Institute for Design and Control
of Mechatronical Systems

Diploma Thesis:

Nonlinear Identification: NLPV Systems

Nichtlineare Identifikation mechatronischer Systeme

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Abstract

This thesis is to be concerned with the identification of linear, parameter-varying (LPV) systems.

In the first part of the thesis, the basics of LPV models are described in a short introduction. Then, an identification procedure developed by Fabio Previdi and Marco Lovera is investigated. They deal with SISO LPV systems with a scheduling variable which is identified and does not have to be measured. This variable is the ouput of a feed forward neural network, whos parameters are optimized in the algorithm. The optimization is done by minimizing a prediction error criterion with a separable least squares algorithm.

In the second part, a new identification algorithm is presented, which considers MISO LPV systems, where the scheduling variable is the ouput of a NARX model. This method consists of two steps:
First, a pure NARX model with polynomial nonlinearities formed of the input and output signals is identified. This problem can be solved using a standard linear least squares method. In order to keep the complexity of the model in a reasonable range, only relevant nonlieraities, according to a simulation error criterion, are considered.
In a second step, the relevant nonlinearities from the first step are used to form a scheduling variable. This NARX model with polynomial nonlinearities is combined with a linear model in order to get a LPV system. Since all parameters, both of the NARX and the linear model, have to be estimated at once, a nonlinear optimization algorithm has to be used. Here, a thrust region method from the matlab® optimization toolbox is used.

Finally, this new algorithm is tested on several simulation and application examples like the airpath, the exhaust gas return system, and the variable geometry turbine system of a diesel engine. For comparison, the mentioned systems were also investigated with other identification algorithms, especially the one from Previdi and Lovera.

Introduction: LPV Systems

State space description: $x_{k+1}=A(\delta_k)x_k+B(\delta_k)u_k$
$y_k=C(\delta_k)x_k+D(\delta_k)u_k$

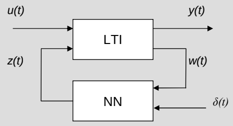
- system matrices depend on parameter-vector δ_k
- most identification algorithms assume that δ_k is measured online
- restrictions of absolute value and rate of change of parameter-vector

Previdi, Lovera:

Input - output description: $y(t)=a_1(t)y(t-1)+...+a_{n_a}(t)y(t-n_a)+b_1(t)u(t-1)+...+b_{n_b}(t)u(t-n_b)$

With the chosen parameter dependency on the scheduling variable z:
$a_i(t)=a_i^{(1)}+a_i^{(2)}z(t)$ $\quad b_j(t)=b_j^{(1)}+b_j^{(2)}z(t)$

scheduling variable is the output of a multilayer feed forward neural network:
$z(t,\eta)=f(w(t),\eta)=\tanh(\boldsymbol{\alpha}^T\tanh(\mathbf{W}w(t)+\boldsymbol{\beta}))$



Parameter estimation:
Parameters of the linear system θ and parameters of the nonlinear part η have to be estimated.
This results in a nonlinear optimization problem with the loss function:
$J_1(\theta,\eta)=\|\mathbf{y}-\Phi(\eta)\theta\|_2^2$

Optimization with separable least squares (SLS) algorithm:
- find initial value $\hat{\eta}$ for η
- find an estimation of θ with the linear least squares solution $\hat{\theta}=(\Phi^T(\eta)\Phi(\eta))^{-1}\Phi^T(\eta)\mathbf{y}$
- new loss function $J_2(\eta)=\left\|\mathbf{y}-\Phi(\eta)(\Phi^T(\eta)\Phi(\eta))^{-1}\Phi^T(\eta)\mathbf{y}\right\|_2^2$
- find an estimation $\hat{\eta}=\arg\min_{\eta}\left\|\mathbf{y}-\Phi(\eta)(\Phi^T(\eta)\Phi(\eta))^{-1}\Phi^T(\eta)\mathbf{y}\right\|_2^2$

Pros and cons:
- dimension of the nonlinear optimization problem is reduced from dim(θ) + dim(η) to dim(η)
- it is critical to find a good initial guess for η

NARX-NLPV model class

First step: identification of a polynomial NARX model

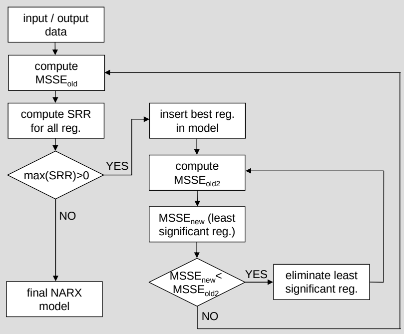
All regressors are rated with the simulation error reduction ratio (SRR)

$$SRR_j=\frac{MSSE(\mathcal{M}_i)-MSSE(\mathcal{M}_{i+1})}{\frac{1}{N}\sum_{t=1}^{N}y^2(t)} \qquad MSSE=\frac{1}{N}\sum_{t=1}^{N}\left(y(t)-y_{SIM}(t)\right)^2$$

Regressor with highest SRR value improves model $\mathcal{M}_i$ best

Iterative algorithm:
- compute SRR for all possible regressors (polynomial nonlinearities)
- insert best regressor in model
- compute MSSE for all regressors inside the model and eliminate least significant one if MSSE increases without it.
- recompute SRR values for all remaining regressors

Flow diagramm: NARX identification



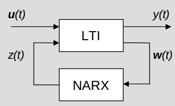
Second step: identification of a LPV model

Chosen regressors of step one form a scheduling variable $z(t,\eta)=\eta_1\text{Reg}_1+\eta_2\text{Reg}_2+...+\eta_{N_{Reg}}\text{Reg}_{N_{Reg}}$
parameters η have to be re-estimated

Regressors built with moving average of input/output signals to get a smooth scheduling variable

Linear system parameters depend on z
$a_i(t)=a_i^{(1)}+a_i^{(2)}z(t)$ $\quad b_j(t)=b_j^{(1)}+b_j^{(2)}z(t)$

Parameter estimation of both η and (a_i,b_j) in one step with nonlinear trust-region algorithm

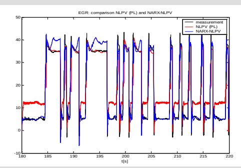


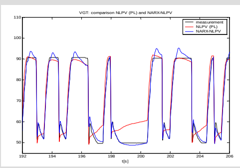
Pros and cons:
- trust-region algorithm is not so sensitive on initial values
- scheduling variable may have a physical meaning
- higher computational effort

Application example: Diesel Engine

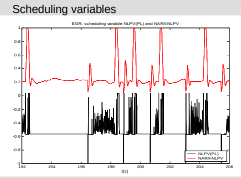
- EGR system: input: manipulated variable
output: actual value, position of valve
- VGT system: input: manipulated variable
output: actual value, position of turbine blade

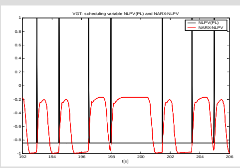
NARX-NLPV and NLPV class of Previdi, Lovera is compared





Scheduling variables



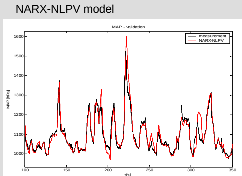


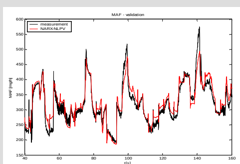
fit-values	NLPV-PL		NARX-NLPV	
	Identification	Validation	Identification	Validation
VGT	76,0	71,3	92,2	91,4
EGR	57,3	59,1	78,7	80,2

Application example: Diesel Engine Airpath

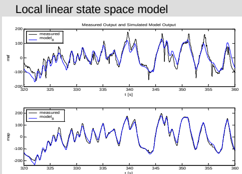
- Input signals: engine speed, injected fuel quantity, position of EGR valve, position of turbine blades
- Output signals: MAP … manifold air pressure
MAF … mass air flow

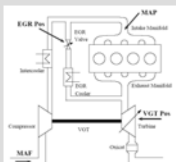
NARX-NLPV model





Local linear state space model





Comparison with fit-value: $fit[\%]=100\left(1-\frac{\sqrt{\sum_{t=1}^{N}\left(\hat{y}(t)-y(t)\right)^2}}{\sqrt{\sum_{t=1}^{N}\left(y(t)-\bar{y}\right)^2}}\right)$

Conclusions and Outlook

Conclusions

- a new identification algorithm for LPV models has been introduced
- the optimization with a trust region method is not sensitive on initial values
- multiple identifications with different initial values are not essential
- nonlinear systems can be approximated with LPV models
- smooth scheduling variable due to polynomial functions
- NARX identification has high computational effort, depending on number of inputs, data points and order of polynomial functions
- no significant improvement of model quality if order of polynomials functions exceeds three
- best results for NARX model with no moving average
- number of values for calculation of the moving average is essential for the quality of the NARX-NLPV model
- multiple identifications with different moving averages of the signals are recommended

Outlook

- physical interpretation of the identified scheduling variable with measurement data which was not used for identification should be investigated in detail
- the influence of the parameter which is used building the moving average signals should be investigated in detail
- some proposals could be introduced to speed up the NARX identification procedure