Linear Switching System Identification Applied to Blast Furnace Data

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Abstract: Switching systems are dynamical systems which can switch between a number of modes characterized by different dynamical behaviors. Several approaches have recently been presented for experimental identification of switching system, whereas studies on real-world applications have been scarce. This paper is focused on applying switching system identification to a blast furnace process. Specifically, the possibility of replacing nonlinear complex system models with a number of simple linear models is investigated. Identification of switching systems consists of identifying both the individual dynamical behavior of model which describes the system in the various modes, as well as the time instants when the mode changes have occurred. In this contribution a switching system identification method based on sparse optimization is used to construct linear switching dynamic models to describe the nonlinear system. The results obtained for blast furnace data are compared with a nonlinear model using Artificial Neural Fuzzy Inference System (ANFIS).

1 INTRODUCTION

An important goal of industries is to produce their products with high quality and low costs. To reach this goal, accurate models of industrial processes are needed for monitoring and to maintain good quality control. Data mining and modeling techniques can be used to build predictive forecasting models, to find alternative actions to be taken, or simply to gain a deeper understanding of the underlying influencing elements.

Having more precise mathematical modes of industrial processes allow engineers to have better control of the processes to improve production and win the competition in markets. One of the industries facing fierce competition is the steel-making industry. According to a review by the Association of Finnish Steel and Metal Producers (Association of Finnish Steel and Metal Producers, 2012), the ongoing political and economic crisis in Europe has radically increased price competition. In this paper, the blast furnace for the steel making process is modeled. One of the reasons which makes modeling of blast furnace particularly complex is the fact that it is impossible to directly observe the process inside the furnace. Optimization of this part is, however, essential for improvement in the overall process and quality of the final product. Because of the very high temperature environment, embedding sensors for gathering data is impossible. Therefore, it is treated as a black-box system, relying on experienced engineers for process monitoring and control.

System identification can give mathematical models based on collected blast furnace data. The final goal of the study reported in this paper is to optimize the blast furnace process and, more specifically to consider the quality indicator which describes the gas utilization rate in the furnace, using external sensor data and other process information for its estimation.

Steel plants use the processed iron which produced in blast furnaces by reducing oxygen from the iron. The process is run continuously, with iron-bearing materials and coke being charged from the top of the furnace (Geerdes et al. 2009). During the reduction process, two kind of reaction, direct and indirect, take place in the furnace. The direct one takes place in the lower part of the furnace and depends on

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consumption of coke. The indirect one occurs in top part, where the gas removes oxygen from the ore. The efficiency of the indirect reaction is often expressed as the gas utilization rate, which is considered as an important performance indicator of the furnace. The process is highly complex from a chemical point of view as it involves numerous factors, nonlinear relations and a certain level of randomness.

There are not many researches on modeling blast furnace dynamics due its highly complex behavior. Mathematical models for describing the process have, for instance, been proposed in (Nath, 2002) and (Danloy et al. 2001). Linear data-driven models have been studied in (Saxn and stermark, 1996), (Korpi et al. 2003) and (Bhattacharya, 2005). Nonlinear soft computing techniques have been applied to blast furnace process modeling in, among other: (Hao, 2004), (Helle and Saxn, 2005) and (Pettersson et al. 2007). A novel approach is presented in (Agarwal et al. 2010) where they train a neural network using multi-objective genetic algorithms based on carbon dioxide content of top gas and silicon content in the hot metal output. In (Bjork et al. 2013), ANFIS allows for customization regarding membership functions, inputs and rules, an appropriate degree of complexity is expected to be found.

Nonlinear systems with several operating regimes can be modeled as switching systems, which switch between a number of operational modes associated with the various operating conditions. In this case the mode is usually known or is a function of known variables. In more general cases, the mode switches may be random, or they may depend on variables which are unknown. In this paper, a switching system model is identified to estimate the gas utilization rate of a blast furnace from available sensor data. Following (Shirdel et al. 2014), the identification problem is posed as a support vector regression (SVR) problem, and the models associated with the various operational modes are found by solving a sequence of sparse optimization problems techniques. The prediction performance of the identified switching system models of the blast furnace are compared with results obtained with models constructed using Artificial Neural Fuzzy Inference Systems (ANFIS).

2 SWITCHING SYSTEM IDENTIFICATION

Hybrid systems are a kind of switching systems characterized by a logical dynamical component, which determines the mode switches, and a continuous dynamical component, which determines the system behavior in the various operational modes. Hybrid systems can be categorized into five classes (Heemels et al. 2001). Piece-wise affine (PWA) systems are a class of hybrid systems whose state input domain is partitioned into a finite number of non-overlapping convex polyhedral regions, with linear or affine subsystems in each region (Sontag, 1981).Piece-wise-linear functions are universal approximation of multivariate functions (Lin and Unbehauen, 1992). Due to their approximate features, piece-wise affine hybrid systems are useful for nonlinear system identification.

One approach to black-box identification of nonlinear dynamical systems using experimental process input-output data is to identify a linear switching system which describes the data. A special problem in switching system identification is the fact that the times of the mode switches may not be known. In these cases the switching times between the various modes should be identified simultaneously with the individual models, which make the identification of switching systems significantly more demanding than standard system identification. Therefore, in many studies of switching system identification various simplifying assumptions have been made.

In order to cope with the challenging problem of simultaneous identification of system modes and parameters, a number of techniques have been developed (Saad et al. 2007), (Aliev et al. 2004). Segmentation of time-varying systems and signals has been discussed in (Ohlsson et al. 2010). Sparse optimization which is based on finding each model sequentially is proposed in (Bako, 2011). In (Shirdel et al. 2014), a method based on support vector regression and sparse optimization techniques was proposed for identification of switching systems. Recently in (Le et al. 2013), an approach to identify hybrid systems with unknown nonlinearities in the sub-models using combination of sparse optimization and support vector machines was presented.

In this paper we consider a switching system described by the time-varying linear model

$$y(k) = \varphi(k)^T \theta(k) + e(k) \tag{1}$$

where $y(k)$ is the output, $e(k)$ is a disturbance, and $\varphi(k)$ is a state vector. The state vector consists of the variables used to predict the output $y(k)$. For example, for autoregressive with exogenous terms (ARX) mode, the state vector takes the form

$$\varphi(k)^T = [y(k-1), ..., y(k-r), u(k), ..., u(k-r)]$$

where $u(k)$ is the exogenous input to the system.

It is assumed that the system dynamics switch between a number of modes, so that

$$\theta(k) \in \{\theta_1, \theta_2, \dots, \theta_M\} \tag{2}$$

where θ_i is the vector of system parameters in the ith mode, and M is the number of modes.

The switching system identification problem consists of finding estimates of the parameter vectors θ_i from empirical process data $\{y(k), \varphi(k), k = 1, 2, \ldots, N\}$. Notably, it is not assumed that the time instants when the various modes have been active are known. This implies that the identification is essentially identical to a combinatorial optimization problem. Although such problems are usually intractable, the switching system identification problem can often be solved with a high degree of accuracy or even exactly via a sparse optimization formulation and l_1-relaxation (Bako, 2011), (Shirdel et al. 2014), (Lughofer and Kindermann, 2010).

The approach used in this paper is based on the fact that if mode i has been active at N_i time instants, then, assuming that $e(k) \leq \varepsilon$, the inequality

$$\left|y(k) - \varphi(k)^T \theta_i\right| \leq \varepsilon \tag{3}$$

holds at these N_i time instants. It follows that the most commonly occurring mode and the associated parameters θ_i can be determined by finding the parameter vector $\hat{\theta}_i$ such that the number N_i of time instants for which the inequality (3) holds is maximized. This is a combinatorial optimization problem, which can be addressed using sparse optimization techniques (Bako, 2011).

In (Shirdel et al. 2014), an approach was proposed using the observation that the constraints (3) are identical with the ε-insensitive cost used in support vector regression. The system parameters associated with a given mode can then be found by solving the optimization problem (Shirdel et al. 2014)

$$Minimize_{\hat{\theta}, \xi^+, \xi^-} \|\hat{\theta}\|_p^p + \sum_{k=1}^{N} C_k (\xi_k^+ + \xi_k^-) \tag{4}$$

subject to the ε-insensitive constraints

$$\begin{array}{rcl} y(k) - \varphi(k)^T \hat{\theta} & \leq & \varepsilon + \xi_k^+ \\ -y(k) + \varphi(k)^T \hat{\theta} & \leq & \varepsilon + \xi_k^- \\ \xi_k^+, \xi_k^- & \geq & 0 \end{array} \tag{5}$$

Here $p = 1$ or 2, corresponding to a linear or, respectively, quadratic programming problem and C_k is trade off weight.

The problem of finding the mode which has been active at the maximum number of time instants corresponds to finding the parameters θ such that the maximum number of variables ξ_k^+, ξ_k^- are zero. This is a sparse optimization problem, for which the second term in (4) provides an l_1-relaxation, and by iterative reweighting applied to the weights C_k the problem can in many cases be solved with a high degree of accuracy (Bako, 2011), (Shirdel et al. 2014). In this way the various system modes and the associated parameter vectors can be computed one by one. We have the following algorithm (Bako, 2011), (Shirdel et al. 2014).

Algorithm. Identification of switching system.

Step 1. Initialization: set $i = 1$.

Step 2. Solve the SVR problem defined by (4), (5) using iterative reweighting of C_k to find a sparse solution in the variables ξ_k^+, ξ_k^-. The solution gives a parameter estimate $\hat{\theta}_i$ for mode i. Remove the data pairs $(\varphi(k), y(k))$ at which mode i has been active.

Step 3. Check the reduced data set for convergence: if all data pairs have been accounted for, stop. Otherwise, set $i := i + 1$ and continue from step 2 using the reduced data set.

3 IDENTIFICATION OF BLAST FURNACE

In this section the switching system identification methods described in section 2 is applied to blast furnace data. The goal of the model is to predict the gas utilization as described by the carbon dioxide content of top gas as a function of measured variables received from sensor data.

Table 1: Inputs.

Input No.	Description
1	Pellets+sinter by total
2	Coke by total
3	Iron by total
4	Pellets+sinter by volume
5	GAS temp PCA_1
6	GAS temp PCA_2
7	GAS temp PCA_3
8	Burden height
9	Blast volume
10	Pressure by volume
11	Oxygen in blast
12	Hydrogen in top gas
13	Oil by blast volume

3.1 The Blast Furnace Data

In a complex plant like blast furnace, much redundant affection can influence our major part of identification which is measured data. For this study, three months of detailed operational blast furnace data was used for training. The final set of preprocessed data consisted of data collected from 2208 hours of furnace

Table 2: Estimated parameters $b_{1,l}^{(i)}$ for input u_1 for various time lags l when using $M = 4$ modes.

Time lag	1	2	3	4	5	6	7	8
Input No.	1							
Subsystem 1	0.000	0.000	0.979	1.075	0.000	-0.815	0.000	0.000
Subsystem 2	0.000	0.000	-0.623	0.000	0.564	0.000	0.816	-0.159
Subsystem 3	0.000	-1.854	0.000	0.000	0.000	0.000	0.000	0.000
Subsystem 4	0.000	0.000	-0.193	0.000	0.000	0.000	-0.396	0.147

operation. After consulting experts, it turned out that many points of data are not sufficiently reliable and should be removed. The final number of data points was therefore 1800.

One of the most important performance indicators of blast furnace is measuring the ratio of carbon monoxide converted to carbon dioxide. This indicator was chosen as the target series for the conducted analysis and modeling. It evaluates performance of the data understanding indirect reduction reaction taking place in the upper part of the furnace and controlling this process by injecting oxygen, can allow furnace to burn less coke and cost saving.

3.2 The Inputs

Input data entails charging data which are precise amounts of burden materials and coke charged into the furnace per time unit, continuous process data from external sensors and data from analysis of hot metal and some other variables. Top-gas exiting the furnace can be considered as an input series. A discussion of the role of hydrogen competing with carbon monoxide in reducing oxygen is given in (Geerdes et al. 2009). The inputs which are used in the modeling of the blast furnace are shown in Table 1.

The output $y(k)$ (carbon dioxide content of top gas) was modeled as function of the input variables $u_j(k)$ in Table 1. The model structure was

$$y(k) = \sum_{j=1}^{13} b_{j,1}(k)u_j(k-1) + \cdots + b_{j,13}(k)u_j(k-13)$$

where the parameters $b_{j,l}(k) \in \{b_{j,l}^{(1)} b_{j,l}^{(2)}, \ldots, b_{j,l}^{(M)}\}$ belong to the set (2) associated with the system modes.

Each input variable affect the process with a time lag. Some of the variables affect the process rapidly, such top gas-related variables, and some others have a slower effect, like charging data. In the identification method used here, the time lags of the various process inputs were obtained as part of the identification process, as the first term of the cost function (4) forces parameter which do not affect the output to zero, cf. (Shirdel et al. 2014), where the approach was used to identify systems of unknown dimensions. Estimated time lags and parameters for modeling with $M = 4$ subsystems for first input are shown in Table 2. It is seen that the time lag of the input is different for different subsystems.

4 RESULTS

In this section, modeling by using the linear switching system identification approach is conducted. The required data was taken from input series based on the consultation of expert (Table 1). The maximum time lag that we allowed our approach to have in this blast furnace system is 8.

The result of each identified linear switching system is given based on root mean square (RMS) error between the estimated output and real output in Table 3. For comparison, the error of ANFIS model output (Bjork et al. 2013) is shown in Table 4. It is seen that the switching system model is slightly more accurate than ANFIS model. A major difference is that in contrast to the approach considered here, in the ANFIS modeling studied in (Bjork et al. 2013) it was not possible to find the optimal time lags, or to include all 13 input variables in the model due to a too heavy computational burden. The output of a switching system model is illustrated in Fig. 2, the mode switches of a system with four modes are shown in Fig. 1.

Table 3: Root mean square error of estimated output of using identified switching system models.

Subsystem of modes	RMSE
1	0.0840
4	0.0571
6	0.0537
8	0.0516

5 CONCLUSION AND DISCUSSION

One application of switching system models is to rep-

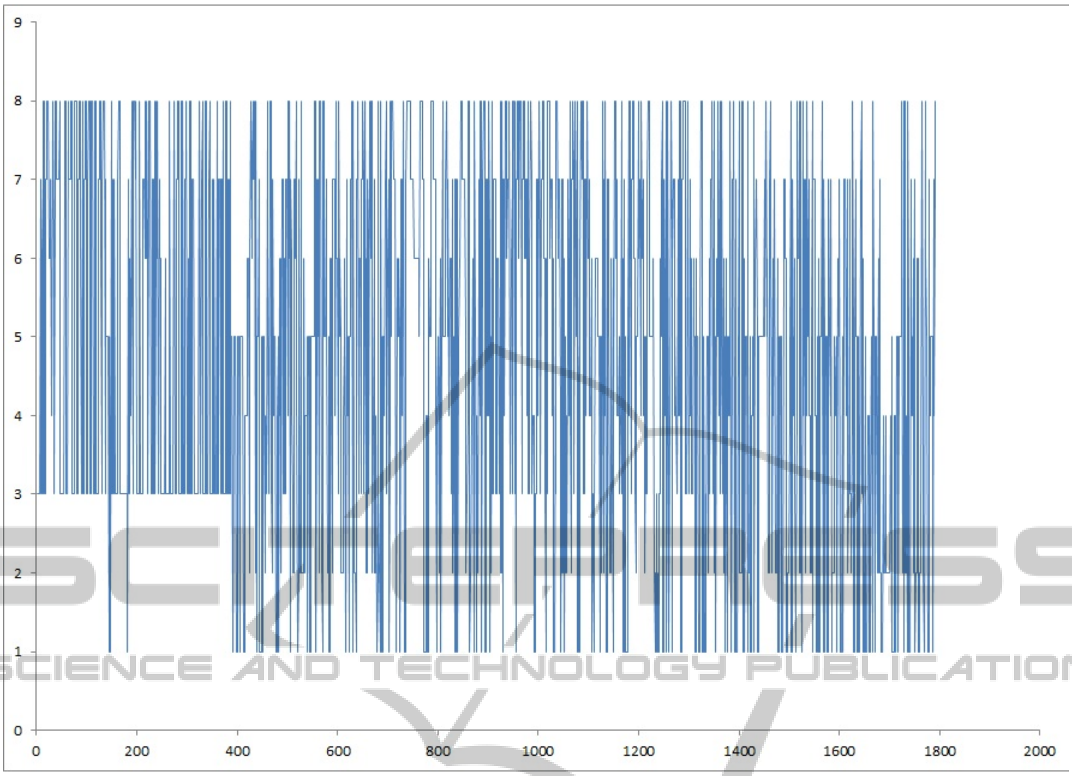

Figure 1: Mode switches of system with eight modes.

Table 4: Root mean square error of estimated output using ANFIS model.

RMSE	Input set
0.054	1,5,10,12,13
0.052	6,7,10,12,13
0.056	1,6,7,10,13

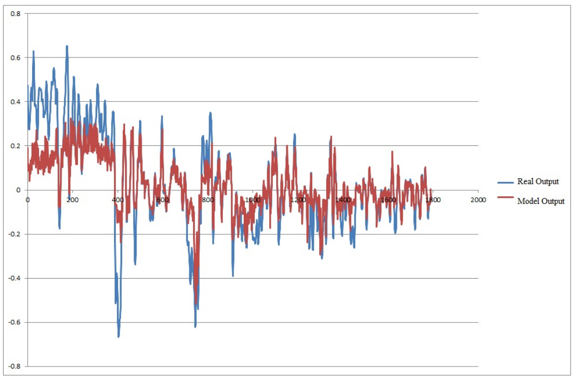

Figure 2: Normalized process output and model output when using linear switching system with $M = 8$ modes.

resent complex systems with a number of simple linear subsystems. In this study, a switching system model of a blast furnace process was identified from experimental process data. The results show that with a relatively few linear systems, quite good models can be obtained, and by allowing more subsystems, the nonlinearities are captured, even so that output is predicted slightly better than with the ANFIS method, cf. Tables 3 and 4.

In future work, we will generalize the approach to nonlinear switching systems for improved accuracy, and also to test the method to other industrial processes.

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