DoE for Engine and Testbench Systems

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Overview

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- Example 1: Optimal DoE for the calibration of a water brake dynamometer
- Example 2: Optimal iterative input design for identification of a Diesel engine air path model
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Introduction
Introduction I

- Research on DoE and optimal input design for the identification of nonlinear systems is a well discussed topic
- Led to the development of specialized tools in the automotive field, now commercially available
- Important factor in improving the calibration speed as well as the performance of engine control systems
Standard DoE tools are based on the estimation of optimal parameters for a given control structure.
Introduction III

- Standard DoE tools are based on the estimation of optimal parameters for a given control structure. For the efficient calibration of model-based controllers, it is important to minimize the measurement effort for model identification.

  Example 1: Optimal DoE for the calibration of a water brake dynamometer.

- There are, however, situations in which it might be better not to assume any special structure, for instance in the case of unknown nonlinearities.

  Example 2: Optimal iterative input design for identification of a Diesel engine air path model.
Example 1: Optimal DoE for the calibration of a water brake dynamometer
Water brake at the combustion engine test bench

- Objective: Operate a combustion engine like in a passenger car or a heavy duty truck

- Equivalent: Tracking of a torque and speed profile (at the crank shaft of the engine)

- State-of-the-art utilization of water brakes
  - Water brakes are used in stationary testing
  - HOWEVER: Mechanical design also allows transient cycles
Inverse torque control

- Objectives
  - Tracking of desired dynamometer torque
  - (Fulfill constraints on temperature at outlet / temperature difference between inlet and outlet)

- Feed forward control
  Calculation of both valve positions from desired torque by inverting the nonlinear static plant behavior

- Feedback control
  Compensation of uncertainties and disturbance effects caused by model-plant mismatch, change of operating point, etc.
Waterbrake model

- For the feed forward part of the controller a model of the water brake is necessary
- Wiener model structure (for fixed speed)
Describing the nonlinear waterbrake map I

- Accurate representation of nonlinear map is essential

- Standard procedure: Grid measurements (e.g. 11x11 = 121 points for 3 speeds = 363 points)

- Grid measurements are time consuming and expensive → goal is to reduce the measurement effort without a significant loss of accuracy

- Utilize a function with limited parameters to approximate the map, e.g.
  - Polynomial function (High number of parameters required for good approximation)
  - Arc tangent function
  - …
Describing the nonlinear waterbrake map II

- Function for fixed speed

\[ T_D = \theta_1 \arctan \left( \theta_3 + \theta_4 \gamma_i + \theta_5 \gamma_o + \theta_6 \gamma_i^2 + \theta_7 \gamma_o^2 + \theta_8 \gamma_i \gamma_o \right) + \theta_2 + \varepsilon \]

- 8 parameters only

- Open questions:
  - What is a suitable number for measurement points?
  - What is an adequate choice for the DoE criterion?
- **DoE criterion**

  - Minimize the maximal error on the operating range
    \[
    \min \max_{\gamma_i, \gamma_o \in [0,100]} \left( T_D - \hat{T}_D(\gamma_i, \gamma_o) \right)^2
    \]

  - This cost function represents the G-optimal design – which for $N \rightarrow \infty$ is equal to the D-optimal design

\[
\min \det \bar{M}_F^{-1}
\]

\[
\bar{M}_F = \frac{1}{N} \left( \sum_{k=1}^{N} \frac{\partial \hat{T}_D(\theta, \gamma_i(k), \gamma_o(k))}{\partial \theta} \right|_{\theta=\theta_0} \frac{\partial \hat{T}_D(\theta, \gamma_i(k), \gamma_o(k))}{\partial \theta^T} \right|_{\theta=\theta_0}
\]
Suitable number of measurement points

- The number of measurement points can be selected according to the density function of an optimal continuous design. Only at some points in the input space the density is higher than zero. These points represent the candidates for measurements.

- The optimal density function can be generated via an asymptotic algorithm
Considered function is nonlinear in the parameters \( \rightarrow \) optimal points depend on the parameter values

\[
T_D = \theta_1 \arctan \left( \theta_3 + \theta_4 \gamma_i + \theta_5 \gamma_o + \theta_6 \gamma^2 + \theta_7 \gamma^2 + \theta_8 \gamma_i \gamma_o \right) + \theta_2 + \varepsilon
\]

Two approaches exist to overcome this dependency

- **Sequential DoE**: Do initial DoE with assumed parameter values, identify the parameter values and define an optimal design with these parameter values
- **Robust DoE**: Assume that the parameters are in a limited range and optimize the design such that it is optimal for all parameter values in this range

A robust approach was sufficient for the water-brake problem

\[
\min \sum_{\theta \in \Theta} \max_{\gamma_i, \gamma_o \in [0,100]} \left( T_D - \hat{T}_D(\gamma_i, \gamma_o, \theta) \right)^2
\]
Optimal DoE for nonlinear static maps IV

- Robust design which approximates continuous design space with 16 points
- Optimal for a wide range of speed
- No online optimization needed

- Maximum error: 41 Nm
- RMS error: 16 Nm
Example 2: Optimal iterative input design for identification of a Diesel engine air path model
Test example setup

- Production 2 liter EU4 common rail Diesel engine
- Dynamical engine testbed
- Development ECU
- Real-time hardware in the loop system for data acquisition and control

<table>
<thead>
<tr>
<th>Quantity</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$MAP$</td>
<td>Mean absolute pressure in the intake manifold</td>
</tr>
<tr>
<td>$n_{me}$</td>
<td>Engine speed</td>
</tr>
<tr>
<td>$O_{2,exh}$</td>
<td>Exhaust manifold oxygen concentration</td>
</tr>
<tr>
<td>$t_{MI}$</td>
<td>Start of main injection</td>
</tr>
<tr>
<td>$P_{rail}$</td>
<td>Common rail pressure</td>
</tr>
<tr>
<td>$m_{tot}$</td>
<td>Totally injected fuel mass per cycle</td>
</tr>
<tr>
<td>$X_{EGR}$</td>
<td>EGR valve position</td>
</tr>
<tr>
<td>$X_{VGT}$</td>
<td>VGT actuator signal</td>
</tr>
</tbody>
</table>
NARX model class

System approximation by a polynomial NARX model:

\[ y(k) = f^l(x(k)) + e(k) = \theta_0 + \sum_{m=1}^{l} \sum_{i_1 \cdots i_m = 1}^{n} \theta_{i_1 \cdots i_m} \cdot \prod_{p=1}^{m} x_{i_p}(k) + e(k) \]

with

\[ x(k) = [y(k-1) \ldots y(k-n_y) \ u_1(k-1) \ldots u_1(k-n_{u,1}) \ u_2(k-1) \ldots u_2(k-n_{u,2}) \ldots u_r(k-1) \ldots u_r(k-n_{u,r})]^T, \ u(k) \in \mathcal{U} \subseteq \mathcal{R}^r \]

\[ n = n_y + \sum_{i=1}^{r} n_{u,i}, \ e(k) \sim \mathcal{N}(0, \sigma^2) \]

structure is **linear in parameters**: Complexity increases exponentially:

\[ y(k) = \varphi(k)^T \theta + e(k) \]
\[ \theta = [\theta_0 \ \theta_1 \ldots \theta_n \ \theta_{11} \ldots \theta_{nn} \ldots \theta_{n^l}]^T \]
\[ \varphi(k) = [1 \ x_1(k) \ldots x_n(k) \ x_1(k)x_1(k) \ x_1(k)x_2(k) \ldots x_n(k)x_n(k) \ldots x_n(k)^l]^T \]

\[ \sum_{i=0}^{l} \frac{(n+i-1)!}{i!(n-1)!} \]
Optimal input design

- Least squares parameter estimation

\[ \hat{\theta}_N = \arg \min_{\theta} \sum_{k=1}^{N} \left( y(k) - \varphi(k)^T \theta \right)^2 = \left( \Phi^T \Phi \right)^{-1} \Phi^T Y \]

- Input design is employed to generate an input sequence \( u^{*N} \) that excites the system in the whole operating range \( \mathcal{U} \) and reduces the variance of the estimated parameter vector.

\[ \text{var} \hat{\theta}_N \triangleq \sigma^2 \left( \Phi^T \Phi \right)^{-1} = \frac{\sigma^2}{N} \overline{M}^{-1} \]

- Minimize the inverted normalized observed information matrix

\[ \overline{M} = \frac{1}{N} \Phi^T \Phi \]
Sequential generation of D-optimal input sequences

- D-optimality:
  \[ u^*_N = \arg \max_{u^N} \det \tilde{M}(u^N) \]

- For static systems an optimal input sequence can be approximated iteratively using the Wynn algorithm
  - Add that point which increases the determinant of the information matrix most
  - The prediction quality of a model can be evaluated by means of the normalized prediction variance:
    \[ d(\xi, u) = \frac{N}{\sigma^2} \text{var}(\hat{y}(u)) \]
    \[ = \phi^T(u) \cdot \tilde{M}(\xi)^{-1} \cdot \phi(u) \]
    - The point that increases det(M) most is the one with the highest prediction variance:
      \[ u^*(k+1) = \arg \max_{u \in \mathcal{U}} d(\xi(k), u) \]
The Wynn algorithm is extended to work also for dynamic systems.

Using the state vector x as free parameter for input design the description can be treated as static.

We have to look further to adapt all components of the state vector → optimization over a receding horizon:

\[ u^{h*}(k + 1) = \arg \max_{u(k+1...k+n_h) \in \mathcal{U}} \sum_{i=k+1}^{k+n_h} \sum_{i=k+1}^{k+n_h} d(\xi(k), x(i)) \]

First element of this sequence is applied to the system → similar to model predictive control.

Length of the receding horizon depends on the system

- For (N)FIR systems \( n_h = 1 \) is sufficient
- For (N)ARX systems similar guidelines as for model predictive control are given
  → select \( n_h \) larger than the slowest rising time.
Iteration loop to adapt the model structure

- The unknown nonlinear structure is approximated iteratively by increasing the polynomial degree of the NARX model.
- As a result, the necessary number of measurements can be minimized

1. Start with \( l = 1 \)
2. Online receding horizon input design for assumed model structure
3. Parameter identification with model pruning
4. Increase polynomial degree \( l = l + 1 \)
5. Online receding horizon input design for model structure considering already measured data
6. Validation with new data
7. If the model is a satisfactory approximation STOP, else add data to existing data and go to 3
Airpath model I

- Model inputs and outputs:

  - The MIMO system is represented by two coupled MISO systems
  - Selected dynamical order: 2 ($n_{u,l}=n_{y,j}=2$)

<table>
<thead>
<tr>
<th>Input variable</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$m_{\text{f,set}}$</td>
<td>mg/inj</td>
</tr>
<tr>
<td>$n_{\text{eng,al}}$</td>
<td>rpm</td>
</tr>
<tr>
<td>$EGR_{\text{pos}}$</td>
<td>%</td>
</tr>
<tr>
<td>$X_{\text{FGT}}$</td>
<td>%</td>
</tr>
</tbody>
</table>

Output variables:
- MAP: mbar
- $MAF_{\text{cyc}}$: mg/cyc

Intake Manifold
- MAP
- $O_{\text{2a}}$
- EGR
- Fuel Injectors

Swirl Valve
- MAP
- $O_{\text{2a}}$
- EGR
- Fuel Injectors

Exhaust Manifold
- MAP
- $O_{\text{2a}}$
- EGR
- Fuel Injectors

Compressor
- MAP
- $O_{\text{2a}}$
- EGR
- Fuel Injectors

Variable Geometry Turbine
- MAP
- $O_{\text{2a}}$
- EGR
- Fuel Injectors
Available computational power was too low for online input optimization for the selected dynamical orders of 2
- Input blocking
- For input design a sampling time of 0.5 s (blocking factor of 5) was selected

In order to avoid an unnecessary increase of the number of regressors, only physical meaningful candidates (only multiplicities with same time lags) were allowed

Iteration stopped at \( l=4 \) → led to a FIT-value for validation of over 98% for both MAP and MAF_{cyc}
Airpath model III

- Detail of the input sequences for the airpath model
Airpath model IV

- Model validation on standard driving cycle (NEDC):
PM emission model I

- Detail of identification sequence for the PM model:

- 6 considered inputs
- Optimal input design until polynomial degree 3 ($l=3$) lasted approx. 2 hours
PM emission model II

- Validation on the NEDC:

- Model shows general validity
- Room for improvement by more accurate measurement devices
Conclusions
Conclusions

- Example 1: Satisfactory application of robust DoE for the calibration of the nonlinear model of a water brake – measurement effort could be reduced by a factor of 8

- Example 2: The proposed iterative method provided sensible results by approximating general nonlinear systems by means of an NARX model

- Choice of data is the really critical step when doing identification of complex systems

DoE is the key issue to exploit complex (automotive) systems.
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http://desreg.jku.at