C99-S02

Title: Optimizing Dyeing Process Control Through Improved Modeling

Goals: The goals of this project are to educate and provide support for graduate students,***[or]*** develop and improve dye process models, develop and improve dye process control systems, and to critically compare and evaluate the performance of control strategies for dyeing systems.

Abstract: This report describes initial project activities for the initiation period March through August 1999. Primary activities were the recruitment of graduate students, beginning the development of a variable structure controller, and investigation of sequential injection analysis (SIA) as a real-time data acquisition system for input to our control systems. We have made very rapid progress in the initiation phase of this project, in large part due to the previously existing facilities, team and working relationships of the Dye Applications Research Group.

Development of a variable structure controller: This work has focused mainly on developing a self-organizing fuzzy logic sliding-mode controller for dyeing process control. This will soon be used to evaluate actual processes involving acid dyes and direct dyes. Modeling and control of a nonlinear system with time delays is a challenging problem, particularly when the system has unknown parameters. This is the case in dyeing processes since, although many chemical reactions can be described in an idealized approximation as first order kinetics, Fickian diffusion or Langmuir models, the real process is actually more complex due to machine dynamics and uncertainties in the system, the dye bath and substrate properties. Also many (perhaps most) of the parameters in those models (e.g. reaction rate constants, sorption rate constants, diffusion coefficients, dyestuff molecular weights) are generally not known to the dyer. Our overall objective in dyeing process control is to select control variables such as temperature, and dye and salt dosing to produce consistency in color shade at minimized cost.

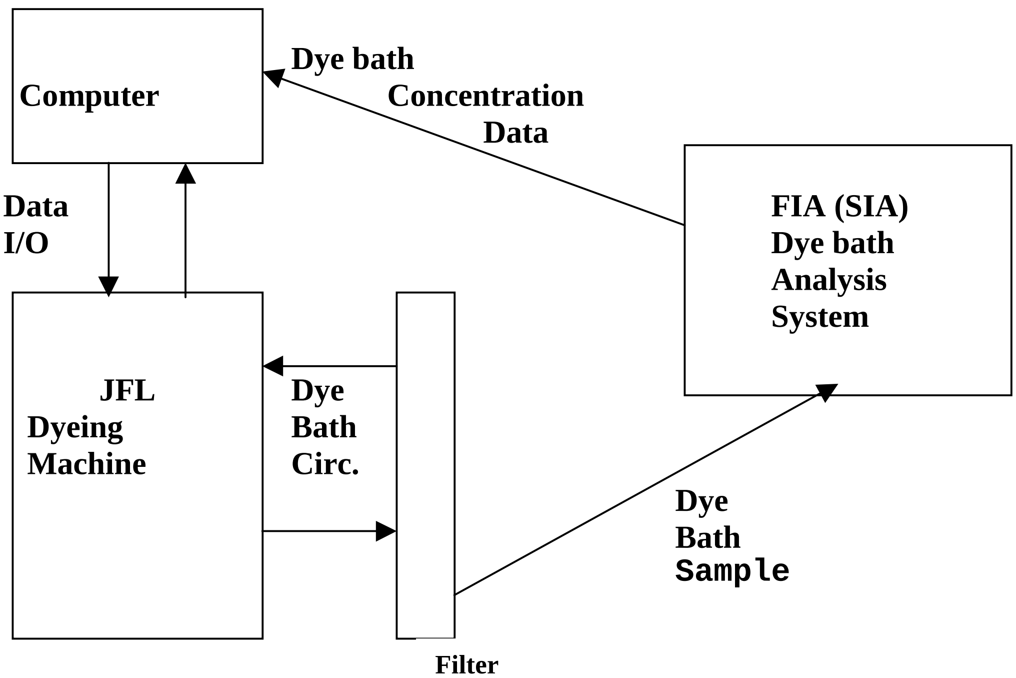
We have developed an experimental testbed that will be used in the design and implementation of a nonlinear controller for dyeing processes. Furthermore, a candidate for the control algorithm is developed which may be tested on the dyeing machine. In order to develop this control algorithm, the parameters for Langmuir models used to represent the dyeing process have been obtained.

We previously developed methods to improve the modeling, monitoring and control of dyeing processes in both laboratory and commercial dyeing machines, using real-time algorithms. The work includes dye bath monitoring by flow injection analysis, neural network, fuzzy logic, adaptive control, and sliding mode process control systems, and closed loop dye and chemical dosing models using real time exhaustion data.

In state-of-the-art commercial dyeing operations, pre-determined dyeing procedures are used with open-loop control. Traditional time-based, temperature-based, and event-based procedures are not individually optimized for each dyeing but are set up for families of dyes, color shades and general classes of substrates. This leads to less than optimum quality, energy consumption and chemical use. In these traditional procedures, dye bath monitoring for dye exhaustion is rarely used. But, if used at all, they are generally based on relatively primitive methods that yield insufficient information, and often are not implemented in real time. Dosing of dyes and chemicals for process control is common but closed-loop control of dosing is not used.

In order to develop and improve the dyeing process models and control systems, during the reporting period we modified a laboratory scale JFL dyeing machine with two control variables: temperature and dosing. Using a DATEX microprocessor, we control the dyeing process according to a predefined sequence. The commercially available control system for this machine can only meet the need of traditional dye bath control with predetermined protocols, e.g., time, temperature and dosing profiles. The commercial system can not be used for real time monitoring, modeling, and control of the dye exhaustion itself. In our present work, we interfaced the JFL dyeing system to a computer which monitors dye concentrations, conductivity and pH in real time. This computer is used for novel dyeing process control using intelligent control methods.

Figure 1: The JFL Experimental Testbed



Test bed schematics with interfaces are shown in Figure 1. We removed the vendor-supplied JFL controller and replaced it with an interface based on a standard CIO-DAS08-AOL board with digital and analog inputs. We use the inputs for various sensors, and the outputs to control dosing pumps, heating and cooling apparatus for the machine. We developed a temperature control algorithm and other necessary algorithms to enable the computer to do all required major control actions. A sampling line with a filter is connected to the dye kier for sampling. Samples are to an FIA system (see our previous reports) to monitor dye concentrations.

For control of the dye system, we developed a self-organizing fuzzy sliding-mode controller (SMC) based on a Langmuir model, to control two-dye combinations. Langmuir model parameters are estimated by first order polynomials using a least-squares recursive method to identify the parameters of the Langmuir model on-line. Those parameters are used as initial conditions for the SMC, which then adapts parameters to real time conditions and non-idealities of the system. If the learning gains for the sliding-mode control are selected larger than the estimation error, the control algorithm guarantees that the sliding variables converge to the desired trajectory.

Controller theory: The Langmuir model we are using can be stated as

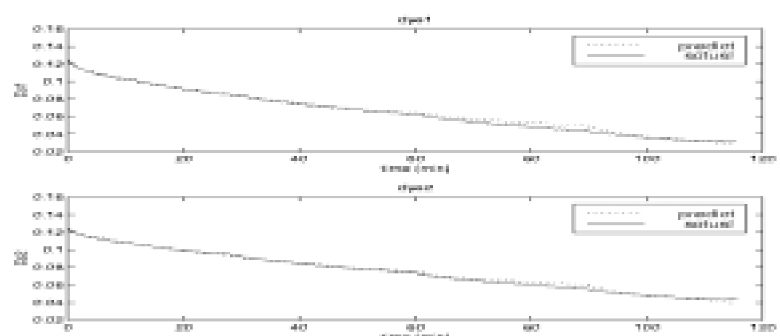
$$\frac{dC_A^F}{dt} = k_A^A C_A^S (S_A - C_A^F - C_{B/A} C_B^F) - k_A^D C_A^F \qquad (1)$$

$$\frac{dC_B^F}{dt} = k_B^A C_B^S (S_B - C_B^F - C_{A/B} C_A^F) - k_B^D C_B^F \qquad (2)$$

where K^A and K^D are approximated by the aforementioned polynomials. Our experiments show that salt decreases the desorption rate constant but has little or no effect on the absorption rate constant. Thus K^A and K^D are approximated and, using the conservation of mass and other considerations, the following results can be obtained.

$$\frac{dC_A^F}{dt} = C_A^S (S_A - C_A^F - C_{B/A} C_B^F) \bullet (\theta_A^1 + \theta_A^2 T + e_A) - C_A^F (\theta_A^3 + \theta_A^4 T + \theta_A^5 S_{alt} + ee_A) \qquad (3)$$

$$\frac{dC_B^F}{dt} = C_B^S (S_B - C_B^F - C_{A/B} C_A^F) \bullet (\theta_B^1 + \theta_B^2 T + e_B) - C_B^F (\theta_B^3 + \theta_B^4 T + \theta_B^5 S_{alt} + ee_B) \qquad (4)$$



The dynamics of the system can thus be represented as follows.

$$\frac{dC_A^S}{dt} = f_A\left(C_A^S, C_B^S\right) + b_{11}\left(C_A^S, C_B^S\right)\cdot T + b_{12}\left(C_A^S, C_B^S\right)\cdot S_{alt} + \Delta_A(t) \tag{5}$$

$$\frac{dC_B^S}{dt} = f_B\left(C_A^S, C_B^S\right) + b_{21}\left(C_A^S, C_B^S\right)\cdot T + b_{22}\left(C_A^S, C_B^S\right)\cdot S_{alt} + \Delta_B(t) \tag{6}$$

or

$$\begin{pmatrix} \dot{C}_A^S \\ \dot{C}_B^S \end{pmatrix} = \begin{pmatrix} f_A \\ f_B \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \cdot \begin{pmatrix} T \\ S_{alt} \end{pmatrix} + \begin{pmatrix} \Delta_A \\ \Delta_B \end{pmatrix} \tag{7}$$

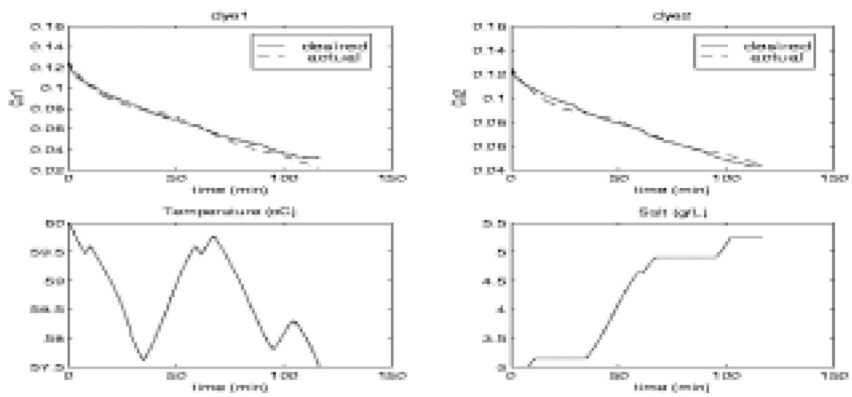
The fundamental control problem we have to face here is to select the temperature and salt concentration that produce the desired color on the substrate at minimum cost/time at the end of the dyeing process. We can use the control system to force C_A^S, C_B^S to follow a desired trajectory $C_{Ad}^S(t)$, $C_{Bd}^S(t)$ for reasons of cost optimization, productivity or quality (e.g. levelness). To control the dynamic system model, we have developed a modification of SMC using a following switching function. Using the Lyapunov function as $V = 0.5\ S^T S$, according to stability theory, proper choice of control inputs guarantees convergence of the method. So, based on the sliding condition, a self-organizing fuzzy sliding-mode controller is developed to construct the nonlinear feedback control law for the dynamic system as

$$T = T_{fz} + T_{vs} \qquad S_{alt} = S_{alt}^{fz} + S_{alt}^{vs}$$

in which T_{fz}, S_{alt}^{fz} are the inferred control variables from a fuzzy rule base and T_{vs}, S_{alt}^{vs} are the variable-structure switching control. T_{fz} and S_{alt}^{fz} are used to approximate the equivalent control through a self-organizing procedure, and T_{vs} and S_{alt}^{vs} are used to compensate for the approximation error and to provide exponential convergence of the sliding variable. Furthermore, the consequent parameters are adjusted in the direction that minimizes the value of V, using the gradient descent method. We select the Lyapunov function to ensure convergence of the method, and proper control of the dyeing system to the desired trajectory.

Controller construction and evaluation: We simulated a two-dye dyeing process with the self-organizing fuzzy sliding mode controller; the concentration of the two dyes in the solution and the control profiles, temperature and salt, are shown in Figure 3. [below]

Figure 3: Controlling Two Dyes Using the SMC. Top plots show each dye concentration; lower left plot shows the temperature control profile; lower right plot shows the salt concentration and dosing control profile



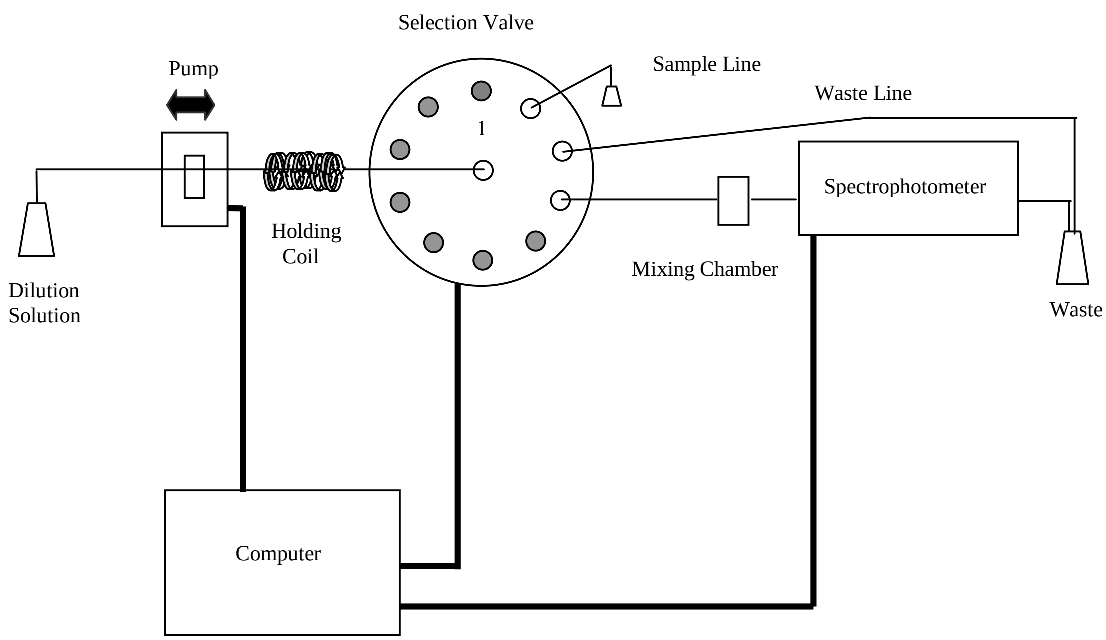
The software for temperature control and the analysis (FIA/SIA) system have been developed using multi-threads. When combined with the SMC, all the tasks can run simultaneously without interference. In this work we have developed an experimental testbed and a modified self-organizing fuzzy sliding mode controller for dyeing process control. Simulation results show that the controller is a viable approach for dyeing applications. Currently we are developing experimental tests, based upon the simulation studies. It is anticipated that these results will show that the SMC can be used for real-time dyeing process control.

Further reading on this subject: We will soon be publishing a paper describing this work in detail. In addition, see (1) Reddy, "Modeling of the Batch Dyeing Process", Masters Thesis, NCSU. (2) Nie and Linkens, "Learning Control Using a Fuzzified Self-Organizing Radial Basis Function Network", IEEE Trans. On Fuzzy Systems, vol 1, no 4, 1993, p 280-287. (3) Lu and Chen, "A Self-Organizing Fuzzy Sliding Mode Controller Design for a Class of Nonlinear Servo Systems", IEEE Trans. On Industrial Elec., vol 41, no 5, 1994, p 492-502.

Sequential Injection Analysis (SIA) data acquisition system: Central to the control problem addressed above is the accurate and rapid determination of dye concentrations and dye bath exhaustion. This is our second major area of progress to date. For this purpose, we are extending our previous FIA/SIA work. Our SIA system configuration consists of a 48000-step syringe pump, a 10-port selection valve, a stainless steel holding coil, a gradient mixing chamber, a fiber optic spectrophotometer, and a computer. Figure 4 displays the configuration of the system hardware.

SIA has is accomplished in two basic steps: preparation and measurement. During the sample preparation cycle, dye bath is drawn up through the sample line and into the holding coil. The dye bath that reaches the holding coil is then swept to the waste container, leaving fresh dye bath in the sample line and fresh carrier in the rest of the system. The measurement cycle starts by drawing up the fresh sample from the sample line into the holding coil. A small portion of the sample is then sent to waste, and the remainder of the sample is then swept toward the mixing chamber and into the flow cell of the spectrophotometer, where measurement takes place.

Figure 4: SIA System Configuration



After construction, our SIA system was tested by taking two sets measurements one day apart. Statistical analysis showed that there is no significant difference (at the 95 % confidence level) between the two SIA means measured on separate days. The precision of the SIA system was also determined by taking ten measurements using 1.0 g/L Direct Red 80. A 40-µL sample size was used for SIA (see Table 3).

Table 1: SIA System Precision

	Value
Mean	0.641
Standard Deviation	0.00255
Percent CV	0.398

These data demonstrate that the precision of the SIA system measurements is excellent.

Three dyes were used in all experiments on cotton. Single-dye and three-dye mixture calibration models were developed on the SIA system.

Table 2: C.I. Names of Direct Dyes Used

Dye Color	Color Index Name (C. I.)
Yellow	Direct Yellow 106
Red	Direct Red 80
Blue	Direct Blue 218

Ten single-dye calibration solutions of different concentrations were prepared for each of the three direct dyes. Concentration values were regressed against SIA absorbance values. Five additional calibration solutions were made for each dye to validate the calibration models. SIA single dye calibration models are displayed in Table 3.

Table 3: SIA Calibration Model for Single Direct Dyes

C.I. Name	Slope	Intercept	Correlation Coefficient (r^2)
Yellow 106	2.07	-0.00280	0.99996
Red 80	2.55	-0.00010	0.99993
Blue 218	1.95	0.00640	0.99996

SIA validation accuracy for one single dye model is listed in Table 4. The actual and predicted concentrations of each dye are shown with the percent error for each prediction.

Table 4: SIA Validation Errors for Direct Blue 218

Actual Conc. (g/L)	Predicted Conc. (g/L)	Absolute Error (g/L)	% Relative Error
0.503	0.508	0.005	0.994
0.397	0.404	0.007	1.76
0.238	0.241	0.003	1.26
0.185	0.187	0.002	1.08
0.079	0.080	0.002	1.27

Twenty seven calibration solutions using all possible combinations of three levels of each dye were prepared. Twenty of these solutions were used to develop the calibration model and the remaining seven solutions were used for validation. A matrix Beer-Lambert absorbance model was obtained by measuring absorbance values of the three-dye mixtures at the λ_{max} of each of the three dyes using SIA using Matlab software, which then calculated the coefficient matrix. Since the three dyes did not interact strongly with each other, a more complex method, such as PLS or neural networks, was not necessary to produce a useful calibration model. For the three-dye mixture models, a 250-μL sample size was used to allow the most strongly absorbing dye in the most concentrated sample to have an absorbance reading near 1.0 A.U.

Prediction errors ranged from 2.9 to –8.6% with an average error of 2.6%. Only three of the errors were larger than 2.9%. Typically, the larger errors are for those dyes that are present in the mixture at low concentrations. In those cases, relatively small absolute errors make a large difference in percent error. Validation accuracy is very good and acceptable. Completion of the comparison of FIA and SIA is expected this fall.

Conclusion: We have started off well in this project and progress toward our goals is outstanding for the first 4 months of the project.

Web site URL: None

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Other Principal Investigators: Keith Beck, Warren Jasper and Gordon Lee