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A Fuzzy-Logic and Multi-Layer Perceptron Hybrid Model Applied to a Real World Steel-Making Problem

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Abstract: *The most interesting properties of neuro-symbolic hybrid models is that they can allow for the combination of knowledge-based and data-based approaches. We have used such a strategy in a large, complex steel-making problem. We present this problem together with one of the hybrid models that have been tested on it. We chose to fully describe this hybrid because it is representative of such data-knowledge integration properties.*

1 Introduction

From 1994 to 1997, the European project MIX has been working on neuro-symbolic hybrid models. Its goal was to better understand this approach, investigate strategies and create tools for a better implementation of neuro-symbolic coupling. This work was assessed on three real world applications, including a steel-making application. Within this latter application, several hybrid models have been tested and a combination of these hybrids has been chosen and implemented on-line in the steel plant. In this paper, we first present the application and two previously existing models that solve it. Then we fully describe one specific hybrid model, in order to underline the performance gain brought by the hybridization and give an example of successful integration of data-based and knowledge-based approaches.

2 The application

The application we are interested in [5] consists of presetting the *rolling force* that is applied to a sheet of steel in a steel rollmill (Figure 1). The value of that force will determine the characteristics of the sheet when it leaves the rollmill. When the rollmill reaches its full speed, external regulations set the rolling force to its optimal value so that

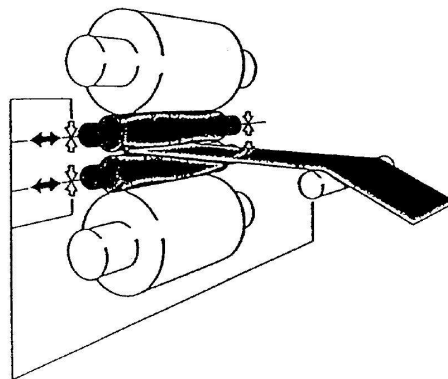


Figure 1: Picture of a steel rollmill

the band has the desired characteristics at the output of the rollmill. The optimal value for a given band can therefore always be known, but only after full speed is reached by the rollmill.

It is necessary to preset the value of the rolling force that will be applied during the transitory period, before full speed is reached. A poor presetting of the force will lead to bad characteristics of the beginning of the steel sheet, that will be wasted, and to unwanted oscillations when the automatic regulations start. For economic and quality reasons, it is important to minimize those two effects; this can be achieved by presetting the rolling force to a value as close as possible to the optimal value at full speed.

This problem has 12 parameters (listed on table 1) regarding the input characteristics of the sheet, and its de-

Number of passes	Width	Thickness
Lubrication	Input tension	Output tension
Roll finish	Length	Diameter
Elongation	Temperature	Resistance

Table 1: The 12 parameters of the application

sired output characteristics.

3 Previous models

Before designing our hybrid model, we had two different models of the application at our disposal: one using a knowledge-based approach (the physical model) and one using a data-based approach (a multi-layer perceptron).

3.1 The physical model

Presetting the rolling force can be done by a model describing the physical processes that take place in the rollmill [7]. This model is a set of equations based on several domains of physics (especially mechanics and thermics). Using 8 of our 12 parameters, the model leads to a value for the rolling force. This value is obtained by following a set of well defined and meaningful steps, as described in [7]; this is clearly a knowledge-based approach to solve the problem.

Unfortunately this model is not very accurate (with an average error rate as defined in section 6.2 of 25%) and its accuracy depends on the region of 12-dimensional space on which it applies. In order to alleviate this problem, one can divide the space into subspaces in which the error of the physical model is almost constant, and, for each subspace, apply an error-correcting α coefficient to the output of the model to determine the final force:

$$rolling_force = \alpha \times physical_model's_force$$

Under this condition, the physical model can give acceptable results. Unfortunately, the definition of an optimal division of the space is a complex problem.

3.2 A multi-layer perceptron

Presetting the rolling force can also be done by a multi-layer perceptron (MLP). A 12x12x6x1 MLP was designed and trained on this task [4]. The inputs of the MLP are the normalized values (in the [0..1] interval) of the parameters listed in table 1. The output of the MLP is the

Cases	Atypical domains
1	Pass number 1
2	Width < 800 mm or > 1700 mm
3	Thickness < 0.6 mm or > 2.0 mm
4	Elongation < 0.4% or > 2.0%
5	Resistance < 160 Mpa
6	Input tension stress < 1.6 T
7	Output tension stress < 2.8 T
8	Lubrication type 2
9	Roll finish = 16/17/19/3E
10	Roll finish = 10 without lubrication

Table 2: Atypical domains

normalized value of the rolling force. The learning algorithm is back-propagation. The MLP has been trained for 1000 epochs using the training set described below. Unlike the physical model, this model does not use any knowledge but only data to achieve its performance.

Previous tests [4] showed that the MLP model had a good accuracy for most data points, but performed poorly on certain specific points. We call a point typical if the MLP gives an accurate reply. If not, the point is called atypical. If a point is in a region of the input space in which the density is high, it is likely to be typical (because the MLP will have learned on a sufficient number of examples in that region), and vice-versa. The atypical points are situated in the atypical domains listed in table 2 [4] and correspond to uncommon customer orders.

4 Architecture of the hybrid system

In order to maximize the performance of the MLP, our hybrid system uses the MLP only to solve typical points. To solve atypical points, the physical model is used. In order to maximize the accuracy of the physical model, we use a fuzzy logic component to compute the error-correcting α coefficients. This component is based on the FuzzyCLIPS [3] engine. FuzzyCLIPS is an extended version of the CLIPS expert system shell developed by the NASA allowing fuzzy and normal terms to be freely mixed in the rules and facts of an expert system. The rules can be defined by an expert, or learned from a data set, which is the approach adopted here. The rules were generated by Iglesias *et al.* [2] using the C4.5 decision tree algorithm [6] and