DIAGNOSIS SYSTEM FOR CONTINUOUS COOKING PROCESS

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Abstract: Industrial systems generate a lot of information for operators. Increased measurement information flow might cause difficulties for the process operators to observe the process states and faulty process operation. In this study, measurements and statistical variables are combined by fuzzy logic to generate key factors for several points in the continuous cooking digester. The overall diagnosis system combines the key factors into one system which is used for the operational purposes and as a helping tool for process condition monitoring.

Keywords: Diagnosis, monitoring, fuzzy logic, operators, controllability

1. INTRODUCTION

The question how the overall system of the sub processes and chains of sub processes can be improved, by means of fault diagnosis (see e.g. (Isermann, 1997)), has not fully answered. In particular, this holds for demanding process conditions such as found in chemical and mechanical pulping. Modern processes generate a lot of information, which can be used for improving the operation of the process and quality of the products. This can be accomplished by combining expert knowledge, modelling, control and fault diagnosis.

Many industrial applications, like continuous digester process, are very difficult to model and control due to the highly non-linear nature of process. The continuous digester is complicated system with long residence times as well as difficult and often insufficient measurement points. High pulp capacity demands and highly alkaline conditions prevents the measuring of temperatures and the alkali content inside the digester. Thus the measurements are located at the input and output flows and on the outside wall of the digester. Due to this the digester control is challenging.

The production rates in the continuous cooking processes have increased continuously. That set demands for process control and can cause faults and disturbances which reduce the quality of the pulp. If the disturbances move too far along the digester axis it is possible that the production must be reduced which in turns causes economical losses to the mill. In order to normalize process operation properly after a process fault the identification of faults should be done as soon as possible. (Tervaskanto *et al.*, 2004)

The fault diagnosis of the chemical processes is an important factor in the quality control of the processes. Diagnosis of the chemical processes are studied in many papers, see e.g. (MacGregor and Kourti, 1995), (Wise and Gallagher, 1996), (Patton *et al.*, 2001), (Dash *et al.*, 2003) and (Lennox *et al.*, 1998). Principal component analysis (PCA) and other statistical methods were used in (MacGregor and Kourti, 1995) and (Wise

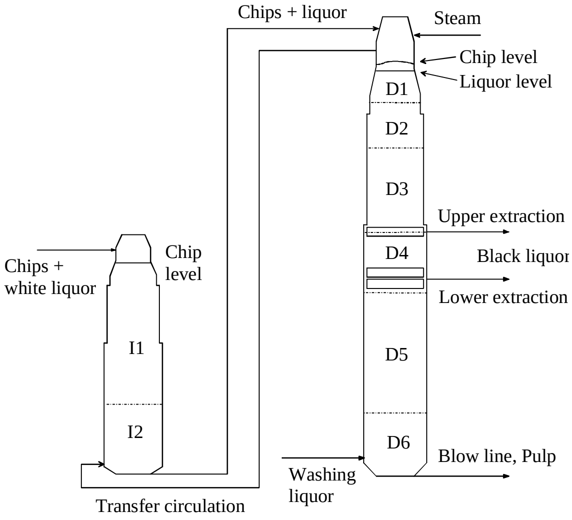

Fig. 1. Impregnation vessel and continuous Kamyr digester.

and Gallagher, 1996). Multiple-model approach was used in (Patton *et al.*, 2001). Fuzzy logic was applied for the fault diagnosis in (Dash *et al.*, 2003). Neural networks were used in (Lennox *et al.*, 1998).

In the field of chemical pulping, there are not too many publications concerning fault diagnosis. Puranen (Puranen, 1999) has formed a disturbance index for process operators to be able to observe faulty process situations. That has been done using measurements and deviations and means and combination has been done using fuzzy logic. Inputs for the index has been the blow-line consistency, kappa number, chip and liquor levels and pressure difference of extraction screens. Diagnosis of the Kappa number control has been studied in (Ahvenlampi and Kortela, 2005).

There are many disturbances in the digester control. The main uncertainties and difficulties in the digester control are following (Lundqvist, 1990): the varying and to a great extent unknown properties of the chips entering the digester system, the behavior of the chip column, the many complex phenomena involved in impregnation, cooking and washing, and the long time delays and the lack of good sensors for crucial variables. Because of these, it is very difficult to observe chemical reactions and material flows in the digester (Lundqvist, 1990). One of the major disturbances in continuous cooking is the varying chip size, which could cause problems in the digester (Tikka *et al.*, 1988), such as unwanted cooking properties. Another major disturbance is the abnormal compaction. Compaction has been researched and simulated for example by (Miyanishi and Shimada, 2001), (Saltin, 1992) and (Härkönen, 1987). One faulty situation affecting the pulp quality is the channelling of the washing liquor in the washing zone. This can cause variance to the blow-line pulp consistency and process delays.

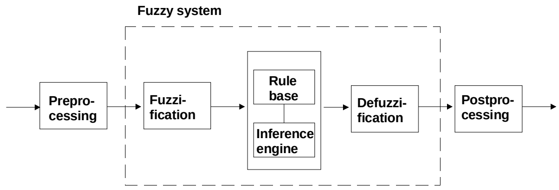

Fig. 2. Fuzzy system.

Process disturbances and faults are controlled and observed from various variables in the operator room at the pulp plant. Especially, under observation are the following variables (if they are measured): surface temperatures of the digester's washing zone, chip and liquor levels, pressure differences in the screen surface and the pulp volume and temperature at the blow-line and at the extraction flows.

In this study, continuous digester in chemical pulping line has been studied. The aim is to optimize the sub process functionality, and to avoid reduced pulp quality. This can be produced by a combination of models, clustering and key factors. Several key factors are introduced for the diagnosis of the digester. The digester diagnosis system is the combination of the indexes.

Structure of the paper is as follows. Process is introduced in the section 2. In the section 3, methods are shortly revised. Digester diagnosis system is presented in section 4. Results and discussion are shown in the sections 5 and 6. Conclusions are presented in the section 7.

2. PROCESS

In this study, a conventional continuous Kamyr process consisting of a impregnation vessel and a steam/liquor phase digester (Fig. 1) is studied. The process has been simplified by removing almost all of the original liquor circulations, thus only the upper and lower extraction screens in the end part of the cooking zone are used. A characteristic of this process are the grade changes between softwood and hardwood done almost every other day.

The active alkali concentrations of the white liquor, the digester feed circulation liquor and the two black liquor circulations from the end of the cooking zone are measured. The sulfide concentration of the white liquor is also measured and it is assumed to stay constant during the cooking. Temperatures are measured from the various parts of the digester.

3. METHODS

3.1 Fuzzy modeling

Fuzzy logic (Zadeh, 1965) is widely used in modelling, identification and control of industrial processes. Fuzzy modeling procedure consists of several phases (Fig. 2).

Fuzzy modelling, identification and control are usually carried out by (Mamdani, 1977) or (Takagi and Sugeno, 1985) type fuzzy models. Mamdani model has fuzzy premise and consequent part.

$$R_i : If\ x_1\ is\ A_{1,i}\ and\ x_2\ is\ A_{2,i}\ then\ y\ is\ B_1 \quad (1)$$

Sugeno model has fuzzy premise part and consequent part is a function. The basic idea in this method is to decompose the input space into different fuzzy regions and using simple models (in many cases linear models) in these regions in the approximation of the system.

$$R_i : If\ x_1\ is\ A_{1,i}\ and\ x_2\ is\ A_2, i\ then\ y = f_i(x) \quad (2)$$

These methods are implemented in many industrial applications.

3.2 PCA

With PCA original input variables $x_1, x_2, .., x_n$ are transformed into new variables $t_1, t_2, \ldots, t_n$, so that new variables are uncorrelated with each other and account decreasing portions of the variance of the original variables. These new variables are principal components and they can be estimated from the eigenvectors of the covariance or correlation matrix of the original input data matrix. The first principal component is the projection on the direction in which the variance of the projection is maximized. (Basilevsky, 1984)

Principal component analysis is a method of expressing a matrix X of input variables as outer products of two vectors, a score T and a loading P with a residual matrix E.

$$X = TP + E, \quad (3)$$

The PCA model can be used in the diagnosis using Q-statistic and Hotelling's T^2 methods.

Q-statistic This statistic indicates how well each sample conforms to the PCA model, measured by the projection of the sample vector on the residual space. Q-statistic or SPE (Squared prediction error) is simply the sum of squares of each row (sample) of E (Wise and Gallagher, 1996).

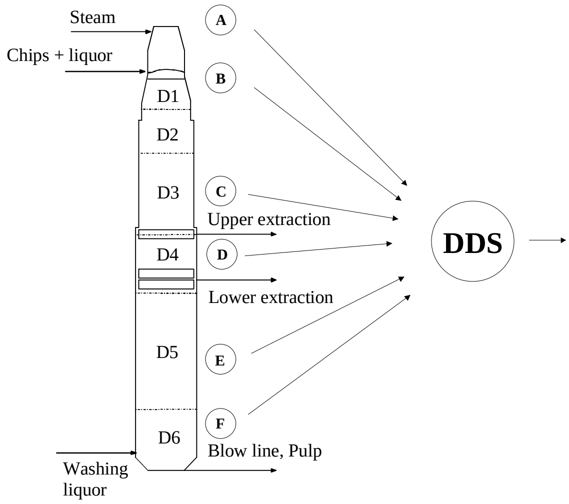

Fig. 3. Digester diagnosis system (DDS).

$$Q_i = e_i e_i^T = x_i(I - P_k P_k^T)x_i^T \quad (4)$$

where e_i is the i^{th} row of E, P_k is the matrix of the first k loadings vectors retained in the PCA model and I is the identity matrix.

Hotelling's T^2 A measure of the variation in the PCA model can be calculated using Hotelling's T^2 statistic (see, e.g. (Wise and Gallagher, 1996)). T^2 is the sum of normalized squared scores and the equation is as follows:

$$T_i^2 = t_i \lambda^{-1} t_i^T = x_i P \lambda^{-1} P^T x_i^T, \quad (5)$$

where t_i is the i^{th} row of the T_k, the matrix of k scores vectors from the PCA model. The matrix λ^{-1} is the diagonal matrix containing inversed eigenvalues with the k eigenvectors retained in the model.

4. DIGESTER DIAGNOSIS SYSTEM

In this section, digester diagnosis system is presented. Various key factors are developed for the continuous digester using fuzzy logic and statistical methods. The digester diagnosis system (DDS) is a combination of several indexes and models. In Fig. 3, the basic idea of the system is shown.

The system is divided into the hierarchical levels:

1. Measurements level (Temperature, etc.)
2. Model level
3. Index level(A,B,C,D,E,F)
4. Subprocess level (DDS)

4.1 Measurements level

In the measurements level, variables (temperatures, pressures, chip and liquor levels, kappa number, etc.) are measured and preprocessed (mean and standard deviation).

4.2 Model level

In the model level, the temperature and alkali profiles for the upper and lower extraction are modeled. In the constructing of the profiles experimental modelling methods are applied. Both multivariate regression and neural networks are used in the identification.

4.3 Index level

The composing of the indexes is performed using measurements, models and statistical methods. The indexes are generated using fuzzy logic. Trapezoidal (Fig. 4) and triangular membership functions are utilized. The outputs of the indexes are formed using singletons and weighted average.

The index level is divided into 6 indexes as follows:

A. Index for the top of the digester
B. Index for the levels
C. Residual index
D. Compaction index
E. Index for the washing zone
F. Index for the bottom of the digester

Index A In the top of the digester (A), the kappa number and the deviation in the chip level are used in the index. This index indicates the quality and disturbances of the entering chips to the digester.

Index B The difference and the deviation between chip and liquor levels are used in the index (B). The abnormal compaction conditions at the top of the digester can be observed from the index.

Index C Residual index (C) is taking into account the difference between the modelling results and measurements. Residuals are used and combined in the index. The development of the cooking can be seen from this index.

Index D Pressure and flow changes over the screen surface are taken into account in the compaction index (D). The abnormal compaction in the cooking zone can be observed from the index.

Index E The washing zone index (E) uses temperature measurement circles in the two layers at the digester wall. The standard deviations of the temperatures in these two circles are used. The

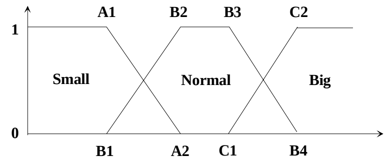

Fig. 4. Trapezoidal membership functions.

channelling and other washing zone disturbances can be observed by this index.

Index F In the bottom of the digester index (F) the kappa number, temperatures and pressures are applied and combined using fuzzy logic. Blowline quality disturbances can be seen by this index.

4.4 Digester diagnosis system

The digester diagnosis system (DDS) collects the information from the index level and generates 2 upper level indexes.

1. The total index: The overall operation of the cooking process at the current time.
2. Minimum index: The weakest link in the system.

The quality of the process is indicated using numerical values and color codes. Numerical values are presented between values 1 and 4, where 4 represents the best case. These values are tuning factors in the system and the values are decided using expert knowledge. Index value 0 indicates that the calculation is not performed in that moment, e.g. during grade changes (if wanted) or measurement failures. Color codes are green (number values from 4 to 3), yellow (number values from 3 to 2) and red (number values from 2 to 1). Green indicates that process is stabile and producing good quality. Yellow is used for slightly reduced and red for very poor quality.

The total index is a combination of all six indexes. Thus one faulty measurement in one index does not affect the total index notably.

5. RESULTS

The digester diagnosis system for the continuous digester is developed. The indexes in faulty operation are shown in Figs.5-8.

In Fig.8, the results from the digester diagnosis system (DDS) is shown. The indexes are plotted using color codes (clusters) for different process states. At the point of 1380 the production has stopped (Fig. 9). The indication of the problems can be seen from the total index (Fig. 8), where the values are decreasing after point 1300. In the index level, the indexes A, B, C and E have

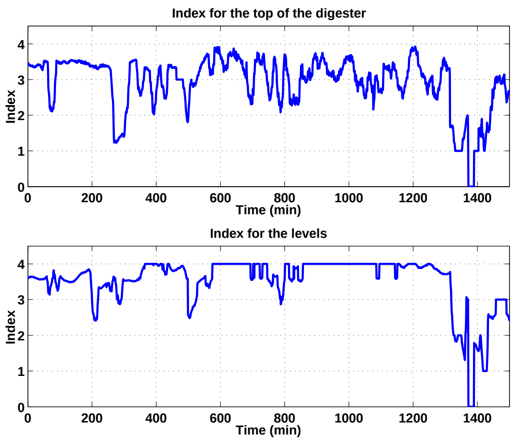

Fig. 5. Indexes A and B in the validation period.

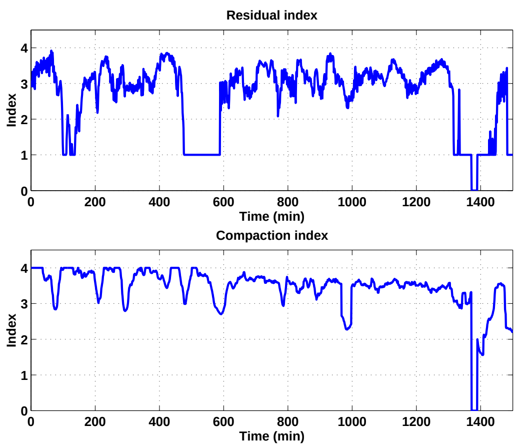

Fig. 6. Indexes C and D in the validation period.

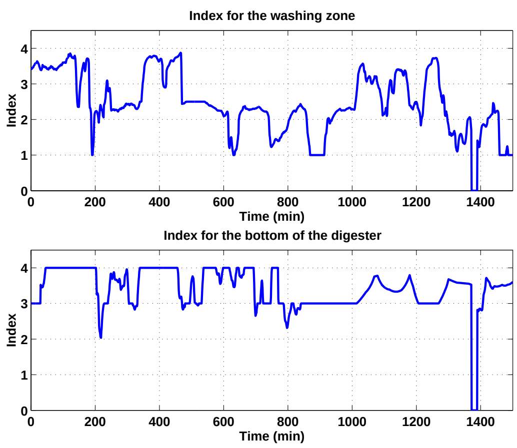

Fig. 7. Indexes E and F in the validation period.

indicated difficulties earlier as shown in the Figs. 5-7.

In Fig. 9, the production rate and kappa number in the same period are shown.

The results are compared with the PCA model using Q-statistic and Hotelling's T^2 methods. PCA model was done using normal operation data (about 30 000 data points). The same measurements were collected as in the DDS. Results are shown in Fig. 10. The PCA model with Q-statistic

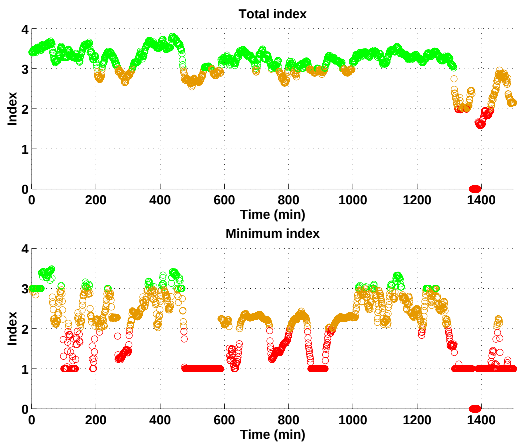

Fig. 8. Total and minimum indexes in validation period.

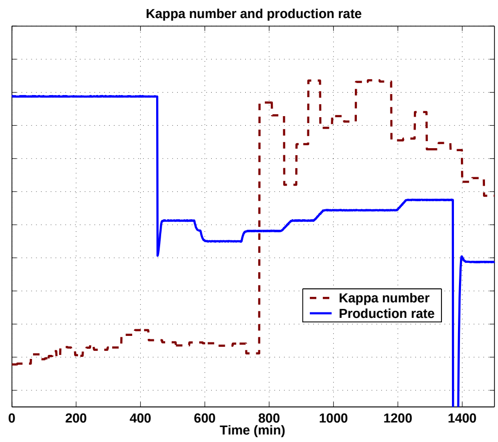

Fig. 9. Production rate and kappa number in validation period.

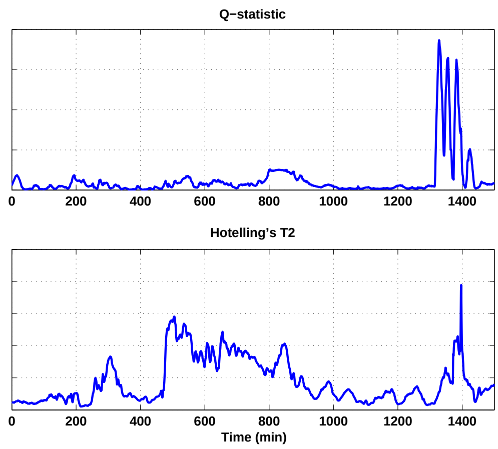

Fig. 10. Diagnosis results of the PCA model.

method is also suitable for the overall index, but it does not indicate, which measurements are indicating the problems in the process.

The grade change can be seen in the total index (Fig. 8) and in the residual index (Fig. 6). The grade change can be also seen from the Hotelling's T^2 index as seen in Fig. 10.

6. DISCUSSION

Industrial systems generate a lot of information for the operators. The increased information can cause difficulties for the operators to observe the process states and faulty process operation.

The controlling of the cooking process is challenging due to the long residence times and hardly measurable variables. The operators have many measurements to monitor and control in the digester. Therefore the collection of the measurements into one system is profitable.

In this study, digester diagnosis system is constructed using several indexes.

During the reduced process operation (Figs. 5-9), the system has warned that the process is not functioning properly. The production stop could have been avoided using DDS.

The diagnosis system will be implemented into the industrial scale chemical pulping plant.

7. CONCLUSIONS

In this study, the diagnosis system for the continuous digester is developed. It can be used as an operational and monitoring tool to indicate possible poor quality and faulty operation. The digester diagnosis system will be implemented into the automation system of the industrial chemical pulping plant.

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