

CLOSED-LOOP IDENTIFICATION OF PLANTS UNDER MODEL PREDICTIVE CONTROL

by

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SUMMARY

The open-loop step testing approach, which is, typically, used in process identification for model-based predictive control (MPC), has some disadvantages. Closed-loop system identification is less intrusive than the open-loop approach and can reduce re-identification time considerably. If the process model is identified while the MPC controller is operating, safety, product quality and optimality problems will be avoided.

For above-mentioned reasons, multivariable closed-loop identification for use in MPC is studied. Relevant closed-loop approaches are reviewed and a closed-loop identification methodology for MPC controlled plants is chosen. Simulations and real process data are used to validate and evaluate this methodology.

Many estimation methods fail when applied directly to closed-loop data, because of correlation between the additive output noise and the plant input. However, the prediction error estimation method can still give consistent estimates in the presence of noise. Therefore, this method is utilised.

In open-loop a persistently exciting plant input ensures identifiability. This does not ensure identifiability in closed-loop. For identifiability in closed-loop either the feedback mechanism should be nonlinear or the reference signal should be persistently exciting. The inter-sampling approach, where the plant output is sampled at a higher rate than the control input, can also ensure identifiability. However, a variance simulation study shows that a model identified with this approach is imprecise when structured tests are not performed.

The direct closed-loop system identification approach, where only the plant output and input are used for identification of the plant, is employed. This approach works irrespective of the feedback mechanism, it ensures consistency and optimal precision, and it makes use of standard MATLAB functions.

In the simulation a multivariable MPC controlled plant is identified from closed-loop data. To evaluate the consistency of the methodology, the plant is identified for different controller settings and different added disturbances. Different methods for ensuring identifiability are also investigated. Together with the standard validation tests used in open-loop identification, models are compared to the open-loop identified model and the stability of the closed-loop systems are examined.

The simulation results show that the proposed methodology gives reliable results for the type of system disturbances and constraints used when structured tests are performed that

ensure persistently exciting reference signals and good signal-to-noise ratios. The results also show that imprecise models are usually identified when only relying on inter-sampling or the nonlinearity of the controller for identifiability.

A part of an industrial multivariable plant is also identified. No structured tests are performed on the plant. Logged data sets from normal operation are used in the identification. It is concluded that the open-loop identified model is not a good representation of the plant in closed-loop operation at the relevant time. Therefore, the results from the comparison between the open-loop and closed-loop identified models are unreliable.

From this experiment a preliminary conclusion is made that an unsatisfactory model will usually be identified from data measured under normal closed-loop control, because the reference signals are usually not persistently exciting and the signal-to-noise ratios are not good.

Keywords: closed-loop system identification, open-loop, model-based predictive control, multivariable, prediction error estimation method, methodology, identifiability, persistently exciting, nonlinear feedback, inter-sampling, validation, evaluation, variance, simulation, process data, signal-to-noise ratio.

SAMEVATTING

Die opelustraptoetsbenadering, wat tipies gebruik word in aanlegidentifikasie vir modelgebaseerde voorspellingsbeheer (MVB), het sekere nadele. Geslotelusstelselidentifikasie het 'n kleiner impak as die opelusbenadering en kan her-identifikasietyd aansienlik verminder. Indien die prosesmodel geïdentifiseer word terwyl die MVB beheerder in bedryf is, sal probleme met betrekking tot veiligheid, produk kwaliteit en optimaliteit vermy word.

Om bogenoemde rede word multiveranderlike geslotelusidentifikasie vir gebruik met MVB bestudeer. Toepaslike geslotelusbenaderings word hersien en 'n geslotelusidentifikasie-metodiek vir MVB beheerde aanlegte word gekies. Simulasies en prosesdata word gebruik om die metodiek te verifieer en te evalueer.

Baie skattingsmetodes faal wanneer dit direk toegepas word op geslotelusdata as gevolg van die korrelasie tussen die aanleginset en ruis op die aanleguitset. Die foutvoorspellingsskattingsmetode kan egter wel konsekwente skattings gee; dus word dié skattingsmetode geïmplimenteer.

In opelus word identifiseerbaarheid verseker deur 'n aanhoudend stimulerende (“persistently exciting”) aanleginset. Dit verseker nie identifiseerbaarheid in geslotelus nie. In geslotelus word identifiseerbaarheid verseker as óf die terugvoermeganisme nie-linieêr is óf die verwysingssein aanhoudend stimulerend is. Die inter-monsteringsmetode, waar die aanleguitset teen 'n hoër spoed as die beheerinsset gemonster word, verseker ook identifiseerbaarheid. 'n Simulasiestudie oor variansie dui egter aan dat 'n model geïdentifiseer met dié metode, sonder gestruktureerde toetse, gewoonlik nie presies is nie.

Die direkte geslotelusstelselidentifikasiebenadering, waar slegs die aanleguitset en -inset gebruik word in die identifisering, word gebruik. Hierdie benadering werk onafhanklik van die terugvoermeganisme, dit verseker konsekwente skattings en optimale presiesheid, en dit maak gebruik van standaard MATLAB funksies.

In die simulasie word 'n multiveranderlike MVB beheerde aanleg geïdentifiseer uit geslotelusdata. Om die konsekwensie van die metodiek te evalueer, word die aanleg geïdentifiseer vir verskillende beheerderstellings en ook verskillende toegevoegde versteurings. Verskillende metodes om identifiseerbaarheid te verseker, word ook ondersoek. Saam met die standaard verifieeringstoetse, wat in opelusidentifikasie gebruik word, word modelle ook vergelyk met opelusgeïdentifiseerde modelle en die stabiliteit van die geslotelusstelsels word ondersoek.

Die simulasieresultate toon aan dat die voorgestelde metodiek betroubare resultate lewer vir die tipe verstourings en beheerderstellings wat gebruik is, wanneer gestruktureerde toetse gedoen word wat 'n aanhoudend stimulerende verwysingssein en 'n goeie sein-tot-ruis verhouding verseker. Die resultate toon ook aan dat daar gewoonlik 'n groot variansie in geïdentifiseerde modelle ontstaan wanneer daar slegs op inter-monstering of 'n nie-liniêre beheerder vertrou word vir identifiseerbaarheid.

'n Deel van 'n multiveranderlike industriële aanleg word ook geïdentifiseer. Geen gestruktureerde toetse word uitgevoer op die aanleg nie. Data, gemonster tydens normale werking, word gebruik vir identifikasie. Daar word tot die gevolgtrekking gekom dat die opelusgeïdentifiseerde model nie 'n goeie voorstelling van die aanleg onder geslotelusbeheer, tydens die toepaslike tyd, is nie; dus is die resultate uit die vergelyking tussen die opelus- en geslotelusgeïdentifiseerde modelle onbetroubaar.

Uit die eksperiment kan 'n voorlopige gevolgtrekking gemaak word dat 'n onaanvaarbare model gewoonlik geïdentifiseer sal word uit data gemonster tydens normale geslotelusbeheer, aangesien in dié geval die verwysingsseine gewoonlik nie aanhoudend stimulerend is nie en die sein-tot-ruis verhouding nie goed is nie.

Sleutelwoorde: geslotelusstelselidentifikasie, opelus, modelgebaseerde voorspellingsbeheer, multiveranderlik, foutvoorspellingsskattingsmetode, metodiek, identifiseerbaarheid, aanhoudend stimulerend (“persistently exciting”), nie-liniêre terugvoer, inter-monstering, verifieer, evalueer, variansie, simulasie, prosesdata, sein-tot-ruis verhouding.

ABBREVIATIONS

AIC	Akaike's Information Theoretic Criterion
ARMAX	Auto-Regressive Moving Average with External input
ARX	Auto-Regressive with External input
ASYM	Asymptotic Method
BJ	Box-Jenkins
CLOSID	Closed-loop System Identification
CV	Controlled Variable
DMC	Dynamic Matrix Controller
DMK	Dimethyl Ketone
FIR	Finite Impulse Response
FPE	Final Prediction Error
IDARX	Multivariable ARX
IPA	Isopropyl Alcohols
IV	Instrumental Variables
LSE	Least-Squares Estimate
MDL	Minimum Description Length
MIBK	Methyl Iso Butyl Ketone
MIMO	Multiple-Input-Multiple-Output
MISO	Multiple-Input-Single-Output
MPC	Model-based Predictive Control
MPCI	MPC and Identification
MV	Manipulated Variable
OE	Output Error
PDF	Probability Density Function
PE	Persistently Exciting
PEM	Prediction-Error Method
PRBS	Pseudo-Random Binary Signal
QP	Quadratic programme
RBS	Random Binary Signal
RMPCT	Robust Model Predictive Control
SCI	Sasol Chemical Industries
SID	System Identification
SISO	Single-Input-Single-Output
SITB	System Identification Toolbox
SNR	Signal-to-Noise Ration
SSF	Sasol Synthetic Fuels
SVD	Singular Value Decomposition
w.p.	with probability
ZOH	Zero-Order-Hold

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