Statistical Modeling and Optimization Approaches for Development of Fuel-Efficient Vehicles

\[ y(\bar{x}) = \sum_{i=1}^{N} C_i \cdot e^{-\frac{1}{2} \sum_{i=1}^{D} \frac{(x_i - \bar{x})^2}{r_i^2}} \]

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− About ETAS

− Challenges of today’s ECU Calibration & Engine Development

− Model based Calibration

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Leading Provider of Solutions and Services for Embedded Systems

- ETAS with over 850 associates is part of the Bosch Group
- Present in 13 countries with 23 offices
- ETAS subsidiary ESCRYP'T is a specialist for embedded systems security

**ETAS Customers and Domains**

- Trusted by OEMs, tier one and ECU suppliers, as well as engineering service providers:
  - Commercial Vehicles
  - Automotive
  - Heavy Duty Engines
  - Railway
  - Powertrain
  - Construction Machines
  - Consumer Electronics
  - Off-Highway

**ESCRYP'T Customers and Domains**

- The ESCRYP'T customer base includes:
  - Automotive
  - Mobile Machines & Transportation
  - Energy
  - Consumer Electronics
  - Mobile Devices
  - Industrial Automation
  - Financial & Government Logistics
  - Health Care
## Corporate Profile

Our Solutions Portfolio

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Challenges of today’s ECU Calibration & Engine Development

Stringent Regulations

- From 2012:
  - CO₂: 130 g CO₂/km

- Target starting from 2020:
  - CO₂: 95 g CO₂/km

- Nitrogen oxide and particle emissions:
  - EURO 3 (1999)
  - EURO 4 (2005)
  - EURO 5 (2009)
  - EURO 6 (2014)

- CO₂ emissions NEDC graph:
  - EU-fleet limit value
Classical calibration procedure: Full factorial variation of all combinations

⇒ Exponential increase with variable valve timing (VVT)

Without VVT:  ~ 250 MP

~10h

Engine with 1 variable Camshaft:  ~2,500 MP

~ 100h

Engine with 2 variable Camshafts:  ~25,000 MP

~1000h
Challenges of today’s ECU Calibration & Engine Development

Conflicting targets

Operating Range:
• Speed
• Load

Engine Parameter:
• Injection Timing
• Ignition Timing
• Fuel Pressure
• Exhaust Gas Recirculation
• Exhaust Camshaft
• Intake Camshaft
• Swirl Valve

Complex Interactions

Example: Modern Gasoline Engine

Replacing the engine by a mathematical model:
\[ y(\bar{x}) = \sum_{i=1}^{N} C_i \cdot e^{-\frac{1}{2} \sum_{i=1}^{D} \frac{(x_{il} - y_i)^2}{\sigma_i^2}} \]

Conflicting Targets

Targets:
• Consumption/CO₂
• Emissions:
  • Soot / Particle
  • NOₓ
  • HC
  • Stability (CoV)
  • Noise
  • Exhaust-Temperature
  • ...

Classical Procedure:
\[ \Rightarrow \] Full variation of all input parameters result in exponential increase of measurement effort!

Virtual Calibration with ASCMO:
\[ \Rightarrow \] Creation of an engine model based on few specific measurements
\[ \Rightarrow \] Optimization of the calibration parameter based on the model (manual or with optimizers)
Agenda

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– Challenges of today’s ECU Calibration & Engine Development
– Model based Calibration
– Case Study
Model based Calibration
From Lab to Math

Measuring at the Real Engine

Calculation of an Engine Model

Calibrate at the Virtual Engine

- ECU Parameter
- Emission
Model based Calibration
Main elements and requirements

Test planning
- Robust
- Scalable
- Easy to use

Modeling
- Highest possible accuracy
- Automated model calculation
- No specific mathematical expertise necessary

Map optimization
- Global: for whole driving cycles
- Considering map-smoothness and gradients
# Model based Calibration

## Principle and advantages of Statistical machine learning methods

### Polynomials or Neuronal Nets

**Principle:**
- Search in a given class of functions (polynomial, neuronal net, ...)
- Fit the model parameter by experts and validation measurements

**Disadvantages:**
- Limited flexibility & danger of over-fitting
- High expertise and assumptions necessary

### Statistical machine learning methods

**Principle:**

\[
y(\vec{x}) = \sum_{i=1}^{N} C_i \cdot e^{-\frac{1}{2} \sum_{i=1}^{D} (x_i - z_i)^2}
\]

- Automatic determination of the most likely function

**Advantages**
- High flexibility without assumptions or expertise
- Gives local confidence interval (model variance)
- Robust against outliers

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**Modeling a complex 1-D signal with classical DoE-Models („Advanced Polynomials“)**

**Training Data**

**Model Prediction**

**Model Variance**

**Validity not supported**

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**Modeling a complex 1-D signal with new statistical machine learning methods**

**Training Data & Model Prediction**

**Model Variance & Validity**

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**Model based Calibration**

**Data from Gasoline Engine**

**Benchmark:**
Comparison of two different neuronal nets from commercial tools against ASCMO

**Example:**
Torque-modelling for a gasoline engine with variable in- & outlet-cam in the whole operating range (speed/load)

**6 Parameter:**
speed, load, 2 cams, AFR and ignition

**Shown:**
Evolution of model-error depending on number of training data:
Neural Net: black + red
ASCMO-approach: blue

⇒ **Neural Net:** insufficient accuracy even with > 1000 training data points
⇒ **ASCMO:** sufficient accuracy reached with 300 training data points
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**Case Study**

**Challenges I/II**

**Parameters:**
- Engine speed
- Injection quantity
- Start of injection
- Charge pressure
- Air mass
- Rail pressure
- Swirl flap
- Variable valve drive
- Low pressure EGR
- Exhaust gas damper

**Quantity and position:**
- Pre-injections
- Post-injections

**Target variables:**
- Fuel consumption
- Exhaust gas emissions
- Response behaviour
- Noise emissions
- Power characteristics

**Boundary conditions:**
- Component protection
- Legal specifications

**Optimization of multiple criteria trade-off**

- Emissions
- Acoustics
- Fuel consumption

Source: Volkswagen
Broad operating region:
Vehicle types: Compact car to SUV
Variants: Eco / Comfort / Sport
Transmission: Manual/Automatic

Vehicle types: Compact car to SUV
Variants: Eco / Comfort / Sport
Transmission: Manual/Automatic

Emissions/fuel consumption
NO\textsubscript{x} = 0.12 g/km
HC = 0.03 g/km
Part = 0.001 g/km
CO\textsubscript{2} = 99 g/km

Source: Volkswagen
Results:

- By using the global engine model with ASCMO the fuel consumption could be reduced by 2 – 4%.
- Reduce particulate emission of a diesel engine by adding a post injection to an existing calibration concept without increasing of fuel consumption.
- Classical approach would require at least 8 weeks for the necessary 10 parameter but with the use of ASCMO global model with 400 data points could be optimised in 1.5 days.
- With ETAS ASCMO, application engineers are able to use DoE independently.
- Since the launch of ETAS ASCMO, the number of DoE users has been increasing rapidly.

Source: Volkswagen
Statistical Modeling and Optimization Approaches for Development of Fuel-Efficient Vehicles

Thank you
Muchas gracias
谢谢
Tack så mycket
Děkuji
धन्यवाद
Mille Grazie
Merci
Hvala
sağ olun
감사합니다.
有難うございました
Спасибо!
Kiitos
Дъякую
Vielen Dank