



CONTROL ENGINEERING LABORATORY

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Tuning of Scaling Factor**

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Leonardo Pirrello^{*}, Leena Yliniemi^{**}, Kauko Leiviskä^{***}

- * Socrates student, Chemical Engineering, University of Palermo
- ** Chief engineer, Control Engineering Laboratory, University of Oulu
- *** Head, Control Engineering Laboratory, University of Oulu

Abstract: The control of the drying process in a rotary dryer is difficult due to delay time and the very complex process that includes the movement of the solids in addition to thermal drying. Thus, even today rotary dryers are partly manually controlled based on the operator's experience and partly automatically controlled relying on conventional control methods.

In this paper, which applies advanced control to a rotary dryer, two different control systems are developed. The first is a self-tuning PID-type pure fuzzy feedback and the second is a self-tuning PID-type hybrid feedback and feedforward. The performances are compared with a traditional PID controller and both control systems give much better results than a traditional PID controller.

Keywords: self-tuning, PID-type fuzzy, rotary dryer, process control

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University of Oulu

**Control Engineering Laboratory
Box 4300
FIN-90014 UNIVERSITY OF OULU**

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1 INTRODUCTION

Confused, indistinct, out of focus, is what is generally meant by the word “fuzzy”. Many of the concepts we use daily are fuzzy, that is, not precisely defined. It is not necessary that a concept is perfectly defined in order to have meaning. Zadeh introduced fuzzy logic in 1965. It is based on qualitative reasoning and seeks to aid the machines to reason in ways similar to the human. It proposes deriving solutions to problems that are not possible to construct with exact mathematical models.

Fuzzy logic control (FLC) combines two different types of information: the numerical measurements of variables and human experts who give the linguistic instruction and description of a process and its control.

The modelling of a rotary dryer is very difficult because it is a non-linear process that depends on time and space. The aim in developing self-tuning fuzzy logic control is in order to design a controller, which adapts to the changes of the process during the operation, resulting in robust responses.

2 DYNAMIC MODEL FOR A PILOT PLANT DRYER

A rotary dryer is a distributed parameter system in which both temperature and moisture are functions of time and space according to the general equation

$$\frac{\partial X_i(l, t)}{\partial t} \pm v_i \frac{\partial X_i(l, t)}{\partial l} = f_i(X_i, l, t) \quad (1)$$

where X_i is the moisture or temperature in the solid or gas phase,
 v_i is the linear velocity in the solids or gas phase,
 l is the axial co-ordinate, and
 t is time.

A positive sign for v_i applies to con-current drying and a negative sign to counter-current drying.

The distributed parameter model is complex and cumbersome to handle, and the temperature and especially the content of solids and drying air inside the dryer are difficult to measure. It is therefore simplified to a lumped parameter model in which the partial derivative of the axial co-ordinate length equals to the total length of the drum. The equation for the gas moisture content is not included in the overall model for the dryer, because it is not measured in the pilot dryer. The model is now of form:

$$\frac{dX_{s,out}}{dt} + v_s \frac{(X_{s,out} - X_{s,in})}{L} = -R_w \quad (2)$$

$$C_s \frac{dT_{s,out}}{dt} + v_s C_s \frac{(T_{s,out} - T_{s,in})}{L} = \frac{U_v V_v}{F_s} (T_{g,out} - T_{s,out}) - \lambda R_w \quad (3)$$

$$C_g \frac{dT_{g,out}}{dt} + v_g C_g \frac{(T_{g,out} - T_{g,in})}{L} = -\frac{U_v V_v}{F_g} (T_{g,out} - T_{s,out}) - \lambda \frac{F_s}{F_g} R_w \quad (4)$$

where the meaning of symbols are, as in Yliniemi (1999): $X_{s,out}$, $T_{g,out}$ and $T_{s,out}$ are the moisture content, the temperature of gas and of solids in the output.

The model is non-linear because the drying rate R_w is generally a non-linear function of solids characteristics and drying air in the falling rate period.

The rate of drying is assumed in this thesis to be a linear function of solids moisture, solid temperature and the temperature of the drying air in the neighbourhood of the operating point according to the equation.

$$R_w = K_1 X_s + K_2 T_s + K_3 T_g \quad (5)$$

where K_1 (1/s), K_2 (1/sK) and K_3 (1/sK) are constants determined experimentally. For the linear approximation of the model it is assumed that the variables deviate only slightly from the operating point. Using Taylor series expansion, the linearised model is in the general form

$$\mathbf{x}=\mathbf{Ax}+\mathbf{bu} \quad (6)$$

$$\mathbf{Y}=\mathbf{Cx} \quad (7)$$

$$\mathbf{x} = \begin{bmatrix} X_{s,out} \\ T_{s,out} \\ T_{g,out} \end{bmatrix} \quad \mathbf{u} = \begin{bmatrix} T_{g,in} \\ T_{s,in} \\ X_{s,in} \\ v_s \\ F_g \\ F_s \end{bmatrix} \quad \mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad (8)$$

$$\mathbf{B} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} & b_{15} & b_{16} \\ b_{21} & b_{22} & b_{23} & b_{24} & b_{25} & b_{26} \\ b_{31} & b_{32} & b_{33} & b_{34} & b_{35} & b_{36} \end{bmatrix} \quad (9)$$

$$\begin{aligned} a_{11} &= -\left(\frac{V_s}{L} + K_1\right) \\ a_{12} &= -K_2, \quad a_{13} = -K_3 \\ a_{21} &= -\frac{\lambda K_1}{C_s} \\ a_{22} &= -\left(\frac{V_s}{L} + \frac{U_v V_v}{C_s F_s} + \frac{\lambda K_2}{C_s}\right) \\ a_{23} &= \frac{U_v V_v}{C_s F_s} - \frac{\lambda K_3}{C_s} \\ a_{31} &= -\frac{\lambda F_s K_1}{C_g F_g} \\ a_{32} &= \frac{U_v V_v}{C_g F_g} - \frac{\lambda F_s K_2}{C_g F_g} \\ a_{33} &= -\left(\frac{V_g}{L} + \frac{U_v V_v}{C_g F_g} + \frac{\lambda F_s K_3}{C_g F_g}\right) \end{aligned} \quad (10)$$

$$\begin{aligned} b_{11} &= b_{12} = b_{15} = b_{16} = b_{21} = b_{23} = b_{25} = b_{32} = b_{33} = b_{34} = 0 \\ b_{13} &= \frac{V_s}{L} \\ b_{14} &= -\frac{X_{s,out} - X_{s,in}}{L} \\ b_{22} &= b_{13} \\ b_{24} &= -\frac{T_{s,out} - T_{s,in}}{L} \end{aligned} \quad (11)$$

$$b_{26} = -\frac{U_v V_s}{C_s F_s^2} (T_{g,out} - T_{s,out})$$

$$b_{31} = \frac{V_g}{L}$$

$$b_{35} = (T_{g,out} - T_{s,out}) \frac{U_v V_s}{C_g F_g^2} + \frac{\lambda F_s}{C_g F_g^2} R_w$$

$$b_{36} = -\frac{\lambda}{C_g F_g} R_w$$

The experimental analysis shows that the delay time of the drum is about 15 minutes.

3 REASON TO APPLY A FUZZY CONTROLLER

A fuzzy control system is a real-time expert system, implementing a part of a human operator's or process engineer's expertise, which does not lend being easily expressed in PID-parameters or differential equations, but rather in situation action rules.

The fuzzy logic incorporates human reasoning in a control algorithm. The fuzzy logic design is not based on the mathematical model of a process. The controller design based on fuzzy logic implements human reasoning which is programmed by fuzzy logic language as membership functions, rules and the rules interpretation.

Fuzzy logic is applied in the systems, which can't be controlled in a satisfactory way with the traditional PID controllers:

- Plant non-linearity. The efficient linear models of the process or the object under control are too restrictive. Non-linear models are computationally intensive and have complex stability problems.
- Plant uncertainty. A plant does not have accurate models due to uncertainty and lack of perfect knowledge.
- Multivariable systems, multiloop systems and environment constraints. Multivariable and multiloop systems have complex constraints and dependencies
- Uncertain measurements. Uncertain measurements do not necessarily have stochastic noise model.
- Temporal behaviour. Plants, controllers, environments and their constraints vary with time. Moreover, time delays are difficult to model.

The advantages to use fuzzy control usually fall into the following categories:

- Robust control. A fuzzy controller is more robust than PID in a system where a traditional controller parameters change or the major external disturbances lead to a sharp decrease in performance. In presence of such disturbances, PID controllers usually are faced with a trade-off between fast reaction, which has significant overshoot or smooth but slow reaction or they even run into problems in stabilising the system at all. In this case, fuzzy control offers ways to implement simple but robust solutions that cover a wide range of system parameters and that can cope with major disturbances.
- Increasing the degree of automation. In many cases of industrial process the degree of automation is quite low. The fuzzy control offers a method for representing and implementing the expert's knowledge.
- Reduction of development and maintenance costs. To develop a fuzzy controller is cheaper than developing a model-based or other controller to do the same thing. It is easier to understand and modify their rules.

4 ADAPTIVE FUZZY CONTROL

Most of real-world processes that require automatic control are non-linear in nature. That is, the values of parameters alter as the operating point changes over time. As conventional control schemes are linear, a controller can only be tuned to give good performance at a particular operating point or for a limited period of time. FLC are non-linear and so they can be designed to cope with a certain amount of non-linear process. However, such design is difficult, especially if the controller must cope with non-linearity over a significant operating range of the process, therefore there is a need for an adaptive control system.

A control system is adaptive when it can adjust automatically its parameters when the characteristics of process change.

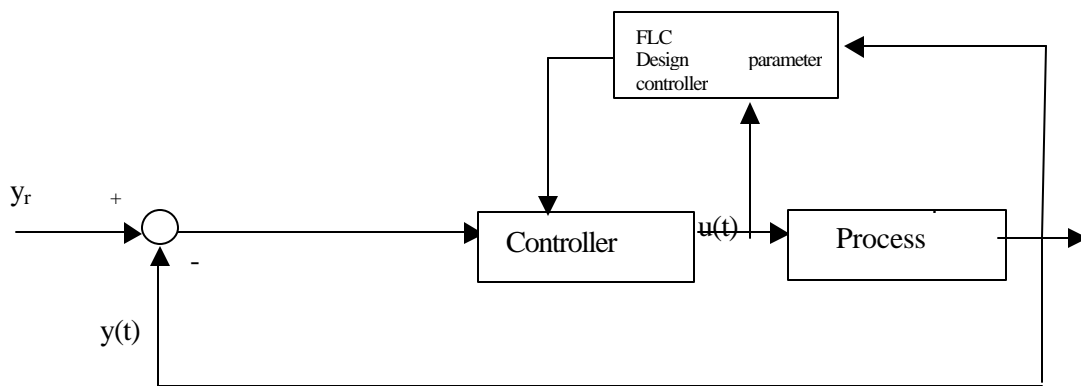


Figure 1. Adaptive control system.

Adaptive controllers generally contain two extra components on the top of the standard controller itself. The first is a process monitor that detects changes in the process characteristics. The second is the adaptation mechanism itself. It uses information passed to it by the process monitor to update the controller parameters. In a PID controller the supervisor controller can set the gains. FLC contains a number of sets of parameters that can be altered to modify the controller performance. These are:

- the scaling factor for each variable
- the fuzzy set representing the meaning of linguistic values
- the if-then rules.

5 DESIGN PROCEDURES FOR AN ADAPTIVE FLC

He et al. (1993) propose a scheme for self-tuning of a conventional PID controller using fuzzy rules. The proportional sensitivity (k_p), integral time (T_i) and derivative time (T_d) are initially calculated using Ziegler-Nichols tuning formula. These three parameters are then modified on-line by a single parameter, which is updated by a rule base defined on e and Δe . It is reported that there is a considerable improvement in the overall performance of the controller over its conventional counterpart. Results in this work show a remarkable reduction in overshoots of second-order processes with dead time but at the cost of increased rise times.

The self-tuning method of FLC 's by Nomura et al (1991) is a well-known gradient descent technique to optimise both the fuzzy antecedent and crisp consequent parts. The controller is tuned iteratively by minimising the square error between the FLC output and the desired output given by the training data. This method simultaneously modifies the crisp consequent values and centres and widths of triangular input fuzzy sets. This off-line tuning method may be very good for time-invariant control system, but its applicability is limited due its dependency on the availability of a reliable set of PI-type data.

Zheng (1992) suggested to tune the parameters of PI-type FLC' s in order of their significance; that is, first parameters with a global affect and then ones with only local affect, hence given the maximum importance to the tuning of SF (scaling factor). Zheng did not provide any algorithm for tuning of FLC' s. He discussed various factors, their interaction, and their impact on the controller performance, which should be considered while designing tuning algorithms for FLC' s. Input and output SF's are recommended to be selected from the knowledge of conventional PI-controller parameters (K_p and T_i) if available, otherwise through trial and error. Simulation result with tuned MF (membership function) shows a marginal improvement in transient response of a second-order linear process where tuning resulted in asymmetric (triangle) MF' s with unequal around $e=0$. Such MF' s contradicts the usual practice where the MF' s take narrow width and become more crowded near the origin to increased sensibility around the steady state condition. Thus, the proposed MF' s tuning scheme cannot guarantee improved performance under a load disturbance, which is a very important criterion for the performance evaluation of any control system.

The gain tuning method of Yoshida et al (1990) assumes all process as first-order system with dead time. The input and output SF's are calculated by some empirical relation involving process parameters. Good control performance for higher order system cannot be ensured by this technique.

Auto-tuning fuzzy controller of Hayashi (1991) considers two tuning functions. From the approximate parameter of the identified plant model (first-order with dead time) the input and output SF's are calculated using the concept of Chien-Rhones-Reswick (CHR) tuning rules for a conventional PI controller. Then the crisp consequent parts are modified by fuzzy rules using overshoot and rise time to improve the control performance.

Linear first-order plant models with dead time have also been considered in the auto-tuning scheme of Iwasaki and Morita (1990). Here, the parameters of an assumed

plant model are iteratively revised through fuzzy inference using differences between the actual plant features (rise time and overshoot) and plant model features.

Palm (1995) proposed to archive the optimal adjustment in the input SF's with the help of input-output cross-correlation function though he assigned a higher priority to the tuning of output SF over that of input SF's. Here the input data are assumed to follow a Gaussian distribution whose parameters are unknown. An optimal input SF is obtained by maximising the cross-correlation function, which is a measure of the statistical dependence between input and output.

Li and Gatland (1996) have also have given more emphasis on the tuning of input and output SF's than of MF' s or rule base. They basically suggested a trial and error method for tuning of input and output SF's for a fuzzy PID controller developed from two FLC in parallel – one is a PI-type and the other is a PD-type.

Maeda and Murakami (1992) suggested fuzzy rule-based schemes for the adjustment of input-output SF's, as well as for the tuning of control rules for Takagi-Sugeno (TS) model. The fuzzy rule-base for tuning has three sets of rules based on three different performance measures: overshoot, rise time and amplitude. After the tuning of SF's the crisp consequent parts of the control rules are modified in each sampling time considering a fuzzy performance index and the deviation of the actual control response from a predefined target response.

To eliminate the overshoot caused by accumulation of control input in a fuzzy PI-type controller Lee (1993) proposed two augmented versions of the conventional fuzzy PI controller using resetting factors. The first of the two fuzzy controllers determines the resetting rate based on error and error rate while the second one uses error and control input. The computation of the resetting factor is driven by a fuzzy rule base. The controller remarkably improves the transient response of a second-order linear system with integrating element. The authors have clearly shown with extensive simulation conducted different type of second-order as well as non-linear system with and without integration that the controller with resetting action is almost similar to a conventional fuzzy PD controller.

6 LATEST APPLICATIONS OF A FUZZY CONTROLLER

Gao, Trautzsch and Dawson (2000) developed a closed loop control system incorporating fuzzy logic for a class of industrial temperature control problems. They propose a unique fuzzy logic controller (FLC) structure with an efficient realisation and a small rule base that can be easily implemented in existing industrial controllers. It was demonstrated in both software simulation and hardware test in an industrial setting that the fuzzy logic control is much more capable than the current temperature controllers. This includes compensating for thermal mass changes in the system, dealing with unknown and variable delays, operating at very different temperature set points without retuning etc. It is achieved by implementing, in FLC, a classical control strategy and an adaptation mechanism to compensate for the dynamic changes in the system. The proposed FLC was applied to two different temperature processes and significant improvements in the system performance are observed in both cases. Furthermore, the stability of the FLC is investigated and a safeguard is established.

Haber et al (2000) generalised the classic self-tuning algorithm, based on pattern recognition of the closed-loop system response, to be applied to fuzzy controller, without any restrictive assumptions. In order to reduce the oscillation and settling time of the system time response, the proposed algorithm acts simultaneously on input and output scaling factors of the fuzzy controller.

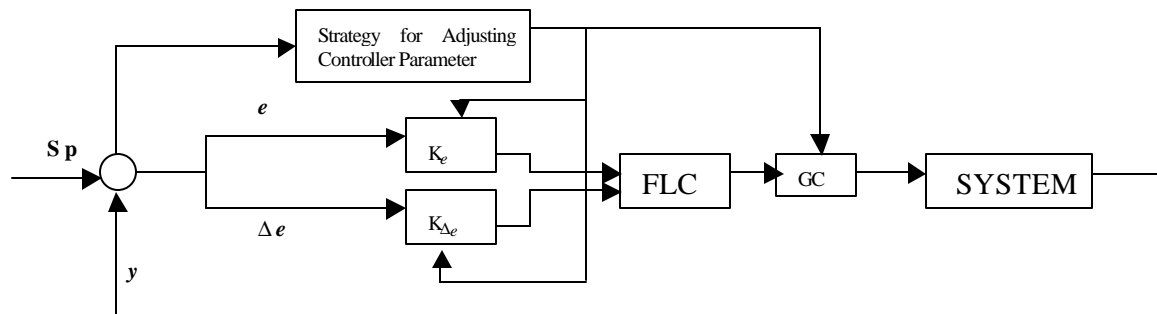


Figure 2. Block diagram of the proposed Self-tuning Hierarchical Fuzzy Control System (ST-HFLC).

The absolute peak value of the error is used as merit figure for properly tuning the scaling factor to which two tuning formulas are also suggested. The resulting block diagram is shown in Figure 2. To demonstrate the improved performance and effectiveness of this scheme, the ST-HFLC is applied to the end milling process. The response of the controlled process using the proposed controller (ST-HFLC), a standard HFLC and an HFLC with a self-regulating output-scaling factor was analysed. The ST-HFLC provides a better transient performance than the others. Without significant variation in rise time, a non-oscillating system with a short settling time can be achieved. These positive features, in the case of this particular application, may represent an increase of cutting tool life as well as the avoidance of chatter marks due to inappropriate cutting conditions.

Lee and Gardunno-Romirez (2000) developed fuzzy scheduling control of a power plant. Current control strategies for fossil fuel power units are multiloop schemes based on conventional PID control algorithms, their effectiveness have been demonstrated regulating by the output variable i.e. power under random load disturbances. Normally, the parameters of the controller are tuned at a predefined operating point (i.e. base load), and left fixed thereafter. However, wide-range load-tracking operation challenges this approach. The performance of the unit may decrease due to the non-linear dynamics of the process, which change with the operating point. Gain scheduling has been pointed out to be an effective strategy for controlling non-linear processes over wide operation regions. A linear controller is designed for the linear approximation of the process at selected operating points. During operation, the parameters of the controller are updated as the operating conditions change. A fuzzy controller is used to extend the operating range of the multiloop control system of a fossil fuel power plant. This controller is used to extend the application range of the control system in a power plant without changing the essential philosophy of the already existing control structure. The operating range of the fossil fuel power unit control system has been extended satisfactorily by directly replacing the original PID controller with the fuzzy PID controller.

Chung et al (2000) proposed a PID fuzzy controller with self-tuning scaling factors. The fuzzy PID-type controller has just two input and the rules is two dimensions. Its performance is also better than the fuzzy PI and fuzzy PD controller. They develop a method to tune the scaling factor of the PID-type fuzzy controller on line. The PID-type fuzzy controller can be decomposed into the equivalent proportional control, integral control and the derivative control components. This method decreases the equivalent integral control component of the fuzzy controller gradually with the system response process time so as to increase the damping of the system when the system is about to settle down, meanwhile keeping the proportional control component not to change too much so as to guarantee quick reaction against the error. The simulation of the PID-type fuzzy controller with the self-tuning scaling factor shows a better performance in the transient and steady state response.

Li and Tso (1999) developed new structures for higher order fuzzy logic control (FLC) systems, which could handle the higher order process and the time delay system as well. Two different approaches are proposed to construct the higher order FLC, namely, the hierarchical structure and the distributed structure. Both structures can be designed via the theory of variable structure control (VSC). The complexity of the structure depends on the order of the process. The necessary and sufficient stability conditions provided by the VSC theory facilitate the design of the nominal scaling gains. The difficulty of the design is to estimate the upper bound of the undesirable dynamics. Practically, this upper bound can be approximated by the peak value of the undesirable dynamics in the steady-state period. The simulation shows that this approximation is feasible and nominal scaling gains designed can lead to a stable and reasonably good performance. The fine-tuning can be more easily carried out to provide a better performance from these nominal values instead of from scratch. The proposed higher order structure can also be used to control the time-delayed process if the delay time is known. The structure configuration depends on the approximation of the delay compensation factor. A first-order approximation is usually accurate enough when the delay is not very long. A partially known delay will result in either overcompensation or undercompensation. The overcompensation seems better than the

undercompensation due to the former contribution to the PID effects. The simulation shows the effectiveness of the proposed structure to both the higher order process and the time-delay system.

7 DETAILED EXAMPLE OF A STFLC

Mudi and Pal (2000) proposed a robust self-tuning of a PI-type fuzzy logic controller (STFLC). The motivation for their research came from the observation that a skilled human operator always tries to manipulate the process input (controller output) usually by adjusting the controller gain based on the current process states (generally e and Δe) to get the current process optimally controller. The exact manipulation strategy of a human operator is quite complex in nature and probably no mathematical model can replace it accurately. They have concentrated only on the tuning of output SF due to its strong influence on the performance and stability of the system. The proposed controller is tuned dynamically by adjusting its output SF in each sampling instance by an updating factor α . The value of α is determined by fuzzy rules defined on e and Δe . The block diagram of a STFPIC is shown in Figure 3.

The output SF of the controller is modified by a self-tuning mechanism, which is shown by the dotted boundary in Figure 3. The MF's for the controller inputs, i.e. e and Δe and incremental change in controller output, i.e. Δu are defined in the common normalised domain $[-1,1]$, whereas the MF's for α is defined in the normalised domain $[0,1]$. They use symmetric triangles with an equal base and 50% overlap with neighbouring MF's as show in Figure 4

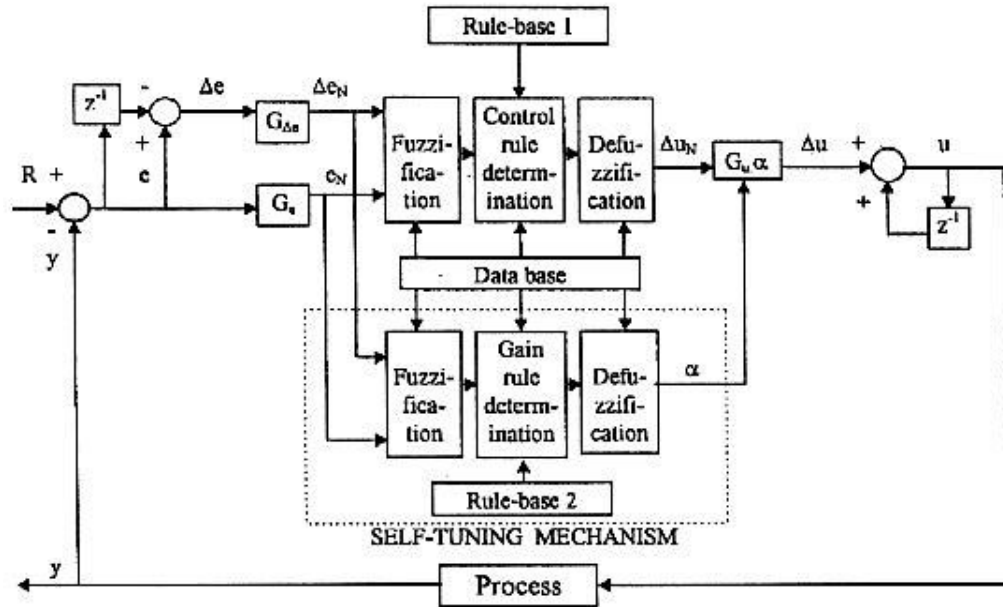


Figure 3. Block diagram of the proposed controller (STFPIC),

The MF's for both normalised inputs (e_N and Δe_N) and output (Δu_N) of the controller have been on the normalised domain. The relationships between the SF's and the input and output variables of the STFPIC are as follows:

$$e_N = G_e * e \quad (12)$$

$$\Delta e_N = G_{\Delta e} * \Delta u_n \quad (13)$$

$$\Delta u = \alpha * G_{\Delta e} * \Delta u_n \quad (14)$$

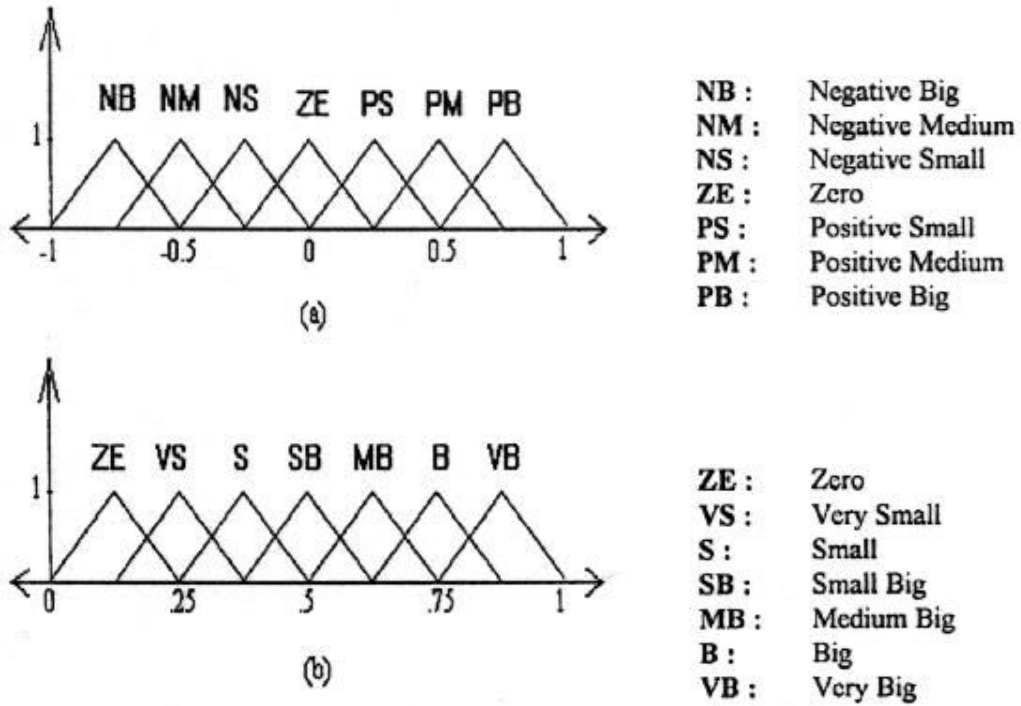


Figure 4. Membership functions.

The operation of a PI-type FLC can be described by the equation

$$u(k) = u(k-1) + \Delta u(k) \quad (15)$$

In this equation k is a sampling instance and Δu is an incremental change in the controller output, which is determined by the rules being of the form:

R_{PI} : If e is E and Δe is ΔE then Δu is ΔU

The rule-base for computing Δu is shown in Table 1. The gain-updating factor α is calculated by fuzzy rules, which are of the form:

R_{α} : If e is E and Δe is ΔE then α is α

The rule-base in Table 2 is used for the computation of α

Table 1. Fuzzy control rules for computation of Δu .

Δe	E	NB	NM	NS	ZE	PS	PM	PB
NB		NB	NB	NB	NM	NS	NS	ZE
NM		NB	NM	NM	NM	NS	ZE	PS
NS		NB	NM	NS	NS	ZE	PS	PM
ZE		MB	NM	NS	ZE	PS	PM	PB
PS		NM	NS	ZE	PS	PS	PM	PB
PM		NS	ZE	PS	PM	PM	PM	PB
PB		ZE	PS	PS	PM	PB	PB	PB

Table 2. Fuzzy rules for computation of α .

Δe	E	NB	NM	NS	ZE	PS	PM	PB
NB		VB	VB	VB	B	SB	S	ZE
NM		VB	VB	B	B	MB	S	VS
NS		VB	MB	B	VB	VS	S	VS
ZE		S	SB	MB	ZE	MB	SB	S
PS		VS	S	VS	VB	B	MB	VB
PM		VS	S	MB	B	B	VB	VB
PB		ZE	S	SB	B	VB	VB	VB

The authors present the following procedure to tune the controller.

Step1: Tune the SF's of a STFPIIC assuming $\alpha=1$ (i. e. FPIC) for a given process. For doing this first, G_e is selected in such a way that the normalised error (e_N) almost covers descent the entire domain [-1,1] to make efficient use of the rule-bases. Then $G_{\Delta e}$ and G_i are tuned to make the transient response of the system reasonably. At the end of this step, beget a good controller without self-tuning and then this controller becomes the starting point for the STFPIIC in step 2.

Step 2: Set the Output SF (G_u) of the STFPIIC three time greater that of FPIC, keeping the values of G_e and $G_{\Delta e}$ same as those of FPIC obtained in Step 1. Make a small adjustment for G_u of STFPIIC, If necessary to realise almost the same rise time as those of the FPIC obtained in step 1.

Step 3. Fine tune the rules for α depending on the type of response wanted to archive.

The performance of the STFPIIC is compared with the FPIC for different type of processes for clear comparison between the conventional and self-tuning FLC's several performance measures such as peak overshoot (%OS), settling time (t_s), rise time (t_r) integral absolute error (IAE) and integral-of-time-multiplied absolute error (ITAE) are used. The table below shows the performance of the first order process with time dead. Three different values of process dead time dead (i.e.L=0.1 L=0.2 L= 0.3) are considered

Table 3. Performance analysis for the first-order process.

L	FLC	%OS	t _s (s)	t _r (s)	ITAE	IAE
0.1	FPIC	25.2	2.7	1.0	0.75	0.84
	STFPIS	5.1	1.1	1.0	0.32	0.62
0.2	FPIC	37.4	4.5	1.1	1.70	1.22
	STFPIC	10.4	2.2	1.1	0.59	0.78
0.3	FPIC	47.3	6.5	1.2	3.29	1.66
	STFLC	19.8	3.6	1.2	1.17	1.08

8 DESIGN PROCEDURE OF THE FLC FOR THE PILOT PLANT ROTARY DRYER

The control of a rotary dryer is difficult because of long dead time, long settling time, large disturbances in the input moisture and in the rate of solids. Because of all these reasons, advanced control methods based on process models, expert systems techniques, fuzzy logic and neural networks are of great interest.

The advantage of a fuzzy logic controller in a rotary dryer is first, that the development of mathematical models is a difficult and time consuming task and besides a lot of information is available from operators. Several input variables have to be set for this system, as shown in Figure 5. The main controlled variable is the moisture of solids coming out from the dryer and the manipulated variables are the temperature of drying air depends on the fuel flow, and the velocity of solids that correlates to the rotation speed of the screw conveyor.

A controller inspired to the Pal and Chung control systems has been designed. The input variables for STFLC are the error in the moisture of outgoing solids and the derivative of error in the output moisture of solids. The temperature of air is the manipulated variable. The MF's and the roles are shown respectively in Figure 4 and in Table 1 and 2.

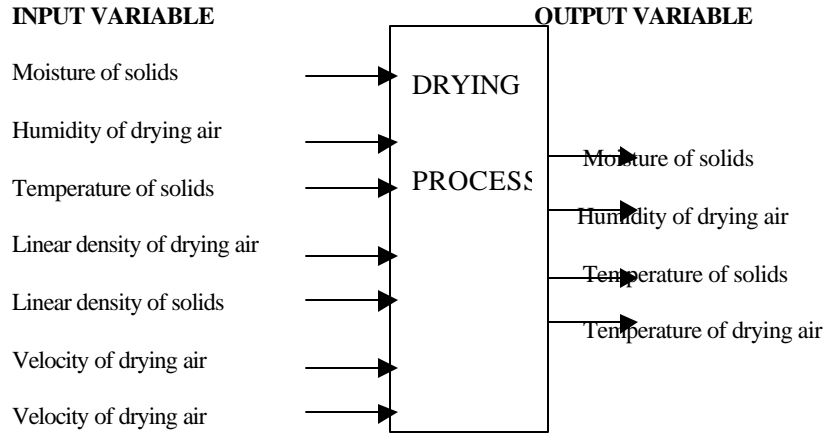


Figure 5. Different input and output variables of a drying process.

The centre of area method (COA) is used to transform the output of the fired rules into the crisp value.

The relationships between the SF's and the input and output variables of STFLC are as follows:

$$e_N = G_e * e \quad (16)$$

$$\Delta e_N = G_{\Delta e} * \Delta u \quad (17)$$

$$\Delta u = \alpha * G_{1\Delta u} * \Delta u \quad (18)$$

The equation (15) was modified to obtain a PID-type fuzzy controller

$$u = G_{2\Delta u} * \Delta u + \int \Delta u dt \quad (19)$$

Tuning procedure for the ST PID-type fuzzy controller:

Step1: Tune the SF's of a ST PID-type fuzzy assuming $\alpha=1$ and $G_{2\Delta u}=0$ (i.e. PI-type fuzzy). For doing this first, G_e is selected in such a way that the normalised error (e_N) almost covers descent the entire domain $[-1,1]$ to make efficient use of the rule-bases. Then $G_{\Delta e}$ and $G_{1\Delta u}$ are tuned to have a good response of the system.

Step2: Keeping the values G_e and $G_{\Delta e}$ from the previous step and tuning $G_{1\Delta u}$ and $G_{2\Delta u}$ with trial and error minimising IAE and ITAE.

Step3: Keeping the values of $G_{\Delta u}$ and $G_{2\Delta u}$ and tuning $G_{\Delta e}$ to minimise the IAE and ITAE. If the in this step the value of $G_{\Delta e}$ is modified go to the step2.

9 THE VELOCITY OF SOLID AUXILIARY MANIPULATE VARIABLE

The aforementioned controller gave the good results in the simulation, but in many cases the manipulated variable values were either too high or too low. It was necessary to introduce the maximum (673 K) and minimum (323 K) limits for the temperature of air input. Even with the introduction of these limits the result was not satisfactory. It is possible to use the solids velocity as the input, as a manipulated auxiliary variable. A second controller operates when it is not possible to achieve the desired temperature. The input of this controller is the error and the derivative of the error the output is solids velocity. An STPID-type fuzzy Sugeno is used, and the input MF's are shown in the Figure 4. In the controller the output is determined by the rules being of the form:

R_{PID} : If e is E and Δe is ΔE then Δu is ΔU

The gain-updating factor α is calculated by fuzzy rules, which are of the form:

R_{α} : If e is E and Δe is ΔE then α is A

Where ΔU and A are singletons

The rules are shown in Table 4 and 5.

Table 4. PID -type fuzzy control rules.

e	NB	NM	NS	ZE	PS	PM	PB
Δe							
NB	-1	-1	-1	-0.6667	-0.3333	-0.3333	0
NM	-1	-0.6667	-0.6667	-0.6667	-0.3333	0	0.3333
NS	-1	-0.6667	-0.3333	-0.3333	0	0.3333	0.3333
ZE	-1	-0.6667	-0.3333	0	0.3333	0.6667	1
PS	-0.6667	-0.3333	0	0.3333	0.3333	0.6667	1
PM	-0.3333	0	0.3333	0.6667	0.6667	0.6667	1
PB	0	0.3333	0.3333	0.6667	1	1	1

Table 5. Fuzzy self-tuning rules.

e	NB	NM	NS	ZE	PS	PM	PB
Δe							
NB	0.875	0.875	0.875	0.75	0.5	0.325	0.125
NM	0.875	0.875	0.75	0.75	0.625	0.325	0.25
NS	0.875	0.625	0.75	0.825	0.25	0.325	0.25
ZE	0.325	0.5	0.625	0.125	0.625	0.5	0.325
PS	0.25	0.325	0.25	0.825	0.75	0.625	0.875
PM	0.25	0.325	0.625	0.75	0.75	0.875	0.875
PB	0.125	0.325	0.5	0.75	0.875	0.875	0.875

The relationships between the SF's and the input and output variables of STFLC are the same as the relationships shown in (16), (17), (18), (19). The control system therefore designed gives big interaction problems between the controller that has the temperature as the manipulated variable and the controller that has the velocity of solids as manipulate variable. It is therefore necessary to introduce a supervisory control system. The new controller's input is the value of the first peak, while the outputs are the values of the scaling factor $G_{\Delta u}$ and $G_{2\Delta u}$. The MF's are shown in Table 6. The rules arise from the simulations: the value of the first peak is associated with the values of gain $G_{1\Delta u}$ and $G_{2\Delta u}$ that minimise IAE and ITAE. The controller must set from the lower peak to the higher peak. The rules are shown in Table 7

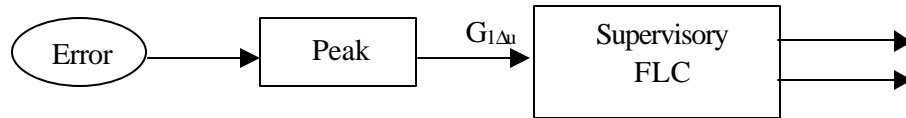


Figure 6. Supervisory FLC.

Table 6. MF's of the supervisory controller.

Membership Function	Range
Negative 7 (N7)	(-0.8,-0.6,-0.576,-0.462)
Negative 6 (N6)	(-0.576,-0.462,-0.351)
Negative 5 (N5)	(-0.462,-0.351,-0.241)
Negative 4 (N4)	(-0.351,-0.241,-0.132)
Negative 3 (N3)	(-0.241,-0.132,-0.0994)
Negative 2 (N2)	(-0.132,-0.0994,-0.0665)
Negative 1 (N1)	(-0.00994,-0.0665,-0.0334)
Zero (ZE)	(-0.0665,-0.0334,0.334,0.0665)
Positive 1 (P1)	(0.00994,0.0665,0.0334)
Positive 2 (P2)	(0.0665,0.0994, 0.132)
Positive 3 (P3)	(0.0994,0.132,0.241)
Positive 4 (P4)	(0.132,0.241, 0.351)
Positive 5 (P5)	(0.241,0.351, 0.462)
Positive 6 (P6)	(0.351,0.462,0.576)
Positive 7 (P7)	(0.462,0.576, 0.6,0.8)

Table 7. Rules.

If peak is N7 then $G_{1\Delta u}$ is 30 and $G_{2\Delta u}$ is 290
If peak is N6 then $G_{1\Delta u}$ is 24 and $G_{2\Delta u}$ is 310
If peak is N5 then $G_{1\Delta u}$ is 28 and $G_{2\Delta u}$ is 280
If peak is N4 then $G_{1\Delta u}$ is 26 and $G_{2\Delta u}$ is 170
If peak is N3 then $G_{1\Delta u}$ is 22 and $G_{2\Delta u}$ is 200
If peak is N2 then $G_{1\Delta u}$ is 23 and $G_{2\Delta u}$ is 350
If peak is N1 then $G_{1\Delta u}$ is 25 and $G_{2\Delta u}$ is 350
If peak is ZE then $G_{1\Delta u}$ is 6 and $G_{2\Delta u}$ is 350
If peak is P1 then $G_{1\Delta u}$ is 21 and $G_{2\Delta u}$ is 360
If peak is P2 then $G_{1\Delta u}$ is 26 and $G_{2\Delta u}$ is 320
If peak is P3 then $G_{1\Delta u}$ is 24 and $G_{2\Delta u}$ is 210
If peak is P4 then $G_{1\Delta u}$ is 30 and $G_{2\Delta u}$ is 270
If peak is P5 then $G_{1\Delta u}$ is 26 and $G_{2\Delta u}$ is 300
If peak is P6 then $G_{1\Delta u}$ is 24 and $G_{2\Delta u}$ is 290
If peak is P7 then $G_{1\Delta u}$ is 29 and $G_{2\Delta u}$ is 300

10 SIMULATION RESULTS

The mathematical model of the pilot dryer presented in paragraph 2 was implemented in Matlab[®] 5.3 Simulink toolbox. The control strategies were implemented using Matlab's Fuzzy logic toolbox. The block diagrams of the ST PID-type fuzzy are presented in Appendix 1. Simulations were run on a standard Pentium PC and they were made mostly for a step change in the input moisture of solids. The results were compared to a traditional PID results.

Figure 6 shows the solids moisture output when the step input to the moisture is very small. In this condition, the control system has only the temperature as manipulated variable Figure 7

Figures 8 and 10 show the solids moisture output when the step change in the input moisture is big and exceptionally big respectively.

The values of the IAE and the ITAE are shown in the Table 8. The results with step positive inputs are different then results with step negative inputs because the maximum and minimum temperatures are asymmetric with respect to the steady state temperature.

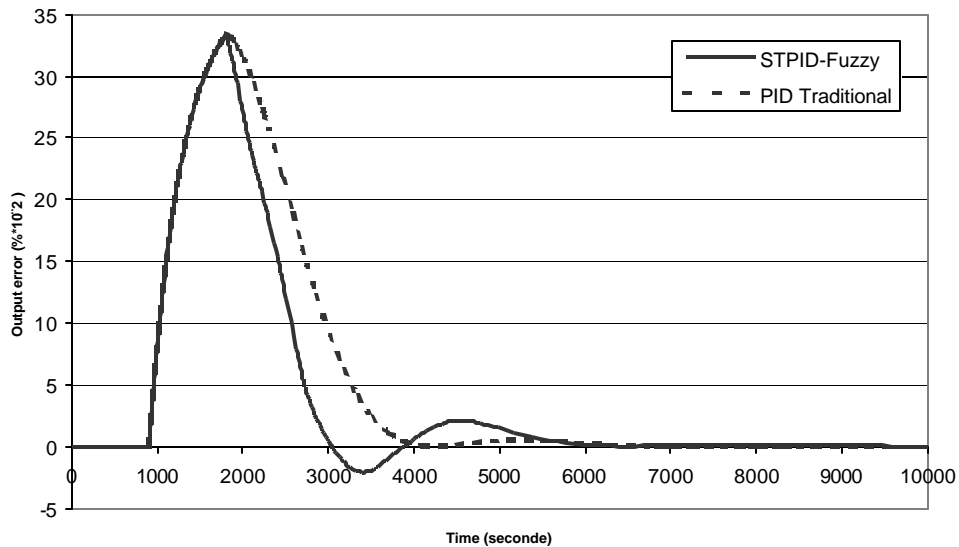


Figure 6. Step change X_s in from 2.4% to 2.46%. Error in the output moisture.

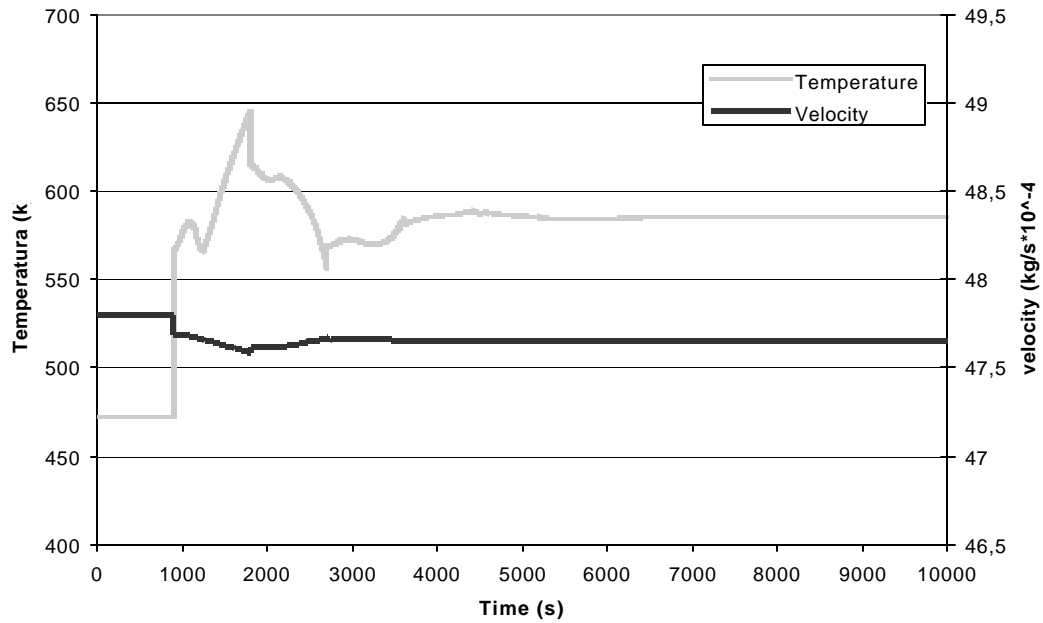


Figure 7. Step change X_s in from 2.4% to 2.46%. Manipulated variable changes.

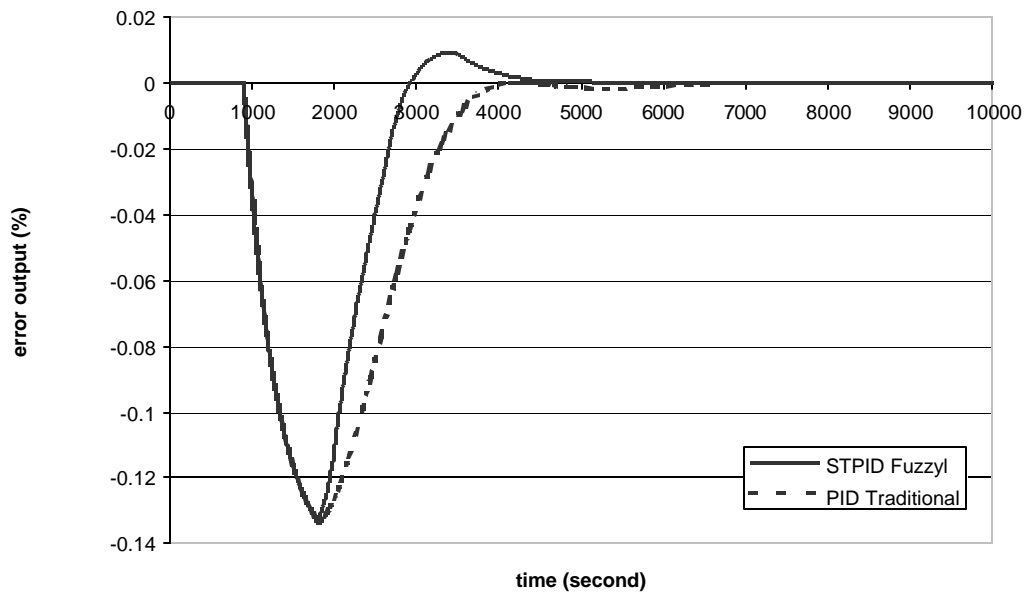


Figure 8. Step change X_s in from 2.4% to 2.14%. Error in the output moisture.

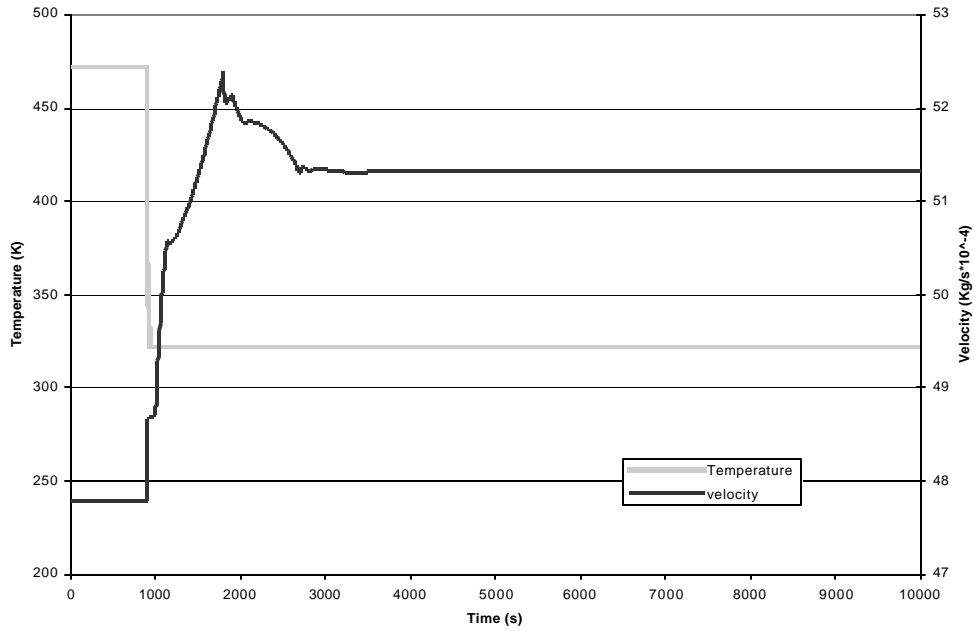


Figure 9. Step change X_s in from 2.4% to 2.14%. Manipulated variable changes.

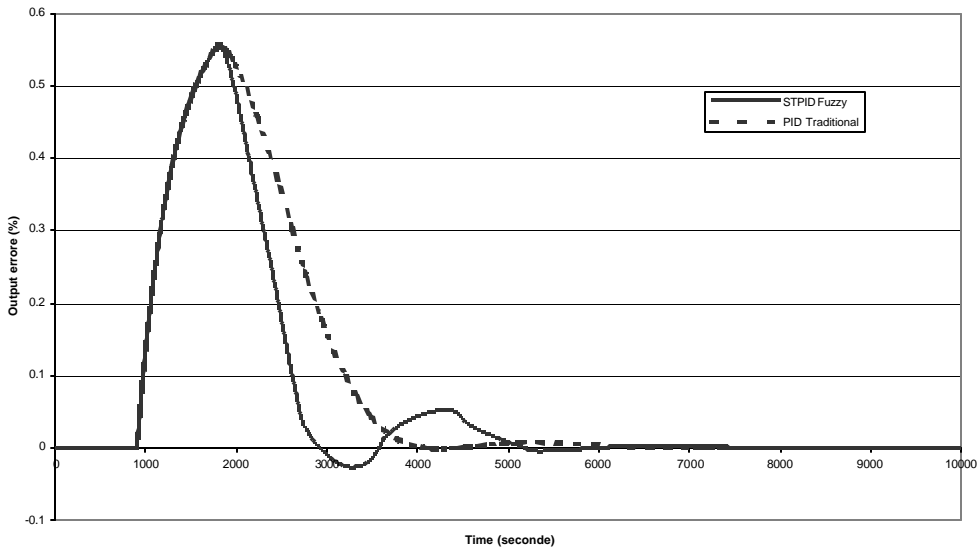


Figure 10. Step change X_s in from 2.4% to 3.4%. Error in the output moisture.

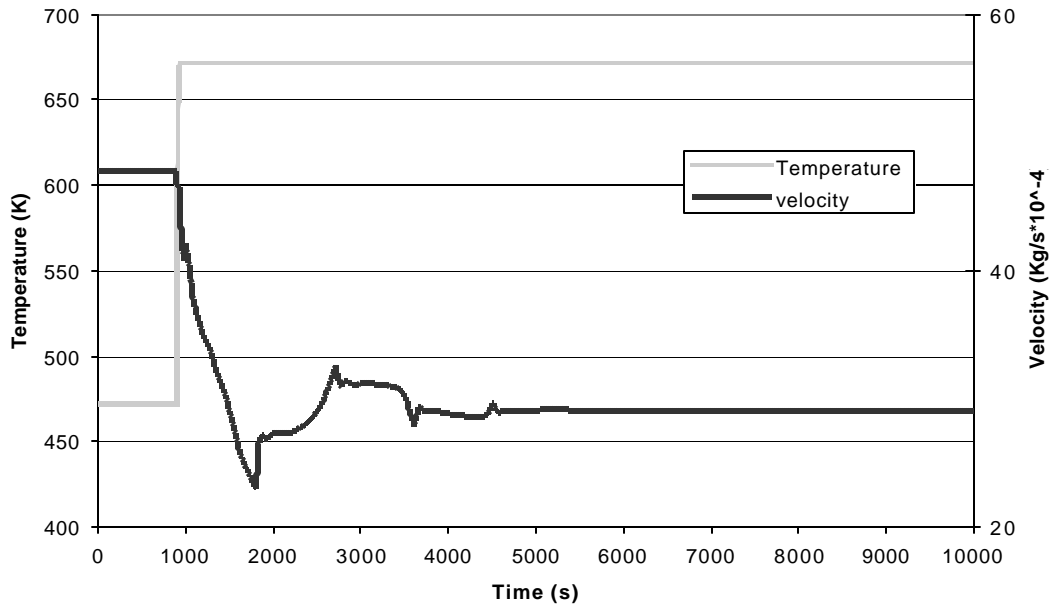


Figure 11. Step change X_s in from 2.4% to 3.4%. Manipulated variable changes.

Table 8. Performance analysis IAE and ITAE.

Step change X_s in	ST PID-type Fuzzy		Traditional PID	
	IAE	ITAE	IAE	ITAE
From 2.4% to 1.4%	7.34	15400	8.61	17800
From 2.4% to 2.16%	1.58	3000	2.067	4270
From 2.4% to 2.34%	0.418	859	0.517	1068
From 2.4% to 2.46%	0.428	899	0.517	1068
From 2.4% to 2.64%	1.63	3160	2.067	4270
From 2.4% to 3.4%	7.06	14500	8.61	17800

11 HYBRID FEEDBACK FEEDFORWARD CONTROL SYSTEM

The supervisory control system shown in Figure 6 was replaced with a feedforward supervisory control system. The new controller is a FLC Sugeno type, the outputs are the values of the scaling factor $G_{1\Delta u}$ and $G_{2\Delta u}$, the MF's and the rules are show in Table 9 and 10. The Simulink[®] block diagrams are presented in Appendix 2.

This control system was tested with a step change input in the moisture and with a combination of secondary disturbances (step change in the in the temperature of solids and in the linear density of solids). The results were compared with STPID pure feed-back and are shown in Table 11 and 12.

Table 9. MF's of the feedforward supervisory controller.

Membership Function	Range
Negative 7(N7)	(-1.5,-1.1,-1.04,-0.84)
Negative 6 (N6)	(-1.04,-0.84,-0.64)
Negative 5 (N5)	(-0.84,-0.64,-0.44)
Negative 4 (N4)	(-0.64,-0.44,-0.24)
Negative 3 (N3)	(-0.44,-0.24,-0.18)
Negative 2 (N2)	(-0.24,-0.18,-0.12)
Negative 1 (N1)	(-0.18,-0.12,-0.06)
Zero (ZE)	(-0.12,-0.06,0.06,0.12)
Positive 1 (P1)	(0.06,0.12,0.18)
Positive 2 (P2)	(0.12,0.18,0.24)
Positive 3 (P3)	(0.18,0.24,0.44)
Positive 4 (P4)	(0.24,0.44,0.64)
Positive 5 (P5)	(0.44,0.64,0.84)
Positive 6 (P6)	(0.64,0.84,1.04)
Positive 7 (P7)	(0.84,1.04,1.1,1.5)

Table 10. Feedforward supervisory controller rules.

If Xs in is N7 then $G_{1\Delta u}$ is 27 and $G_{2\Delta u}$ is 330
If Xs in is N6 then $G_{1\Delta u}$ is 25 and $G_{2\Delta u}$ is 320
If Xs in is N5 then $G_{1\Delta u}$ is 27 and $G_{2\Delta u}$ is 290
If Xs in is N4 then $G_{1\Delta u}$ is 28 and $G_{2\Delta u}$ is 280
If Xs in is N3 then $G_{1\Delta u}$ is 20 and $G_{2\Delta u}$ is 290
If Xs in is N2 then $G_{1\Delta u}$ is 17 and $G_{2\Delta u}$ is 290
If Xs in is N1 then $G_{1\Delta u}$ is 14 and $G_{2\Delta u}$ is 360
If Xs in is ZE then $G_{1\Delta u}$ is 5 and $G_{2\Delta u}$ is 350
If Xs in is P1 then $G_{1\Delta u}$ is 13 and $G_{2\Delta u}$ is 400
If Xs in is P2 then $G_{1\Delta u}$ is 13 and $G_{2\Delta u}$ is 300

If Xs in is P3 then $G_{1\Delta u}$ is 16 and $G_{2\Delta u}$ is 280
If Xs in is P4 then $G_{1\Delta u}$ is 27 and $G_{2\Delta u}$ is 290
If Xs in is P5 then $G_{1\Delta u}$ is 27 and $G_{2\Delta u}$ is 280
If Xs in is P6 then $G_{1\Delta u}$ is 25 and $G_{2\Delta u}$ is 310
If Xs in is P7 then $G_{1\Delta u}$ is 28 and $G_{2\Delta u}$ is 330

Table 11. Performance analysis of ST PID fuzzy hybrid feedback feedforward compared with ST PID pure fuzzy feedback.

Step change Xs in	ST PID Fuzzy Feedforward Feedback		ST PID Pure Fuzzy Feedback	
	IAE	ITAE	IAE	ITAE
From 2.4% to 1.4%	6.88	14300	7.34	15400
From 2.4% to 2.16%	1.46	2660	1.58	3000
From 2.4% to 2.34%	0.416	847	0.418	859
From 2.4% to 2.46%	0.4246	883	0.428	899
From 2.4% to 2.64%	1.469	2618	1.63	3160
From 2.4% to 3.4%	6.846	13970	7.06	14500

Table 12. Performance analyses for combination of different disturbances.

	ΔXs in	ΔTs in	ΔFs in	IAE	ITAE
STPID FF and FB	0	-4.385	100	0.2977	706
STPID FB Pure	0	-4.385	100	0.2934	692.9
STPID FF and FB	0.06	0.877	-50	0.5109	1101
STPID FB Pure	0.06	0.877	-50	0.5301	1188
STPID FF and FB	-0.06	-4.385	100	2.007	21270
STPID FB Pure	-0.06	-4.385	100	0.7149	1992
STPID FF and FB	0.24	0.877	-50	1.661	3900
STPID FB Pure	0.24	0.877	-50	1.708	3380
STPID FF and FB	-0.24	-4.385	100	1.846	4664
STPID FB Pure	-0.24	-4.385	100	1.841	3655

12 CONCLUSION

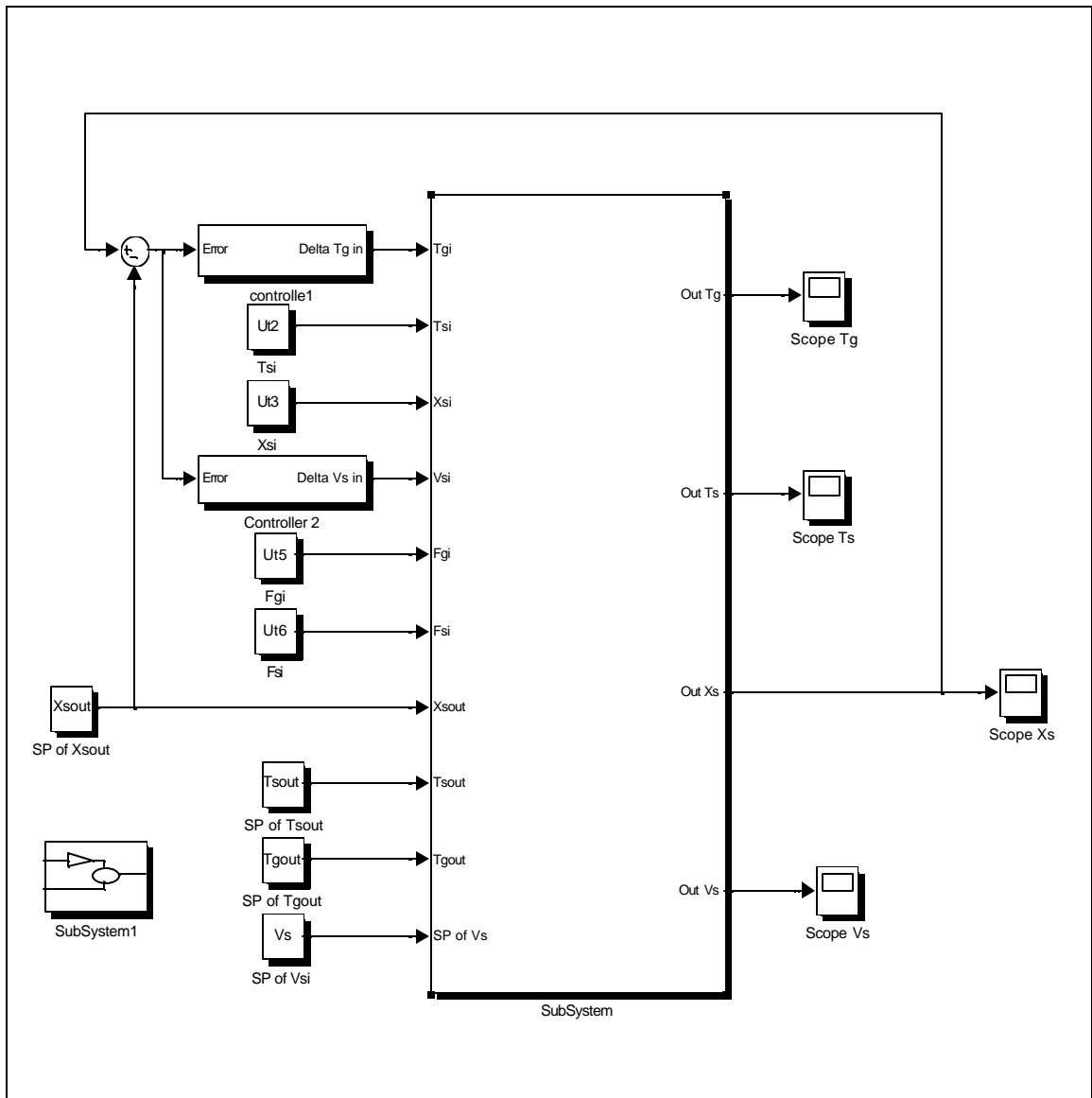
Two different control systems were proposed. The first is an STPID-type pure fuzzy feedback controller and the second is a STPID-type fuzzy hybrid feedback and feed-forward controller. Both control systems give better results than a traditional PID. The hybrid controller gives very good results when step disturbances occur in the input moisture of solids. The performance of this controller gets worse when there are the secondary disturbers. The feedback indices IAE and ITAE are a bit higher when the disturbers are only the step in the input moisture of solids. The performance of this controller doesn't get worse when there are secondary disturbances.

13 REFERENCES

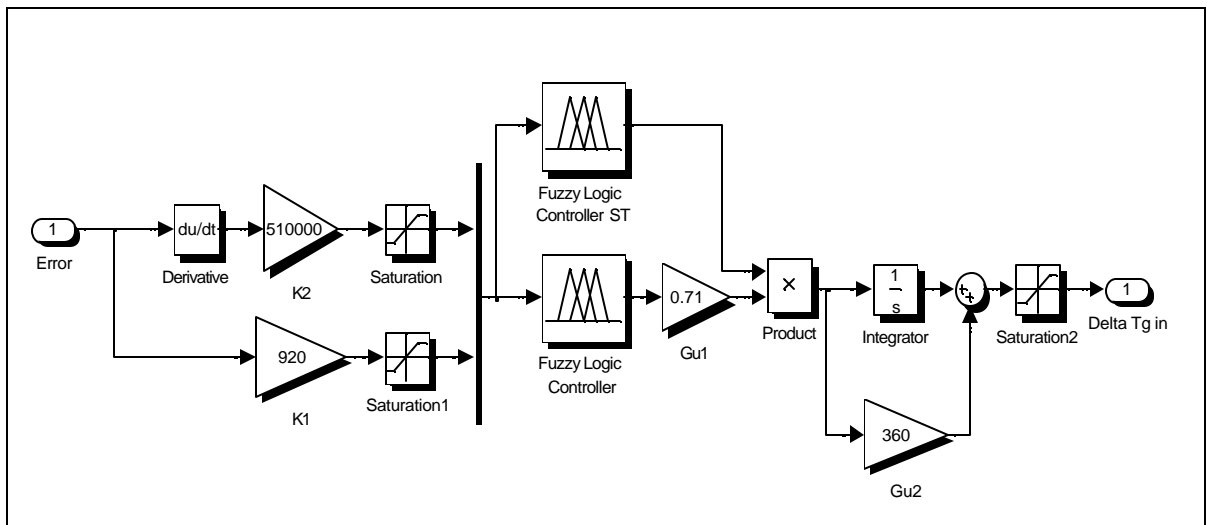
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APPENDIX 1

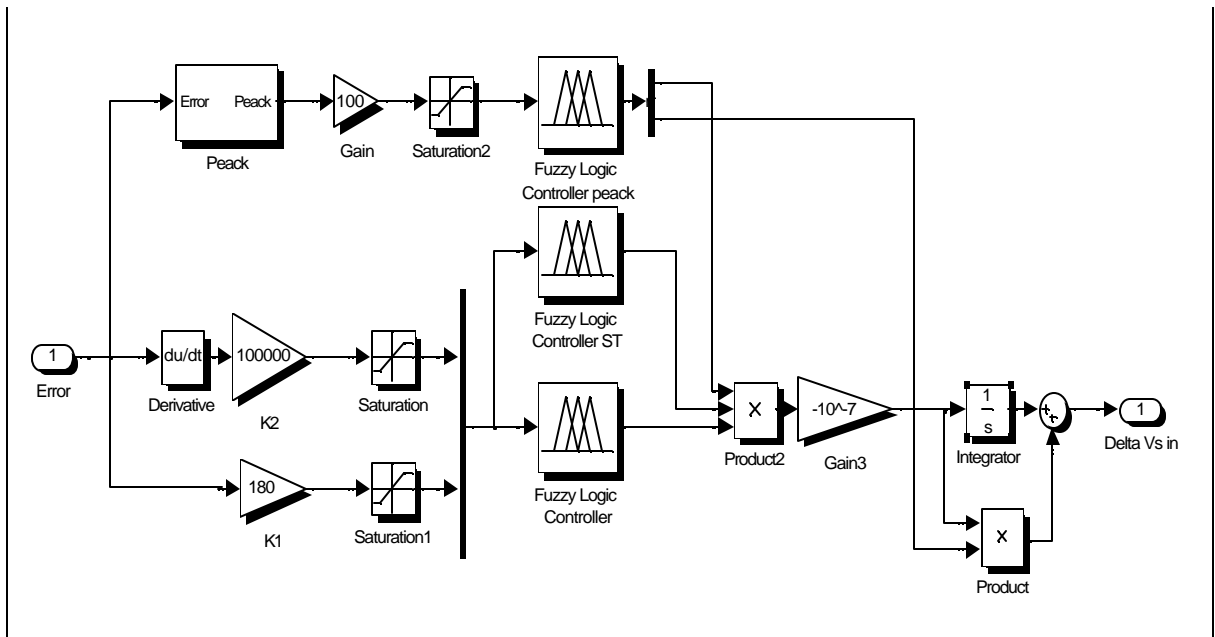
Feedback control system



Self Tuning PID-type fuzzy with Temperature Air Input as Manipulate Variable

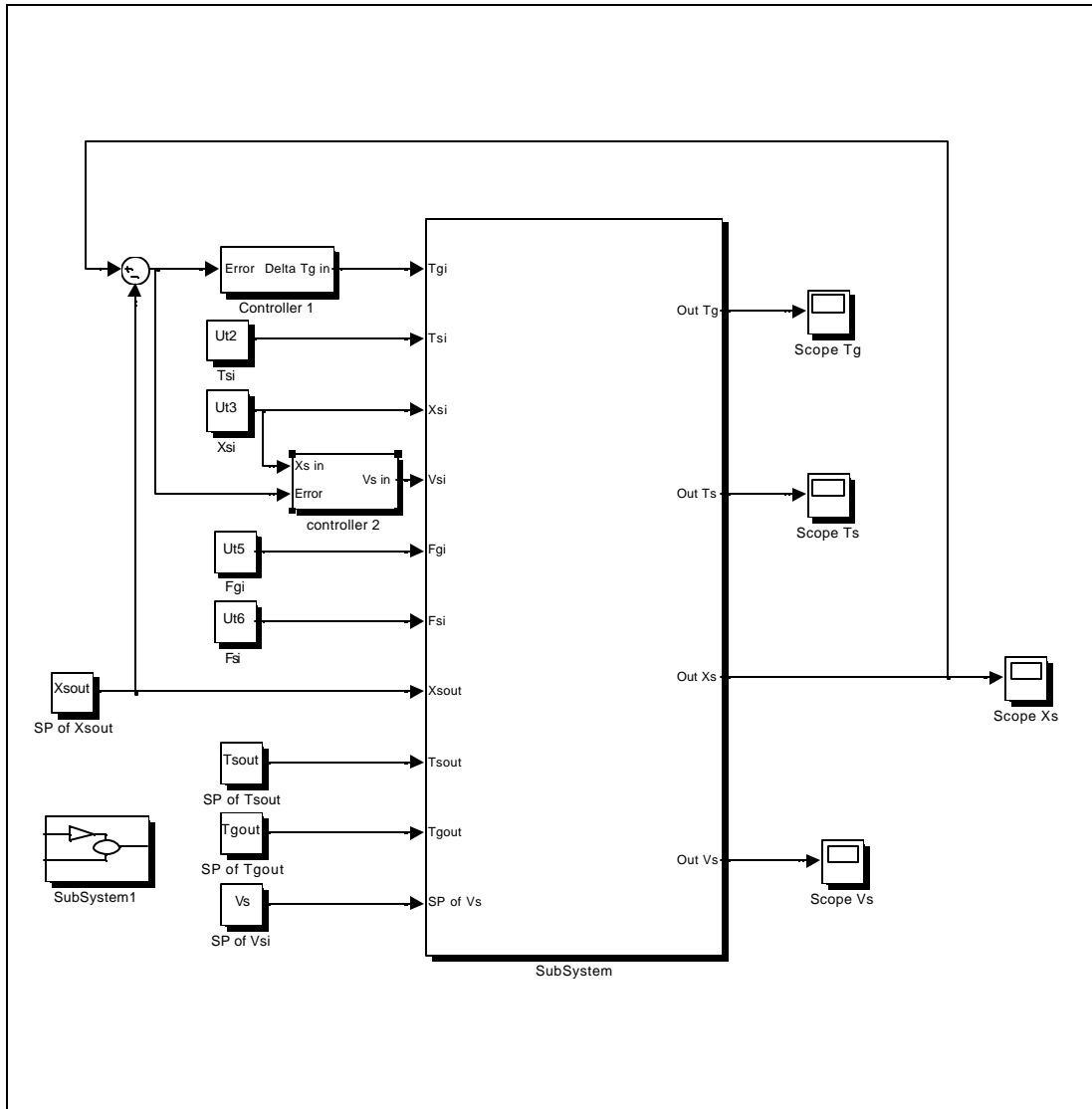


Self Tuning PID-type fuzzy with Velocity Solids Input as Manipulate Variable

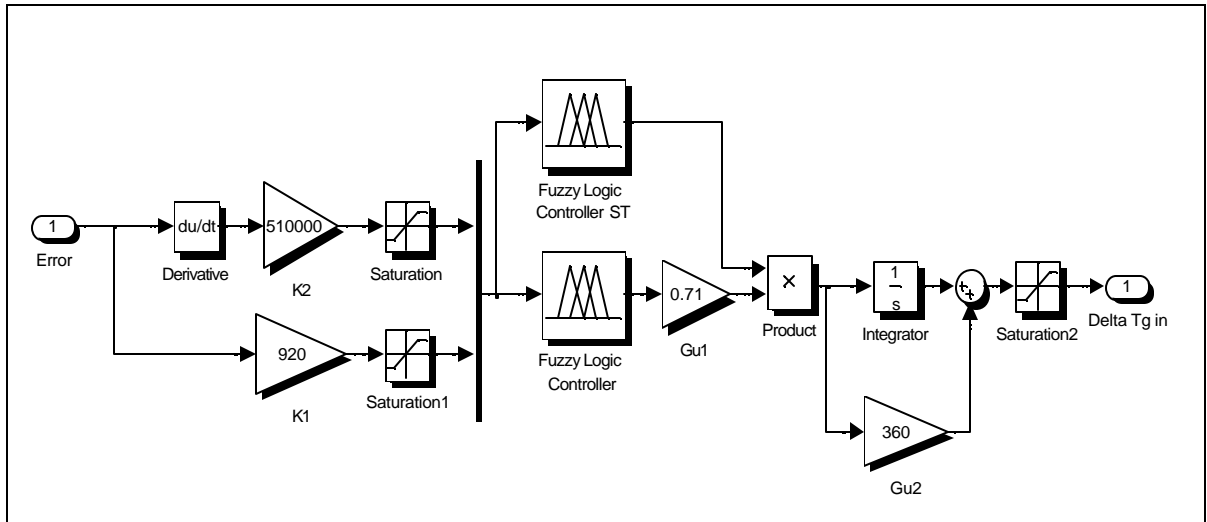


APPENDIX 2

Hybrid feedback feedforward control system



Self Tuning PID-type fuzzy with Temperature Air Input as Manipulated Variable



Self Tuning PID-type fuzzy with Velocity Solids Input as Manipulate Variable

