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Development of a Self-Tuning Fuzzy Logic Controller (STFLC) for a Rotary Dryer

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Abstract: It is well known that the control of a rotary dryer is difficult due to long delay times of the process. The main target of this research was to find a self-tuning technique for tuning the parameters of the fuzzy logic controller, which has been developed to the pilot plant rotary dryer located in the Control Engineering Laboratory at the University of Oulu. The aim is to improve the performance of the FLC by making the responses more robust to the input disturbances of the process, mainly to the input moisture of solids.

First, the literature review is made in order to see the current situation of the self-tuning FLC's, and then one self-tuning technique presented in the literature is selected and applied to the tuning of the hybrid PI-FLC and of the pure FLC used in the control of the rotary dryer. The resulting control behaviour has been examined with simulations and the comparison with the results achieved with the FLC's without self-tuning is made.

Keywords: rotary dryer, self-tuning of fuzzy controllers, process control.

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1 Introduction

For developing control systems, there are two important information sources: *sensors*, which provide numerical measurements of variables, and *human experts* who give linguistic instructions and descriptions about the process. Fuzzy logic was created to combine these two different types of information by handling the imprecise information coming from human operators. The self-tuning of a fuzzy logic controller (FLC) aims to adapt the controller, directly applied to the process, to different operating conditions and to eliminate the disturbances occurring in the process.

For the successful design of a FLC the proper selection of input and output scaling factors and/or the tuning of other controller parameters, such as the construction and representation of the rule base or the determination of the shape and position of the membership functions, are crucial jobs. Basically, there are two different tuning approaches for achieving the optimal parameters of the FLC i.e. *on-line* and *off-line* tuning.

In the on-line approach, the tuning is achieved by adding to a controller the construction, which can change the parameters of the FLC during operation according to some performance evaluation criterion. The off-line approach uses knowledge about the optimum performance and adjusts the parameters when the controller is not running. The main difference between these two methods is that the off-line approach has no real-time feedback. A FLC is called adaptive if any of its tuneable parameters as scaling factors (SF's), membership functions (MF's) and rules changes when the controller is in operation, otherwise it is a non adaptive or conventional FLC. An adaptive FLC that fine-tunes an already working controller by adjusting either its SF's or MF's or both of them is called a *self-tuning* FLC. On the other hand, a FLC is called *self-organising* when its rules are changed automatically.

This research aims to develop a self-tuning FLC (STFLC) to the pilot plant rotary dryer. It acts as the supervisor of the low-level fuzzy controller by tuning on-line its output scaling factors using a gain updating factor. This high level controller has been combined with the hybrid PI-FLC and with the direct FLC which have been developed to the pilot plant dryer [2]. The behaviour of the STFLC has been examined with simulations and also compared with the results achieved by the hybrid PI-FLC and the direct FLC.

2 Why a self-tuning fuzzy logic controller (STFLC) for a rotary dryer ?

Long time delays and settling times, large disturbances in the input moisture of solids, unmeasurable changes in solids, and high non linearity of the process make the control of a rotary dryer difficult [2]. To eliminate these problems, fuzzy logic has proved its effectiveness [2]. The reason to develop the STFLC is to design the controller, which adapts to the changes of the process during the operation resulting in robust responses.

This research is a part of the larger research project where the modelling and control of a rotary dryer has been examined and the performance has been tested both with simulations and experiments with the pilot plant dryer [2,3].

Because the field of the STFLC is new, first the literature review from different approaches for developing STFLC is presented. Then one of the self-tuning methods presented in the literature is chosen and a STFLC to the pilot plant rotary dryer is developed.

3 Literature review

Daugherity *et al.* (1992) [4] describe a self-tuning fuzzy controller where the scaling factors of the inputs are changed in the tuning procedure. The process in which the tuning method was applied was a simple gas-fired water heater, since it is widely used in the petrochemical industry and an accurate simulation model is available. The aim is to replace an existing PID controller with a fuzzy controller, using initial guesses as to the fuzzy membership functions and rules to tune the fuzzy controller for optimum performance and to compare the performance of three control regimes i.e. PID, not-tuned FLC and self-tuning FLC.

A single input / single output process is considered. The FLC has two control inputs: the current error and the change of error. The control action is the change in the manipulated variable. The tuning of the two scaling factors for the two control inputs is done automatically by a fuzzy set of meta rules. The performance measures for tuning are the overshoot, rise time and the amplitude of oscillation of the transient response of the process. The rules for tuning are of the form:

IF performance measure IS X, THEN scaling factor IS Y,

where *performance* measure is one of three above mentioned performance measures. *X* is a fuzzy set describing the performance measures and*Y* is a fuzzy set describing the scaling factor correction.

By changing the scaling factor of each controller input, the weight given to the input of the controller is changed. For example, if the system response is slower than desired, the effect of the error on the system must be increased. Hence, the error scaling factor is increased. Similarly, if the overshoot or amplitude of oscillation is higher, the effect of the change of error on the controller should be bigger. Hence, the appropriate scaling factor is increased.

The proposed algorithm was developed and the performance of the three control regimes (PID, not-tuned FLC and self-tuning FLC) was examined. To assess the robustness of the controller, it was compared with the PID controller when both had 3% zero-mean noise added to the temperature sensor. The tuning was accomplished in 13 steps with the scaling factors initialised to unity. Without some form of adaptive tuning, both controllers come out of critical damping once the process parameters are changed. However, the fuzzy controller is more robust under such changes.

Takagi (1992) [5] describes how neural networks (NN) and fuzzy logic have been applied to consumer products. First, the background why both these technologies have been applied to this field is described. Secondly, the overview of the fusion technology of neural networks and fuzzy logic is given. As a good example of the R&D process, the application of neural nets to the design and tuning of fuzzy system is introduced. Applications of both technologies are categorised into the following four cases:

- NN's being used to automate the task of designing and fine tuning the membership functions of fuzzy systems,
- both fuzzy inference and neural network learning capabilities provided separately
- NN's work as correcting mechanisms for fuzzy systems, and
- NN's used to customise the standard system according each user's preferences and individual needs.

Finally, the new trend that aims at the realisation of adaptive systems for the user is discussed. As examples of the trend, reducing pre-heating time in a Sanyo fan heater, fine-tuning of an air conditioner, Sharp new heater and refrigerator are introduced.

Zheng *et al*. (1992) [6] present a self-tuning fuzzy controller (STFLC) which can emulate not only the control experience of human expert, but also the strategies or thinking of the expert to be utilised in developing a fuzzy controller. The remarkable feature of a STFC is its dynamic knowledge, which is constructed by a multi-layer rule base. In this case, the lower rule set, called the control rule set, effects the process to be controlled directly as general fuzzy control. The upper layer rule sets, called tuning rule sets, adjust the control rule set and membership functions of input and output variables. Tuning rule sets are composed of two groups, called the tracking tuning rule set and the specifying tuning rule set, respectively. With tuning rule sets, the control rule set and MF's can be adapted not only for different systems, but also for different control stages of the same system. Upon tuning rule sets, there is a supervisor to manage these tuning rule sets during the real-time operation.

For the convenience of tuning, the control rule set and MF's are represented by few significant parameters. One parameter, which is called the rule adaptive coefficient, and which indicates the relative weight of the two inputs, can be used to tune the control rule set including two inputs (error and change of error) and one output. The rule set with more inputs and outputs can be similarly formulated using more parameters or using several rule sets as above. As a trade off between simplicity and universality, a set of trapezoidal MF's with four parameters, peak width a, base width b, interval c and uniform ratio r, is used.

For the control rule set, the different inputs should be considered with different weights at the different control stages by adjusting the rule adaptive coefficient k. As for MF's, the ones with smaller peak width a and interval c will be more sensitive to the change of the system. The uniform width fuzzy sets suit better for the non linear system. Larger base width gives more overlap of the MF's and it can be used for more complex case.

The typical response to a step change can be divided into three stages; rise stage, peak stage and stabilisation stage. The inputs of tracking tuning rules are the same as for the control rule set. The outputs are the parameters k, a, b, c and r. The basic idea of tracking tuning rule set is to limit the control objective in different control stages and use a different control rule set and MF's to reach the desired objective. It is equivalent to decoupling of a complex system into some simple ones dynamically.

The specifying tuning rule set is used to evaluate the control quality after the whole control procedure. The inputs of this rule set are three specifications of transient response characteristics: rise time, settling time and overshoot. The outputs are the parameters k, a, b, c, r. If rise time is too long, the rule adaptive coefficient k should be adjusted to increase the weight of speed unit. To minimise overshoot, the system should use less control force when it goes near its set point. Decreasing weight of speed unit and increasing the peak width a of MF's guarantee this.. Decreasing the interval c in MF's reduces the settling time. The control rule can be activated in a smaller range around its set point to achieve higher accuracy.

The example from the fuzzy control of the floating object is used in demonstrating the effectiveness of this method. Its main advantages over a general FLC are stronger control capability, increased flexibility and robustness shorter developing cycle, and combining fuzzy and non-fuzzy inference.

He *et al.* (1993) [7] present a fuzzy self-tuning PID control scheme for controlling industrial processes. The essential idea of the scheme is to parameterise the well-known Ziegler-Nichols tuning formula by a single parameter α and then to use an on-line fuzzy inference mechanism to self-tune this parameter. The fuzzy tuning mechanism, with process output error and change of error as inputs, adjusts α in such a way that it speeds up the convergence of the process output to a set point and slows down the divergence trend of the output from the set point. The three PID parameters are related to the single parameter α using also the ultimate gain and the ultimate period extracted from the Ziegler-Nichols initialisation pre-tuning of the controller prior to its actual use. The form of the parameterisation is inspired by the Ziegler-Nichols formula and in fact reduces to it when α = ½.

The fuzzy self-tuning mechanism will generate α given the instant values of e (error) and Δe (change of error) at time t. It is composed of two parts: a fuzzy core and a conditional updating formula for α. To ensure a speed fuzzy inference, both the range of interest for e and that for Δe are covered by seven different fuzzy sets. Bell-shaped MF's and the fuzzy linguistic output variable H divided into seven fuzzy sets are used.

After defuzzification the numerical value of α using the crisp value of H and the recursive equation to update α is resulted. The algorithm was tested using simulation with response to step changes in the set point and load disturbance. Neither experimental trials nor any evidence of the controller robustness were examined.

Tönshoff & Walter (1993) [8] present a method, which uses neural networks and other intelligent technologies for adjusting the design parameters of FLC for grinding control. Two distinct controllers are used. In case of high deviations between the normal and controlled value, the first controller is activated. Its input may lie in the entire range and it gives the controller output as an absolute value. At a low deviation, an incremental controller, which input covers only a limited range, is used. By means of this integration, a parameter deviation can be avoided even with time variant system behavior.

In the development and employment of the fuzzy controller two disadvantages came up: subjectivity and high adjustment effort. Therefore neural networks are used. The identification method suggested can map the dynamic behavior represented by training data. For obtaining the training data stimulation by nominal value steps is ideal. A random data program generates these steps; thus process data are obtained according to objective criteria. Only triangular and trapezoidal sets are used.

To automate the parameterisation of MF's the method of Differential-Competitive-Learning (DCL) is used. This approach places MF's only where also training data are found. Furthermore, the density of fuzzy sets follows the density of data distribution.

Automatic generation of production rules extracts regularities hidden in the structure of training data and transforms them into a number of fuzzy rules. With the large amount of training data, it often happens that the algorithm described produces production rules with identical IF parts but different THEN parts. To solve this conflict the introduction of a so called logical value of production rule is suggested. This value is derived from the product of the MF value to which the exact input and output variables belong to the linguistic terms of a production rule. After all the training data are considered according to this method, the fuzzy algorithm still shows gaps because the training data do not represent all theoretically possible process situations. To overcome this drawback, the use of a backpropagation network seems suitable. Finally, for reducing the cycle time of the future fuzzy control the number of production rules is minimised by integrating rules with identical output terms. The fuzzy controller proposed is able to reproduce the behaviour of dead-beat controller fully, but it seems to be difficult to implement it on-line depending on hard computation requirements.

Lui *et al.* (1994) [9] introduce a novel self-tuning adaptive resolution (STAR) fuzzy control algorithm. One of the unique features is that the fuzzy linguistic concepts change constantly in response to the states of input signals. This is achieved by modifying the corresponding membership functions. This adaptive resolution capability is used to realise a control strategy that attempts to minimise both the rise time and the overshoot. In this approach, the controller rule base will not change, but the definition of the linguistic concepts such as “positive large” adapt constantly to environmental requirements. The thesis is that the resolution (or granularity) of these variables does not need to be constant, but it can change so that fine resolution at the operating point can be maintained, but coarse granularity elsewhere. This approach has been applied for a simple two input-one output fuzzy controller.

A conventional fuzzy controller with error (e) and change of error (Δe) as inputs and the control force (u) as output is selected. The STAR algorithm modifies the linguistic definitions on-the-fly in order to force the (e, Δe) trajectory to a region where error and change of error have different signs. On the surface (e, Δe) four states are identified representing the following control strategy. At state 1 the controller becomes a proportional one and it exerts the biggest possible u. To avoid overshoot, the controller must at the appropriate time generate u in the opposite direction when the actual error is close to zero. The controller becomes derivative (state 3). Before reaching this state the controller can go to state 2 where the controller's output is zero (a relaxation state). Then after state 3, both e and Δe should be very small and it can enter into state 4, which uses conventional fuzzy control method to bring the close-loop system to the desired set point. The STAR fuzzy controller has been simulated to control the inverted pendulum problem in software and compared to the conventional PD controller. The algorithm is then used to control a real inverted pendulum. The STAR algorithm is implemented in both controllers. Experimental results show the cascaded controller is robust against disturbances and uneven load. Compared to the conventional fuzzy controller, the STAR approach reduces the positional overshoot and also the angular error in the steady state.

Ramkumar & Chidambaram (1995) [10] present a fuzzy self-tuning PI controller for controlling a bioreactor. The basic idea is to parameterise the Ziegler-Nichols tuning formula by two parameters α and β and then to use an on-line fuzzy inference mechanism to tune the PI controller parameters i.e. proportional gain and reset time. The fuzzy self-tuning method uses the process output error as input and the tuning parameters α and β as outputs. The ranges of membership functions are selected based on the simulation study. In real situation these ranges will be fixed from the knowledge of the operators. The rules are developed and examined for their correctness. The rule base is formed after an iterative process, in which new rules are added and some existing rules are deleted or changes are made in the existing ones. After several simulation runs, a set of seven rules is extracted. Simulation studies of the non linear bioreactor model show that the present method is superior to that of fixed parameters conventional PI controller for both servo and regulatory problems. The present fuzzy logic controller is robust to process parameter uncertainties and to changes in magnitude and direction of the disturbances

Jung *et al.* (1995) [11] present a self-tuning fuzzy water level controller based on the real-time tuning of the scaling factors for the steam generator of a nuclear power plant. This method uses an error ratio as a tuning index and a variable reference tuning index according to system response characteristics for advanced tuning performances. The variability of the reference tuning index is introduced taking into account that the different stage of the system response to an input change has different slit. The method has two different indices for overshoot and undershoot to reduce the number of control intervals for tuning. The values of error and change of manipulated variable are used to determine the grade of instantaneous system performance for scaling factor tuning.

The simulations on the compact nuclear simulator set up at the Korea Atomic Energy Research Institute, where reactor dynamics are simulated by SMABRE code, are carried out to test the proposed algorithm. In these simulations the steam generator water level error signal, which gives feedback effects, is tuned. The output signal of the controller is not tuned, because this signal effects the stability of the system. Only the input scaling factor of the low-level fuzzy controller of the plant is tuned. Any evidence about the robustness of this controller has not been examined.

Chiricozzi *et al.* (1995) [12] propose a new gain self-tuning method for PI controllers based on the fuzzy inference mechanism. The purpose was to design a FLC to adapt on-line the PI controller parameters.

The essential idea is

- to define a dynamically changing reference trajectory on the error and change of error surface, where they call it “sliding trajectory”;
- to compute the error area between the sliding trajectory and the effective one with a special algorithm using this quantity as a performance index to evaluate the system response;
- to draw a fuzzy relationship between the PI gains' correction parameters and the performance index;
- to calculate and to tune PI gains based on the fuzzy inference mechanism.

The aim of the method is to improve the step change response gradually and to assure a certain system overshoot target reached with a reasonable rise time. This algorithm was tested in the PM synchronous motor drive speed control scheme with different set points and extreme initial conditions.

Shimojima et al. (1995) [13]] propose a new supervised self-tuning fuzzy modelling, which consists of some membership functions expressed by the radial basis function with insensitive region. Genetic algorithms (GA) take care of learning. The steepest descent method is also utilised for tuning the shapes of the membership functions and consequent parts of the rules. A hierarchical fuzzy inference is also proposed, because the hierarchical structure is very powerful for increasing input values. The proposed hierarchical fuzzy inference considers the relations among inputs and it does not lose the accuracy of the output value.

There are two tuning methods. One is the coarse tuning with GA and the other is the fine-tuning by the gradient descent method. The effectiveness of the proposed method for approximating analytical functions with a minimum number of MF’s and rules has been shown. No evidences of experimental trials neither of robustness of this algorithm are provided. Moreover, its on-line applicability is not indicated.

Miyata *et al.* (1996) [14] propose a generation of piecewise membership functions in the fuzzy control by the steepest descent method. In this algorithm, MF’s of the premise for each rule are tuned independently. Besides only theMF’s corresponding to the given input and output data for the learning can be tuned efficiently. Comparing to the conventional triangular and bell-shapedMF’s, an expansion of expressiveness is indicated. The learning procedure needs the objective function, inspired to the mean squared error of the controlled output, to be implemented. The tuned values of parameters describing the piecewise linear membership functions (five parameters for each MF) minimise the magnitude of this objective function. Through these adjustments, the desired inference rules can be obtained step by step. This algorithm has been tested on a travelling control of a parallel parking of an autonomous mobile robot. The latter is a system with 3 input variables, each input with 3 linguistic labels, and hence 3^3 (=27) reasoning rules are prepared. The fired outputs of rules are crisp values. It has been proved that in this algorithm the expressiveness is expanded and hence the adaptability is improved compared to that by the conventional method (i.e. with triangular or bell-shapedMFs). This reduces the iterative computation greatly in number. However, the determination of some initial learning coefficients remains unsolved.

Wang & Chai (1996) [15] develop a learning algorithm to train the simplified fuzzy inference network (SFIN), used for the implementation of the fuzzy logic controller, to match the given input-output pairs. This learning algorithm firstly views the FLC as a four-layer feedforward network and secondly uses the chain rule to determine gradients of the output errors of the SFIN with respect to its design parameters. Furthermore it uses a prior knowledge for the real world problems to choose a structure of SFIN and to estimate its initial premise and consequent parameters. After this preliminary step, the on-line adaptation of the SFIN-fuzzy controller is achieved using a GPC performance index instead of that one used in the learning approach, getting the so called self-tuning fuzzy logic controller (SFLC).

The algorithm has been tested using simulations of a non linear plant with non-minimum phase characteristics and designing a controller with only two inputs and a single crisp output. The given SFLC may work well for some set points with some robustness. However, it fails when the set points change, a larger system parameters change or larger disturbances appear.

Routray *et al.* (1996) [16] introduce a fuzzy logic controller based on the tuning of the controller parameters for the rectifier side current regulator and inverter side gamma controller in a high voltage direct current (HDVC) system. A typical point-to-point system has been taken with the detailed representation of converters, transmission links, transformers and filters. The current error and change of error and the gamma error and its change are used as the principal signals to adjust the proportional and integral gains of the rectifier pole controller and the inverter gamma controller. The system aims at the optimum performance under various normal and abnormal conditions. A fuzzy logic based approach for the on-line tuning of the control parameters is presented. A satisfactory accuracy of the parameter adaptation is obtained by referring the fuzzy subsets to the normalised values of the variables involved in the fuzzy logic. The tuning rule base tries to emulate operator experience on gain tuning. Finally a comparative study has been done with and without tuning, but using an electromagnetic transient simulation program. No experimental tests are provided.

Chen & Lin (1997) [17] present a methodology to tune the initial membership functions of a fuzzy logic controller for controlled systems. These membership functions of the controller output are adjusted according to the performance index of sliding mode control, so trying to propose a real time simultaneous tuning method. The input variables i.e. output error and change in output error define this performance index. The general gradient method is adopted to alter the output fuzzy set in the direction of the gradient of the performance index. The idea is to change overall fuzzy controller output under system operation to get small performance index (minimisation problem). In order to reduce the running time of fuzzy controller and simplify the approximate reasoning, a simplified fuzzy approximate reasoning method, which treats the consequent part of control rules as a centre point, is used. In order to assess the tuning fuzzy controller, a non linear inverted pendulum system and ac oscillating system are selected for numerical examples. The proposed algorithm has not been tested on experimental systems, nor any evidence of its robustness is provided.

Leu *t al.* (1997) [18] present the adaptive fuzzy-neural controllers tuned on-line for a class of unknown non linear dynamical systems. To approximate thelinearisation of the unknown non linear dynamical system, the fuzzyapproximator is established. Furthermore, the control law and update law to tune on-line both the B-spline membership functions and the weighting factors of the adaptive fuzzy-neural controllers are derived. For developing the on-line tuning of the fuzzy B-spline membership functions, the functions have critical characteristics of uniform distribution and fixed number of control points. The superiority of the on-line tuning of both membership functions and weighting factors over the tuning of only the weighting factors is demonstrated. The proposed algorithm has not been tested on experimental systems. The robustness property of the controller is also not mentioned.

Lin & Wang (1997) [19] have developed an adaptive fuzzy controller for a serial-link robot arm. The proposed rotated fuzzy basis function (RFBF) controller is a more flexible fuzzy basis function expansion to approximate unknown functions of the robot model. It is only based on a general three-layer neural network that implements a fully adaptive fuzzy radial basis function expansion. The architecture of the neural network is basically a multilayer neural network where radial functions are used instead of sigmoid functions in hidden neurones. The major differences between RFBF networks and three-layer neural networks are the processing elements of neurones and the input-to-hidden layer interconnection weights. Any general learning algorithm can be used to train the network. All the parameters of RFBF can be tuned on-line when the number of rules is determined. By combining the dead zone functions and robustness techniques, they can show that the controller is robust. Simulations of the proposed controller on the PUMA 560 robot manipulator arm are taken into account to demonstrate the effectiveness. The proposed controller is also compared with the well-known Slotine Li’s adaptive controller.

Takagi (1997) [20] presents a skill-based PID control scheme, which extracts skills of human experts as PID gains. This controller was designed by using a three-layered artificial neural network together with a conventional PID controller.

The digital PID controller produces a control signal by using the proportional, integral and derivative actions and the main task of the neural network is to tune the parameters K_C (proportional gain), T_i (reset time) and T_d (rate time) of the PID controller. To achieve this goal the NN uses the following inputs:

- Output of the system y
- Control signal u
- Set point value r
- Error signal e
- Signal of the change in the target value ”h” (if r rises up or falls down then h is positive or negative)

The NN is trained using a couple of data u* and y* performed by a human expert. Using the error signal e* := r – y*, the training process is performed off-line by adjusting the connection weights so that the following cost function may be reduced at any time based on the error back propagation method, considering u* as the teaching signal:

Cost function $E(t) := \frac{1}{2} s^2 (t)$
$s^2 (t) := du^* (t) - du (t)$ where $d=1-z^{-1}$

In order to make the training faster in the transient time, the error signal s (t) is different compared with the usual form (u* - u).

After the NN has been tuned enough, i.e. the cost function has become small enough, the skill-based PID controller can be constructed by inserting it to the closed loop control system.

The NN includes three layers: one input, one hidden and one output and threshold. The hidden and output layers use sigmoid functions given by respectively:

$F (x) := 1/(1+e^{-ax}) - \frac{1}{2}$
$G (x) := c/(1+e^{-bx})$

where a, b and c are positive constants.

The update algorithm of the connection weights, by which the cost function is reduced at every time, is derived by differentiating partially the cost function with the respect to the connection weights.

The behaviour of the proposed skill-based PID controllers is investigated by applying them to an experimental air pressure control system. The objective is to control the air pressure y in the tank level to any desired value by manipulating the control valve angle u. In order to keep the linearity of the control system, the valve angle is limited. The number of nodes in the input and hidden layers were set to 35 and 25. Furthermore, the parameters of the sigmoid function were set as a=1, b=1 and c=10.

By examining the parameters of the PID controller being the outputs of the NN, it is found the control was very aggressive when the target value increased. After the step change in the target value had been made, both the proportional gain and the rate time increased quickly and then decreased while the system approached the steady state. On the contrary, the reset time decreased very quickly and at once increased to the steady state. In this way the proportional, integral and derivative actions of the PID controller were increased by the NN during the transient state and then decreased quickly while the system achieved the steady state resulting in faster responses.

Finally in this paper the study on the interpretation of the human skill was made from the standpoint of control engineering through the Bode diagram of a PID controller. The parameters of the PID controller were calculated using different steps.

As the conclusion it can be said that the gain K_C should be smaller in order to assure the stability of the control system (especially at the steady state), and conversely K_C should be made as big as possible in order to improve the tracking property (during the transient state). The parameters T_i and T_d are changed depending on the current state.

Ying (1998) [21] investigates the analytical structure of the Takagi-Sugeno (TS) type fuzzy controllers, which were unavailable in the literature. The TS fuzzy controllers employ a new and simplified TS control rule scheme in which all the ruleconsequents use a common function and are proportional to one another, greatly reducing the number of parameters needed in the rules. Other components of the fuzzy controllers are general: arbitrary input fuzzy sets, any type of fuzzy logic and the generalised defuzzifier, which contains the popularcentroid defuzzifier as a special case.

It has been proved that all these TS fuzzy controllers are non linear variable gain controllers and characteristics of the gain variation areparametrised and governed by the rule proportionality. All these results come from the analytical investigations and from the comparison with the conventional counterpart (PID controllers). The wide knowledge gap in the current literature regarding the analytical structure of the TS fuzzy controllers and their possible connection with conventional controllers is tried to bridge.

The proposed controller scheme does not match the problem of fuzzy self-tuning exactly, but it is an alternative way to build up a new improved fuzzy controller in the hybrid system using also the variable gain as a tuneable parameter.

Chung *et a.* (1998) [22] propose a self-tuning fuzzy controller with a smart and easy structure. The tuning scheme allows to tune the scaling factors by only seven rules. The aim of the controller is to obtain a satisfactory performance, for rise time, overshoot and steady-state error for the step response.

The structure of this controller consists of two fuzzy logic controllers: one is a PI-type fuzzy controller at low level directly applied to the process; the other one is the fuzzy supervisory tuner controller which adjusts the scaling factors of each MF of the low level controller. This means that the self-tuning controller adjusts three scaling factors for the three linguistic variables of the PI-type fuzzy controller, i.e.G_e (scaling factor of error) G_{ce} (scaling factor of change of error) and G_{cu} (scaling factor of change of manipulated variable).

The requirements are smaller overshoot, faster rise-time, smaller steady state error and smaller load effect. Since the PI-type fuzzy controller is used the steady state performance is certainly better. The strategy is that the system has a positive large acceleration at the beginning. In other words the scaling factor is increased such that the rise time and settling time are reduced. On the other hand the system has a negative acceleration when the output signal is near the set point, i.e. the scaling factors have to be reduced such that the overshoot is reduced or prevented. The seven tuning rules constructed use ratio error (i.e. current /(set point - initial system output)) as input variable and variation of scaling factors of e,ce and cu as output consequent variables. For each linguistic variable seven labels are definedMF's for the output variables of the FLC tuner controller are the same. The actual scaling factors are obtained using formula, which correlates to the incremental factors. In this formula w is the convergent coefficient and if it is wanted get faster rise time it would be increased. To evaluate the performance and characteristics of the proposed scheme, this technique is applied to a third order plant with delay time. This controller shows some robustness but no experimental trials are made.

Mudi & Pal (1998) [23] present a simple but robust model for self-tuning FLC's. Because this method will be later applied to the pilot plant dryer it will be presented quite detailed as follows.

According to Mudi & Pal the adaptive tuning of a FLC is based on adjusting the output scaling factor (SF) of a FLC on-line by fuzzy rules according to the current trend of the controlled process. The rule-base for tuning the output SF is defined based on the error (e) and the change of error (Δe) of the controlled variable using the most common and unbiased membership functions (MF's). The error e is taken as the difference between the set point and the output controlled variable. The proposed self-tuning technique is applied to both PI and PD-type FLC's by making the simulation analysis for a wide range of different linear and non linear second order processes including a marginally stable system. The performance of the proposed STFLC is compared with the corresponding conventional FLC in terms of several performance measures such as peak overshoot, settling time, rise time, integral absolute error (IAE) and integral-of-time absolute error (ITAE) in addition to the responses due to stepwise set point changes and load disturbances.

For the successful design of a FLC the right selection of the input-output SF's and/or the tuning of the other controller parameters are crucial tasks, which in many cases are done through trial and error or based on some training data. From the various tuneable parameters, SF's have the highest effect due to their global effect on the control performance. Both input and output SF's or only one of them could be tuned. Nowadays, no conventional method, which helps to choose the tuneable parameters exists. However, the relative importance of the input and output SF's on affecting the performance of a FLC is yet to be fully established. According to the analogy with a human operator, the output SF should be considered as a very important parameter of the FLC since its function is similar to the controller gain.

In the scheme presented in the paper the FLC is tuned on-line the controller being in use by adjusting dynamically its output SF by a gain updating factor α. The value of α is determined from the knowledge of control engineering. The gain i.e. the output SF of these controllers (PI and PD-type FLC) is adjusted on-line according to the current states of the controlled process. Although the characteristics of a PI or a PD-type FLC depend on both input and output SF's, their objective is to adapt only the output SF for the given input SF. The adaptive FLC is used to fine-tune the already working PI or PD-type FLC by modifying its output SF i.e. its gain.

All the MF's for the low-level controller (PI or PD-type FLC) inputs i.e. error and change of error and for the incremental change in the controller output for the PI-type FLC or in the controller output for the PD-type FLC are defined on the common interval [-1,1]; whereas the MF for the gain updating factor α is defined on [0,1]. The MF's are symmetric triangles (except the two MF's at the extreme ends) with the equal base and 50% overlap with neighbouring MF's.

All the linguistic variables use seven labels even if α is defined on the [0,1] interval, which is different from the others' common interval [-1,1]. This is obtained translating the [-1,1] MF's (NB, NM, NS, ZE, PS, PM and PB) along the horizontal axis by an amount +1 and then mapping it on the interval [0,1] by = 0.5(x+1) where x is defined on [-1,1], so getting the MF's (ZE, VS, S, SB, MB, B and VB) for the linguistic variable α. In this way the volume of data base is the same as a conventional FLC has without self-tuning, though one more linguistic variable α is included in the new STFLC.

The scaling factors for the inputs and the output (G_u) of the low level FLC are determined based on the knowledge about the process to be controlled and sometimes through trial and error to achieve the best possible control performance. On the other hand, the actual output of the STFLC is obtained by using the effective SF (α*G_u) where α is computed on-line using a model independent fuzzy rule base defined in terms of e and Δe as follows:

R_α: IF e is E and Δe is ΔE THEN α is $\overline{\alpha}$

In determining the rules it is important to take into account the following:

- controllers produce the lower overshoot and reduce the settling time. The controller gain is set small when the error is big but e and Δe are of opposite signs i.e. IF e is PB and Δe is NS THEN α is VS. To minimise the effects of the delayed control action due to the inherent process dead time or measuring lag, the small gain is essential to maintain the performance within the acceptable limit, especially when the process dead time becomes considerably big. When the error is big but e and Δe are of the same sign, the gain should be made very big to prevent the additional worsening situation (i.e. IF e is PB and Δe is PS THEN α is VB).

- depending on the process trend, there should be a wide variation of gain values around the set point i.e. when the error is small to avoid large overshoot and undershoot i.e. IF e is ZE and Δe is NM THEN α is B, in order to prevent the upward motion from the set point more severely resulting in a smaller overshoot;

- to eliminate any load disturbances the gain of the controller should be as high as possible especially around the steady state conditions (i.e. IF e is NS and Δe is NM THEN α is B). However, at the steady state (e and Δe $\cong$ 0) the controller gain should be very small (i.e. IF e is ZE and Δe is ZE THEN α is ZE).

It is important to note that the rule base for the computation of α depends always on the choice of the rule base for the controller in this structure. The gain of this STFLC is not constant when the controller is in operation. It is modified in each sampling time by the updating factor α, which depends on the trend of the controlled process output. This controller is basically an adaptive feedback loop controller and α results in non linear function of e and Δe.

If the control surface of the STFLC is compared with the surface of the conventional FLC, it can be seen that the surface of the STFLC is more non linear and smoother compared with the other one. Moreover it is very important to note that α is independent on any process parameter. The value of α depends only on the instantaneous process states.

For tuning the proposed controller the following steps are used:

1. tune the SF's of the STFLC without tuning the gain and assume that α=1 for a given process to achieve a reasonably good control performance. Because the well-defined method for the determination of SF's does not exist, the suitable values of the SF's are selected from the knowledge of the process and sometimes through trial and error. Finally the good controller without self-tuning is as result. The output of the STFLC is nearly three times greater than that obtained in step 1 keeping the values of the input SF's same as the values of the conventional FLC. This is found experimentally as the aim to maintain the same rise time as the conventional FLC.

2. fine tune the rules for α depending on the type of the response wanted to achieve. For example if it is wanted further to reduce the overshoot at the cost of increased rise time then the value of α should be kept very small up to medium values of e (i.e. IF e is PM and Δe is NS THEN α is VS, and not simply S).

It is observable that in the presence of the same training data systematic methods like gradient descent method may be developed for such tuning. In this study any fine-tuning of the parameters is not used. Rather the most common type of unbiased MF's is used. The rule base for α is designed based on the intuitive analysis of the desired system performance and on the most often used control rule base.

Only simulations using a second order process with dead time for testing the proposed controller STFLC have been used. The performance of the two proposed controllers (PI and PD-type FLC) is compared with the corresponding conventional FLC by using several performance indices.

The simulation results show that rise time both for the conventional and self-tuning FLC is almost same. Using the STFLC the overshoot was decreased and the better control performance could be achieved, but with a considerably reduced overshoot and much improved overall response. The control simulations made both for stepwise set point changes and load disturbances use the same rule base and MF's for all processes with different values of dead time for establishing the robustness of the proposed structure.

Mamdani type inference and centre of area for defuzzification are used to eliminate extra computational need. For the numerical integration the fourth-order Runge-Kutta method with an interval of 0.1 sec for the simulation of the processes is used.

The main feature of the proposed scheme is that it depends neither on the process being controlled nor on the controller used. Conceptually, this scheme differs from the others presented in the literature, because it mimics the operator's action as the aim to achieve the desired operation of the process.

The proposed self-tuning method may be possibly applied for the tuning of the input SF or both input and output SF's simultaneously which can improve the performance of the FLC.

It is also possible to design a hybrid controller in which a fuzzy rule based system will modulate the output of a non-fuzzy controller such as a Ziegler-Nichols tuned controller. The output modulation may be realised using a SF according to the present case. The same rule base used for tuning the output SF of the fuzzy sliding mode controller may not be satisfactory in such cases because the control objectives of the conventional and fuzzy controllers are not identical.

4 Design procedure of the STFLC for the pilot plant rotary dryer

The above literature review shows that two kinds of methods for developing a self-tuning fuzzy controller exist: the one is based on neural networks whereas the other uses fuzzy logic. To keep the structure of the controller as simple as possible and to avoid heavy computation, a fuzzy logic supervisor controller based on meta rules is selected. Following the way proposed by Mudi and Pal **[23]** the supervisor controller tunes the output scaling factors of the low-level controller using a gain updating factor. Furthermore the inputs of the supervisor controller are selected the same as the ones of the low-level controller. This reduces the amount of memory required for the data base.

The design procedure of the STFLC to the pilot plant rotary dryer is as follows:

Step 1: System functional requirements. As the previous studies [1,2] have proved the fuzzy logic controller applies to the control of a rotary dryer. The aim of the STFLC is to improve the performance of the existing fuzzy controllers by utilising the operator's expert knowledge.

Step 2: Definition of system parameters. The main controlled variable is the output moisture of solids and the main manipulated variable is the input temperature of drying air, which correlates to the fuel flow. The velocity of solids which correlates to the rotational speed of the screw conveyor can be used as an auxiliary manipulated variable. The main disturbances are the variations in the input moisture of solids and the feed flow.

Step 3: Definition of system parameters in terms of fuzzy sets. The input variables for the STFLC representing the contents of rule antecedents are as follows:

- Error in the output moisture of solids (***input 1***);
- Change in the error of the output moisture of solids (***input 2***);

The controller output representing the contents of the rule consequent is as follows:

- Gain updating factor (***output***);

Step 4: Formulation of control rules. The control rule based on the analysis of the controlled response and on the experience is of the form:

IF input 1 is $\{I_{1j}\}$ ***AND input 2*** is $\{I_{2j}\}$ ***THEN output*** is {*zero, small, medium, big, very big*}, where I_{1j} and I_{2j} are fuzzy sets defined in the low level controller data base. The number of rules depends on the number of labels for the input linguistic variables chosen for the supervisor controller.

In this application the fuzzification is made using the Min-Max algorithm. The inference engine or rule firing is based in the one-level forward data-driven inference, which is the generalisation of the modusponens rule of inference.

Step 5: Selection a method of defuzzification. The centre of area method (COA) is used to transform the output of the fired rules into the crisp value.

Step 6: Simulation tests. The controller has been implemented inMatlab®, using Simulink and Fuzzy Logic Toolbox. Simulations have been carried out using the hybrid PI-FLC and the direct FLC as low level controllers [1] and making step changes in the main disturbance variable i.e. the input moisture of solids.

5 Design of the STFLC for the hybrid PI-FLC

The structure of the STFLC controller supervising the hybrid PI-FLC is presented in Annex 1.

In order to assure the simplicity of the controller, the trapezoidal membership functions have been chosen to the different linguistic variables and their labels of the FLC in the hybrid PI-FLC **[2]**. Also the shape of the membership functions of the output (gain updating factor) of the STFLC is trapezoidal. The different linguistic variables and their labels are presented in Table 1.

Table 1. Different linguistic variables and labels.

Variable	**Label**
Error in the output moisture of solids	very negative negative zero positive very positive
Change in the error of the output moisture of solids	negative zero positive
Gain updating factor	zero small medium big very big

The membership functions were determined experimentally and they are presented in Annex 2. The number of rules is 15 and they are presented in Table 2.

Table 2. Fuzzy rule base for the STFLC in the hybrid PI-FLC.

		Error in output moisture of solids		Change in error		Gain updating factor
1	IF	very negative	AND	negative	THEN	very big
2	IF	negative	AND	zero	THEN	big
3	IF	zero	AND	positive	THEN	big
4	IF	positive	AND	negative	THEN	small
5	IF	very positive	AND	zero	THEN	medium
6	IF	very negative	AND	positive	THEN	small
7	IF	negative	AND	negative	THEN	very big
8	IF	zero	AND	zero	THEN	zero
9	IF	positive	AND	positive	THEN	big
10	IF	very positive	AND	negative	THEN	small
11	IF	very negative	AND	zero	THEN	medium
12	IF	negative	AND	positive	THEN	small
13	IF	zero	AND	negative	THEN	big
14	IF	positive	AND	zero	THEN	medium
15	IF	very positive	AND	positive	THEN	very big

6 Design of the STFLC for the direct FLC

The structure of the STFLC controller supervising the direct FLC is presented in Annex 3.

The trapezoidal membership functions have been selected to the different linguistic variables and their labels of the direct FLC [2] to keep the controller simple. The membership functions of the output (gain updating factor) of the STFLC have been chosen as in the previous case. The different linguistic variables and their labels are presented in Table 3.

Table 3. Different linguistic variables and labels.

Variable	**Label**
Error in the output moisture of solids	very negative negative small negative very small negative zero very small positive positive very positive

Change in the error of the output moisture of solids	negative
	zero
	positive
Gain updating factor	zero
	small
	medium
	big
	very big

The membership functions were determined experimentally and they are presented in Annex 4.

The number of rules is 27 and they are presented in Table 4.

Table 4. Fuzzy rule base for the STFLC in the pure FLC.

		Error in output moisture of solids		Change in error		Gain updating factor
1	IF	very negative	AND	negative	THEN	very big
2	IF	negative	AND	zero	THEN	medium
3	IF	small negative	AND	positive	THEN	small
4	IF	very small negative	AND	negative	THEN	big
5	IF	zero	AND	zero	THEN	zero
6	IF	very small positive	AND	positive	THEN	big
7	IF	small positive	AND	negative	THEN	small
8	IF	positive	AND	zero	THEN	medium
9	IF	very positive	AND	positive	THEN	very big
10	IF	very negative	AND	zero	THEN	medium
11	IF	negative	AND	negative	THEN	big
12	IF	small negative	AND	negative	THEN	big
13	IF	very small negative	AND	zero	THEN	medium
14	IF	zero	AND	negative	THEN	big
15	IF	very small positive	AND	negative	THEN	small
16	IF	small positive	AND	zero	THEN	medium
17	IF	positive	AND	negative	THEN	small
18	IF	very positive	AND	negative	THEN	small
19	IF	very negative	AND	positive	THEN	small
20	IF	negative	AND	positive	THEN	small
21	IF	small negative	AND	zero	THEN	medium
22	IF	very small negative	AND	positive	THEN	small
23	IF	zero	AND	positive	THEN	big
24	IF	very small positive	AND	zero	THEN	medium
25	IF	small positive	AND	positive	THEN	big
26	IF	positive	AND	positive	THEN	big
27	IF	very positive	AND	zero	THEN	medium

7 Simulation results

The simulations have been carried out using the mathematical model of the pilot dryer implemented in Matlab functions. The proposed controller has been implemented using Fuzzy Logic Toolbox and Simulink in theMatlab environment.

The parameters of the model used are reported in the thesis [2]. Different step changes in the input moisture of solids (the main disturbance) have been made and the responses of the self-tuning controller have been compared with the ones achieved by the original controllers.

Figures 1…3 present the output moisture of solids of the self-tuning hybrid PI-FLC and of the original hybrid PI-FLC when different step changes in the input moisture content ($X_{s,\ in}$) occur.

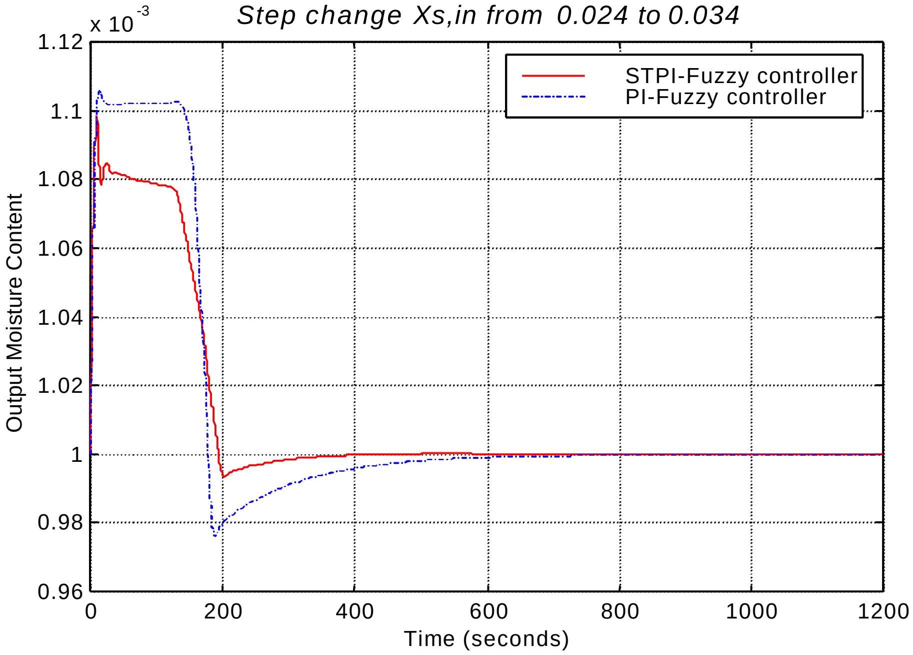

Figure 1. The simulated behaviour of the output moisture of solids achieved by the self-tuning hybrid PI-FLC and by the hybrid PI-FLC for a step change from 2.4% to 3.4% in the input moisture of solids.

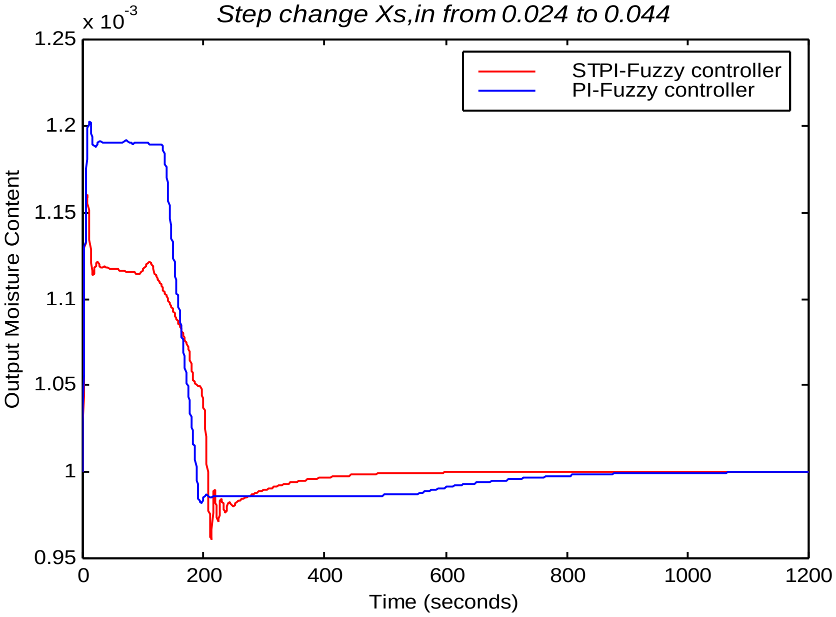

Figure 2. The simulated behaviour of the output moisture of solids achieved by the self-tuning hybrid PI-FLC and by the hybrid PI-FLC for a step change from 2.4% to 4.4% in the input moisture of solids.

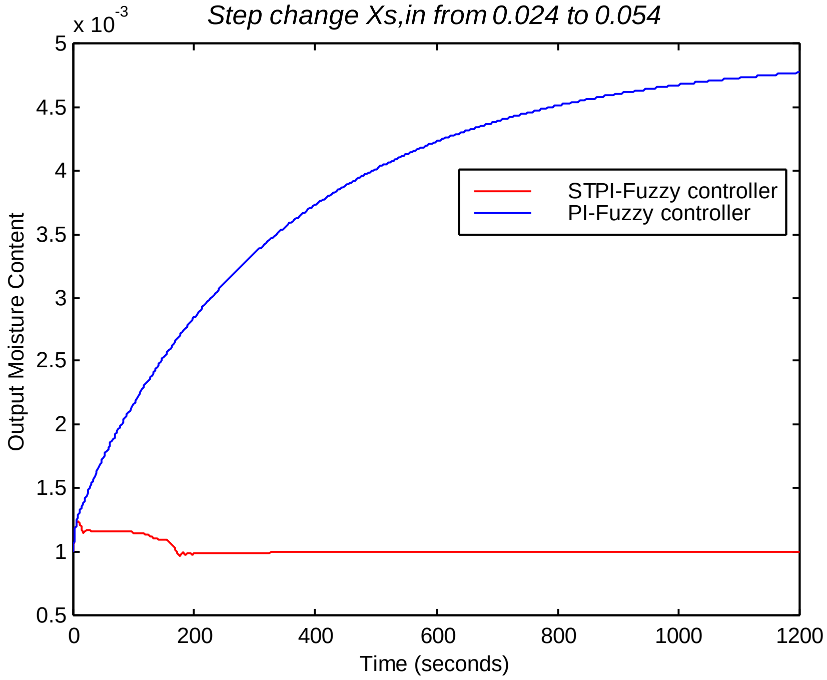

Figure 3. The simulated behaviour of the output moisture of solids achieved by the self-tuning hybrid PI-FLC and by the hybrid PI-FLC for a step change from 2.4% to 5.4% in the input moisture of solids.

Figures 4 and 5 present the output moisture responses of the self-tuning direct FLC and of the direct FLC when step changes in the input moisture content ($X_{s,\ in}$) are carried out.

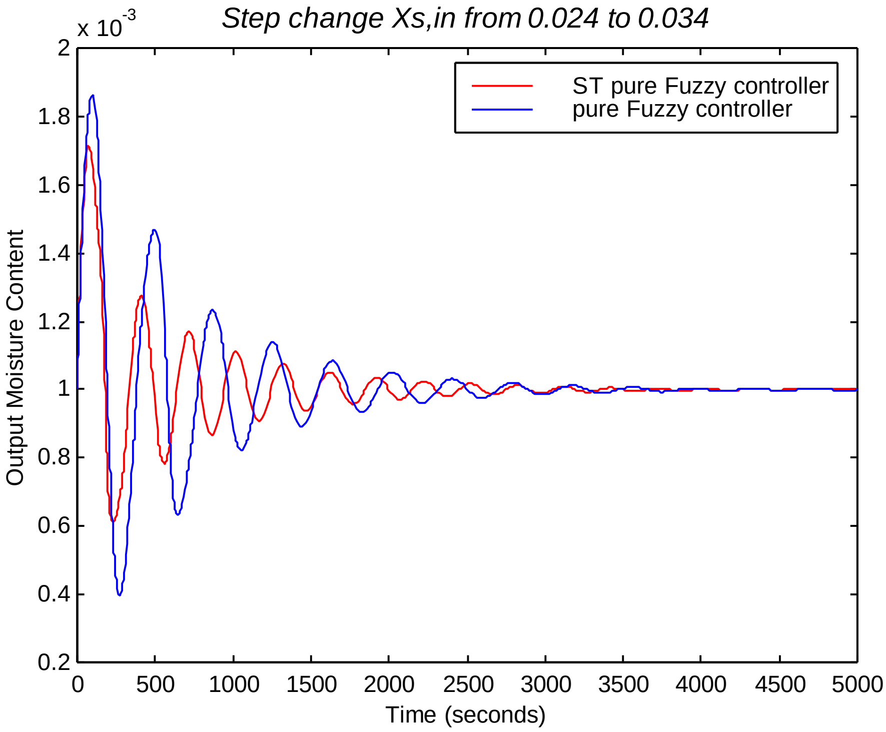

Figure 4. The behaviour of the output moisture of solids achieved by the self-tuning direct FLC and by the direct FLC for a step change from 2.4% to 3.4% in the input moisture of solids.

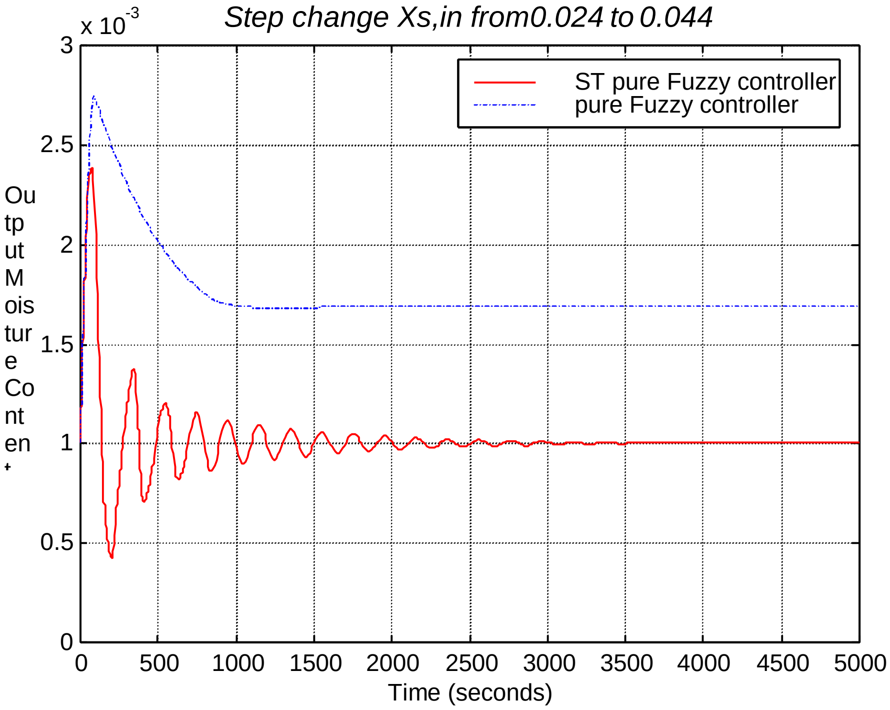

Figure 5. The behaviour of the output moisture of solids achieved by the self-tuning direct FLC and by the direct FLC for a step change from 2.4% to 4.4% in the input moisture of solids

As Figure 4 shows big oscillation can be observed and it might be due to the fact that the direct FLC was designed using different parameters for the mathematical model, and the simulations have been carried out using the updated parameters for the model. Particularly the parameter k_1, which affects strongly the drying rate, has decreased more than three times from 0.0033 to 0.001 [2].

The performance of the different controllers has been evaluated using time-integral performance indices. Taking into account that the maximum value of the error in the output moisture of solids is small, the IAE (integral of the absolute error) and the ITAE (integral of time-weighted absolute error) have been chosen as suitable performance indices. The resulting values are presented in Table 5.

Table 5. Performance indices for the different controllers.

Figure no°	Controller	IAE	ITAE
1	Self- tuning hybrid PI-FLC	0.0203	1.6888
1	Hybrid PI-FLC	0.0294	3.4739
2	Self- tuning hybrid PI-FLC	0.0373	4.0530
2	Hybrid PI-FLC	0.0448	6.0904
4	Self-tuned direct FLC	0.0810	31.816
4	Direct FLC	0.1166	55.791

As Figures and indices show, the STFLC improves the performance of the low level controller decreasing the settling time (ITAE) and slightly decreasing the maximum error (IAE). As the disturbance increases the difference of performances becomes more considerable. The STFLC is able to eliminate a very big disturbance while the FLC without self-tuning becomes unstable (See Figure 3 for the hybrid PI-FLC) or shows an offset (See Figure 5 for the direct FLC).

The results show the improved robustness of the STFLC. Deeper investigations should be made using more accurate process model and experiments with the pilot plant dryer.

8 Conclusions and further developments

In this research the STFLC was developed based on the tuning of SF's and tested with simulations. Firstly the vast literature review has been presented and then the STFLC is proposed. The design of this supervisor controller has been applied to two different low-level controllers (hybrid PI-FLC and direct FLC) developed for the pilot plant rotary dryer. Both controllers have been implemented using Matlab functions and their behaviour has been examined with simulations. The results show the improved robustness in the controlled response. However, the structure of the controller was kept simple.

As one possible further development of this design, an optimisation algorithm for tuning the several parameters of a FLC could be used, since the parameters of both supervisor and low-level fuzzy controllers have been tuned manually and this task has been revealed quite hard to achieve. Among the several algorithms proposed in the literature, the Table-Lookup scheme proposed by Wang [24], seems to be suitable for this purpose. It is based on one-pass operation for generating fuzzy rules by integrating linguistic rules and generated rules from numerical data into a combined rule base.

The fine tuning of the FLC's would be off-line and based on training data available from experiments. Furthermore the characteristics of the algorithm should keep the overall controller structure as simple as possible. This feature could be significant for the implementation in real-life controllers.

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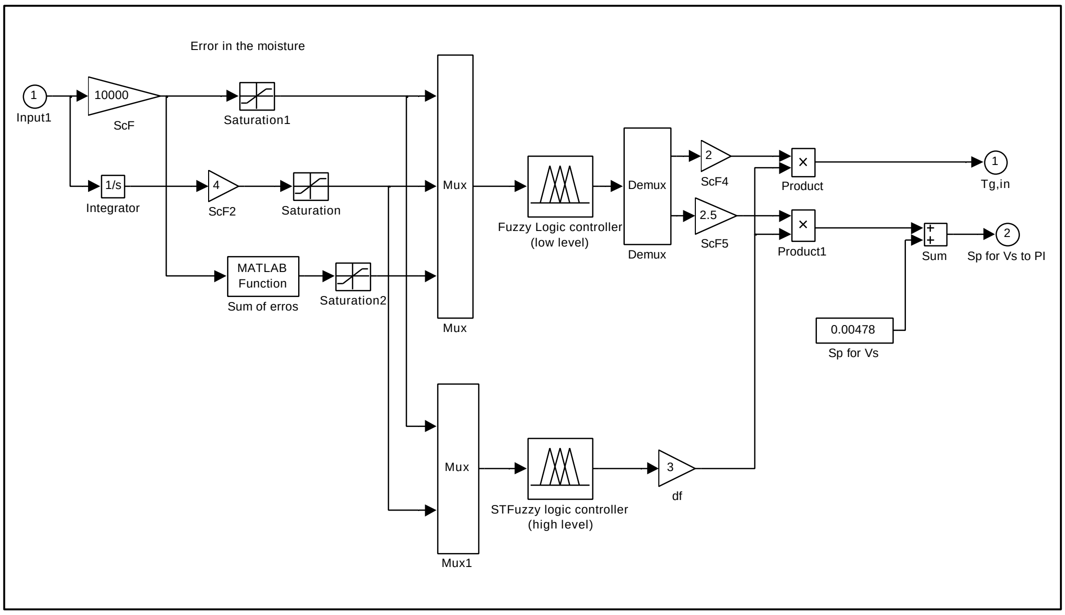
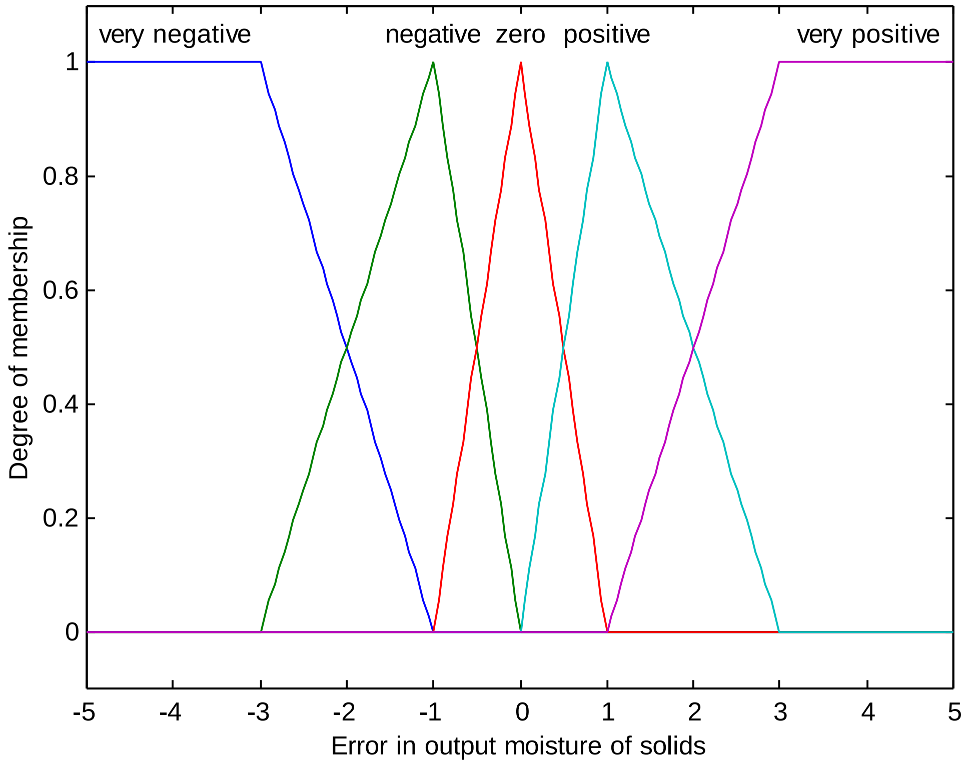
ANNEX 1.

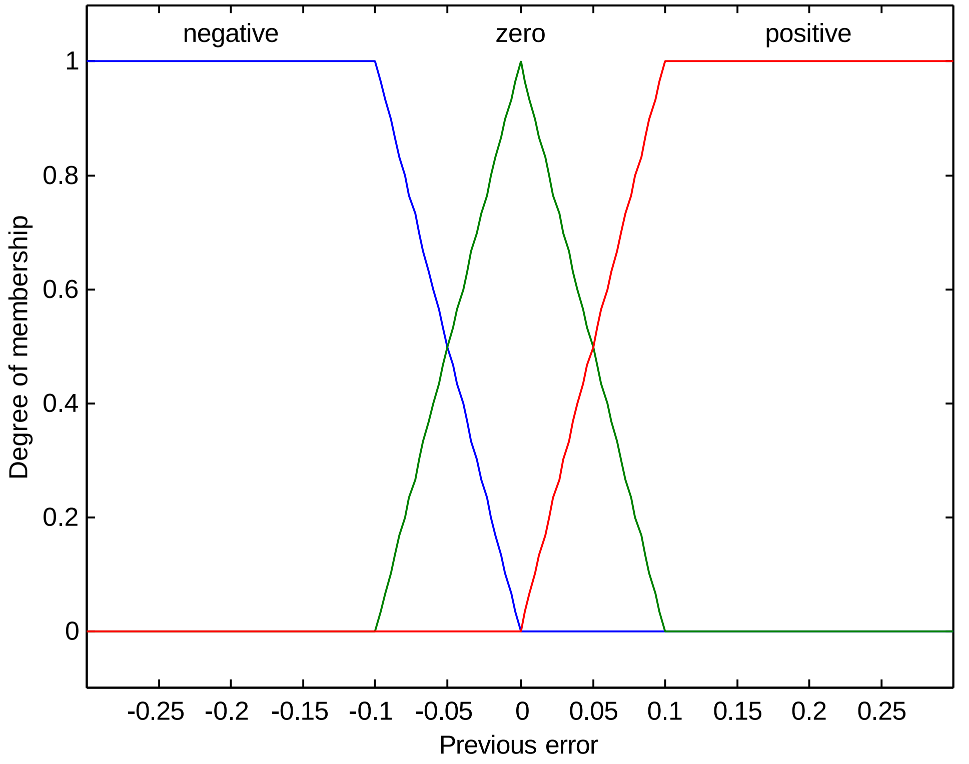


Simulink block diagram of the STFLC applied to the hybrid PI-FLC.

ANNEX 2.

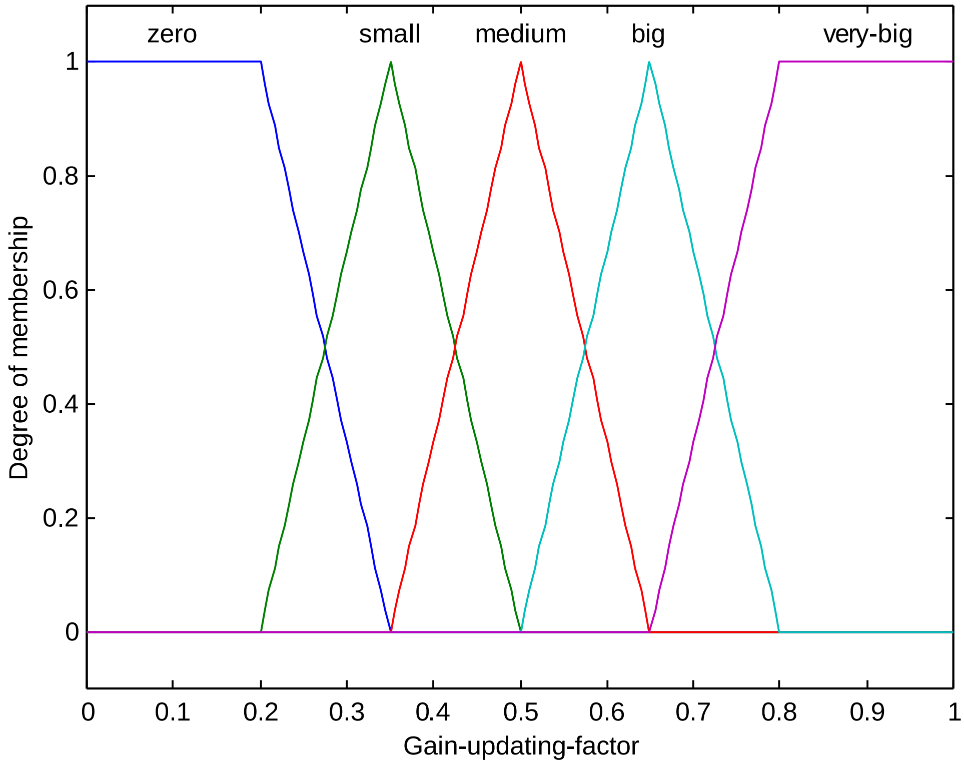
Trapezoidal membership functions of the input variables of the STFLC for the hybrid PI-FLC.



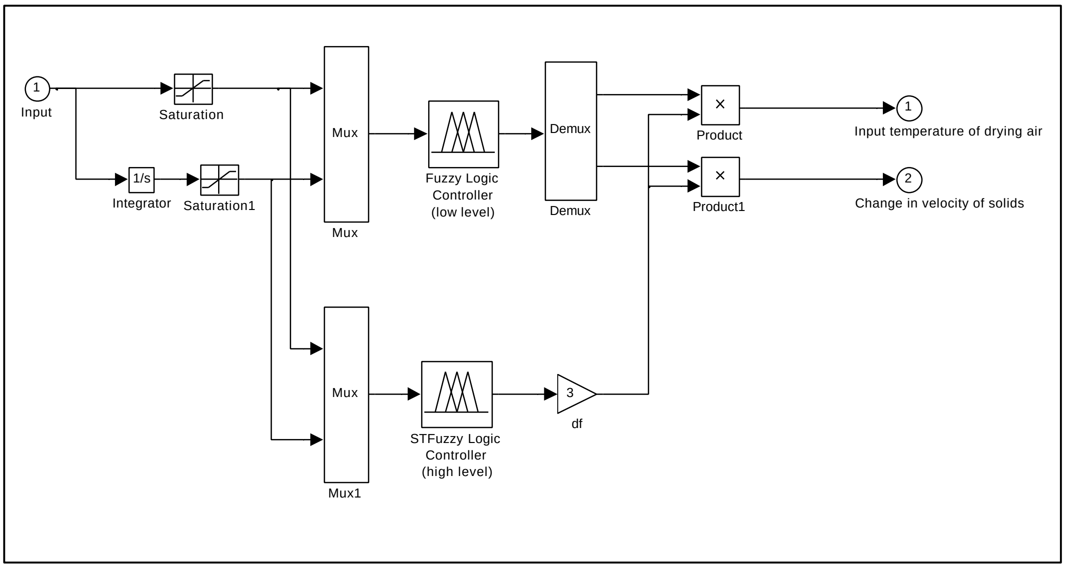


ANNEX 2.1.

Trapezoidal membership functions of the output variable of the STFLC for the hybrid PI-FLC.

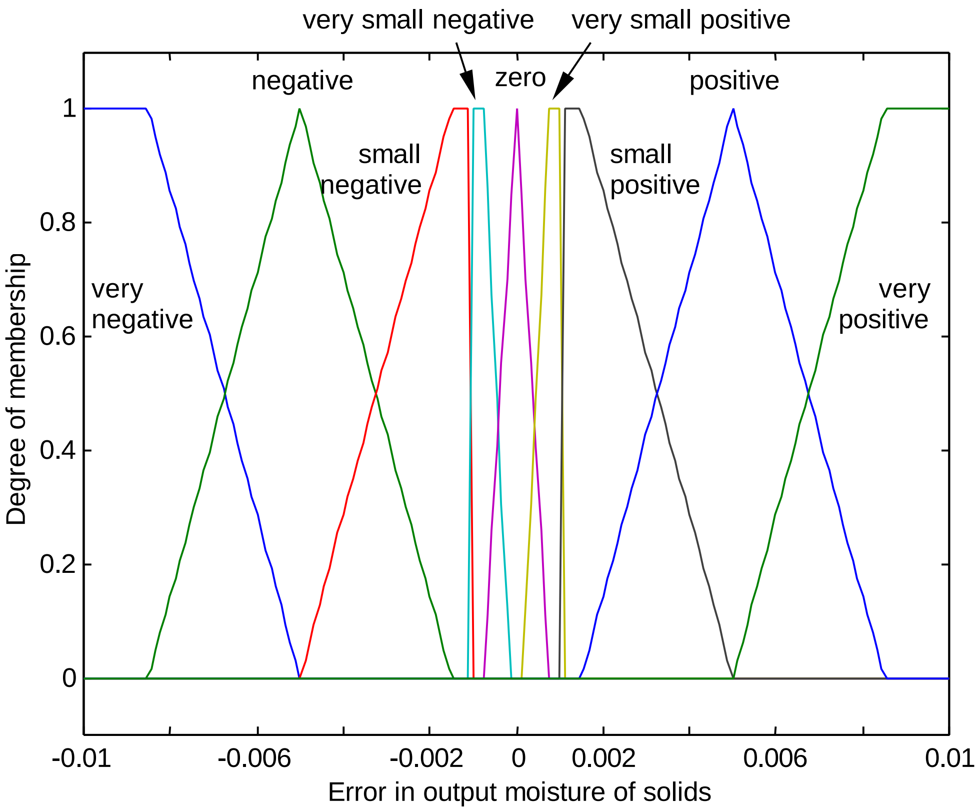


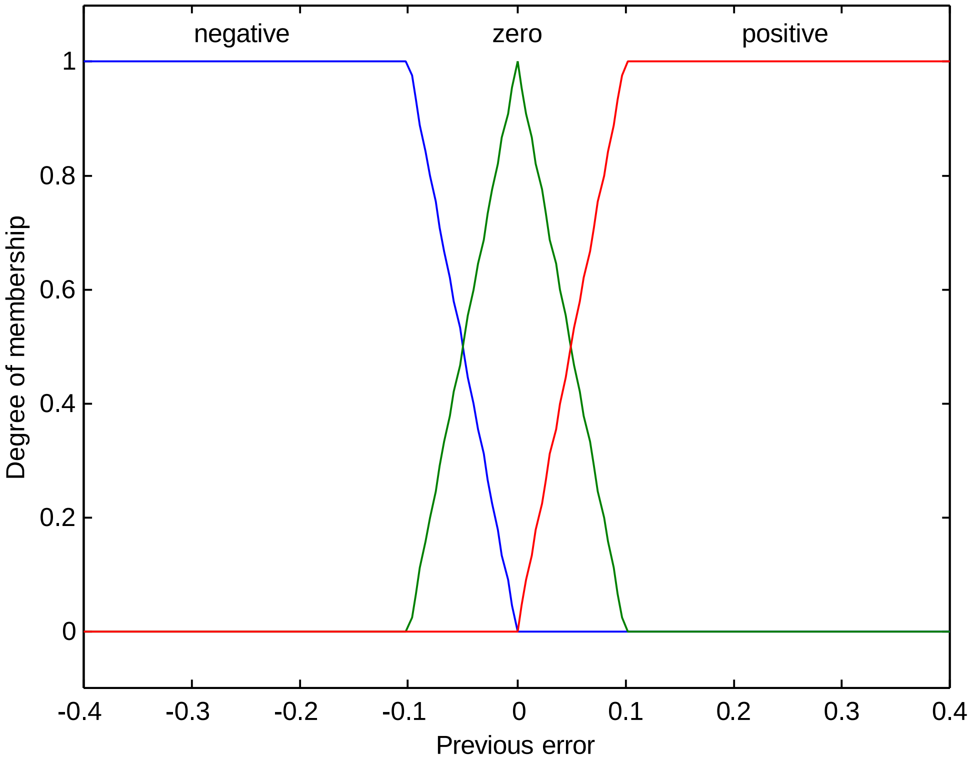
ANNEX 3.



Simulink block diagram of the STFLC applied to the direct FLC.

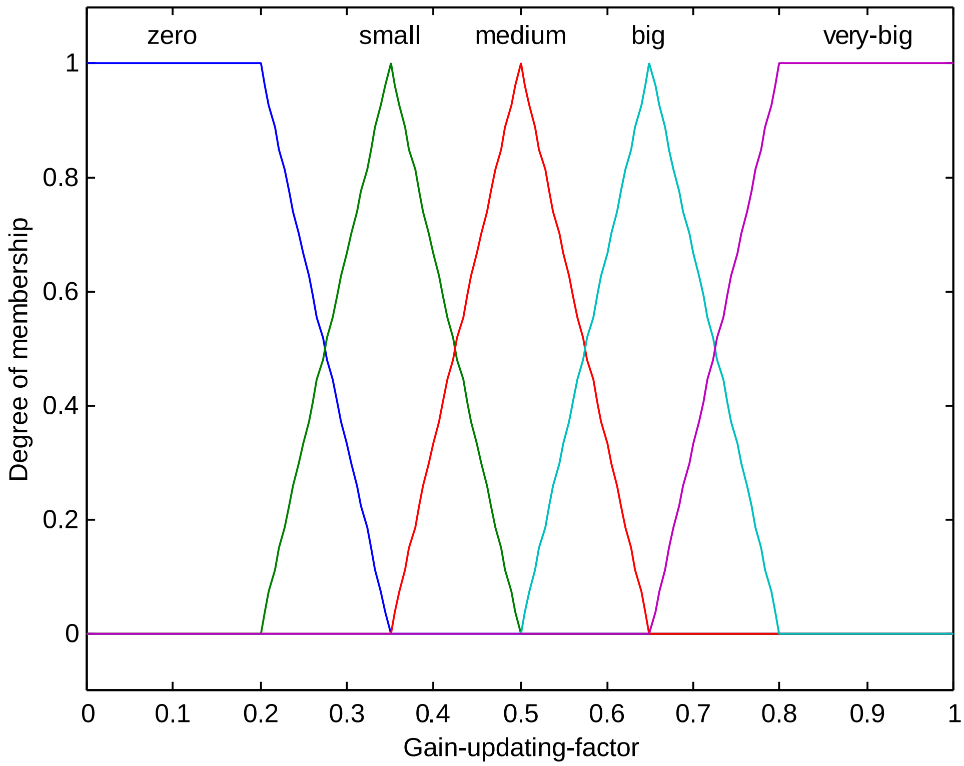
Trapezoidal membership functions of the input variables of the STFLC for the direct FLC.





ANNEX 4.1.

Trapezoidal membership functions of the output variable of the STFLC for the direct FLC.



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