DIGITAL ECOSYSTEM FOR THERMAL MANAGEMENT SYSTEMS

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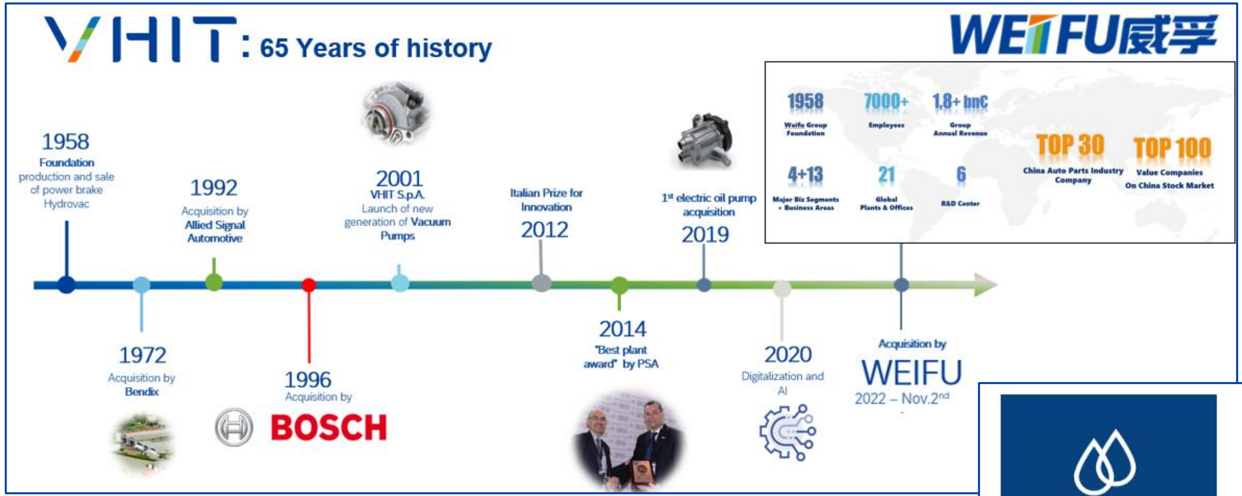
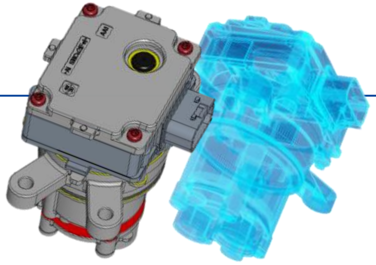
VHIT

Digital Ecosystem for Thermal Management Systems

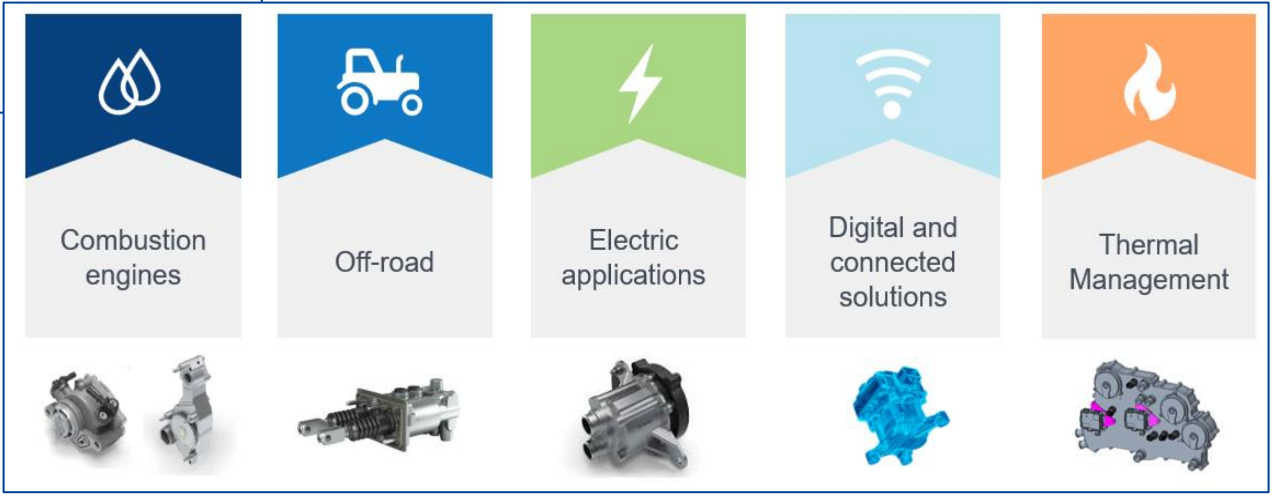
Company history and area of activity





Electric Oil pump
for eAxle
cooling & lubrication

Digital Twin



Digital Twins in the Automotive Industry
Applications to Full Vehicle and Components

Digital Twin:	Virtual representation of a physical asset or process

Full vehicle applications

- Test **Integration** and **Compatibility** of components before building a prototype
- Route **Planning**
- Enhance overall **Vehicle Efficiency**
- Optimize **Maintenance Schedule** identifying components close to fault

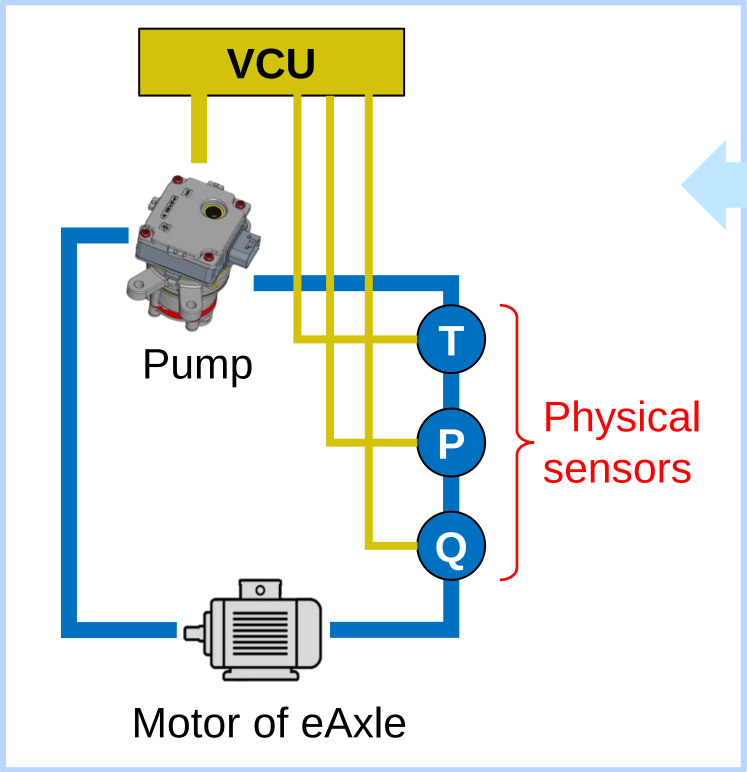
Single component applications

- **Estimation** of internal signals that can't be sensed, or **Virtual Sensors** to replace physical ones
- **Test** different **component Design** before building a prototype
- Real-time **Monitoring** of performance and **Fault Detection**

Focus on Digital Twin application at component level, rather than at vehicle level

Digital Twins in the Automotive Industry

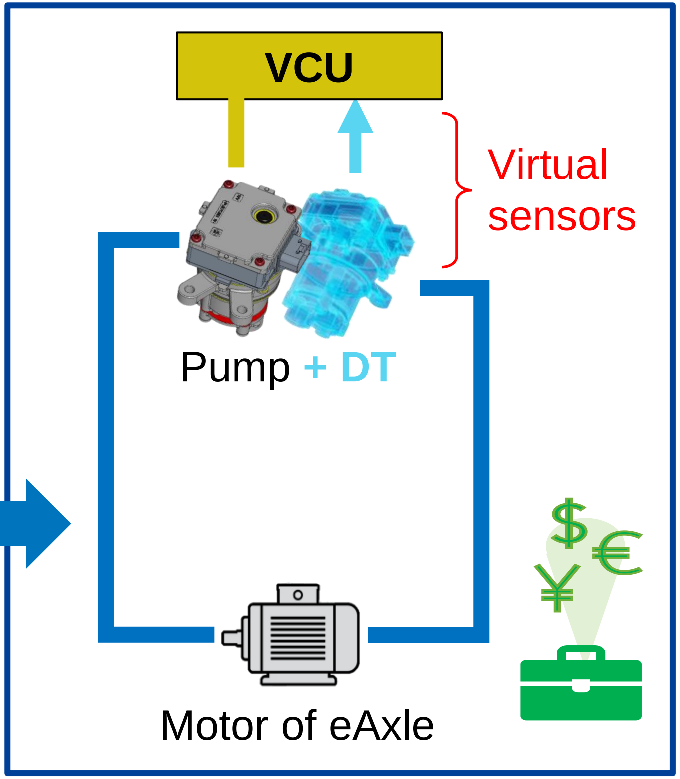
Real use case: Virtual Sensors



Example: Lubrication Oil circuit

Current
- Physical sensors
- Complex architecture
- Sensors placed in hostile environment

Innovative
- Virtual sensors
- Reduce components
- Reduce complexity
- Cost-effective

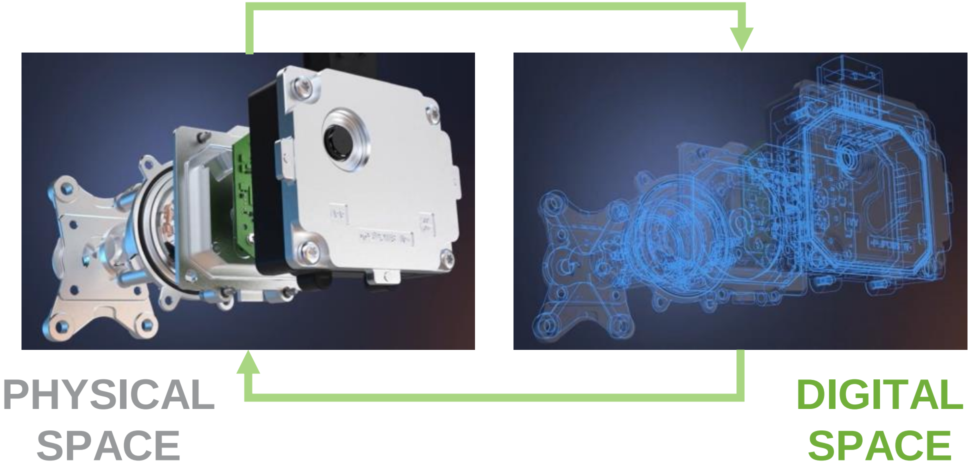


Digital Twin → elimination of physical sensors with technical and economical benefits

Use Case: eLOP
Digital Twin roadmap

Digital Twin **advantages**:

- **Development of Virtual Sensors.**
- Integration of eLOP DT in larger eAxle simulation.
- Remaining Useful Life (RUL) Estimation.
- Continuous Development to optimize pump design.

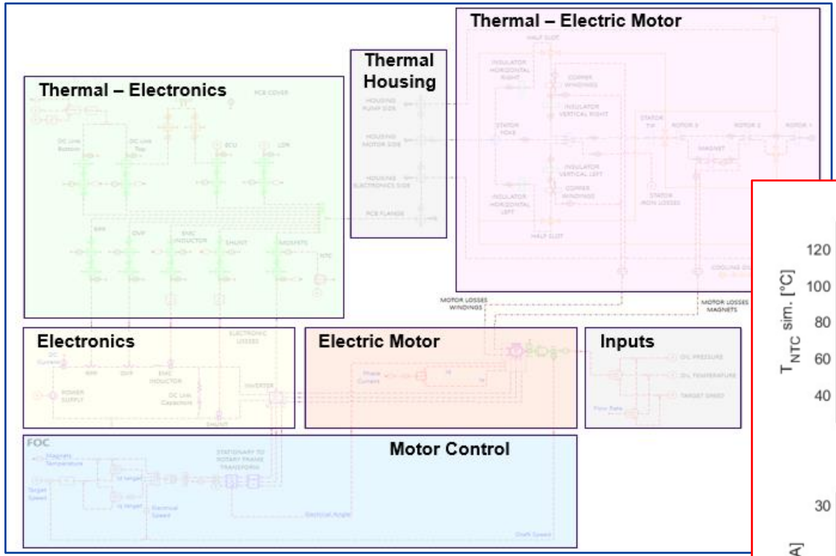


1. Experimental Data acquisition
2. Multi Physics Modelling / CFD
3. Validation with Experimental Data
4. DOEs for simulation-based data generation
5. Machine Learning for Data-based models
6. Deployment on suited platform

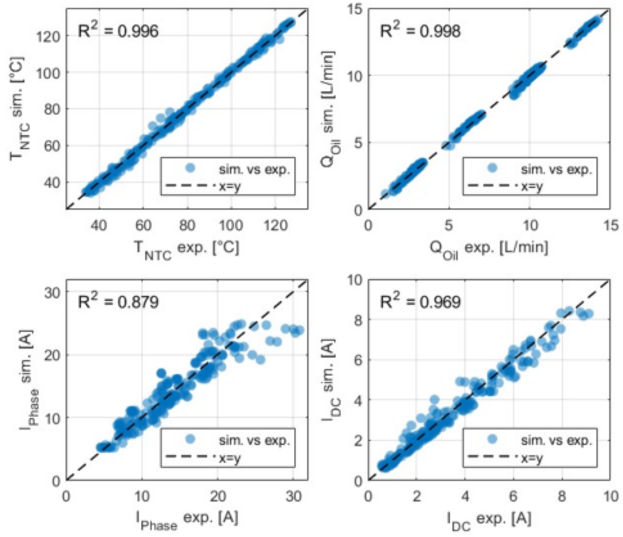
Holistic roadmap from Experimental Data to deployment via Machine Learning and AI

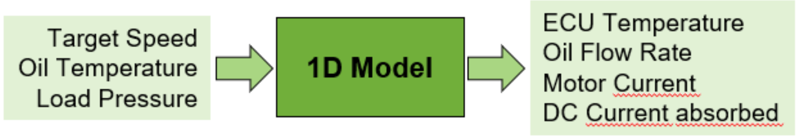
Use Case: eLOP

Model structure and validation



Multi-physics model





Model Validation based on **Experimental Data:**

- Wide range operating conditions considered in the validation process → **Generalization**
- Verified on the signals available from the pump communication → **Good accuracy**
- Based on physics laws and first principles → **Interpretability**

Model validation

Multi-physics 1D pump model, validated on real experimental data

Use Case: eLOP
Virtual Sensors – Outputs

4 inputs from pump

- $Speed$
- T_{NTC}
- I_{Phase}
- V_{DC}

Thermal → Temperature of single components

T_{Magnet} $T_{Windings}$ $T_{Mosfets}$
$T_{Inductor}$ T_{RPP} T_{OVP}
$T_{DC-Link}$ T_{Shunt} $T_{Motor\ Housing}$
$T_{PCB,Flange}$ $T_{PCB,Cover}$ $T_{Oil\ Out}$

Hydraulics/Mechanical → Pump hydraulic performance

$Torque$ Q_{Oil} P_{Oil}

Electronics → Currents/Voltages

V_d I_d $V_{DC-Link}$
V_q I_q $I_{DC-Link}$
I_{DC} $BemfMag$ p_f

Several outputs

These can be either implemented
- **on edge**
- **in cloud**

These are the most relevant for the pump operation. ($T_{Oil\ Out}$, Q_{Oil}, P_{Oil})

These are the most relevant for RUL estimation. ($V_{DC-Link}$, $I_{DC-Link}$)

Only 4 inputs… …….. inserted into the model, generate several outputs

Use Case: eLOP

Virtual Sensors – Development

Validated **Simulation model (AMESim)** → Generate dataset 4414 points (DoE) — **Training data**

Experimental Data acquisition → 332 **test** points — **Test data**

Available signals (Features)

Speed	T_{NTC}	I_{Phase}	V_{DC}
2500 RPM	35°C	18 A	24 V
…	…	…	…
2000 RPM	63°C	26 A	24 V

Virtual Sensors →

Target signals

Q_{Oil}	T_{Oil}	P_{Oil}
15 L/min	30°C	0.5 bar
…	…	
9 L/min	59°C	2 bar

Train and Test **Machine Learning** regression models:

1. Polynomial Regression
2. Gaussian Process Regression
3. Neural Network

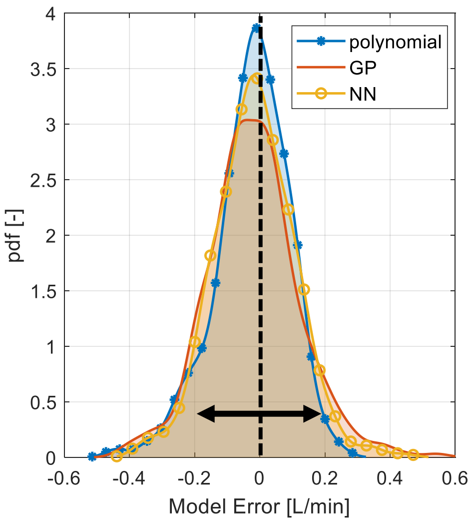
Training and learning phase is foundamental to get reliable results

Use Case: eLOP
Virtual Sensors – Test

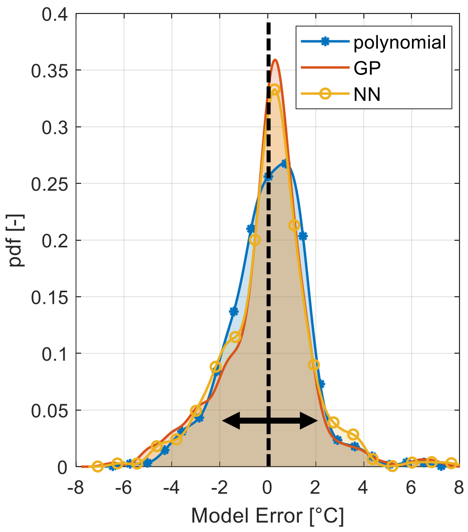
Performance of the trained algorithms is compared on experimental data:

- All sensors are **centered** (zero mean error)
- **Variability** is in line with expected accuracy

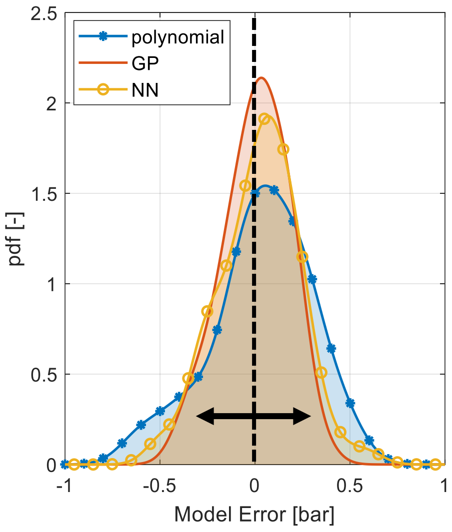
Flow Rate [L/min]



Oil Temperature [°C]



Oil Pressure [bar]



Prediction **accuracy** for each model in terms of RMSE:

	Poly.	GP	NN
$Q_{Oil}\ [L/min]$	**0.11**	0.14	0.13
$T_{Oil}\ [°C]$	**1.61**	1.79	1.76
$P_{Oil}\ [bar]$	0.29	**0.19**	0.21

Performance is aligned with expectations

Use Case: eLOP

Virtual Sensors – Deployment

@ VHIT - offline

Data Collection
test benches +
simulation

Model Training

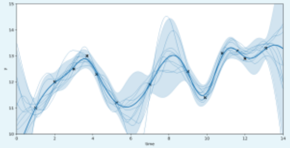
@ Cloud Level

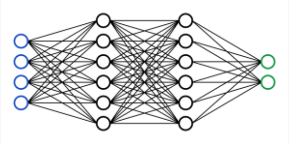
Communicate signals to Cloud

Cloud Compute

Deploy models in Cloud

Gaussian Process



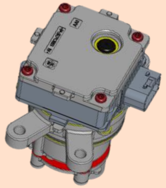


Neural Network

- Fine tuning available
- Remote control
- Cloud connection required
- Complex and expensive models

@ Physical Level

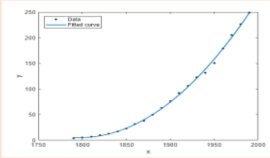
On Road Inputs

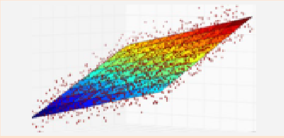


Edge Compute

Port models in Edge

Polynomial Regression





Map-based estimation

- No fine tuning
- No cloud connection neede
- Immediate answer
- Cheap and simple models

Use Case: eLOP
Take aways

- Digital Twins can be applied also at component levels
- They allow the substitution of physical sensors with virtual sensors, with technical and economical benefits
- Virtual sensors can be used to predict several parameters, with an high accuracy
- The use of Digital Twins is compatible either with edge or cloud applications
- State of Health (SoH) and Residual useful Life (RuL) can be predicted

THANK YOU!

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