Closing the loop in engine control by virtual sensors

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Message

Actually obvious:

• Closing the loop requires measuring the target variables – no commercially available sensors do or will in the next future
• Virtual sensors offer substantial advantages in terms of price and reliability

Logic, but less obvious:

• The design of a virtual sensor for engine control is not trivial

Unexpected:

• The real problem are the setpoints
• Going from heuristical tuning to systematic optimization requires models. **Virtual sensors are just this – and already in the right form.**
• Mean value models seem to be the wrong approach for control system design
Overview

- Engine control and sensors
- Virtual sensor design
- Sensors vs. virtual sensors
- Optimization by virtual sensors (still in work)
- Conclusion and outlook
Framework

• Work performed in projects of the Linz Center of Competence in Mechatronics and Austrian Science Foundation

• Support by BMW Motors

• Tests on a dynamic engine test bench (AVL APA) under PUMA Open and ISAC, BMW M47Ü2 Diesel Engine, test vehicle 320d
Engine control and sensors

- The single most important engine control problem is a nonlinear optimal problem with constrained inputs and finite horizon

\[
\min_{u(t), t \in [0,1120]} \int_0^{1220} \dot{q}_{fuel}(t) dt
\]

Under the boundary conditions:

\[
M(u(t)) = M_{ref}(t) \quad u(t) \leq u(t) \leq \bar{u}(t) \\
\int_0^{1220} \dot{q}_{Xi}(t) dt \leq \bar{Q}_{Xi}
\]

Torque necessary to track the speed

All manipulated variables

Bounds on pollutants
Numerical solution seems possible but

\[ \min_{u(t), t \in [0, 1220]} \int_0^{1220} \dot{q}_{fuel}(t) dt \]

Under the boundary conditions:

\[ M(u(t)) = M_{ref}(t) \]
\[ u(t) \leq u(t) \leq \bar{u}(t) \]
\[ \int_0^{1220} \dot{q}_{Xi}(t) dt \leq \bar{Q}_{Xi} \]

~ Measured
Dependency on \( u \)
unknown

Can be estimated

For production: no idea!

Furthermore: computing intensive, slow
Restating it as a tracking problem

Transforms the optimization problem into a time reference

Forces the value to follow the references

Estimates unmeasured quantities

Leap of faith...
Motivation

Basic idea of the standard solution

- Single SISO control loops (sometimes with feedforward) are not optimal
- Reference chosen empirically, usually interpolating steady state optimal points (in the sense of the optimal problem). How do you get the right ones?

Combustion

Air path control

\[ \alpha \rightarrow FF \]

\[ C \rightarrow EGR \rightarrow VGT \]

\[ \text{Inj} \rightarrow \text{Thumble} \]

\[ w^* \rightarrow \text{Combustion} \rightarrow y \]
Tracking with original setpoints

Faster in transients

Tracking with reachable setpoints

Effect on emissions

Explicit MPC: NOx: 110  Opacity: 50
compare: original (non reachable) setpoints
Reference ECU: NOx: 100  Opacity: 100
Explicit MPC: NOx: 136  Opacity: 56
Commercial NOx sensors

Problems: cross sensitivities (but in some cases, like SCR, can be exploited) and especially start delay and magnesium poisoning
Virtual sensors

- Essentially models of the unmeasured quantity
- Two approaches
  - Simple models with error feedback (e.g. Kalman filters)
  - Simulation models (if possible, FIR to avoid integrator effect)
- Error-feedback approach requires appropriate measurement
- Simulation models require model: where from?
  - First principles?
  - Data?
Virtual sensor design

- ANN seem a sensible choice (universal approximators)
- However, universal approximators are not a sensible choice (not even for interpolation)
- Goal is not to approximate, but to discover!
Leap of faith

• Identification = hypothesis testing

"Leap of Faith: Search for global patterns in observed data to allow for data-driven interpolation" (Ljung)

• In other words: use physical knowledge, but otherwise expand the number of hypothesis

• Problem: curse of dimensionality

• Solution: balance act between generality and specificity

• Idea: data regularization

• Hardly expressable in mathematical terms, therefore algorithmic approach
Why not simple approaches?

Forward selection?

- Build a list of possible nonlinear variables NARX like)
- Test correlations
- Take the most important one
- Orthogonalize the rest
- Add the second important one
- Does not really work, parallel
  Testing of many hypothesis with almost equal fitness leads to random solutions
Procedure

Pre-Analysis:
Delay time estimation, system order estimation, variable selection

Signal conditioning:
Filtering, delay time removal

Evaluation function

Functional Basis

Optimization
Forward Selection

Result:
Compact analytical formula

Source:
L. del Re, P. Langthaler, C. Furtmüller, S. Winkler, M. Affenzeller: NOx Virtual Sensor Based on Structure Identification and Global Optimization, SAE 2005
GP life cycle

- GP produces automatically programs, formulas are programs
- 1st Lifecycle:

  Population of programs (formulas)
  - Select parents according to their fitness
  - Evaluate formulas
  - Generate new formulas
Crossover und Mutation in GP

- mutation und crossover work (without direction) through the exchange of sub-trees of formula structures
- selection step ist directional
Sensor equations

\[ NO_x(t) = -618075 + 1343.69 \frac{MAP}{q_f[0]} + 122687q_f[t] + 1773.99n_e[0] - 2237.22n_e[-6] \]

- 1411.65q_f[-1] + 985.414n_e[-1] - 0.4241MAF^2_{[0]} + 0.0468 \frac{MAP[0]}{q_f[0]} - 3644.35q_f[0] \]
- 0.9736n_e[0] - 0.6043n_e[-1] - 1.9056n_e[0]n_e[-1] - 0.00009n_e[-6]n_e[-1] + 1.3913n_e[0]n_e[-1] + 36.8357q_f[0] + 0.0005n_e[-1]n_e[0] + 0.0002n_e[0]n_e[-1] + 2.2976n_e[0]n_e[-6] + 0.0002n_e[0]

- 0.0031MAF^2_{[0]}q_f[0] + 0.1059q_f[t]MAF^2_{[0]} - 1.9615 \frac{MAP[0]}{q_f[0]} n_e[0] + 0.0006 \frac{MAP[0]}{q_f[0]} n_e[0] \]
- 0.0007n_e[-6]n_e[-1] + 0.0004n_e[0]n_e[-1] + 3.1911n_e[0]q_f[0] + 0.4816n_e[-6]q_f[0] - 0.0014q_f[0]n_e[0] \]
- 0.0025q_f[t]n_e[-1] + 0.0632q_f[t]n_e[0] - 169.906q_f[t]n_e[0] + 0.1931 \frac{MAP[0]}{q_f[0]} n_e[-1] \]
- 2.9012q_f[-1]q_f[0] + 0.0021q_f[-1]n_e[0]

\[ PM(t) = +56471.2 - 50.3297MAF(t) + 6.2108 \frac{MAP(t)}{q_f(t)} + 5269.49q_f(t) + 53.5576n_e(t - 43) \]

- 4832.23q_f(t - 1) - 266.622n_e(t - 1) - 144.394q_f(t - 13) + 46.1934n_e(t - 13) - 0.0297n_e(t - 43)^2

+ 0.2581n_e(t - 1)^2 + 0.0145n_e(t - 2)^2 - 0.0175n_e(t - 1)n_e(t - 13) - 11.0518q_f(t)q_f(t - 1)

- 0.0109 \frac{MAP(t)}{q_f(t)} n_e(t - 13) + 0.1933 \frac{MAP(t)}{q_f(t)} q_f(t - 13) - 0.0453n_e(t - 43)n_e(t - 13)

+ 4.2878n_e(t - 43)q_f(t - 1) - 4.5072q_f(t)n_e(t - 43) + 0.0013q_f(t)n_e(t - 43)^2

- 0.0012q_f(t - 1)n_e(t - 43) - 0.0329 \frac{MAP(t)}{q_f(t)} n_e(t - 43) + 0.0366 \frac{MAP(t)}{q_f(t)} n_e(t - 1)

- 0.0004q_f(t)n_e(t - 1)^2 + 0.0004q_f(t)n_e(t - 2)^2 - 5.8414MAF(t)q_f(t) + 6.0555MAF(t)q_f(t - 1)

- 0.7923 \frac{MAP(t)}{q_f(t)} q_f(t - 1) - 0.0001n_e(t - 1)n_e(t - 2)^2 + 0.139MAF(t)n_e(t - 1)

- 0.0681MAF(t)n_e(t - 43)
Validation NOx

Comparison between measured and estimated data validation
Comparison virtual sensor vs ANN

- Only standard ECU signals
- Validation with FTP-75, warm engine
- **Model inputs:** engine turning speed, injection quantities and timing, boost pressure, air coolant and exhaust temperatures, fresh air mass, environment pressure
- **ANN:** max. 2 hidden Layers, max. 25 nodes/Layer
Comparison virtual sensor vs ANN
Comparison virtual sensor vs ANN
Opacity [%]

time [s]
Error distribution

- Standard ECU-Measurement signal
- FTP-75, warm engine

Error distribution for GP based approach almost symmetrical
Possible uses of virtual sensors

- Cold start
- Fall back sensor
- FDI
- Resampling
- **Model for optimization**
Validity test: MPC results are reproduced correctly

Table 3. Comparison of the cost function

<table>
<thead>
<tr>
<th>MAF / MAP</th>
<th>Objective</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECU</td>
<td>measured</td>
<td>measured</td>
</tr>
<tr>
<td>MPC</td>
<td>measured</td>
<td>measured</td>
</tr>
<tr>
<td>MPC</td>
<td>measured</td>
<td>computed</td>
</tr>
<tr>
<td>Optimal infeasible</td>
<td>computed</td>
<td>computed</td>
</tr>
<tr>
<td>Optimal feasible</td>
<td>computed</td>
<td>computed</td>
</tr>
</tbody>
</table>

Table 4. Increase of VGT Activity

<table>
<thead>
<tr>
<th>VGT Activity</th>
<th>EGR Activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>ECU</td>
<td>100 %</td>
</tr>
<tr>
<td>MPC</td>
<td>122.3 %</td>
</tr>
<tr>
<td>Optimization</td>
<td>122.3 %</td>
</tr>
</tbody>
</table>

Figure 9. Cumulative Values of NOx
Conclusions

• Virtual sensors are feasible also for very complex systems

• They will hardly work alone but cross coupling with other sensors can be exploited to track system changes

• They can be used to close the loop from two sides:
  – They can reduce the requirements on hard sensors, in particular, they can overcome critical operating phases (like engine warm up)
  – They can be used to optimize the strategy
  – Final tuning will be still necessary, but not indispensable
The right way?

- Plausibility check: what is the alternative? CAMEO
- CAMEO is converging to the same kind of models…
- This can lead to a change of paradigms:
  - Instead of making the best out of your parts
  - make the best out of your system
  - to this end, start by describing in a control suitable way the most difficult part (combustion)
  - and then use them to optimize the control system design