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Improving Adaptive-network-based Fuzzy Inference Systems (ANFIS): A Practical Approach

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Abstract: This study is addressed to improving the quality of the signal of the ANFIS (Adaptive-Network-based Fuzzy Inference System) reducing the level of fluctuations in the output due to periodical disturbances. The fuzzy filter computes the disturbances as periodic signals with two components, one at high frequency and other at low frequency. The filter was incorporated in the layer 0 and it can be applied iteratively to effectively reduce heavy noise.

Key words: Wood dryer, fuzzy logic, control process, spectral density, noise

INTRODUCTION

Fuzzy inference has numerous applications, ranging from control to forecasting. A number of researchers have suggested how such systems can be tuned during application to enhance inference performance. The inference parameters that can be tuned include the central tendency and dispersion of the input and output fuzzy membership functions, the rule base, the cardinality of the fuzzy membership function sets, the shapes of the membership functions and the parameters of the fuzzy and and or operations, however, some authors ignore the consequences that any external or uncontrollable parameters (ratio signal/noise, disturbances etc) can produce in the quality of the inference parameters such that any effort in tuning them can be unsuccessful.

As we mentioned earlier, the application of the fuzzy logic to industrial level generally, is well accepted; however no formal methods to identify the fuzzy inference rules exist. Terptra,[1] uses an implicit fuzzy model (a fuzzy rule base) to analyse quantitative statements of the differences between the actual values and those predicted by quantitative models of the behaviour of the system with and without faults. Sensor (and other) data, which contain no readily discernable message, can be transformed via pattern recognition into clear-cut information useful for decision-making. Since artificial intelligent classify data effectively, it would seem that an artificial neural network or fuzzy logic would be an appropriate tool to try complex plants[2,3]. On line self-organizing and adaptive control are particularly desirable. Layne introduced a new control algorithm, which was developed from linguistic self–organizing. The algorithm has the advantage of improved performance feedback and more efficient knowledge-base modification over the linguistic. The performance criterion is no longer just a compromise between rise-time and overshoot but can be accurately quantified to virtually any form of desired performance using an appropriate reference model.

Li,[4] a mathematical model conventional model reference adaptive control theory is used for tuning and adaptation system. Lin and Chiu [5] presented an on-line learning model reference self-organizing fuzzy logic controller, however the rule base modification was elaborate and demanded that the output fuzzy sets be singletons. Review work published suggests that direct adaptive fuzzy control based on self-organizing concepts and reference model tracking responses would yield a viable solution to the problem of automatic rule generation and tuning fuzzy control systems, however the treatment of the signal using field data is ignored. This contribution explores the basic adaptive noise cancellations using a fuzzy approach. Simultaneous cancellation of noise and periodical disturbances and tuning the inference parameters improve the quality of the ANFIS and it was demonstrated using a wood dryer as reference. The specific objectives were to:

- Construct of an adaptive-network-based fuzzy inference system
- Analysis of the possible periodic disturbances and design of the fuzzy filter
- Evaluation of the new ANFIS using a pilot plant

ANFIS. Background: The ANFIS (Adaptive-Network-based Fuzzy Inference System) is a hybrid neuro-fuzzy inference system that emulates a Sugeno controller[6-9]. ANFIS uses a feed-forward neural network with six layers that is adapted by a supervised learning algorithm. The network uses unweighted connections and works with

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different activation-functions in each layer (Fig. 1). The rule set of fuzzy if-then rules with *n* inputs looks like this

$$\textbf{Rule if } \xi^{(1)} \text{ is } A_j^1 \wedge \ldots \wedge \xi^{(n)} \text{ is } A_j^{(n)} \text{ then } \eta = \omega^{(0)} + \omega^{(1)}\xi^{(1)} + \ldots + \omega^{(n)}\xi^{(n)} \tag{1}$$

The learning-algorithm modifies the premise parameters of the fuzzy sets ω_j and the parameters ω_j of the conclusions according to the presented training data set. In common, ANFIS can be defined as follows:

Layer 0: This layer consists of the *n* inputs $\xi^{(1)} \ldots \xi^{(n)}$

Layer 1: Every node in this layer is an adaptive one. The nodes are used to model the membership-functions of the linguistic expressions

$$\mu_{A_j}^{(i)}(\xi^{(i)}) = \frac{1}{1 + \left| \frac{\xi^{(i)} - c_j^{(i)}}{a_j^{(i)}} \right|^{2b_j^{(i)}}} \tag{2}$$

where $A_j^{(k)}$ is a generalized bell fuzzy set defined by the parameters $\{a_j^{(i)}, b_j^{(i)}, c_j^{(i)}\}$, with c as middle point, b as $\text{slope} = \pm \frac{b}{2a}$ and a as deviation.

Layer 2: The function is a T-norm operator that performs the firing strength of the rule, e.g, fuzzy AND. The simplest implementation just calculates the product of all incoming signals.

Layer 3: Every nodes *n* in this layer is fixed and determines a normalized firing strength. It calculates βj, the ratio of the *jth* rule's firing strength to the sum of all rules firing strength.

Layer 4: The nodes in this layer are adaptive and are connected with the input nodes (of layer 0) and the preceding node of layer 3. The calculation result σ_j is the weighted output of the rule j and is determined by

$$\sigma_j = \beta_j \left(\omega_o^{(j)} + \omega_1^{(j)}\xi^{(1)} + \ldots + \omega_n^{(j)}\xi^{(n)} \right) \tag{3}$$

Layer 5: This layer consists of one single node ✱, which computes the overall output as the summation of all incoming signal.

In contrast to most other neural approaches, ANFIS uses an efficient, non-interactive learning method: An over-determined equation system can be solved in order to get the optimised parameters of the fuzzy-system.

Decomposition of the disturbances: Previous practical experience over the equipment (the dryer) has indicated that disturbances have hidden a natural response of the process at low ratio signal/noise in the closed-loop in an interval from 0.05 to 0.5 Hz approximately. Observing the values, the response of the controller shows an oscillation to high frequency overlapping to another one of low frequency. Both frequencies are produced for the flow of the steam to the entry of the dryer. Observing the tuning of the original ANFIS, the period of the high frequency affects directly desired membership functions (*x* and *y*) of the fuzzy IF-THEN rules for achieving control goal as illustrated the (Fig.1). The installation of filters (hardware) in the system was not enough because the noise can be reduced but not eliminated, such that, small signal/noise ratios could be present and affect the inference parameters.

For reduce the effect of the disturbances over the ANFIS controller, a method for analyses the perturbation is introduced. This method is applied to situations where the process disturbances can be modelled as periodic signals with two components one at high frequency and other at low frequency, with small signal-noise ratio in the process variable measurement. Before to include the additional membership function and fuzzy rule for the detection of noise is important to review as the disturbance was analysed.

Reviewing the literature[10,11] the Power Spectral Density (PSD) expression of both disturbances (high and low frequencies) is given by:

$$P(K,w) = \frac{\frac{m}{2}}{\left[\frac{K}{w} + \frac{\text{sen}\theta(w)}{|G_p(jw)|} \right]^2 + \left[K + \frac{\cos\theta(w)}{|G_p(jw)|} \right]} \tag{4}$$

where *m=1* or *2* and $w_{min}<w<w_{max}$ and *K* is a constant of amplification. The total power will be summations of both components. Analysing the behaviour of *K*, the absolute maximum Eq. (4) is

$$K_{max}(w) = -\frac{\cos\theta(w) + \left(\frac{1}{w}\right)\text{sen}\theta(w)}{|G_p(jw)| \left[1 + \left(\frac{1}{w}\right)^2 \right]} \tag{5}$$

and

$$\lim_{K\to\infty} P(K,w) = 0 \tag{6}$$

$$\lim_{K\to 0} P(K,w) = \frac{m}{2}|G_p(jw)|^2$$

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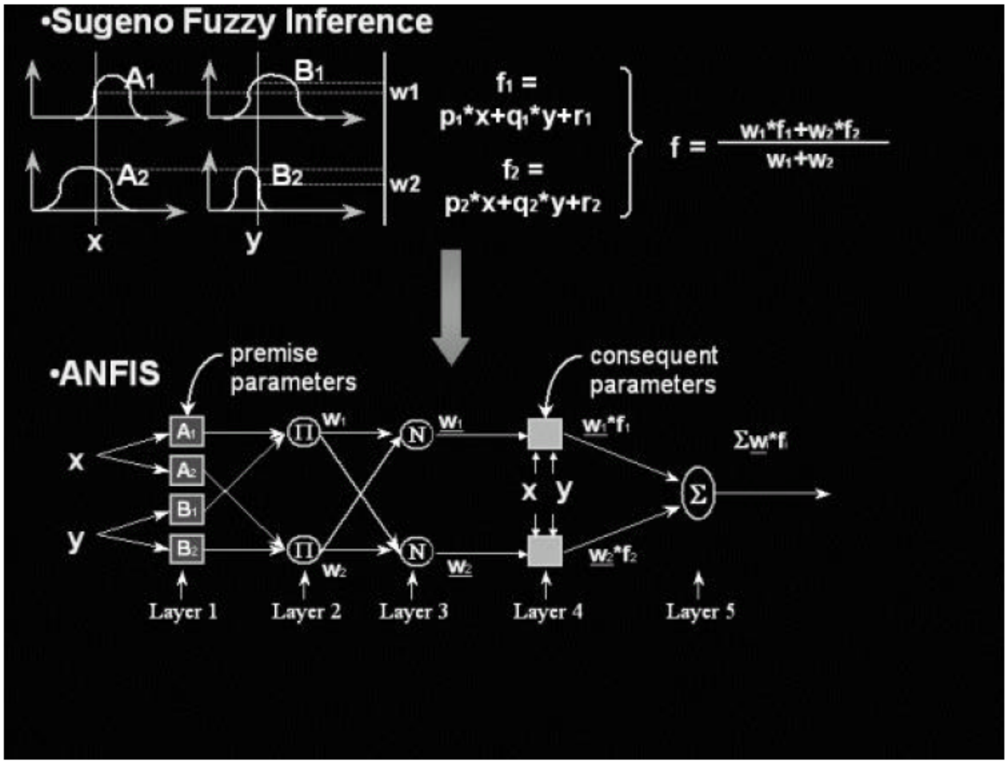

Fig. 1: ANFIS structure

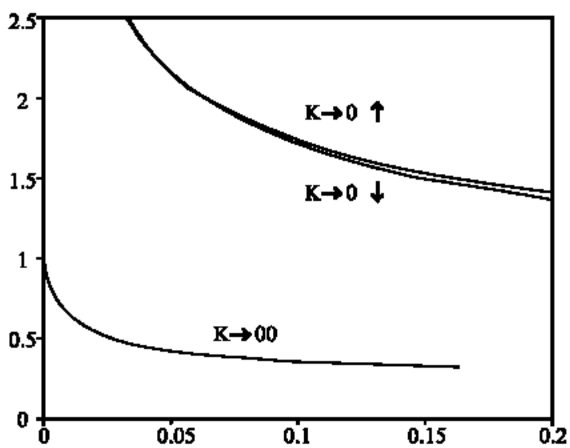

Fig. 2: Contour of variences according to the value of K

The above expression means that when the gain value is high the noise is cancelled immediately, however when K goes to zero do not exist control in the system and it is working at open loop.

The frequencies of disturbances were estimated from 0.05 Hz until 0.5 Hz for each input (wood temperature, air wet bulb temperature, dry bulb temperature and pressure). The frequency range is further partitioned by the algorithm until a result is obtained. The Fig. 2 illustrates the output variance vs input variance according to the value of K. Working an upper bound of K, the ratio output variance/input variance changes quickly and in critical conditions, K takes the value of K_{max}, the system has stability problems. Observing the Fig.2, when the value of K is high the output variance decreases sharply, we concluded that the optimal value is 0.72 K_{max}.

Based on the previous analysis, a fuzzy noise membership function is proposed. The detector was installed in the layer 0 and it is based on the PSD (Power Spectral Density) explained before. For to detect the noise, a membership function $m_N(u)$ was defined . The expression is the following:

$$m_N(u) = \begin{cases} 0 & PSD_{[illegible]}(K,u) \le PSD_{[illegible]}(K_{[illegible]},u) \\ 1 & \text{otherwise} \end{cases} \quad (7)$$

The membership function is likely to be an S-shaped function. The noise inference rule consists in a simple rule as follows:

IF (input is noise) THEN (output is noise)

The membership function for output was developed according to the behaviour of K as we mentioned earlier. The new membership functions (detection and applications) wereapplied to the inputs in the layer 0

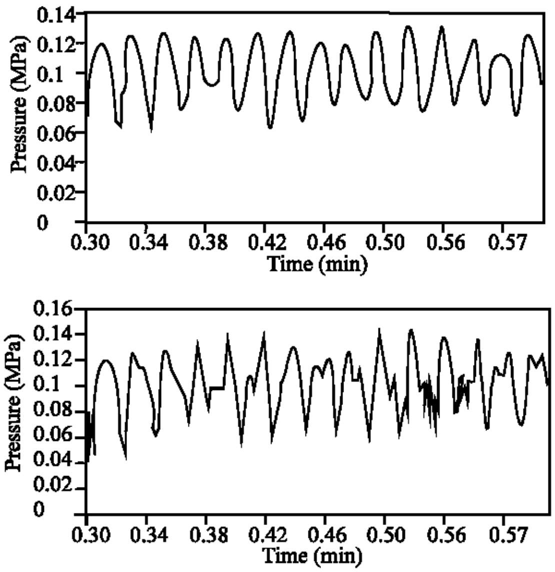

Fig. 3: Response of the pressure with (a) and without (b) fuzzy noise filter

When the noise is detected the signal is amplified

$$m_{Nb}(u) = \begin{cases} 0 & PSD_{mean}(K,u) \le PSD_{mean}(K_{max},u) \\ 0.72K_{max}u & \text{otherwise} \end{cases} \quad (8)$$

before they can be processed for the controller (ANFIS)[14]. This fuzzy filter gives a clean signal as in the next section is demonstrated.

RESULT

A wood dryer was used as pilot equipment. The dryer works between 92.5 and 103°C, depending on the drying schedule and the species of wood, (Fig. 3). The ventilating fans inside are installed between the trusses. The heating system works with steam to 110°C and the tubes are made of stainless steel. The controlled variables are: Temperature and Pressure and the manipulated variables are steam flow (one modulating valve was installed) and fan speed. For guarantee a good behaviour of ANFIS, we have to consider the following aspects[12-14].

- The user should define distinctive rule-bases for different situations during workdays. These rule-bases are processed independent of each other corresponding to the current situation. The task of the user is to inform the system about the current situation. Besides, the user should be able to instruct the system not to adapt the current rule base. This enables a single modification of the current temperaturewithout modifying the rule-base permanently.
- The rule-base must consist of a suitable number of rules. It can be shown that if the number of rules isn't restricted, a zero-order Sugeno model has unlimited approximation, in the case that the rule base consists of to few rules, the system has convergence problems.

At operating conditions, the dryer was tested using pinewood. As indicate the Fig. 1, the controlled variables and manipulated variables have Gaussian distributions. The temperature (controlled variable) has the lowest value in 92.5°C, the highest value in 103°C and the maximum in 92.5°C. The pressure changes from 0.1 to 0.2 MPa with a maximum in 0.11MPa. For manipulated variables: the fan speed changes from 0% to 100% and the maximum is 60%. The flow steam changes from 0 m^3/h to 20.0 m^3/h and the maximum is in 11.8 m^3/h. Observing the Fig. 3, the quality of the signal is better using ANFIS+ fuzzy noise filter, the "jitters" were reduced and the quality of the signal improved. In the Fig. 4, the temperature was maintained in the set point (371 K) and the manipulated variables; see Fig. 5, settled down at 72% (fan) and 13.1

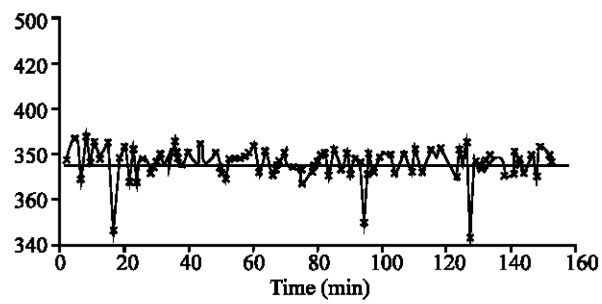

Fig. 4: Behaviour of the temperature using pinewood

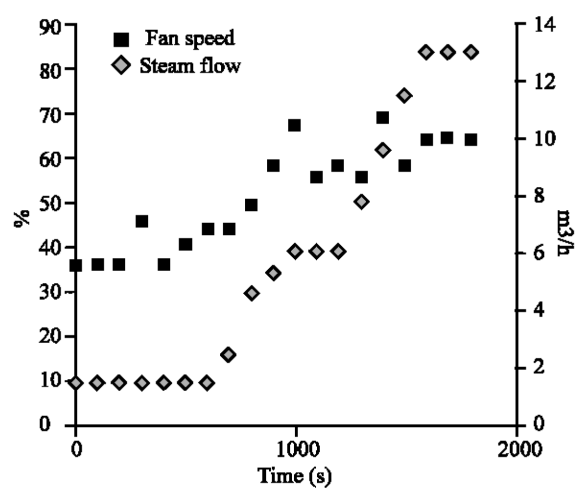

Fig. 5: Behaviour of the manipulated variables in operating conditions

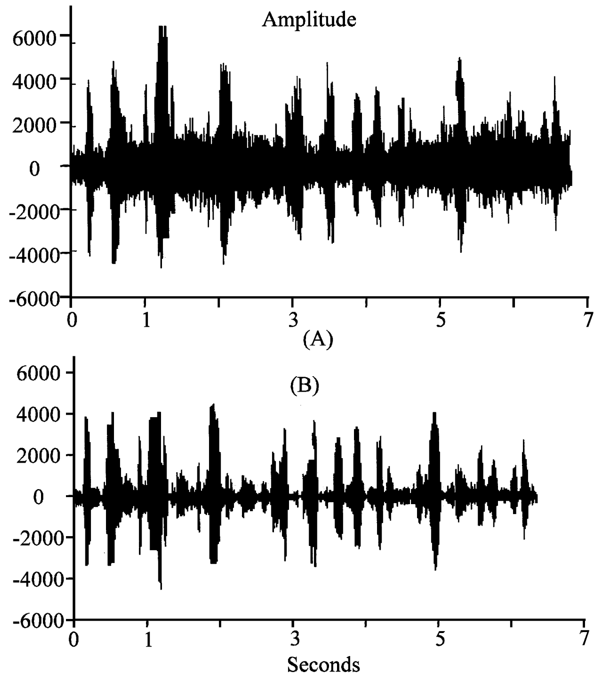

Fig. 6: An Example of noisy (a) and clean (b) signal

m^3/h (steam flow). Although its relative simplicity and the straightforward implementation of the fuzzy operators, the fuzzy filter is able to compete with state-of-the-art filter techniques for noise reduction. A numerical measure, such as MSE (Mean Square Error) and visual observation show convincing results. Finally, the fuzzy filter scheme is sufficiently simple to enable fast hardware implementations.

Finally, a considerable improvement can be seen in the (Fig. 6) where the noisy and clean signals are compared. Compared with the traditional ANFIS, the introduction of the new membership function in ANFIS increases the recognition rates in consequence, the quality of the signal is improved considerably and also the control system.

CONCLUSIONS

In order to improve the quality of the signal in ANFIS a simple fuzzy filter was created and incorporated to the layer 0 of the system. The new ANFIS requires lower computational complexity and the results indicated that the dryer works without problem and the quality of the signal and the response of the system improved greatly.

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