Expert Systems with Applications 40 (2013) 5188–5196

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A hybrid intelligent system for PID controller using in a steel rolling process

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ARTICLE INFO

Keywords:
Steel rolling process
Knowledge engineering
PID
Open-loop tuning
Ruled-based system
Hybrid intelligent system

ABSTRACT

With the aim to improve the steel rolling process performance, this research presents a novel hybrid system for selecting the best parameters for tuning in open loop a PID controller. The novel hybrid system combines rule based system and Artificial Neural Networks. With the rule based system, it is modeled the existing knowledge of the PID controller tuning in open loop and, with Artificial Neural Network, it is completed the rule based model that allow to choose the optimal parameters for the controller. This hybrid model is tested with a long dataset to obtain the best fitness. Finally, the novel research is validated on a real steeling roll process applying the hybrid model to tune a PID controller which set the input speed in each of the gearboxes of the process.

1. Introduction

It is well known that there are a lot of industrial process far away from the optimal point of operation (Marlin, 2000). This fact is due to a lot of reasons, but only some of them are very significant in order to get a better performance (Marlin, 2000). Astrom and Hagglud in Åström and Hägglund (2009) indicate that one of the most important fact is to choose the adequate control technique. In this sense, several works have been developed with the aim to improve the behavior and consequently make the process more optimal. For instance (Ko et al., 2011) proposes an efficient control method to minimize process error and to reduce process variance in semiconductor manufacturing, in Chen et al. (2008) is described an intelligent adaptive control system for multiple-input multiple-output (MIMO) uncertain nonlinear systems and, in Etik et al. (2009) is showed a controlled fuzzy expert system to provide the conditions necessary for operating rooms. Depending of the control technique used different results are achieved. These techniques must be selected based on the desired response of the system. Some of these typical control methods are: PID control is the most common solution for the practical control loops (Åström and Hägglund, 2009), non-linear control (Haddad and Chellaboina, 2011), it would be used when the process is non linear; adaptive control (Sastry and Bodson, 2011), it would be used for process that are non-linear or changes are introduced on it during the operation; Model Predictive Control, it would be used to address process with difficult dynamics (Camacho and Bordons, 2004).

Despite PID controller is applicable in most control loops cases, but for certainly processes it has some limitations. For these processes it is possible to make changes in the controller topology achieving good results. For instance in Astrom and Wittenmark (1994) an adaptive PID controller is implemented for non linear systems or changes in it are made; (Rugh, 1991) introduces the Gain Scheduling concept for non linear systems with predicted variations in the process; in Bahill (1983) is showed the predictive PID controllers to address non-minimum phase systems.

The experience of human experts is used to create rule based systems models (Hayes-Roth et al., 1983; Cimino et al., 2012). Expert people extract rules from a system operation and then they structure it according to the system performance (Hayes-Roth et al., 1983). These methods allow the developed model to emulate the experts behavior in a certain field (Hayes-Roth et al., 1983; Hayes-Roth, 1985), and have been one of the most used methods in both research and operation (Hayes-Roth, 1985). There are several examples of those models, for instance: (Olugu and Wong, 2012) shows an expert fuzzy rule-based system applied to the automotive industry; (Chang et al., 2011) makes a comparison between a rule-based expert system and optimization models in a small drinking water network; in Liu et al. (2010) a rule-based control system design for smart grids were developed. It is possible to create models based on Intelligent Systems. In particular models based on Artificial Neural Networks (ANN) are usually used to improve the fitting of some models (Bishop, 2006). As examples of works where ANN are used to create models are: (Garliauskas, 2004) describes the model created for mapping the evaluation of transmitted information in the biological area; in Stanikunas and Vaitkevicius (2000) is showed the model developed for color constancy based on Four-layer neural network; (Alvarez-Huerta et al.,

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http://dx.doi.org/10.1016/j.eswa.2013.03.013

2011) shows the model developed to predict the drywell temperature of a nuclear power plant.

Many are the methods and applications that combine rule-based systems and models based on (ANN). For instance (Ferreiro-Garcia, 2012) shows a model to improve the heat exchanger supervision using neural networks and rule based techniques. In Srivastava et al. (1999) a knowledge-based conceptual neural network is developed for fast voltage contingency selection and ranking. Chaoui et al. (2004) proposes a control strategy based on Artificial Neural Networks for a positioning system with a flexible transmission element, with a rule-based supervisor for online adaptation of the parameters of the reference model.

Usually, the control loops of steel rolling process are conventional, and the operators therefore require no ongoing training and updating. Thus, it is necessary that the improvements should aim to complement the monitoring and control applications with which the operators are fully familiar. There are several previous works which tries to get this improvements (Chen et al., 2010; Wan et al., 2008; Maheral et al., 1995; Sbarbaro-Hofer et al., 1993). In this work a novel hybrid intelligent system for PID controller tuning in open loop is proposed. It is based on a rule based expert system combined with Artificial Neural Networks. With the proposal it is possible to tuning the PID controller with the optimal parameters according with the operation point of the steel rolling process on load.

One approach, to solve the above problems, is to create a generic decision method, based on a conceptual model describing the necessary steps to be achieved in order to obtain the PID controller parameters for open-loop empirical adjustment method. The novel model presented in this study was developed based on six different sets of expressions with highly satisfactory results commonly used in control systems.

The rest of the paper is organized as follows: first, the different intelligent classification method used in this study are describe in Section 2. Section 3 describes the procedure to tune a PID controller in open loop and the different expressions considered for selecting the PID parameters. Section 4 describes the novel hybrid system; its components, dataset, experiments and results are presented. Section 5 presents the empirical application of the novel hybrid system on steel rolling process. Finally the conclusions and future work are present.

2. Classification methods

In this section is described briefly the classification techniques are used in the model approach. Three methods were taken into account.

2.1. Artificial Neural Networks, ANN

The ANNs (Artificial Neural Networks) are computational algorithms based on the functioning of the human brain. Once of the most used ANN is the MLP (Multilayer Perceptron) (Bishop, 2006). The MLP is composed by one input layer, one or more hidden layers and one output layer (see Fig. 1), all of them made of neurons and pondered connections between neurons of each layer. Applying the *Theorem of Universal Approximation* (Hornik et al., 1989), can be demonstrated that only one hidden layer is needed to model a nonlinear projection between input and output layer.

A MLP with one hidden layer, can be written mathematically as show in the Eq. (1).

$$y_k^p = F_k\left(\sum_{i=1}^{L} w_{ik}\, F_i\left(\sum_{j=1}^{N} w_{ji}\, x_j^p + b_i\right) + b_k\right) \quad (1)$$

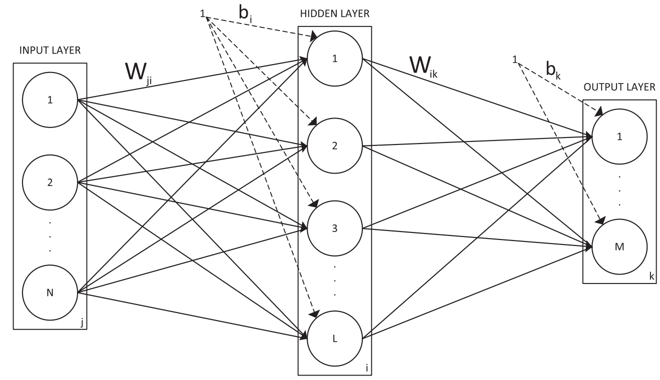

Fig. 1. Architecture of Multilayer Perceptron with 1 hidden layer.

Where:

$F_k \rightarrow$ Activation function of neurons of the output layer.
$w_{ik} \rightarrow$ Weight vector of connections from neurons of hidden layer to neurons of output layer.
$b_k \rightarrow$ Bias of neurons of the output layer.
$k \rightarrow$ Number of neurons of the output layer.
$F_i \rightarrow$ Activation function of neurons of the hidden layer.
$w_{ji} \rightarrow$ Weight vector of connections from neurons of input layer to neurons of hidden layer.
$b_i \rightarrow$ Bias of neurons of the hidden layer.
$i \rightarrow$ Number of neurons of the hidden layer.
$x_j^p \rightarrow$ p-th input pattern.
$j \rightarrow$ Number of neurons of the input layer (equals to dimension of the input data).
$y_k^p \rightarrow$ Predicted output for the p-th input pattern.

2.2. Support Vector Machines, SVM

SVM is described as a statistical learning method based on a structural risk minimization procedure (Cristianini and Scholkopf, 2002). The basic concept of the algorithm is a mapping of the input space into a higher dimensional feature space. Mapping can be done either linearly or non-linearly, according to the used kernel function. In the new feature space, the SVM constructs separating hyperplanes that are optimal in the sense that the classes are separated with the largest margin and minimum classification error. The optimal hyperplane can be written as a combination of a few

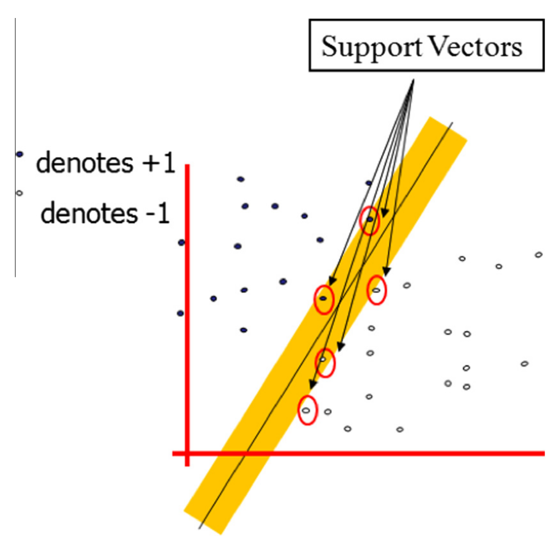

Fig. 2. SVM classification with $\epsilon - insensitive$ loss function.