ROLLING MILL FORCE CONTROL BY A NEURAL NETWORK (1)

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Abstract

In this paper, the identification and control in the hot rolling mill process provide real application of non linear neural control. Different control structures based on neural model of the simulated plant are proposed. The results of the neural model are tested and compared, to obtain a solution of the force control problem to obtain a better strip crown. Knowing the advantage of the non linear modeling technique, all neural approaches increase the control precision.

Key-words: Force control; Rolling mill; Neural net; Inverse dynamic.

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1 INTRODUCTION

In the hot rolling process, the strip tickness is reduced by passing through a preset roll gap between two work rolls that are supported by two larger-size rolls. As shown in Figure 1, the separation forces causes roll deflection, roll indentation, and mill stretch.The thickness difference (center edge) is called “strip crown” due of the normal thicker central gauge. Many efforts have been made to control strip crown for better yield and quality, and also “strip shape” for better operation and usage ratio.
Strip shape, which is generated by strip crown ratio changes between stands, could causes more operating problems than strip crown and shape relies on the crown control devices and the set-up model.
In this article we discuss the impovement of the crown control by acting in the tensiometer or looper subsytem.
For the development on the crown and shape control, we used the looper interstand which apply to the strip a tension in such a way that the rolling force stays constant in all time instants.
The improvement of the strip crown is obtained by the application of a constant rolling force that is not altered by the cold points in the strip.
The cold points in the strip have a greater resistance to deformation which produces an increase in the rolling mill force.
This rolling force variation produces geometric changes in the stands that causes deviations in the roll gap . There are changes due to temperature variations of the material , primarily produced at the furnaces , by skid marks. The roll gap variation produce changes in the output thickness of the strip and in the too.
This article shows an improvement in the strip characteristics using as control variables roll gap, input tensions and output tensions of the strip, against disturbances caused by the cold points due the table transport rolls .

In this article we will first discuss the relationship between strip crown and strip shape. Followed by neural control for strip crown and shape.-

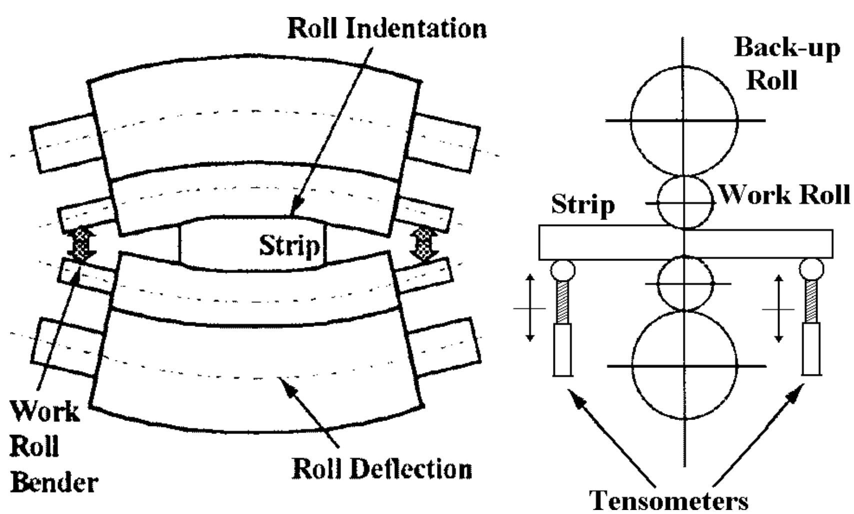

Figure 1. Strip crown generated due to roll identation and deflection

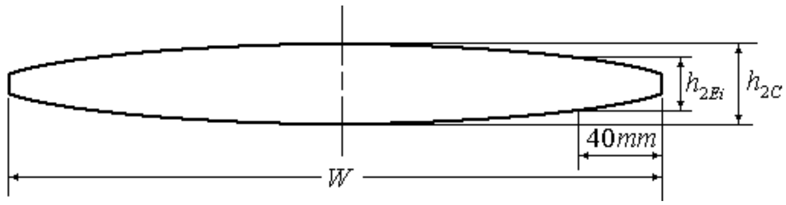

Figure 2. Strip crown

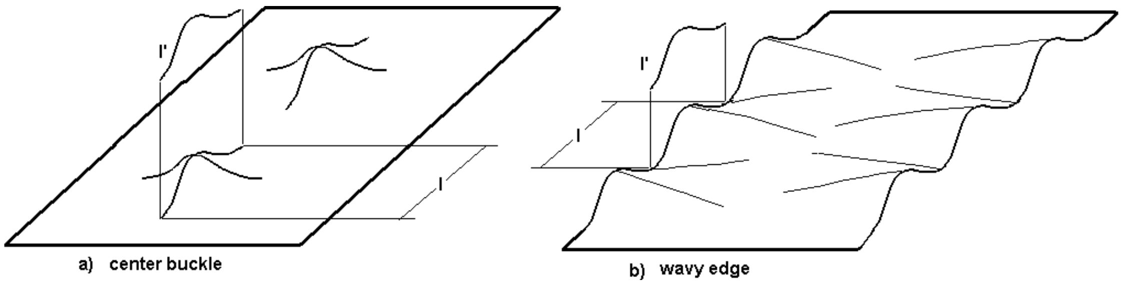

Figure 3. Strip shape

2 STRIP CROWN AND SHAPE RELATIONSHIP

Crown and shape are highly related variables. Shape control is normally implemented by adjusting strip profile. Due to Poisson´s effect, metal rolled in the vertical direction (strip crown) flows to the longitudinal direction and results in uneven elongation (strip shape). Detailed discussion can be found elsewhere in the literature [3,7,8,9]. Although there are various terminologies used in the metal processing industry, the most popular definition of strip crown Cr. is defined as the thickness difference between the center line gauge and the average gauge of strip edge lines as shown in Figure 2. The edge lines are about 25-50 mm from the strip edges depending on cold or hot rolling process or the costumer preference. Crown ratio is defined as the ratio of strip crown to strip central thickness. I-Unit is adopted in the industry as measurement of the strip shape As shown in Figure 3, this is defined based on engineering strain (I-Unit)

$$U = \frac{L' - L}{L} .10^5 . \quad (1)$$

where:

L: is the strained length.

L´: is the unstrained length.

$$Cr = h_{2Center} - \left(\frac{h_{2left} + h_{2Rigth}}{2} \right) \quad (2)$$

and:

$h_{2Center}$: Output thickness at the strip center.

h_{2Left} : Output thickness at the strip left border (40mm from the left border).

$h_{2rRigth}$: Output thickness at the strip right border (40mm from the right border).

For simplicity in this article we consider the total crown as:

Cr= $h_{2Center}$- h_{2Left}.

The crown can be measured on-line using the X-ray sensor at last stand.

The off-line measurement can be done by slicing the strip into slender ribbons and measuring L' e L (ribbons test) or using the shape measurement table [25]. If strip shape is assumed to be a sine wave, then $U=2.\pi^2.S^2 \approx 25.S^2$.
For convenience, this article will follow I-Unit hereafter.A positive measurement describes "wavy edge" and negative shape, "center buckle" as shown in Figure 3.
Many studies were made to investigate the relationship between crown and shape changes [6,11,12,13,14,15].

3 PLANT MODEL

The rolling mill process is an apparently a simple process that, in practice requires an advanced technological approach. The modeling of the process presents several difficulties. The most important ones are the following.

- The model which predicts strip deformation is a complicated function of strip entry conditions, input and output tension. Tensiometer are subject to the effects of nonlinearities such as rate limits and hysteresis. With many advanced control methods a non-linear model is required, usually complex mathematical representation, which while enabling the multivariable nature of the problem to be considered, also introduces an additional model error.
- Parameters of the model are uncertain. The strip deformation is dependent upon a large number of parameters which are determined from a combination of approximations to complex rolling theory and rolling itself. Parameter values may be estimated from a wide range of experimental data.

The plant model considered is the hot rolling mill process in the last stand of tandem mill. It was modeled in two parts, the first one was the thickness and rolling mill force model and the other one was the crown model. It was used the last stand measured data from the rolling process to tuning the theoretical models [3,4 and 5] that were used to predict the rolling force and the output thickness Figure 5. The Model´s inputs are the input and output tension, the input thickness, rolling speed, temperature of the strip, and the roll gap. To obtain the strip crown we used a mathematical model. Since there are many crown and shape control models proposed in the literature [6,11,12,13,14,15] , however,the most influent and widely adopted method is due to Shohet and Townsed who introduced the influence coefficient method (ICM) [8,9] to apply this method it was needed knowing the input strip crown, for simplicity we consider the input crown null (Cr=0).

This method was later improved by varius researchers to generate a better solution [10,16,17].The accuracy of crown/shape model has been tested and proved using a large amount of measured data.

4 CONTROL MODELING WITH NEURAL NETWORKS.

The characteristics of the plant can be represented by a neural network, e.g. the radial Basis Function network (RBF). Other neural network types, such as the Multilayer Perceptron, can be chosen as well, but the RBF offer some distinctive advantages. The learning algorithm is simple and it easy to obtain a uniform distribution of the modeling error over the complete space of training patterns. Here a special type of RBF network is used, the Gaussian network as shown in Eq.(5) Ref.[26]. It can be described by.

$$\hat{f}(x,w)=\sum_{i=1}^{n} w_i.\varphi_i(x) \quad (3)$$

$$\varphi_i(x)=\gamma(|x-x_i|) \quad (4)$$

where $\gamma(.)$ is normally a Gaussian function

$$G(x)=\exp\left(\frac{x^T.\Sigma^{-1}.x}{2}\right) \quad (5)$$

multidimensional with variance $\Sigma=\sigma^2 I$ or covariance . Notice that the Gaussian is centered at $\mathbf{x_i}$ with variance $\boldsymbol{\sigma^2}$, so its maximum response is concentrated in the neighborhood of the input $\mathbf{x_i}$, falling-off exponentially with the square of the distance. The Gaussians are thus an example of local elementary functions. If we substitute Eq.(5) in (3) we obtain the following implementation for approximation of the function f(x):

$$\hat{f}(x,w)=\sum_{i} w_i.G(|x-x_i|) \quad (6)$$

which implements the input-output map of the RBF network.

Let us think of an arbitrary function and a set of localized bell shaped functions (of the Gaussian shape). Function approximation in a limited area of the input space requires:

- the placement of the localized Gaussians to cover the space
- the control of the width of each Gaussian
- the setting of the amplitude of each Gaussian.

If we can accomplish these three tasks we can approximate arbitrary continuous functions with an RBF network.

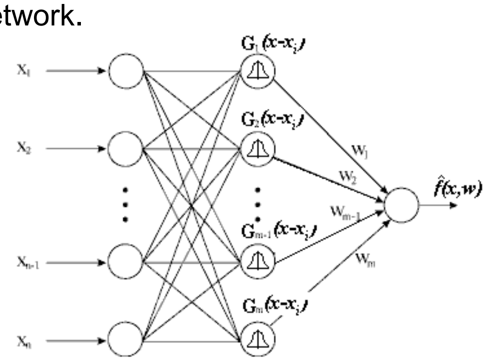

Figure 4. Radial Basis Neural net

Figure 4 shows m neurons with a Gaussian transfer function, each of them representing the calculations for a single center point xi according to equation (6). The single output neuron with the linear transfer function evaluates the weighted sum using the values wi as weights for the results of the previous layer.

In this application one static net with 25 neurons was trained to be the inverse function of the plant , in the next figure we can show the plant and it inverse.
We use real rolling data to validate and tune an Rolling simulation Model , based on the models of Orowan[1] and Alexander[2]. This model is used to generate a larger data base for a better training of the neural network as shows in Figure 5.

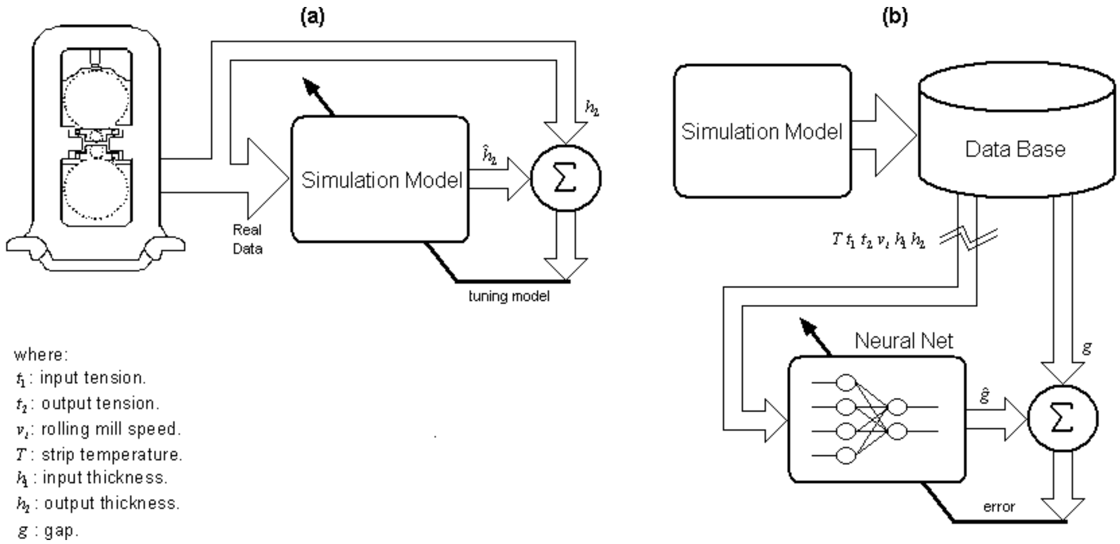

Figure 5. (a) ajust and validate a rolling model. (b) model training for the neural controller

5 BASIC CONTROL MODEL

The basic control objective is to keep the output thickness as close as possible to a reference value, for any variation of temperature, or by the variation of some of the input variables of the system.
Conceptually the most fundamental neural network based controllers are probably those using the "inverse" of the process as the controller. The most simple concept is called *direct inverse control*. There are several references available that uses the idea [1,2].
As in the former approach, in this scheme the main idea is to compensate the nonlinear relation among the plant variables by introducing the nonlinear inverse model of the system in the loop [1,2]. In this sense the PI controller regards the plant as a linear system with unit gain. If the inverse of the model is not perfect, the PI controller helps to reduce the sensitivity of the whole system against this kind of error and provides zero steady state error.
The general structure is shown in Figure 6.

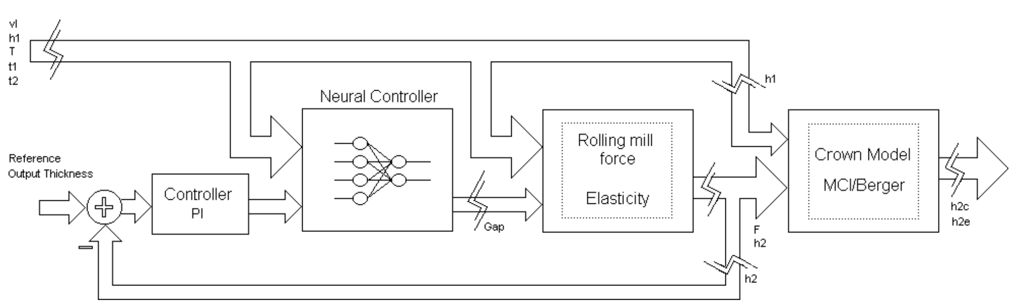

Figure 6. Inverse Control (Gap) with ANN

Figure 7 shows the results obtained with this approach. These results were obtained with real industrial rolling data . It is worth noting that the main difference from the conventional approach Force Feed Forward lies at the beginning and at the end of the trial. This improvement is due to the use of the knowledge acquired during the training period.

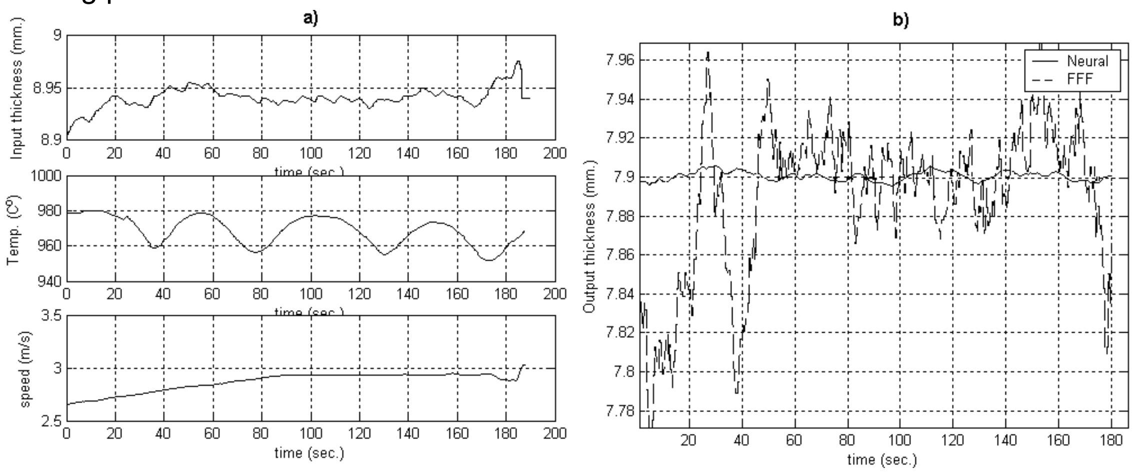

Figure 7. a) input thickness Temperature and rolling milll variation; b) Output thickness with force feed forward control (FFF) and direct-inverse function control.

6 IMPROVED CONTROL MODEL

In order to make the control in the plant , we will act not only on gap as in the previous case, also the control will act on the input and on the output tension of the strip to maintain the roll force constant.
In this control strategy, is possible to obtain the desired exit response acting on these three control variables (roll gap, input tension and output tension).

To obtain the neural controller, the roll gap information to train the net was obtained from the plant model inverse function, the information to train input and output tension was given by a data base obtained with the maintenance of constant rolling mill force for any input thickness or temperature variation based on the theoretical models [3,4 and 5].
The complete control model simulation is shows in **Figure 8.**

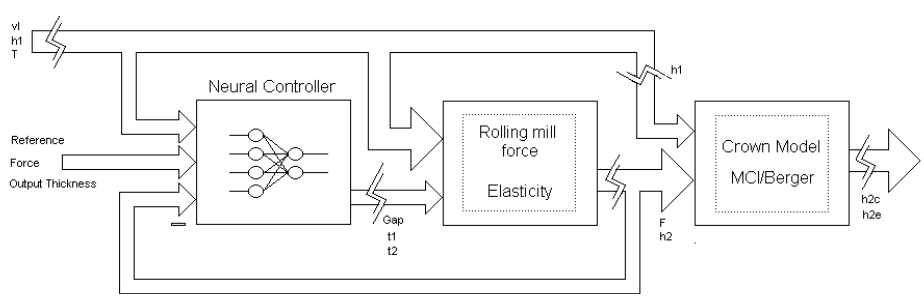

Figure 8. Inverse Control (Tension/Gap) with ANN

where:

t_1: input tension.

t_2: output tension.

v_l : rolling mill speed.
T : strip temperature.
h_1 : input thickness.
h_2 : output thickness.
g : gap.

In the next figures we show the simulation results for two control strategies (gap control and tension/gap control). For an input strip thickness of 4mm and output strip thickness 3.15mm and a sinusoidal temperature variation that represents the cold points in the strip.

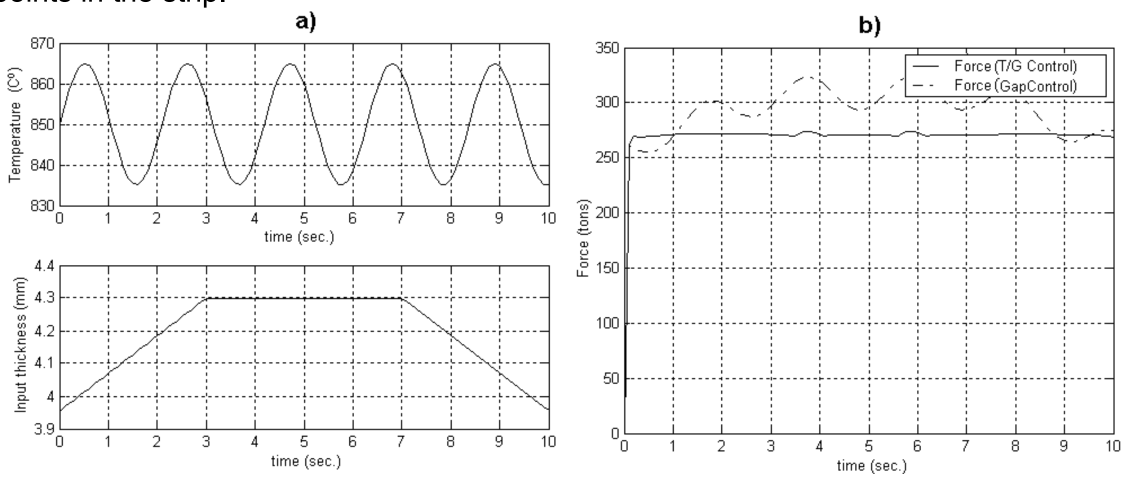

Figure 9. a) : input thickness and temperature variation b): Rolling Mill force and gap with gap control and Tension/Gap Control.

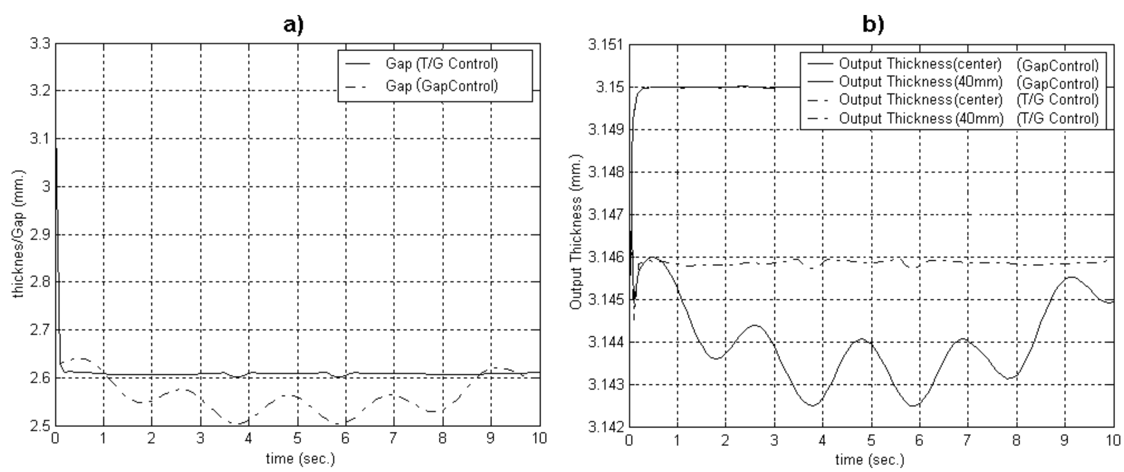

Figure 10. b)Output thickness in the strip center and in the strip border (40mm) with gap control (MISO) and Tension/Gap Control (MIMO).

In the following figure (Figure) shows the estimated strip crown and shape distribution with tension/gap control and with gap control, we can see that crown and shape was reduced in the last case.

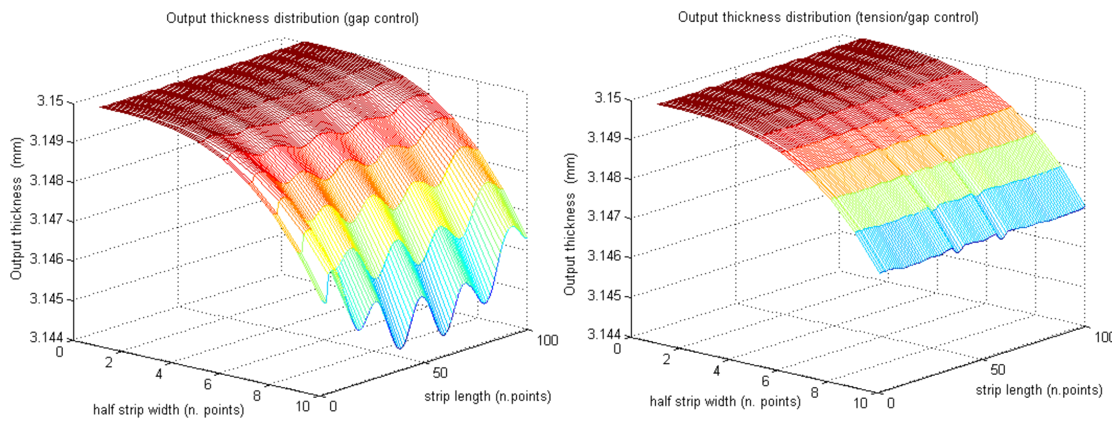

Figure 11. Output thickness distribution a)with gap control b)with tension/gap control

7 CONCLUSION

This article described the neural crown control based in nonlinear control and this research represent an alternative to Force Feed Forward system (FFF-AGC). But the neural control proposed needs a good measurement the strip temperature to provide a good tension/gap control. In this article was treated the force, crown and shape with their internal coupling considered in the influence coefficient method to calculate the strip crown. The bending force used in the simulation was zero. The improvement obtained in the simulation was that the tension/gap control reduce 1/3 part of the strip crown and in the same time eliminate the strip shape.

It was considered the influence of cold points , and we suggest , under the good results obtained by the simulations , it seems to be a good tool to verify the influence of another disturbances .

The proposed control strategy can run in parallel with the real process , without interfering in it , to be validated for an alternative on line application .

Acknowledgment

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CONTROLE DE FORÇA DE LAMINAÇÃO POR UMA REDE NEURAL[1]

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Resumo

Neste artigo mostra-se uma possível aplicação real das redes neurais para controle não linear e identificação e controle aspectos importantes de um processo de laminação a quente. São propostas diferentes estruturas de controle baseadas em modelo neural da planta identificada. Os resultados do modelo neural são testados e comparados para obter uma boa solução do problema de controle da coroamento. Conhecendo as vantagens das técnicas de controle não linear, todas as aproximações neurais acrescentam mais precisão ao controle.

Palavras-chave: Controle de força; Laminação; Redes neurais; Função inversa.