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Published in: Journal of Process Control

DOI: 10.1016/j.jprocont.2013.03.006

Published: 01/01/2013

Document Version Peer-reviewed accepted author manuscript, also known as Final accepted manuscript or Post-print

Please cite the original version:

Zakharov, A., Tikkala, V.-M., & Jämsä-Jounela, S.-L. (2013). A fault detection and diagnosis approach based on nonlinear parity equations and its application to leakages and blockages in the drying section of a board machine. *Journal of Process Control*, *23*(9), 1380-1393. https://doi.org/10.1016/j.jprocont.2013.03.006

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Fault detection and diagnosis approach based on nonlinear parity equations and its application to leakages and blockages in the drying section of a board machine

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Abstract

This study aims at providing a fault detection and diagnosis (FDD) approach based on nonlinear parity equations identified from process data. Process knowledge is used to reduce the process nonlinearity from high to low-dimensional nonlinear functions representing common process devices, such as valves, and incorporating the monotonousness properties of the dependencies between the variables. The fault detection approach considers the obtained process model to be nonlinear parity equations, and fault diagnosis is carried out with the standard structured residual method. The applicability of the approach to complex flow networks controlled by valves is tested on the drying section of an industrial board machine, in which the key problems are leakages and blockages of valves and pipes in the steam-water network. Nonlinear model equations based on the mass balance of different parts of the network are identified and validated. Finally, fault detection and diagnosis algorithms are successfully implemented, tested, and reported.

Keywords: nonlinear model identification, gray-box model identification, fault detection and diagnosis, nonlinear parity equations, flow networks, leakages and blockages, multicylinder drying

1. Introduction

The current market conditions force the process industries to cut expenses by reducing downtime caused by unplanned and planned shutdowns and the time of sub-optimal operations. Nowadays, one of the essential requirements for safe, efficient, and reliable processes is early detection and isolation of abnormal dynamic states and equipment failures. This allows taking appropriate actions in order to maintain operations and to prevent damage or accidents which may cause a shutdown. To this end, there has been increased interest in process monitoring and fault diagnosis methods in the process industry. The key phase of the development of a fault detection and diagnosis (FDD) system is the process model formulation because the model quality predefines the efficiency of the FDD system in terms of the detection results and the false alarm rate. The process characteristics determine which types of models are to be used: dynamic or steady-state, linear or nonlinear. Most FDD research has focused on linear dynamic and nonlinear steady-state methods, which are selected depending on the trade-off between the degree of process nonlinearity and the importance of its dynamic properties.

This study focuses on FDD in nonlinear systems. Various nonlinear modifications of the linear principal component analysis (PCA) method are naturally used for nonlinear steady state FDD because each dimension eliminated from the process data enables introducing an algebraic equation, several of which a steady-state model is composed of. The list of methods based on nonlinear steady state models include: generalized PCA, bottleneck PCA, kernel PCA, principal curve PCA, and self-organizing maps (SOM).

The input set of variables can be augmented with nonlinear computed variables before the PCA method is used (so called generalized PCA). In Kämpjärvi et. al. [1], an ethylene-cracking furnace was analyzed, and process knowledge was used to augment a set of 9 measured input variables with 16 computed variables, which were responsible for providing an insight into the nonlinear process characteristics and distinguishing the changes caused by faults from the effect of the disturbances. The main drawback of the approach is that the proper

determining of the computed variables requires comprehensive process knowledge and various transformations must usually be tried.

Kramer [2] developed a nonlinear PCA method based on the 'bottle-neck' neural network containing three hidden layers: the mapping layer involved in modeling the score vector, the outputs of the middle layer representing the scores, and the 'demapping' layer involved in computing the model output. The dimension compression is achieved by limiting the number of nodes in the middle hidden layer, which is known as the bottle-neck layer, to the desired number of principal components. Some FDD applications of the method were reported by Thissen et al. [3] and Doymaz et al. [4]. Alternatively, input-training networks were proposed to build nonlinear PCA models in Tan and Mavrovouniotis [5] and applied to FDD by Jia et al. [6] and Zhu and Li [7]. Despite the presented applications, the general limitations of the neural networks prevent wide industrial use of the method, see for example Lennox et.al. [8]..

The kernel PCA introduced in Schölkopf et al. [9] is an alternative nonlinear PCA technique which transforms the input data to a high-dimensional feature space using a kernel function and then applies the ordinary linear PCA to the transformed data. Lee et al. [10] transferred an ordinary PCA-based monitoring framework utilizing T^2 and SPE statistics to kernel PCA technique. This approach was successfully applied to a simple nonlinear example and to a wastewater treatment plant, however only few industrial applications of the method have yet been reported.

PCA using principal curves was introduced by Dong and McAvoy [11]. Each point of a principal curve is equal to the mean value of the data samples, whose projection on the curve coincides with the point, and therefore a principal curve can be constructed iteratively in a straightforward way. Huang et. al. [12] successfully applied principal curve PCA to FDD of a small two-input two-output system, however when the method was tested on Tennessee-Eastman process, it can diagnose only about 50% of the studied faults.

Self-organizing maps (SOMs) represent the input data as a low-dimensional map (2-d maps are most frequently used) preserving the topological properties of the input data. Process data representing both healthy and faulty process conditions can be used to train a SOM, which is able to distinguish between normal and faulty process states. For example, in Kämpjärvi et. al. [1], the data used to train a SOM was obtained from an ethylene cracking process to represent normal operational conditions and faults in a feed analyzer and in an effluent analyzer. Jämsä-Jounela et. al. [13] trained two separate SOMs to detect dust aggregations and concentrate aggregations in a flash-smelting furnace. Tikkala et. al. [14] trained a SOM to detect fouling of a thickness sensor in a board machine. To conclude, SOMs are frequently used as a kind of classifier oriented at the fault diagnosis of a limited number of highly important faults in a process which take place regularly enough to be described sufficiently well with process data. However, the potential faults in processes are usually numerous, and faulty data is frequently unable to describe many of them.

The multi-linear model approach is based on a divide-and-conquer strategy in which a number of local linear models are used to describe the process. In the simplest case, a single model is selected depending on the current operational conditions to describe the system (the models are not mixed), see for example Bhagwat et. al. [15]. However, this approach is not suitable to provide a continuous transition between the local models, which in turn can cause false alarms when a change of operational conditions results in a change of the relevant local model. A solution of this problem can be found for example in Razavi-Far et. al. [16], who describe the process dynamics with a Takagi-Sugeno fuzzy system mixing local linear models. The model was applied to the detection of faults in a U-tube steam generator of a nuclear power plant. Sadeghian and Fatehi [17] used a similar method for modeling and detection of faults in a cement rotary kiln. Alternatively, Ng and Srinivasan [18] obtained overlapping sets of process data using fuzzy c-mean clustering and constructed an individual PCA model for every set. Although a single PCA model was selected for FDD depending on the

current operational conditions, the presented method prevents false alarms during changes of the relevant local PCA models because the local models are joined to each other in the sense that they overlap at the edges.

Existing model-based FDD methods, such as the parity equations method, are easy to use, and they are able to provide reliable results when the process model is accurate. On the other hand, it can be seen from the presented literature review that existing nonlinear data based FDD methods including the model identification step suffer from numerous limitations and, in particular, usually require significant efforts by human experts. To conclude, further progress in FDD requires the development of model identification methods providing maximum accuracy and transparency of the resulting models, which can be achieved by incorporating some additional process features into model identification. In particular, none of the nonlinear methods mentioned takes into account the following two process features: First, the process nonlinearity can frequently be reduced to the nonlinearities related to small parts of a chemical process or even devices, and these nonlinearities typically involve no more than three variables. Second, the nonlinear dependencies between the process variables are typically monotonous with respect to the variables they involve. In particular, these process features present in a flow network controlled by valves, which can be found in many chemical applications.

This paper presents a gray-box identification method which obtains models reproducing the mentioned process features. As a result, more accurate FDD is achieved with these models. Moreover, the nonlinear functions representing the process devices or small groups of them are easy to interpret, which enables the creation of transparent models. The proposed approach is tested on the drying section of a board machine. The paper is organized as follows. Section 2 contains the description of the identification method and the FDD approach based on the mentioned nonlinear model identification method. Section 3 presents the drying section of a board machine. Section 4 contains the details of implementation of the FDD system for the drying section. Finally, the test results and a conclusion are provided in Sections 5 and 6.

2. A fault detection and diagnosis approach based on nonlinear parity equations identified from process data

The proposed approach carries out the fault detection and fault diagnosis tasks with the nonlinear parity equations and structured residuals methods. The parity equations are obtained as the model equations derived using the gray-box nonlinear identification technique presented in Section 2.2.

2.1 Fault detection and diagnosis based on nonlinear parity equations

The proposed fault detection involves off-line and on-line stages. In the off-line stage, the standard deviation of the model equation errors is estimated by validating the equations with data unused for identification, and the estimations are used together with the target false alarm rate to design the thresholds for the cumulative sum (CUSUM) test. In the on-line stage, the residuals of the equations are obtained by substituting the current values of the process variables and the computed variables into the equations. The residuals are evaluated against the fault detection thresholds with the CUSUM test, and then a decision about the presence of faults in the process is made.

The fault diagnosis methods based on various classifiers require both healthy and faulty process data, and therefore these methods are aimed at recognizing a limited number of faults taking place more or less regularly. However, the potential sensor and actuator faults are typically numerous, and the faulty data is not rich enough to describe all of them. In contrast, the structured residual method used by the proposed FDD approach requires neither description of the possible faults with faulty data nor modeling of the faults while both are infeasible. In brief, the results of the CUSUM evaluation of the residuals are collected and considered as a pattern, which is compared to the patterns contained in the residual-fault incidence matrix to identify the fault candidates.

2.2 A method for nonlinear gray-box model identification

The identification method presented below was developed to reproduce two process features, namely the lowdimensional nonlinearities related to the process devices and the monotonous properties of these nonlinearities. To incorporate the process features, the identification method utilizes the available process knowledge to determine the structure of the model equations and derives estimations of the model parameters from process data. In more details, the process knowledge is used to design a number of model equations, representing a mass or an energy conservation law for a part of the process, and the nonlinear functions involved to the model equations are related to the process devices. Since the process nonlinearities related to most of the devices – such as valves, pumps, tanks and reactors – typically involve no more than three variables, they can be described using nonlinear functions of no more than three arguments. The model equations of the following form can be considered in the result:

$$\sum_{i=1}^{k} a_i x_i + \sum_{i=1}^{l} F_i^1 (x_i^1) + \sum_{i=1}^{m} F_i^2 (x_i^2, y_i^2) + \sum_{i=1}^{n} F_i^3 (x_i^3, y_i^3, z_i^3) = \mathbf{0},$$
(1)

where the variables x, y, and z are some process variables or computed variables, k is the number of linear terms used in the equation with coefficients a_i , and l, m and n are the numbers of the nonlinear functions with one, two and three arguments respectively. The nonlinear functions F^1 , F^2 and F^3 are defined using the following parameterization:

$$F^{1}(\mathbf{x}) = \sum_{i=1\dots p} b_{i} g_{i}^{\mathbf{x}}(\mathbf{x}) , \qquad (2)$$

$$F^{2}(x, y) = \sum_{i=1...p} \sum_{j=1...q} b_{i,j} g_{i}^{x}(x) g_{j}^{y}(y) , \qquad (3)$$

$$F^{3}(x, y, z) = \sum_{i=1...p} \sum_{j=1...q} \sum_{l=1...r} b_{i,j,k} g_{i}^{x}(x) g_{j}^{y}(y) g_{k}^{z}(z) , \qquad (4)$$

where b_i , b_{ij} and b_{ijk} are the coefficients of the nonlinear functions, and p, q, and r are the numbers of basis functions g_i^x , g_j^y and g_k^z related to the process variables x, y, and z respectively. The basis functions can be selected in many ways; for example, a set of the piecewise linear basis functions defined according to equation (5) and shown in Figure 1 can be used:

$$g_{i}^{t}(\mathbf{U}) = \begin{cases} (t - t_{i-1})/(t_{i} - t_{i-1}) & \text{if } t_{i-1} \leq t < t_{i} \\ (t_{i+1} - t)/(t_{i+1} - t_{i}) & \text{if } t_{i} \leq t < t_{i+1}, \text{ for } i = 2... \text{ p-1} \\ \mathbf{0}, & \text{otherwise} \end{cases}$$

$$g_{0}^{t}(\mathbf{t}) = \begin{cases} (t_{1} - t)/(t_{1} - t_{0}) & \text{if } t_{0} \leq t < t_{1} \\ \mathbf{0}, & \text{otherwise} \end{cases}$$

$$g_{p}^{t}(\mathbf{t}) = \begin{cases} (t - t_{p-1})/(t_{p} - t_{p-1}) & \text{if } t_{p-1} \leq t < t_{p} \\ \mathbf{0}, & \text{otherwise} \end{cases}$$
(5)

where t denotes one of the process variables x, y, and z, and t_i , i = 0, ..., p is a grid defined for that process variable x, y, or z.

The number of nodes in the grids must be a compromise between the number of the model parameters to be estimated from the data and the ability of the models (2)-(4) to approximate the nonlinear functions. In practice, the grids of the variables involved to one and two-dimensional nonlinearities can be denser and it might be possible to estimate the parameters of the nonlinearities (2) and (3) from the available process data for grids containing up to 10 nodes or even more. For the three-dimensional nonlinear functions, the limited accuracy of the model must be preferred to avoid overfitting, and the reasonable number of nodes in the grids could usually be about 5 or 6 or even less. In this study, the nodes were selected so, that the intervals between two sequential nodes contain approximately the same number of data samples.



Figure 1. A set of piecewise linear basis functions for a 5-node grid

The model equations (1) involve the low-dimensional nonlinearities reproducing the process devices, which enables incorporating the knowledge of the process structure to the model. Moreover, the proposed parameterization of the nonlinear functions defined by equations (2)-(4) is suitable to obtain the desired monotonous properties of these functions. For example, the flow through a valve $F^2(v, P)$ can be often considered as a nonlinear function of the degree of valve opening and the pressure drop at this valve. If the piecewise linear basis functions are selected according to equation (5), the two-dimensional nonlinear function $F^2(v, P)$ described by equation (3) monotonously increases with respect to both arguments if and only if the following conditions are fulfilled:

$$b_{i,j} \ge b_{i-1,j}, \ i = 1, ..., p, j = 0, ..., q$$

$$b_{i,j} \ge b_{i,j-1}, \ i = 0, ..., p, j = 1, ..., q$$
(6)

Generally, the monotonous increase and decrease conditions for a nonlinear function involving one, two, or three variables with respect to some or all these variables can be imposed as constraints on its coefficients, as done in equation (6).

The coefficients of the linear terms a_i used in the model equations and the coefficients b_i , $b_{i,j}$, $b_{i,j,k}$ defining the nonlinear functions are determined from process data with the least squares method. The left sides of equations (1) are linear with respect to these parameters. Taking into account the linear constraints representing the monotonousness conditions, a quadratic programming (QP) task must be solved to define the coefficients of equation (1). To avoid the trivial solution when all model parameters are zero, at least one of the coefficients a_i in at least one of the equations must be set to the value 1. The following simple example presenting the identification of a model of a single valve illustrates these statements: if there is a set of data samples of the flow through a valve Q_n which is described as a function of the degree of valve opening v_n and the pressure difference ΔP_n , where n = 1, ..., N is the sample number, and if the following variables are defined as follows:

$$c_{i,n} = g_i^p (\Delta P_n)$$

$$d_{j,n} = g_j^v (v_n)$$
(7)

then the sum of the squared errors of the equation:

$$F^2(\boldsymbol{v}, \boldsymbol{P}) = \boldsymbol{Q} \tag{8}$$

is a quadratic function of the coefficients b_{ij} of the nonlinear function $F^2(v, P)$:

$$\min \sum_{n=1...N} (Q_n - \sum_{i,j} b_{i,j} c_{i,n} d_{j,n})^2 = \min \sum_{i,j} \sum_{k,l} H_{i,j,k,l} b_{i,j} b_{k,l} - \sum_{i,j} f_{i,j} b_{i,j} H_{i,j,k,l} = \sum_n c_{i,n} d_{j,n} c_{k,n} d_{l,n}$$

$$f_{i,j} = -2 \sum_n Q_n c_{i,n} d_{j,n}$$
(9)

The flow through a valve monotonously increases with respect to the valve opening and the pressure difference, which results in the constraints defined by equation (6). Equations (9) and (6) define the quadratic programming task that must be solved to identify the coefficients $b_{i,j}$ defining the valve model. The coefficients of the general equation (1) containing several nonlinear functions and linear terms can be similarly estimated.

Nonlinear model identification methods based on neural networks are known to be unreliable outside the operating conditions described by the data which is used to train the network (the training data). The proposed identification method can avoid this problem if the parameters of the model equations are defined by considering an extra term (a flattening term) together with the standard least squares term as the objective to be minimized:

$$\min[\sum_{i=1}^{N} \sum_{k=1}^{M} \alpha_{k} e_{ik}^{2} + \sum_{i=1}^{L} \beta_{i} C_{i}], \qquad (10)$$

where *N* is the number of data samples, *M* is the number of the model equations in the form defined by equation (1), e_{ik} is the error of equation *k* for data sample *i*, α_k is a non-negative coefficient defining the relative weight of equation *k*, β_i are nonnegative weights defining the desired strength of the function flattening, and *L* is the number of different nonlinear functions used in the model equations. The total curvature C_i of the nonlinear function number *i* is computed as the sum of the local curvatures of the function at the inner points of the one, two, or three-dimensional grid. The local curvatures are defined as the sums of squared second order divided differences according to equations (11)-(13):

$$\Delta b_{i} = \left(\left(\frac{b_{i+1} - b_{i}}{x_{i+1} - x_{i}} - \frac{b_{i} - b_{i-1}}{x_{i} - x_{i-1}} \right) \mathbf{I} \left(\frac{x_{i+1} - x_{i-1}}{2} \right) \right)^{2}$$
(11)

$$\Delta b_{i,j} = \left(\left(\frac{b_{i+1,j} - b_{i,j}}{x_{i+1} - x_i} - \frac{b_{i,j} - b_{i-1,j}}{x_i - x_{i-1}} \right) \mathbf{I} \left(\frac{x_{i+1} - x_{i-1}}{2} \right) \right)^2 + \left(\left(\frac{b_{i,j+1} - b_{i,j}}{y_{j+1} - y_j} - \frac{b_{i,j} - b_{i,j-1}}{y_j - y_{j-1}} \right) \mathbf{I} \left(\frac{y_{j+1} - y_{j-1}}{2} \right) \right)^2, \quad (12)$$

$$\Delta b_{i_{i}j_{i}k} = \left(\left(\frac{b_{i+1,j,k} - b_{i,j,k}}{x_{i+1} - x_{i}} - \frac{b_{i,j,k} - b_{i-1,j,k}}{x_{i} - x_{i-1}} \right) \mathbf{I} \left(\frac{x_{i+1} - x_{i-1}}{2} \right) \right)^{2} + \left(\left(\frac{b_{i,j+1,k} - b_{i,j,k}}{y_{j+1} - y_{j}} - \frac{b_{i,j,k} - b_{i,j-1,k}}{y_{j} - y_{j-1}} \right) \mathbf{I} \left(\frac{y_{j+1} - y_{j-1}}{2} \right) \right)^{2} + \left(\left(\frac{b_{i,j+1,k} - b_{i,j,k}}{y_{j+1} - y_{j}} - \frac{b_{i,j,k} - b_{i,j-1,k}}{y_{j} - y_{j-1}} \right) \mathbf{I} \left(\frac{y_{j+1} - y_{j-1}}{2} \right) \right)^{2} + \left(\left(\frac{b_{i,j+1,k} - b_{i,j,k}}{y_{j+1} - y_{j}} - \frac{b_{i,j,k} - b_{i,j-1,k}}{y_{j} - y_{j-1}} \right) \mathbf{I} \left(\frac{y_{j+1} - y_{j-1}}{2} \right) \right)^{2} + \left(\left(\frac{b_{i,j+1,k} - b_{i,j,k}}{y_{j+1} - y_{j}} - \frac{b_{i,j,k} - b_{i,j,k-1}}{y_{j} - y_{j-1}} \right) \mathbf{I} \left(\frac{y_{j+1} - y_{j-1}}{2} \right) \right)^{2} + \left(\left(\frac{b_{i,j+1} - b_{i,j,k}}{y_{j+1} - y_{j}} - \frac{b_{i,j,k} - b_{i,j,k-1}}{y_{j} - y_{j-1}} \right) \mathbf{I} \left(\frac{y_{j+1} - y_{j-1}}{2} \right) \right)^{2} + \left(\left(\frac{b_{i,j+1} - b_{i,j,k}}{y_{j+1} - y_{j}} - \frac{b_{i,j,k} - b_{i,j,k-1}}{y_{j} - y_{j-1}} \right) \mathbf{I} \left(\frac{y_{j+1} - y_{j-1}}{2} \right) \right)^{2} + \left(\frac{b_{i,j+1} - b_{i,j,k}}{y_{j+1} - y_{j}} - \frac{b_{i,j,k} - b_{i,j,k-1}}{y_{j} - y_{j-1}} \right) \mathbf{I} \left(\frac{y_{j+1} - y_{j-1}}{y_{j} - y_{j-1}} \right)$$
(13)

These local curvature terms have positive values in the conditions in which the function behaves nonlinearly, and the terms have a value of zero otherwise. The relative importance of the flattening term is low under the operating conditions covered by the process data. In contrast, under the operating conditions not described by the data, the role of the flattening term becomes dominant and the model is forced into a plane shape. As a

result, this technique enables extrapolation of the identified process model linearly to the operating conditions unexplored by the data. This results in higher reliability of the obtained models.

A detailed description of the identification of a model for the steam-water network of a drying section is presented in Section 4.

2.3 Comparison of the proposed method to MLP and polynomial models by simulating

2.3.1 Comparison to neural networks

Identifying a 'general' nonlinear multivariate function with neural networks typically requires an enormous amount of data to avoid overfitting and achieve good model accuracy, and therefore it is frequently not feasible in process industry applications. This section aims to demonstrate that considering the structure of nonlinearity can significantly improve the accuracy of models identified from a limited amount of data. The following simple test function was identified using MLPs and the proposed method:

(14)

$$f(x, y) = \sqrt{x} + (y - 0.5)^3, x, y \in [0, 1]$$

To obtain data for model training, both *x* and *y* were generated randomly using the uniform distribution, and Gaussian noise with variance of 0.01 was added to the computed function values. Noiseless data was used for model testing to properly evaluate the model accuracy. MLP with a single hidden layer containing two nodes and the proposed method representing the function as a sum of two one-dimensional functions were tried. Given plenty of training data (1,000 samples), both methods achieved approximately the same accuracy (the square root of the MSE is about 0.05 for the testing data). Both methods have a similar number of parameters to estimate from the data (9 for the MLP and 10 for the proposed method). While training MLP, 30% of available data was used as a validation data set to avoid overfitting. In each case, MLP was trained 30 times, and the lowest square root of MSE for the testing data was selected to ensure that a lower estimation for the network accuracy was obtained. A relatively large amount of noiseless data (1,000 samples) was used for testing all models to ensure that the accuracy was properly evaluated.

Comparison of the MLP and the proposed method is presented in Table 1 for different size of the training data sets. The accuracy of the proposed method agrees with the level of the noise in the training data in all cases. This is not true for the MLP, which often had to be stopped to avoid overfitting when the modeling errors were much higher than the actual noise level (the square root of MSE ranges from 0.158 to 0.193). The reason for this is that the MLP, which is not restricted by the structure of the nonlinearity and the monotonousness constraints, better adapts to the noise. In opposite, knowing the structure of the function (in this case, knowing that the function is a sum of two one-dimensional functions) helps to filter out the noise efficiently. On the training data sets less than 100 samples, the proposed method significantly outperformed the neural network approach, whereas given large amounts of training data both methods provided comparable results. Since the model identification in process industry applications is usually carried out with a limited amount of data, the proposed identification method may be more efficient than the neural network technique.

Data used for	MLP with 2 nodes		The proposed method	
training	Mean sqrt of MSE	Lowest sqrt of MSE	Sqrt of MSE for the	Sqrt of MSE for the
	for the training data	for the testing data	training data	testing data
N = 15	0.178	0.200	0.085	0.118
N = 20	0.158	0.198	0.089	0.069
N = 30	0.162	0.179	0.085	0.068

Table 1. Comparison of the proposed method and the neural networks

N = 50	0.183	0.131	0.103	0.073
N = 70	0.193	0.135	0.110	0.052
N = 100	0.177	0.118	0.103	0.051
N = 150	0.184	0.057	0.112	0.042
N = 200	0.178	0.050	0.113	0.040
N = 1 000	0.166	0.049	0.114	0.039

2.3.2 Comparison to polynomial models

Model identification based on polynomial models makes use of the assumption that the function to be identified is sufficiently smooth (high-order derivatives are bounded). If the function to be identified is smooth and it has only a small number of input variables, identification with polynomial models is very efficient. However, as the number of variables increases, the number of polynomial terms of higher orders grows explosively, and this identification approach starts suffering from overfitting. Moreover, some functions that can occur in practice may require high-order polynomials to be approximated reasonably well. In this section, two case studies are presented to demonstrate the above statements.

In the first study, the following function is identified:

$$f(x_1, x_2, x_3, x_4, x_5) = 2 + x_1^2 x_2^2 - 2 \exp(-x_3^2 - x_4) + \sin(\pi x_5 - \pi/2), x_1, x_2, x_3, x_4, x_5 \in [0, 1]$$
(15)

All terms of the function possess bounded high-orders derivatives, and therefore this function can be approximated very accurately with a third order polynomial. To obtain data for model training, both x and y were generated randomly using the uniform distribution, and Gaussian noise with variance of 0.01 was added to the computed function values. A relatively large amount of noiseless data (1,000 samples) was used for testing of all models to ensure that the accuracy was properly evaluated.

Polynomial models of the third order with 56 terms and the proposed identification method (considering two two-dimensional and one single-dimensional nonlinearities) were tested, and the comparison is shown in Table 2. On the small training data sets, the magnitude of the errors in both methods on the training data was smaller than the noise level, which indicates that both methods suffered from overfitting. However, a comparison of the errors on the training data proves that the polynomial identification was more vulnerable to overfitting, and the proposed identification method was able to achieve better model accuracy at the testing data set. Given the large amounts of training data, both methods demonstrated similar performance.

Data used for	Identification with third order polynomials		The proposed method	
training	Sqrt of MSE for the	Sqrt of MSE for the	Sqrt of MSE for the	Sqrt of MSE for the
	training data	testing data	training data	testing data
N = 50	0.000	1.370	0.048	0.128
N = 70	0.035	0.248	0.058	0.098
N = 100	0.060	0.130	0.072	0.089
N = 150	0.068	0.076	0.076	0.054
N = 200	0.076	0.064	0.083	0.054
N = 300	0.088	0.048	0.093	0.040
N = 500	0.094	0.039	0.097	0.038
N = 1000	0.100	0.024	0.100	0.028

Table 2. Comparison of the proposed method and the polynomial models on a smooth function

In the second case study, the last term in equation (15) was replaced by a function, which is almost constant when x_5 approaches to unity:

$$f(x_1, x_2, x_3, x_4, x_5) = 2 + x_1^2 x_2^2 - 2 \exp(-x_3^2 - x_4) - 1/(1 + \exp(15x_5 - 5)), x_1, x_2, x_3, x_4, x_5 \in [0, 1]$$
(16)

Actually, the last term in (16) possess large high-order derivatives, and therefore it cannot be approximated well with a third-order polynomial. At the same time, a similar function behavior can be found in the process industry. The same two identification methods are compared in the same way as is done in the previous test. The results, presented in Table 3, demonstrate that the identification with polynomial models performed considerably worse than the proposed identification approach.

Data used for	Identification with third order polynomials		The proposed method	
training	Sqrt of MSE for the	Sqrt of MSE for the	Sqrt of MSE for the	Sqrt of MSE for the
	training data	testing data	training data	testing data
N = 50	0.000	1.498	0.053	0.134
N = 70	0.049	0.507	0.069	0.101
N = 100	0.092	0.200	0.087	0.090
N = 150	0.105	0.138	0.091	0.063
N = 200	0.107	0.104	0.091	0.051
N = 300	0.111	0.100	0.093	0.047
N = 500	0.115	0.090	0.096	0.036
N = 1000	0.117	0.083	0.097	0.030

Table 3. Comparison of the proposed method and the polynomial models on a non-smooth function

3. Description of the drying section of **a** board machine, control strategy, and the faults to be diagnosed

3.1 Process description

The drying section of a board machine uses heating to evaporate water from the board. Since only an insignificant amount of moisture is removed from the board after the drying section, the drying section is typically controlled to achieve the specified moisture of the ready product. In multi-cylinder drying, which is the most common drying method, the process contains a number of consecutive steam drying cylinders combined into several drying groups. The process under consideration contains 5 groups, as shown in Figure 2. The steam-heated cylinders are shown in orange, and the board web is presented by the red line. In order to control web curl, the last drying group (group 5) is composed of two steam groups (groups 8 and 7) comprising cylinders placed above and below the web respectively. The felts shown in Figure 2 with blue lines provide proper contact between the board and the cylinders. The felt tension is maintained by the leading rolls indicated in green, purple and blue.

In fact, a complex steam-water network with a number of recirculation streams is needed to support the desired conditions in the cylinders and provide the acceptable energy efficiency of the drying process.

The steam-water network of the drying section is presented in Figure 3. Steam is supplied by two steam feed flows to the steam groups (5 bar steam is used by groups 1, 2, and 3; 10 bar steam is used by groups 3, 4, 7, and 8). A part of the 5 bar feed steam flow is also sent to the calender and to the heat exchangers, which are used to control the temperature in the plant building. The flow rate, pressure, and temperature are measured in both feed steam flows. In addition, the pressure is measured immediately before and after each steam group.

Since there are no valves between steam groups 3, 4, 7, and 8 and the respective condensate tanks 4, 5, 8, and 9, one can conclude that the pressure in the condensate tanks is the same as the pressure immediately after the respective steam groups. In contrast to this, there are valves between the steam groups 1 and 2 and the condensate tanks 2 and 3. The pressure in condensate tank 2 is measured. The pressure in tank 3 is not measured; instead, it is assumed that the pressure in this tank is the same as the pressure before the steam group 1. The process data contains the control signals sent to all valves (the degrees of valve opening). Finally, the levels of the condensate tanks are tightly controlled, and the variation in the levels can be neglected.



Figure 2. The drying section of the board machine



Figure 3. Simplified scheme of the steam-water network of the drying section

3.2 The control strategy

The main objectives of the drying section control are to control the evaporation of water, the removal of moist air, and the tension of the fabrics of the drying groups. Efficient evaporation of water is achieved by regulating the steam usage and the temperature profile in the drying section. Each steam group has its own controllers to control the steam pressures, steam pressure differences between the steam and condensate headers, and the level of the condensate tanks. The main operating principles of control are similar for each steam group, see Figure 4. The pressure valves placed before the groups are used to control the pressure in the cylinders. The pressure controller of group 7 follows the set point given to the pressure of group 8 with an operator-given ratio coefficient. Higher steam pressure is required in the lower cylinders in order to control the curling of the board. The valves placed after the steam groups are adjusted to keep the pressure drop in the groups constant. The pressure difference between the steam header and the condensate tank must be high enough to enable efficient condensate removal from the cylinders but simultaneously low enough not to blow steam directly through the cylinders. The level of the condensate tanks is controlled with the valves placed after the tanks.



The tension of the fabrics is controlled in order to provide proper support to the web.

Figure 4. Control of a cylinder group of the drying section

3.3 The faults to be diagnosed

The FDD system has to focus on the most frequent faults in the section which can cause the most expansive losses of productivity and quality deviations of the ready board. According to Jämsä-Jounela et. al. [19], the key faults to focus on are the leakages and blockages of valves and pipes in the steam-water network of the drying section. Small-magnitude faults may cause energy losses, but a large fault could even cause inability of the control system to maintain the required quality of the ready product and may cause a plant shutdown.

4. Testing of the FDD approach in the drying section

The aim of this section is to test the general FDD approach presented in Section 2 in the drying section. First, the design of the model equations is presented, and then the data preprocessing and the identification of the equations are described. Finally, the selection of a condensate valve model is discussed.

4.1 Estimation of flow rates in the steam-water network using valve models

To detect and diagnose the leakages and blockages in valves and pipes in the steam-water network, a model is needed which consists of equations representing the mass balance of different parts of the network. Mass balance equations are normally based on flow rate values, however only two flow rate measurements of the feed steam flows in the network are available. Even though the pressure measurements and the degrees of valve opening cannot be used directly in the mass balance equations, these variables enable estimating the flow rates through the valves according to equation (14) and Figure 5:



Figure 5. Estimation of the flow rate through a valve

4.2 The list of the model equations and the faults

The simplified scheme of the steam-water network results in two equations (18-19) for the feed steam flows, presented in Figure 6, and four equations (20-23) for the steam groups, presented in Figure 7.

$$f_{3,in\ 10}(V_3,\Delta P_3) + f_{4,in}(V_4,\Delta P_4) + f_{7,in}(V_7,\Delta P_7) + f_{8,in}(V_8,\Delta P_8) - F_{in,10} = 0,$$
(18)

$$f_{1,in}(V_1, \Delta P_1) + f_{2,in}(V_2, \Delta P_2) + f_{3,in}(V_3, \Delta P_3) + F_{Calend} - F_{in,5} = \mathbf{0}.$$
 (19)

$$f_{8,cond}(V_{8,cond},\Delta P_{8,cond}) + f_{8,pdiff}(V_{8,pdiff},\Delta P_{8,pdiff}) - F_{8,in} = \mathbf{0},$$
(20)

$$f_{7,cond}(V_{7,cond}, \Delta P_{7,cond}) + f_{7,pdiff}(V_{7,pdiff}, \Delta P_{7,pdiff}) - F_{7,in} = \mathbf{0},$$
(21)

$$f_{4,cond}(V_{4,cond}, \Delta P_{4,cond}) + f_{4,pdiff}(V_{4,pdiff}, \Delta P_{4,pdiff}) - F_{4,in} = \mathbf{0},$$
(22)

$$f_{3,cond}(V_{3,cond},\Delta P_{3,cond}) + f_{3,pdiff}(V_{3,pdiff},\Delta P_{3,pdiff}) - F_{3,in\,5} - F_{3,in\,10} - F_{4,cond} = \mathbf{0}.$$
 (23)



Figure 6. The parts of the network related to the mass balance of 10 bar and 5 bar feed steam flows



Figure 7. The parts of the network related to the mass balance of steam groups

A part of 5 bar feed steam flow is used to heat the plant building up, and the measurements of that part of the 5 bar steam flow were not available for the research. In the result, the mass balance of 5 bar steam flow was not accurate enough to estimate precisely the steam flows to groups 1 and 2 and to identify the mass balances of these groups. The 10 bar and the 5 bar steam flow mass balances are sensitive to the following faults:

- leakages of the pipes between the 10 bar and 5 bar steam flow measurements and the pressure valves,
- blockage of the pressure valves of groups 3, 4, 7, 8, and groups 1, 2 and 3,
- faults in the 10 bar and 5 bar steam flow measurements.

The mass balances of groups 8, 7, 4 and 3 are sensitive to the following faults in the groups:

- blockage of the pressure, pressure difference and condensate valves,
- leakage of the pipes connecting the pressure valves with the cylinders, the cylinders and the condensate tanks, the condensate tanks and the pressure difference valves, the condensate tanks and the condensate valves,

• faults in the condensate pumps (which results in wrong estimations of the condensate outflows from the groups)

After a fault is detected, the process is further monitored to decide whether each equation is fullfiled and to determine the sign of the residuals for the violated equations. According to the structured residual approach, the decisions on each model equation are collected to a pattern, and faults are identified by matching the current pattern to the patterns produced by the faults.

4.3 Data preprocessing

Data collected between 1 March 2010 and 31 August 2010 was used for testing the method. Data preprocessing aimed to exclude irrelevant process data related to plant shutdowns and data related to large process disturbances. Moreover, steady-state process data is needed for identification of a steady-state model. The relevant data was selected according to the following criteria:

- The plant shutdowns were identified and excluded by checking the production rate and the rotation speed of the cylinders in the drying section.
- Data was excluded that showed that the simplified scheme of the steam-water network is not valid. Specifically, the simplified scheme does not include a number of flows aimed to increase the control capacity, which are rarely used. If at least one of these flows was nonzero (the degree of the opening of the related valve was positive), the data sample was not used for model identification.
- The transitions were excluded by considering the changes of the setpoints of the key control loops, such as the basis weight, the moisture and the thickness of the board, and the rotation speed of the cylinders in the drying section.
- Data related to large-magnitude disturbances was identified and excluded by checking the control error of the moisture of the final product.

Next, the delays between the variables were determined by performing cross-correlation analysis between the pairs of process variables. The delays were then compensated by time shifting. However, in this case, this step was unnecessary because the delays did not play a significant role in the process. The sampling time was 1 minute, and the largest delay found was only two minutes.

4.4 Identification of the parameters of the model equations

The pressure differences between the points before and after all valves were computed from the pressure measurements. To obtain a more uniform distribution of the data, logarithms of the pressure differences instead of the pressure differences themselves were used as the inputs of the valve models. Grids with 5 nodes were selected for the inputs of the nonlinear functions representing the valve models in equations (18-23). Next, a set of 5 piecewise linear functions were constructed for each input of the nonlinear functions.

In fact, many nonlinear functions are used in more than one equation. For example, the function representing the valve placed before the steam group 8 was involved in the equations representing the mass balance of the 10 bar feed steam flow and the mass balance of steam group 8:

$$F_{8,in} = f_8(V_8, \Delta P_8).$$

The nonlinear functions involved in more than one equation can be used for sequential identification of the model equations, which helps to avoid solving a relatively complex QP problem. In brief, the equations

(24)

involving the available measurements were identified by solving the related quadratic programming problems. The process data was entered into the nonlinear functions involved in the equations that had already been identified to compute the flow rates through the related valves for every data sample. Next, these flow rates were entered into the unidentified model equations, and these equations were then identified by solving the related QP problems. This procedure was repeated until all model equations were identified.

In this example, the equation related to the mass balance of the 10 bar steam feed flow was identified first, and the coefficients of the nonlinear functions $f_{3,in 10}$, $f_{4,in}$, $f_{7,in}$, and $f_{8,in}$, which are related to the valves placed before the steam groups 3, 4, 7, and 8, were obtained. Similarly, the equation related to the mass balance of the 5 bar steam feed flow was identified, and the coefficients defining the nonlinear functions $f_{1,in}$, $f_{2,in}$, and $f_{3,in 5}$, which are related to the valves placed before the steam groups 1, 2, and 3, were obtained. At the next stage, the process data was entered into the nonlinear functions identified in the previous step to estimate the steam flow rates to the steam groups $F_{3,in 5}$, $F_{3,in 10}$, $F_{4,in}$, $F_{7,in}$ and $F_{8,in}$. These flow rate estimations were then entered into the rest of the model equations. The model equations related to the mass balance of the steam groups 4, 7, and 8 were identified, and the coefficients of the nonlinear functions related to the pressure difference control valves $f_{4,pdiff}$, $f_{7,pdiff}$, and $f_{8,pdiff}$ and the condensate tank level control valves $f_{4,cond}$, $f_{7,cond}$, $f_{8,cond}$ are obtained. Finally, the nonlinear function $f_{4,cond}$ related to the control valve for the level of the condensate tank 5 was used to compute the condensate inflow rate $F_{4,cond}$ into the condensate tank 4, and the equation related to the mass balance of steam group 3 was then identified.

4.5 Selection of the structure for the model of the control valve of the condensate tank 5 level

The accuracy of the identified equations has been evaluated, and the equations related to the mass balance of the feed steam flows and the steam groups 8 and 7 have been found to be sufficiently accurate. In contrast, the error of the equation representing the mass balance of steam group 4 was too big for reliable fault detection. In fact, the condensate outflow from tank 5 passes through the combination of a pump and a one-side valve connected in parallel (see Figure 8) which are placed before the control valve. In order to describe the condensate flow rate more precisely, a nonlinear function of three variables (the degree of valve opening, the pressure in condensate tank 5, and the pressure in condensate tank 4) was tried:

$$f_{4,cond}(v_{4,cond}, P_{4,cond}^{before}, P_{4,cond}^{after}) + f_{4,pdiff}(v_{4,pdiff}, \Delta P_{4,pdiff}) - F_{4,in} = \mathbf{0}$$

$$\tag{25}$$

Compared to equation (22), the pressure difference $\Delta P_{4,cond}$ has been replaced by the pressure before and the pressure after the condensate valve. The nonlinear function representing the condensate valve in (25) must monotonously increase with respect to the first two inputs and must monotonously decrease with respect to the last input. The parameters of equation (25) can still be identified by solving a quadratic programming task.



Figure 8. Diagram of the condensate outflow from the condensate tank 5

The equations representing the mass balance of steam group 4 were identified both with two-input (equation (22)) and three-input (equation (25)) models of the condensate valve. For the identification, 4000 data

samples were used, while 600 samples were reserved for testing of the equation. Table 4 summarizes the percentage of variation of the inflow rate $F_{4,in}$ into group 4 captured by the valve models according to equations (22) and (25). The table proves that equation (25), employing the three-input nonlinear function to describe the condensate outflow from tank 5, is more precise.

	R ² captured, data used for	R ² captured, data used for
	identification	testing
The valve model with two inputs	88.1 %	89.2 %
The valve model with three inputs	95.0 %	95.0 %

Table 4. Comparison of two model structures for the control valve of the level of the condensate tank 5

5. Results

This section presents the evaluation of the effect of the monotonousness conditions and the model flattening, the results of the validation of the model equations, and two fault case studies.

5.1 Study of the effect of the monotonousness conditions

To test the effect of the monotonous conditions, the equations were identified twice: under the monotonousness conditions and without imposing these conditions. The data used to identify the equation consisted of 4000 samples, while 600 samples were reserved for validation. Table 5 presents the variation of the inflow rate $F_{4.in}$ into the group captured by the nonlinear functions in equation (25). The results of the testing of the model equations with and without the monotonousness conditions show that the equations employing non-monotonous valve models demonstrate less accuracy due to adaptation to the process noise. Both valve models of the condensate valve are presented in Figure 9 for the valve opening degree equal to 75%.

Table 5. Comparison of the results of monotonous and non-monotonous models of condensate valve of steam group 4

	R ² captured, training data	R ² captured, validation data
Monotonous valve models	95.0 %	95.6 %
Non-monotonous valve models	96.3 %	90.3 %





5.2 Study of the effect of the flattening

The process data was often distributed very non-uniformly, and the data used for identification of the model equations did not cover all possible operational conditions. Therefore, the operational conditions of the valves can move to unexplored zones during on-line fault detection. To demonstrate the ability of flattened models to

remain trustworthy in the unexplored operational conditions, the equation related to the mass balance of the 10 bar steam feed flow was identified twice: first, flattening of the nonlinear functions was used and next the equation was identified without flattening. The equation was identified using 4600 samples, and 1000 samples were reserved for testing. Both the flattened and the non-flattened models of the valve placed before the steam group 7 are presented in Figure 10. The range between the smallest and the largest flow rates according to the non-flattened valve model is 7.1 I/s, while the range for the flattened valve model is only 4.4 I/s. As a result, under the unexplored operating conditions, the flow rate estimation according to the non-flattened model is shown in Table 6.

The flattened valve models are able to explain a smaller percentage of the variation of the flow rate $F_{in, 10}$ of the 10 bar steam feed flow in the testing data than in the data used to identify the equation. However, the accuracy of the flattened model in the testing data can be considered as acceptable since some increase of the equation error occurs due to the nonlinear character of the process.

	R ² captures, data used to identify	R ² captures, data used to test the
	the model	model
Original monotonous model	99.5%	61.5 %
Flattened monotonous model	99.5%	84.0 %

Table 6. Comparison of the results of the original and the flattened monotonous models





5.3 Results of validation of the identified model

The model equations were identified using the data collected between 1 March 2010 and 11 July 2010, and the process data obtained between 12 July and 24 July is used for model testing. The equations related to the mass balance of the 5 bar steam feed flow and the steam group 3 were not tested due to the lack of fault-free data. The results of the evaluation of the identified model equations are presented in Table 7. For all equations, the sum of terms involved in the equations with a negative sign (inflows) and the sum of terms involved with a positive sign (outflows) are computed separately, and the percentage of variation of the first sum explained by the second sum is provided in the table. In addition, the errors of the model equations are obtained by entering the process data into the equations. The standard deviation of the errors of the model equations is shown in the table.

Model equation	Data used to ide	entify the equations	Data used to test the equations	
	R ² captured	Standard deviation	R ² captured	Standard deviation
10 bar steam feed flow	99.5 %	0.116 l/s	97.9 %	0.107 l/s
5 bar feed steam flow	91.9 %	0.167 l/s	-	-
Steam group 8	94.1 %	0.056 l/s	91.4 %	0.077 l/s
Steam group 7	91.2 %	0.046 l/s	93.6 %	0.046 l/s
Steam group 4	95.0 %	0.090 l/s	95.6 %	0.092 l/s
Steam group 3	96.9 %	0.133 I/s	-	-

Table 7. Summary of the developed model equations

5.4 Comparison to the neural networks

To compare the proposed method against the neural networks, the model equations were identified in the same order using a multilayer perceptron (MLP). The 10 bar feed steam flow equation was identified using a MLP with a single hidden layer. The same data collected between March 1, 2010 and July 11, 2010 was used to train the networks, and 20 percent of the data samples selected randomly from this data set were used for validation. To test the accuracy of the obtained models, the same data collected between July 12 and July 24 was used. The results summarized in Table 8 demonstrate that significant overfitting takes place in all cases when the number of nodes is more than 5. Therefore, the network with 3 nodes (which for the testing data has an accuracy comparable to the proposed method results) was selected for further analysis. However, the difference between the neural network models and the equation obtained by the proposed method is that the neural network models do not reflect the actual structure of the process described by Equation 18.

 Table 8. Accuracy of the neural network models estimating the 10 bar feed steam flow

Number of	Standard deviation of the error		
nodes	Training data	Testing data	
3 nodes	0.129 l/s	0.111 I/s	
5 nodes	0.109 l/s	0.143 l/s	
7 nodes	0.110 l/s	0.160 l/s	
10 nodes	0.096 l/s	0.144 I/s	
15 nodes	0.077 l/s	0.207 I/s	

Estimating the steam flows to the groups is necessary to construct equations representing the mass balance of these groups. However, the neural network models (which do not reflect the actual structure of the process) do not provide any reliable estimations of these flows. Therefore, the flows to the groups were estimated approximately in the following way: the degree of the valve opening and the pressure drop at a single valve were fed to the model inputs, and the rest of the inputs were replaced by the mean value of the respective signals. The resulting estimations of the steam flows to the groups were used to create the neural network models of steam groups 8, 7, and 4, and the equation for Group 3 was not considered due to the limited amount of data available. MLP models with a single hidden layer having 7 and 4 nodes were tried, and the MLPs with 7 nodes provided slightly more accurate models. The results (summarized in Table 9 for the MLP models with 7 nodes in the hidden layer) clearly demonstrate that the accuracy of the neural network models is insufficient for fault detection of moderate magnitude faults. (The captured variance of the testing data stays

below 90 % in all cases). This demonstrates the benefits of considering the structure of the nonlinearities, which results in better accuracy of identified models.

Model equation	Training data		Testing data	
	R ² captured	Standard deviation	R ² captured	Standard deviation
Group 8	95.7 %	0.073 l/s	87.6 %	0.152 l/s
Group 7	87.0 %	0.057 l/s	75.7 %	0.088 I/s
Group 4	93.1 %	0.095 I/s	79.7 %	0.158 l/s

Table 9. Accuracy of the neural network models with 7 nodes for the steam groups 8, 7 and 4

5.5 Case study 1: blockage of the valve placed before the steam group 3

The fault considered in this example is blockage of the valve placed on the 5 bar steam feed flow to steam group 3, as shown in Figure 11. The equation related to the mass balance of the 5 bar feed steam flow is presented in Figure 12. The solid blue line is used for the measured flow rate of the 5 bar steam feed without the flow rate of the feed steam to the calendar. The dashed red line represents the sum of estimated flow rates of the 5 bar feed steam to steam groups 1, 2, and 3. In the faultless conditions, these two values almost coincide, and the difference between them clearly indicates the fault. Next, the equation related to the mass balance for steam group 3 is presented in Figure 12. The solid line represents the sum of estimations of the flow rates of the 5 bar steam and 10 bar steam feed flows to steam group 3, and the flow rate of the condensate tank 5 to condensate tank 4. The dashed line is used for the sum of estimations of the steam flow rate out of steam group 3 and the condensate flow rate out of condensate tank 4. The fault can be clearly seen in this equation as well.

Due to the valve blockage, the equations related to the mass balance of the 5 bar steam feed flow and the steam group 3 have large residuals, while the rest of the equations remain undisturbed. This pattern makes it possible to diagnose the fault location unambiguously among the patterns produced by the faults. The maintenance records confirm the fault that was diagnosed by the FDD system, and the valve controlling the 5 bar feed steam flow to steam group 3 was replaced.



Figure 11. Location of the blocked valve



Figure 12. Equations related to the mass balance of the 5 bar steam feed flow (left) and steam group 3 (right)

5.6 Case study 2: fault in the measurement of the flow rate of the 10 bar feed steam

The location of a fault in the measurement of the 10 bar feed steam flow is shown in Figure 13. The fault is clearly visible in Figure 14, starting approximately at sample 2500, which corresponds to the 24th of February 2011. The solid blue line is used for the measured flow rate of the 10 bar steam feed flow rate, and the dashed red line represents the sum of estimated flow rates to steam groups 3, 4, 7, and 8. Since all the other equations remain undisturbed the fault is unambiguously diagnosed among the fault patterns. The fault lasts until the end of the validation data (end of March 2011). According to the maintenance records, the measurement device was replaced on the 4th of June.



Figure 13. Location of the faulty measurement



Figure 14. Equation related to the mass balance of 10 bar steam feed flow

6. Conclusion

In this study, a gray-box method is proposed for deriving nonlinear steady-state models from process data. The method contains the following three aspects: Firstly, the resulting models describe the process nonlinearity by means of low-dimensional nonlinear functions, representing the nonlinearity related to the most common devices used in the chemical industry, such as valves, pumps, pipes, tanks, chemical reactors, and basic combinations of these devices. This makes it possible to ignore the insignificant relations between the process variables during the model identification task and makes it possible to improve the accuracy of the obtained models. Secondly, monotonousness conditions are imposed on the nonlinear functions according to the general properties of the devices related to these functions. This results in a further improvement of model accuracy. Thirdly, flattening of the nonlinear functions is used while defining the parameters of the model equations. This technique enables extrapolating the process models linearly to operating conditions not described by the process data. The aim is to achieve better reliability of the resulting model even under these unexplored conditions. The proposed method is compared to MLP and polynomial model approaches by simulating.

The study also proposes a fault detection and diagnosis approach based on the identified models. The standard structured residuals approach is selected for fault diagnosis because it requires neither description of the possible faults with faulty data nor modeling of the faults. In fact, the structured residual approach can fail to diagnose small magnitude faults correctly, because some of the equation residuals can be properly recognized as nonzero residuals whereas others can be still classified as normal due to insufficient fault magnitude. In this case, the final diagnostic decision must be done by the plant experts on the basis of process knowledge and the history of the equation residuals provided by the proposed method.

Finally, the identification method is applied to the steam-water network of the drying section of a board machine, and the FDD system is implemented to detect and diagnose valve leakages and blockages in the network. The effect of the monotonousness conditions and the flattening of the nonlinear functions are demonstrated. The identified models are validated and shown to have good accuracy. Two case studies of a valve blockage and a measurement fault are provided.

Acknowledgements

This research has been conducted as a part of the European Union Seventh Framework Program FP7/2007-2013 under grant agreement n° 257580.

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