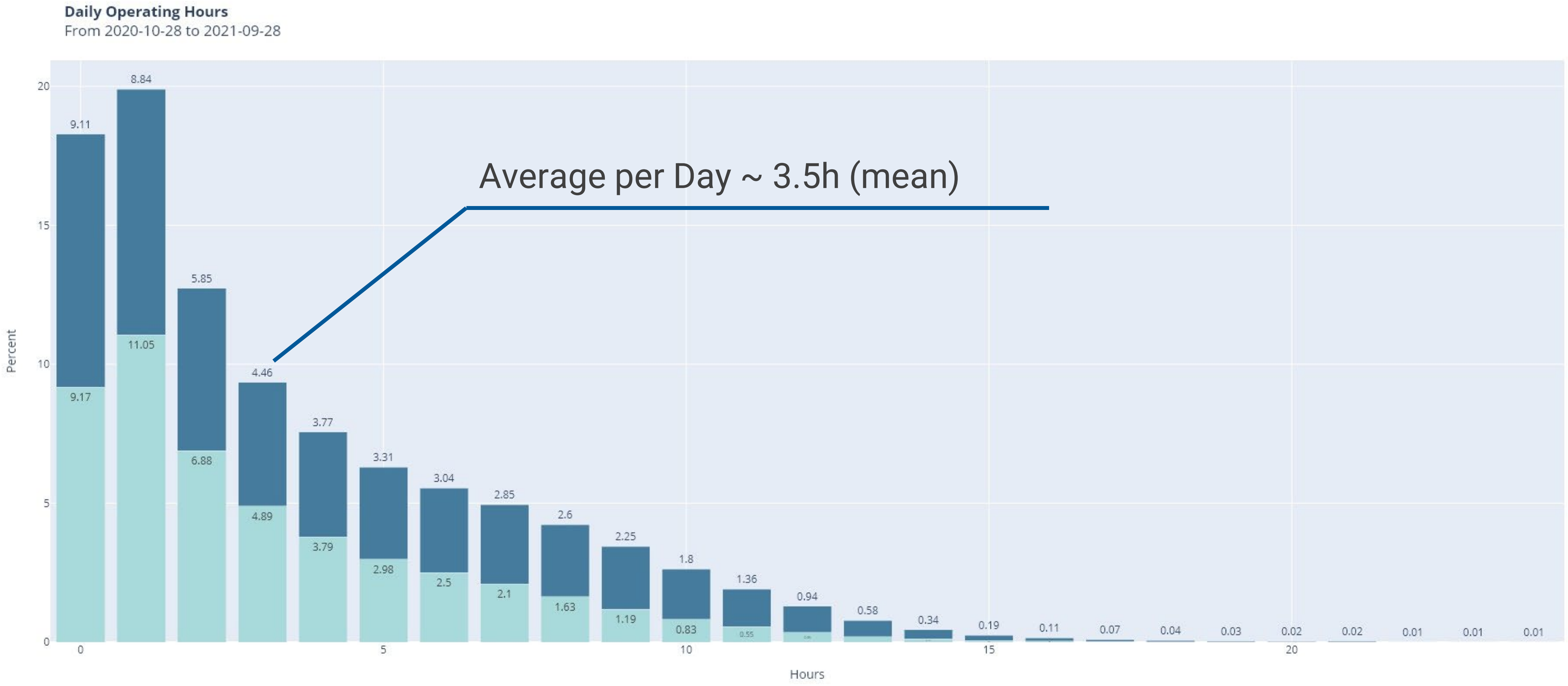
Date (Day | Week | Month)



Total (Working Class)

Operating Hours - Distribution

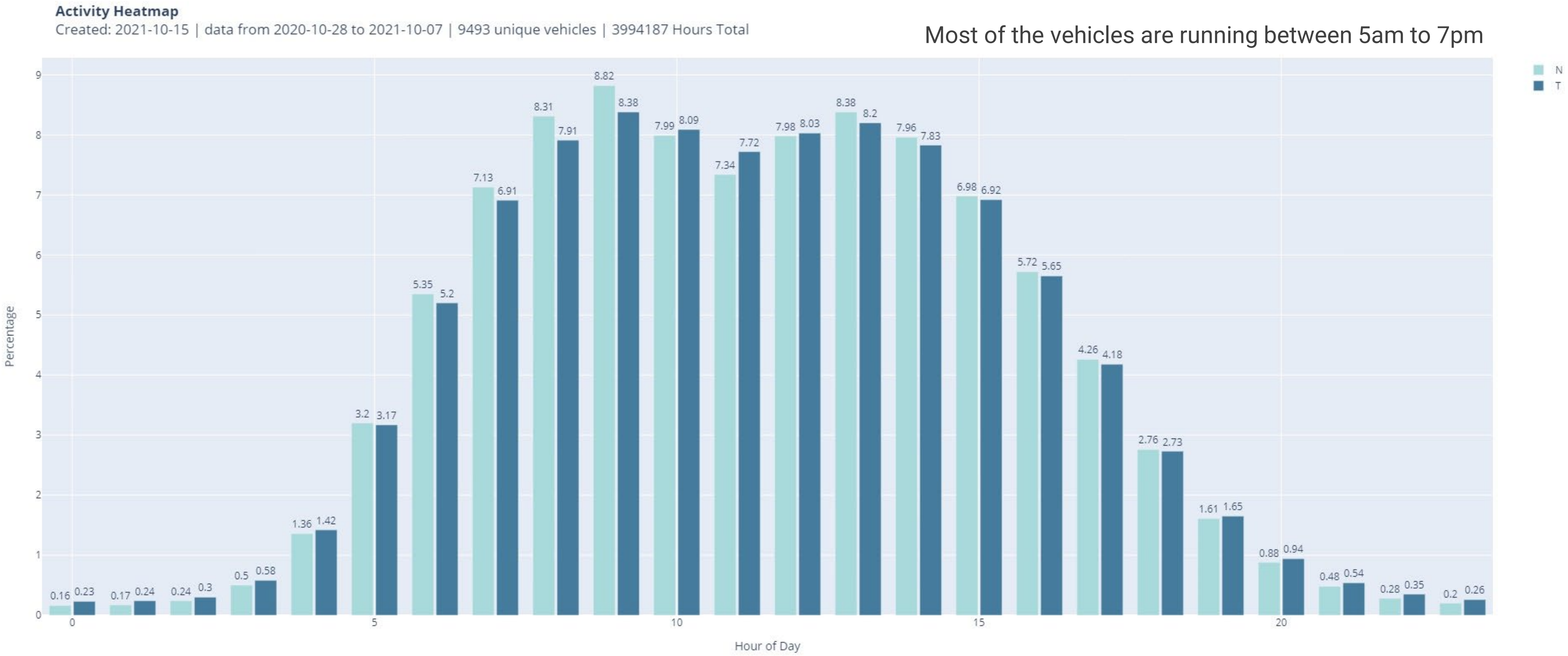
Average Operating Hours per Day



Operating Hours - Activity Heatmap

When on the day the vehicles are operated

Most of the vehicles are running between 5am to 7pm



Forecast the Next Service Date

Proposed Modeling Process

TRAINING

1.) Training Data

VIN	Day	Month	CW	Country	Average Temp.	Min. Temp.	Max. Temp.	Engine Hours
AX501	Monday	January	4	Finland	-1.9	-5.5	-0.5	3.1
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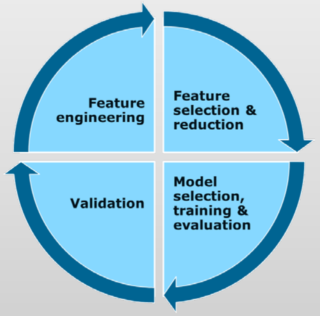
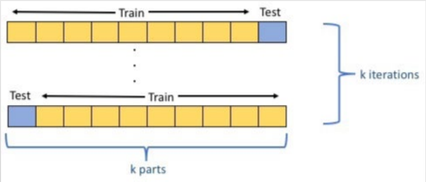
AX501	Wednesday	January	4	Finland	-1.5	-5.9	-0.4	3.4
AX501	Thursday	January	4	Finland	-1.3	-5.6	-0.1	3.2
AX501	Friday	January	4	Finland	-1.1	-6.2	-0.4	3.2
AX501	Saturday	January	4	Finland	-2.1	-5.6	-0.4	3.0
AX501	Sunday	January	4	Finland	-1.3	-6.2	-1.0	2.2
AX501	Monday	February	5	Finland	-2.4	-6.6	0.0	2.0
AX501	Tuesday	February	5	Finland	-2.3	-6.8	0.1	2.5

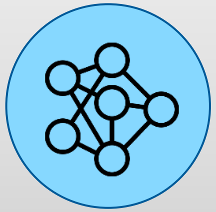
2.) Model Creation



3.) Model Validation



4.) Final Model



INFERENCE

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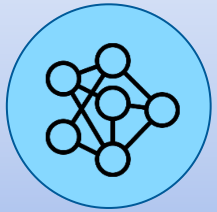
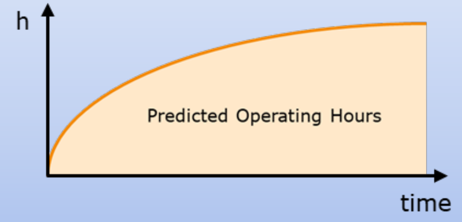
AX501	Friday	January	4	Finland	-1.1	-6.2	-0.4
AX501	Saturday	January	4	Finland	-2.1	-5.6	-0.4
AX501	Sunday	January	4	Finland	-1.3	-6.2	-1.0
AX501	Monday	February	5	Finland	-2.4	-6.6	0.0
AX501	Tuesday	February	5	Finland	-2.3	-6.8	0.1

2.) Model Execution



3.) Predict Operating Hours



4.) Service-Date Forecast

Forecast the Next Service Date

Training Data for the Forecasting Model

Example:

VIN	Day	Month	CW	Country	Average Temp.	Min. Temp.	Max. Temp.	Avg. Operation Hours
AX501	Monday	January	4	Finland	-1.9	-5.5	-0.5	3.1
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AX501	Monday	February	5	Finland	-2.4	-6.6	0.0	2.0
AX501	Tuesday	February	5	Finland	-2.3	-6.8	0.1	2.5

explanatory variables (features)

response (predicted) variable

Further Inputs

- Customer Operation Profile Groups (e.g., based on engine map, usage behavior, percentage of certain field operations, usage profile, etc.)
  → unsupervised
- Vehicle model, type (e.g., harvester, tractor, etc.)
- Rainy & sunny days based on historical climate for this location (e.g., 20 out of 30 rainy days)

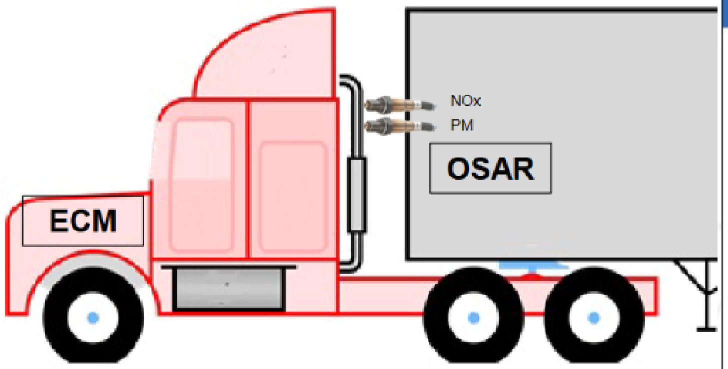
Analysis of Telemetry Fleet Data

Onboard Emission Sensing for Heavy Duty Applications

Public

UC Riverside System Setup

On-Board **S**ensing, **A**nalysis, and **R**eporting **(OSAR)**
System Design

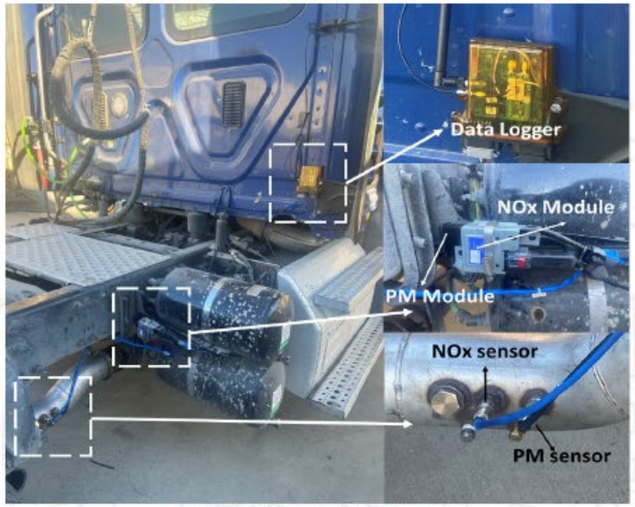


Generation 2 systems completed using NOx and PM commercial sensors and 30 are installed operating for 1 year or more.

EmTrac-6 Core Telemetry System

NOx/O2 Module | PM Module | Data Logger (CAN, GPS, LTE) | GPS & LTE Antennas

Typical sensor package includes NOx, PM, Cellular, vehicle/equipment CAN, and GPS



Typical on-road vehicle install

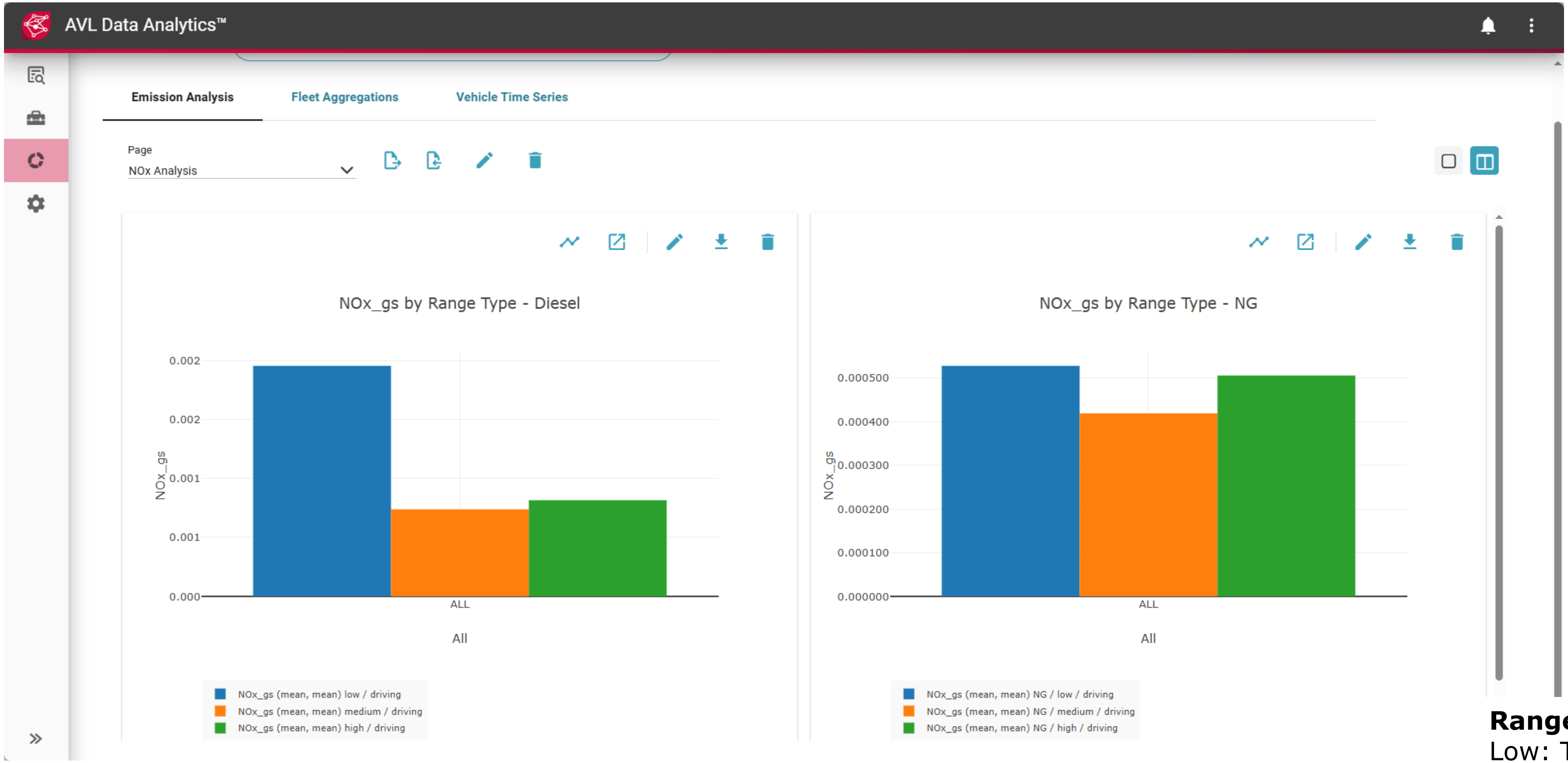
In partnership with EmiSense *For more information on EmTrac: pt@emisense.com*

3

Analysis of Telemetry Fleet Data

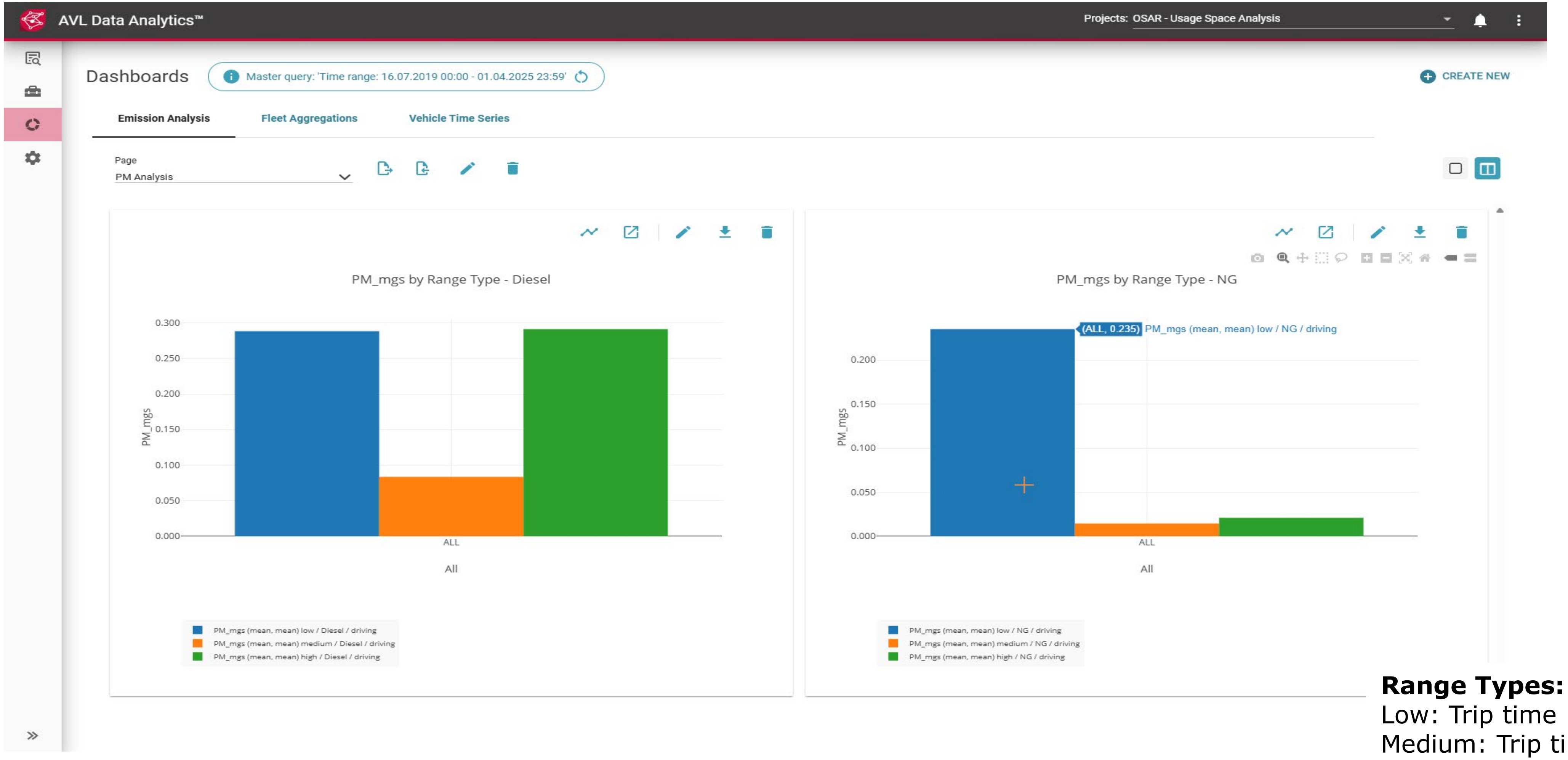
OSAR Emission Analysis

NOx Emissions by Fuel Technology



Range Types:
Low: Trip time < 5 Min
Medium: Trip time < 60 Min
High: Trip time > 60 Min

PM Emissions by Fuel Technology



Range Types:
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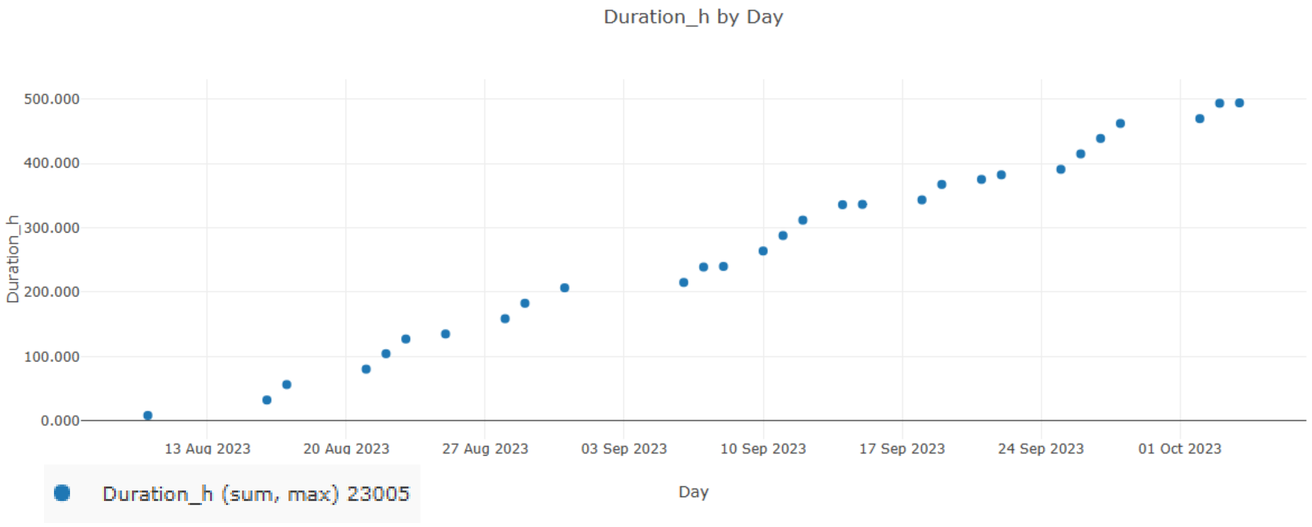
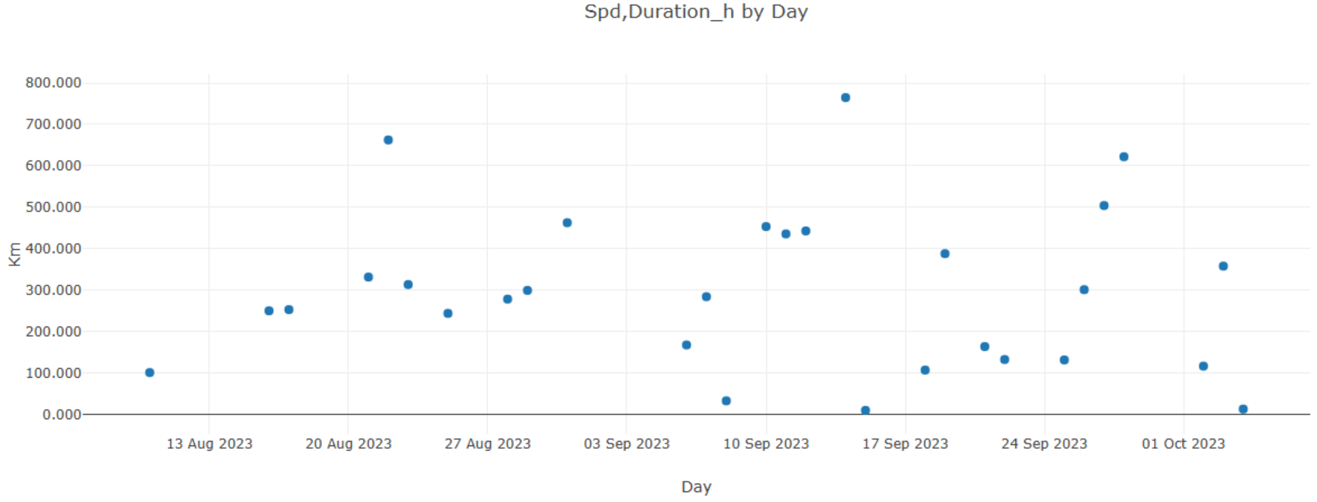
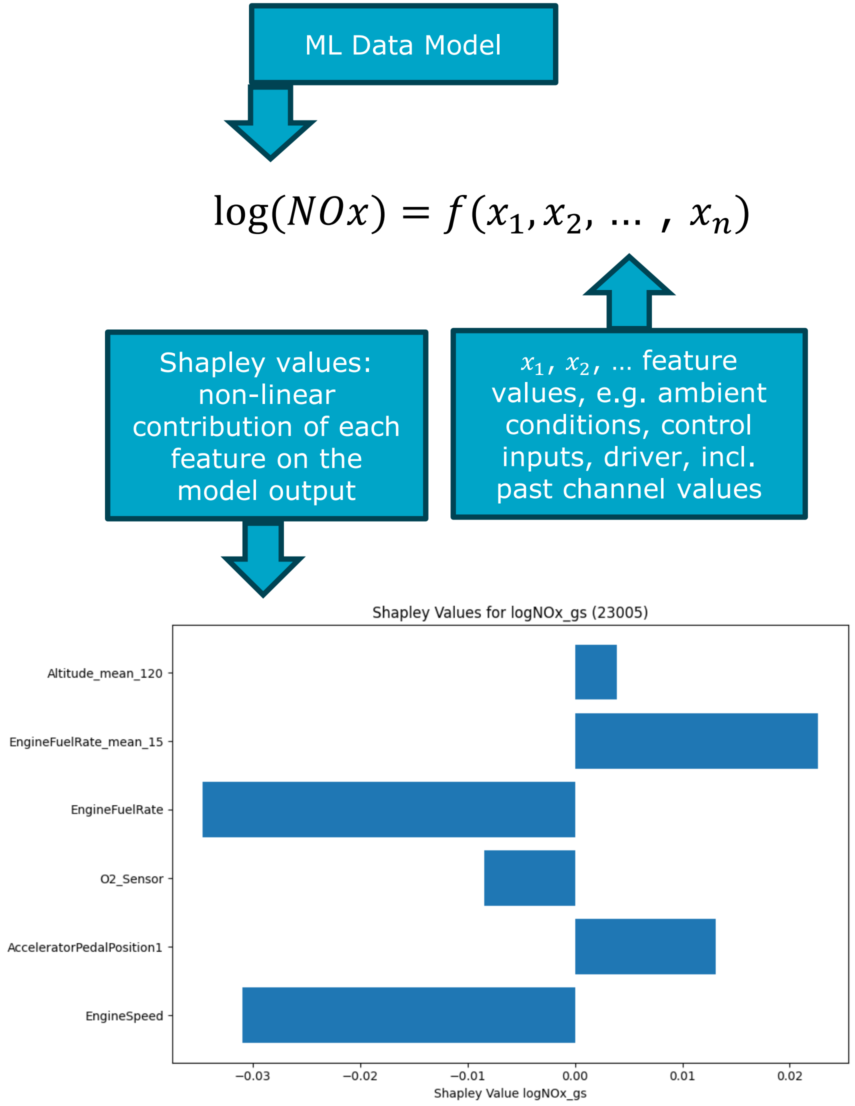
Deeper Dive into Vehicle 23005





Emission Analysis with ML-Based Analytics

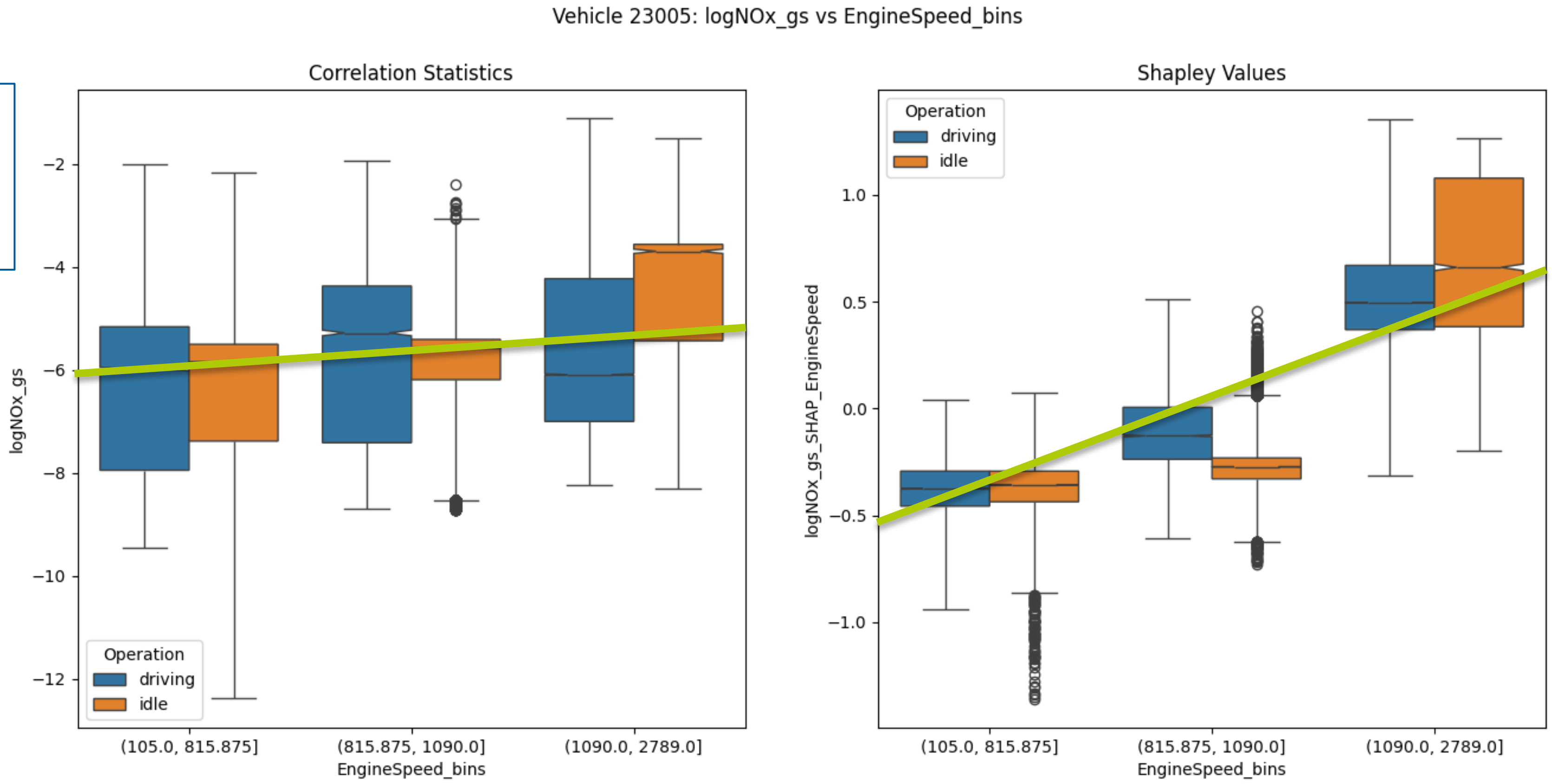
- Event-Based Analytics
  - Efficient analysis of large time series data
  - Event-based channel aggregation: operating modes, range types
- Model-based Data Analytics
  - Event-based ML models
    - Model Inputs: Engine Speed, Vehicle Speed, Engine Fuel Rate, O2, Ambient Temp, ..
    - Model Outputs: NOx, PM, …
    - Meta-data: fuel technology, model type, vocation
  - ML-Based Analysis
    - Sensitivity Analysis
    - Root Cause Analysis
    - Anomaly Detection



Correlation & Model-Based Analysis

NOx vs Engine Speed

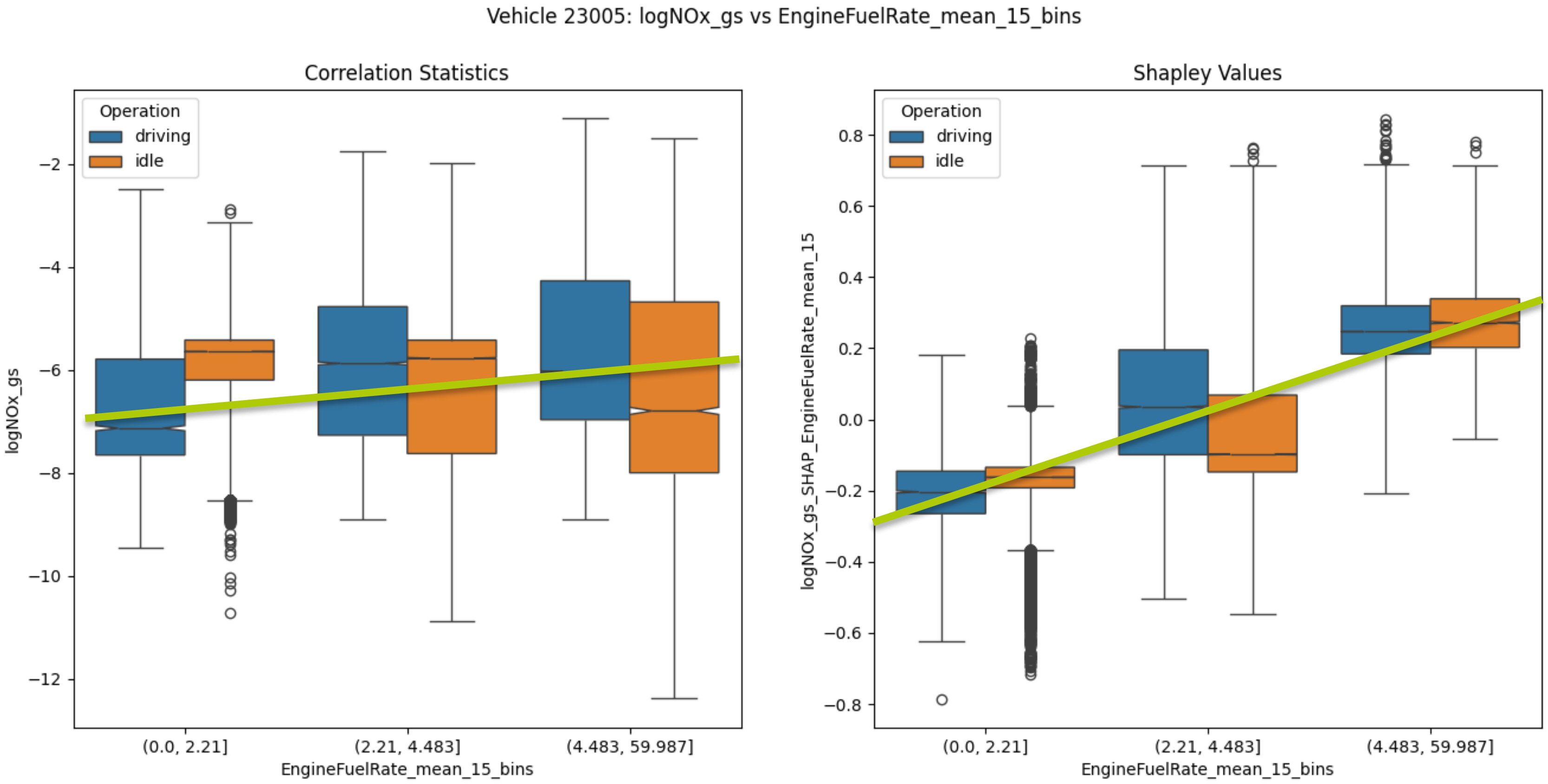
Effect of Model Inputs not identified by Correlation



Model-based Analytics explain isolated effect of input features

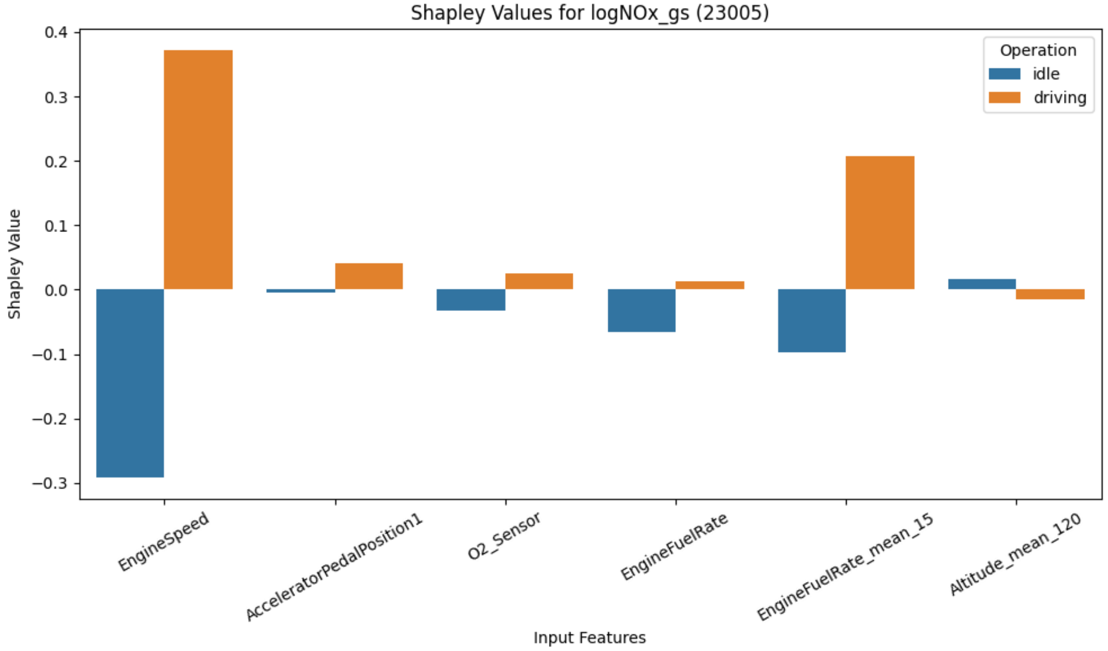
Correlation & Model-Based Analysis

NOx vs Engine Fuel Rate

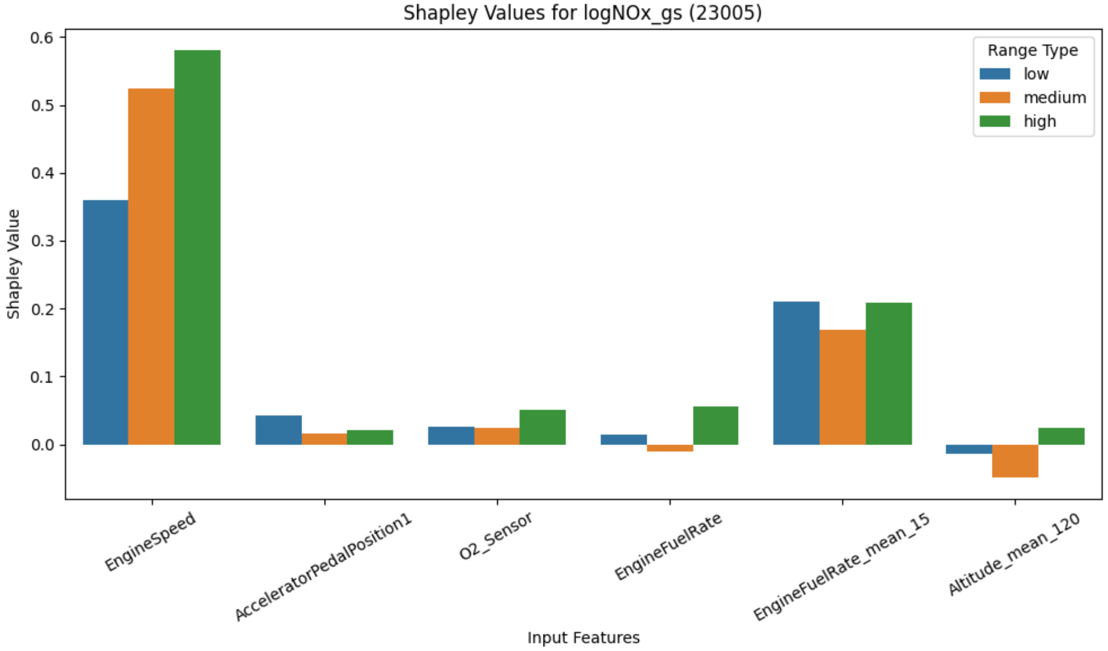


ML-Based Sensitivity Analysis: NOx

Operation Mode



Range Type (driving operation only)

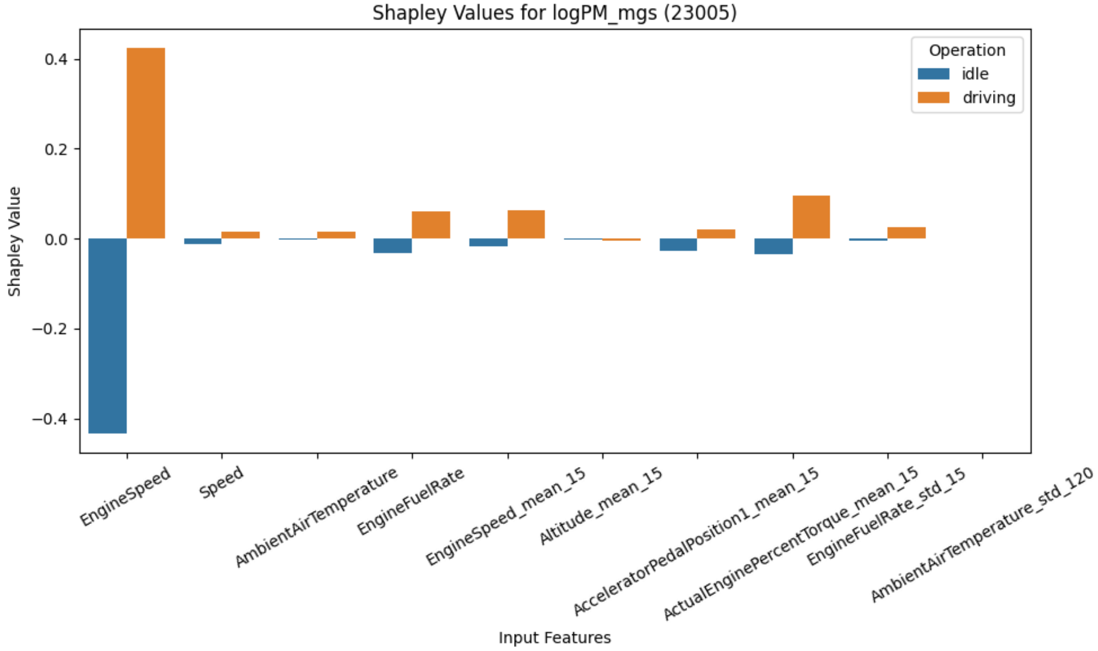


Large fleet datasets require isolated analysis of different data groups, e.g. based on operation modes, fuel technology, vehicle types, environment conditions, …

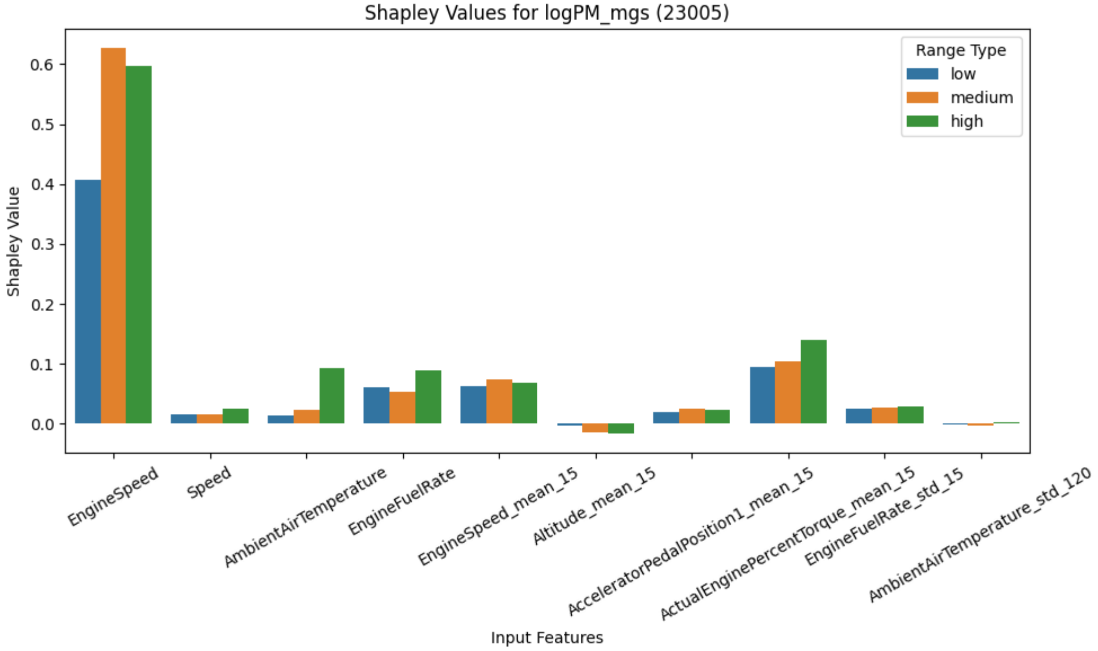
Range Types:
Low: Trip time < 5 Min
Medium: Trip time < 60 Min
High: Trip time > 60 Min

ML-Based Sensitivity Analysis: PM

Operation Mode



Range Type (driving)



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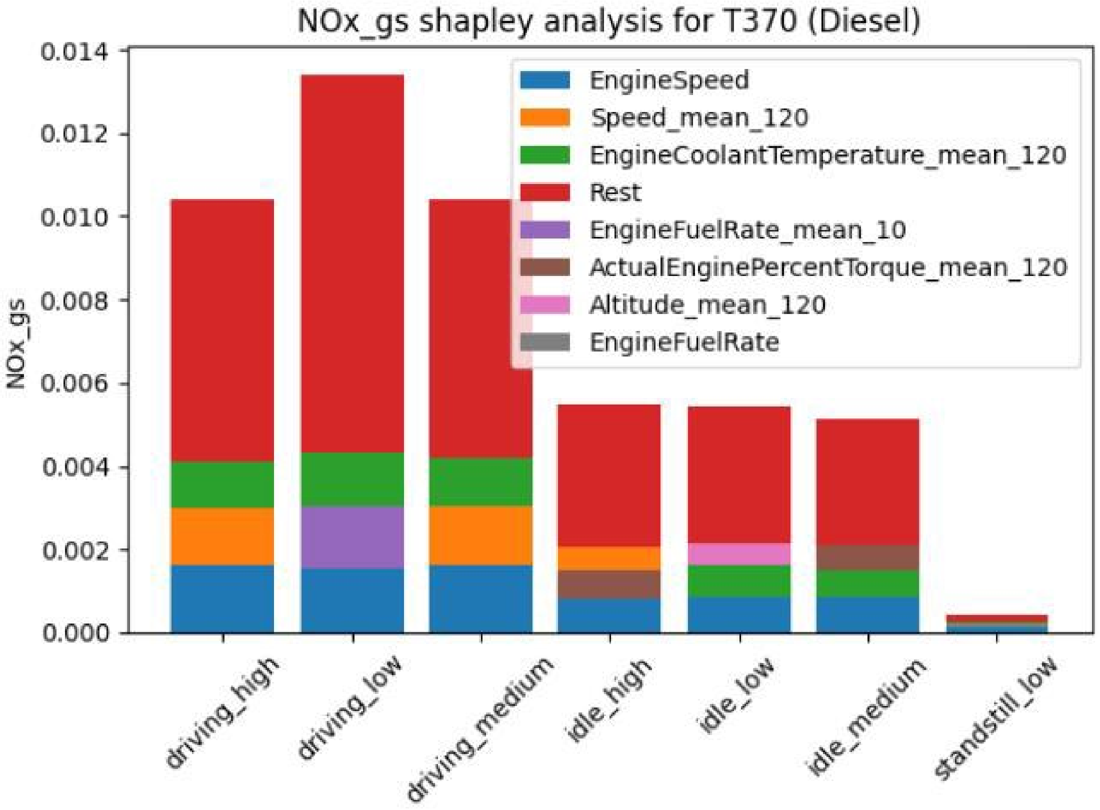
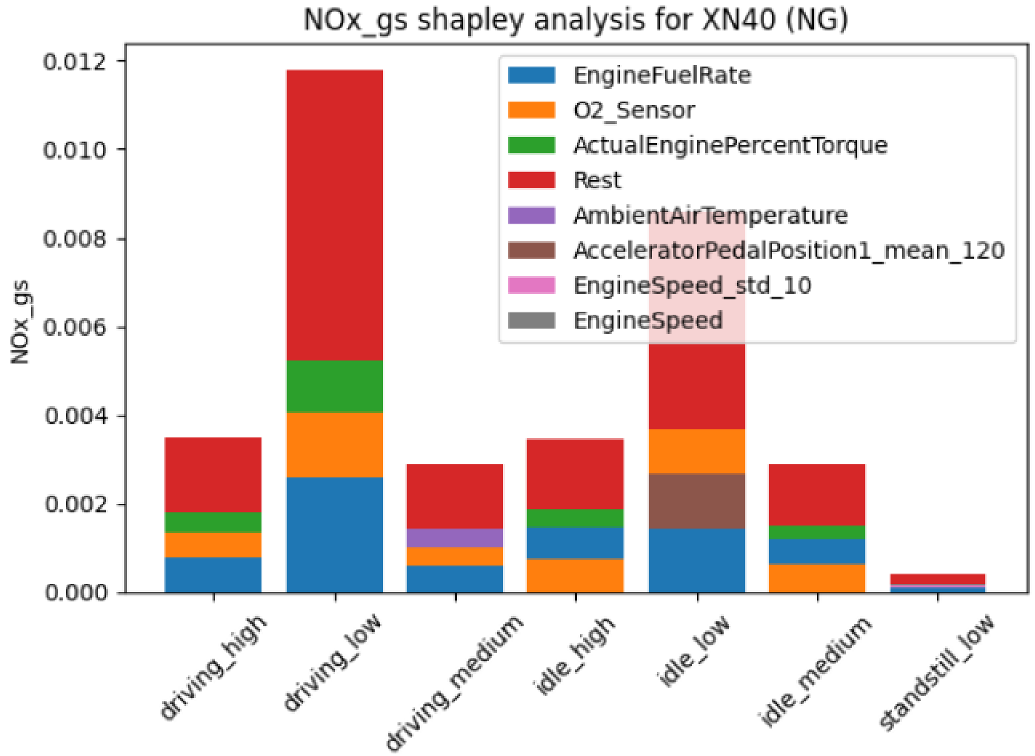
Analysis of Telemetry Fleet Data

Fleet Shapley Analysis

Public

Main NOx Influence Parameters





Range Types:
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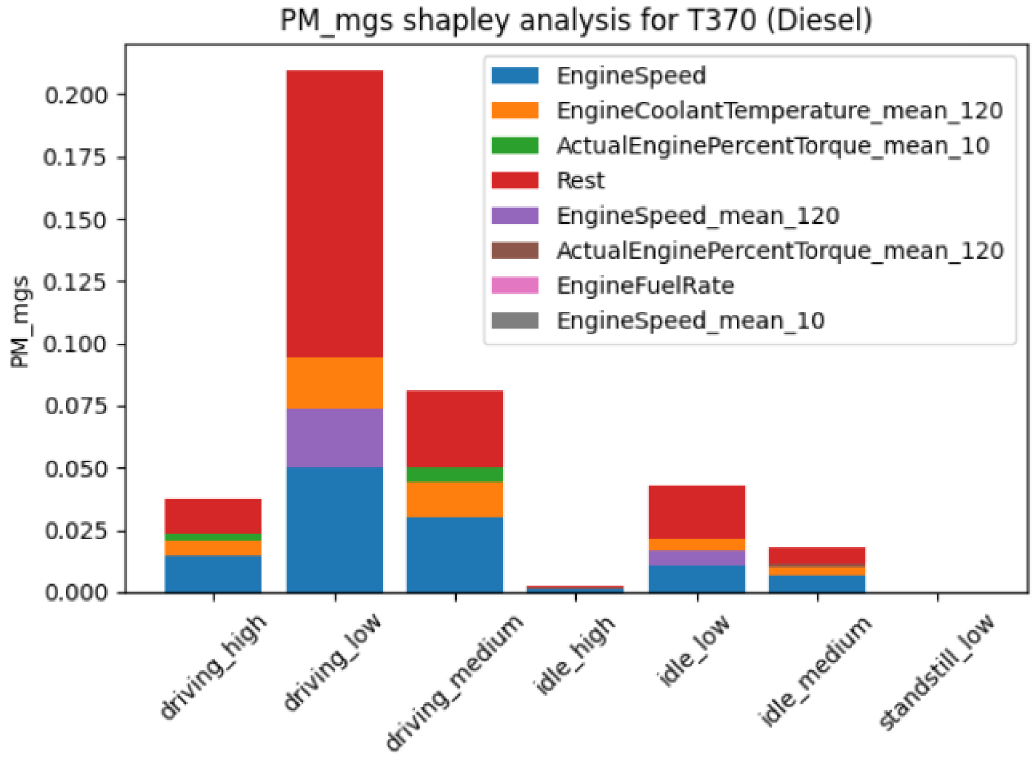
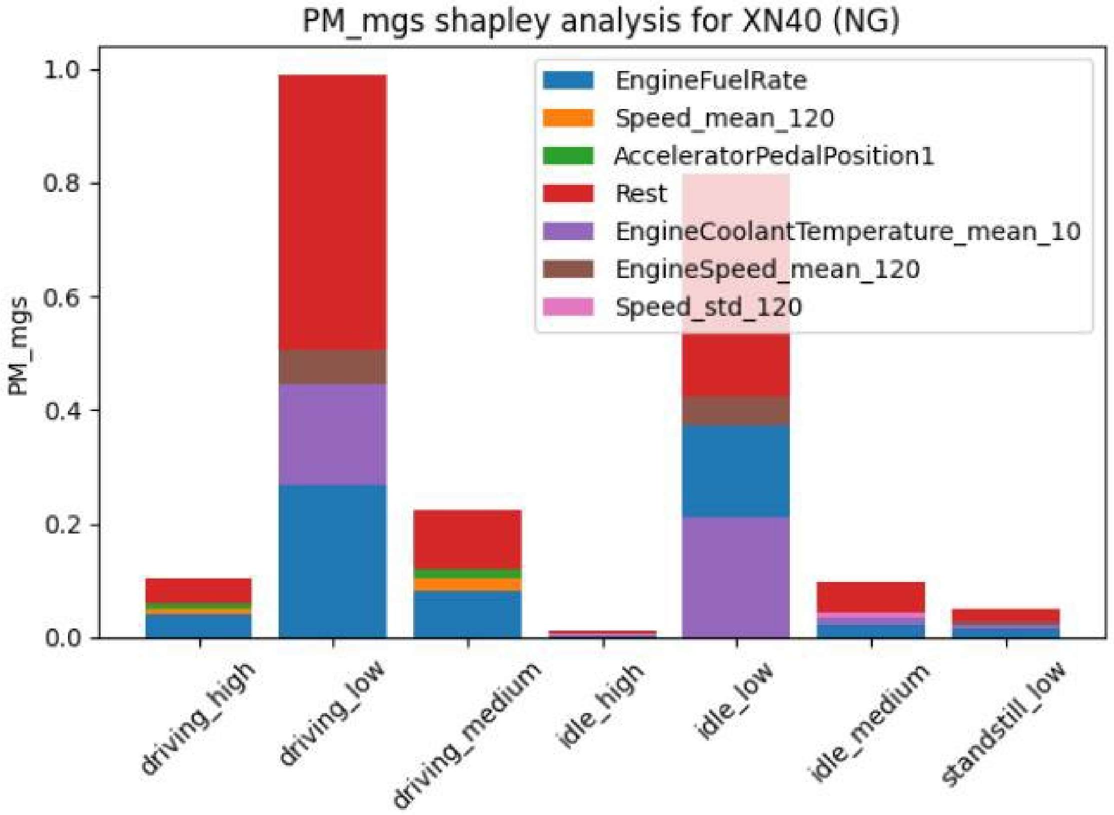
Main PM Influence Parameters





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Technology Route Selection

Proposed Modeling Process

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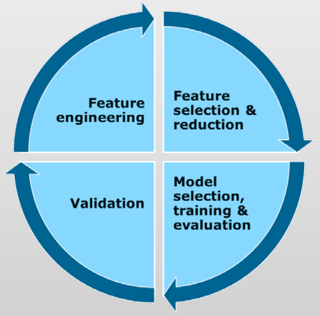
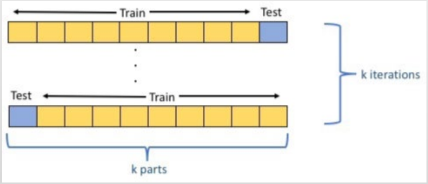
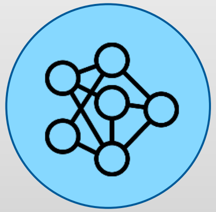
2.) Model Creation



3.) Model Validation



4.) Final Model



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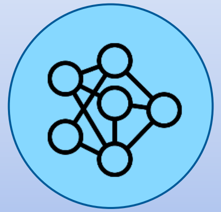
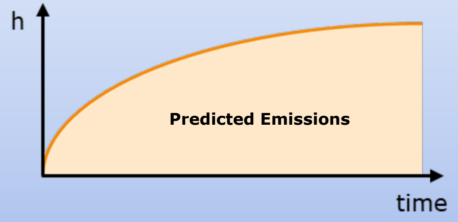
AX501	Wednesday	January	4	Finland	-1.5	-5.9	-0.4
AX501	Thursday	January	4	Finland	-1.3	-5.6	-0.1
AX501	Friday	January	4	Finland	-1.1	-6.2	-0.4
AX501	Saturday	January	4	Finland	-2.1	-5.6	-0.4
AX501	Sunday	January	4	Finland	-1.3	-6.2	-1.0
AX501	Monday	February	5	Finland	-2.4	-6.6	0.0
AX501	Tuesday	February	5	Finland	-2.3	-6.8	0.1

2.) Model Execution



3.) Predicting Emissions

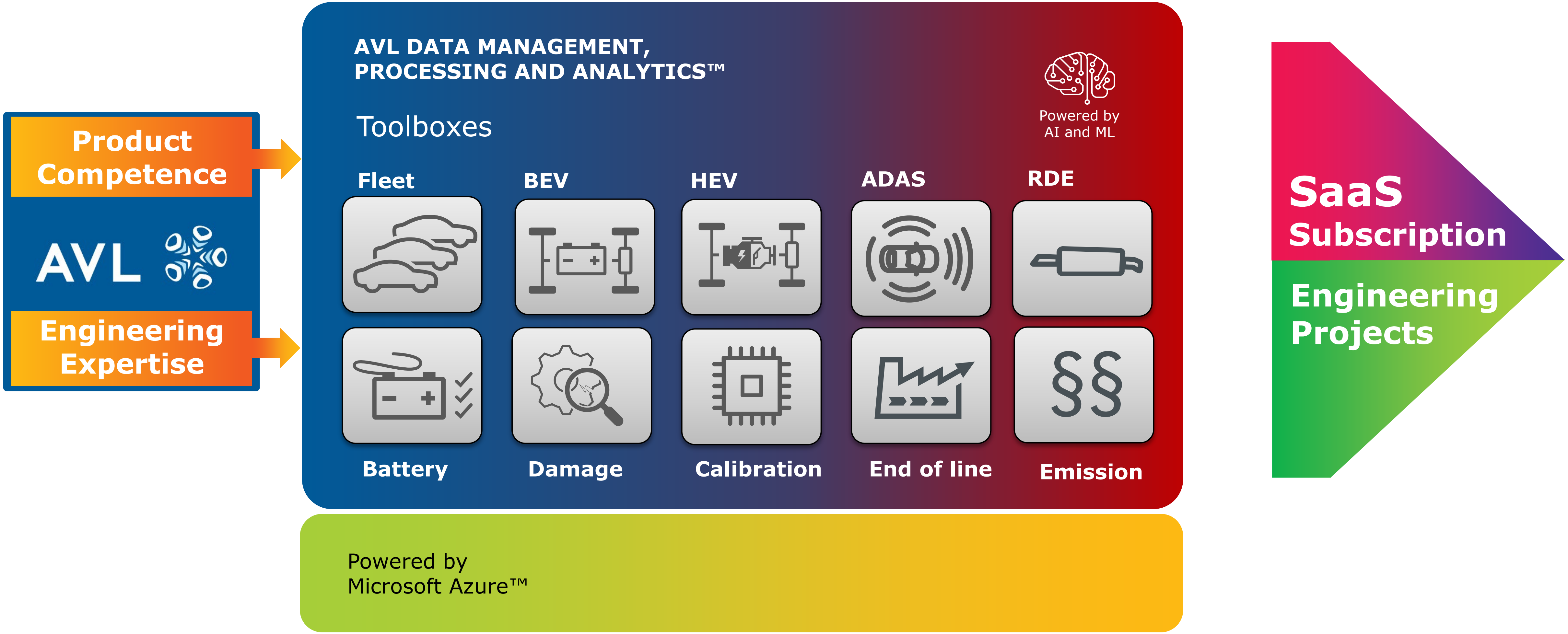


4.) Technology Route Selection

Transform Data to insights

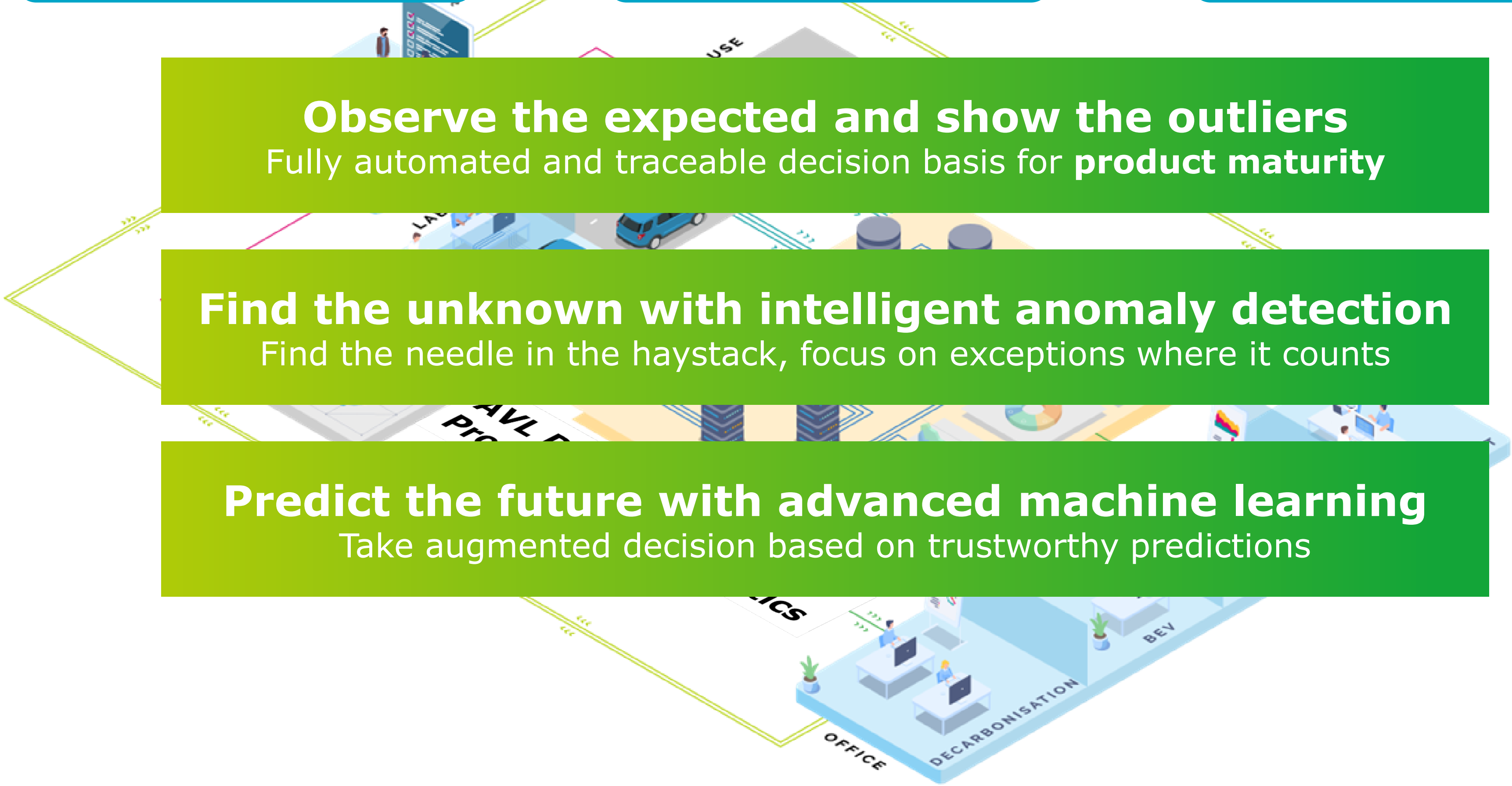
Data Analytics Solution

Transform Data Streams to Application Specific Insights



Boosting Engineering Efficiency

(Big) Data Streams → Transform to Insights → Decisions



Observe the expected and show the outliers
Fully automated and traceable decision basis for **product maturity**

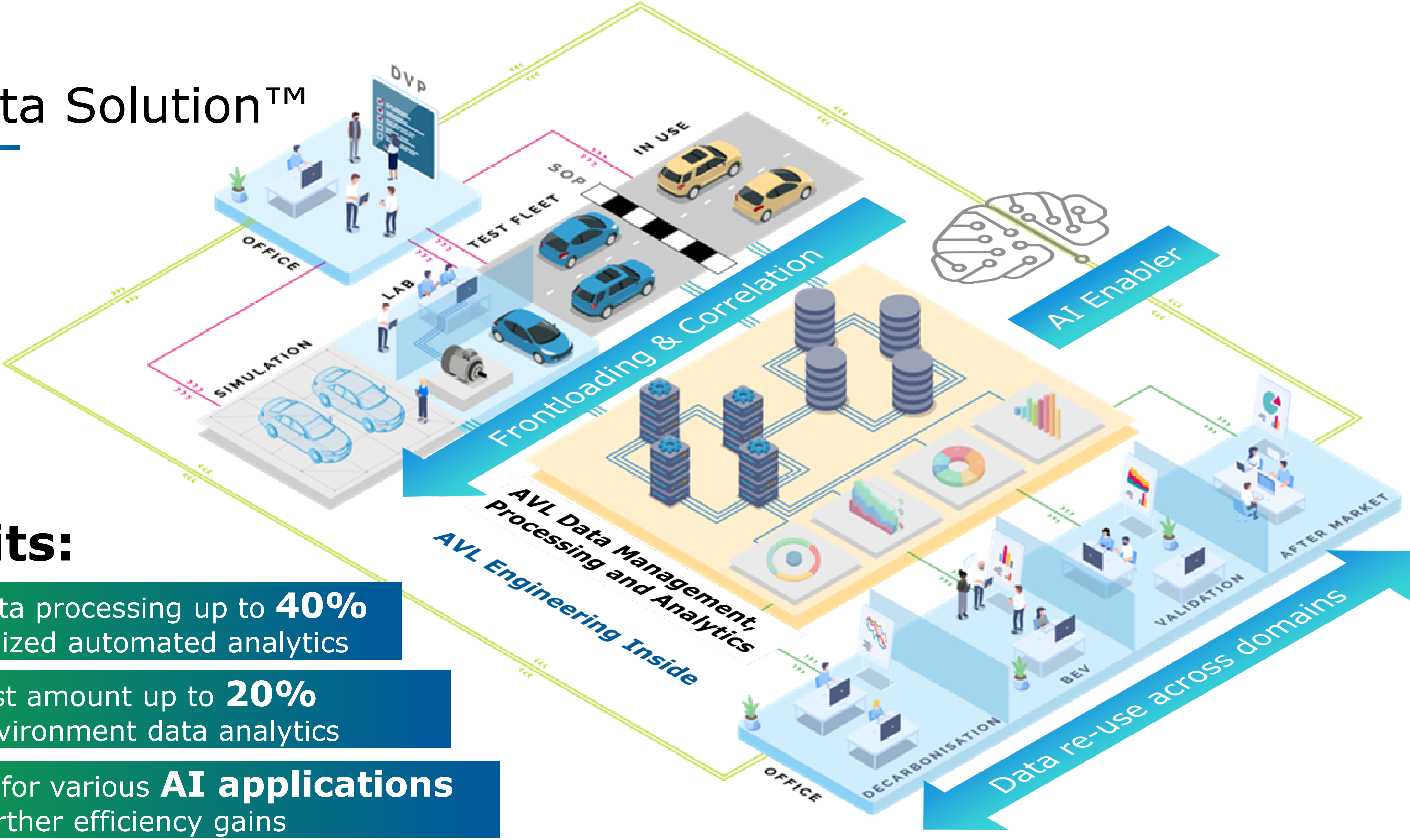
Find the unknown with intelligent anomaly detection
Find the needle in the haystack, focus on exceptions where it counts

Predict the future with advanced machine learning
Take augmented decision based on trustworthy predictions

Transform Data to insights

Benefits

AVL Data Solution™



Benefits:

Reduced data processing up to **40%** by standardized automated analytics

Reduced test amount up to **20%** by cross environment data analytics

Basis for various **AI applications** for further efficiency gains


AVL
Thank You

Backup

What is a Shapley Value

Shapley values are a method based on game theory to explain the output of machine learning models. They fairly assign a value to each feature, representing its contribution to the model's prediction.

- Imagine each feature as a player in a cooperative game. The model's prediction is the payout. Shapley values calculate the average contribution of each feature across all possible feature combinations.

The Shapley value φ_i for feature i is given by:

$$\varphi_i = \Sigma [(|S|! * (|F| - |S| - 1)! / |F|!) * (v(S \cup \{i\}) - v(S))]$$

Where:

- S is a subset of all features F that does not include i
- v(S) is the model prediction using subset S
- |S|! and |F|! are factorial terms for weighting