Interval Type-1 Non-Singleton Type-2 TSK Fuzzy Logic Systems Using the Kalman Filter - Back Propagation Hybrid Learning Mechanism

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Abstract. This article presents a novel learning methodology based on the hybrid mechanism for training of interval type-1 non-singleton type-2 Takagi-Sugeno-Kang fuzzy logic systems (IT2 TSK NSFLS1). The process of combining multiple computational intelligence techniques to build a hybrid model has become increasingly popular. As reported in the literature, the performance indices of these hybrid models have proved to be better than the individual training mechanism when used alone. In this work using non-singleton input-output data pairs during the forward pass of the training process, the output is calculated and the consequent parameters are tuned by recursive filter method (REFIL), a Kalman filter type. In the backward pass, the error propagates backward, and the antecedent parameters are tuned by back-propagation method (BP). The proposed hybrid methodology was tested thought the modeling and prediction of the steel strip temperature as it is being rolled in an industrial hot strip mill, and for comparative purposes, under the same controlled conditions maintained on previous work related to IT2 TSK hybrid training. Results show the performance of the hybrid learning method (REFIL-BP) both, using singleton, and type-1 non-singleton input-outputs data pairs. The latter is capable of compensate the IT2 TSK predictor's tuning for uncertain measurements, whilst the former cannot. Also, the results show that the hybrid models perform better than the individual techniques when used alone for the same datasets.

Keywords: IT2 TSK fuzzy logic systems, ANFIS, hybrid learning.

1 Introduction

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. The 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 FLSs, none of antecedent and consequent parameters of the IT2 FLS is fixed at starting of training process; they are tuned using exclusively steepest descent method. In [1] recursive least squares (RLS) and recursive Kalman filter (REFIL) algorithms are not presented as IT2 FLS learning methods.

The aim of this work is to present and discuss the hybrid-learning algorithm for antecedent and consequent parameters tuning during training process for interval type-1 non-singleton type-2 TSK FLS (IT2 TSK NSFLS-1 or IT2 NS1 ANFIS) systems, using during the forward pass of training REFIL method, while during the backward pass, the BP method.

The hybrid algorithm for IT2 Mamdani FLS has been already presented elsewhere [2], [3], [4], [5] and [6] with three combinations of the learning method: RLS-BP, REFIL-BP and orthogonal least-squares-BP (OLS-BP). The hybrid algorithm for singleton IT2 TSK SFLS (IT2 ANFIS) has been presented elsewhere [7] and [8] with two combinations of the learning method: RLS-BP and REFIL-BP, whilst the hybrid algorithm for interval non-singleton type-1 IT2 TSK NSFLS-1 (IT2 NS1 ANFIS) has been presented in [9] and [10] only with the hybrid learning mechanism RLS-BP. There does not seem to be any other mention of type-1 or type-2 non-singleton IT2 TSK FLS in the literature [1], using the REFIL-BP learning mechanisms. It has been never presented before.

In this work, the IT2 TSK NSFLS-1 system that uses the hybrid learning mechanism (REFIL-BP) has been developed and implemented for temperature prediction of the transfer bar at hot strip mill (HSM). The same data-set used in previous works [7], [8], [9], and [10] in order to serve as comparison of functionality and stability of the novel hybrid mechanism and for comparation results. The intention of this paper is to show the implementation in a real industrial application of the (REFIL-BP) hybrid mechanism, training a non-singleton type-1 IT2 TSK FLS.

2 Proposed Methodology

Most of the hot strip mill processes are highly uncertain, non-linear, time varying and non-stationary [2,11], having very complex mathematical representations. IT2 NS1 ANFIS takes easily the random and systematic components of type A or B standard uncertainty [12] of industrial measurements. The non-linearities are handled by FLS as identifiers and universal approximators of nonlinear dynamic systems [13,14,15,16,17]. Stationary and non-stationary additive noise is modeled as a Gaussian function centered at the measurement value [1]. 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].

The BP learning method for IT2 TSK SFLS has been used as a benchmark algorithm for parameter estimation or systems identification [1]. To the best knowledge of the authors, IT2 NS1 ANFIS approach has not been reported in the literature [1,18].

2.1 Hybrid REFIL_BP Method in IT2 ANFIS Training

The IT2 NS1 ANFIS is trained using the hybrid mechanism: it uses REFIL during forward pass for tuning of consequent parameters as well as the BP method for tuning of antecedent parameters, as shown in Table 1. It has the same training mechanism as the type-1 ANFIS [18, 19], the RLS-BP hybrid combination.

Table 1. Two passes in hybrid learning procedure for IT2 NS1 ANFIS (REFIL-BP)

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

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:

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

where e^t is the error function at time t, $f_{IT2-FLS}\left(\mathbf{x}^{(t)}\right)$ is the output of the IT2 FLS using the input vector $\mathbf{x}^{(t)}$ from the non-singleton type-1 input-output data pairs, and $y^{(t)}$ is the output from the non-singleton type-1 input-output data pairs.

3 Application to Transfer Bar Surface Temperature Prediction

3.1 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.

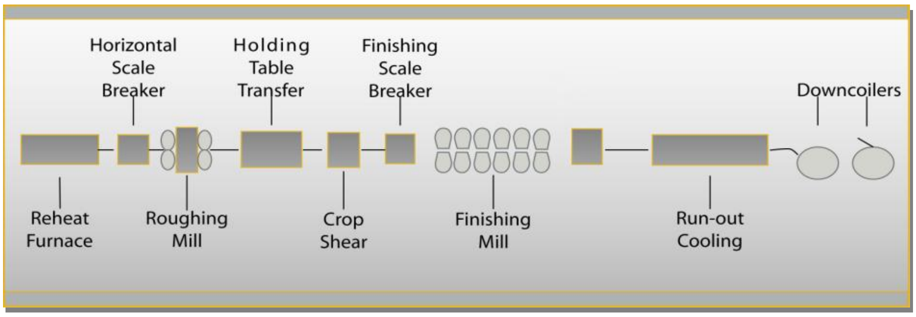

Fig. 1. Typical hot strip mill

A model-based set-up system [20] calculates the FM working references needed to obtain gauge, width and temperature at the FM exit stands.

3.2 Design of the IT2 NS1 ANFIS

The architecture of the IT2 NS1 ANFIS is established in such a way that its parameters are continuously optimized. The number of rule-antecedents is fixed to two, one for the roughing mill (RM) exit surface temperature, and one for transfer bar head traveling time. Each antecedent-input space is divided in three fuzzy sets (FSs), fixing the number of rules to nine. Gaussian primary membership functions (MFs) of uncertain means are chosen for the antecedents. Each rule of the IT2 NS1 ANFIS 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). Each input value has one standard deviation parameter, giving fourteen parameters per rule.

3.3 Input-Output Data Pairs

From an industrial HSM, noisy non-singleton type-1 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.

3.4 Fuzzy Rule Base

The IT2 NS1 ANFIS fuzzy rule base consists of a set of IF-THEN rules that represents the model of the system. The IT2 NS1 ANFIS system 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:

$$R^i : IF \quad x_1 \quad is \quad \tilde{F}_1^i \quad and \quad x_2 \quad is \quad \tilde{F}_2^i, \quad THEN \quad Y^i = C_0^i + C_1^i x_1 + C_2^i x_2 \ . \tag{2}$$

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.

3.5 Input Membership Functions

The primary MFs for each input of the IT2 NS1 ANFIS are Gaussians of the form:

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

where: $\sigma_k \in [\sigma_1, \sigma_2]$ k=1,2 (the number of type-1 non-singleton inputs), and $\mu_{Xk}(x_k)$ centered at the measured input $x_k = x'_k$. The uncertain standard deviation σ_1 of RM exit surface temperature measurement was initially set as 13.0°C and the uncertain standard deviation σ_2 of head-end traveling time measurement was initially set to 1.91s.

3.6 Antecedent Membership Functions

The primary MFs for each antecedent are FSs described by Gaussian 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 $m_k^i \in [m_{k1}^i, m_{k2}^i]$ 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 fuzzy sets are uniformly distributed over the entire input space.

3.6 Consequent Membership Functions

Each consequent is an unnormalized interval type-2 TSK FLS with $Y^i = [y_l^i, y_r^i]$ where

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

and

$$y_r^i = \sum_{j=1}^{p} c_j^i x_j + c_0^i + \sum_{j=1}^{p} \left| x_j \right| s_j^i + s_0^i \ . \qquad \textbf{(6)}$$

both, are unnormalized type-1 TSK FLS, where c_j^i denotes the center (mean) of C_j^i and s_j^i denotes the spread of C_j^i, with $i = 1,2,3,..,9$ and $j = 0,1,2$. Then y_l^i and y_r^i are the consequent parameters.

4 Application Results

The IT2 NS1 ANFIS (REFIL-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 fifty 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 NS1 ANFIS (REFIL-BP) system was based on root mean-squared error (RMSE) benchmarking criteria as in [1].

Fig. 2 shows the RMSEs of three non-hybrid IT2 TSK ANFIS systems trained using only the BP algorithm fort both, antecedent and consequent parameters; all of them for fifty epochs' of training for the case of products of type C.

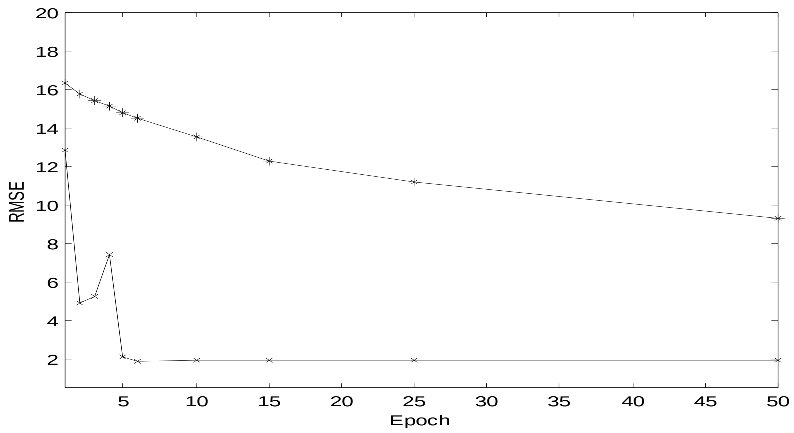

Fig. 2. (*) RMSE IT2 TSK SFLS (BP-BP) (+) RMSE IT2 TSK NSFLS1 (BP-BP)

Fig. 3 shows the RMSEs of two IT2 TSK ANFIS systems trained using the proposed hybrid REFIL-BP algorithm, for products of type C. For this experiment, starting at epoch 1, the IT2 NS1 ANFIS has better performance than the singleton IT2

ANFIS. When compared to the IT2 TSK NSFLS1 (BP) systems, the proposed hybrid approach IT2 TSK NSFLS1 (REFIL-BP) proved to be better in terms of both, the temperature prediction with only one epoch and several epochs of training.

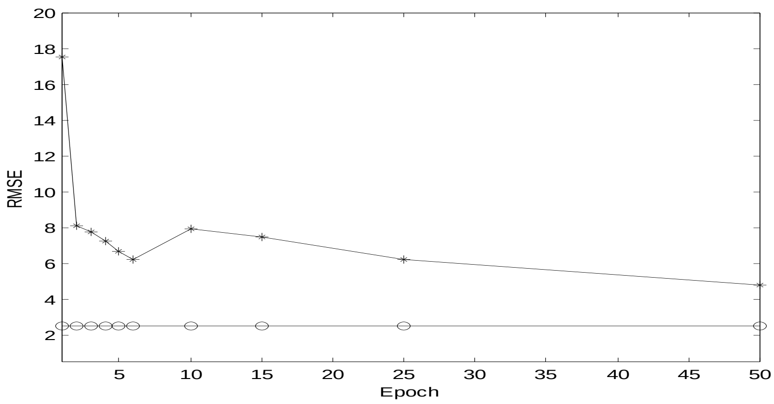

Fig. 3. (*) RMSE IT2 TSK SFLS (REFIL-BP) (o) RMSE IT2 TSK NSFLS1 (REFIL-BP)

5 Conclusions

An IT2 NS ANFIS using the hybrid REFIL-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 NS1 ANFIS absorbed the uncertainty introduced by all the factors: the antecedent and consequent initially values, 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 of the steel coil temperature. It has also been envisaged its application in any uncertain and non-linear system prediction and control, as in furnace temperature control, aerospace stability control, turbine trust control and especially in those applications where there are measurements uncertainty.

The proposed hybrid IT2 NS1 ANFIS (REFIL-BP) system has the good performance and stability after only one epoch of training: an important characteristic for computational intelligent systems when there is a chance of only one epoch of training. It is required to emphasize that the used IT2 ANFIS systems are very sensitive to the values of learning parameter's gain.

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