Orthogonal-Back Propagation Hybrid Learning Algorithm for Interval Type-2 Non-Singleton Type-2 Fuzzy Logic Systems

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Abstract. This article presents a new learning methodology based on an hybrid algorithm for interval type-2 non-singleton type-2 fuzzy logic systems (FLS) parameters estimation. Using input-output data pairs during the forward pass of the training process, the interval type-2 FLS output is calculated and the consequent parameters are estimated by orthogonal least-square (OLS) method. In the backward pass, the error propagates backward, and the antecedent parameters are estimated by back-propagation (BP) method. The proposed hybrid methodology was used to construct an interval type-2 fuzzy model capable of approximate the behavior 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 advantage of the hybrid learning method (OLS-BP) over that with only BP.

1 Introduction

Interval type-2 fuzzy logic systems (FLS) constitute an emerging technology. In [1] the interval type-2 FLS learning methods are one-pass and back-propagation (BP) methods. One-pass method generates a set of IF-THEN rules by using the given training data once, and combines the rules to construct the final FLS. In back-propagation, none of antecedent and consequent parameters of the interval type-2 FLS are fixed at starting of training process; they are tuned using BP method. Recursive least-square (RLS) is not presented as interval type-2 FLS learning method.

One-pass and Back-Propagation (BP) are presented as type-2 FLS learning methods in [1]. One-pass method generates a set of IF-THEN rules by using the given

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training data once, and combines the rules to construct the final fuzzy logic systems (FLS). None of the antecedent and consequent parameters of interval type-2 FLS are fixed at the start of the training process in BP; instead they are tuned by using the steepest descent method. To the best knowledge of the authors, the hybrid learning method has not been reported in type-2 FLS.

Only the BP learning method for type-2 FLS has been proposed in the literature, therefore one of the main contributions of this work is to implement a new hybrid learning algorithm for interval type-2 FLS, in view of the success of the hybrid learning method in type-1 FLS [2]. In [3, 4] it is shown that hybrid algorithms improve convergence over the BP method. In the forward pass, FLS output is calculated and the consequent parameters are estimated by either RLS [2] or REFIL [5] methods. In the backward pass, the error propagates backward, and the antecedent parameters are estimated by the BP method. In [3, 4] one of the proposed hybrid algorithms is based on RLS, since it is a benchmark algorithm for parameter estimation or systems identification. In addition, the parameter estimation method called REFIL, has also been used since it improves performance over RLS [5]. Convergence of the proposed methods has been practically tested; however mathematical proof is still to be done in general for hybrid learning algorithms.

This papers proposes a hybrid learning algorithm for interval type-2 FLS for antecedent and consequent parameter estimation during training process using input-output data pairs. In the forward pass, FLS output is calculated and the consequent parameters are estimated using REDCO [5] a recursive orthogonal least-square (OLS) learning method. In the backward pass, the error propagates backward, and the antecedent parameters are estimated by the BP method.

A second but very important purpose of this paper is to propose an application methodology based on interval type-2 FLS and the hybrid learning method mentioned above for hot strip mill (HSM) temperature prediction. Interval type-2 FLS is suitable for industrial modelling and control applications. The scale breaker (SB) entry mean and surface temperatures are used by the finishing mill set-up (FSU) model [6] to preset the finishing mill (FM) stand screws and to calculate the transfer bar thread speed, both required to achieve the FM exit target head gage the target head temperature.

In temperature prediction, the inputs of the fuzzy type-2 models, used to predict the SB entry temperatures, are the surface temperature of the transfer bar at the roughing mill (RM) exit (x_1) and the time required by the transfer bar head to reach the SB entry zone (x_2). Currently, the surface temperature is measured using a pyrometer located at the RM exit side. Scale grows at the transfer bar surface producing a noisy temperature measurement. The measurement is also affected by environment water steam as well as pyrometer location, calibration, resolution and repeatability. The head end transfer bar travelling time is estimated by the FSU model using FM estimated thread speed. Such estimation has an error associated with the inherent FSU model uncertainty. Although temperature prediction (y) is a critical issue in a HSM the problem has not been fully addressed by fuzzy logic control systems [1, 3, 4].

The proposed algorithm is evaluated using an interval type-2 non-singleton type-2 FLS inference system (type-2 NSFLS-2) which predicts the transfer bar surface temperature at the SB entry zone.

This work is organized as follows. Section 2 gives the hybrid learning problem formulation for interval type-2 fuzzy logic systems. Section 3 presents solution as an adaptive training algorithm. Section 4 shows an interval type-2 NSFLS-2 application for HSM temperature prediction using the hybrid learning method. Conclusions are stated in Section 5.

2 Problem Formulation

Most of the industrial processes are highly uncertain, non-linear, time varying and non-stationary [3, 4, 7], having very complex mathematical representations. Interval type-2 FLS take easily the random and systematic components of type A or B standard uncertainty [8] of industrial measurements. The non-linearities are handled by FLS as identifiers and universal approximators of nonlinear dynamic systems [9, 10, 11]. The stationary noise and non-stationary additive noise are handled in natural way by interval type-2 FLS [1]. Such characteristics make interval type-2 FLS a very powerful inference system to model and control industrial processes

In [1] only one-pass and back-propagation (BP) algorithms are presented as interval type-2 FLS learning methods. Three basic problems for which it is not possible to use RLS on interval type-2 FLS are explained:

1. The starting point for the RLS method to designing an interval singleton FLS is a type-1 Fuzzy Basis Function (FBF) expansion. No such FBF expansion exists for a general type-2 non-singleton type-2 FLS. Since an interval type-2 FLS output $y(\mathbf{x})$ can be expressed as:

$$y(\mathbf{x}) = \frac{1}{2}\left[\mathbf{y}_l^T \mathbf{p}_l(\mathbf{x}) + \mathbf{y}_r^T \mathbf{p}_r(\mathbf{x})\right] . \quad (1)$$

with M ordered rules, it looks like a least-squares method can be used to tune the parameters in $\mathbf{y}_l^T$ (matrix transpose of M left-points y_l^i of consequent centroids) and $\mathbf{y}_r^T$ (matrix transpose of M right-points y_r^i of consequent centroids). Unfortunately, this is incorrect. The problem is that in order to know the FBF expansions $\mathbf{p}_l(\mathbf{x})$ and $\mathbf{p}_r(\mathbf{x})$, each y_l^i and y_r^i (the M left-points and right-points of interval consequent centroids) must be known first. Because at initial conditions of the calculations there are no numerical values for those elements, it is impossible to do this; hence the FBF expansions $\mathbf{p}_l(\mathbf{x})$ and $\mathbf{p}_r(\mathbf{x})$ cannot be calculated. This situation does not occur for type-1 FBF expansion.
2. Although y_l and y_r (the end-points of interval type-2 FLS center-of-sets type-reduced set Y_{COS}) can be expressed as an interval $\left[\underline{f}^i, \overline{f}^i\right]$ in terms of

their lower ($\underline{f}^i$) and upper ($\overline{f}^i$) M firing sets, and the corresponding M consequents left and right-points, y_l^i and y_r^i , as:

$$y_l = y_l\left(\overline{f}^1,...,\overline{f}^L,\underline{f}^{L+1},...,\underline{f}^M,y_l^1,...,y_l^M\right) . \quad (2)$$

$$y_r = y_r\left(\underline{f}^1,...,\underline{f}^R,\overline{f}^{R+1},...,\overline{f}^M,y_r^1,...,y_r^M\right) . \quad (3)$$

where L and R are not known in advance [1]. L is the index to the rule-ordered FBF expansions at which y_l is a minimum, and R is the index at which y_r is a maximum. Once the points L and R are known, (1) is very useful to organize and describe the calculations of y_l and y_r.

3. The next problem has to do with the re-ordering of y_l^i and y_r^i [1]. The type-1 FBF expansions have always had an inherent rule ordering associated with them; i.e. rules $R^1, R^2,...,R^M$ always established the first, second,…, and Mth FBF. This order is lost and it is necessary to restore it for later use.

3 Problem Solution

3.1 Type-2 FLS

A type-2 fuzzy set, denoted by $\tilde{A}$, is characterized by a type-2 membership function $\mu_{\tilde{A}}(x,u)$, where $x \in X$ and $u \in J_x \subseteq [0,1]$ and $0 \le \mu_{\tilde{A}}(x,u) \le 1$.:

$$\tilde{A} = \{((x,u),\mu_{\tilde{A}}(x,u)) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1]\} . \quad (4)$$

This means that at a specific value of x , say x' , there is no longer a single value as for the type-1 membership function (u'); instead the type-2 membership function takes on a set of values named the primary membership of x' , $u \in J_x \subseteq [0,1]$. It is possible to assign an amplitude distribution to all of those points. This amplitude is named a secondary grade of general type-2 fuzzy set. When the values of secondary grade are the same and equal to 1, there is the case of an interval type-2 membership function [1, 12, 13, 14, 15].

3.2 Using Recursive OLS Learning Algorithm in Interval Type-2 FLS

Table 1 shows one pass learning algorithm activities BP method.

Table 1. One Pass In Learning Procedure for Interval Type-2 FLS

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

The proposed hybrid algorithm uses recursive OLS during forward pass for consequent parameters tuning and BP during backward pass for antecedent parameters tuning, as shown in Table 2.

Table 2. Two Passes In Hybrid Learning Procedure for Interval Type-2 FLS

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

3.3 Adaptive OLS-BP Hybrid Learning Algorithm

The hybrid training method is based on the initial conditions of consequent parameters: y_l^i and y_r^i. It presented as in [1]: Given N input-output training data pairs, the hybrid training algorithm for E training epochs, should minimize the error function

$$e^{(t)} = \frac{1}{2}\left[f_{s2}\left(\mathbf{x}^{(t)}\right) - y^{(t)}\right]^2 \quad . \tag{5}$$

4 Application to Transfer Bar Surface Temperature Prediction

4.1 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 FM. There are several mathematical model based systems for setting up the FM. There is a model-based set-up system [6] 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.

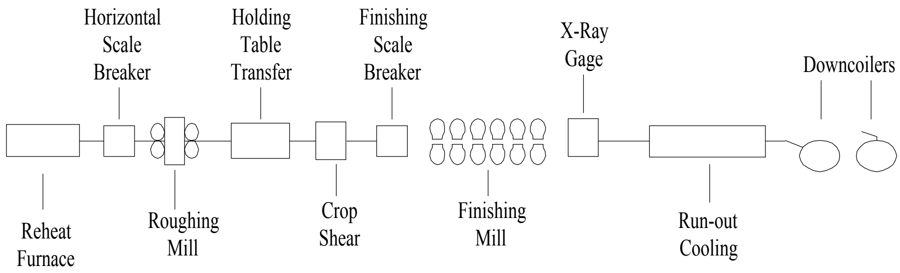

Fig. 1. Typical hot strip mill

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.

4.2 Interval Type-2 Fuzzy Logic System Design

The architecture of the FLS was established in such way that parameters are continuously optimized. The number of rule-antecedents was fixed to two; one for the RM exit surface temperature and the other for transfer bar head traveling time. Each antecedent-input space was divided in five fuzzy sets, fixing the number of rules to twenty five. Gaussian primary membership functions with uncertain means were chosen for both, the antecedents and consequents. Each of the rules of the interval type-2 NSFLS-2 is characterized by six antecedent membership function parameters and two consequent parameters. Each input value has two standard deviation parameters: given ten parameters per rule.

The resulting interval type-2 FLS uses type-2 non-singleton fuzzification, maximum t-conorm, product t-norm, product implication and center-of-sets type-reduction.

4.3 Noisy Input-Output Training Data Pairs

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

4.4 Input Membership Function

The primary membership functions for each input of the interval type-2 NSFLS-2 was:

$$\mu_{X_k}(x_k) = \exp\left[-\frac{1}{2}\left[\frac{x_k - x_k'}{\sigma_{X_k}}\right]^2\right]. \tag{6}$$

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 whose values varies over an interval of values $[\sigma_{k1}, \sigma_{k2}]$. The standard deviation of the RM exit surface temperature measurement, σ_{X_1}, initially varies over [11.0, 14.0] ^oC interval, whereas the standard deviation head end traveling time measurement, σ_{X_2}, initially varies over [1.41, 3.41] s interval. The uncertainty of the input data was modeled as non-stationary additive noise using type-2 fuzzy sets.

4.5 Antecedent Membership Functions

The primary membership function for each antecedent was a Gaussian with uncertain means as:

$$\mu_k^i(x_k) = \exp\left[-\frac{1}{2}\left[\frac{x_k - m_k^i}{\sigma_k^i}\right]^2\right]. \tag{7}$$

where $m_k^i \in \left[m_{k1}^i, m_{k2}^i\right]$ is the uncertain mean, σ_k^i is the standard deviation, $k = 1,2$ (the number of antecedents) and $i = 1,2,..25$ (the number of M rules). The means of the antecedent fuzzy sets were uniformly distributed over the entire input space. m_{11} and m_{12} are the upper and lower values of the uncertain mean, and σ_1 is standard deviation of input (x_1). m_{22} and m_{22} are the upper and lower values of the uncertain mean and σ_2 is standard deviation of input (x_2).

4.6 Fuzzy Rule Base

The type-2 fuzzy rule base consists of a set of IF-THEN rules that represents the model of the system. The interval non-singleton type-2 FLS have two inputs $x_1 \in X_1, and, x_2 \in X_2$ and one output $y \in Y$, which have a corresponding rule base size of $M = 25$ rules of the form:

$$R^i : IF \quad x_1 \quad is \quad \tilde{F}_1^i \quad and \quad x_2 \quad is \quad \tilde{F}_2^i, \quad THEN \quad y \quad is \quad \tilde{G}^i \; . \tag{8}$$

where $i =$ 1,2,…25, $\tilde{F}_1^i$ is the (x_1) input type-2 fuzzy set, $\tilde{F}_2^i$ is (x_2) input type-2 fuzzy set and $\tilde{G}^i$ is the consequent type-2 fuzzy set. These rules represent a fuzzy relation between the input space $X_1 \times X_2$ and the output space Y, and it is complete, consistent and continuous [16].

4.7 Consequent Membership Functions

The primary membership function for each consequent is a Gaussian with uncertain means, as defined in (7). Because the center-of-sets type-reducer replaces each consequent set $\tilde{G}^i$ by its centroid, then y_l^i and y_r^i are the consequent parameters. Because only the input-output data training pairs $\left(x^{(1)} : y^{(1)}\right), \left(x^{(2)} : y^{(2)}\right), \ldots,$ $\left(x^{(N)} : y^{(N)}\right)$ are available and there is no data information about the consequents, the initial values for the centroid parameters y_l^i and y_r^i may be determined according to the linguistic rules from human experts or be chosen arbitrarily in the output space [16]. In this work the initial values of parameters y_l^i and y_r^i are such that the corresponding membership functions uniformly cover the output space.

4.8 Results

An interval type-2 NSFLS-2 system was used to predict the transfer temperature. For each of the two methods, BP and hybrid OLS-BP, we ran fifteen epoch computations; using eighty-seven input-output training data pairs, 250 parameters were tuned. The performance evaluation for the learning methods was based on the benchmarking root mean-squared error (RMSE) criteria [1]:

$$RMSE_{s2}(*) = \sqrt{\frac{1}{n} \sum_{k=1}^{n} \left[Y(k) - f_{s2-*}\left(\mathbf{x}^{(k)}\right)\right]^2} \; . \tag{9}$$

where $Y(k)$ is the output training data from the model using ten check data pairs, $RMSE_{s2}(*)$ stands for $RMSE_{s2}(BP)$, and for $RMSE_{s2}(OLS-BP)$, and were obtained when applied BP and hybrid OLS-BP learning methods to an interval type-2

NSFLS-2. Fig. 2, shows RMSE of the two used interval type-2 NSFLS-2 with fifteen epochs' computations for the case of type A coils. It can be appreciated that after four epochs, the hybrid OLS-BP has better performance than BP method.

5 Conclusion

In this paper we have developed an orthogonal-BP hybrid algorithm to train an interval type-2 NSFLS-2 and used to predict HSM transfer bar temperature. The interval type-2 NSFLS-2 antecedent membership functions and consequent centroids successfully absorbed the uncertainty introduced by the training noisy data. The uncertainty of the input data measurements was modeled as stationary additive noise using type-2 fuzzy sets. The selected initial values of the antecedent and consequent parameters can affect the results of the interval type-2 FLS predictions. BP and OLS-BP methods were tested and parameters estimation has been demonstrated. There is a substantial improvement in performance and stability of the hybrid method over the only BP method. The hybrid OLS-BP achieves the better RMSE performance as can be seen in the experimental results. It has been shown that the proposed methodology can be applied in modeling and control of the steel coil temperature. It has also been envisaged its application in gage, width and flatness prediction.

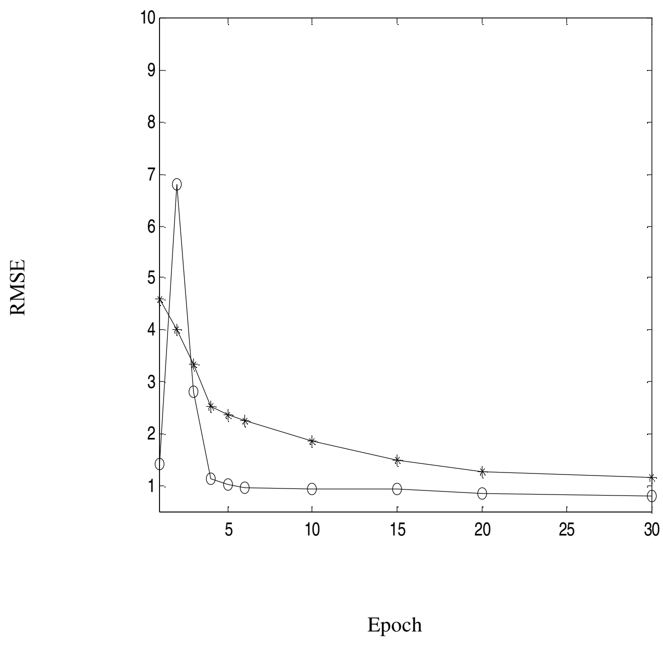

Fig. 2. Type-2 NSFLS-2 (*) RMSEs2 (BP) (o) RMSEs2 (OLS-BP)

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