

Dynamic Simulator for Dosing of Water Treatment Chemicals

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Abstract

Dynamic simulators were developed for analysing of two water treatment processes. Simulators contain a dynamic linguistic equation (LE) model for the water treatment unit, controllers for dosing of chemicals and a soft sensor describing the quality of inlet water. Simulators were built in Matlab Simulink. Dynamic LE models have been tested with on-line data collected from two flotation units. According to these tests, the generated dynamic models provided a good prediction for the outlet turbidity. Simulators were also extended to a tuning and testing environment for controllers. Simulation makes the implementation of controllers faster at a mill.

Keywords: water treatment, simulation, modelling, chemical dosing

1. Introduction

In the pulp and paper industry a huge amount of water flows through different processes. For environmental and economical reasons, the plant recycles the water as much as possible. Before recycling the water is purified to a certain degree. The chemical treatment is one of the purification methods. The dosing control of chemicals is very demanding because the quality of water may fluctuate considerably and the effects of chemicals on the purification result are nonlinear. Chemicals are quite often dosed on the basis of the flow rate which does not always guarantee the adequate purification efficiency.

Process simulators are effective for developing, testing and tuning the controllers. Different control methods can be tested safely in changing process conditions without disturbing the process. Furthermore, the chemical dosage can be optimised and the quality of water can be analysed in the simulator. However, a reliable process model is essential for process simulations.

Chemical water treatment includes complex nonlinear phenomena such as coagulation and flocculation processes. Modelling of these complicated processes is mainly data-based or empirical due to a lack of comprehensive physical models. Intelligent methods such as linguistic equations and neural networks can be applied for the modelling of nonlinear interactions between input and output variables. Methods are effective when enough on-line data of good quality is available from the process. If enough a priori

information exists on the process a rule-based system can be used (Gagnon et al., 1997, Lei et al., 2002, Valentin et al., 1999).

This paper describes dynamic simulators implemented for two water treatment units in pulp and paper industry. Main purpose of the simulators was to get the environment for developing, testing and tuning the controllers and to get the tool for analysing the operation of the process. Principal component analysis (PCA) and partial least squares (PLS) regression are not well suited for this nonlinear problem because their models are linear. Linguistic equation (LE) approach combines linear methodologies with nonlinear scaling (Juuso, 2004). The LE approach is used in this study for both modelling and control in the Matlab environment.

2. Modelling Approach

2.1 Modelling strategy

Reliable process data and understanding phenomena taking place in the process are very important for data-based modelling and process analysis. Without this knowledge the development of a reliable data-based model can be difficult particularly in the case of a complicated process. Experimental design technique and step response tests are utilised to evaluate the effect of the dosages of chemicals on treatment results. The quality of water is studied in order to understand the requirements for the dosage of chemicals before modelling. It also helps to choose right on-line measurements. Process can be monitored by several indirect and direct properties of water such as turbidity, conductivity, suspended solids, colloid extractives, anionic/cationic compounds, pH and temperature.

A steady state LE model is developed using data, which is collected during the experimental follow-up in the process to find out the strength of interactions between variables and the range of fluctuations. A dynamic model is built up in Matlab Simulink environment by introducing dynamic structures to the steady state modelling technique. The process delays are also taken into account in the model. Typically, doses of chemicals and measurements of inlet water that give response to the output were chosen as the inputs. The output describes the purification result such as turbidity. The dynamic model has been tested by independent on-line data from different process conditions. Quite often on-line measurements do not describe well enough the quality of water and its changes. There can be an effect on chemical consumption but that can not be seen by current on-line sensors. Those cases need an on-line soft (model based) sensor, e.g. a sensor for calculating the quality index of incoming water (Ainali et al, 2002).

The dynamic simulator contains the dynamic LE model, controllers and soft sensors in the Matlab Simulink environment. Controllers can be a feedback controller, a feedforward controller or an adaptive feedback controller (Joensuu et al., 2004) depending on the process and chemicals.

2.2 LE method

The linguistic equation (LE) consists of two parts: interactions are handled with linear equations, and nonlinearity is taken into account by membership definitions. A general LE model consists of equations represented by

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

where X_j is a linguistic level for the variable j , $j=1, \dots, m$. The directions and strengths of the interactions are presented by interaction coefficients A_{ij} . The bias term B_i was introduced for fault diagnosis systems to shift the model from the origin. Modelling with LE method has following stages: first membership definitions are generated by using on-line data, then linguistic relations are obtained by nonlinear scaling of data with these definitions, and finally linear regression of the scaled data (linguistic relations) is used in generation of the linguistic equations. Model parameters (A_{ij} , B_i) which are obtained from linear regression are same for every time point in simulation. (Juuso, 2004, Järvensivu, et al., 2001).

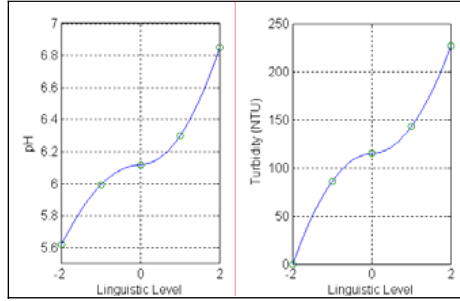


Figure 1. Examples of membership definitions for pH and turbidity.

Linguistic levels of the input variables are determined by means of membership definitions. These definitions scale the real values of variables to the linguistic levels with the range of $[-2 \ +2]$. Membership definition contains two monotonously increasing functions. The first function determines the linguistic values between -2 and 0 , and the second polynomial determines the linguistic values between 0 and 2 (Figure 1). Usually these functions are obtained from process data so that minimum, average and maximum values of real data corresponding to the linguistic values -2 , 0 and 2 . The sensitivity analysis of each model is based on the fuzziness obtained as a linguistic residual of the equation.

3. Results

In this paper, results are represented for two flotation units. The quality and amount of incoming water fluctuates greatly in both units. In the first flotation unit, process water is treated with a polymer which reacts with extractives forming pitch sludge. The basic dynamic LE model of this flotation unit is represented by

$$X_{turb}(t) = - \left(\frac{A_{pH} X_{pH}(t) + A_{chem} X_{chem}(t - \alpha) + A_{turb_prev} X_{turb_prev}(t - \beta)}{A_{turb}} \right). \quad (2)$$

The linguistic level of outlet turbidity ($X_{turb}(t)$) is here calculated on the basis of pH (pH) of incoming water, polymer dosage ($chem$) and previous calculated turbidity ($turb_prev$). The time delay of the polymer (α) is a moving average and the delay of the

previous calculated turbidity (β) is same as a sampling time. The interaction coefficient of the variable j is A_j and the linguistic level of the variable j is X_j .

The dynamic simulator contains a dynamic LE model, a soft sensor and a controller (Figure 2). As the reaction of the polymer is fast and the delay of the flotation basin is short, the response time of the polymer is short enough for the feedback (FB) control. The adaptation of the feedback LE controller was needed because process conditions change strongly and fast. The changes are detected by the soft sensor which calculates the quality index of incoming water.

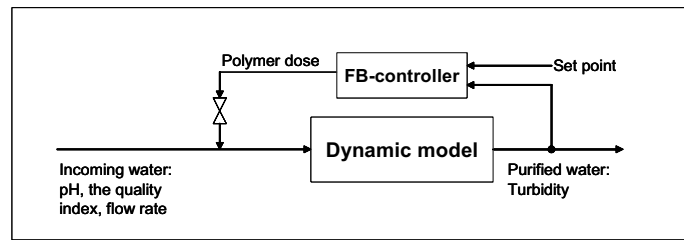


Figure 2. Dynamic simulator with the adaptive feedback controller.

The dynamic model was tested with independent on-line process data sets collected during several months. According to testing results the model predicts very well the outlet turbidity. Variations of the response are well explained by the model, e.g. the value is 90 % for a testing example shown in Figure 3. Also the fuzziness of the equation is very low throughout the tests.

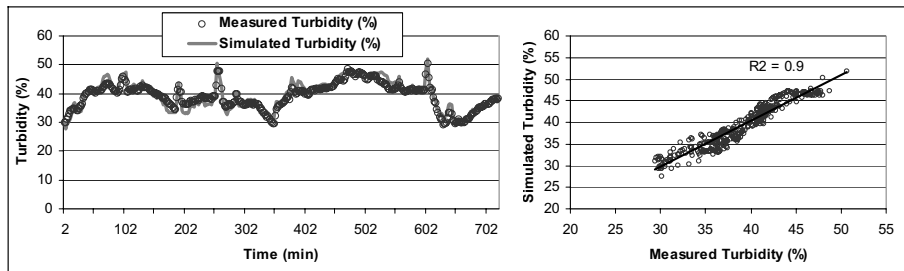


Figure 3. A testing example of the dynamic model by the independent on-line data.

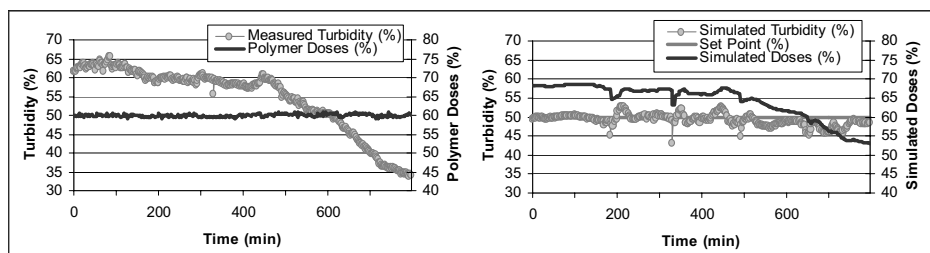


Figure 4. On-line process data (left) and simulation results of the FB controller (right).

The adaptive feedback controller was tuned in the dynamic simulator. Finally testing of the adaptive LE controller was carried out by on-line data in the simulator. In Figure 4 real measured values and simulated values from a testing example are represented. In

the flotation unit, turbidity of purified water varies a lot due to a constant dosage of polymer. In the simulator the set point of turbidity was selected 50 %. As the adaptive LE controller keeps the set point value well, the controller would improve the performance of this flotation unit.

The second flotation unit is used for removing of suspended solids and extractives from process water by means of two chemicals. The basic LE model for linguistic levels of outlet turbidity ($X_{turb}(t)$) is represented by

$$X_{turb}(t) = \frac{A_{SS} X_{SS}(t) + A_{chem1} X_{chem1}(t - \alpha_1) + A_{chem2} X_{chem2}(t - \alpha_2) + A_{turb_prev} X_{turb_prev}(t - \beta)}{A_{turb}} \quad (3)$$

Inputs of the model are the amount of suspended solid in incoming water (SS), doses of two chemicals ($Chem1$, $Chem2$) and previous calculated turbidity ($turb_prev$). The time delays of the chemicals (α_1 , α_2) are moving averages and the delay of the previous calculated turbidity (β) is same as a sampling time.

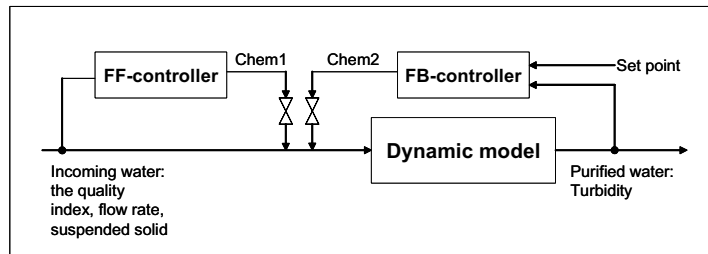


Figure 5. Dynamic simulator with the feedforward and the adaptive feedback controllers.

The dynamic simulator contains the dynamic LE model for the flotation basin, controllers for two chemicals and a soft sensor for the detection of incoming water quality (Figure 5). The soft sensor calculates the quality index of incoming water which correlates with cationic demand of incoming water (Ainali et al., 2002). The faster effecting chemical (Chem2) is controlled by an adaptive feedback LE controller. More slowly affecting chemical (Chem1) is controlled by a feedforward controller.

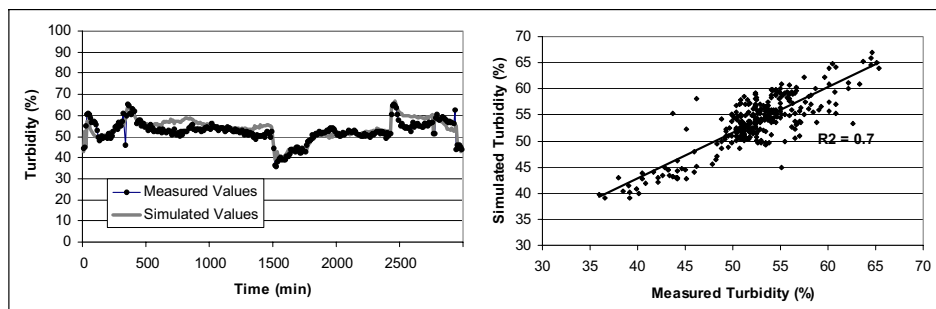


Figure 6. A testing example of the dynamic LE model by independent on-line data.

Testing of the dynamic model was done using plenty of independent on-line process data. A testing example with good R^2 value is shown in Figure 6. Tuning and testing of the controllers were carried out with on-line data in the simulator. The adaptive feedback controller keeps the set point (47 %) value well (Figure 7). The feedforward

controller takes in advance into account process changes detected by the soft sensor. The chemical consumption can be optimized by this controller. Controllers have been successfully implemented at a mill. Simulation made the implementation faster. Any re-tuning of control parameters was not needed.

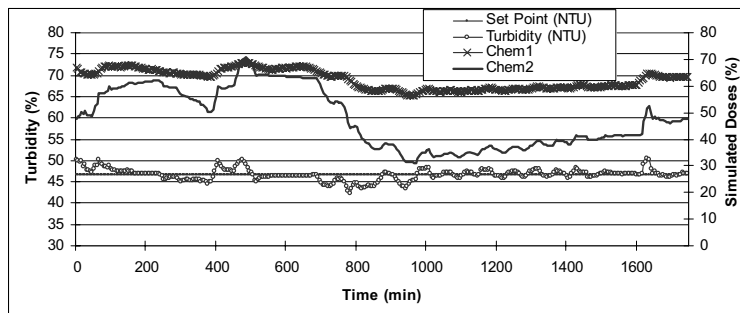


Figure 7. Performance of the FF and the FB controllers in the simulator.

4. Conclusion

Dynamic simulators have been tested with on-line data collected from plants. According to these tests, the generated dynamic models calculate a good prediction for the outlet. So far simulators have been used for developing, tuning and testing of controllers. Simulation has also been proved to be a fast and practical tool for analysing the behaviour of the process and fluctuations in water quality, for example identifying different process states and understanding most important variables influencing on the efficiency of purification. This requires reliable data from a broad range of process operation. Experimental design and step response test are necessary to get enough information with the minimum number of experiments. Controllers tuned with the dynamic simulator have been successfully implemented at a mill without any re-tuning of control parameters.

References

- Ainali I., Piironen M. & Juuso E., 2002, In Proceedings of SIMS 2002- 43rd Conference on Simulation and Modelling, Oulu, Finland, September 26-27, 247-252.
- Gagnon, C., Grandjean, B.P.A & Thibault, J., 1997, Artificial Intelligence in Engineering II. Elsevier Science Ltd., 401-404.
- Joensuu I., Piironen M. & Juuso E. 2004, In Proceedings of IFAC Workshop on Advanced Fuzzy/Neural Control, Oulu, Finland, September 16-17, 127-131.
- Juuso, E.K., 2004, International Journal of Approximate Reasoning, 35, 307-337.
- Järvensivu M., E.K. Juuso and O. Ahava (2001). Engineering Applications of Artificial Intelligence, 14, 629-653.
- Lei, L., Ratnaweera, H. & Lindholm, O, 2002, Chemical Water and Wastewater Treatment VII, Proceedings of the Gothenburg Symposium (2002), Gothenburg, Sweden, June 17-19 2002, 253-260.
- Valentin, N. & Denocux, T., 1999, In Proceedings of Water Quality Technology Conference, 909-916.