huberGroup

VIRTUAL SENSORS –

SUBSTITUTION OF AUTOMOTIVE SENSORS BY ARTIFICIAL NEURAL NETWORKS

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INDUSTRIE PREIS 2010
KATEGORIESIEGER

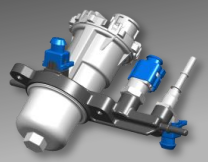
CONTENT

- Huber Group Company Profile
- Idea 2 Concept
- Artificial Neural Networks (ANN)
- SCR-Systems: Virtual NO_x-Sensor
- DPF-Systems: Virtual PM-Sensor
- Conclusion

Huber Group: Range of Services

Business Fields

Engineering
Hardware | Software | Mech. Design | Prototyping | Application

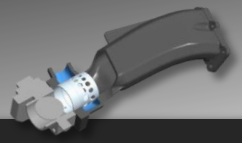


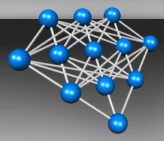
Testing
Equipment | Durability Testing | Test vehicles

Production
Electronic Manufacturing | Mechanical Assemblies

Systems / Products

Emission Reduction	EGR | SCR | DPF | Fuel Injection | Emission Relevant Components
Automotive Control Systems	Electronic Control Units | Diagnostic tools | Sensors | Actuators
Innovations	Virtual Sensors | AUTOSAR | SimuFuel® | Alternative cDPF-Regeneration





IDEA 2 CONCEPT

- Current emission concepts are based on:
  - Cost-intensive sensors (No_x-Sensor etc.)
  - Highly sophisticated modelling
  - Map-based parameterization
- Idea:
  - Using ANN instead of physic-based modelling

IDEA 2 CONCEPT

- Current Scenarios:

I. SCR – Systems

- Substitution of NO_x-Sensor (upstream SCR-catalyst) by ANN

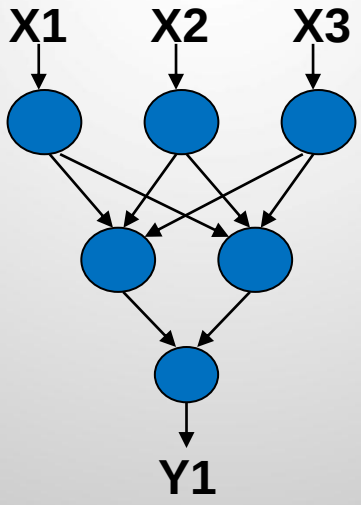
II. DPF – Systems

- Virtual PM-Sensor instead of soot raw emission model

and many more

SCHEMATIC DESCRIPTION OF A SIMPLE NEURAL NETWORK

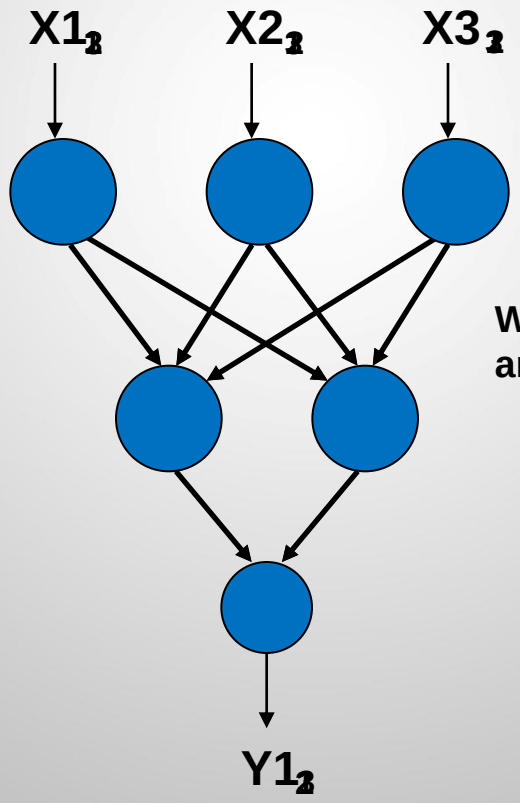
- The neural network describes the interconnection of artificial neurons
- Each neuron represents a simple arithmetic unit
- The neural network forms a connectionist system
  → Interaction of many interconnected single units
- A neural network is able to learn by example – it is trained in a target-oriented manner to fulfil its task
- The aim is to use the association ability of the neural networks to be able to determine a target variable, using the “knowledge” from real and not trained input variables



Neurons in a simple neural network

Learning Process

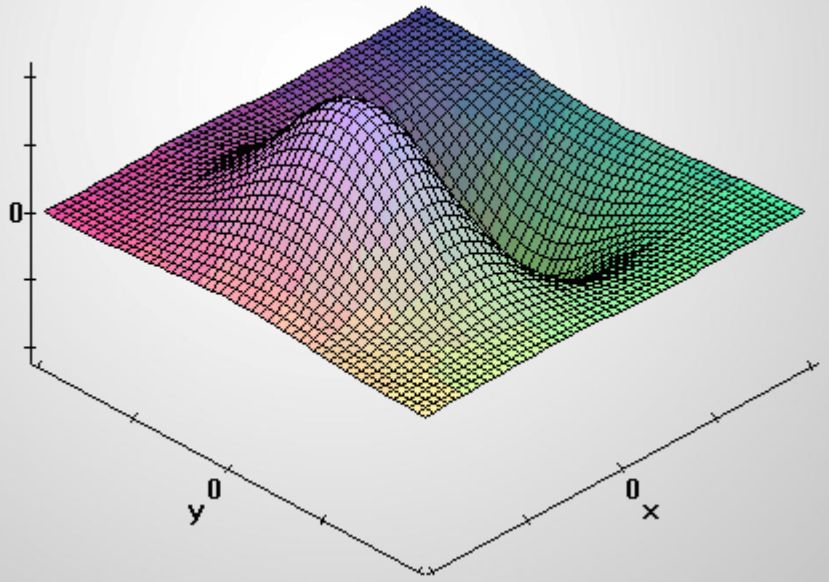
- Learning is to be understood as optimizing the weighted connections between single neurons;
- The “knowledge” of a neural network is stored in its weighted connections
- Supervised learning includes one output vector per input vector, on which the weighted connections are optimized



Weighted connections are trained

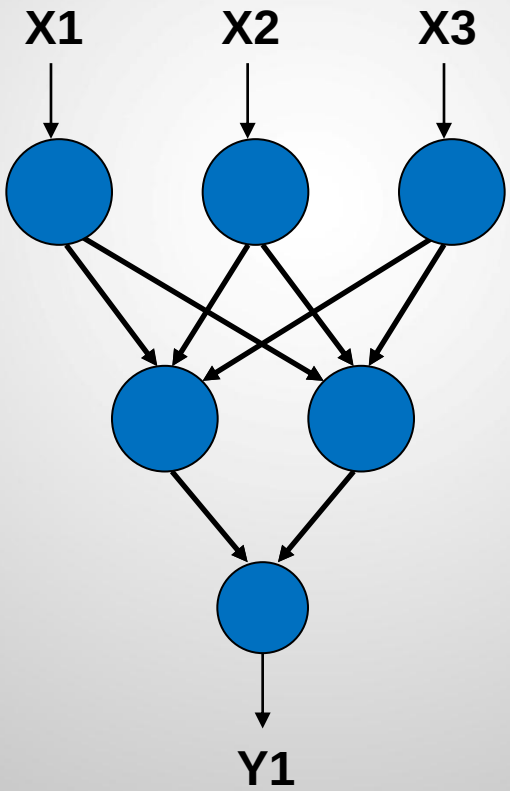
Learning Process

- The aim of the learning process is to reduce the global error to a minimum
- The error for a neuron with two weighted inputs can be displayed as error surface
- The learning algorithm is expected to achieve the global error minimum



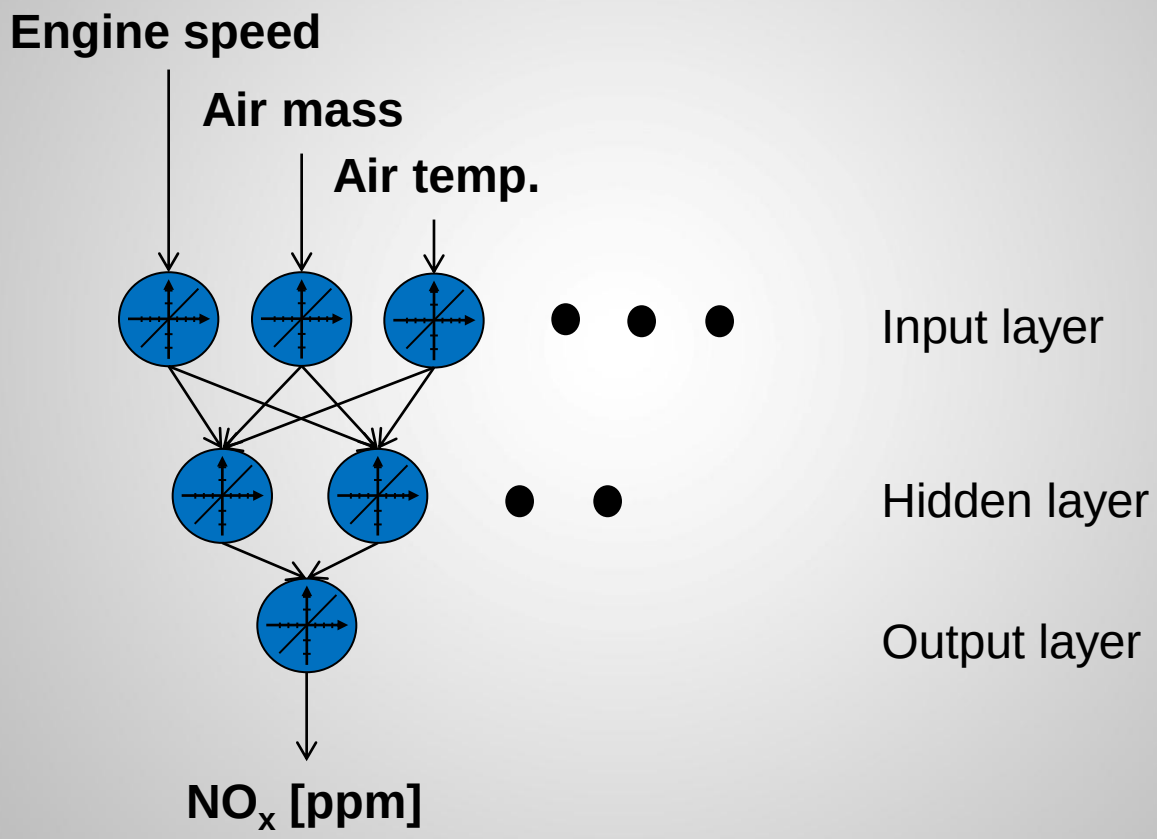
USE OF A TRAINED NETWORK

- Input data under real operating conditions are generated to a new output inside the network structure by the trained weights and activation functions
- Each neuron describes a simple function (linear function, TanHyp…)



After training weights are fixed

Example: Neural Network Structure



I. SCR – System / Substitution of NO_X-Sensors

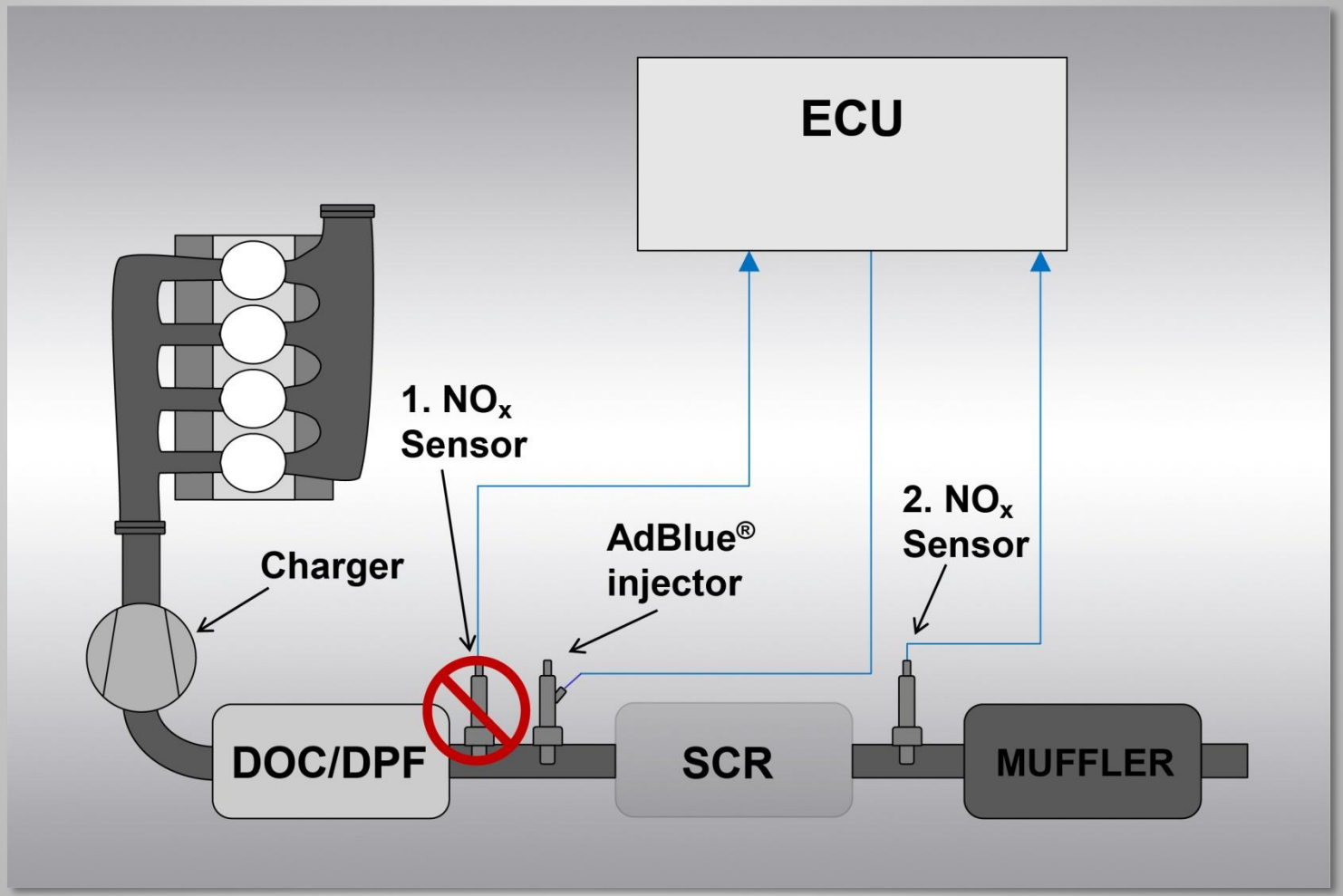
- Motivation: Cost reduction because the Pre-Cat-No_x-Sensor becomes redundant

  Reduced calibration costs through the use of already available test data

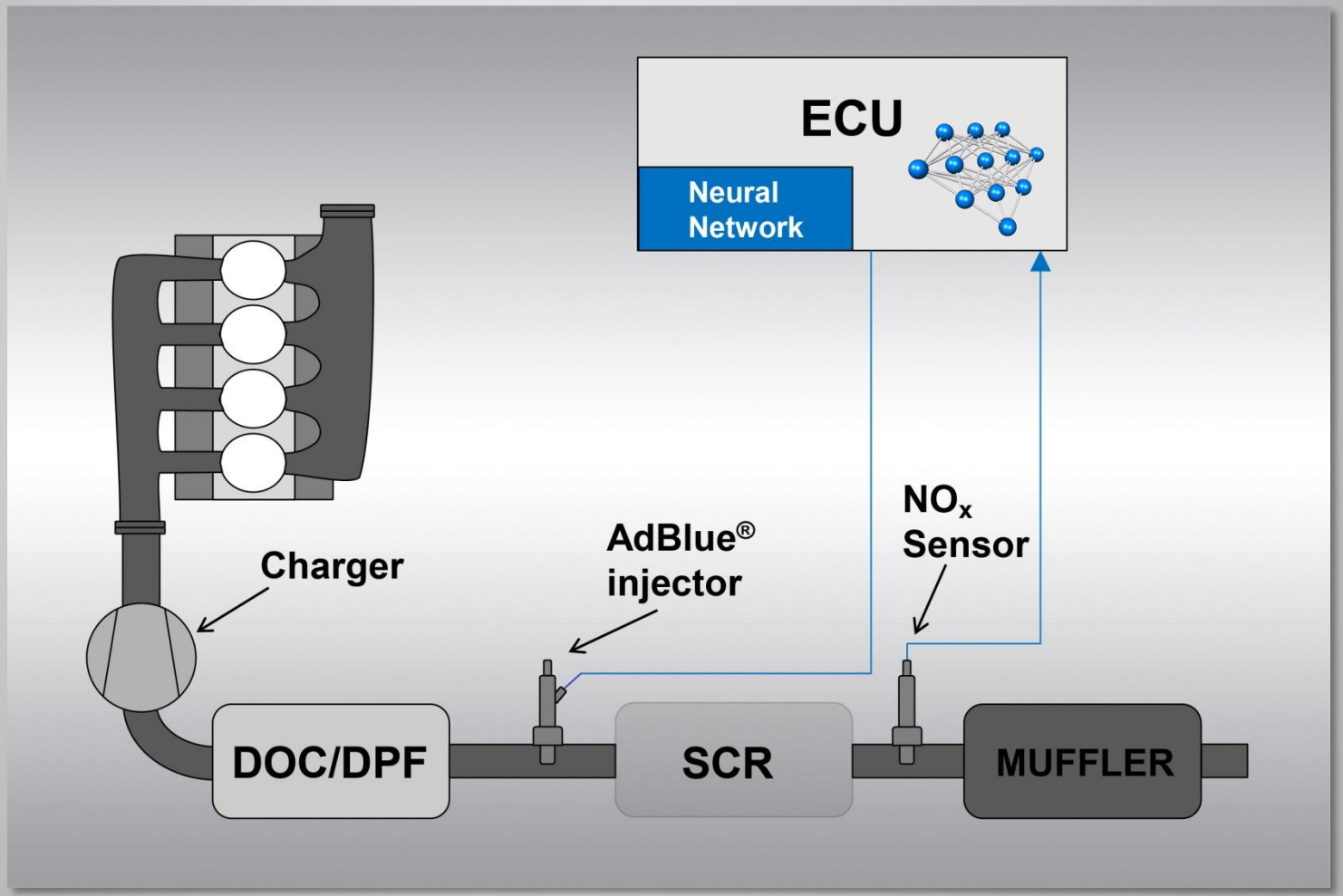
- Result: ECU or embedded code generating No_x-concentrations in real-time depending on the vehicle and operating conditions by using a trained neural network

- Reference: NO_x-Sensor (e.g. Continental or NGK)

CONVENTIONAL SCR-SYSTEM



SCR-System with Neural Network



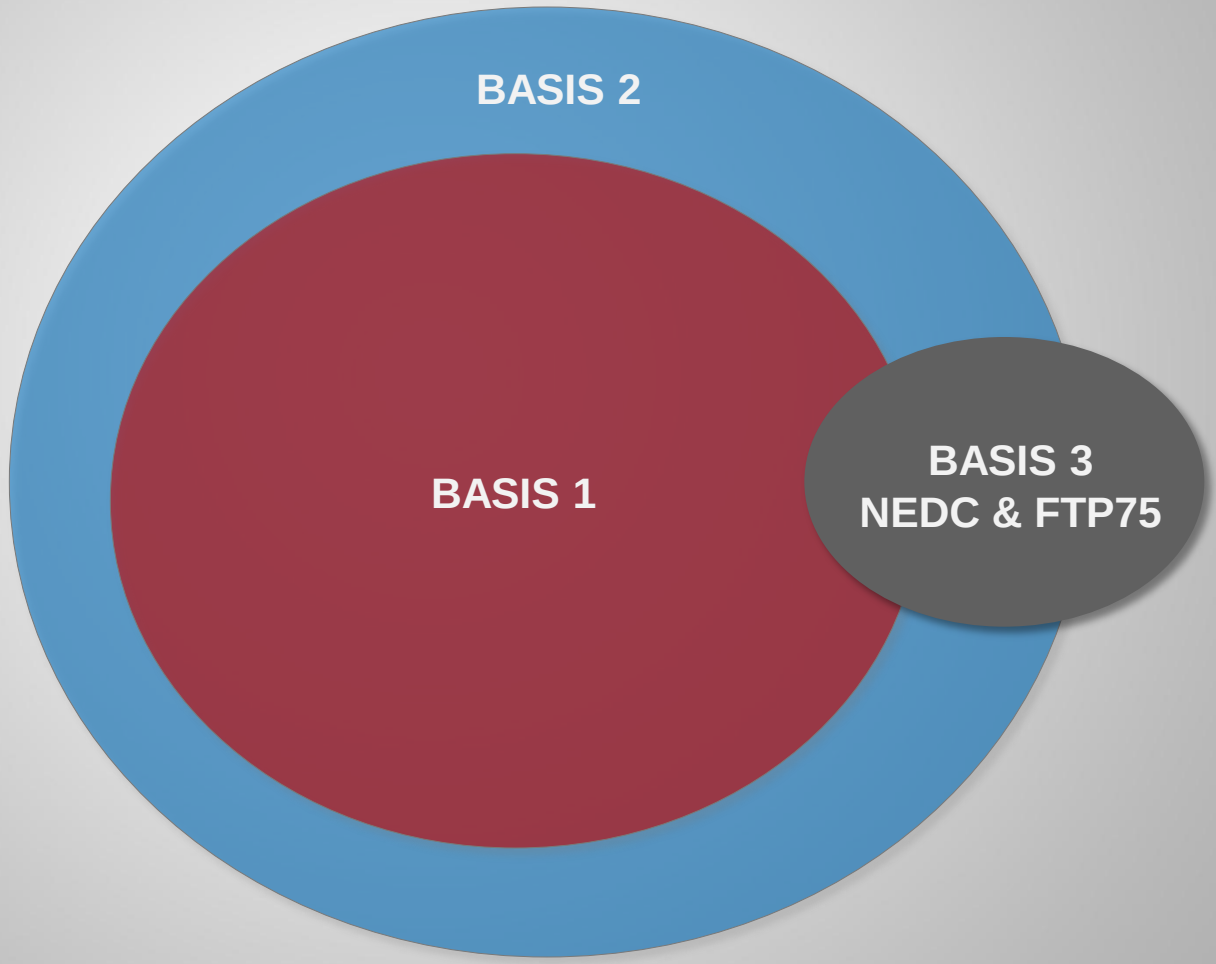
VIRTUAL NO_X-SENSOR / DEVELOPMENT MILESTONES

- Determination ANN ✓
  - Optimal network structure for problem definition
- Adjustment of learning algorithm ✓
  - Problem oriented learning algorithm
- Creation of suitable training data sets ✓
  - Methods for specific data sourcing from available test data
- Integration of the trained network in an add-on control unit ✓
  - Tests have been successfully completed
- Validation of results ✓

Sample Data Sets for Training

- **BASIS 1**
  - Composite data set (diverse routes: city, country road, highway ~ 4h)
- **BASIS 2**
  - BASIS 1 plus NEDC & FTP75 test cycles
- **BASIS 3**
  - NEDC & FTP75 Test cycles

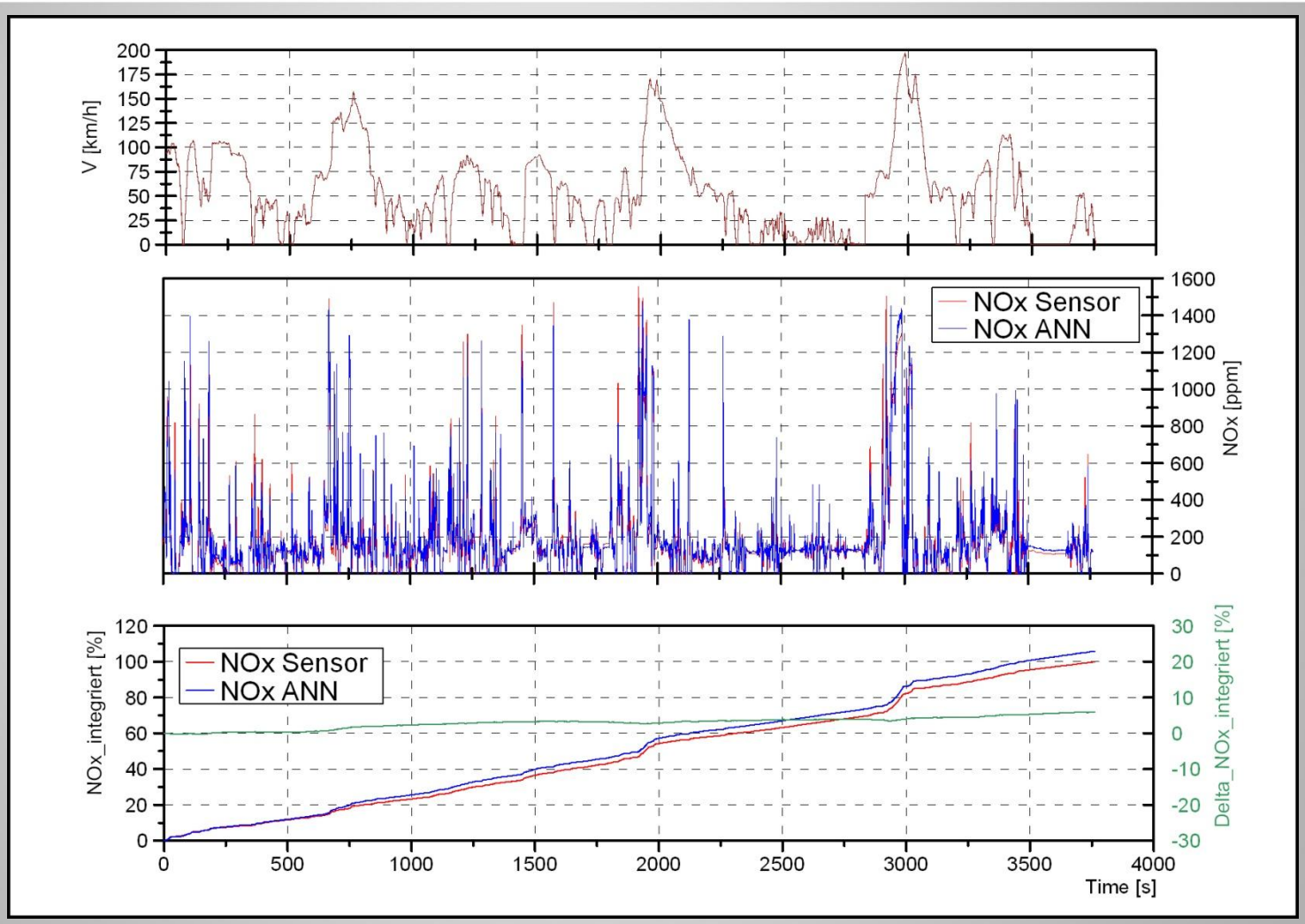
Sample Data Sets / Qualitative Overlap



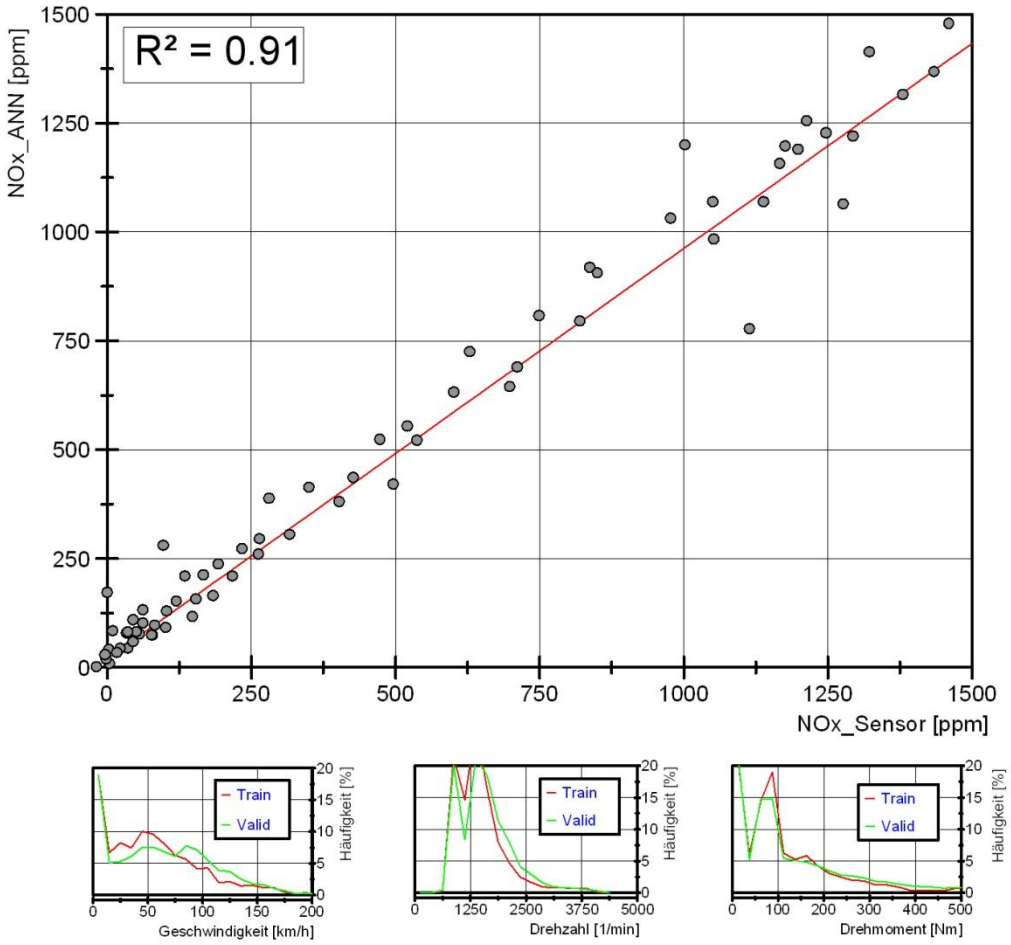
Sample Data Sets for Validation

- **VALID 1**
  - A part of the training data set BASIS1 not used for training
- **VALID 2**
  - Mixed single runs (city, country road, highway)
- **VALID 3**
  - NEDC Cycle

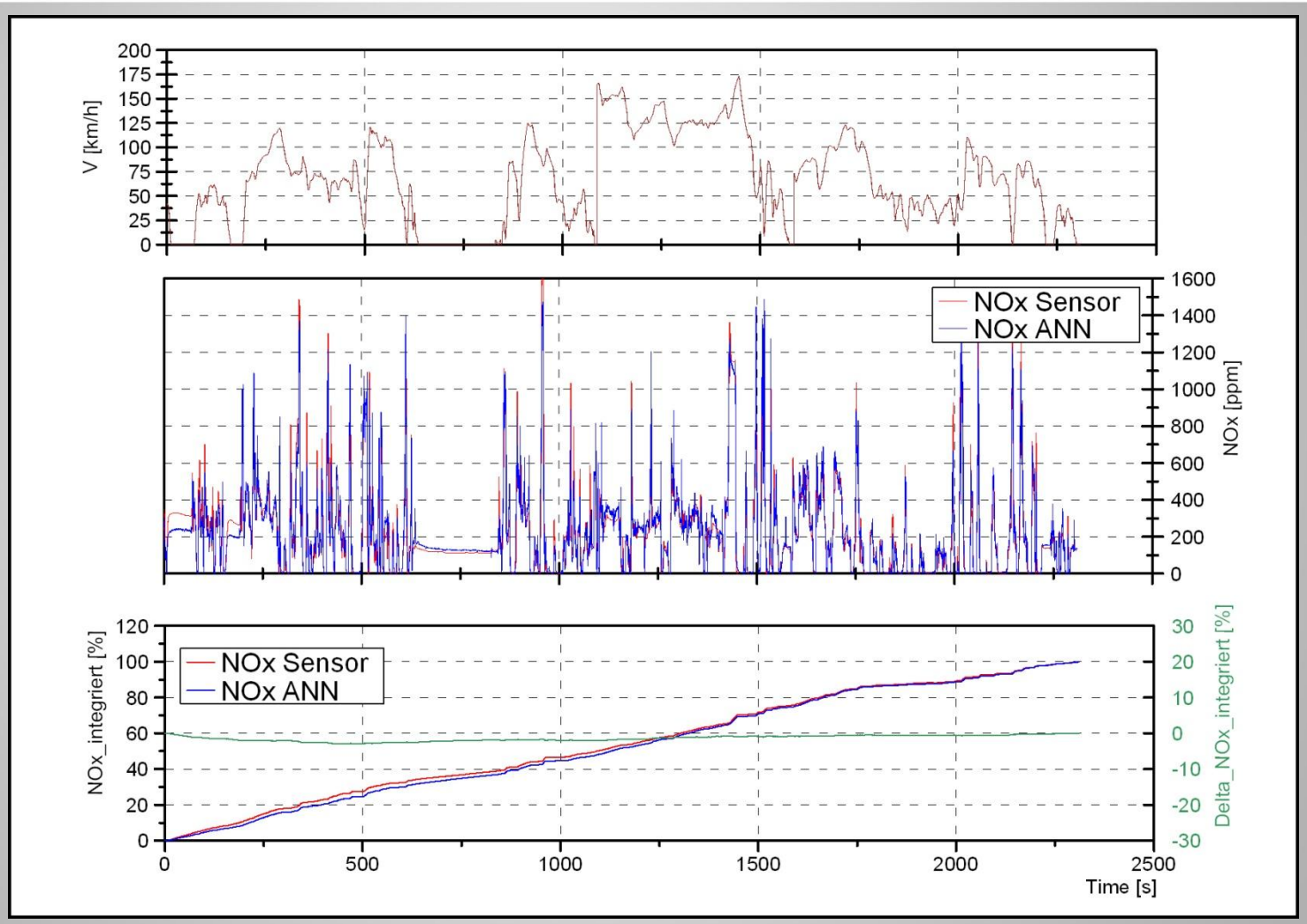
Validation Example / Results of mixed drive 1



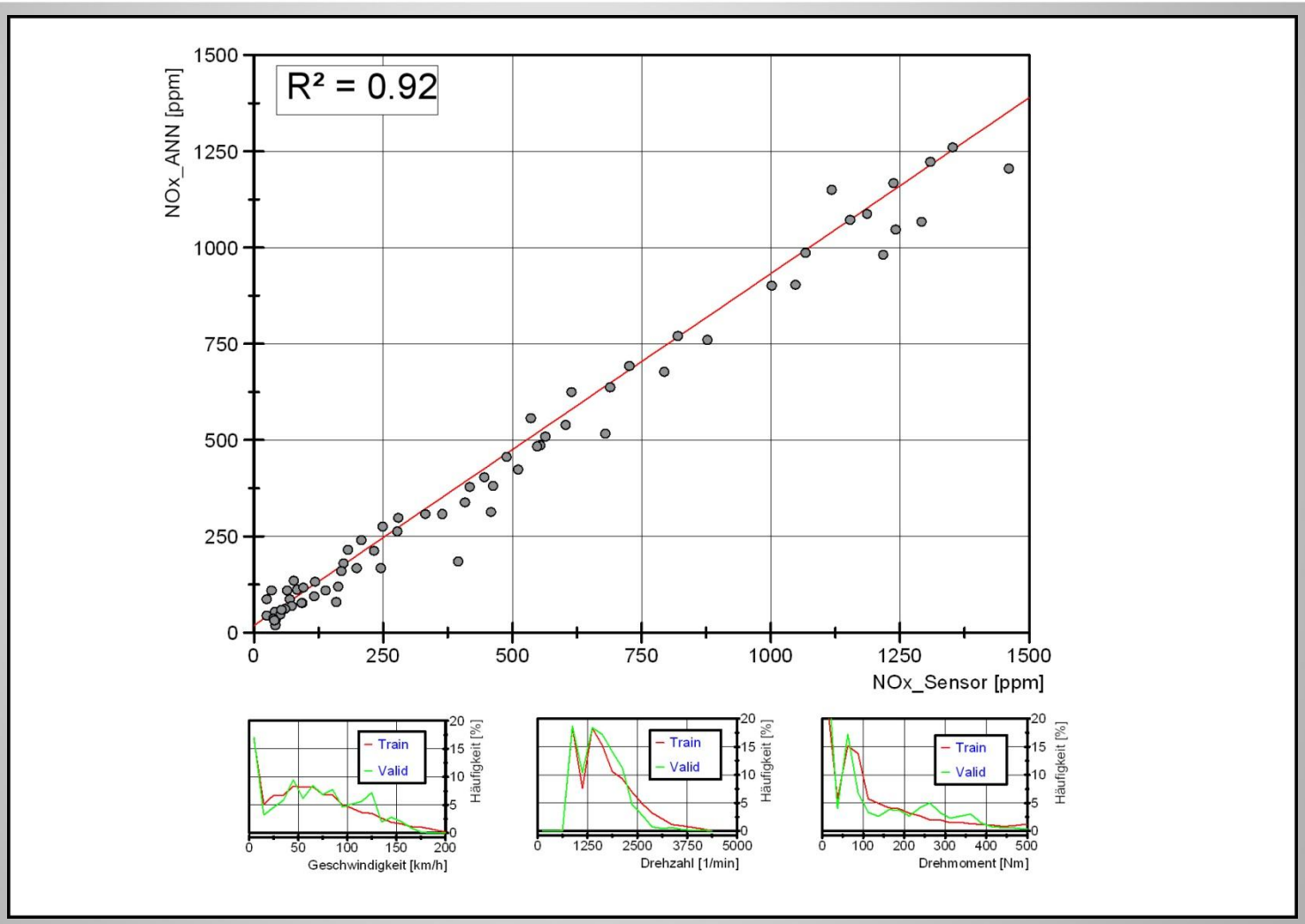
Validation Example / Results of mixed drive 1



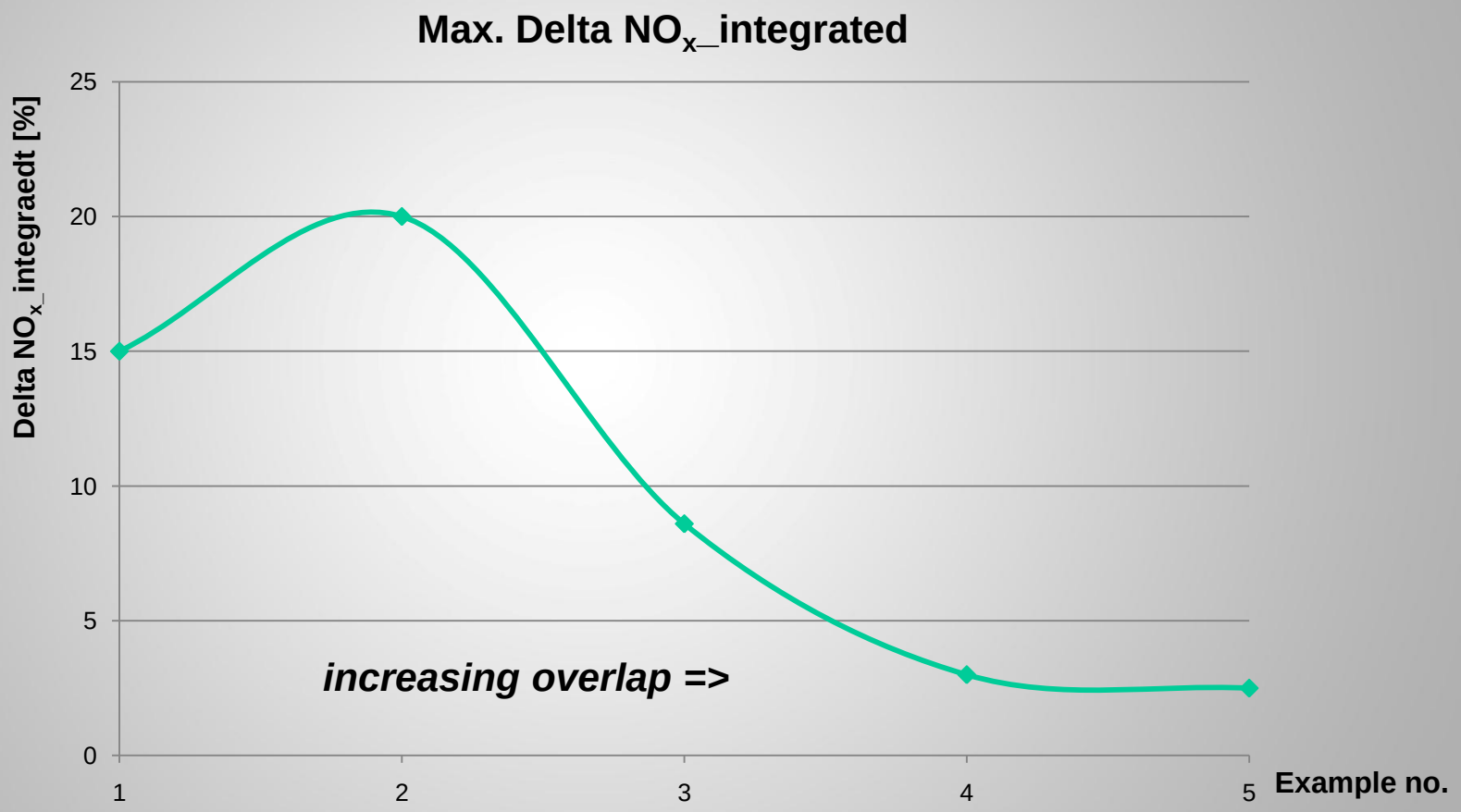
Validation Example / Results of mixed drive 2



Validation Example / Results of mixed drive 2



Influence Overlap Ratio (Validation to Training data)



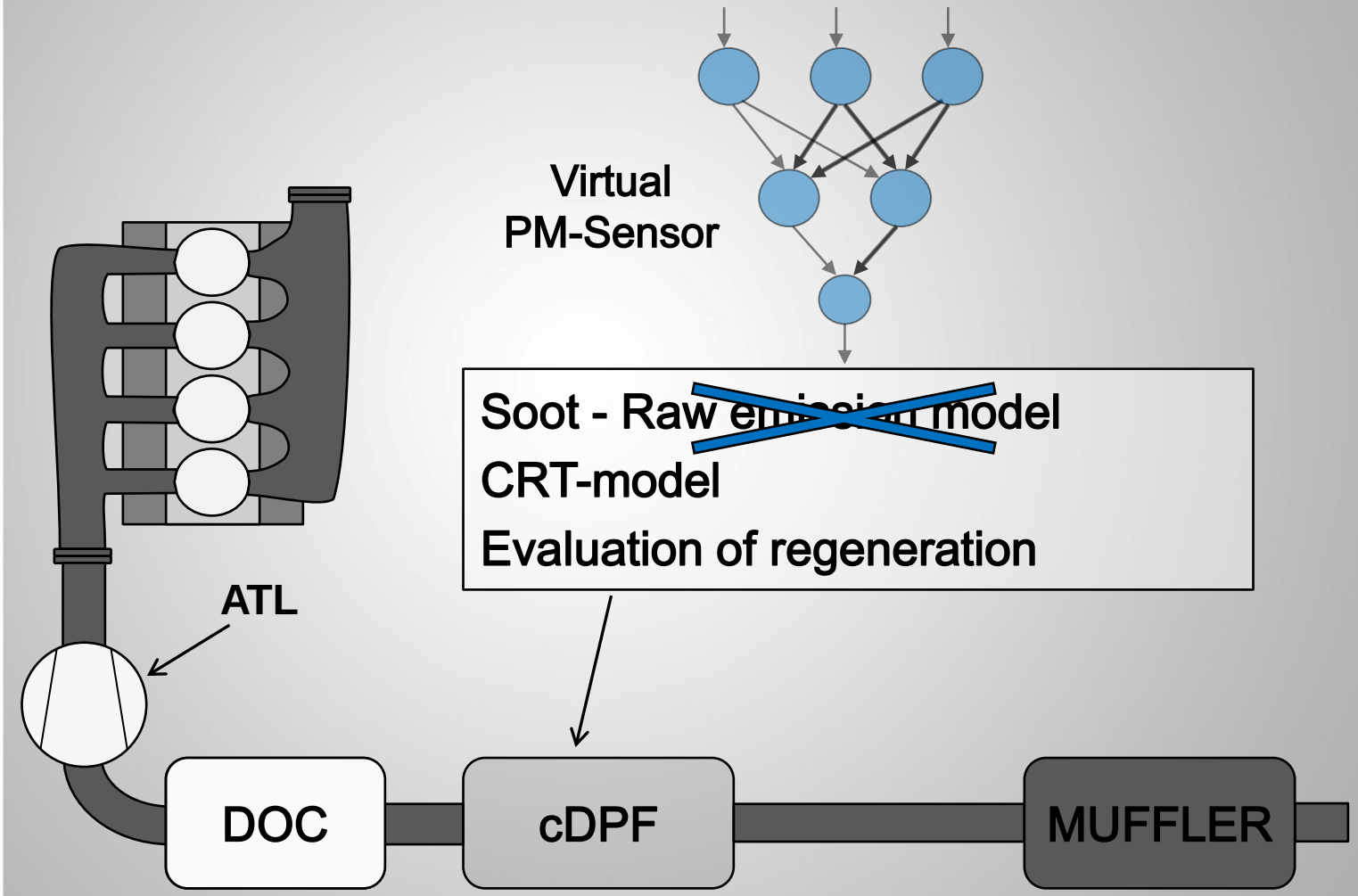
Integration of a trained Network in a Control Unit

- Memory requirement << 100 Kbyte
- Computing time depending on network structure << 100 ms
  (with a 16bit-controller)
- In modern automotive system environment (Tricore / 32bit) much faster

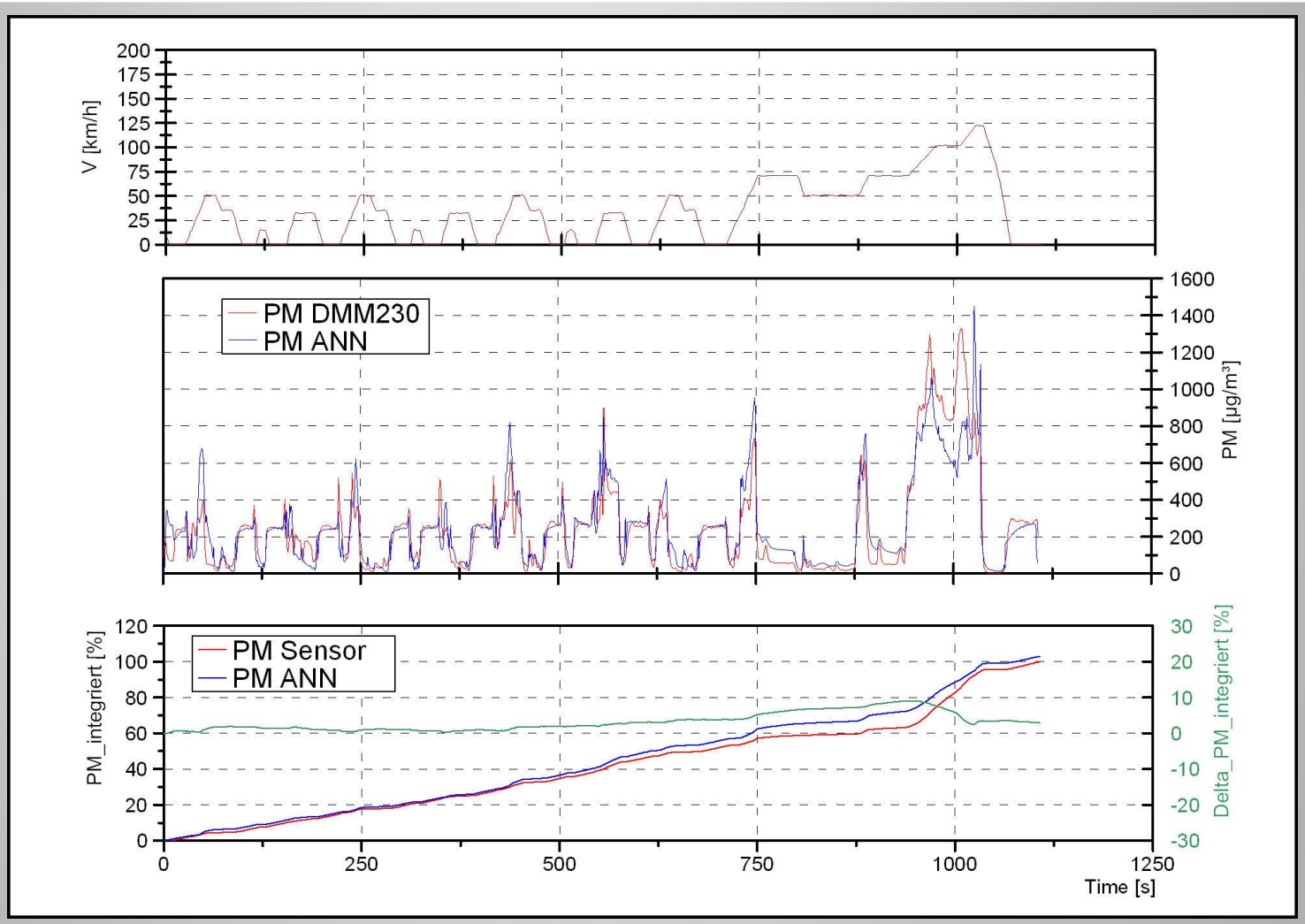
II. Virtual PM-Sensor

- Motivation: Optimization of PM-regeneration without any complex and error-prone soot model
- Intention: Online determination of the PM-raw emissions via ANN and implementation of this “Virtual PM-sensor” into the DPF-regeneration strategy
- Reference: Online measurement of PM with Dekati DMM230

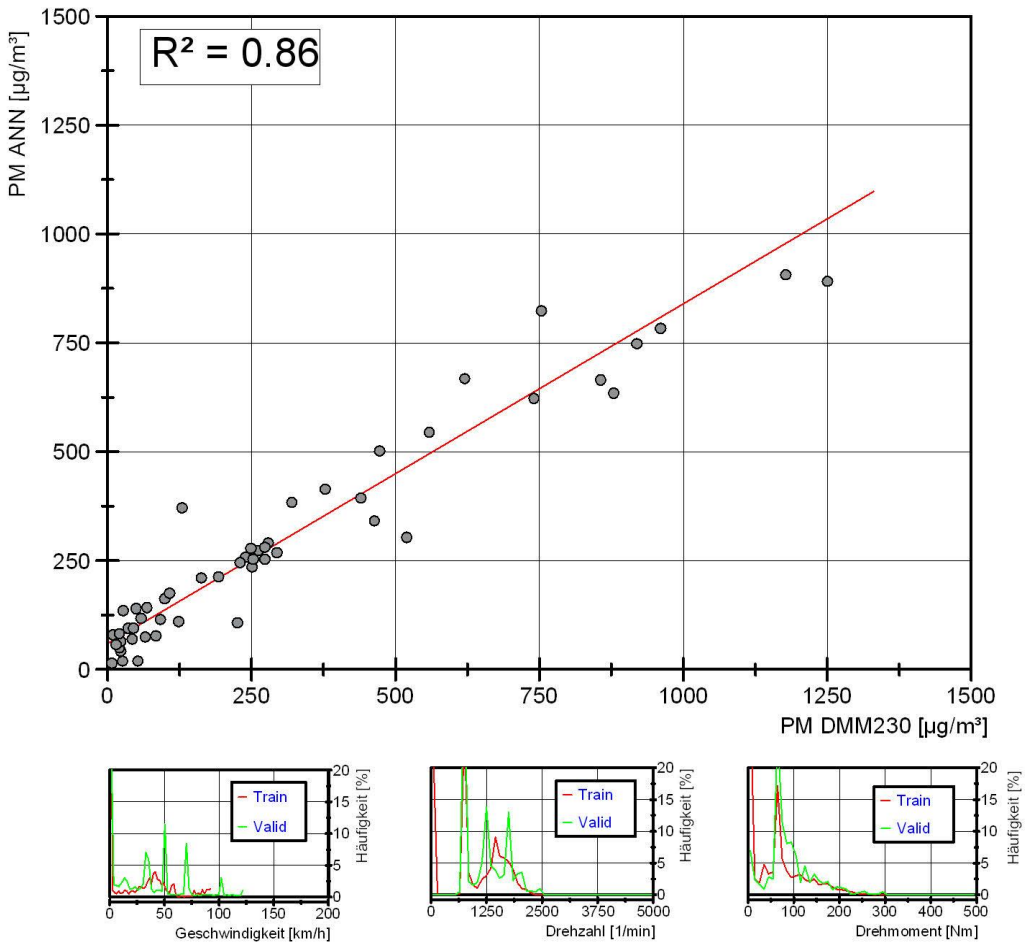
cDPF-System



Validation / Results for Train: FTP75 – Valid: NEDC



Validation / Results for Train: FTP75 – Valid: NEDC



Next Steps

- PM-emission measurements in road tests with DMM230
- Development of a method to create training data sets
- Optimization of ANN-structure
- Determination of learning algorithm

CONCLUSION

- ANN offer a large potential to substitute physical sensors
- Virtual sensors allow cost optimization concerning calibration efforts compared to model-based solutions
- ANN allow “mathematical solutions”, based on real test data, when multi-dimensional systems are getting too complex or prone to error
- Especially dynamical behaviour of ANN outperforms model-based approaches

THANK YOU FOR YOUR ATTENTION