MODEL-BASED MONITORING OF IMMOBILIZED YEAST FERMENTATION USING FUZZY LOGIC AND LINGUISTIC EQUATIONS

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Abstract: Continuous fermentation requires fast and precise response to any changes in process conditions. Nowadays control systems are either lacking or inadequate for this purpose. This paper introduces a model-based system for detecting operating conditions. The system based on the Linguistic Equation (LE) approach was developed and tested in immobilized yeast fermentation. The created models can be used for monitoring and diagnostics of fermentation and flavour formation. By creating grounds for prediction of quality factors the models increase options to control the product quality in different cases. The modular model library is expandable.

Keywords: Nonlinear analysis, Multivariable systems, Fault detection, Biotechnology, Fuzzy systems, Modelling, Reasoning.

1. INTRODUCTION

Efficient use of fermentation vessels is crucial in brewing economy since fermentation is the most time consuming step in the production of beer. Fermentation with immobilized yeast brings about advantages compared with conventional processes, such as a very rapid process without interruptions in the production (Linko *et al.*, 1998; Virkajärvi and Linko, 1999; Virkajärvi, 2001).

The Hartwall Lahti brewery has used immobilized yeast in secondary fermentation in full production scale, 300,000 hectolitres/year. The primary fermentation capacity has been scaled up to 200,000 Litres per year (Kronlöf and Virkajärvi, 1999). Recently primary and secondary fermentation have been combined to form a complete fermentation block producing quality beer in less than two days (Kronlöf *et al.*, 2000).

Brewing is based on ethanol fermentation but the most important aim is a balanced flavour not the highest possible ethanol yield. The desired traditional flavour is based on a balance of numerous compounds. Most of these compounds are produced during the main fermentation, which is a rather complex biochemical process with many side-reactions. The taste threshold is very small for many flavour compounds, e.g. diacetyl, which in lager beer indicates the maturity level of the beer. (Virkajärvi and Linko, 1999)

The aim of this research is to improve the monitoring and control of the continuous main fermentation with model-based methods. Fast and precise response to changes in process conditions requires an early detection of the changes in the flavour balance. It should be possible to validate the results with process knowledge based on experience, learning and remembering.

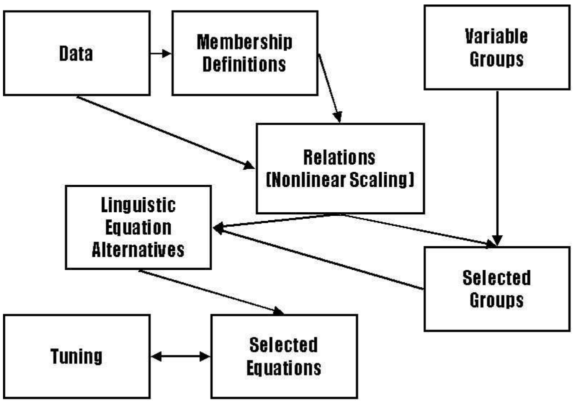

Fig. 1. Data-based modelling with linguistic equations.

Case-based reasoning (CBR) is a problem solving paradigm for finding out the solution to a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation (Aamodt and Plaza, 1994). The CBR approach has been already earlier extended to model-based systems in an indicator developed for the prediction of paper machine runnability (Juuso, 1999). The foundation of this application is a case base containing Linguistic Equation (LE) models of various operating situations with different amount of breaks. The indicator compares online measurements to the examples and uses the information of the best fitting case to identify the current situation (Ahola *et al.*, 2004).

In the LE approach, non-linear multivariable models are constructed in three steps: directions of interaction are handled with linear equations, nonlinearities are taken into account by membership definitions and time delays depend on operating conditions. The models can be generated directly from data with an interactive approach which includes several stages (Fig. 1). (Juuso, 2004).

This study is based on pilot scale experiments with extensive measurements. The modelling of different cases in immobilized yeast fermentation was done using FuzzEqu toolbox based on Linguistic Equations (LE) approach in Matlab environment. This paper presents a small explanatory example of the model system.

2. MODELLING WITH LINGUISTIC EQUATIONS

Data-driven modelling with the Linguistic Equation (LE) approach consists of nonlinear scaling and linear regression. Delays between the two reactors shown in Fig. 2 must be taken into account. Variable groups (on right side in Fig. 1) are analysed since the number of variables is high.

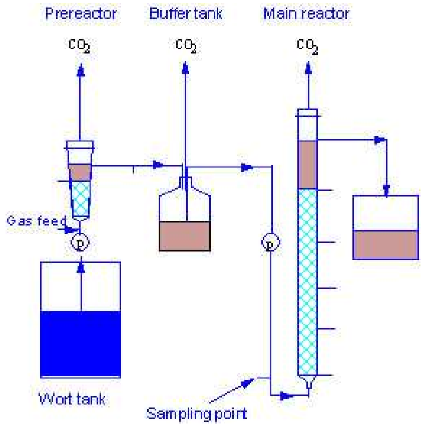

Fig. 2. Pilot scale continuous fermentation system.

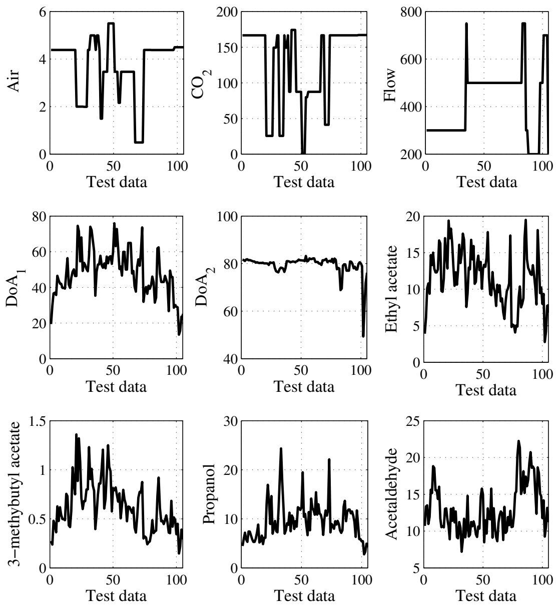

Fig. 3. The measurement data from the pilot scale continuous fermentation.

2.1 *Material and methods*

Experiments were carried out in pilot scale in VTT Biotechnology, which is an expert organisation that carries out technical and technoeconomic research and development work in Finland. The system consists of two reactors and a buffer tank between them (Fig. 2). During the first test campaign in 1996-1997, the immobilized main fermentation was stable for more than 14 months (Virkajärvi, 2001). Aroma analyses were performed for both reactors with from 3 to 5 days intervals. Aeration and carbon dioxide were recorded with same time intervals. The data set contains totally 79 records for 19 variables. As additional tests were needed for modelling, three short test periods with wider range of flow were arranged in 2001-2003. These tests also provided more material for model validation.

All the time, operating condition changes were quite moderate. Therefore, a spline-based interpolation was used for constructing a set of measurements for training, testing and dynamic modelling. The complete data set contains 108 records for 19 variables: the data set for nine variables is presented in Fig. 3. The additional measurements are 2-methyl propanol, 3-methyl butanol and 2-methyl butanol. All the aroma compounds are measured in both reactors.

Modelling was done on the basis of the first 250 days of the first test campaign, and the rest of the data was used for testing these models. The model library contains models for both reactors.

2.2 Nonlinear scaling

For nonlinear models, the scaling technique must be nonlinear as the model equations are linear. The scaling functions called membership definitions provide non-linear mappings from the operation area of the (sub)system, defined with feasible ranges, to the linguistic values represented as a real-valued interval $[-2, 2]$. Membership definitions are represented by two second order polynomials, one for negative and one for positive side. Membership definitions defined by five real values and corresponding linguistic levels very low, low, normal, high, and very high, which correspond to integer numbers -2, -1, 0, 1 and 2 (Fig. 4). (Juuso, 2004)

The membership definitions were generated from the full data set to cover the whole operating area. Linguistic relations are obtained by nonlinear scaling with the membership definitions. An example of the measurements after non-linear scaling with these definitions is presented in Fig. 5. Only the actual measurements from the first 250 days were used for modelling. As the training material contained only 50 data points, the full range $[-2, 2]$ of the scaled data was not available for all the variables.

2.3 Interactions

The basic element of a linguistic equation (LE) model is a compact equation

$$\sum_{j=1}^{m} A_{ij} X_j + B_i = 0, \tag{1}$$

where X_j is a linguistic level for the variable $j, j = 1...m$. The direction of the interaction is represented by interaction coefficients A_{ij}. The bias term B_i was introduced for fault diagnosis systems. Values X_j are here called as relations (Fig. 5) as they have a linguistic meaning.

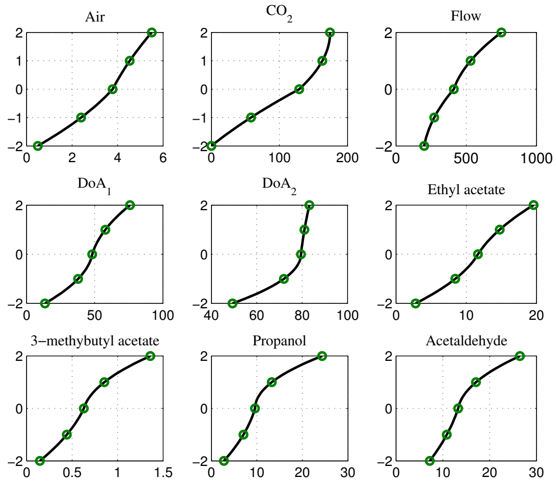

Fig. 4. Membership definitions for nine variables.

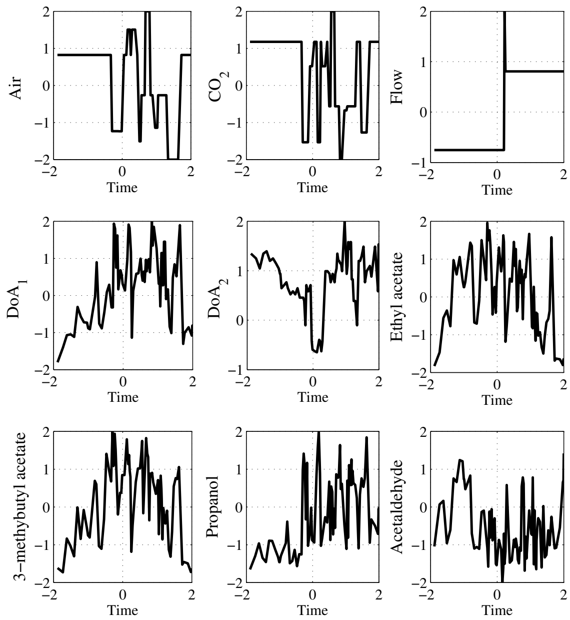

Fig. 5. Relations obtained from the actual data with nonlinear scaling.

A LE model with several equations is represented as a matrix equation

$$AX + B = 0, \tag{2}$$

where the interaction matrix A contains all coefficients A_{ij} and the bias vector B all bias terms B_i. Equation alternatives defined by interactions and bias terms are generated with linear regression for predefined variable groups (Fig. 1). The number of alternatives could be reduced with correlation analysis or with principal component analysis.

Selecting equations from these alternatives is based either on the overall fit or on the prediction performance. Tuning algorithms reduce the error

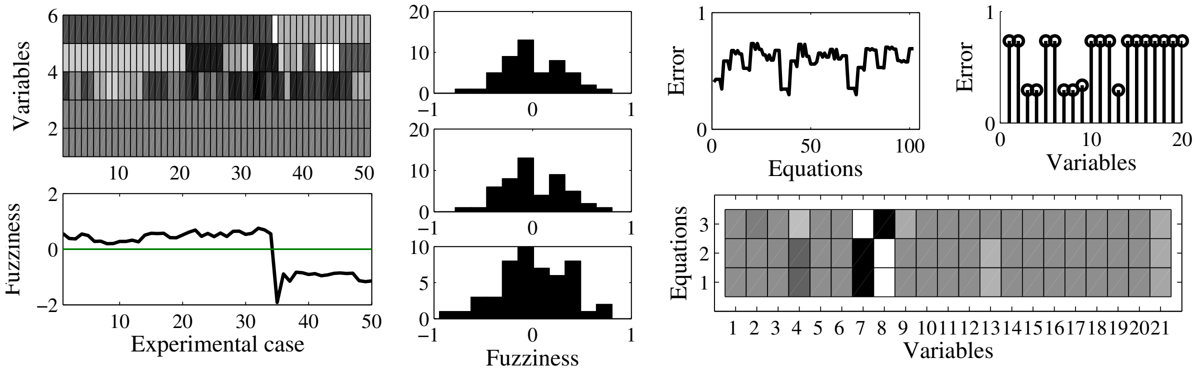

Fig. 6. LE model generation: relations and fuzziness of one equation (left), distribution of fuzziness of selected equations (center) and selection of three five variable equations from 102 alternatives (right).

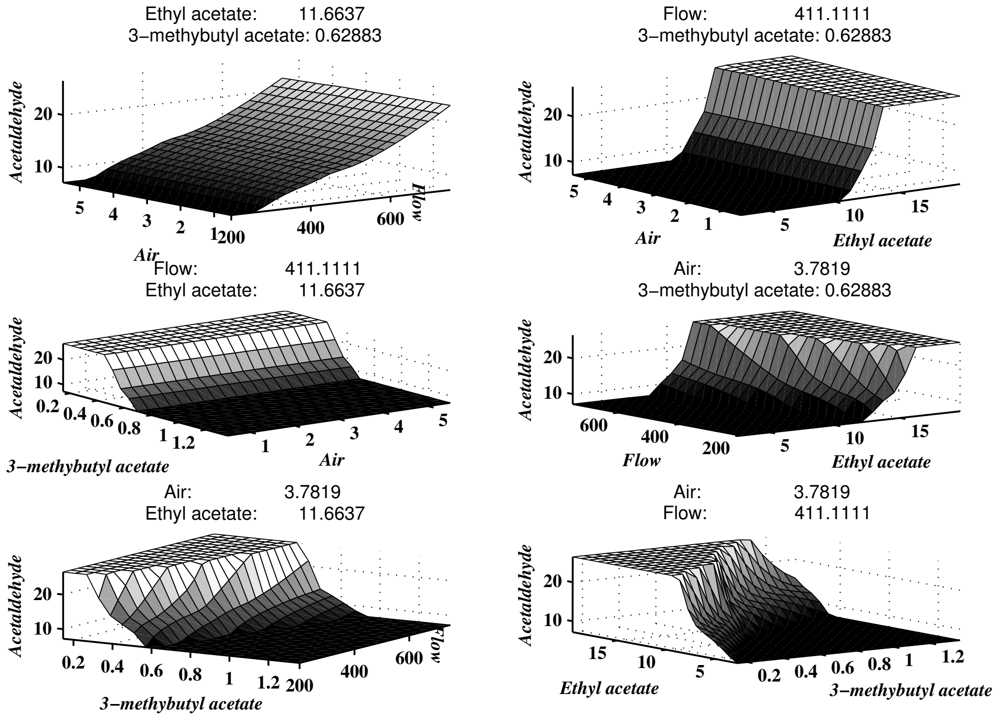

Fig. 7. Model surfaces of a five variable LE model on a normal operating point.

between model (selected equations) and the training data by modifying membership definitions, linguistic equations or both.

The LE models were generated for five variable groups, each group contains two of the three control variables (air, CO_2 and flow) and three flavour compounds or attenuation. The development principle is presented in Fig. 6 for the variables shown in Fig. 4. Three equations with lowest fuzziness (right) were selected in this case. The resulting equations are linear and can be used to any direction. Interaction surfaces are always linear. Interaction coefficients can also be changed manually with sliders.

The nonlinear behaviour can be assessed with model surfaces, e.g. in a five variable equation model shown in Fig. 7, each subplot corresponds to a situation where the other two variables are in normal value. Other local nonlinear models can be selected by changing these values with sliders. These model surfaces are used in knowledge-based model assessment.

3. OPERATING CONDITIONS

Fuzzy linguistic equations are essential in present applications of linguistic equations in fault diagnosis and dynamic modelling. Fuzzy methods take care of the smooth transitions between the cases, and the degree of membership evaluated from the fuzziness of the equations.

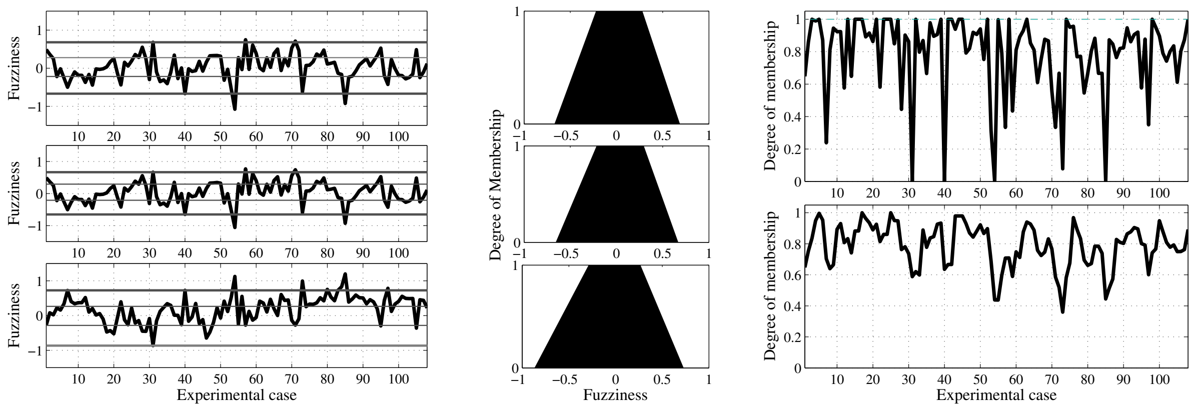

Fig. 8. Detection of operating conditions with LE models: fuzziness and limits of fuzziness for three equations and the resulting degrees of membership for each data point (upper curve) and a moving average (lower curve).

The fuzziness,

$$S_j = \sum_{j=1}^{m} A_{ij} X_j + B_i, \qquad (3)$$

is the basis of the detection of operating conditions. The vector defined by interaction coefficients and bias terms is normalised for each equation. The fuzziness S can be used for clustering the data on the basis of the interaction directions. For larger models, the equation system is a set of equations where each equation describes an interaction between two to five variables.

Detection of operating conditions is based on fuzziness (Eq. 3): the degree of membership for an equation is obtained from the fuzziness (left in Fig. 8) and the limits defined for the fuzziness (center). The degree of membership for each equation is one if the corresponding fuzziness is close to zero and goes to zero with increasing fuzziness.

The degree of membership for the case is obtained from the membership degrees of the equations by fuzzy reasoning and filtered with moving average (right in Fig. 8). Equations can have different weight factors depending on the sensitivity of the equation for the case detection. FuzzEqu Toolbox provides tools for experimenting with different methods and windows.

4. RESULTS AND DISCUSSION

The modelling was done efficiently and the results were promising for the further use. The model based on the first 250 day operates fairly well throughout the tests (Fig. 8). The effect of the flow can be seen as a slight decrease in the degree of membership although the range of the flow was much wider in the latest test material (Fig. 3). Some fluctuations of flavour ingredients were detected for only short time periods as the process was stable. Time span of these fluctuations was usually too short for development of specialised models.

A more detailed model with seven equations for all the prereactor measurements indicates clear differences in the end of the test period. All the equations have there high fuzziness (Fig. 9) and the degree of membership for the model goes to very low values (Fig. 10). The effect of the flow to the concentrations is natural, increasing or decreasing. Insight to the process operation is maintained since all the modules can be assessed by expert knowledge and membership definitions relate measurements to appropriate operating areas.

Linguistic equations provide a very compact implementation method for varying operating conditions since only five parameters (Fig. 4) are needed for each variable. For the fermentation application the combination of fuzzy logic and linguistic equations provides several improvements:

- The linguistic equation (LE) modelling approach is very efficient. Compact models provide insight to the process.
- Performance of the data-based models is good for the flavour compounds and control variables in both the prereactor and the main reactor, especially for alcoholes.
- Modelling of special cases requires more tests with changing operating conditions.
- Detection of fluctuations in the balance of the flavour ingredients with this type of models is a feasible approach.
- Models provide useful information for monitoring and control.
- Extension with continuous analysis of the fermentation and the flavour ingredients would be beneficial.

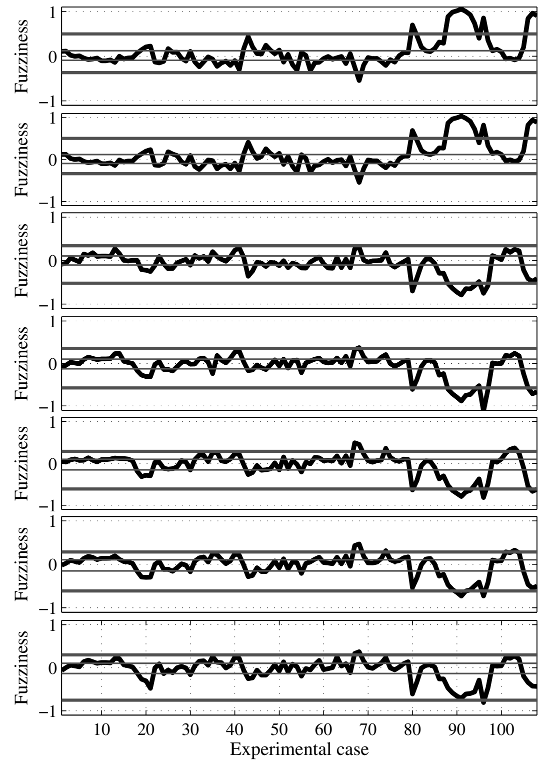

Fig. 9. Fuzziness of the seven equations developed for selected five variable groups of 11 variables.

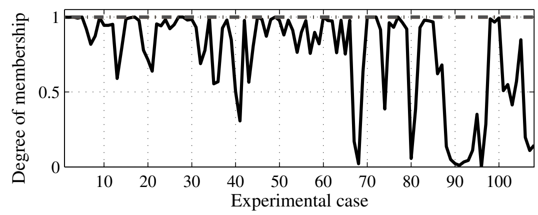

Fig. 10. Degree of membership of the LE model.

Each equation can be used for dividing the data into three categories defined by the fuzziness level: fuzziness is close to zero in the normal operation (Level 0), large positive values correspond to a different situation (Level +1), and large negative values to a third situation (Level -1). Since each level can be considered as a fuzzy label, the data set can be used for generating a fuzzy relational model. For seven equations there are 2187 alternatives but very few of them have considerable degree of membership.

This provides a basis for finding similar situations, i.e. cases where same fuzzy relations have high degrees of membership. According to the results this approach is clearly feasible but the data set is still too limited for completing the proposed analysis with steady-state models. The emphasis is now moving to LE based dynamic models and their use as process condition indicators.

5. CONCLUSIONS

The model-based system based on linguistic equations is efficient for detecting fluctuations of operating conditions in the immobilized yeast fermentation. Deviations from the normal operation can be detected, and the modular model library is expandable and a good basis for development of controllers.

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