ADVANCED APPLICATION OF STATISTICAL AND FUZZY LOGIC CONTROL TO TEXTILE PROCESSES

Third Annual Report To
The National Textile Center

Principal Investigators
J.L. DORRITY G. VACHTSEVANOS

Graduate Students
Gary Daves
Sungshin Kim
Amit Kumar

School of Mechanical Engineering
School of Electrical Engineering
School of Textile & Fiber Engineering
Georgia Institute of Technology
Atlanta, Georgia

September 1, 1994

Introduction

Slashing is a very critical textile process since it directly affects the productivity in weaving. The primary function of slashing is to apply a homogeneous liquid mix of chemicals, binders and lubricants in the most efficient manner possible, to produce better weaveable warps. This report presents the results obtained from experimentation carried out jointly with our industrial partners during this reporting period. Modeling of the slasher is under way; validated models are illustrated in the following sections.

A slasher has three operating modes of beamer speed, a normal running speed (60 -100 y/min.), creep speed (1-6 yd./min.) and transition state in which the machine is accelerated or decelerated. In normal running mode the speed is varied to keep the exit moisture content constant. No moisture control is enforced during the other two modes. A typical slasher is described in detail in a previous report [1].

The slashing process is highly nonlinear and difficult to understand. The operating parameters are not optimized leading to reduced productivity and creating numerous maintenance problems. Issues like system integration, and reliability are almost absent, thus compounding the problem [1]. Our objective is to model slasher dynamics by new techniques, validate these models and experiment with them to evaluate improved control schemes and drying alternatives. The following text describes briefly the methodology, integration of slashing with other processes and design of a fuzzy logic controller.

Approach

An interdisciplinary team including representatives of the Schools of Textile and Fiber and Electrical Engineering and Mechanical Engineering are attacking the problem. The proposed control philosophy is based on a two-level hierarchy, where optimizing global control techniques generate command signals, set points and parameter values for low-level conventional controllers. A detailed description is available in report [1].

Modeling

Process modeling of a slasher has been carried out with conventional and new control techniques. Current controls vastly depend on heuristics, experience and "what works best"; for example, the slasher is essentially operating open-loop during ramp-up and ramp-down from creep and normal speeds, respectively. The modeling of the slasher is kept simple without losing the pragmatic view. This has enabled us to see the "big picture".

Integration Issues

The scope of integration as related to this project is to control and utilize the flow of information among the immediate operations critical to the slasher(warping, slashing and weaving). The objective is to maximize the productivity and at the same time reduce defects in each of the subsequent operations. Some of the issues that we are trying to address, are how to integrate the information at the supervisory level from warping and weaving to optimize and coordinate the performance of the slasher, produce preventive maintenance schedules and smooth day to day variations at the source. The supervisory control is also capable of merging the high level production schedule information with historical data to account for any changes in yarn, size and styles. Experiments are under way with approximately 45,000 yards of yarn (37's cc, 50/50 Poly/Cotton, 9000 end) being tracked from warping to weaving. This yarn is treated under varying slashing conditions. Results from data analysis are expected by the end of November 94. An experiment of this magnitude on a commercial basis has never been attempted before.

Experiments and Data Collection

A rational set of experiments was designed to monitor the slasher performance. Data was collected to model the operational behavior of the machine under varying conditions of speed, can pressure and nip pressure. The scope of the experiments designed covered both the steady state and transient state and the relationships between control variables. The number of replicates was kept small to reduce cost. All the experiments were done on a commercial full-scale state-of-the-art (West Point, four size-box) slasher at Springs Industries Kershaw Plant (SC.). The data collected from the experiments has provided us valuable information regarding the process itself and its relationship with the critical performance measurement parameters. It has also given us a rational basis for building high level fuzzy logic modeling and optimization routines. Figures 1 through 12 illustrate typical responses of the primary output variables, (exit moisture and add-on) to commanded changes in input variables (nip pressure, steam pressure and speed). These trials were conducted with a warp of 37's cc 50/50 PC with 9000 ends. Add-on is measured at each size box with Strandberg microwave sensors, while all other variables are measured with standard instrumentation.

In Figure 1, step changes in size box nip pressure resulted in a decrease of 0.8% Add-on. The magnitude of the changes was smaller than expected, but that would vary with roll cover hardness. Figure 2 shows a decrease in add-on with increasing speed. This is opposite to the experience on some slashers, but was also true on another plant's slasher running a similar product. Figure 3 shows a typical underdamped response of exit moisture caused by an underdamped response of the steam cans. This can be significantly reduced by improved controller tuning. Figure 4 shows change in exit moisture with decreasing speed, the steam cans were maintained at constant pressure. Results of tests done at Air Products laboratory show that increasing nip pressure results in a slight drop in strength, a small decrease in penetration, but no significant change in elongation, encapsulation or hairiness (figure 5-8). The latter result would indicate that nip pressure is a reasonable control variable for Add-on. The change noted in strength results from the change in Add-on and would be kept constant when Add-on is kept constant.

Drying Can Modeling

To combat the problem of the yarn weakened by overdrying during the creep (slow) mode of slasher speed, various options were considered. The one that shows the most promise was to remove energy from the steam cans by removing the steam. Since cans are pressurized, the steam can be exhausted

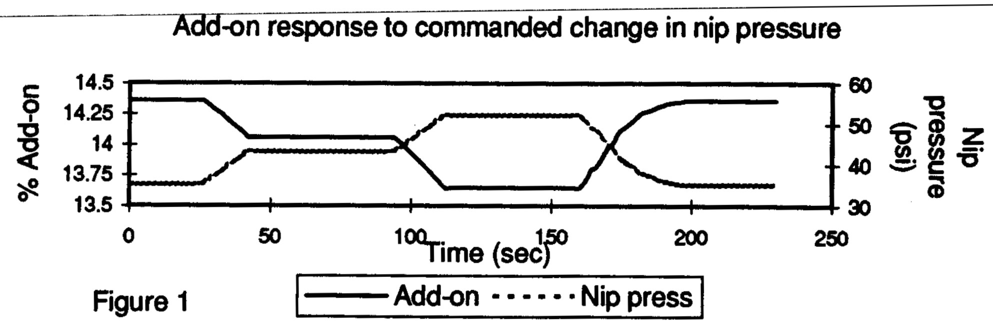

Figure 1

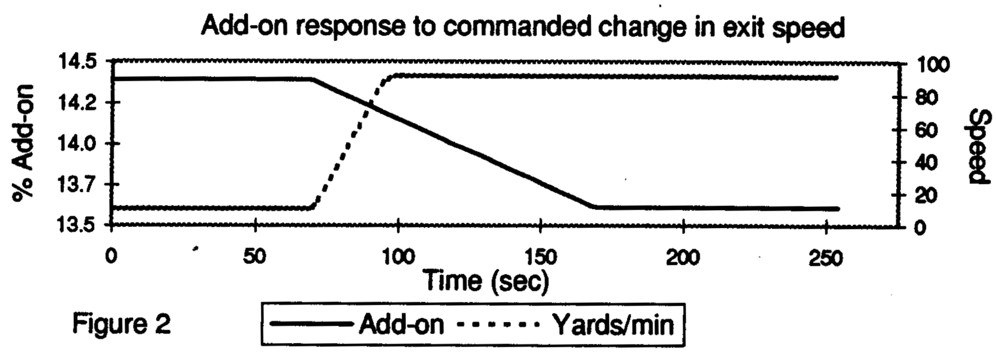

Figure 2

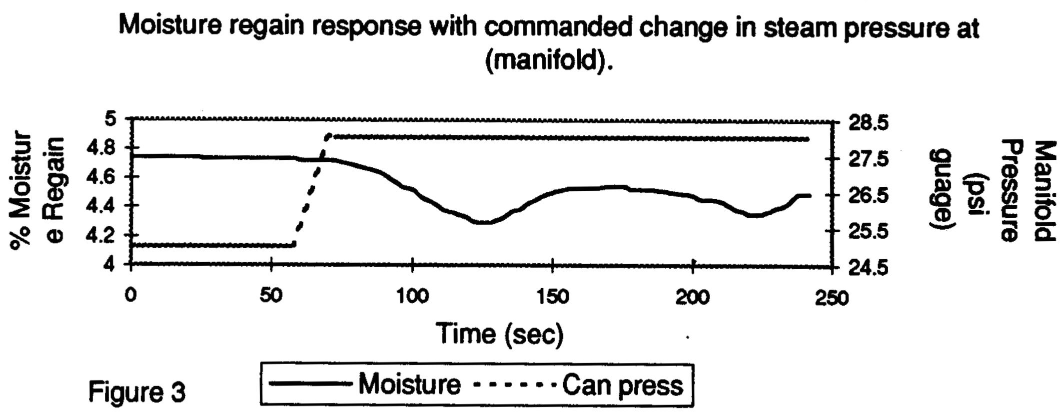

Figure 3

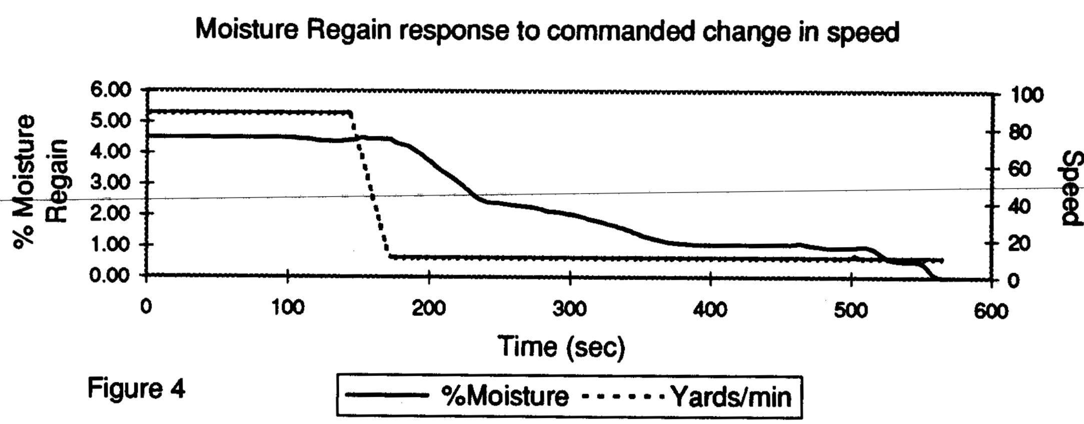

Figure 4

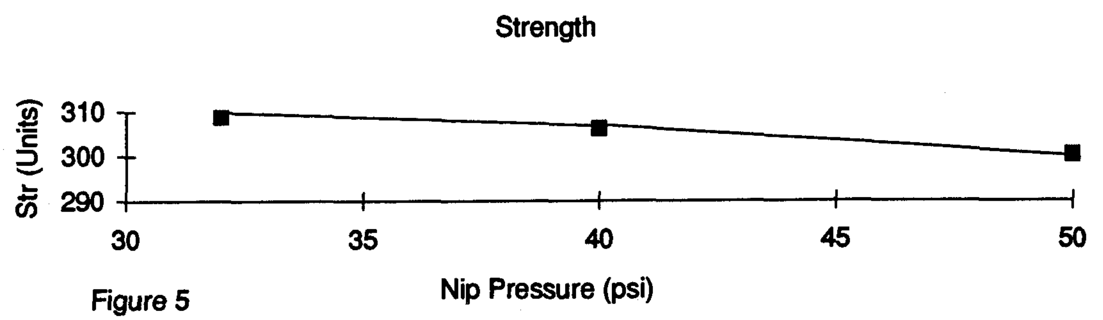

Figure 5

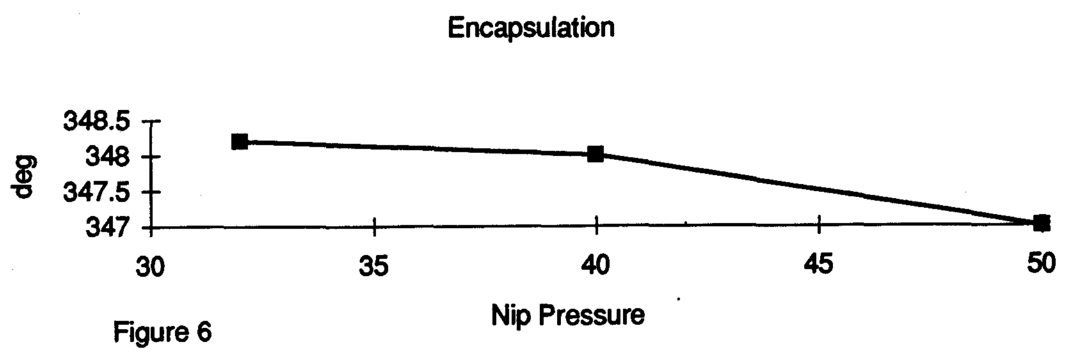

Figure 6

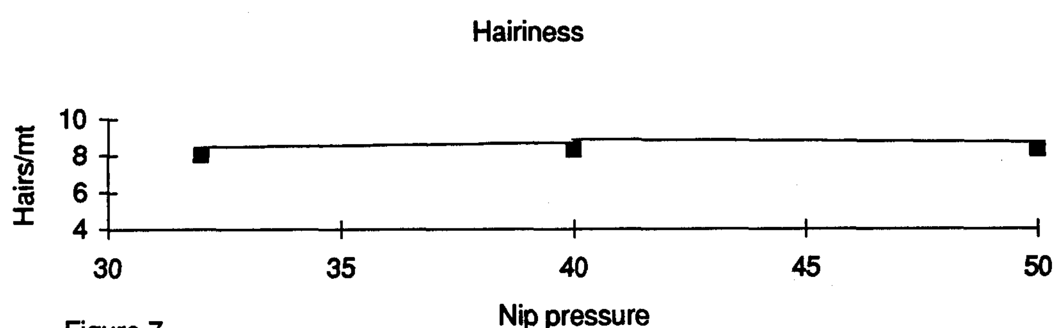

Figure 7

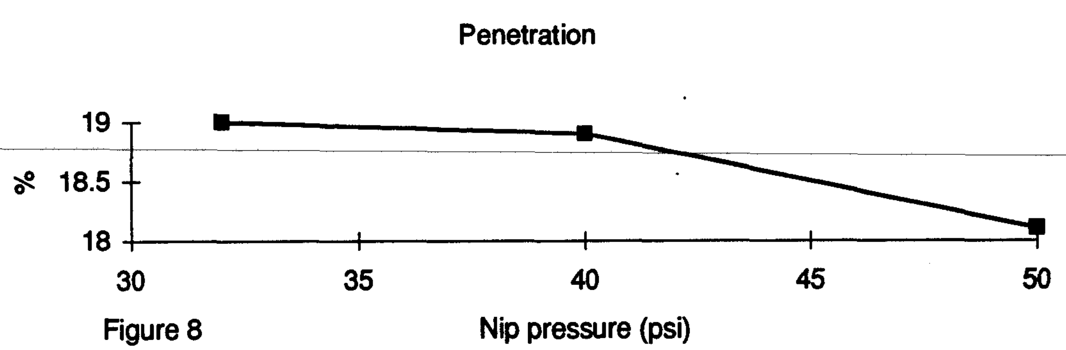

Figure 8

outside the plant through pipes. To determine the feasibility of removing the steam to reduce overdrying, two forms of analysis are being performed, experimentation and theoretical modeling.

The theoretical model is based on first concepts of thermodynamics, fluid mechanics, and heat transfer. The model for the steam in the can allows for both real gas (for superheated vapor region) and saturated steam. Due to the complexity of the model containing time dependent differential equations, a computer program has been developed to solve the problem using numerical methods. A fourth-order Runge-Kutta routine is used to solve the differential equations, and a successive substitution subroutine is used to solve accompanying algebraic equations. The theoretical model is very close to completion and has given early, order-of-magnitude approximations for the length of time necessary to bring the steam can down to atmospheric pressure. Figure 9 shows the output of the model for the can with nozzle (without pipe attached) and shows pressure and energy remaining in the can decreasing in the anticipated exponential decay. The experimental part will be a simulation of an actual production-sized can under pressure releasing steam through a pipe to the outside of the building. The tests will be conducted at Georgia Tech using three sizes of openings to allow for a correlation to be done for design work. The correlation could be used to evaluate time of exhaust with the consideration of economic factors such as larger bearings needed for can journals with larger openings. Time of exhaust, pressure and temperature inside the can will be measured to help correlate the experimental results with the theoretical model. The experiments will be run during September and October. The experiments and theoretical model can also be used to determine the dynamics of the steam exhaust process to enable better control when slowing the slasher. Determining the exhaust dynamics is a very most important part of the project due to the necessity of good control to prevent overdrying.

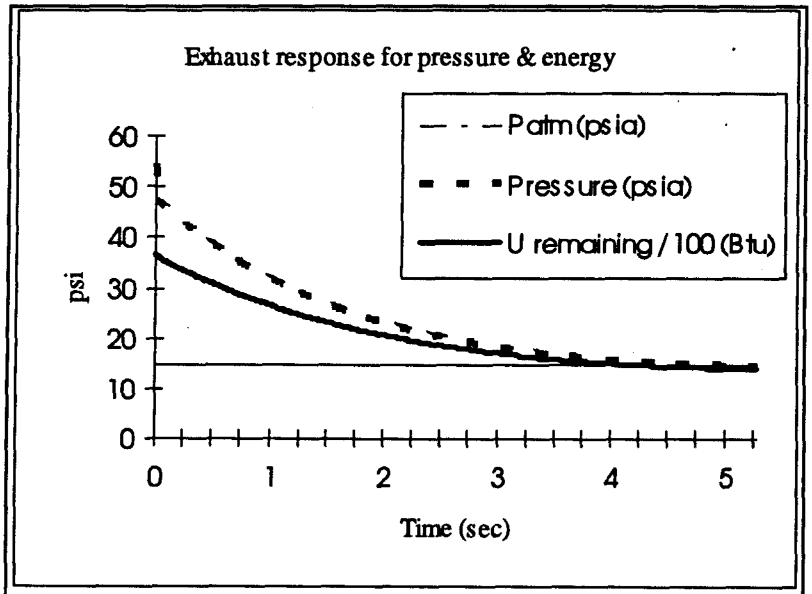

Fig 9. Pressure and energy in drying can during exhaust of steam

Fuzzy Modeling

Fuzzy model identification based on fuzzy implications and fuzzy reasoning is one of the most important aspects of fuzzy system theory because of its simple form as a tool and its power for presenting highly nonlinear relations. The structure of a fuzzy model is the same as that of fuzzy control rules. In other words, a fuzzy model describes the dynamic features of the process using "if - then" statements that consist of premise and consequent parts [8],[9]. The fuzzy model is, therefore, defined as a finite set of linguistic relations or rules, $\{R^i; i=1,\dots,m\}$ which together form an algorithm

$$R^i: \quad \text{If } \{x_1 \text{ is } A_1^i\} \text{ and } \{x_2 \text{ is } A_2^i\} \cdots \{x_n \text{ is } A_n^i\} \text{ Then } \{y \text{ is } B^i\} \qquad (1)$$

where $x_k (1 \le k \le n)$ are input variables, y is the output, and A_k^i and B^i are fuzzy variables. After constructing the fuzzy model using linguistic rules, the compositional rule of inference is called upon to infer the output fuzzy variable from given input information as :

$$R \circ S = \int_{X\times Z} \vee_{y \in Y} \left[\mu_R(x,y) \wedge \mu_S(y,z)\right] / (x,z) = Q \qquad (2)$$

where $\vee$ is the symbol for the max. operation and $\wedge$ is the min. operation. R, S and Q are fuzzy relations from X to Y, Y to Z and X to Z, respectively [10]. The centroid method is finally used to arrive at a crisp value from the output.

Process modeling of the slasher is carried out by adopting a generic approach which entails both conventional and new system-theoretic techniques. Field experience shows that most of the individual controls on slashers are highly nonlinear in nature; i.e. drying rate of steam cans. The majority of the existing slashing machines are custom-made with virtually no variation in control strategies. Let us illustrate the proposed fuzzy modeling approach with an example. Consider the drying section of the slasher. Fuzzy modeling of the exit moisture is based upon input-output data. Two input variables (can pressure and nip pressure), and one output variable (exit moisture) are monitored. A clustering algorithm, fuzzy c-means, is applied to the raw data resulting in 9 clusters. From these, we derive membership functions for each input variable; with three linguistic terms for each variable the rule base contains nine rules. The output variable is assigned five membership functions. A typical rule is of the form:

If Can pressure is LARGE and Nip pressure is SMALL
Then Exit moisture is NEGATIVE SMALL. (3)

Figure 10 shows a fuzzy model of the exit moisture content with respect to the can pressure and the nip pressure [8],[9].It is derived from a rule-base (Table I) based upon experimental data (Table II) ; the membership functions are shown in Figure 11.

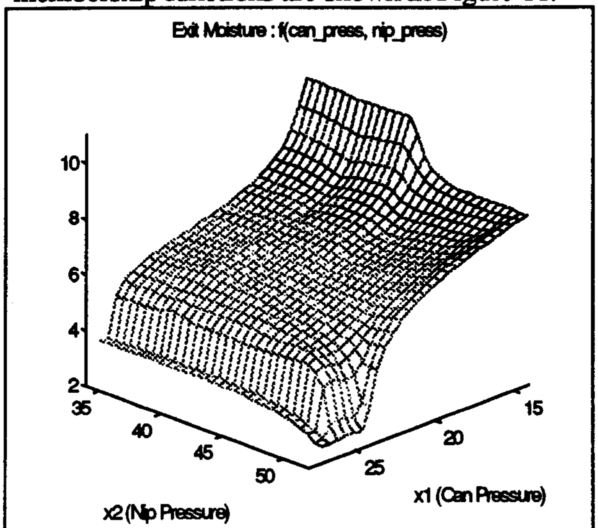

Fig 10. Fuzzy model of the exit moisture.

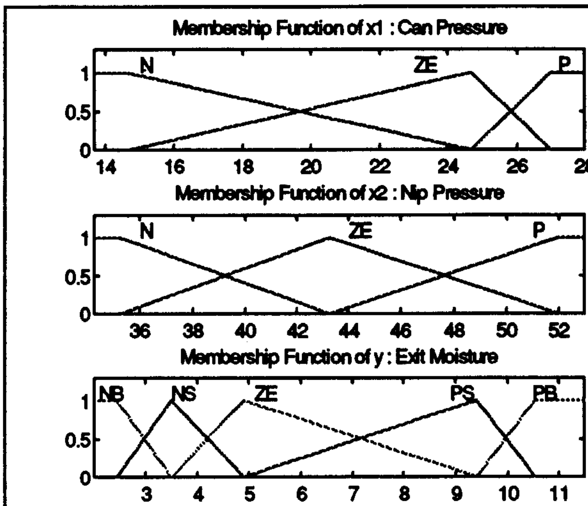

Fig 11. Membership functions

Table I. Rule base for the exit moisture.

x1 (Can Pressure)	x2 (Nip Pressure): N	ZE	P
P	NS	NS	NB
ZE	ZE	ZE	NB
N	PB	PB	PS

* N(small), ZE(moderate), P(large), NB(negative big), NS(negative small), ... PB(positive big).

Fuzzy Optimization

Fuzzy optimization is used to find the conditions that give the maximum or minimum value of a fuzzy model. Most industrial processes consist of several local controllers that require set points in order to achieve the best possible performance. Due to the complexity and uncertainty of the system, it is difficult to optimize the set points through monitoring or data analysis. Fuzzy optimization is

Table II. Experimental data for modeling the exit moisture.

	1	2	3	4	5	6	7	8	9
Can Press. (psi)	14.68	14.67	14.68	24.67	24.96	24.53	26.99	27.00	27.00
Nip Press. (psi)	35.25	43.50	52.00	35.33	43.33	52.00	35.00	43.00	52.00
% Exit Moisture	10.56	10.53	9.42	5.62	4.18	2.80	3.79	3.22	2.11

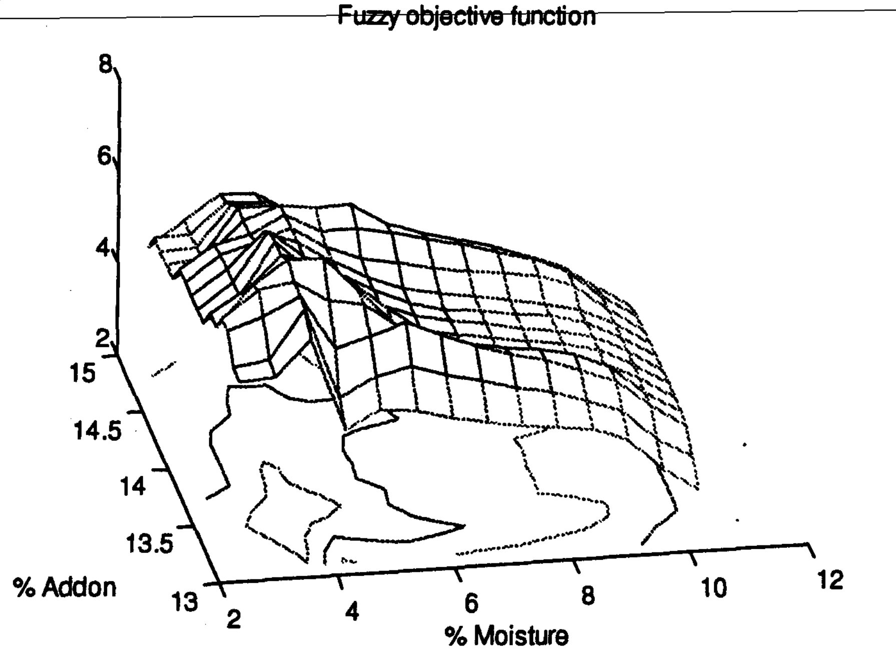

Figure 12: Fuzzy cost function

carried out on the basis of a fuzzy model not a mathematical model. With heuristic operator information or input-output data a fuzzy performance index or cost function can be constructed [11],[12].

For example, Figure 12 depicts the cost function (f_{pi}) associated with the performance of the slasher. Here, % add-on, % moisture are the process variables and the cost is an estimate of performance or the basis of heuristic or experimental information.

The optimization algorithm is based on the Nelder and Mead's flexible polyhedron search procedure, called the simplex method [13], or a genetic algorithm (GA) [14]. A GA is a general search method based on the ideas of genetics and natural selection. GAs have shown to be effective optimization tool when the function spaces are not smooth or continuous where calculus-based methods are difficult to apply. For best results in weaving, the slasher must be optimized so that it outputs a high quality yarn. Due to the complexity and uncertainty of the slasher machine it is difficult to optimize the set points. The objective is to find a set of optimum parameters using the fuzzy model and fuzzy optimization techniques. For a population of 70, a crossover rate of 0.75, a mutation rate 0.001 and a generation of 4, the simulation results show that the maximum value is 8.31 (= max.$\{f_{pi}\}$, $0<f_{pi}<10$), for which the % moisture is 3.74 and the %add-on is 13.58 as shown in Figure 13.

Fuzzy Control

It is believed that complexity and uncertainty can be more efficiently resolved through intelligence. Uncertainty in a dynamical system includes parametric disturbances, unmodeled dynamics and external noise. The decision making process of a human operator is characterized by his capability to handle vague and imprecise concepts which are often expressed linguistically. Fuzzy set theory [4] and fuzzy logic [5] can make reliable decisions with ambiguous and imprecise events or facts by representing them in linguistic terms. We apply fuzzy logic control (FLC) to the drying rate of the slasher. A similar approach is used to control other slasher major subsystems. An error model for fuzzy logic feedback systems is formulated as follows: The process dynamics are defined by $\dot{x}(t) = f(x(t),u(t))$ (4)

The FLC structure is represented as

$$u(t) = g(e(t), x^d(t))$$

where $e(t) = x^d(t) - x(t)$ (5)

Now, the error system is defined by $\dot{e}(t) = \dot{x}^d - f(x^d - e, g(e, x^d)) = h(e, x^d, \dot{x}^d)$. (6)

The objective is to maintain closed loop stability of the error system using a phase portrait assignment algorithm [6], i.e.,

$$\lim_{t\to\infty} e(t) \to 0 \cdot \qquad (7)$$

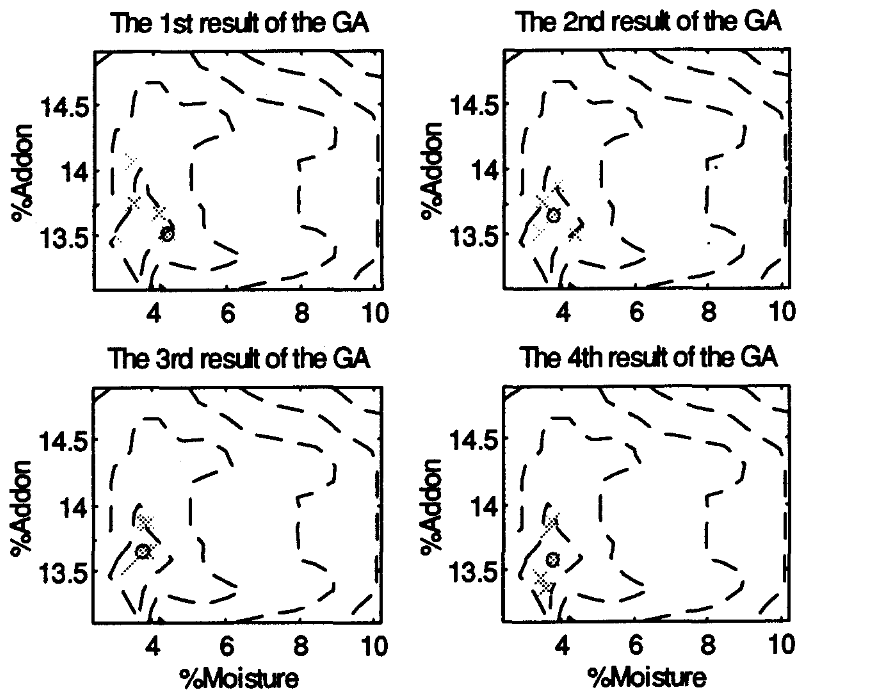

Figure 13. The results of the fuzzy optimization.

We perform this regulation via a Fuzzy Decision Hypercube (FDHC) [7] with the following control law:

$$u = g(e, x^d) = g(\int h d\tau, x^d) \quad .(8)$$

The design procedure can be divided into four stages: phase-portrait assignment algorithm, selection of membership functions, compositional rule of inference and defuzzification. The rule base used in the Drying Rate control is shown in Table III. The linguistic rule base if - then statements contains rules of the form:. If y is NB, Then u is PVB. (9)

where PVB(Positive Very Big), PB(Positive Big), PM(Positive Medium), PS(Positive Small), SZ(Small Zero), NS(Negative Small) are typical linguistic terms employed in the rule base.

Summary Of The Project to Date

A hierarchical control architecture is proposed has been developed and is applied to textile processes based upon experimental input-output data.

- A rule-based fuzzy modeling technique is applied to the Drying subsystem of the process. A FLC is used to control moisture content in the yarn and is shown to outperform a conventional control law.
- An experimental data-base is compiled describing the slashed yarn characteristics which are used to construct the fuzzy model and to derive the global optimization routines for the hierarchical supervisory level.
- Control loops for the slasher model have also been simulated on a PC486 machine to design and compare new control strategies.
- We have developed a simulation of a slasher on the Honeywell TDC3000™ automated process control platform. It demonstrates the present control strategy, its limitations and potential for improvement. Fuzzy control in a hierarchical system has the potential for dramatically improving slashing and weaving performance..

Acknowledgments

This project is being funded by The National Textile Center, a consortium of universities formed through federal government funding to address the needs .of the textile and allied industries in a comprehensive and coordinated way. Four universities (Auburn, Clemson, Georgia Tech and North Carolina State), which collectively produce over 90% of US textile related academic research and degrees are participating in this effort. The project team acknowledges the assistance and participation of personnel, raw material, process and testing from Springs Industries., West Point Foundry and Strandberg Engineering, Air Products.

References

[1] Second Annual Report, "Advanced application of statistical and fuzzy control to textile processes," The National Textile Center. Sep 1, 1993

[2] Y.E. Mogahzy and W.S. Perkins, "Effect of Creep-Related Overdrying in Sizing on Warp Characteristics and Weaving Performance," *Textile Res. J.*, 62(6), pp317-324, 1992

[3] Electric Power Research Institute (EPRI - CU - 7006), Project 2893-6-8, November 1990.

[4] G. J. Klir and T. A. Folger, *Fuzzy Sets, Uncertainty and Information.* New Jersey: Prentice Hall, 1988.

[5] L.A. Zadeh, "Fuzzy sets as a basis for a theory of possibility," *Fuzzy Sets and Systems*, vol. 1, pp. 3-28, 1978.

[6] H.Kang and G.J. Vachtsevanos, "Nonlinear Fuzzy Control Based on the Vector Fields of the phase Portrait Assignment Algorithm," *Proc. of the ACC '90*, pp.1479-1484, San Diego, 1990.

[7] H.Kang and G.J. Vachtsevanos, "Fuzzy Hypercubes: Linguistic Learning/Reasoning Systems for Intelligence Control and Identification," *Proc. of the IEEE CDC*, pp.1200-1205, Brighton, England, Dec, 1991.

[8] R. M. Tong, "The evaluation of fuzzy models derived from experimental data ," *Fuzzy Sets and Systems*, vol. 4, pp. 1-12, 1980.

[9] M. Sugeno and K. Tanaka, "Successive identification of a fuzzy model and its application to prediction of a complex system," *Fuzzy Sets and Systems*, vol. 42, pp. 315-334, 1991.

[10] L.A.Zadeh, "Outline of a new approach to the analysis of complex systems and decision processes," *IEEE Trans. Syst. Man and Cybern.*, vol. SMC-3, No. 1, pp. 28-44, Jan. 1973.

[11] S.S. Rao, K. Sundararaju, B.G. Parkash and C. Balakrishna, "Multiobjective fuzzy optimization techniques for engineering design," *Computers Structures*, vol. 42, No. 1, pp. 37-44, 1992.

[12] G. Vachtsevanos, J.L. Dorrity, A. Kumar and S.S. Kim, "Advanced application of statistical and fuzzy control to textile processes," *IEEE 1993 Annual Textile, Fiber and Film Industry Technical Conf.*, Atlanta, GA, pp. 28-35, May, 1993.

[13] S.S. Rao, *Optimization : Theory and Applications*, New York, John Wiley Sons, pp. 292-300, 1984.

[14] C.Z. Janikow and Z. Michalewicz, "A specialized genetic algorithm for numerical optimization problems," *Proc. of the 2nd Int. IEEE Conf. on Tools for Artificial Intelligence*, p.798-804, Nov. 1990.

[15] Textile Short Course on Slashing , *Conference Proceedings*, Auburn Univ. Dept. of Textile Engineering, 1985-1990