Clustering and fault diagnosis approach in controllability of Kappa number

Timo Ahvenlampi & Urpo Kortela
University of Oulu, Department of Process and Environmental Engineering,
Systems Engineering Laboratory, P.O. Box 4300, FIN-90014 University of Oulu, Finland.
timo.ahvenlampi@oulu.fi

***Abstract*—The controllability of the Kappa number in the continuous digester is considered. The Kappa number is one quality measure of the pulp cooking process, but usually the only available on-line measurement. It is a measure of the residual lignin content in the pulp. The cooking of the pulp mainly takes place in the digester, where the significant part of the lignin is removed from the chips.**

The control of the Kappa number is carried out mainly in the top of the digester; therefore it is important to get some indication of the quality (Kappa number) beforehand. The residence time from the top of the digester to the bottom of the digester, where the on-line Kappa number is measured, is about 300 minutes. The Kappa number is predicted in the top of the digester using SOM and fuzzy clustering. The data is collected from industrial conventional continuous digester. Good results were achieved using the hybrid system.

I. Introduction

Modeling and identification are important parts of a good control design, supervision and fault diagnosis systems [1]. Industrial processes are usually highly non-linear and very difficult or impossible to make good models with conventional modeling techniques. This kind of systems can be called complex systems. Pulp and paper processes are examples of this kind of systems.

Modeling and identification of complex systems may be carried out by e.g. fuzzy logic and neural networks. Fuzzy modeling can be implemented by Mamdani- [2] and Sugeno models [3]. Sugeno models have a fuzzy premise part and a piecewise linear consequent part while in Mamdani models both parts are fuzzy. If there are many inputs in the system, identification of these models needs a lot of calculations, but new methods have been proposed to overcome this problem.

Many of these methods are based on fuzzy clustering [1], [4]: Sugeno-Yasukawa [5] developed Mamdani models, Kim et al. [6] developed a method which collected good parts from Sugeno & Yasukawa [5] and obtain Takagi & Sugeno [3] models. The use of fuzzy clustering in the partitioning makes identification easier and better results can be achieved.

The studied process is a conventional continuous digester. Most of the kraft pulp is produced in the continuous digesters [7]. In a typical chemical pulping process (Fig. 1) the pre-treated and penetrated wood chips are fed into the impregnation vessel and pulp digester where lignin is removed from the chips with the aid of the chemical reactions. Thus the wood fibres are separated from each other. The kraft pulping process has been widely investigated during recent years and the optimal cooking conditions in the chip scale are well known. The usual problem however is that the optimal conditions in the digester scale cannot be ensured. Reasons for this are the large dimensions of the process equipments, inadequate measurements and residence time of several hours.

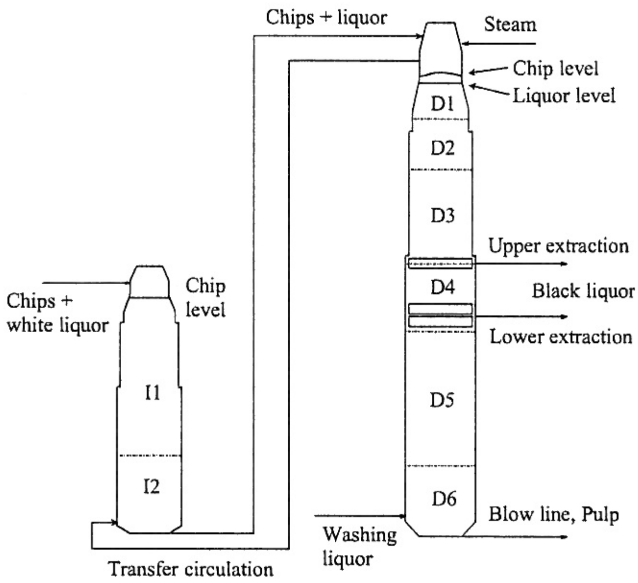

Fig. 1. Impregnation vessel and continuous Kamyr digester.

The quality of the pulp is characterized e.g. with pulp's strength, viscosity, yield and Kappa number. The Kappa number indicates the residual lignin content of the pulp in the blow line and the main variables affecting it are the temperatures and chemical concentration in the digester. The control of the Kappa number is very important part of the continuous cooking process. The steady blow line Kappa number enables the optimized chemical consumption in the following parts of the fibre line. The quality of the pulp has a major effect on the quality of the entire fibre line and of the final paper. [8].

The Kappa number is one of the most important quality indicators of the cooking process. Therefore the control of the Kappa number is essential. In the conventional cooking the main control actions are carried out in the top of the digester, but the on-line measurement of the Kappa number is located in the bottom of the digester. The residence time between these points is about 300 minutes. It is obvious that with the prediction of the Kappa number in the top of the digester more information can be achieved and control actions can be executed more rapidly than without any prediction. The prediction can give new information of the changes and the direction of the change earlier.

The main variables affecting to the Kappa number are the temperature, the alkali concentration and the cooking (residence) time. The temperature is controlled at the top of the digester using steam temperature. The alkali (white liquour) is added into the feed circulation flow of the impregnation vessel and digester. The alkali is impregnated into the chips in the impregnation vessel, before the cooking operation takes place in the digester. The air is removed from the chips before impregnation vessel in order to impregnate the chips better with the effective alkali. The lignin is partly removed in the impregnation vessel (I1-I2 in the Fig.1), due to the quite high temperature and alkali addition in the feed of the impregnation vessel. The main part of lignin removal occurs in the upper part of the digester, which is called the cooking zone (D1-D4 in the Fig. 1) or bulk zone. The pulp is washed in the counter-current washing zone (D5 and D6 in the Fig.1).

The Kappa number is modeled or predicted in several studies, e.g. [9],[10],[11],[12] and [13]. Neural network trained with back propagation learning rule was used in Dayal [9]. In Musavi et al. [10] radial basis function neural network model was constructed. They used neuro-fuzzy system in the Kappa number prediction in Musavi et al. [11]. Gustafson's Kappa number model [13] is used in the real-time Kappa number modeling in Rantanen et al.[14]. The prediction of the Kappa number using gray-box approach is considered in [15].

Table I. Variables of the system.

Variables	Unit
Feed alkali concentration to the digester	g/l
Temperature at the top of the digester	K
Production rate at the top of the digester	adt/d
Kappa number at the top of the digester	
Kappa number at the blow line	

In this study Kappa number is predicted at the top of the digester using the main variables affecting the Kappa number. The inputs and output of the system are presented in the Table I. The input variables in the combined system are the same as in Gustafson's Kappa number model. There are 4 inputs: feed alkali concentration to the digester, the temperature and production rate at the top of the digester. The production rate is used as a residence time of the system. These variables are measured on-line. The sampling time for the temperature and production rate is one minute and for the alkali concentration 20 minutes. Also the Kappa number at the top of the digester is used as an input of the model. This lignin removal in the impregnation vessel is calculated using Gustafson's Kappa number model [13] in the initial phase. Kappa number is a measure of the lignin content. The rate equation for the initial phase delignification is:

$$\frac{dL}{dt} = k_{il} e^{(17.5-8760/T)} L \qquad (1)$$

where L is the lignin content at time t
k_{il} is a species specific constant.
T is temperature.

The monitoring of the process and prediction of the Kappa number is implemented by combination of the SOM and fuzzy clustering. The quantization error is used in the coloring of the trends of the input measurements and the predicted output. The traffic light colors are used as in Ahvenlampi et al. [16]. If the system is in normal process state the signal is green. The slight deviation from the normal operation point is indicated using yellow color and very big changes are colored with red. The final prediction model is carried out with Gustafson-Kessel fuzzy clustering model. Good results were achieved using the system.

Structure of the paper is following. Used methods are introduced in chapter II. Results are considered in chapter III. Discussion and conclusions presented in chapters IV and V.

II. Used methods

Fuzzy clustering methods can be used in modeling, identification and pattern recognition [17]. In this section several objective functions used for Takagi-Sugeno model identification, usually minimized by fuzzy clustering methods, are presented. Also SOM and combined clustering system are presented. Data to be classified in c clusters is arranged in a vector $Z = \{z_1, z_2, ..., z_N\}$. In this study the consequent parameters for Sugeno models are estimated using weighted least squares.

A. Fuzzy c-means

Fuzzy c-means is a widely used algorithm for fuzzy identification. The FCM cost function is usually formulated as [17]:

$$J(Z;U,C) = \sum_{i=1}^{c}\sum_{k=1}^{N} (\mu_{ik})^m D_{ik}^2 \qquad (2)$$

where $C = \{c_1, ..., c_c\}$ are the cluster centers (prototypes) to be determined, $U = [\mu_{ik}]$ is a fuzzy partition matrix [17]

$$D_{ik}^2 = (z_k - c_i)^T B (z_k - c_i) \qquad (3)$$

is a distance (norm) defined by matrix B (usually the identity matrix), and m is a weighting exponent which determines the fuzziness of the resulting clusters.

B. Gustafsson-Kessel algorithm

Gustafsson-Kessel algorithm [18] (Appendix A) is the mostly used extension of the FCM in identification [1]. In this method, norm can be different with every cluster and method has the advantage of looking for variable size hyper ellipsoids. New distance to use in (2) becomes:

$$D_{ikBi}^2 = (z_k - c_i)^T B_i (z_k - c_i) \qquad (4)$$

In this way, quasi-linear behaviours of the existing operating regimes are detected quite correctly. Improved covariance estimation for Gustafson-Kessel algorithm has been introduced in [19].

C. *Number of the clusters*

Finding the correct number of the clusters is one of the main problems of the clustering. There are many methods which are used in this problem, see e.g. [1], [20] and [21]. If there is a slight error in the choice of the number of the clusters, it can cause the detection of the clustering structure very difficult. The search of the right number of the clusters is the key element of the cluster analysis and it might be the most important question concerning all clustering algorithms.

Fuzzy hypervolume [21] is calculated using following equation

$$F_{hv} = \sum_{i=1}^{C} \left[\det\left(F_i\right)\right]^{1/2} \tag{5}$$

D. *SOM*

The SOM [22] (Appendix B) is unsupervised artificial neural network. The network is normally two-dimensional mapping / projection of the data group. The visualization of the map is easier in the two-dimensional map. In the training of the SOM network data points are sequentially introduced to the SOM. In each iteration, the SOM neuron, which is closest to the input unit is selected with the equation (5). This unit is the Best Matching Unit (BMU) or winner.

$$\|z - m_c\| = \min_i \left\{\|z - m_i\|\right\} \tag{6}$$

The weight vectors are updated using following formula. Only the weight vectors, which are inside the neighborhood radius, are updated.

$$m_i\left(t+1\right) = m_i\left(t\right) + h_{ci}\left(t\right)\left[z\left(t\right) - m_i\left(t\right)\right] \tag{7}$$

E. *Clustering and fault diagnosis system*

The clustering and fault diagnosis system is formulated with the combination of SOM and fuzzy clustering algorithm. The SOM is used as a first clustering method [23] and a fault diagnosis tool in the system.

First the SOM is trained with the normal operation data, which is normalized between [0,1]. The inputs to the system are the temperature, alkali content, production rate and Kappa number at the top of the digester. The output is the Kappa number at the blow line of the digester. The SOM codebook matrix (50 times 40 matrix) is used as input data for fuzzy clustering identification. When the clustering and fault diagnosis system is formulated, the validation data is put through the SOM network and the best matching unit is found. The best matching units are used with the fuzzy clustering model. The quantization errors are used in the coloring of the trends of the measured inputs and the predicted output. The size of the error is used in the color-coding. In normal process state the color code is green. Yellow color is used in the slight deviations from the normal operation and very big changes are colored with red color code. The structure of the system is illustrated in the Fig. 2.

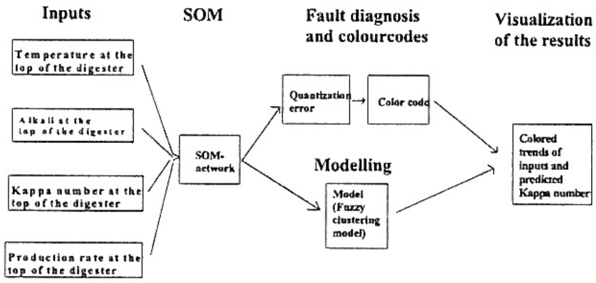

Fig. 2. Clustering and fault diagnosis system.

III. MAIN RESULTS

In this study the Kappa number is predicted in the conventional digester. The clustering and fault diagnosis system is combined with the SOM and fuzzy clustering. The modeling data (about 30 000 data points) was normal operation data from the industrial continuous digester. The outliers and faulty measurements were filtered out from the data. The inputs were temperature, alkali, Kappa number and production rate at the top of the digester. The output is the predicted Kappa number at the bottom of the digester. The system was validated with data from the same industrial digester, but from different time periods.

The size of the SOM network structure was 50 times 40. The SOM codebook vector (2000 neurons) was an input data for the fuzzy clustering model. Used fuzzy clustering method was Gustafson-Kessel algorithm. The fuzzy clustering model was divided into 4 local models (clusters) according to fuzzy hybervolume [21].

Fault diagnosis phase uses different size quantization errors to indicate the deviations from the normal operation points. Thus, this information is used in the coloring of the Kappa number prediction trend with the colors (green, yellow, red). In the Figs. 3 and 4 are shown the situations where the errors deviate and the trends have changing colors. In these figures the deviations are caused by the grade changes and the shutdown. In the Fig. 3 is two grade changes in the points 700 and 3500. In the Fig. 4 the grade changes are in the points 600 and 2900. The shutdown can be seen in the Fig. 4 in the point 3800.

In the Figs. 5 and 6 is a situation where the system is not normal. There is grade changes in the points 450 and 3250. The slight deviation can be seen in the point 2750 and it can be seen from the both Figs. 5 and 6, where the trend color is yellow and also red. Same kind of example is illustrated in the Figs. 7 and 8, where the grade changes are at the points 500 and 3750. The operational failure is in the point 2450, which has been identified by the system.

The validation results of the clustering and fault diagnosis system (CFS) and least squared (LS) method are presented in the table II.

Table II. MSE for the validation periods 1 and 2.

Prediction method	Period 1	Period 2
LS	68.3052	7.9574
CFS	5.4703	5.4209

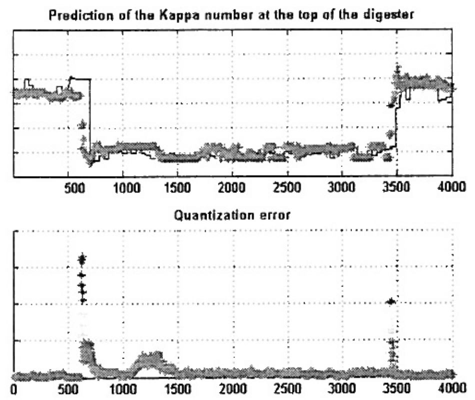

Fig. 3. Kappa number prediction with the color-coding. The grade changes are interpreted as faulty operation. Solid blue line is the delayed on-line measurement of Kappa number at the blowline (Fig. 1) of the digester and colored (green-yellow-red) dotted line is the predicted Kappa number at the top of the digester.

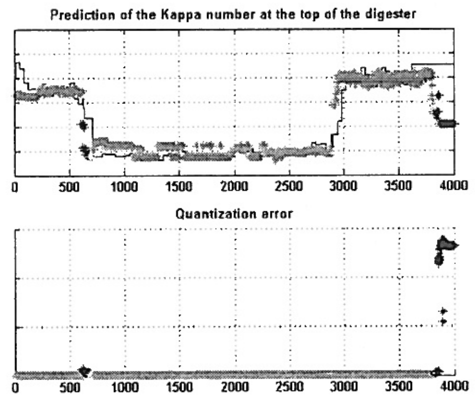

Fig. 4. The coloring of the grade changes and shutdown.

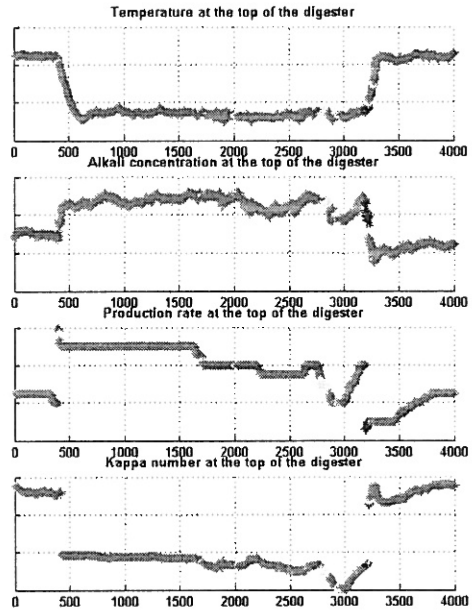

Fig. 5. Input measurements colored with color-coding results from the quantization errors (Period 1).

IV. Discussion

The sampling interval of the on-line Kappa number measurements is about half an hour. Hence it is useful to get also continuous information of the quality properties. The control of the Kappa number is carried out mainly in the top of the digester, therefore it is important to get indication of the quality (Kappa number) beforehand to execute necessary control actions soon enough. The residence time from the top of the digester to the blow line of the digester, where the on-line Kappa number measurement is located, is about 300 minutes.

In this study hybrid system for the monitoring of the process and prediction of the Kappa number in the blow line of the digester is constructed and validated. The system is implemented with combination of SOM and fuzzy clustering model.

As shown in the Figs. 3-8, the results of the fault diagnosis and clustering system are very accurate. The proposed method is suitable for the optimisation and the fault diagnosis of the kraft cooking process. In the case of major process changes the adjustment and verification of the model parameters into the optimal form is quite easy.

Fault diagnosis is carried out using the quantization errors in the coloring of the trends of the input measurements and predicted Kappa number. In the Figs. 3-8 quite big deviations are only colored. Thus, the system is not too sensitive to small deviations. The error size can be used as a tuning factor to the system. The color changing size can be small, if every deviation is desired to be shown and if only big disturbances are needed to be shown the tuning factor can be bigger. The color can be used to observe the failures in the input measurements or deviation from the good operation points. Yellow and red colors indicate also that the prediction may be inaccurate.

The method will be tested also with the Lo-Solids cooking and the possibility to implement the system into the automation system is considered. The hybrid system will be used also as a fault diagnosis and redundant system for Gustafson's Kappa number model.

V. Conclusions

The applicability of SOM and fuzzy clustering approach in the controllability of Kappa number was considered. The results showed the usability of the combined hybrid system in the monitoring of the process and prediction of the Kappa number.

VI. Acknowledgment

The research study is funded by Stora Enso Oyj, Metso Automation Oy, Metsä-Botnia Oy, Andritz Oy and the National Technology Agency (Tekes). The authors would like to

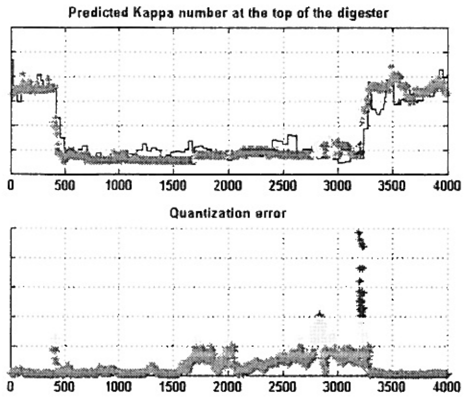

Fig. 6. Predicted kappa number and the quantization error at the same time period as the input measurements in the Fig. 5.

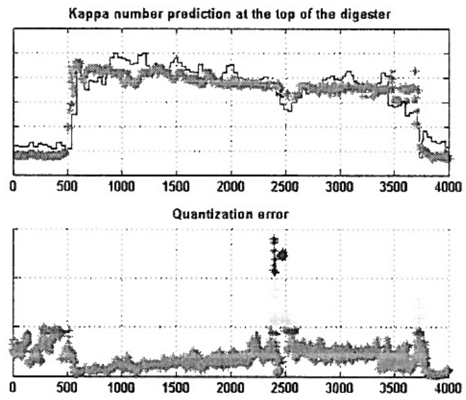

Fig. 8. Predicted kappa number and the quantization error at the same time period as the input measurements in the Fig. 7.

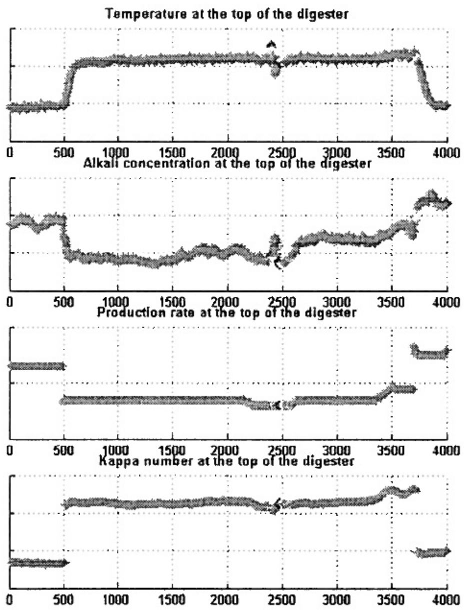

Fig. 7. Input measurements colored with color-coding results from the quantization errors (Period 2).

thank the partners for the special knowledge and process data provided.

Appendix A

Process of Gustafsson-Kessel algorithm:

Step 1: Compute the cluster centres

$$c_i^{(l)} = \frac{\sum \left(\mu_{ik}^{(l-1)}\right)^m z_k}{\sum \left(\mu_{ik}^{(l-1)}\right)^m}, 1 \leq i \leq C$$

Step 2: Compute fuzzy covariance matrix:

$$F_i = \frac{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m \left(z_k - c_i^{(l)}\right)\left(z_k - c_i^{(l)}\right)^T}{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m}, 1 \leq i \leq C$$

$$B_i = \rho_i \det\left(F_i\right)^{1/n} F_i^{-1}, 1 \leq i \leq C$$

Step 3: Compute the distances:

$$D_{ik}^2 = \left(z_k - c_i\right)^T \left(z_k - c_i\right), 1 \leq i \leq C, 1 \leq k \leq N$$

Step 4: Update the partition matrix:

$$\mu_{ik}^{(l)} = \frac{1}{\sum_{j=1}^{C} \left(D_{ik}/D_{jk}\right)^{2/(m-1)}}$$

iterate until $\left\| U^{(l)} - U^{(l-1)} \right\| < \varepsilon$.

Appendix B

The training of the SOM network is following

Step 1: Give initial values for neighborhood radius N(t) and learning rate

Step 2: Choose the steps K

Step 3: Choose one vector from the learning data x

Step 4.: Find c, BMU (best matching unit) from the initialized network, which distance is closest to the input vector z. Euclidian distance is used.

$$\|z - m_c\| = \min\left\{\|z - m_i\|\right\}$$

Step 5: The updating of the weight vectors. Only the weight vectors, which are inside the neighborhood radius, are updated.

$$m_i(t+1) = m_i(t) + h_{ci}(t)\left[z(t) - m_i(t)\right]$$

Step 6: Set $t = t + 1$. If $t = K$, stop. Else go to step 3.

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