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Interval Type-1 Non-Singleton Type-2 TSK Fuzzy Logic Systems Using the Hybrid Training Method RLS-BP

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***Abstract*–This article presents a new learning methodology based on a hybrid algorithm for interval type-1 non-singleton type-2 TSK fuzzy logic systems (FLS). Using input-output data pairs during the forward pass of the training process, the interval type-1 non-singleton type-2 TSK FLS output is calculated and the consequent parameters are estimated by the recursive least-squares (RLS) method. In the backward pass, the error propagates backward, and the antecedent parameters are estimated by the back-propagation (BP) method. The proposed hybrid methodology was used to construct an interval type-1 non-singleton type-2 TSK fuzzy model capable of approximating the behaviour of the steel strip temperature as it is being rolled in an industrial Hot Strip Mill (HSM) and used to predict the transfer bar surface temperature at finishing Scale Breaker (SB) entry zone. Comparative results show the performance of the hybrid learning method (RLS-BP) against the only BP learning method.**

I. Introduction

INTERVAL type-2 (IT2) fuzzy logic systems (FLS) constitute an emerging technology. In [1] both, one-pass and back-propagation (BP) methods are presented as IT2 Mamdani FLS learning methods, but only BP is presented for IT2 Takagi-Sugeno-Kang (TSK) FLS systems. One-pass method generates a set of IF-THEN rules by using the given training data one time, and combines the rules to construct the final FLS. When BP method is used in both Mamdani and TSK FLS, none of antecedent and consequent parameters of the IT2 FLS are fixed at starting of training process; they are tuned using exclusively steepest descent method. In [1] recursive least-squares (RLS) and recursive filter (REFIL) algorithms are not presented as IT2 FLS learning methods.

The hybrid algorithm for IT2 Mamdani FLS has been already presented elsewhere [2, 3, 4] with three combinations of learning methods: RLS-BP, REFIL-BP and orthogonal least-squares (OLS)-BP, whilst the hybrid algorithm for singleton IT2 TSK FLS (IT2 TSK SFLS or IT2 ANFIS) has been presented elsewhere [5] with two combinations of learning methods: RLS-BP and REFIL-BP.

The aim of this work is to present and discuss a new hybrid learning algorithm for interval type-1 non-singleton type-2 TSK FLS (IT2 TSK NSFLS-1 or IT2 NS1 ANFIS) using RLS-BP combination in order to estimate the antecedent and consequent parameters during the training process. The proposed IT2 TSK NSFLS-1 inference system is evaluated making transfer bar surface temperature predictions at Hot Strip Mill (HSM) Finishing Scale Breaker (SB) entry zone.

II. Proposed Methodology

A. Input-Output Data Pairs

Most of the industrial processes are highly uncertain, non-linear, time varying and non-stationary [2, 6], having very complex mathematical representations. Interval type-2 TSK NSFLS-1 takes easily the random and systematic components of type A or B standard uncertainty [7] of industrial measurements. The non-linearities are handled by FLS as identifiers and universal approximators of nonlinear dynamic systems [8, 9, 10, 11]. Stationary and non-stationary additive noise is modeled as a Gaussian function centred at the measurement value. In stationary additive noise the standard deviation takes a single value, whereas in non-stationary additive noise the standard deviation varies over an interval of values [1]. Such characteristics make IT2 TSK NSFLS-1 a powerful inference system to model and control industrial processes.

Only the BP learning method for IT2 TSK SFLS has been proposed in the literature and it is used as a benchmark algorithm for parameter estimation or systems identification on IT2 TSK FLS systems [1]. To the best knowledge of the authors, IT2 TSK NSFLS-1 has not been reported in the literature [1, 12, 13], using neither BP nor hybrid RLS-BP training.

One of the main contributions of this work is to implement an application of the IT2 TSK NSFLS-1 (IT2 NS1 ANFIS) using the hybrid REFIL-BP learning algorithm, capable of compensate for uncertain measurements.

B. Using Hybrid RLS-BP Method in Interval Type-2 TSK FLS Training

The Table 1 shows the activities of the one pass learning algorithm of BP method. Both, IT2 TSK SFLS (BP) and IT2 TSK NSFLS-1 (BP) outputs are calculated during forward pass. During the backward pass, the error propagates backward and the antecedent and consequent parameters are estimated using only the BP method.

TABLE I
ONE PASS IN LEARNING PROCEDURE FOR IT2 TSK SFLS

	Forward Pass	Backward Pass
Antecedent Parameters	Fixed	BP
Consequent Parameters	Fixed	BP

The proposed hybrid algorithm (IT2 NS1 ANFIS) uses RLS during forward pass for tuning of consequent parameters as well as the BP method for tuning of antecedent parameters, as shown in Table II. It looks like Sugeno type-1 ANFIS [13, 14], which uses RLS-BP hybrid learning rule for type-1 FLS systems.

TABLE II
TWO PASSES IN HYBRID LEARNING PROCEDURE FOR IT2 NS1 ANFIS

	Forward Pass	Backward Pass
Antecedent Parameters	Fixed	BP
Consequent Parameters	RLS	Fixed

C. Adaptive Learning Algorithm

The training method is presented as in [1]: Given N input-output training data pairs, the training algorithm for E training epochs, should minimize the error function:

$$e^{(t)} = \frac{1}{2}\left[f_{IT2-FLS}\left(\mathbf{x}^{(t)}\right) - y^{(t)}\right]^2 \tag{1}$$

D. Hot Strip Mill

Because of the complexities and uncertainties involved in rolling operations, the development of mathematical theories has been largely restricted to two-dimensional models applicable to heat losing in flat rolling operations.

Fig. 1, shows a simplified diagram of a HSM, from the initial point of the process at the reheat furnace entry to its end at the coilers.

Besides the mechanical, electrical and electronic equipment, a big potential for ensuring good quality lies in the automation systems and the used control techniques. The most critical process in the HSM occurs in the Finishing Mill (FM). There are several mathematical model based systems for setting up the FM. There is a model-based set-up system [18] that calculates the FM working references needed to obtain gauge, width and temperature at the FM exit stands. It takes as inputs: FM exit target gage, target width and target temperature, steel grade, hardness ratio from slab chemistry, load distribution, gauge offset, temperature offset, roll diameters, load distribution, transfer bar gauge, transfer bar width and transfer bar temperature entry.

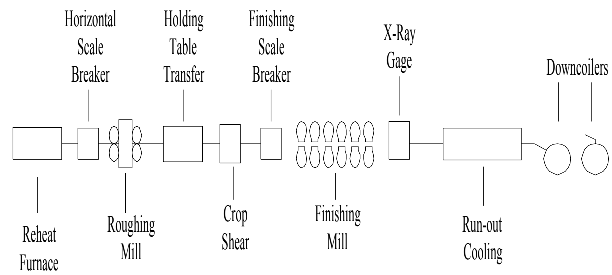

Fig. 1. Typical Hot Strip Mill

The errors in the gauge of the transfer bar are absorbed in the first two FM stands and therefore have a little effect on the target exit gauge. It is very important for the model to know the FM entry temperature accurately. A temperature error will propagate through the entire FM.

E. Design of the IT2 NSFLS-1

The architecture of the IT2 TSK NSFLS-1 was established in such away that its parameters are continuously optimized. The number of rule-antecedents was fixed to two; one for the Roughing Mill (RM) exit surface temperature and one for transfer bar head traveling time. Each antecedent-input space was divided in three fuzzy sets (FSs), fixing the number of rules to nine. Gaussian primary membership functions (MFs) of uncertain means were chosen for the antecedents. Each rule of the each IT2 TSK NSFLS-1 is characterized by six antecedent MFs parameters (two for left-hand and right-hand bounds of the mean and one for standard deviation, for each of the two antecedent Gaussian MFs) and six consequent parameters (one for left-hand and one for right-hand end points of each of the three consequent type-1 FSs), giving a total of twelve parameters per rule. Each input value has one standard deviation parameter, giving two additional parameters.

F. Noisy Input-Output Training Data

From an industrial HSM, noisy input-output pairs of three different product types were collected and used as training and checking data. The inputs are the noisy measured RM exit surface temperature and the measured RM exit to SB entry transfer bar traveling time. The output is the noisy measured SB entry surface temperature.

G. Fuzzy Rule Base

The IT2 TSK NSFLS-1 fuzzy rule base consists of a set of IF-THEN rules that represents the model of the system. The IT2 TSK NSFLS-1 has two inputs $x_1 \in X_1$, $x_2 \in X_2$ and one output $y \in Y$. The rule base has $M = 9$ rules of the form:

$$R^i : IF \quad x_1 \quad is \quad \tilde{F}_1^i \quad and \quad x_2 \quad is \quad \tilde{F}_2^i,$$

$$THEN \quad Y^i = \quad C_0^i + C_1^i x_1 + C_2^i x_2 \tag{2}$$

where Y^i the output of the ith rule is a fuzzy type-1 set, and the parameters C_j^i, with i = 1,2,3,…,9 and j = 0,1,2, are the consequent type-1 FSs.

H. Input Membership Functions

The primary MFs for each input of the interval type-2 NSFLS-1 are Gaussians of the form:

$$\mu_{X_k}(x_k) = \exp\left[-\frac{1}{2}\left[\frac{x_k - x_k'}{\sigma_{X_k}}\right]^2\right] \tag{3}$$

where: k = 1,2 (the number of type-2 non-singleton inputs), $\mu_{X_k}(x_k)$ is centered at $x_k = x_k'$ and σ_{X_k} is the standard deviation. The standard deviation of the RM exit surface temperature measurement, σ_{X_1}, was initially set to 13.0 ^oC and the standard deviation of head end traveling time measurement, σ_{X_2}, was initially set to 2.41 s. The uncertainty of the input data is modeled as stationary additive noise using type-1 FSs

I. Antecedent Membership Functions

The primary MFs for each antecedent are interval type-2 FSs described by Gaussian primary MFs with uncertain means:

$$\mu_k^i(x_k) = \exp\left[-\frac{1}{2}\left[\frac{x_k - m_k^i}{\sigma_k^i}\right]^2\right] \tag{4}$$

where $m_k^i \in \left[m_{k1}^i, m_{k2}^i\right]$ is the uncertain mean, with k =1,2 (the number of antecedents) and i = 1,2,..9 (the number of M rules), and σ_k^i is the standard deviation. The means of the antecedent FSs are uniformly distributed over the entire input space.

Table 3 shows the calculated interval values of uncertainty of x_1 input, where $[m_{11}, m_{12}]$ is the uncertain mean and σ_1 is the standard deviation for all the 9 rules. Fig. 2 shows the initial MFs of the antecedents for of x_1 input.

TABLE III
x_1 INPUT INTERVALS OF UNCERTAINTY

FS	m_{11} ^oC	m_{12} ^oC	σ_1 ^oC
1	950	952	60
2	1016	1018	60
3	1080	1082	60

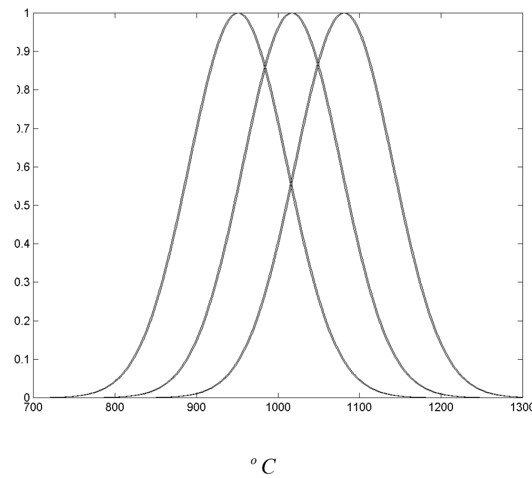

Fig. 2. MF s of the Antecedents for x_1 Input

Table 4 shows the interval values of uncertainty for x_2 input, where $[m_{21}, m_{22}]$ is the uncertain mean and σ_2 is the standard deviation for all the 9 rules. Fig. 3 shows the initial MFs of the antecedents for of x_2 input.

TABLE Iv
x_2 INPUT INTERVALS OF UNCERTAINTY

Product Type	m_{21} s	m_{22} S	σ_2 s
A	32	34	10
B	42	44	10
C	56	58	10

The standard deviation of temperature noise σ_{n1} was initially set to 1 ^oC and the standard deviation of time noise σ_{n2} was set to 1 s.

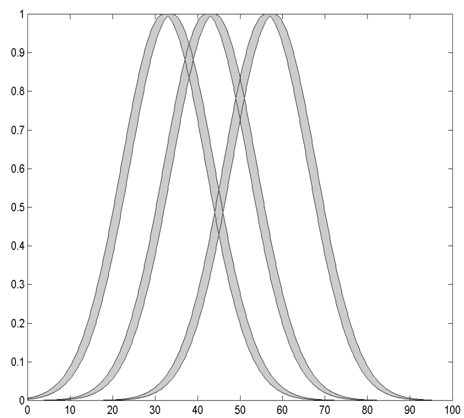

Fig. 3. MFs of the Antecedents for of x_2 Input

J. Consequent Membership Functions

Each consequent is an interval type-1 FS with $Y^i = [y_l^i, y_r^i]$:

$$y_l^i = \sum_{j=1}^{p} c_j^i x_j + c_0^i - \sum_{j=1}^{p} |x_j| s_j^i - s_0^i \tag{5}$$

and

$$y_r^i = \sum_{j=1}^{p} c_j^i x_j + c_0^i + \sum_{j=1}^{p} |x_j| s_j^i + s_0^i . \tag{6}$$

where c_j^i denotes the center (mean) of C_j^i , and s_j^i denotes the spread of C_j^i , with $i = 1,2,3,..,9$. Then y_l^i and y_r^i are the consequent parameters. When only the input-output data training pairs $(x^{(1)} : y^{(1)})$,…, $(x^{(N)} : y^{(N)})$ are available and there is no data information about the consequents, the initial values for the centroid parameters c_j^i and s_j^i can be chosen arbitrarily in the output space [16-17]. In this work the initial values of c_j^i were set equal to 0.001 and the initial values of s_j^i equal to 0.0001.

III. Results

The IT2 TSK NSFLS-1(RLS-BP) system was trained and used to predict the SB entry temperature, applying the RM exit measured transfer bar surface temperature and RM exit to SB entry zone traveling time as inputs. We ran fifteen epochs of training; one hundred and ten parameters were tuned using eighty seven, sixty-eight and twenty-eight input-output training data pairs per epoch, for type A, type B and type C products respectively.

The performance evaluation for the hybrid IT2 TSK NSFLS-1 (RLS-BP) system was based on root mean-squared error (RMSE) benchmarking criteria as in [1]:

$$RMSE_{IT2-FLS}(*) = \sqrt{\frac{1}{n} \sum_{k=1}^{n} \left[Y(k) - f_{s2-*}\left(\mathbf{x}^{(k)}\right) \right]^2} \tag{7}$$

where $Y(k)$ is the output data from the input-output checking data pairs.

$RMSE_{IT2-FLS}(*)$ stands for $RMSE_{TSK2,SFLS}(BP)$ [the RMSE of the IT2 TSK SFLS (BP)] and for $RMSE_{TSK2,NSFLS-1}(BP)$ [the RMSE of the IT2 TSK NSFLS-1(BP)], whereas $RMSE_{TSK2,NSFLS-1}(REFIL - BP)$ [the RMSE of the IT2 TSK NSFLS-1(RLS-BP)] is obtained when the hybrid algorithm is applied to IT2 TSK NSFLS-1.

Fig. 4 shows the RMSEs of the two IT2 TSK SNFLS-1 systems and the base line IT2 TSK SFLS (BP) for fifty epochs' of training for the case for type C products. Observe that from epoch 1 to 4 the hybrid IT2 TSK NSFLS-1 (RLS-BP) has better performance than both: the IT2 TSK SFLS (BP) and the IT2 TSK NSFLS-1 (BP). From epoch 1 to 4 the RMSE of the IT2 TSK SFLS has an oscillation, meaning that it is very sensitive to its learning parameters values. At epoch 5, it reaches its minimum RMSE and is stable for the rest of training.

V. Conclusions

An IT2 TSK NSFLS-1 (IT2 NS1 ANFIS) using the hybrid RLS-BP training method was tested and compared for predicting the surface temperature of the transfer bar at SB entry. The antecedent MFs and consequent centroids of the IT2 TSK NSFLS-1 tested, absorbed the uncertainty introduced by all the factors: the antecedent and consequent values initially selected, the noisy temperature measurements, and the inaccurate traveling time estimation. The non-singleton type-1 fuzzy inputs are able to compensate the uncertain measurements, expanding the applicability of IT2 NS1 ANFIS systems.

It has been shown that the proposed IT2 NS1 ANFIS system can be applied in modeling and control of the steel coil temperature. It has also been envisaged its application in any uncertain and non-linear system prediction and control.

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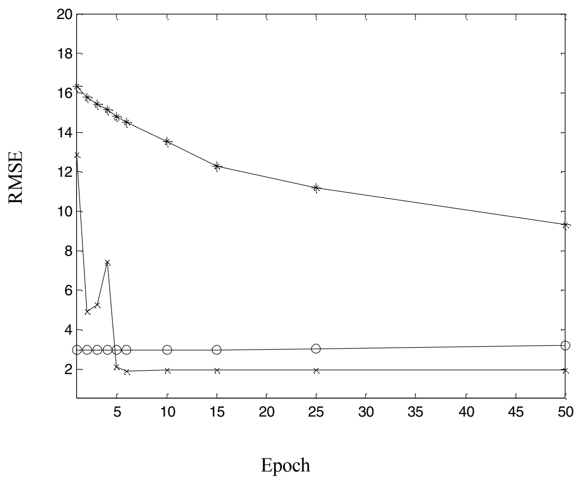

Fig. 4 (*) RMSE $_{TSK\ 2,\ SFLS}$ (BP) (+) RMSE $_{TSK\ 2,\ NSFLS\text{-}1}$ (BP) (o) RMSE $_{TSK\ 2,\ NSFLS\text{-}1}$ (REFIL-BP)

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