# Development Of Strategy Of Wet End Retention Control through Simulation Of Classical PID And Artificial Neural Network Models

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### **ABSTRACT**

This paper arises from an investigation into the use of an artificial neural network for modeling and control of the retention process in the wet end of paper machine. The neural network model is used for those parts of the system where no physical model is readily available due to complexity of the process. For the purpose of neural control structures, a direct and inverse neural model of retention process using three layer perceptron network was created. The classical controller strategy has also been developed and analyzed. The performance tests for both the controllers (PID and ANN) were realized in the simulation environment with Matlab / Simulink tool. As encouraging results were found from simulation, the proposed ANN control strategy can be successfully applied to mill retention control.

Key words: Retention, wet-end, ANN, ash content, consistency, PID.

#### Introduction

Retention is an important factor in wet end chemistry control of a paper machine. As per definition, retention of a material is the fraction of that material fed to the machine through the head box slice that is retained in the paper sheet. Definitions of retention depend on the specific types of materials retained on wire such as total solids, filler (ash), fines, retention aids, chemicals, sizing particles, interfering substances and fibers. This is further defined based on either overall retention, first pass retention or first pass total solids retention or total solids retention, considering paper located at pope reel at the dry end of the entire machine or paper web leaving the couch roll at the end of wet end formation stage. Definition may also be used for any part of the machine, such as for any sectional drainage element of Fourdrinier, at the end of the press section etc.

Retention influences paper machine runnability, material loss levels, and chemical efficiency (1, 2). Further it describes the efficiency in the each and individual drainage elements as well as

the same for the entire wet end of paper machines. The information of total solids in the headbox and the white water and filler consistency level gives an early indication of potential problems in the wet end. Therefore retention is considered today, an important parameter whose measurement and control finds use to understand precisely the wet end chemistry and the state of the wet end by monitoring and controlling the stability of paper machine. New demands for better retention control have arisen from increased production speed, improved use of various chemicals, enhanced formation, and environmental requirement and so on. However, retention control is a very complex task and continuous attempts are being made to develop new and improved control systems (1-14). Accurate on-line measurement and monitoring of variables affecting retention is also very difficult due to lack of appropriate sensor.

In practice, the most common variables of interest to measure are the headbox flow rate, the consistencies of various white water streams flowing through the forming fabric, and the consistency of the paper on the top of the forming fabric (2). Flow of stock as well as white water can be measured in the sections of headbox and wire. Various methods are available for flow measurements, such as chemical method (TIS 0410-09), ultrasonic flow

meters, blow sample method (TIS 0410-07), indirectly by flow balance calculations or using mass measuring gauge (TIS 0502-12). If more than one number of trays is used, to estimate the first pass retention accurately, one has to measure white water consistencies and precise measurement of the white water flows to all the trays concerned. In many mills the flow rates are not easy to measure. Headbox slice bleeds can introduce error in to the way headbox flows are used and can even enrich white water consistency (2).

## **Modeling of retention process**

Owing to the complicated nature of the wet end of paper machines, retention is affected by many variables. Some typical variables affecting retention are: retention aids (polymers), stock pH values, stock flow rate, shear forces, pulp quality (CSF), head box slice geometry, raw material contaminants, drainage, machine speed and structure of white water system etc. as shown in figure 1. As a result, it is a multiple input and single output system (7). Moreover, owing to constant variations of all of the input variables during paper production and the involvement of fluid dynamics during the formation phase on the wire section, the system is dynamic, nonlinear and stochastic. An added complexity is that the retention is coupled strongly with other chemical systems in the wet end, such as sizing and wet strength control systems. This

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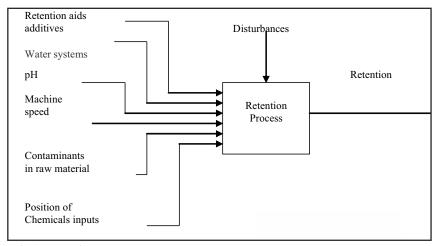


Fig 1: Retention Process

Table 1: Model Equations proposed by different investigators

Researchers	Model Equations for Retention				
Orccotoma et	$R = (T_W/T_H)*100$ (1)				
al. (4)	$T_{w}=(?_{1}^{n}M_{i})_{w}$ (2)				
	$R_i=100(M_i)_w/(M_i)_H$ (3)				
Balderud and	$Y_i = (M_i)_h / T_H$ (4)				
Wilson (6)	$R = ?_1^n Y_i R_i$ (5)				
	T <sub>W</sub> , the total fibrous material in the web T <sub>H</sub> , the delivered stream through the				
	headbox slice. M <sub>i</sub> is the mass associated to the ith fibre fraction in the pulp, M				
	represents the total fibrous material in the web.				
	R <sub>i</sub> , the partial retention of each fraction, Y <sub>i</sub> , the mass fraction of each fibre				
	component in the headbox				
	$\gamma(k)=K(1-C_{ww}/C_{H})$ (6)				
Wang et al.	K is the machine dependent constant, $\gamma(k)$ , the retention value at sample				
(7)	number k, Cww, and CH are white water and headbox consistencies				
	respectively				
	$R(\%) = 100*(C_H Q_H - C_{ww} Q_{ww}) / C_H Q_H$ (7)				
Leiviska(3),	$Q_{ww} = KQ_H \qquad(8)$				
Kaunonen et	considering that the white water volumetric flow depends linearly on the				
al. (5)	flow,				
	$R(\%)=(1-KC_{ww}/C_H)*100(9)$				
	Q <sub>H</sub> and Q <sub>ww</sub> m the volumetric flows from the headbox and the wire section				
	K is the coefficient				

means that an accurate physical model of the retention process is very difficult to obtain and as a result, model - based feedback control of retention has remained a unsolved problem (7).

One of the retention terms, called first pass retention (R) is an important parameter and is derived from steady state mass balance around the forming section defined by Orccotoma et al. (4) given in Eq.1. Further considering the fiber size distribution in the pulp, the total fibrous material in the web, the partial retention of each fraction, R, and the mass fraction of each fiber component, Y<sub>i</sub> in the headbox can also be written (Eq.2-4).

Various investigators (3-6) have proposed both static and dynamic models for retention process for control purposes. These are shown in table 1. It is generally not practical in paper

mills to measure T<sub>w</sub>, T<sub>H</sub> and some of the parameters given in the above models. Therefore, more frequently (6-12), the first pass total solids retention (FPSR, γ) for routine control purpose has been considered as

$$\gamma$$
=[(C<sub>H</sub>-C<sub>ww</sub>)/C<sub>H</sub>]\*100 ......(10) Where  $\gamma$  reflects the percentage of fiber and other additives (i.e. fillers and process chemicals) remaining in the final produced paper and thus indicates both the efficiency of the use of raw material and the runnability of paper machines.

# Analysis and Development of Steady State Models

The first pass retention (FPR) represented by Eq.10 is an approximation which can be derived from the first principle mass balance equations and remains valid with certain assumptions as shown under:

First pass total solids retention, FPTSR;  $\gamma_{15}$  is defined without any approximation as follows:

FPTSR,  $\gamma_{ts}$ 

=  $100 \times [(total solids flow in paper) /$ (total solids flow from headbox)]  $= 100 \times (M_c C_c) / (M_{HB} C_{HB}) \dots (11)$ where,  $M_{HB}C_{HB} = M_{ww}C_{ww} + M_cC_c$ or  $M_c C_c = M_{HB} C_{HB} M_{ww} C_{ww}$ Using the above relation one can get,  $\gamma_{ts} = 100 \times [(M_{HB}C_{HB} M_{ww}C_{ww})/(M_{HB})$  $= 100 \times [(C_{HB} M_{ww} C_{ww} / M_{HB}) / (C_{HB})]$   $= 100 \times [\{C_{HB} (M_{ww} / M_{HB}) C_{ww}\}] / C_{HB}$ ....(12)  $=100 [1-K_1 C_{WW}/C_H]$ 

This model corresponds to that proposed by Leiviska (3) and Kaunonen et al. (5).

In general the ratio,  $K_1$  is on the order of 98-99%.

If  $M_{ww}/M_{HB} \approx 1$ , the FPTSR can be approximated as:

 $\gamma$ = 100 × [(C<sub>HB</sub> C<sub>ww</sub>) / (C<sub>HB</sub>)] thus corresponds to the approximate model given in Eq.10.

Where,  $M_c$ ,  $M_{HB}$ ,  $M_{ww}$  represent mass flow rate and  $C_c$ ,  $C_{HB}$ ,  $C_{ww}$  indicate consistency in fraction for couch, headbox and white water respectively. In deriving the above approximate FPR equation from the material balance, two assumptions must be made (1-2).

- (i) The headbox solids are all divided between the sampled tray & the paper. In other words the total headbox solids equal the total paper solids plus total sampled tray solids.
- (ii) All the waters flowing from the headbox flows into the sampled tray i.e none goes with the paper. In practice, the paper leaving the couch roll contains only 1-2% of the total water coming from the headbox, the second assumptions will appear to be reasonable.

However, the situations is not so straight forward with respect to the first assumption that all headbox solids flow to the sampled tray can be met in at least three ways on a given paper machine. These are as follows:

If a paper machine has only one white water tray, then most of the solids flowing from the headbox that are not retained in the paper will flow into the tray with the white water & FPR equations should be applied.

If the machine is configured in such a way that all the white water from various trays is collected & mixed at some point and a representative sample of the mixed white water is taken, then FPR equations will also hold good.

If the white water flowing to all trays has the same consistency then FPR equation will provide a reasonable estimate of FPR.

Correspondingly ash retention (FPAR),  $\gamma_a$ , fines retention,  $\gamma_f$  and dissolved solids retention,  $\gamma_{ds}$  can be written as

$$\begin{split} & FPTAR, \gamma_{a} {=}~100 {\times} \left[ (M_{HB}C_{HB}A_{HB}\,M_{ww}C_{ww}\,A_{ww}) / (M_{HB}C_{HB}A_{HB}) \right] \\ & = 100 {\times} \left[ (1~M_{ww}C_{ww}\,A_{ww}/\,M_{HB}C_{HB}\,A_{H}) \right] \\ & = ~100~X~\left[ 1 {-} (M_{ww}/M_{HB}) (C_{ww}/C_{HB}) (A_{ww}/A_{HB)} \right] \\ & \gamma_{f} {=}~100 {\times} \left[ (~M_{HB}C_{HB}~f_{HB}~M_{ww}C_{ww}~f_{ww}) / (M_{HB}C_{HB}f_{HB}) \right] \\ & \gamma_{ds} {=}~100 {\times} \left[ (~M_{HB}DS_{HB}~M_{ww}~DS_{HB}) / (~M_{HB}DS_{HB}) \right] \end{split}$$

Taking the ratio,  $M_{ww}/M_{HB}$ , equal to 1 in all the cases, one can arrive at the following retention equations. FRAR=100% x  $(C_{HB}A_{H} - C_{ww} A_{ww})/C_{HB}$  $A_{HB}$  .....(13) Similarly for fines retention

FP FNR = 100 x  $(1-C_{ww} f_{ww}/C_{H} f_{H})$ This equation corresponds to the same

reported in literature (2, 9).  $FPDS=100\times[(M_{HB}DS_{HB}\ M_{ww}\ DSww)/($  $M_{HB}DS_{HB}$ ] =100 x (1-DSww/DS<sub>HB</sub>)

Where,  $A_{H.}$   $A_{ww.}$   $f_{H.}$   $f_{ww.}$   $DS_{HB}$ ,  $DS_{ww}$  refer to ash level, fines content and dissolved solids content in headbox and tray respectively.

The first pass fiber retention, (FPFR),  $\gamma_{\rm F}$  can also be written as

$$\begin{split} FPFR &= \gamma_{_{F}} = 100 \times [(\ M_{_{HB}}C_{_{HB}}\ F_{_{HB}}\ M_{_{ww}}\\ C_{_{ww}}F_{_{ww}})/(\ M_{_{HB}}C_{_{HB}}F_{_{HB}})] \approx &100 \times [(C_{_{HB}}\\ F_{_{HB}}\ C_{_{ww}}F_{_{ww}})/(C_{_{HB}}F_{_{HB}})] \end{split}$$

However, this retention term should be a constant quantity. In order to validate it the fiber flow with white water should be zero. Therefore, this retention term has practically no effect on retention. Balderud and Wilson(6) reported based on the work of Orccotoma et al.(14) retention of individual that components are close to constant over a reasonable operating regime. The observed variation in total retention was due to variations in the fines content and to a smaller degree, variations in the fines retention.

It is already indicated that the pulp stock consists of many components with 4 principal fractions, accepted fibres (R 200), fines (filler and pulp fines, P200), total dissolved solids, and water. These aspects have been dealt with extensively by Orccotoma et al. (14) using twin wire former systems.

In the present work, the first pass retention,  $\gamma$ , considering only the effects of two components (n=2), namely the fines, f and fibers, F in the pulp stream from the headbox, one can easily find the following material balance equations

$$\gamma = Y_f \gamma_f + Y_F \gamma_F \qquad \dots \dots (15)$$

$$Y_f + Y_F = 1$$

$$\gamma = (\gamma_f - \gamma_F) Y_f + \gamma_F \qquad \dots \dots (16)$$

This steady state model will be used for simulating the retention with fibers and fines.

# Measurement of control parameters and its sensitivity

Regardless of which definition is used to calculate first-pass total solids retention or first-pass ash retention, it is absolutely critical that the consistencies and ash levels must be determined with good precision (2). In fact, the retention equations involve ratios of the experimental variables and errors in the measured consistency data can be greatly amplified in the final calculated retention values.

Small errors in the headbox and tray consistency and ash data can produce large variation in the calculated first pass retention values. For example, it can be shown that a 0.02 % deviation in the absolute headbox or tray consistencies can result in a 6% change in the calculated absolute first pass total solids retention. To avoid this problem, it is absolutely necessary that all weighing associated with first pass retention consistency and ash content data be made to the nearest 0.001 measurement units (2). The advanced consistency measurement methods used in retention applications rely on a combination of optical measurement principles including depolarization, absorption (attenuation and extinction), and scattering (3).

# Modeling of Closed loop control system

Only few control strategies are available (1-2, 7) for single closed loop systems for controlling consistency and ash content (2) and only ash content (7) in which filler is controlled by a PID controller.

Scott (2) has pointed out that on-line real- time SISO feedback control of recycled white water consistency can be a way to retention control. It was also pointed out that thick stock wet end chemistry processes and machine direction basis weight variation play key roles in this regard. As the thick stock consistency, percent retention and white water consistency are all interlinked; the variability of retention strongly depends on variations in qualities of the thick stock and recycled white water consistency. Hence papermaker's control strategy should be to minimize the variation in the recycled white water consistency.

More advanced closed loop retention control system using two consistency sensors (headbox and white water tray) and a computational module has also been proposed (13). The sensors were capable of determining both the total consistency and ash consistency of the sampled streams. It has been found that the total recycled white water consistency measurement provided the quickest response to a process disturbance and would therefore, be the best control variable. To circumvent large variations that affect retention should be dealt with in the thick stock area before the furnish reaches the basis weight valve. Included in this category are variations in fines and ash levels, interfering substance concentration, and dissolved substance concentration and surface charge.

Paulapuro et al. (11) and Rantala et al. (12) developed adaptive retention control model with data from pilot paper machine using a Kajaani electronic RM-200 retention monitoring system to perform on-line measurement of both total and ash consistencies in the headbox and white water. The basic parts of wet end and retention control are shown in fig.2 which is self explanatory. In a simplest system the paper machine has a fourdrinier wet end, a pulp system with a refining stage and a white water system whose openness can be changed. The wet end has an open hydraulic head box, two direct presses, and a sampling felt with which sample sheets can be taken from the web to be dried separately. Technical data for the experimental paper machine are also used for artificial neural network training.

Since too high retention can affect the formation and lead to flocculation during the drainage phase, it is therefore important to control the retention at a specified level.

This in fact, forms the main goal of the above work, where a dual-polymer retention aid system is used to minimize the variation of retention.

Simulation was used to validate the model and the visual comparison of the simulated results with the measured data was made.

The generalized model can be used to represent the dynamic and nonlinear relationship between retention and the related most sensitive input variables, such as retention aids.

To develop model of retention control process Orccotoma et al. (14) has considered two zones in the forming section of the paper machine. The whitewater from the first zone is collected in the silo, suctioned by the mixing pump, and mixed with thick stock (short circulation loop). The resulting stream from the mixing pump is directed to the headbox. The whitewater from the second zone is collected in the whitewater chest and used for pulp dilution throughout the mill. The parameters (total fibrous material retention, long fiber retention, fines retention, water retention) for both zones represent the fraction of each obtained.

 $= \begin{bmatrix} 1.28(s+1.44) & (s+0.28)/ & (s+1.40) \\ (s+0.44) \end{bmatrix} F_1 + \begin{bmatrix} 0.26(s+1.44) & (s-0.01) & /(s+1.40) & (s+0.44) \end{bmatrix} C_1 + \begin{bmatrix} -0.63(s+1.44) & (s+0.80)/ & (s+1.40) \\ (s+0.44) \end{bmatrix} Y_1 + \dots (17)$ 

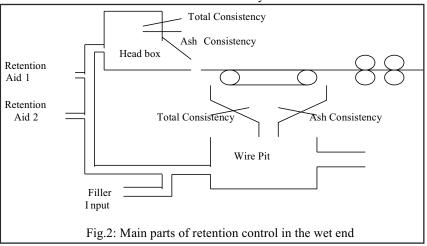
Transforming the eqn. (17) in discrete form (z-domain) one can get the following equation as under

 $\begin{array}{lll} (z) &=& [(1.28z^2\text{-}2.538z\text{+}1.258)/(z^2\text{-}1.982z\text{+}0.9818)]F_1 &+& [(0.26z^2\text{-}.5163z\text{+}0.2563)/(z^2\text{-}1.982z\text{+}&0.9818)]\\ C_1+[(0.63z^2\text{+}1.2446z\text{-}0.616)]Y_1 &..... &(18) \end{array}$ 

The eqn .18 can be used for simulation for retention in digital control system.

To reduce variability of the output variables in the paper machine, the physical properties of thick stock should be constant (13). Fluctuations of the consistency, the fines content and the dissolved solids generally cause variations in the first pass retention and basis weight.

In the retention process, according to the zones there are two control loops namely master and slave. When the



pulp component that is retained on the web during paper forming.

The dynamic model of retention process developed by Orccotoma [14] based on first principles contains two parameters namely, the first pass retention, and basis weight BW, as output variables. There is one input variable, thick stock flow, F1, and two disturbances, the consistency, and the fines content of the thick-stock stream, denoted by C<sub>1</sub> and Y<sub>1</sub>, respectively. The dynamic model is therefore, a MIMO (multi-input multi-output) system. On simplifying this model by assuming that there is little or no interaction of basis weight variation with retention and then after decoupling the dynamic model for single output, retention parameter, the following scaled transfer function of the paper forming section is

slave loop responds faster than master, this cascade control system will have improved stability, allow larger value of controller gain  $K_c=10$  and  $K_i=0.5$ . Both parameters of controller need to be used in the master loop for getting the closed loop response.

Several observations can be made about modeling equation for the closed loop system of negative feedback cascaded structure. Equation 19 is the block diagram for the retention process in terms of transfer functions of measuring element, controller, and valve with cascade structure. This is obtained by applying feedback, eqn. (19a), on the basis weight and represents the effect of changes in basis weight set point, BW<sub>SP</sub>, and both disturbances, C<sub>1</sub> and Y<sub>1</sub>. In this case

cascading is required. The modeling of cascading loop of retention process can thus be described in terms of overall closed loop transfer function as follows(fig. 3).

$$\begin{split} (s) &= \left[ (G_c G_v G_{21}) / \left( 1 + G_c G_v G_{11} G_m \right) \right] BW_{sp} \\ (s) &+ \left[ G_{d21} - \left\{ (G_{d11} G_m G_c G_v G_{21}) / (1 + G_m G_c G_v G_{11}) \right\} \right] Y_1(s) \\ &+ \left[ (G_{d12} G_m G_c G_v G_{21}) / (1 + G_m G_c G_v G_{11}) \right] Y_1(s) \\ &+ \left[ (S) \right] \\ &+ \left[ (S) \right]$$

(19a)

Where  $G_e$ ,  $G_m$ ,  $G_v$  are the transfer functions of controller, the measurement and the thick-stock control valve respectively.

G<sub>ii</sub> and G<sub>dii</sub> are the ijth elements of the process and the disturbance transfer functions as shown in eqn. (17) in analog form. It is noteworthy to mention that in a commercial paper machine, the flow of a retention aid polymer is used as input variable for control of retention. Therefore, the model from eqn. (17) represents the short recirculation loop when no chemical is used for control of retention and represents the overall dynamics of the retention process in terms of measuring element, controller, valve, and process and disturbance transfer functions. As already indicated, eqn. (18) is the analogous form for dynamics in discrete control systems.

# Development of Classical control strategy

Wang et al. (7) also proposed adaptive retention control strategy with a dual component system where a PID controller is used for each retention aid. Since retention aids have limited power to control retention, the control range of retention aids can be improved by also controlling the headbox consistency (2, 4). The proposed control system manipulates both headbox ash content and retention simultaneously (7). Ash content is the ratio of the ash consistency to the total consistency as shown in Eq.13. This can also be shown in fig. 3, in which the filler is to be controlled by a PID controller.

In the present study, a simplified classical control system has been designed with the above concept of negative feedback structure but without considering inner cascading loop of figure 3.

For design of classical controller (PI/PID), the values of steady state gain, K, integral time,  $\tau_{\scriptscriptstyle I}$  and derivative time,  $\tau_{\scriptscriptstyle D}$  are required. These controller parameters are generally adjusted or tuned with the process under

examination when closed loop control schemes are designed. There are several procedures available in literature for tuning like Ziegler Nichols, Cohen Coon, on-line simulation etc. PID controller has been taken from Matlab simulink library.

In the present investigation, the estimation of parameters for PI / PID controller for retention process and the final tuning were done by trial and error methods through computer simulation technique using Simulink software inbuilt in Matlab simulation package. The final values of tuned parameters for classical controller in the closed loop system with the retention process been found of the order: proportional gain, K = 1.0, integral time = 0.5 min., derivative time = 0.0. In fact, the derivative time was found insignificant which can be neglected for practical and

neurons in hidden layer and one in output layer with sigmoid activation functions. The neural network can either be trained using supervised or unsupervised learning. To solve the present problem of training back propagation neural network (BPNN), an algorithm has been developed in a similar way (16) as shown in fig.4.

# Development of ANN controller for the case of retention in the wet end:

Rooke and Wang (8) probably for the first time applied semi-physical method i.e. combined neural network (black box model) and physical model to the retention process in papermaking. The retention included fines, fillers and fibres on the papermaking wire.

In this present investigation ANN control strategy has been developed as follows:

 $G_{dij}$  $Y_1$  $G_{dii}$  $G_v$  $G_{m}$ Fig. 3: Retention control system

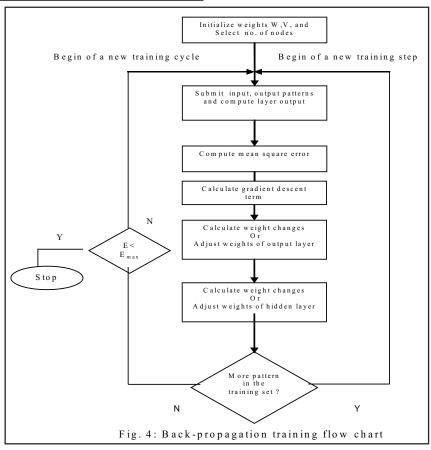
economic reasons. With very small value of derivative time, it is usually uneconomical to use PID controller. Hence use of PI controller in the design of classical control strategy has been considered adequate.

# ANN modeling for the case of retention in the wet end of paper machine

For modeling of ANN, the important parameters are (15-17): momentum coefficient (rate or factor), α, learning rate(or coefficient) η, number of hidden nodes, n, activation function (or transfer function, or squashing function), threshold function, identity function, weight vectors W, V, mean squared error, tolerance, accuracy, gradient descent term for back propagation network (BPN), and gain (sigmoidal gain for sigmoid function),  $\lambda$ or scaling factor and delta rule. The multi-layer neural network is now developed for retention process under investigation. In the present investigation, the network is designed with 3:4:1 node for input, hidden and output layers. It indicates that there are three neurons in input layer, four

The reference and actual data are used as inputs for design of ANN control strategy. These inputs are represented by one vector. The input of process uses an output for ANN controller, which is the appropriate signal for retention at desired level. The direct inverse training and the control loop are shown in figs. 5 and 6. In fig.5 training of a network as a direct inverse of a simulated retention process is shown, where neural network is trained to model the inverse of a plant. This modeling is similar to the system identification problem. In Fig. 6, it is shown that after the neural network learns the inverse model; it is used as a forward controller. This methodology only works for a plant that can be modeled or approximated by an inverse function  $(F^{-1}) = 1$  and the output (y(k))approximates the input  $F_1/C_1$  as shown in fig.5.

The training pattern required for ANN is obtained using simulated data from PI/PID controller. The ANN is, however, trained using the back propagation algorithm. During training, weights and biases of neural network are adjusted to minimize the negative gradient descent term /error. The network performance analysis and the training is stopped when desired goal is reached. The number of layers and



number of neurons in different layers are decided by trial and error methods. In this network analysis sigmoid activation function is used because it is most widely used function compatible to MATLAB software.

## Comparison between conventional and ANN controllers:

The closed loop control system for retention process is also simulated with MATLAB Simulink toolbox. The PID simulation response as well as closed loop response is shown in fig.7. In this figure the response profiles of controller refer the following:

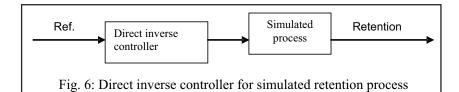
Data 1 shows the closed loop response (with feedback element), whereas data 2 shows PID controller response only (open loop), and data 3 indicate the set point (reference data).

This simulated data obtained from PID has been used for designing the ANN controller.

Fig. 8 indicates the training response of the ANN controller. The lower line conveys the minimum error between process data and training data (this error goal is selected for training. It is well known that error should be minimum so that the ANN controller is trained well). The profle shows the training of the ANN. During training the neural network, the network performance in terms of parameter, gradient descent term of the order of 9.82 e<sup>-005</sup> and error goal 0.0001 are met at 101 epochs which indicates that the network is well trained at 101 epochs.

It is well known that for successful design of control system, the closed loop response (output) dynamics is usually tested with some input function and the parameters like rise time, decay ratio, delay time, settling time and overshoot values are observed. For best controller the values will be as small as possible irrespective of whether the controller are of PID type or ANN based.

The PID controller developed indicates delay time of the order of 1.25s, rise time of 25s and settling time of 26s. On the other hand, the developed ANN



controller response removes overshoot of the order of 0.1, delay time of 0.5s, and settling time of 0.1s. The comparison between ANN and PID controller is made in fig.9 and data from fig.9 are also shown in table 2.

The ash content data from mill was analyzed statistically. These data have also been used for training the neural network. The comparison between mill data and ANN data are shown in figs.9 &10. For normalized values, the individual data collected from process or controller are divided by highest value of data. Thus one can get the data in the range of 0 to 1 which is useful for ANN training. The number of samples here indicates the number of data. In fig.10, mill data are compared with ANN data and the output response in terms of ash content in % is shown. Maximum error of the order of 7.32, minimum error of the order of 0.21 and

average error of the order of 3.507 for ash content (ANN and Mill Data) were obtained. The variations of retention and ash content as a function of time are shown in figs. 11a and 11b.

Experimental data obtained on retention(9) in terms of fines content, FPR(First pass retention), FPFR(first pass fiber retention) are drawn in fig. 11 where the profile in the middle indicates fines content in %, the top curve shows FPR in % and the bottommost profile indicates fiber content in % with respect to time.

Fig. 11a further indicates the maximum, minimum and average values for the fines content (in percentage) of the order of 52.1, 41.1 and 46.57 respectively. Max., min. and average values for the FPR (in percentage) were found 73.2, 60.6 and 66.544 respectively and also max., min. and average values for the FPFR (in

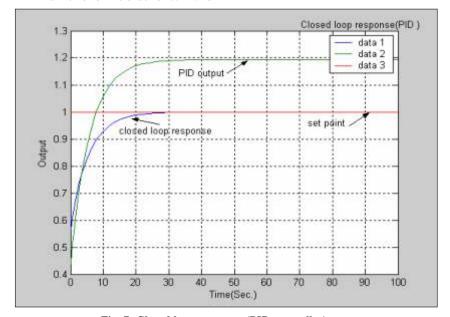
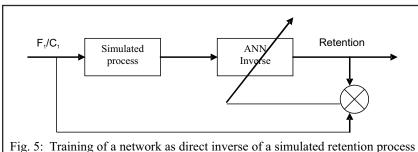


Fig. 7: Closed loop response (PID controller)



percentage) were 35.5, 24.16 and 29.623 respectively. The data from fig. 11 are given in table 3.

Fig.11b is drawn between % SRT (% solid retained by a drainage element) obtained from TIS 0410-07 TAPPI as a function of number of samples (data 1, 2....n). % SRT is calculated from the equation,  $100* S_1/S_{final} = 100*(S_3-S_2)/S$ based on TIS 0410-07 where S<sub>1</sub>S<sub>2</sub> and S<sub>final</sub> are the solids leaving, drained

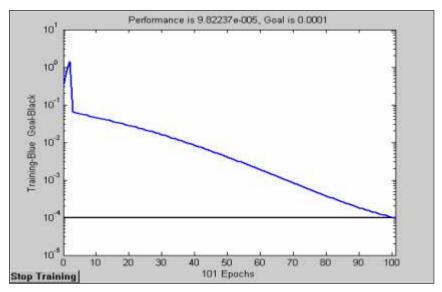


Fig. 8: Training response

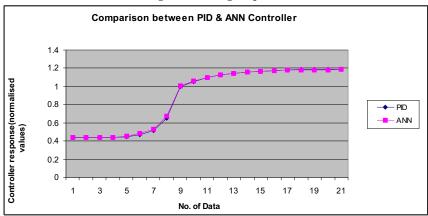


Fig. 9: Comparison between PID & ANN Controller Table-2: Errors between simulated data and ANN data

Performances criteria	PID controller	ANN controller
Min. value	0.438	0.439
Max. value	1.190	1.185
Mean	0.890	0.892
Median	1.096	1.099
Std.	0.335	0.332
Range	0.752	0.742
Min. error be	0.001(0.23%)	
Max. error b	0.005(0.42%)	

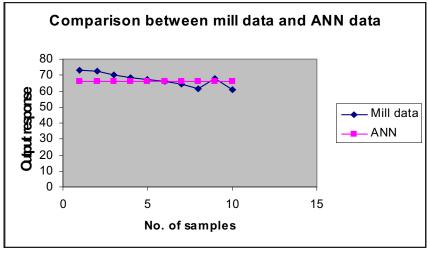


Fig.10: Comparison between Mill data (Ash content) and ANN data

from an element of wire and entering from headbox on wire respectively which are obtained from mass flow measurement given in TIS 0502-12. These are given in table 4. The calculated data are shown in table.4. The figure 11b shows the comparison between mill (% solid retention) and neural network data. It indicates the minimum error, maximum error, and average error of the order of .007, 6.573, and 1.151 respectively. The data from fig. 11b are also given in table 4. It is evident from the table and from the figures that the PID controller data, simulated data with ANN strategy and mill data are tallying very satisfactorily.

#### Conclusion

The neural network model developed is found to work well in the control of retention process in the wet end. The results of simulation reveal that the ANN data values revolve around those of mill data. The mill data tally very closely with the simulated data. The results further also indicate that performances of PID and ANN are comparable. Thus it can be concluded that ANN based control can be used effectively for retention control in a paper mill.

#### References

- Kocurek, M.J., Pulp and Paper Manufacture, Vol. 7, Paper Machine Operations, Joint Textbook Committee of the Paper Industry, Tappi, CPPA, 1991
- 2. Scott W.E., Principles of Wet End Chemistry, Tappi Press, 1995
- 3. Leiviska, K., Paper making science and technology, Process control, Book 14, Finnish Paper Engineers, Association and TAPPI, 1999.
- Orccotoma, A.J., Paris, J. and Perrier, M. Dynamic analysis of fibrous material and dissolved solids distributions in the wet end of a newsprint mill, Appita Journal, Vol. 52, March, 1999, PP 105-113.
- Kaunonen, A., Lehmikangas, K., Nokelainen, J Tappi 1991, Papermakers Conference Proceedings, Tappi press, Atlanta, p.19
- Balderud, J. and Wilson, D.I. Parameters affecting disturbance propagation through the wet end of a paper machine, Appita Journal, Vol.58 (1), pp.40-46, 2005.
- 7. Wang, H., Wang A.P. and Duncan, S. R., Advanced Process Control in Paper and Board making, Pira International, 1997.
- 8. Rooke, P.E. and Wang, H. Applying

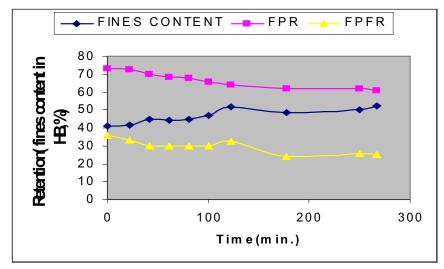


Fig.11a: Retention data

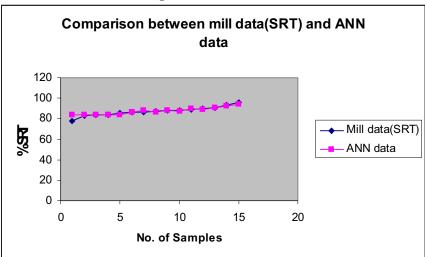


Fig.11b: Comparison between mill data and ANN (Solid retention)

Table-3: Retention data(mill data)

Fines content,%	FPR	FPFR	
41.10	73.20	35.50	
41.67	72.50	33.30	
45.00	70.00	30.00	
44.16	68.33	29.67	
45.00	67.50	30.00	
46.67	65.80	30.00	
51.67	64.17	32.50	
48.33	61.67	24.16	
50.00	61.67	25.80	
52.10	60.60	25.30	

Table-4: Mill data for SRT and ANN data

No. of Samples	Mill data(SRT)	ANN Data	Error	% Error
1	0.809	0.878	-0.069	-8.53
2	0.872	0.880	-8.0X10 <sup>-03</sup>	-0.917
3	0.877	0.878	-1.0X10 <sup>-03</sup>	-0.11
4	0.88	0.876	4.0X10 <sup>-03</sup>	+0.45
5	0.89	0.876	0.014	+1.57
6	0.90	0.900	0.0	+0.0
7	0.91	0.920	-0.01	-1.099
8	0.91	0.900	-0.01	-1.099
9	0.92	0.920	0.0	0.0
10	0.92	0.914	6.0X10 <sup>-03</sup>	+0.652
11	0.93	0.937	-7.0X10 <sup>-03</sup>	-0.753
12	0.94	0.935	5.0X10 <sup>-03</sup>	+0.532
13	0.95	0.948	$2.0 \text{X} 10^{-03}$	+0.21

- combined neural network and physical modeling to the retention process in papermaking, Appita Journal, Vol. 55(4), July, 2002, pp.281-287.
- 9. Wu, M.R., Paris J. and Van de Ven, T.G.M. Pilot Paper Machine Trials on the retention of fresh and recirculated fines with PEO/Cofactor retention aid system. Journal of pulp and Paper Science, Vol. 33 (3), 2007, pp. 143-149.
- 10. Onabe, F. Measurement and Control in paper chemistry in: paper chemistry, ed.Roberts, J.C., Chapman and Hall Press, London, 1991
- 11. Paulapuro, H., Uronen, P. and Zhao, J. Identification of the pilot paper machine for adaptive retention control. Proc. Control systems, pp.279-281, Whistler, 1992.
- 12. Rantala, T., Tarhonen, P. and Koivo, H.N., Adaptive Retention Control in a paper machine, Proc. Control systems'92, pp.101-106, Whistler, 1992.
- 13. Nolelainen, J., Piirainen, R., and White, C, Practical Experiences of white water consistency control of a paper machine wet end, Tappi 1993 Papermakers Conference Proceedings, Tappi press, Atlanta, p.227-238, April 18-21, 1993.
- 14. Orccotoma, A.J. Paris, J. and Perrier, M, Paper machine controllability: effect of disturbances on basis weight and first-pass retention, Journal of Process Control, 11, 2001, pp 401-
- 15. Nancy J. Sell P.E, Process control fundamentals for the pulp and paper industry, TAPPI process control textbook, Tappi Press, Atlanta, GA, 1995, pp.428.
- 16. Kisi, O. and Uncuoglu, E, Comparison of three backpropagation training algorithm for two case studies, Indian Journal of Engineering and Material Sciences, vol. 12, Oct 2005, pp 434-442.
- 17. Willis M.J., and Montague G.A., Artificial neural networks in process estimation and control, Automatica, 28(6), 1992, pp.1181-1187.