Electric Vehicle Battery Data Analytics

Webinar 09.02.2023

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AVL List GmbH (Headquarters)

Public

Today’s Presenters

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Dipl.-Ing Aeronautical Engineering

Project Manager IODP – Dev. Process Innovation & Implementation

~10 years at AUDI AG Ingolstadt

~2 years at AVL Process Innovation

Gerhard Schagerl

Master of Science

Product Line Manager Data Intelligence

Market and customer focused data business enthusiast

20 years in automotive industry

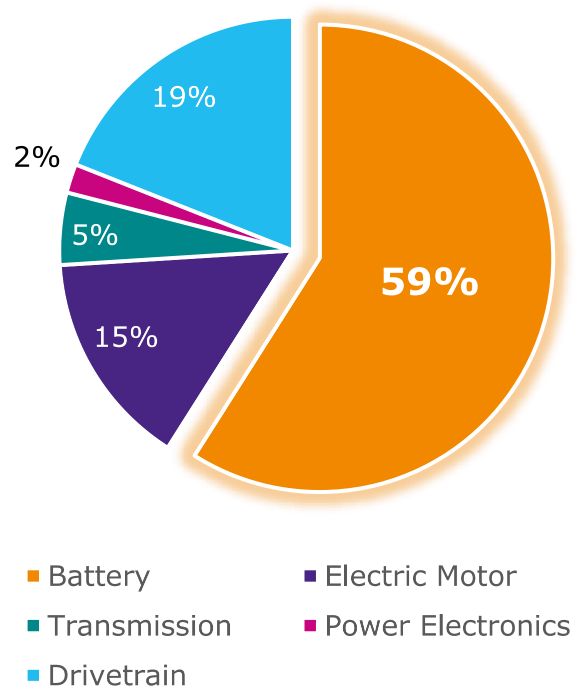
Today’s Agenda

What? – Battery & Data Intelligence

Why – Battery as most expensive Component

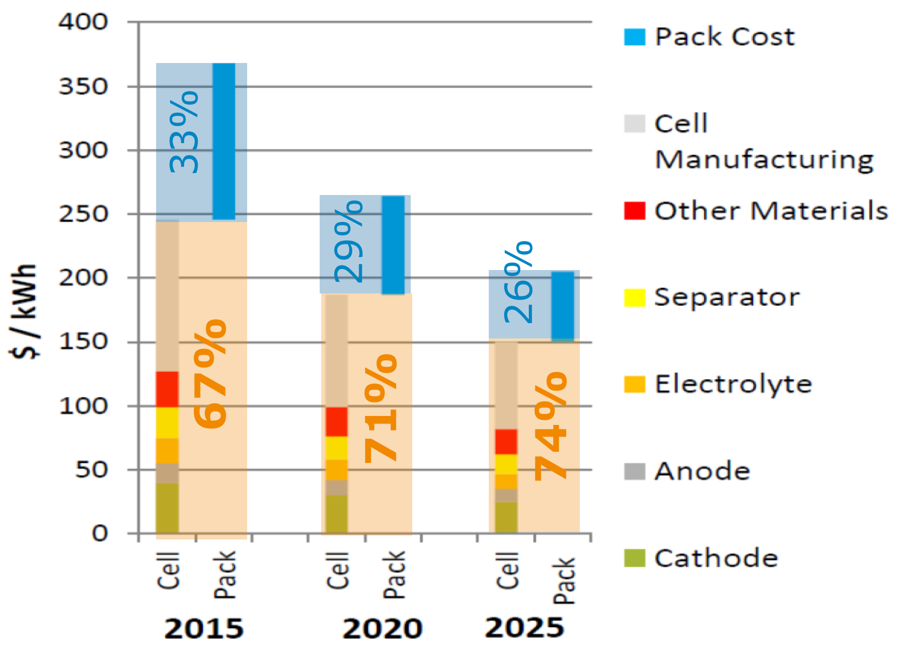
The battery is the most expensive component of a BEV

BEV Powertrain Cost Breakdown



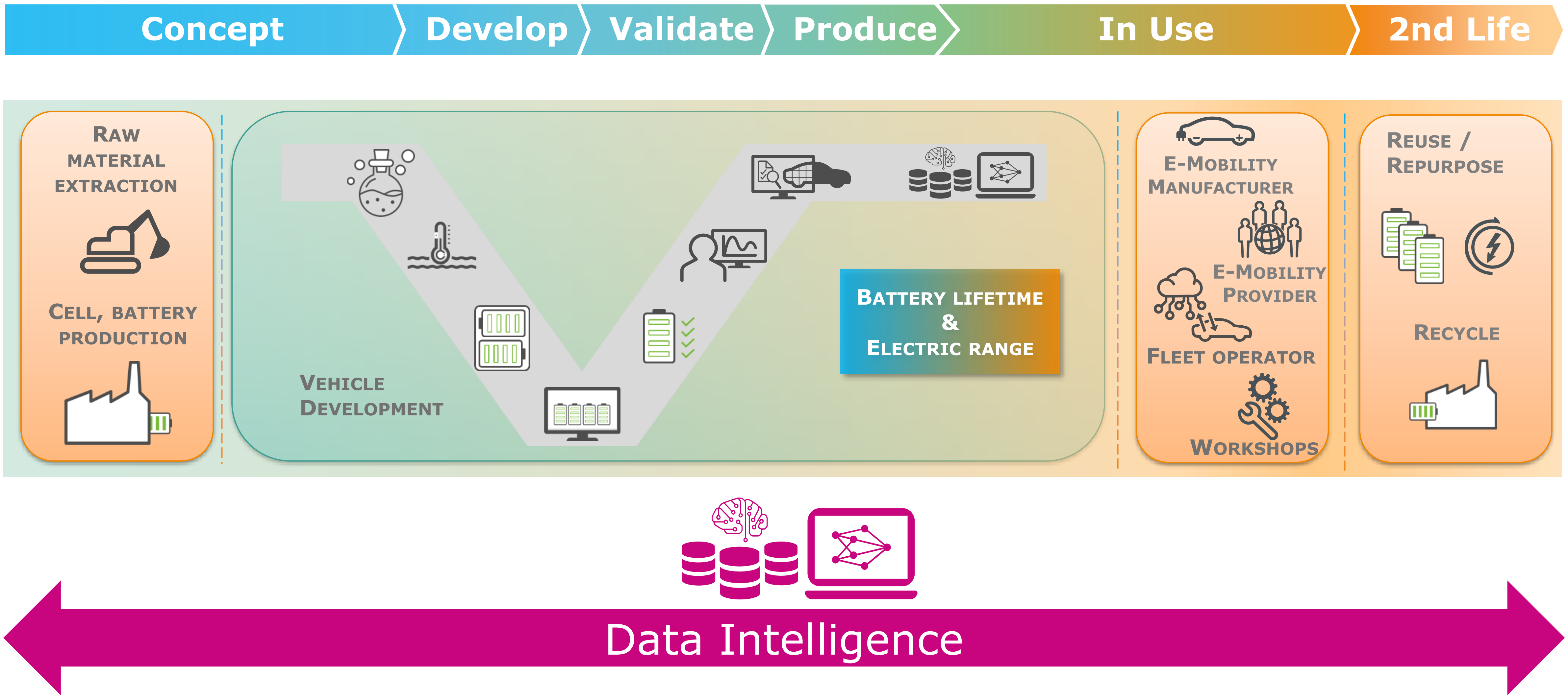
Sources: Valuewalk; Barcleys Research

Battery Pack Cost Breakdown

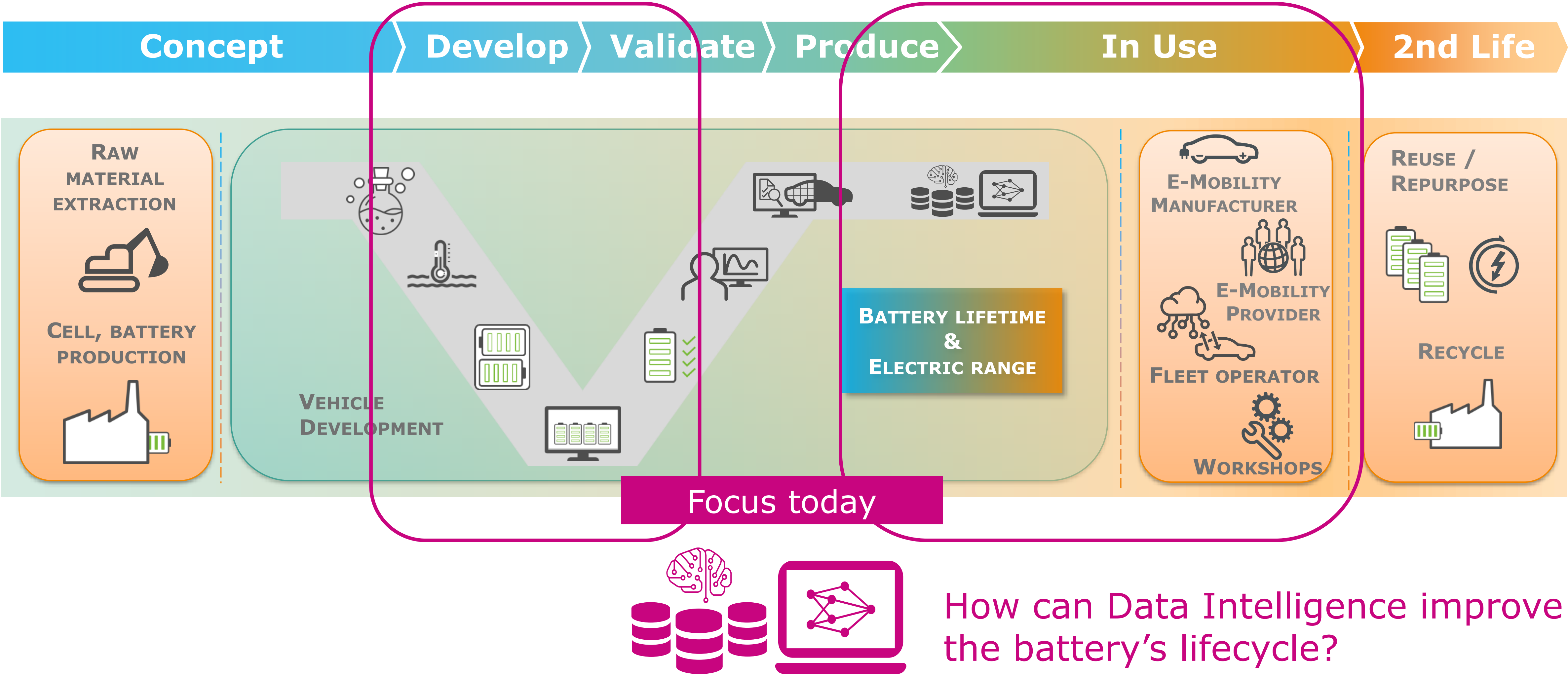


Sources: teen, M., Lebedeva, N., Di Persio, F. and Boon-Brett, L., EU Competitiveness in Advanced Li-ion Batteries for E-Mobility and Stationary Storage Applications – Opportunities and Actions,EUR 28837 EN, Publications Office of the European Union, Luxembourg, 2017, ISBN 978-92-79-74292-7, doi:10.2760/75757, JRC108043.

How?
AVL Battery Lifecycle Management Approach



Data Intelligence within the AVL Battery Lifecycle Management Approach



How can Data Intelligence improve the battery's lifecycle?

Battery Data Intelligence

Use Cases Development and Testing

Public

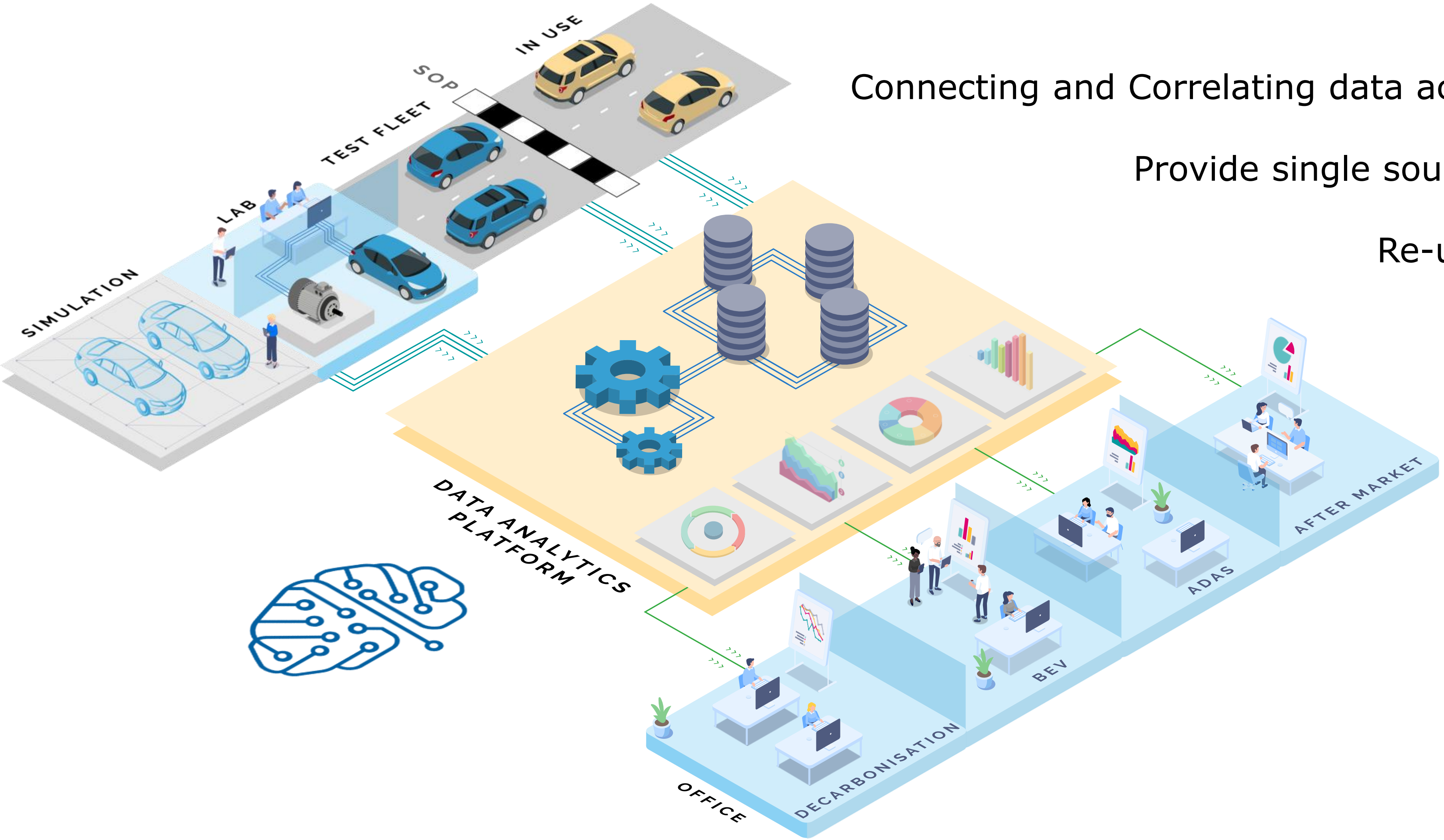
Example: Battery and Cell Development Tasks

Cell Selection	Simulation	Pack Hardware Design	BMS Software Design
Validate cell supplier	Get model parameters	Understand & prevent aging	Get BMS algorithm data

At different stages of the battery development testing is necessary – with different purposes!
And DATA is generated!

What about Analyzing, Reusing, Cross-Learning with DATA INTELLIGENCE?

AVL Data Analytics Platform



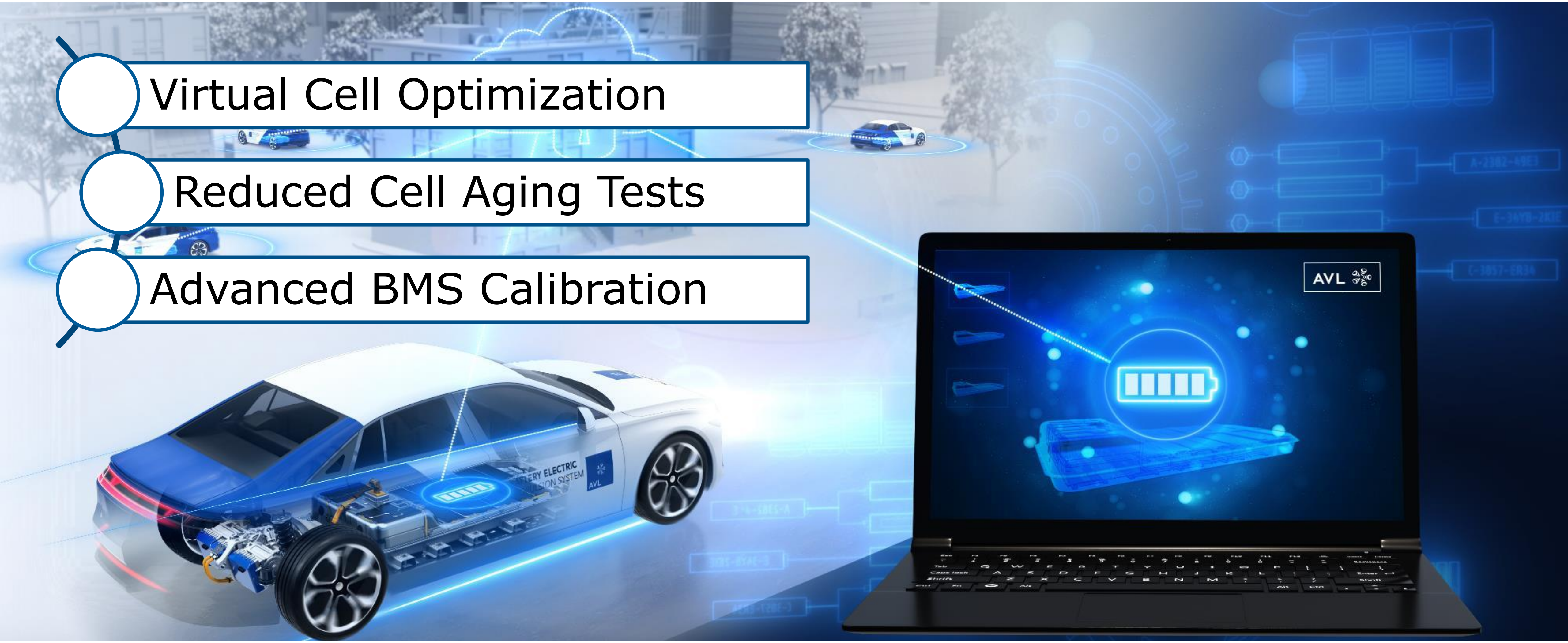
Connecting and Correlating data across development phases

Provide single source of truth to all domains

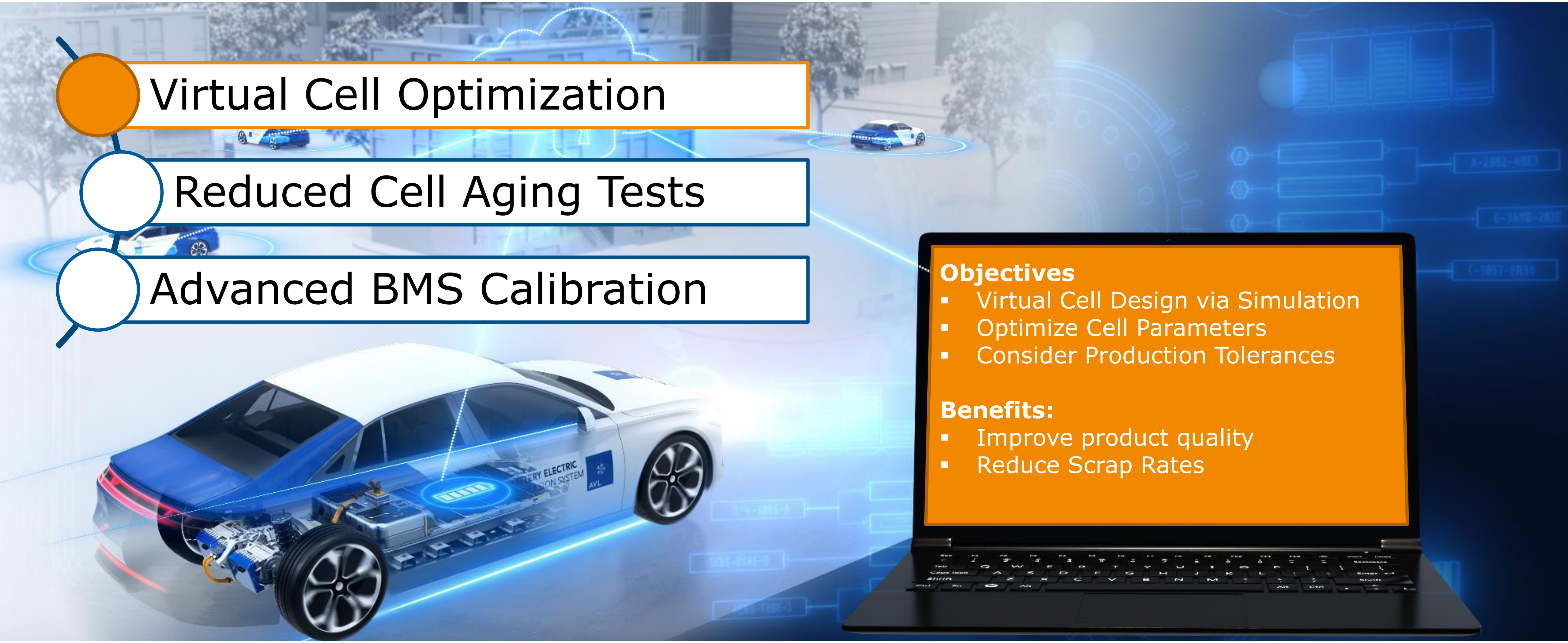
Re-use data instead of re-test

Use Cases of
Data-Analytics in Battery Development and Testing

- Virtual Cell Optimization
- Reduced Cell Aging Tests
- Advanced BMS Calibration



Use Cases of
Data-Analytics in Battery Development and Testing



1. Virtual Cell Optimization
2. Reduced Cell Aging Tests
3. Advanced BMS Calibration

Objectives
- Virtual Cell Design via Simulation
- Optimize Cell Parameters
- Consider Production Tolerances

Benefits:
- Improve product quality
- Reduce Scrap Rates

Virtual Cell Optimization
Find Optimum Combination of Cell Properties

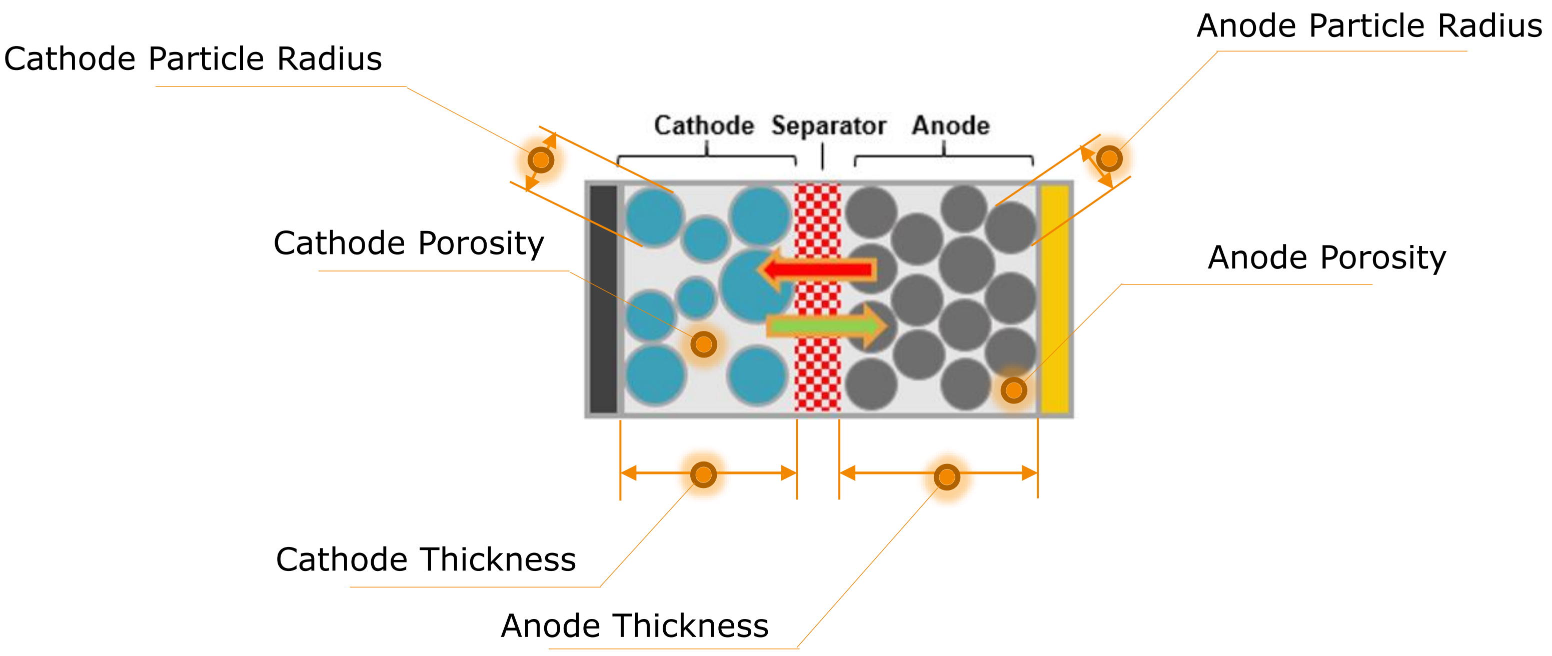
Maximize:

Cell Capacity

Charge Capability

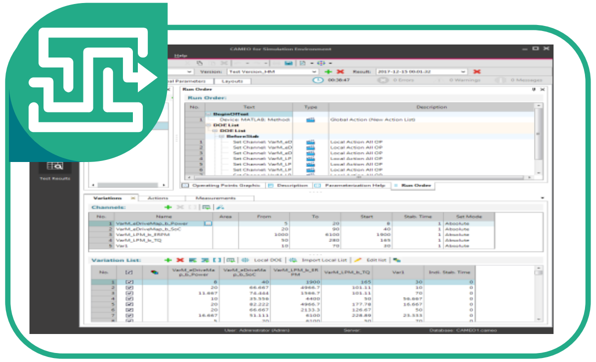
Minimize:

Losses



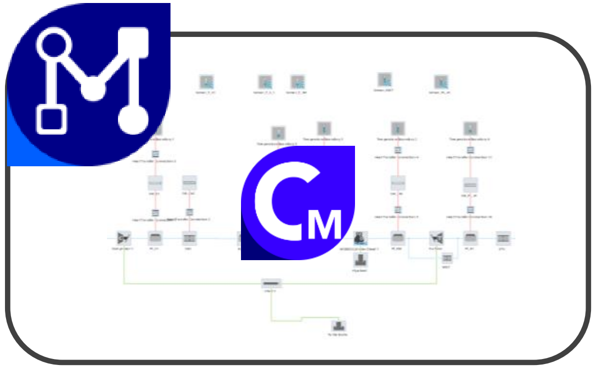
Anode Particle Radius:	1 - 10 µm	Porosity Cathode:	0.15 - 0.5 Ratio	Cathode thickness:	50 to 100 µm
Cathode Particle Radius:	1 - 10 µm	Porosity Anode:	0.15 - 0.5 Ratio	Anode thickness:	60 to 120 µm

Virtual Cell Optimization
Find Optimum Combination of Cell Properties



Parameters

KPIs

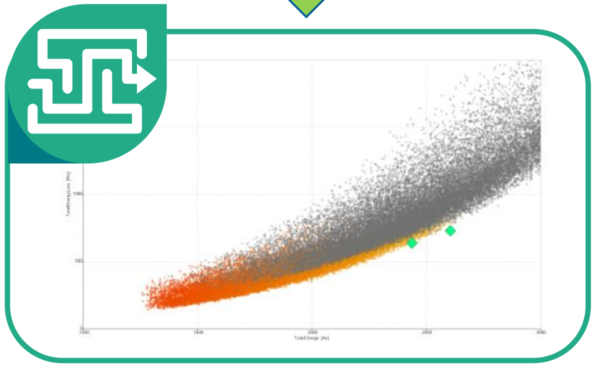


Optimization

Simulation

Result

Active DoE

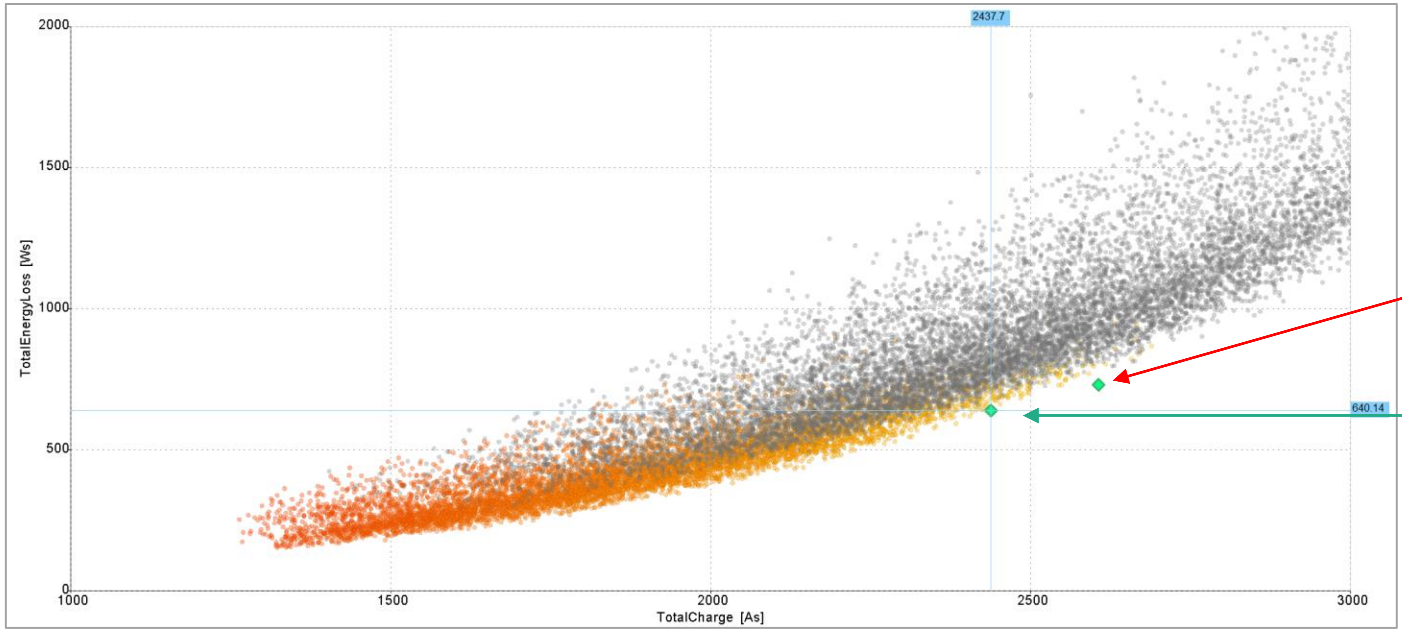


Result

Classic DoE (Design of Experiments):
Test (Simulate) – Model – Predict – Optimize

<u>Active DoE:</u>
Model and Predict during the test:
Bring Knowledge forward to the testing phase

Virtual Cell Optimization
Example Results for Robust Optimization of Cell Properties

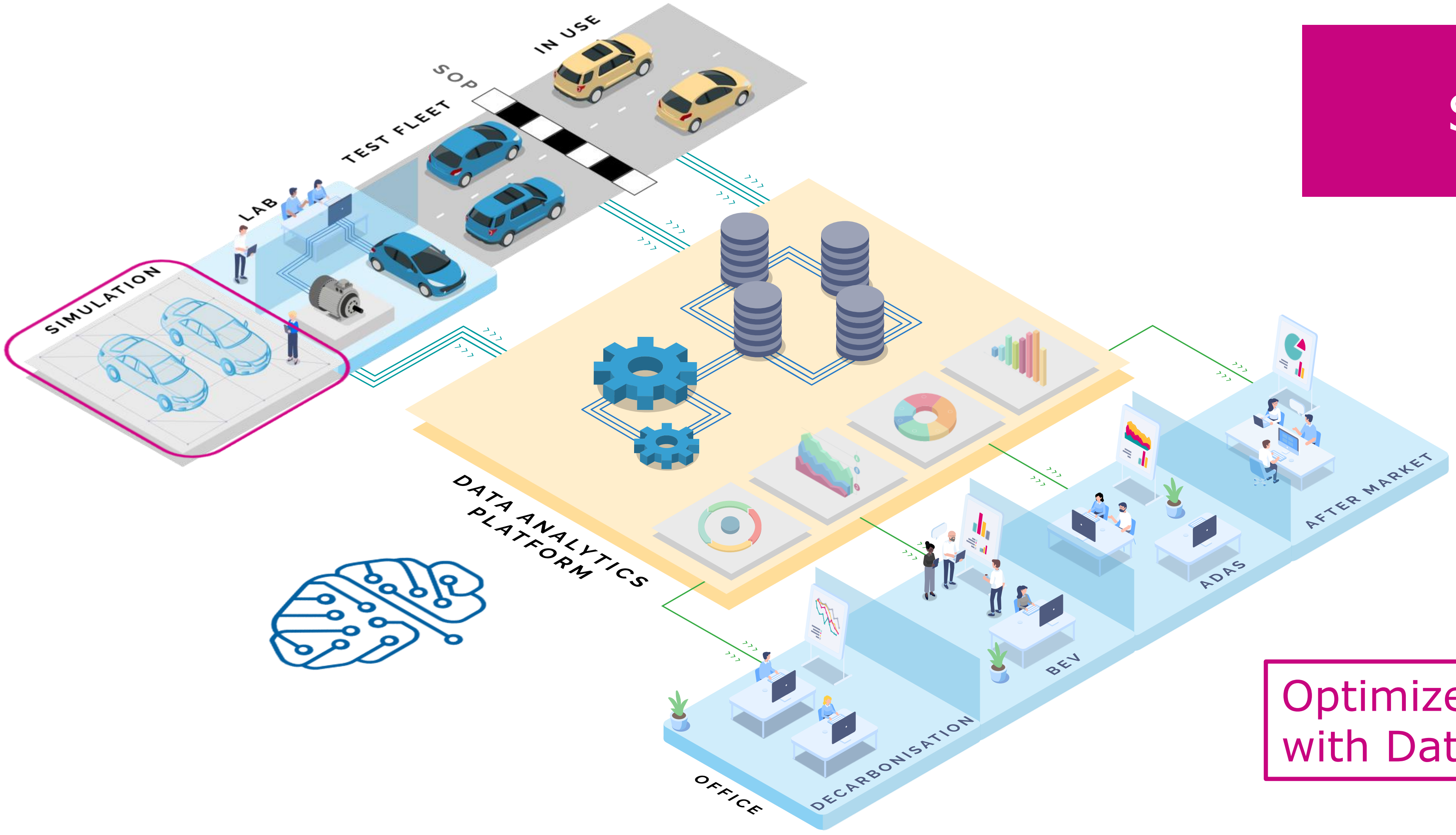


Original Trade-Off Optimized Result

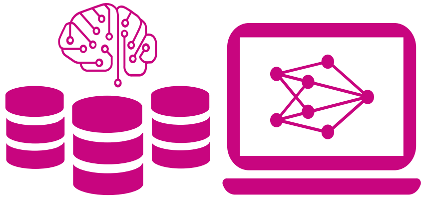
Production Robust Optimized Result

Cell can be produced with given Tolerances:
- 2437 As Capacity
- 640Ws Losses
- 5% Accepted Scrap Production

AVL Data Analytics Platform

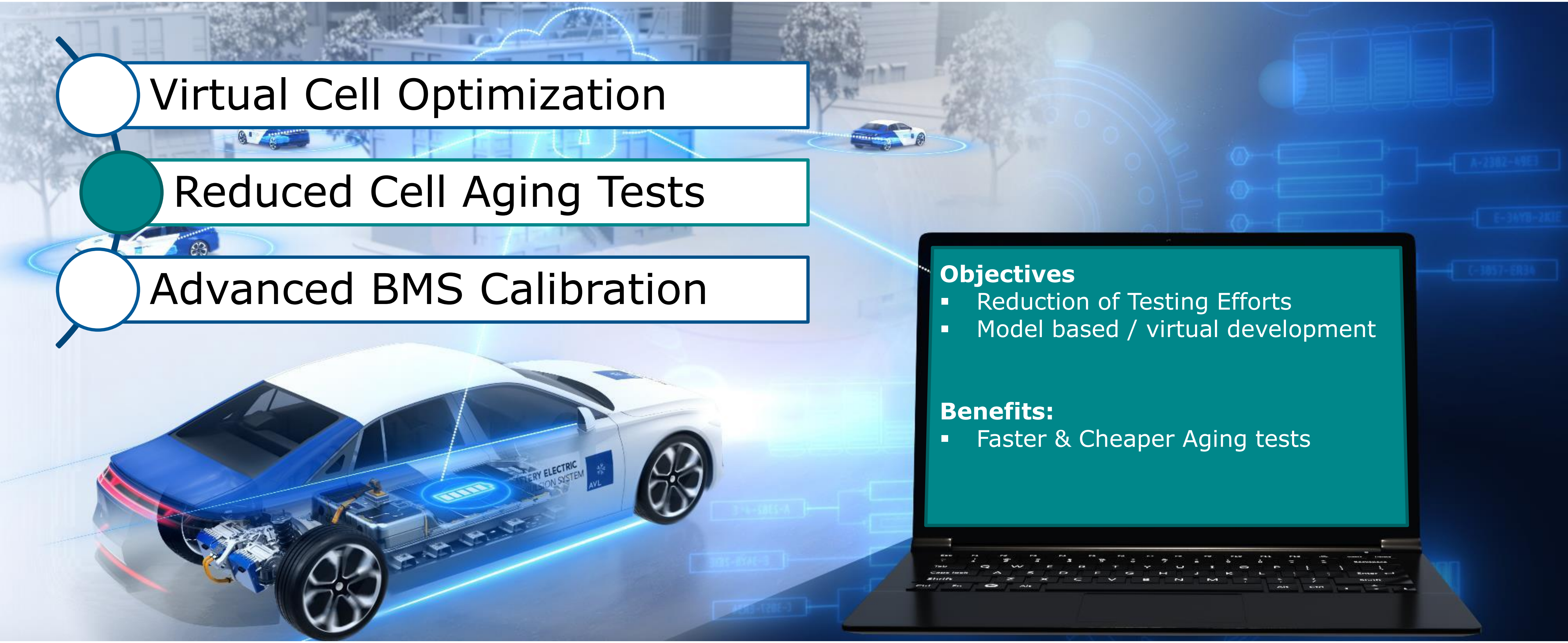


Simulation



Optimize your Cell Design with Data Intelligence

Use Cases of
Data Analytics in Battery Development and Testing

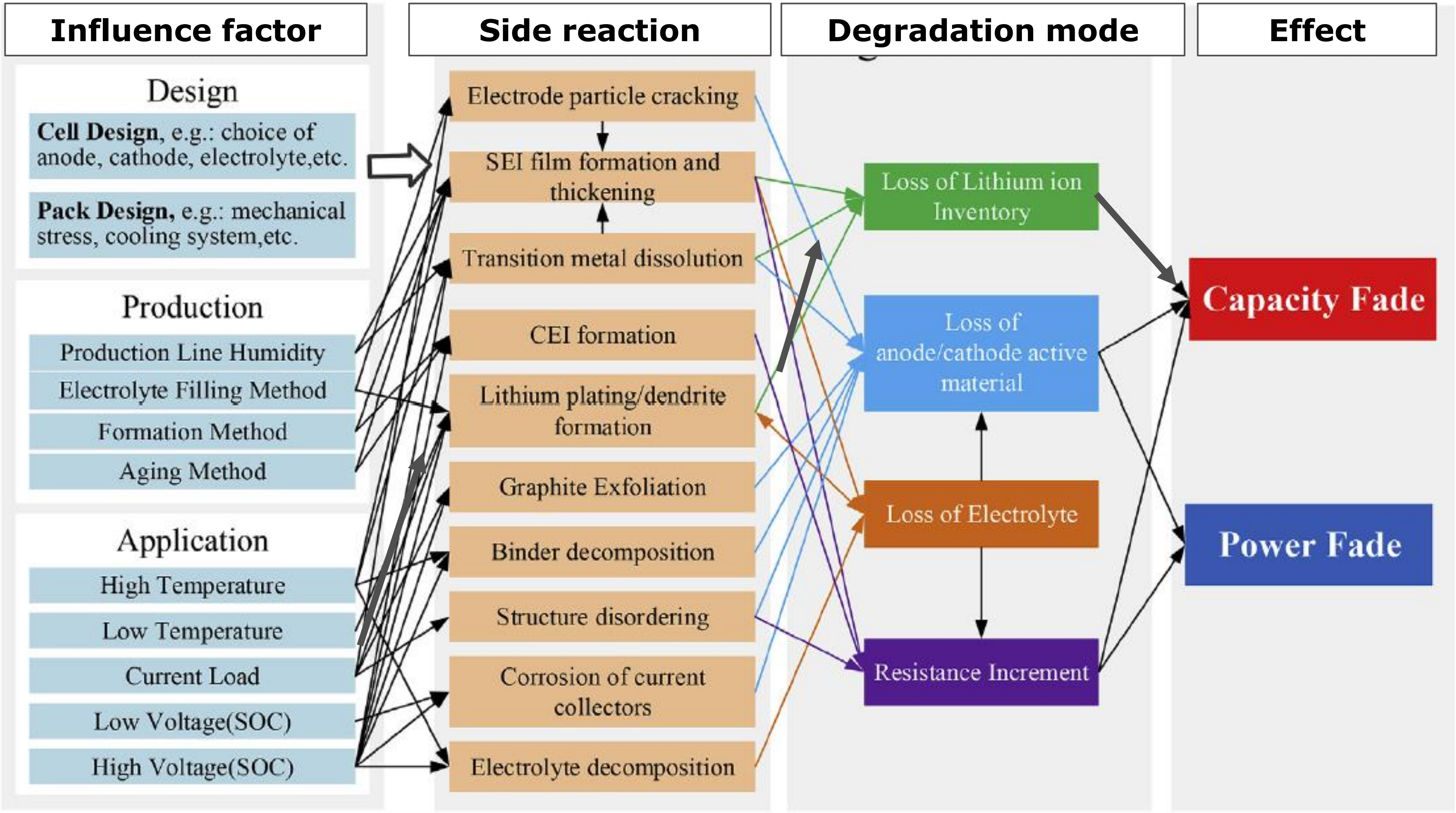


- Virtual Cell Optimization
- Reduced Cell Aging Tests
- Advanced BMS Calibration

Objectives
- Reduction of Testing Efforts
- Model based / virtual development

Benefits:
- Faster & Cheaper Aging tests

What is Happening in Terms of Ageing?



Adapted from Han, Xuebing, et al. *eTransportation* 1 (2019): 100005

Battery Cell Ageing Model
Impact factor analysis / Artificial cycle construction

T … Temperature

CC … Charge current

ADC … Average discharge current

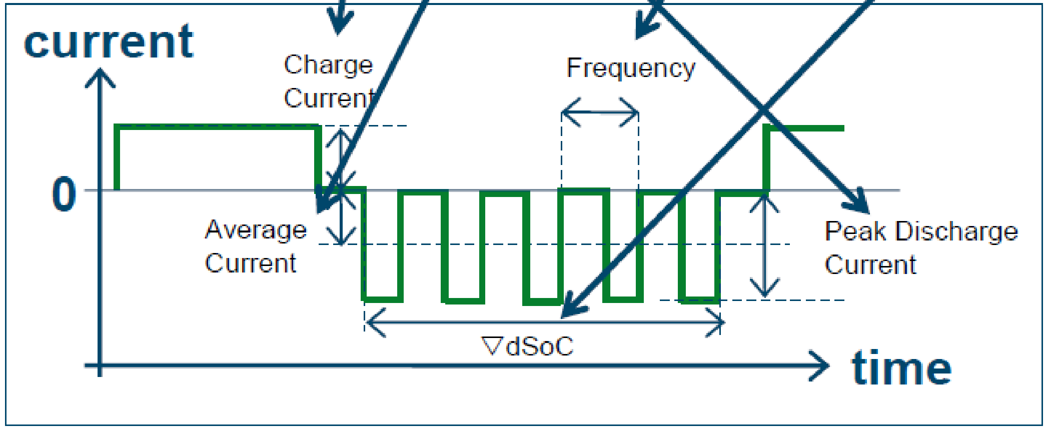
PDC … Peak discharge current

F ... Pulse frequency

SOC … State of charge

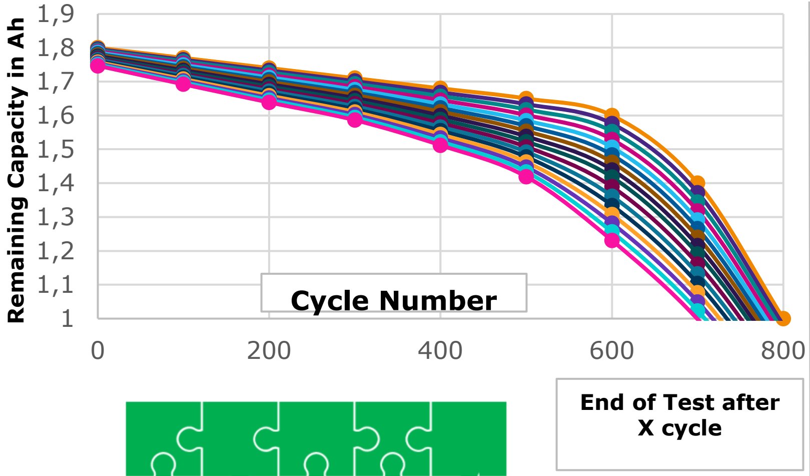
dSOC … Delta SOC

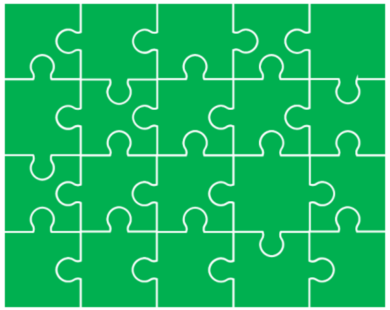
Load Point	T	CC	ADC	PDC	F	SoC	dSoC
L27	40	2,4	8	10	0,03	55	80



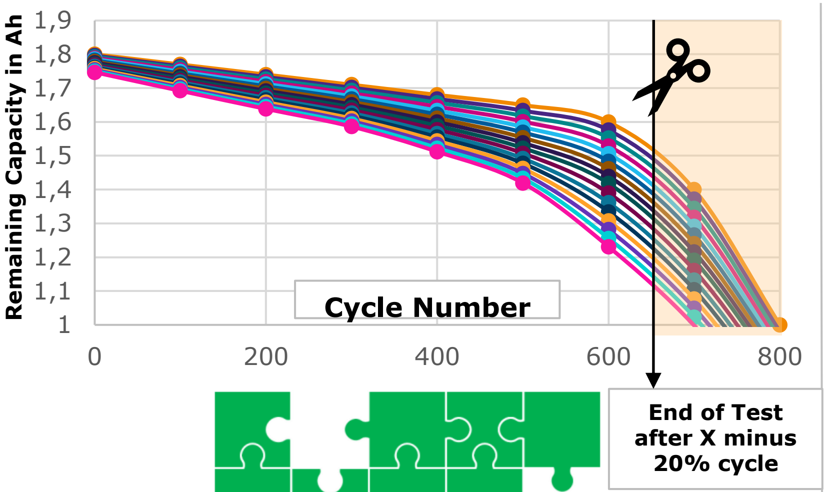
Project ALICe

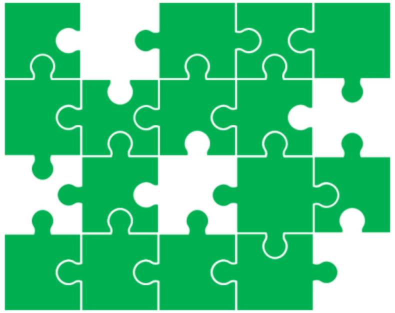
Reduction of Ageing Measurement Time
Use Ageing Information from Faster Ageing Cells for Extrapolation





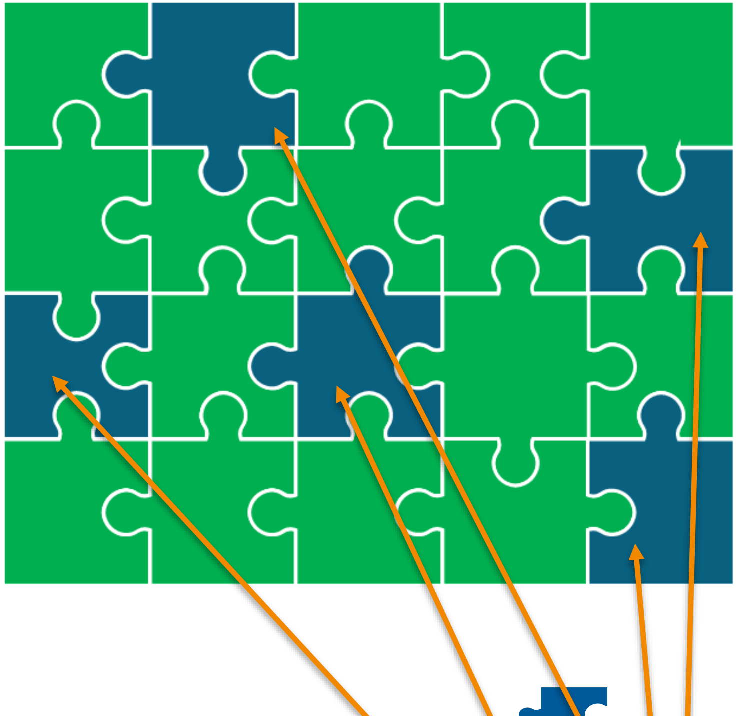
Ageing Model

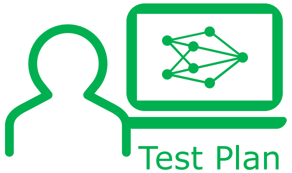




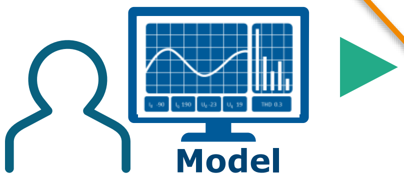
Reduce testing time by trimming the design points which need longer ageing time

Model uses the data from faster ageing cells to predict the EoL characteristics of the slower ageing cells



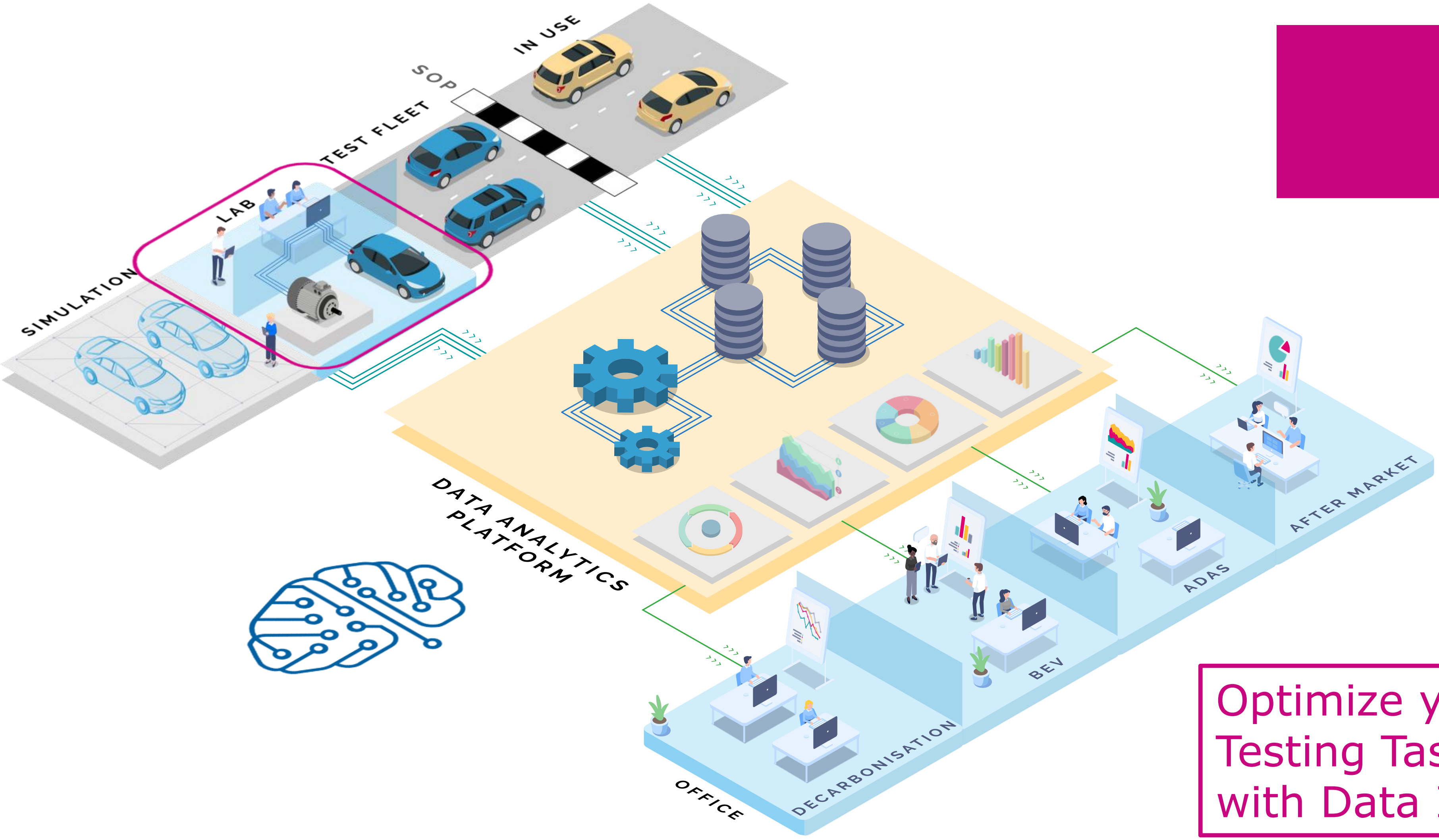


Test Plan

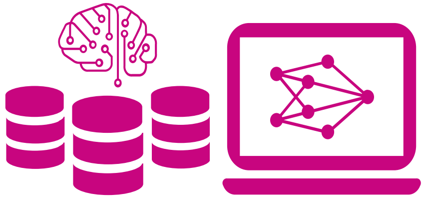


BENEFIT: Reduction of test time by 20%

AVL Data Analytics Platform

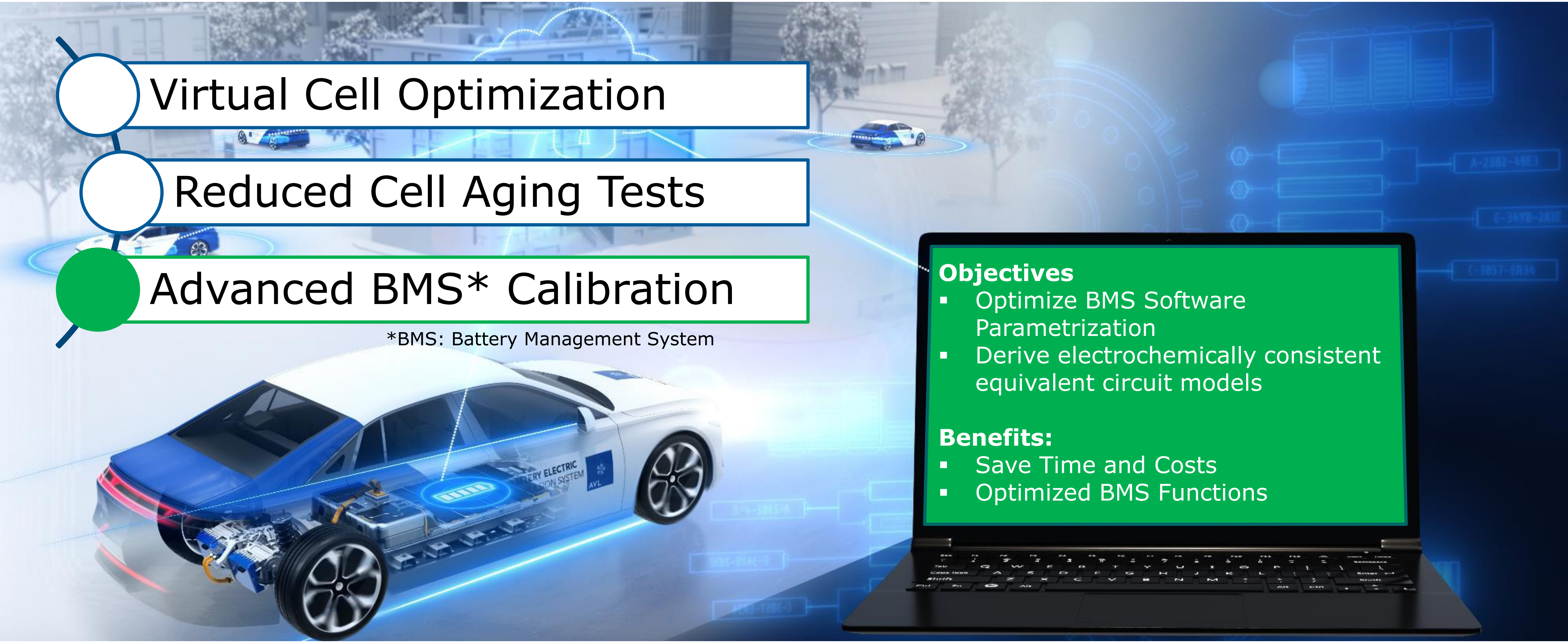


LAB



Optimize your
Testing Tasks and Efforts
with Data Intelligence

Use Cases of
Data Analytics in Battery Development and Testing



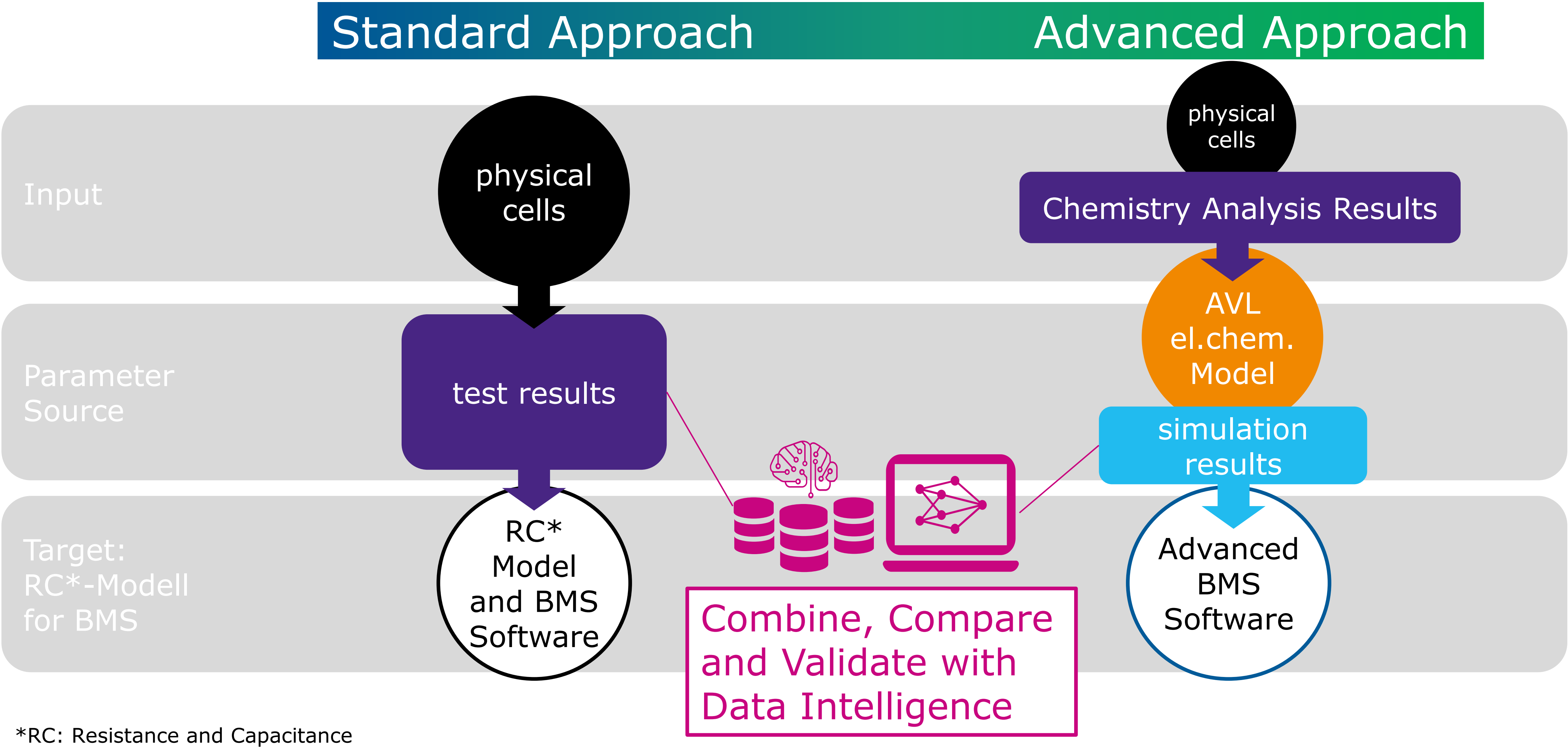
- Virtual Cell Optimization
- Reduced Cell Aging Tests
- **Advanced BMS* Calibration**

*BMS: Battery Management System

Objectives
- Optimize BMS Software Parametrization
- Derive electrochemically consistent equivalent circuit models

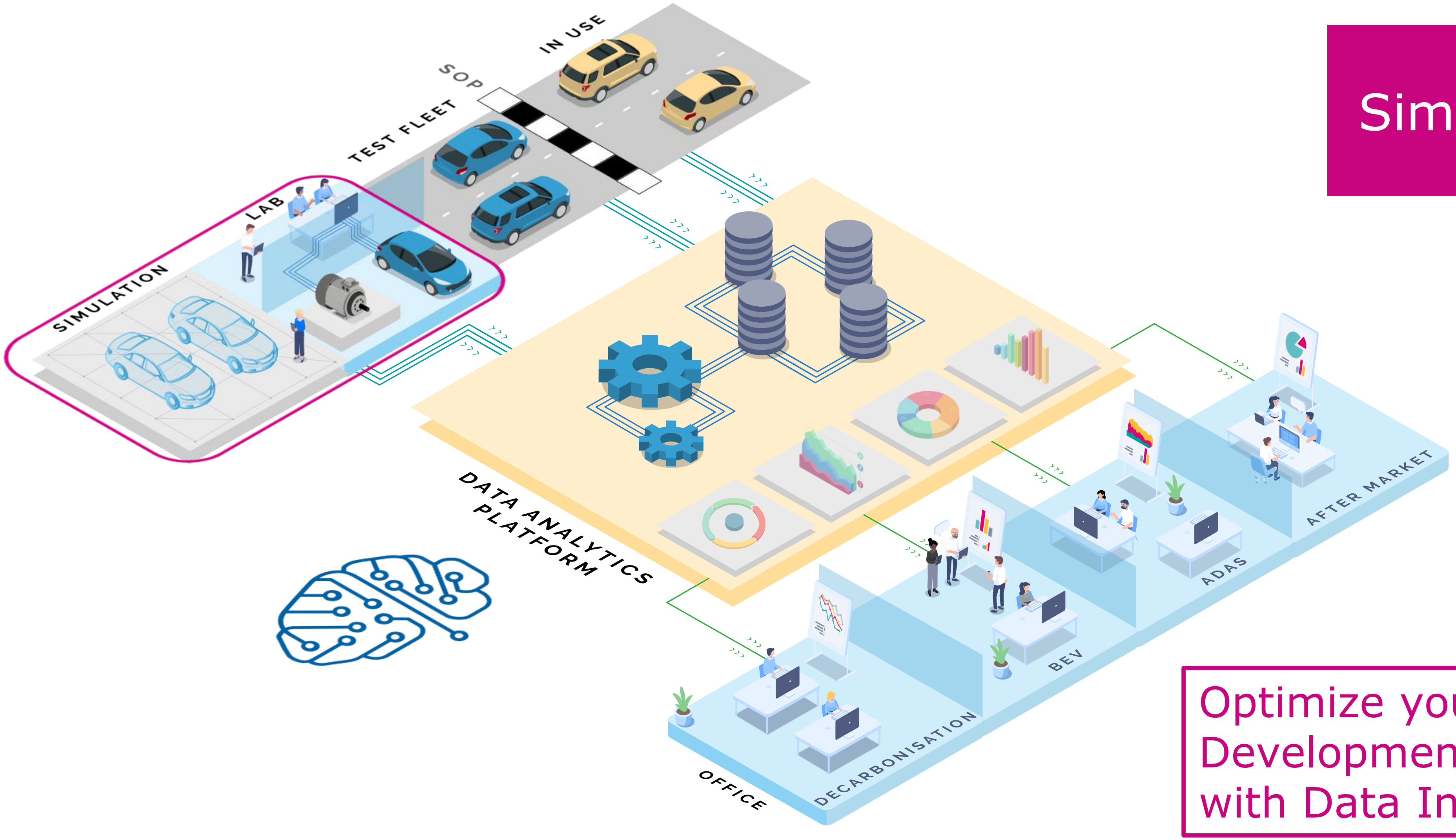
Benefits:
- Save Time and Costs
- Optimized BMS Functions

Derive RC*-Model parametrization via Intelligent Combination of Simulation and Testing

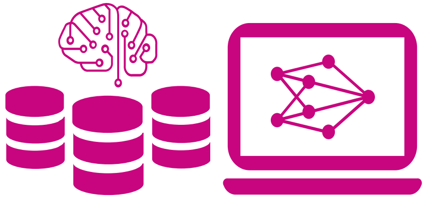


*RC: Resistance and Capacitance

AVL Data Analytics Platform



Simulation and LAB



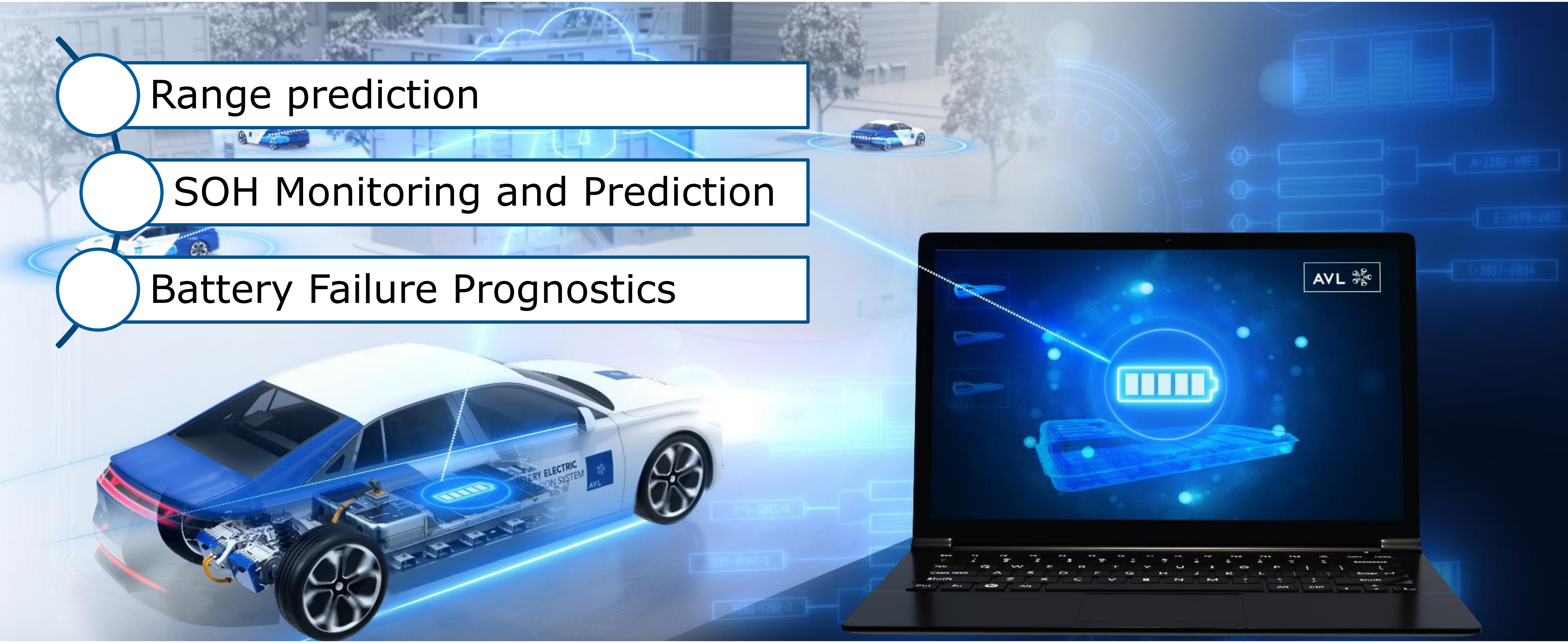
Optimize your BMS Development Tasks and Efforts with Data Intelligence

Battery Analytics for Vehicle Fleets

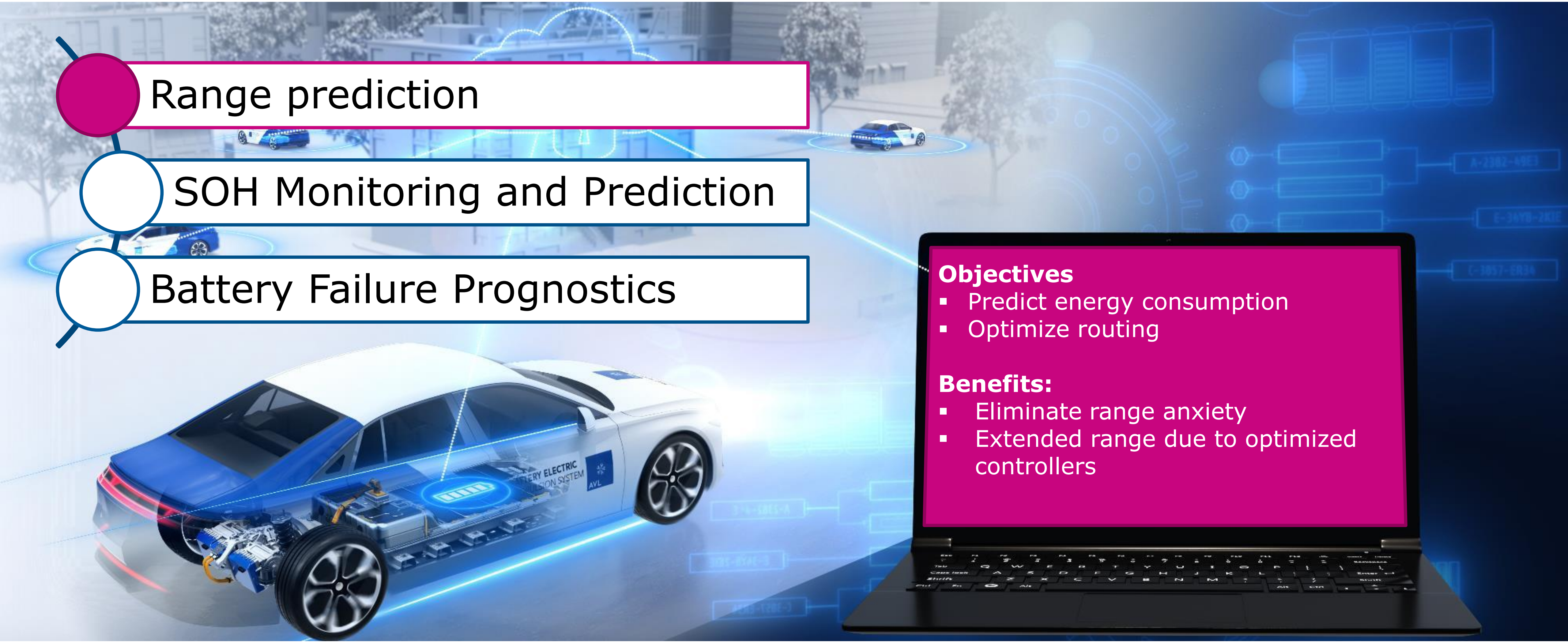
Public

Battery Analytics Objectives for Vehicle Fleets

- Range prediction
- SOH Monitoring and Prediction
- Battery Failure Prognostics



Battery Analytics Objectives for Vehicle Fleets



- Range prediction
- SOH Monitoring and Prediction
- Battery Failure Prognostics

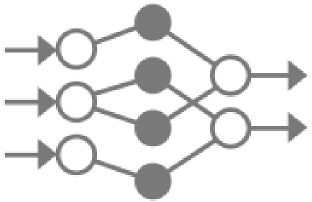
Objectives

- Predict energy consumption
- Optimize routing

Benefits:

- Eliminate range anxiety
- Extended range due to optimized controllers

Traditional Range Calculation vs. AI Range Prediction



Traditional range prediction

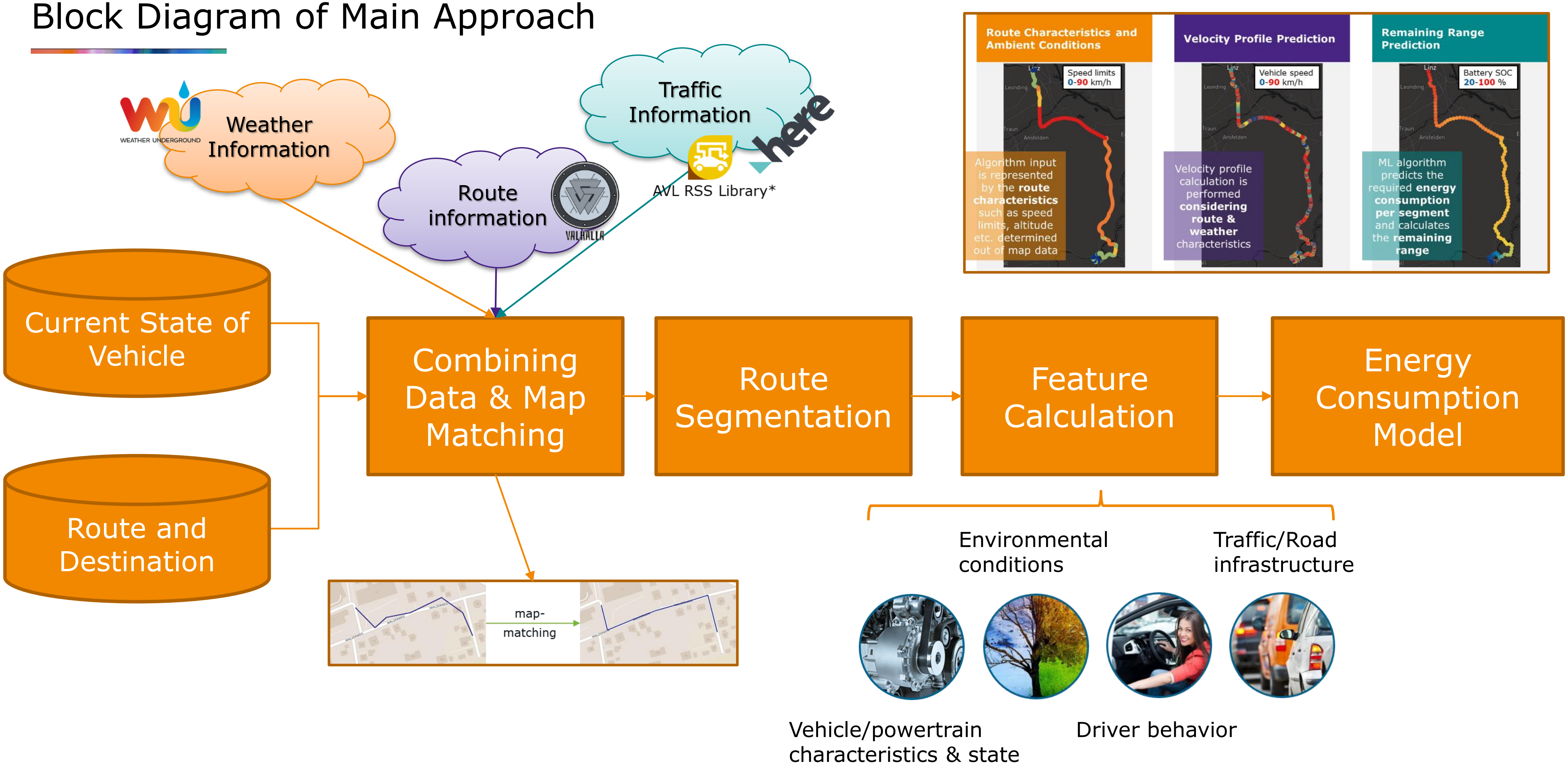
- Vehicle data from the last minute
- Vehicle mass, drag, …
- Current SOC
- On-board calculation

AI based range prediction

- Trained on energy consumption of complete customer fleet
- Considering:
  - Current SOC
  - Ambient conditions and driving style
  - Route and traffic
  - SOH
- On-board and cloud calculation

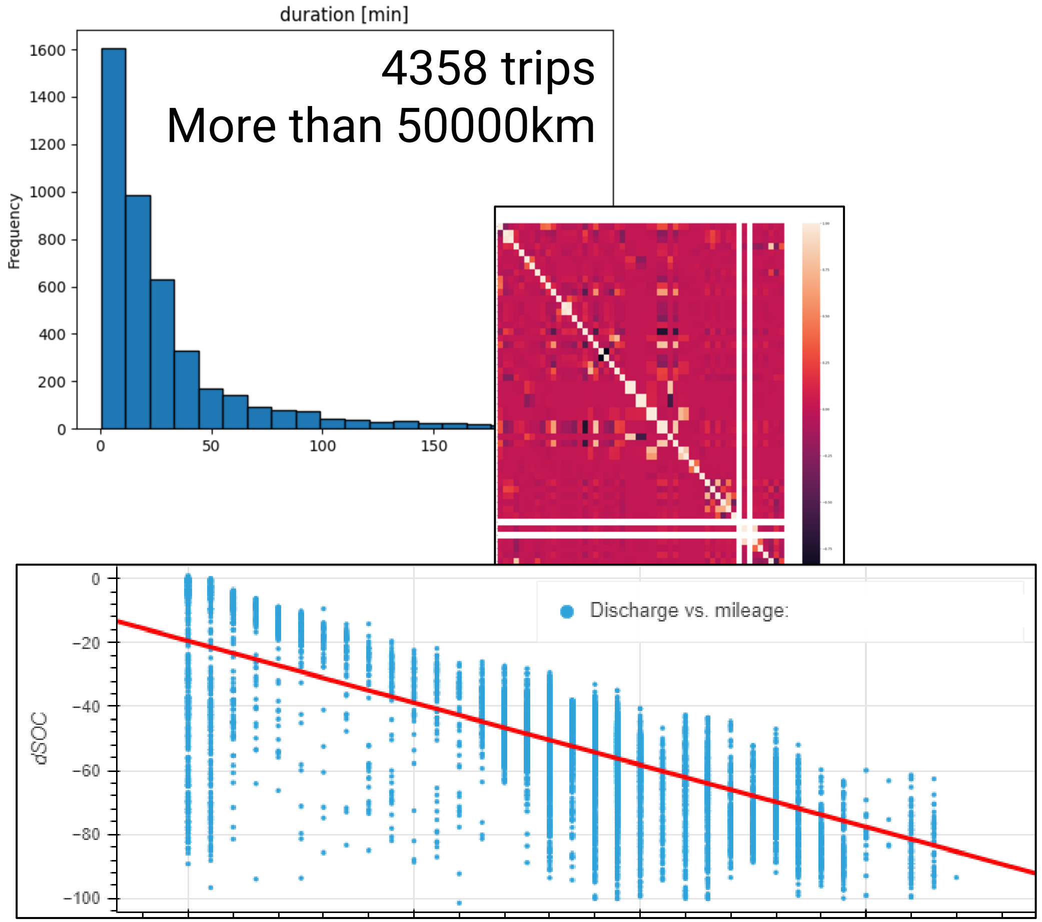
Methodology

Block Diagram of Main Approach



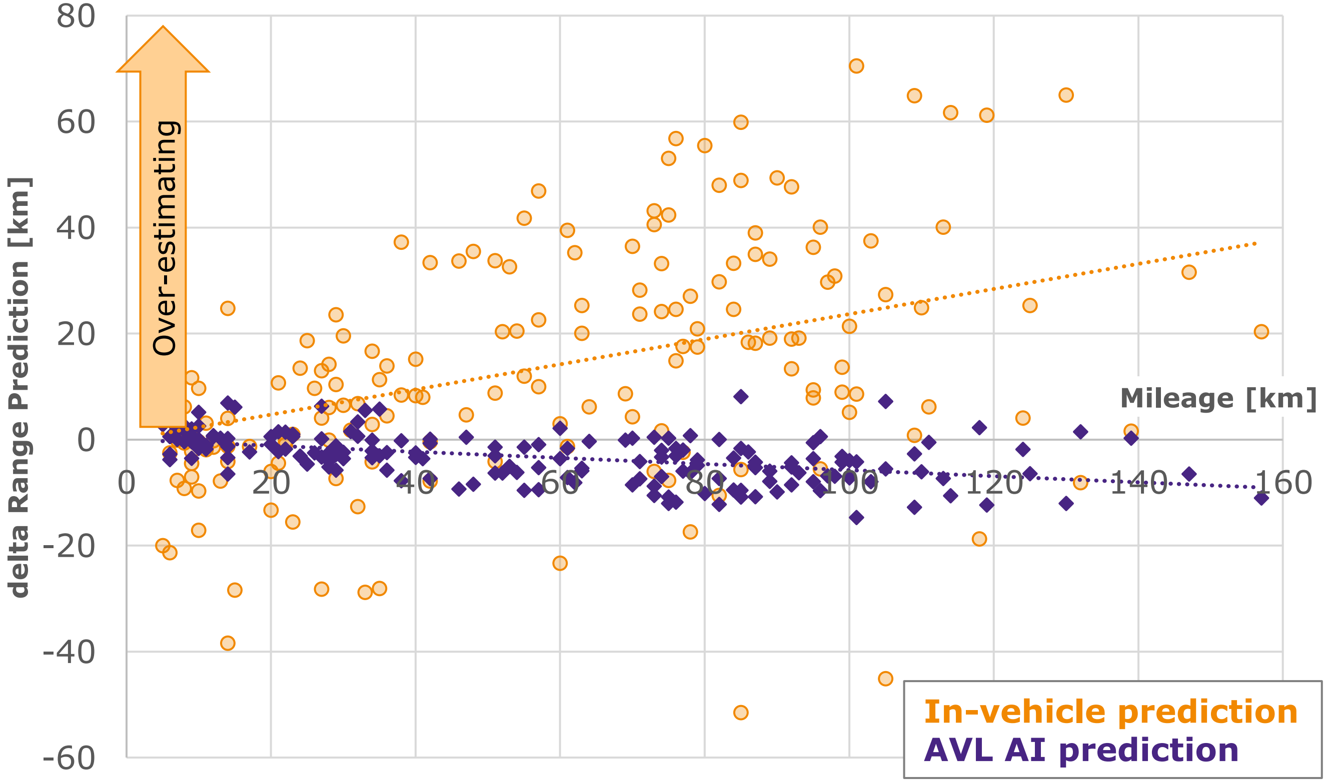
AI Range Prediction Results

Trained on:

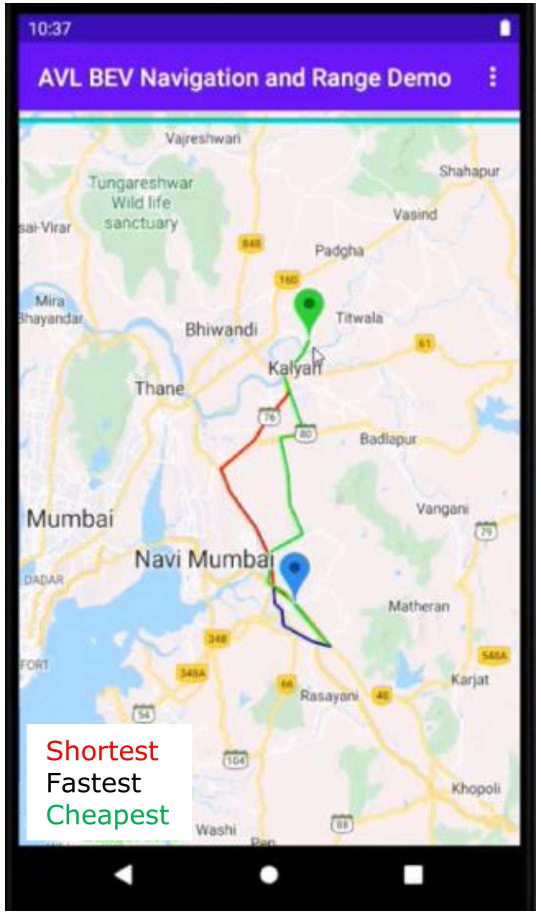


Results:

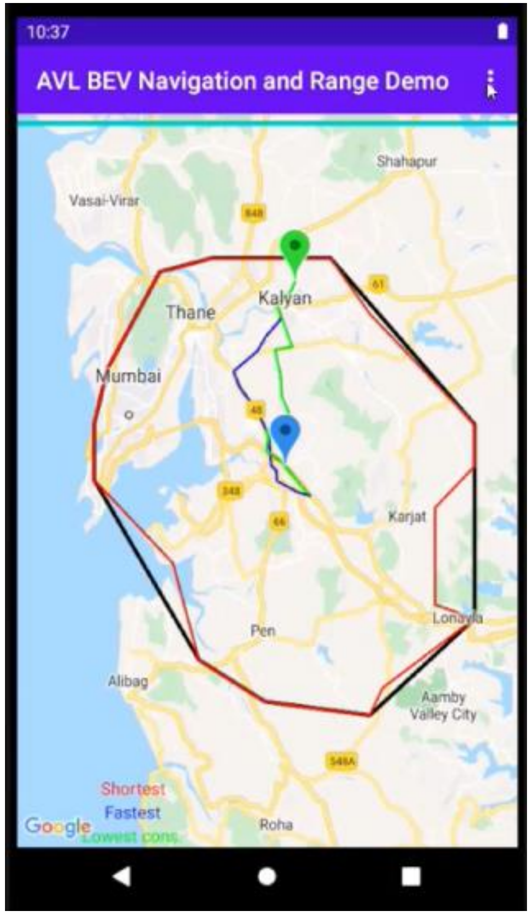
3x Better Prediction Accuracy…
… on the safe side



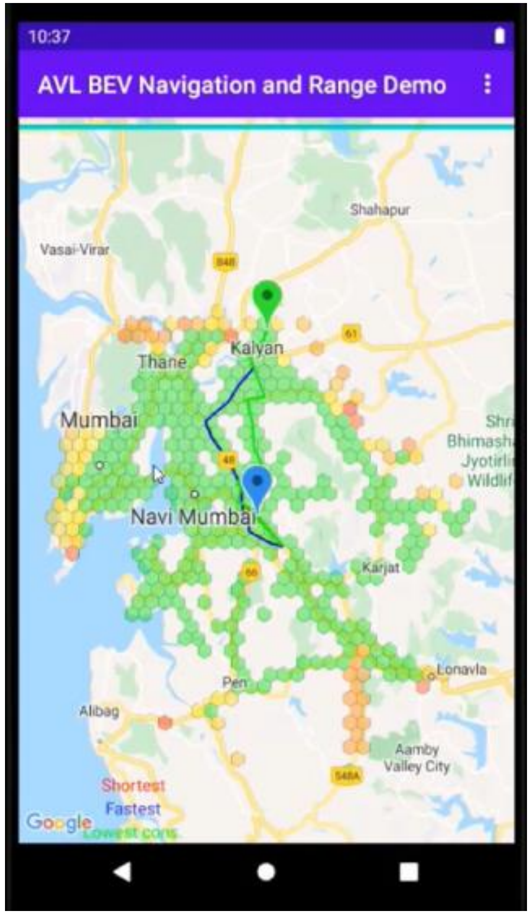
AI Range Prediction for BEV Routing



Energy Optimal Route



Range Polygon



Reachable Points

Benefits of AI Range Prediction

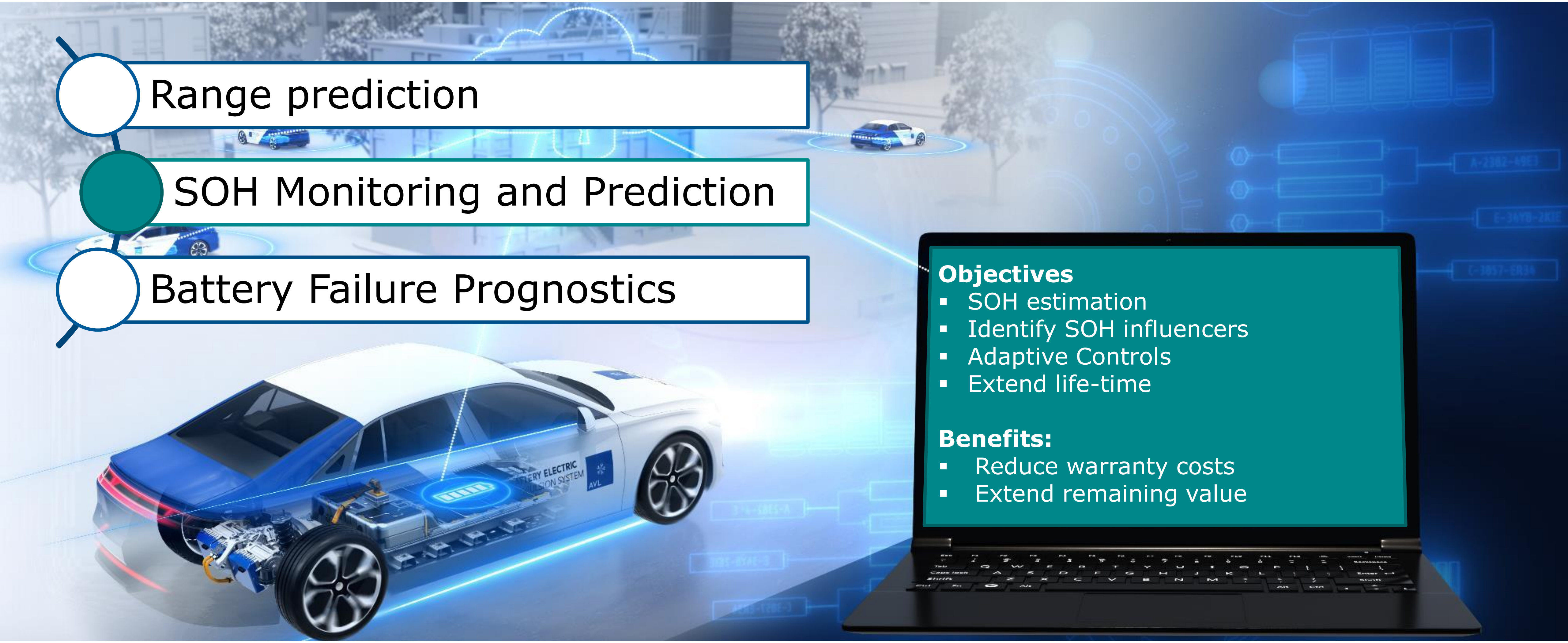
Unique Features:

- Use connectivity features to consider current ambient conditions and traffic situation
- Combine multiple models to improve prediction quality

Benefits:

- Eliminate range anxiety → Improved customer satisfaction
- Recommendations for Driver
- Optimized controls to extend real life range
- Optimize fleet operation, logistic efficiency and TCO

Battery Analytics Objectives for Vehicle Fleets



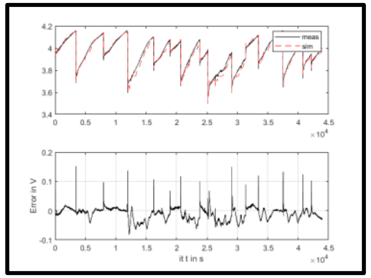
- Range prediction
- SOH Monitoring and Prediction
- Battery Failure Prognostics

Objectives
- SOH estimation
- Identify SOH influencers
- Adaptive Controls
- Extend life-time

Benefits:
- Reduce warranty costs
- Extend remaining value

Fleet Data Analytics for Battery Electric Vehicles

SoH estimation On-board or Off-board
(RC-Modelling for single vehicle)

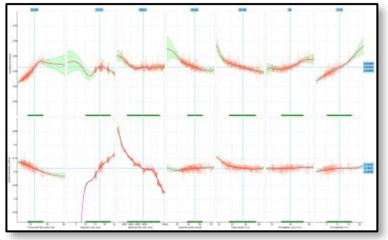


Current RC & SoH for each vehicle

Estimation of battery health based on RC parameter identification for dynamic driving cycles for each vehicle.

Cross-device event-based analytics and RUL prediction in the cloud

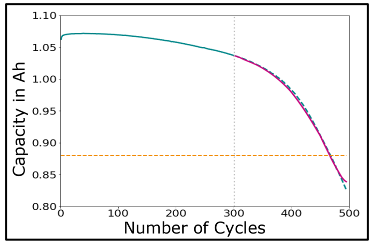
Range and SoH
(Meta modelling for complete fleet)



Influencing factors on range & SoH for complete fleet

Neural network model training for range and SoH depending on driving and ambient conditions based on the complete fleet.

Lifetime Prediction
(Machine learning incl. federated learning for model training)



Remaining useful life for each vehicle

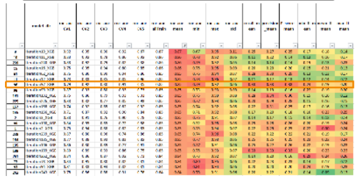
Machine learning approach to predict the future behavior of the SoH based on the historic battery data. A federated learning approach is used to train the corresponding model over several fleets.

Identification of SOH Influencing Factors

Result
(events and aggregates)

→ Model/Training/Validation parameterization

→ Model training and selection



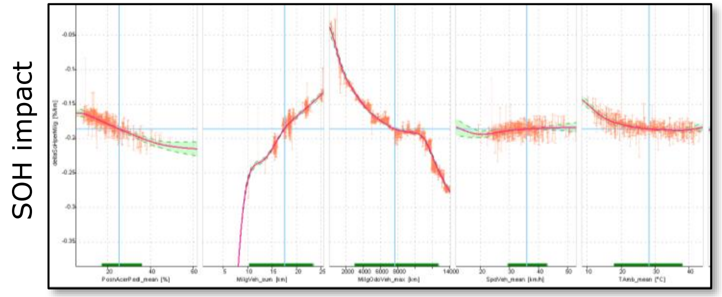
→ Multi dimensional response surface model

No.		☑	PosnAcerPedl_me	MilgVeh_sum	MilgOdoVeh_max	SpdVeh_mean	TAmb_mean	THvbatMax_max	THvbatDelta	EperMilg	deltaSoHperMilg	dSOCperMilg
			[%]	[km]	[km]	[km/h]	[°C]	[°C]	[°C]	[kWh/km]	[%/km]	[%/km]
			Variation	Variation	Variation	Variation	Variation	Variation	Variation	Response	Response	Response
4999	19	☑	13.053	12.859	5228	25.707	31.431	42	17	0.032012	-0.27996	0
5801	25	☑	1.3238	0.56175	1557	10.073	31.551	40.5	1	0.013494	-4.9844	-1.7802
5896	25	☑	6.9416	16.092	3248	19.825	33.091	46.5	21.5	0.02222	-0.19886	-1.9028
2271	7	☑	7.118	15.417	3744	19.444	26.654	35.5	2.5	0.022235	-0.15567	-1.9394
4944	19	☑	9.0126	25.647	3976	25.049	32.565	40	15	0.022058	-0.12477	-1.9558
3789	13	☑	8.3822	31.62	3115	22.974	36.765	38.5	4.5	0.022839	-0.088551	-1.9711
3807	13	☑	13.243	31.568	3585	27.009	44.398	39	6.5	0.022607	-0.10137	-1.98
4986	19	☑	9.3128	25.722	4953	25.191	31.308	41.5	16.5	0.022759	-0.13996	-2.0049
3689	13	☑	10.251	23.531	1269	25.033	25.303	30	4	0.02312	-0.10199	-2.0071
4542	18	☑	13.206	31.625	1430	32.723	37.603	42	17	0.023027	-0.088537	-2.0079
3687	13	☑	10.424	23.623	1221	25.021	27.522	33.5	4	0.023089	-0.1016	-2.0108
3691	13	☑	9.3143	23.524	1318	23.938	26.346	31.5	4	0.022572	-0.10202	-2.0158
2362	7	☑	9.6307	21.854	5564	23.809	31.374	44	2.5	0.023396	-0.12812	-2.0252
270	2	☑	7.9213	15.422	5224	19.629	26.1	37.5	3	0.023361	-0.18156	-2.0305
2367	7	☑	5.853	15.405	5659	17.447	27.035	43.5	4	0.023193	-0.18176	-2.0383
304	2	☑	9.3105	21.876	5937	24.41	31.985	46.5	3.5	0.023537	-0.12799	-2.039
5163	20	☑	7.9609	29.601	2866	20.858	26.436	34.5	5.5	0.023437	-0.13513	-2.0405

Every row represents one event (Example: "driving" – from standstill to next standstill)

All aggregates which can be considered as variational influence to energy consumption

Response properties from the powertrain system (mainly energy spent per drive event, or SoH)

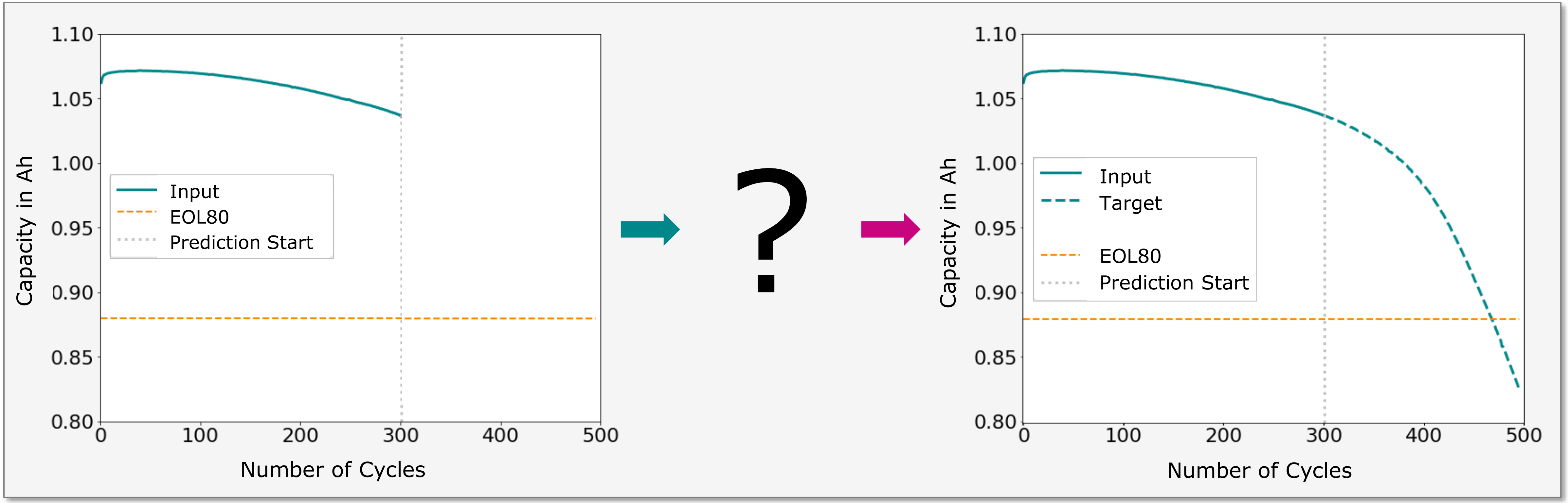


The response surface model describes the parameters which have the highest impact on battery aging.

Data-Driven Battery Degradation Prediction

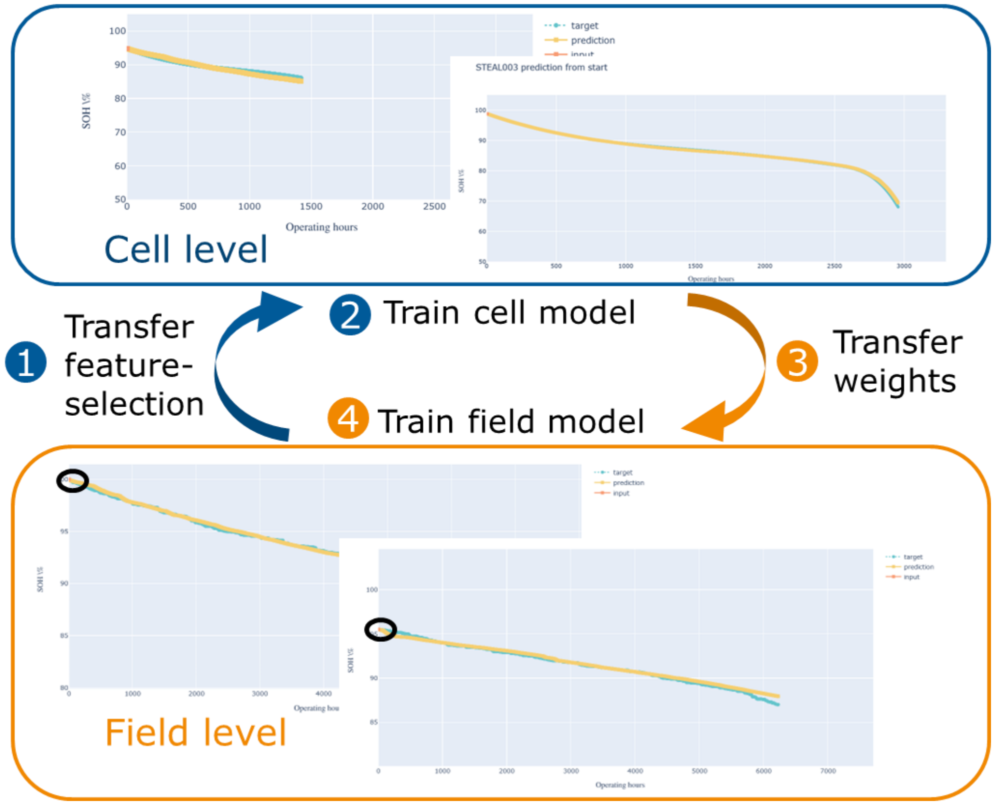
Question

How to predict the future battery degradation from historical data?

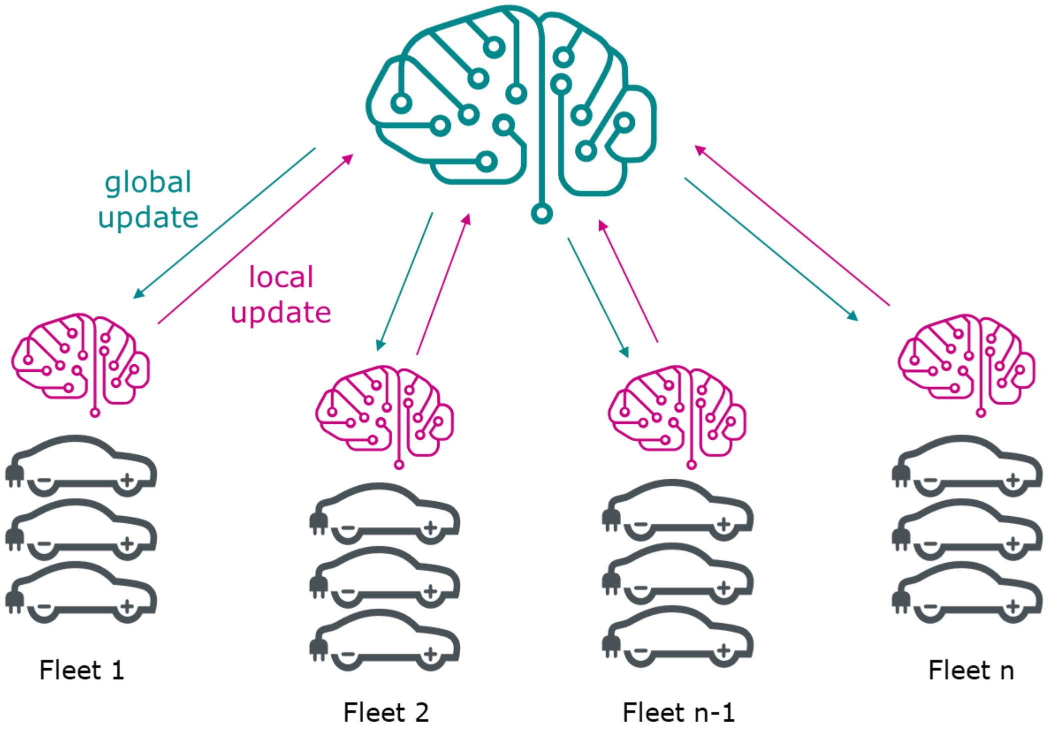


Advanced Data Intelligence Technologies for Prediction of remaining Useful Life

Transfer Learning



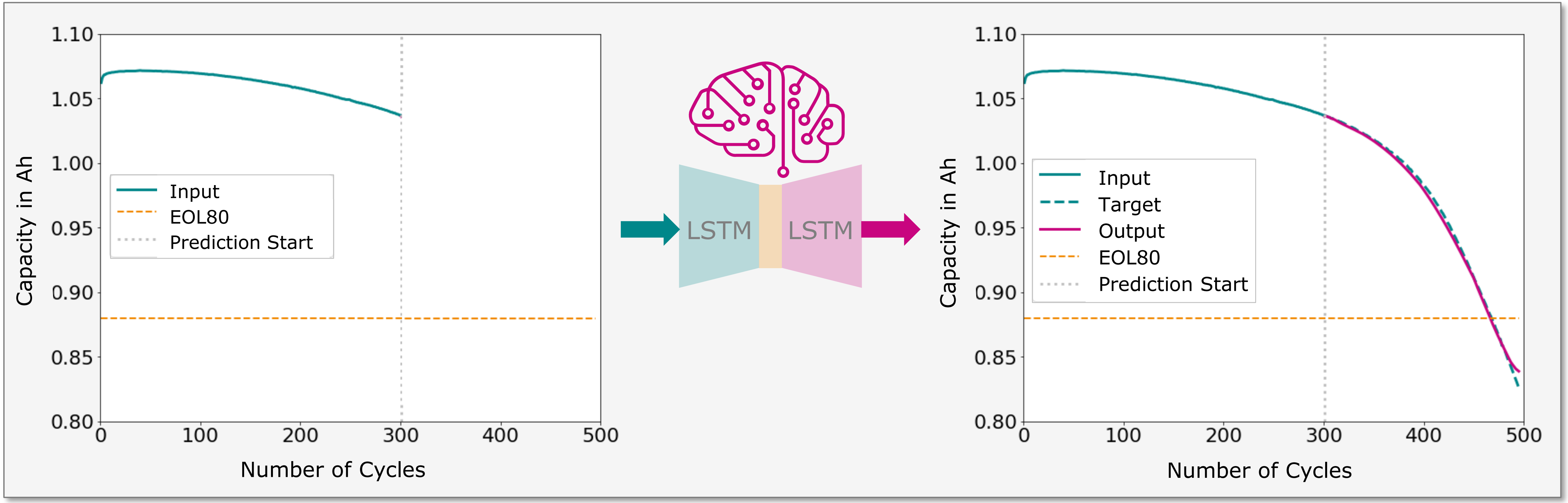
Federated Learning



Data-Driven Battery Degradation Prediction

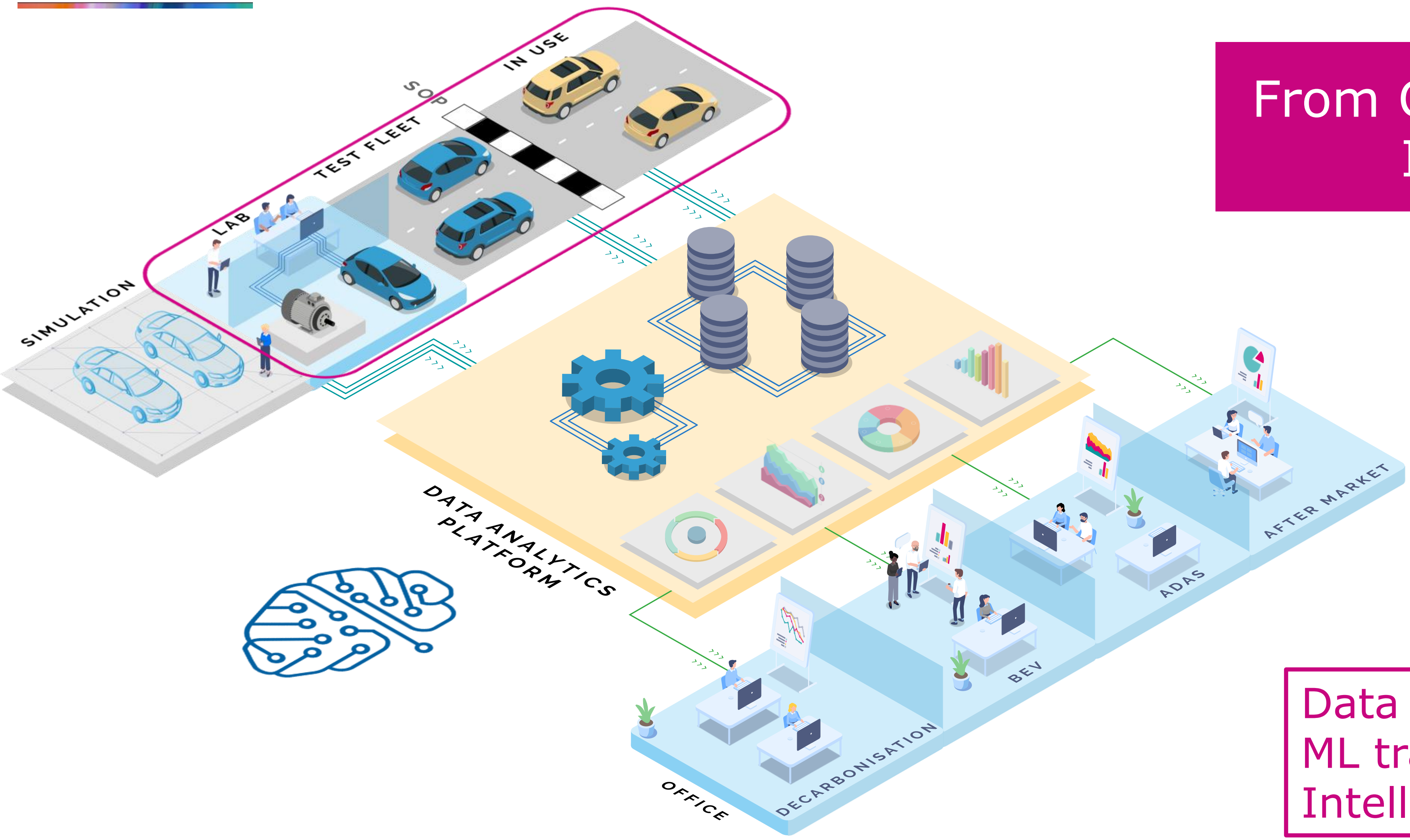
Model Approach

Neural network based on a Long Short-Term Memory (LSTM) Encoder-Decoder architecture[1]

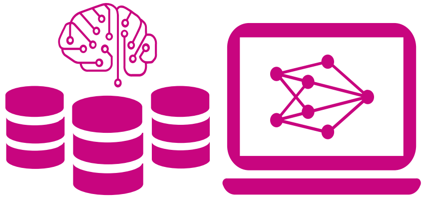


[1] The architecture was chosen similar to W. Li et al., „One-shot battery degradation trajectory prediction with deep learning," Journal of Power Sources, vol. 506, p. 230024, 2021, DOI: 10.1016/j.jpowsour.2021.230024.

AVL Data Analytics Platform

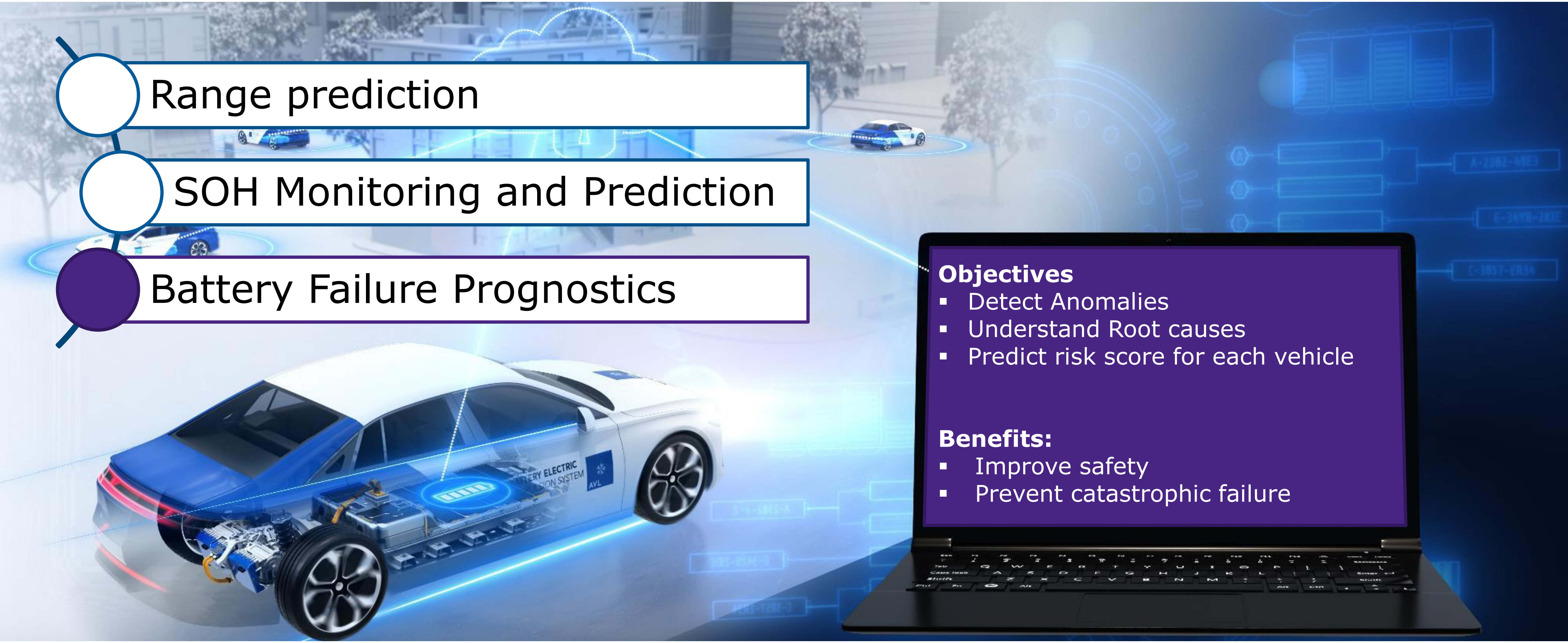


From CELL TEST to IN-USE



Data Aggregation and ML training with Data Intelligence Platform

Battery Analytics Objectives in Development and Testing



- Range prediction
- SOH Monitoring and Prediction
- Battery Failure Prognostics

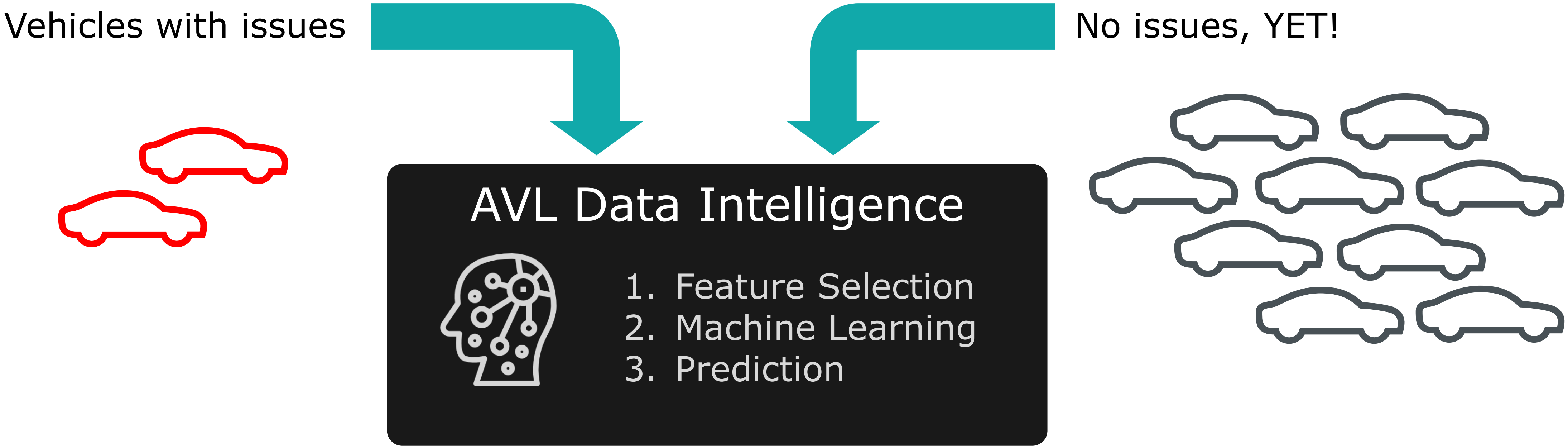
Objectives

- Detect Anomalies
- Understand Root causes
- Predict risk score for each vehicle

Benefits:

- Improve safety
- Prevent catastrophic failure

Prognostics Approach



Prognostics Approach

Vehicles with issues

No issues, YET!

AVL Data Intelligence

1. Feature Selection
2. Machine Learning
3. Prediction

Likely to show issues soon!

Failure prediction for
each vehicle and
each component

Fleet Data Analytics for Battery Electric Vehicles
After Sales Issue Prediction, In-field Trouble Shooting

Consumer fleet
- DTCs
- Telematics

Workshops / Dealers
- Services
- Part replacements
- Warranty claims
- Diagnosis

Ambients
- Weather
- Traffic situation
- Road infrastructure

AVL Data Intelligence

1. Feature Selection
2. Machine Learning
3. Prediction

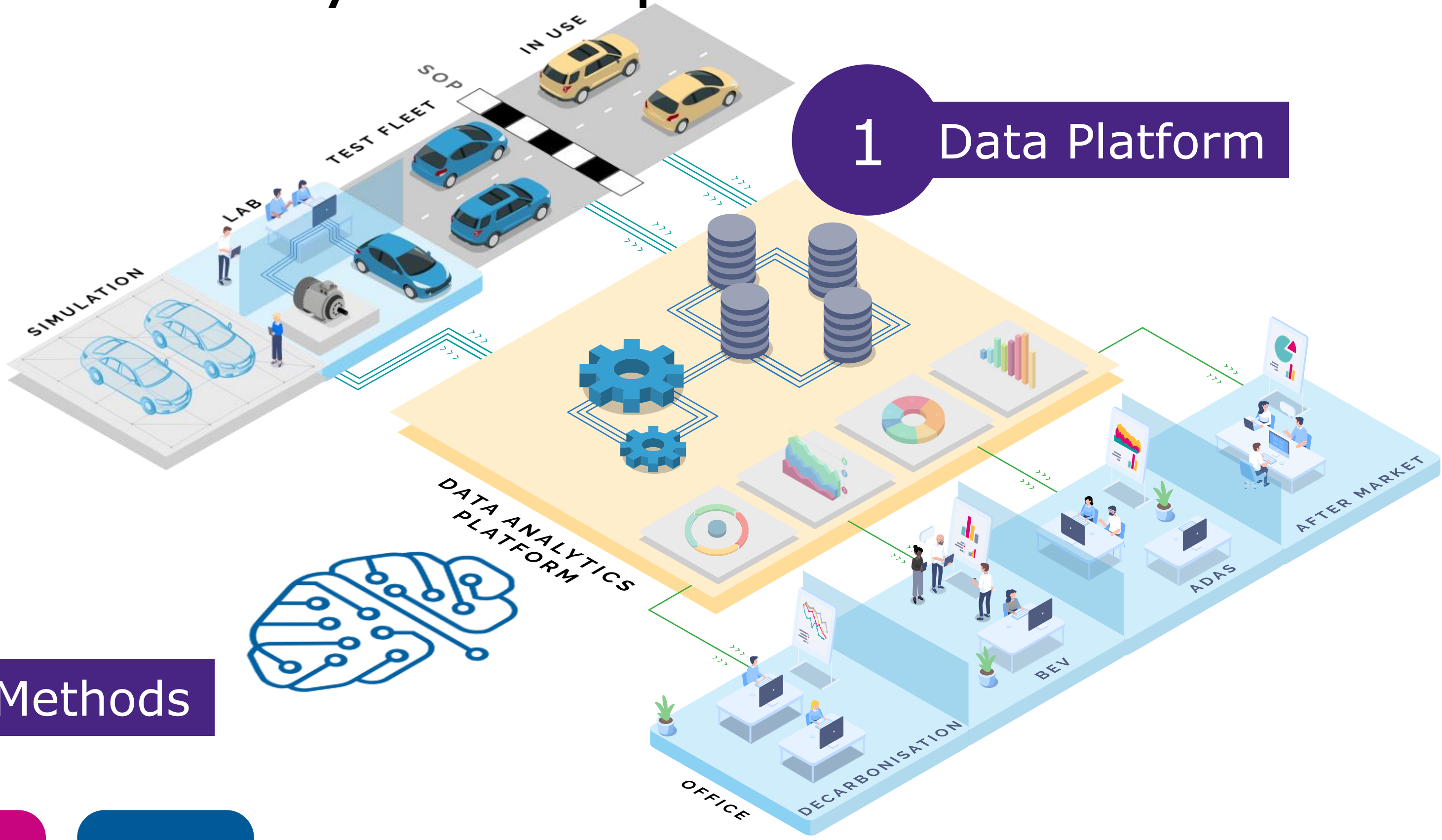
Deliverable 1:
Failure prediction model

Deliverable 2:
Risk of failure for every VIN

VIN	Risk
1FAFP45X83F403461	87,6%
1C4NJPBA1CD661292	82,7%
1G8ZF5287XZ363384	79,3%
WMWRC33474TC49530	74,1%
WP0CA29924S650563	68,9%
WV2YB0257EH008533	64,1%
5TEWN72N63Z275910	60,7%
1GCFG25F6V1059733	54,1%
2G1WH55K5Y9322458	52,7%
SAJWA2GEXBMV00832	46,0%
5XYKT3A69DG353356	43,6%
2B3ED56F5RH142129	43,4%
4V4N99EH3CN554692	42,5%
1G4HP54KX24151104	42,2%
1FMCU14T6JU400773	36,2%
JHMSZ542XDC028494	30,8%
1GCHK23244F199207	28,1%
JH4DA9340LS003571	26,5%
1FAFP58S11A177991	23,5%
JM3TB2MA5A0235007	19,2%
JH4DC2380RS000036	16,2%
WBACB4324RFL14401	11,0%

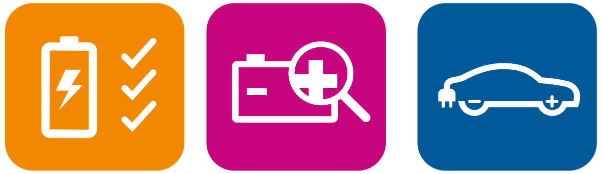
Conclusion

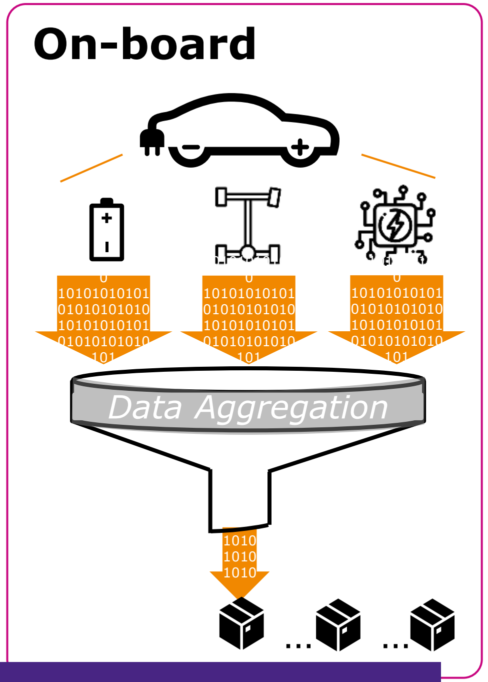
Battery Data Analytics Requirements



1 Data Platform

2 Analytics Methods





3 Integration Know-How

AVL Battery Analytics References

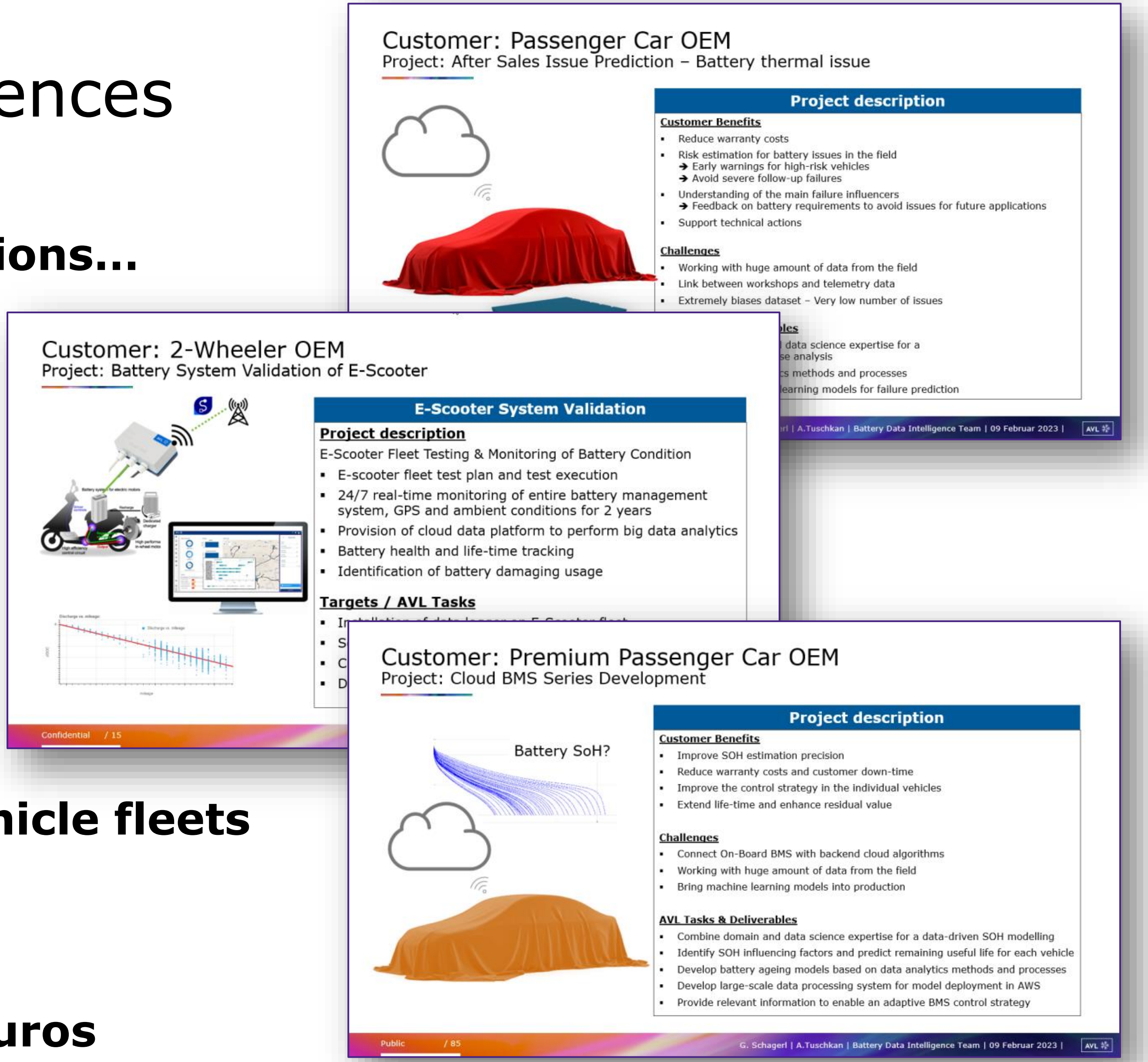
Analytics applied to various applications…

- Passenger Cars, Trucks
- 2-wheelers and stationary systems

For system validation and
Series development

Deployed and operated on global vehicle fleets

Realised savings worth millions of Euros



Key-Benefits of Battery Analytics

Improved operation strategy and utilization: driving, charging, parking

Preventive failure detection and predictive maintenance indications

Reduction of costs

Valuable input for next generation battery system development

Q/A

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