IDENTIFICATION OF OPERATING REGIMES OF BIOTECHNOLOGICAL PROCESS

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Application of methods for identification, based on explicit decomposition of operation region of dynamic systems, is of large interest in synthesis of optimal control of biotechnological processes, which are nonlinear and are characterized with complex dynamic behavior. The local dynamical models of biotechnological processes are using in the model-based control, model-predictive control, adaptive control and other control techniques.

For modeling of a real biotechnological process in the present paper is used a software tool for multimodel identification - Operating Regime Based Modeling and Identification Toolkit (ORBIT) version 2.1, worked in MATLAB version 6.0 / Simulink version 4.0. Here is obtained mathematical models for a several operating regimes of process, which are characterized with local non-variable structure, but with local variable parameters. For assessment of adequateness of local models is used Least squares method (LSM). The high precision of global model is guarantied by the higher precision of the local models.

INTRODUCTION

Dynamical behaviour of many processes could be described as sequence of phases. In such processes, the transition between phases often comes relatively fast, but the moment, when it happens is difficult to be predicted because of its sensitivity toward model parameters. Examples for such processes are consecutively reactions in periodic reactor, attenuation fluctuations, and periodic growth of cells. For modeling of processes with complex dynamical behaviour is felicitous to apply an approach for modeling with variable structure. Thus is attaining compromise between simplicity of model and necessary accuracy of process presentation. Fir chemical and biochemical processes the construction of submodels could be motivated by the boundary stages and boundary factors used in them. When it is possible, physical significant structures are used in the application of an approach for modeling with the variable structure.

THEORETICAL PREMISES

Identification of biotechnological processes, based on operating regimes

There is a growing interest in modeling and identification methods based on explicit decomposition of the operating range of dynamical systems in determination of medels of precesses with the compex dynamical behaviour.

For modeling of complex dynamical processes is ued software tool for multimodel identification, based on program MATLAB – ORBIT, developed by SINTEF и Norwegian University of Science and Technology.

ORBIT is an interactive environment for computer aided modeling and system identification, typically leading to mathematical models that can be described as grey-box models. ORBIT proposes a possibility for non-linear system identification as well. ORBIT can on one side simply act as a graphical user interface that lets you specify how the decomposition can be. On the other side ORBIT can act as an automatic modeling tool that will identify decomposition that best matches some data set using a heuristic search algorithm. The ORBIT core contains the GUI, parameter- and structure-identification algorithms, model-validation algorithms, and model database management, as well as interfaces for various generic MATLAB tools and toolboxes. The ORBIT Control Design toolkit (ORBITcd) supports design of gain-scheduling-like non-linear controllers on the basis of ORBIT models.

Modelling involves the following major stages: 1) Planning of experiment and collecting experimental data; 2) Selection and definition of set of operating points and variables that will characterizes the operating regimes, and their range; 3) Select a decomposition into operating regimes and obtaining of an adequate local model structure and local model validity functions for each regime; 4) Identification of known local model parameters.

The choice of a set of operating points includes a determination of a subset of the variables, which are characterized operating regimes. For a local model structures is important operating points to hold variables that tkake up momlinearities.

Any model will have a limited range of validity. Model that has a range of validity less than the desired range of validity will be called a local model, as opposed to a global model that is valid in the full range of operation. The region in which a local model is valid, is called an operating regime. A non-linear modeling problem can be solved within the operating regime based modeling framework by decomposing the operating range into a number of operating regimes, and developing simple linear models within each operating regime [3, 1].

ORBIT can support a wide range of model representations. The advanced user is free to include customised or generic model representations in this library by programming the required MATLAB functions.

Mathematically, the NARX model representation relates an input vector u(t) to an output vector y(t) by

$$y(t)=\sum_{i=1}^{N} f_i(\psi(t);\theta_i)\omega_i(z(t))+e(t) \quad (1)$$

$$\psi(t)=(y(t-1),\ldots,y(t-ny),u(t),\ldots,u(t-nu))^T \quad (2)$$

$$z(t)=H(y,u)(t) \quad (3)$$

where e(t) represents the unmodeled dynamics and noise.

A block diagram for this model is provided in Fig.1.

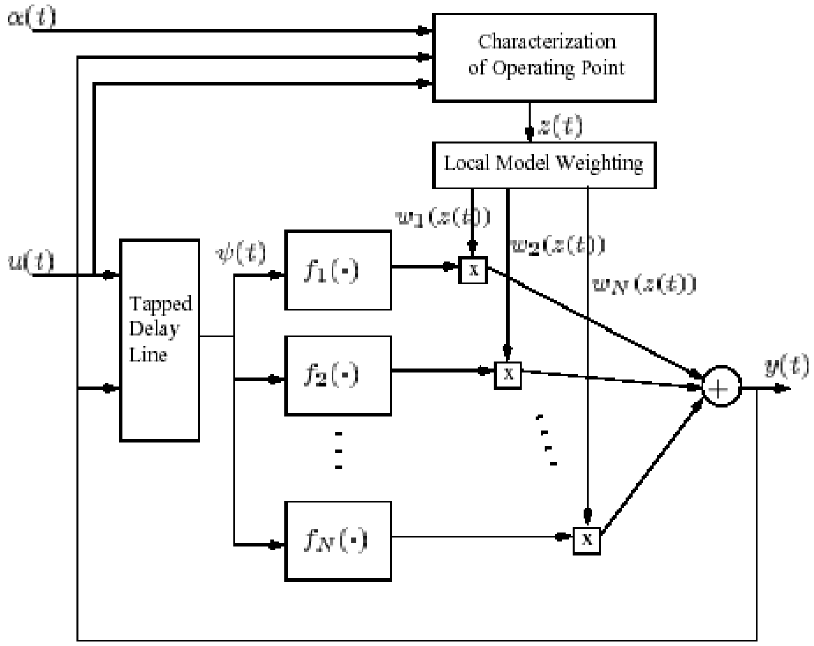


Fig.1 Selected data instances for model design

The elements of this model representation are:

- The functions $f_1,\ldots,f_N$, defines a set of local models;
- The local model parameters are lumped into a vector θ_i;
- The integer parameters ny and nu define the order of the NARX model;
- The positive definite weighting functions $\omega_1\ldots.\omega_N$, will define the relative weight of the local models at each operating point;
- The variables that characterize the operating regimes.

In ORBIT, the operating regimes and weighting functions are parameterized in terms of axis-parallel hyper-rectangles with soft edges.

The operating regimes can be viewed as fuzzy sets, which are characterized by their membership functions.

The parameter identification problem consists of determining the local model parameters. In ORBIT it is defined as an extended optimization problem, see [3].

ORBIT contains three basic parameter identification algorithms that can be applied to solve the optimization problems resulting from the data, priorknowledge and user selections:

- The prediction error method;
- Least squares method;
- Locally weighted least squares method when the criterion function is quadratic.

The structural parameters of ORBIT models are:

- The number of operating regimes, and their location in the operating space;
- The integer parameters in the local models, such as order.

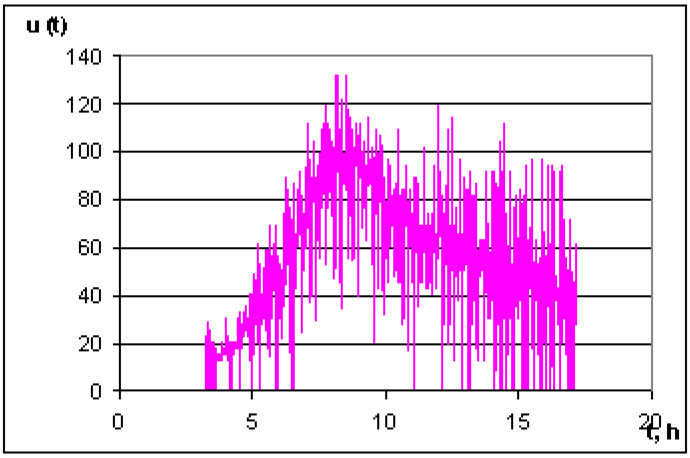
ORBIT supports structural identification of these parameters on the basis of optimization of statistical criteria based on separate validation data, that all estimate the mean squared prediction error.

The set of model structures defined by the possible operating regime decompositions is viewed as a tree. At each node in this tree there can be integer parameters related to the local models. ORBIT allows the user to interactively explore the model structure tree. User-specified sub-trees can be searched to the desired depth. There is used a heuristic search method [2]. The user may keep promising models and validate and compare them using other methods, such as simulation and residual analysis.

There are some commonly used validation methods that are supported by ORBIT. A database of models can be stored in ORBIT, and viewing simulation/prediction results can compare selected models.

EXPERIMENTAL CONDITIONS

The used data are from experiment, proceeded with a boitechnological fermentation process.



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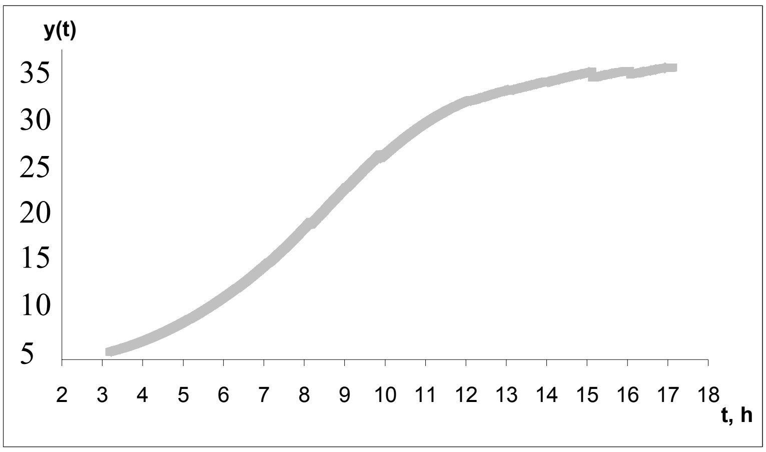

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Fig.2 Selected data instances for model design

REZULTS OF MULTIMODEL IDENTIFICATION

For modeling of a studying process in the presented paper is used a software tool for multimodel identification - Operating Regime Based Modeling and Identification Toolkit (ORBIT) version 2.1, worked in MATLAB version 6.0.

There are obtained mathematical models for two operating regimes for a process based on input-output data sequences, which are characterized with the local nonvariable structure, but with local variable parameters. The data, used for identification of models are shown in figure 2.

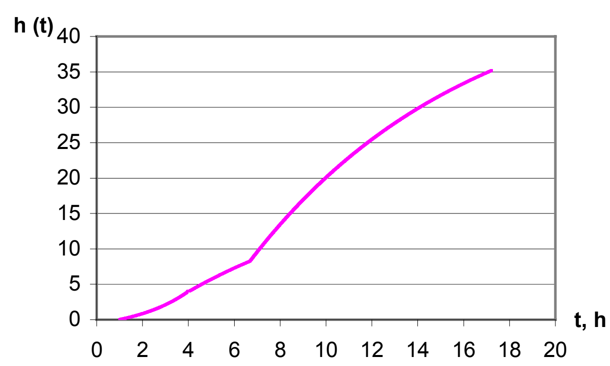
The both NARX models are identifying with the usage of least squares method and identification data. The simulation of models is shown on figure 3b.

The parameters of obtained local models and the corresponding residual errors for each of them are given in table 1.

For estimation of adequacy of local models is used the least squares algorithm. The high accuracy of global model is guarantied by the high accuracy of local models.

Table 1. NARX-models of studying process

Model 1							
Koef.b_i	0.00002738	0.0001479	0.000346	0.0002458	0.0005729	0.0003465	0.00001745
Koef.a_j	1	2.387	7.144	7.827	6.102	2.283	- 0.00262
Average residual:				0.0021394			
Model 2							
Koef.b_i	0.0003847	0.002151	0.007467	0.01616	0.02587	0.01459	0.008717
Koef.a_j	1	4.976	18.02	33.63	39.07	18.62	0.004881
Average residual:				0.0057474			
Average residual for a global model:				0.064562			



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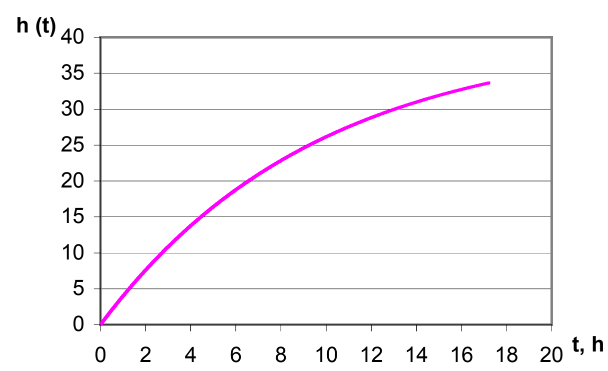

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Fig.3 Comparison of transition characteristics for a both modeling methods – multimodel (a) and global modeling (b)

CONCLUSIONS

There is a growing interest in modeling and identification methods based on the explicit decomposition of the operating range of dynamic systems into operating regimes and the use of simple local models within each operating regime.

Such dynamic models have found wide applicability in model predictive control [2], gain scheduling control [3] and fuzzy control [3].

The choice of local model structures and local model validity functions is closely related to the decomposition of operating regimes. The only one, the best model structure doesn't exist using this approach. It processes a sufficient flexibility with respect of different structure choices, as regime decompositions, whose variables characterize operating regimes and local model structures. In conjunction with its simplicity and transparency, this flexibility is the basic reason for the importance of this application.

For performing of multimodel identification in the present research is used a software tool ORBIT. ORBIT implements much of the current state-of-the-art in operating regime based modeling and identification technology including Takagi-Sugeno-Kang fuzzy models, in a exible and integrated environment.

Multimodel modelling, submitted in the presented paper gives better presentation of a studying process than those reached with using of global model (fig.3) and gives less residual error (table 1).

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