A Non-lineal Mathematical Model for Annealing Stainless Steel Coils

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Abstract: Stainless steel manufacturing has experienced a high growth. Nowadays the stainless steel manufacturing is an industry with many applications. Annealing process is an important process in the production of stainless steel coils. The aim of this research is to obtain the classification of defective annealed coils. So a nonlinear mathematical model has been developed for the annealing process. In this research the following techniques have been used: SOM neural networks and classifications methods. For testing, temperature signals were collected along the annealing furnace, also speed signal of the production line were collected. These signals are correlated with each one of the manufactured coils.

1 INTRODUCTION

The conventional method to model the heating of a furnace consist on solving simultaneously the equations for radiation, convection and transmission.

This study proposes a new approach, using data mining tools and neural networks to schedule and control the annealing furnace line for stainless steel. The following data are available: speed, temperature and the parameters of the furnace. With these data annealed coils can be classified in well annealed coils and bad annealed coils. The following aims are pursued: Reducing energy consumption, optimizing output temperature, improving the surface quality and optimizing the annealing time to increase productivity.

2 ANNEALING PROCESS

The purpose of the annealing process is to remove metal defects, to make it easier to work with. In cold rolling, the thickness of a coil is reduced to the desired thickness, but this process gives raise to deformation in the crystalline structure of the metal, that can be recovered by annealing. The annealing is usually associated with other complementary processes, such as superficial pickling. Resulting in a production line type AP (Annealing and Pickling).

A coil circulates inside the annealing furnace whose temperature must be maintained during the time required on order that the annealing process to occur. This time depends on the material thickness, ranging from one to five minutes. The furnace is divided into six zones, each one of which has its burners and temperature control. The calculation of temperature points determine the ideal amount of heat to be transferred to the zone controllers, according to optimum heat-up curve (Spinola, 2008).

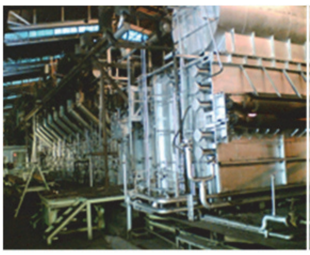

Figure 1: Annealing furnace.

3 AIMS

The target of the investigation is to individually analyze annealing of each coil, considering the

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passage of the coil in each zone of the furnace applying the model of heating of the annealing furnace explained in Par. 4. Control of the heating furnace is the calculation of heating points to be permanently transferred to each area of the furnace, with the aim of accomplishing the following: Attain a decrease in temperature as close as possible to the desired temperature, accommodation of operating conditions according to the ratio variations on the temperature of the furnace, minimize the consumption of energy by optimizing heating methods, classification of coils according to their behaviour in the oven and prediction of the furnace operating points based on initial conditions.

Data Mining tools and multivariate statistics are useful when there is a significant historical volume and good quality (Chapple, 2002). The thermal energy received by each of the coil while in the furnace can be calculated (Spinola, 2004). To do this, the temperatures applied to each coil in each area, top and bottom, are obtained from the data files where they have been continuously registered. The next step will be to rank the coils, depending on the energy received as “bad annealed” or “well annealed according to their characteristics, size and type of steel. With all of this a model of annealing will be made and a table of values of temperature and speed set points will be obtained. Studying coil population using ANN and classification to obtain an improved model it is possible to reduce annealing transition time between coils of different steel grades and dimensions, optimizing the thermal transitions of the different types of coils.

4 HOW TO OBTAIN THE ANNEALING VALUE

In order to make easy the analysis and visualization of the annealing of a complete coil, the process consists in integrating the heat-up curve of all of the points of the heated material along the furnace and determines the temperature set points of the other points of the heated coil. To summarize heating information of each element we define the function Ann1(d) as the integral in Eq 1.

$$Ann1(d) = \int_{t\_in}^{t\_out} f_1(T(t, x(t)))dt \qquad (1)$$

Where d is the position of the coil element, *t_in* and *t_out* are the time when the coil element enters and exits the furnace and T(t,x(t)) is the temperature at time t and position x(t) along the trajectory of the element inside the furnace.

Let Tr be the annealing temperature. Function f1 is 0 below Tr and it is equal to T above it, as the annealing is performed above this specific temperature. If the temperature is below this value, the coil is heated, but the grain structure is not recrystallized and the contribution to the Ann1 value is null. The physical dimension of Ann1(d) is temperature by time (ºC* sec), and represents the amount of effective thermal energy received by the coil element d. But the function Ann1 depends deeply on the critical value Tr. Although only high temperatures recrystallize the stainless steel, possibly there is not such a key value and temperatures just below Tr also affect the metal. For this reason an alternative function, Ann2, was proposed.

It integrates function f2. We chose an interval Tm – Ta which should contain the critical value Tr. The function slope above Ta is m2 which should be 0 or slightly above. This formula has a different physical meaning. If we choose m2=0 and a coil element is heated inside the furnace with a constant temperature greater than Ta, Ann2(x) will be the total time the element has been inside the furnace. The time the element is exposed to a temperature below Tm does not count at all, but the time the coil is heated with a temperature from Tm to Ta is proportionally counted. So, this function calculates the annealing compensated time an element stays in the furnace. If we choose m2>0, temperatures higher than Ta overcompensate the annealing time, as the annealing process speed and the temperature are related. The parameter m2 reflects that fact (Spinola, 2004).

$$Ann2(d) = \int_{t\_in}^{t\_out} f_2(T(t, x(t)))dt \qquad (2)$$

5 TOOLS AND METHODS

In order to classify the annealing of stainless steel coils, a kind of neural network, self-Organizing Maps (SOM) has been used. The software tools used to implement the Classification program are Matlab 7.0 and The Self-Organizing Map Program Pakage by Kohonen, that implements the techniques of neural networks we need (Kangas, 1997). The SOM consists of a two-dimensional lattice that contains a number of neurons (Kohonen, 1992).

The Gaussian function has been chosen as the neighbourhood function and the rectangular structure as the topology of the map as we can see in the figure 2. A prototype vector is associated with each neuron.

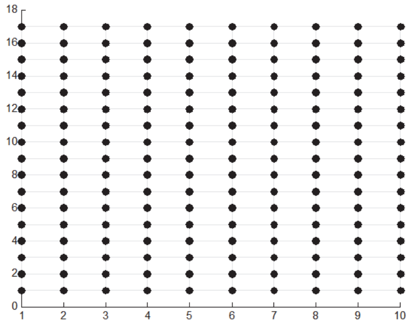

Figure 2: Training map.

For training and visualization purposes, the sample vectors are assigned to the most similar prototype vector, or best-matching unit (BMU), which means that input vectors which are relatively close in the input space should be mapped to units that are relatively close on the lattice. Once the map has been trained, it is ready for post-processing and evaluation.

In this study we have calculated the values of annealing temperatures and speeds of the coil points located every 10 meters and the average of these values for each coil.

The input vector has the main variables that take part in that annealing process. They are: annealing calculated with Rec 1 equation, annealing calculated with Rec2 equation, heating, top and bottom temperatures of six zones, steel band speed, length, wide and thickness. In that way, the vector is such as [Stainless_steel_type Rec1Sup Rec1Inf Rec2Sup Rec2Inf CalorSup CalorInf Output_temperature Speed thickness Wide Length Z1Sup Z1Inf Z2Sup Z2Inf Z3Sup Z3Inf Z4Sup Z4Inf Z5Sup Z5Inf Z6Sup Z6Inf]. Due to the number and variety of data for each type of steel coils we have decided to use a few of them for training and the others for validation.

Scaling of variables is of special importance in the Toolbox. Typically, one would want the variables to be equally important.

The number of units in each map is calculated using a heuristic formula determined by the SOM method. It is based on Map_units=5* dlen ^0.54321 * k where dlen represents the number of vectors used in the training and k = 4 because a 'big' map has been chosen. After the number of map units has been determined, in this map 168, the map size is fixed [17, 10]. Then the SOM is initialized by a linear initialization along two greatest eigenvectors tried. After initialization, the SOM is trained in two phases: first rough training and then fine-tuning.

6 ANALYSIS OF RESULTS

We have built and trained a SOM neural network, using real data coil measured in a production line in the Acerinox factory in Algeciras.

The U-matrix displays distances between neighboring map units, and shows the structure of a cluster map: high values of the U-matrix indicate a cluster border, uniform areas of low values indicate clusters themselves. Each component plane shows the values of one variable in each map unit.

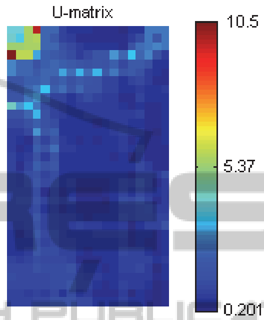

Figure 3: U-matrix.

The result of training is shown in Figure 4. This figure shows the matrix distances and projections of each variables of the input space. This type of network elements, called neurons, are arranged in a two-dimensional network, each of these elements will be calculated in the learning process of the network. They are representatives of different states of annealing, such as: excess, lack or correct annealing. The objective of this type of network is to determine relationships inherent in data according to their relationships. So, our objective is to visually determine relationships between the different variables of interest in our study.

In figure 4, we can see the homogeneity of the variables representing the temperature of the annealing furnace. The left top colour blue represents highest temperatures and corresponds to highest values of annealing and the thickness of the steel band. On the other hand, we also note that the width and length have no real connection to the others variables. Finally, the velocity tends to be higher in cases of lower annealing and lower in cases of higher annealing.

Two of the properties most of the measures of SOM Quality try to evaluate are vector projection, which is sometimes referred to as "topology preservation", and vector quantization. Technically, there is a trade off between these two, increasing projection quality usually decreases the projection properties. The Quantization Error (QE) is computed by determining the average distance of the sample vectors to the cluster prototype vectors by which they are represented. We have obtained a quantization error of 0,985 and a topographic error of 0,026. All entries area presented to SOM network are assigned to a cluster. The Clustering process groups those areas or clusters where the Euclidean distance between adjacent vectors is lesser (Kohonen, 1997). To measure how an entry point belongs to the cluster it has been assigned to, the quantization error can be used. This error is calculated as the Euclidean distance between the inlets to the vector of the neuron is activated.

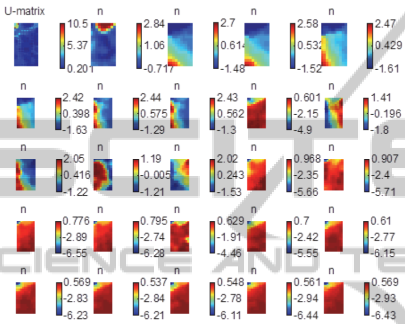

Figure 4: Projections of each variable of the input space.

Figure 5: Clusters.

Finally, the structure is chosen optimal using the Davies-Bouldin index considering both the distance between clusters as internal distance of each cluster.

The red zone represents the coils that have less heating than required, the yellow zone the well annealing coils and the blue zone represents the coils with excess of heating ant the dark blue the rest.

7 CONCLUSIONS

An alternative and successful approach has been introduced based on neural networks for classification of data series and it has been applied to the classification of annealing data acquired in a stainless steel production line. The main results obtained in this investigation are: An improved clustering algorithm that generates clusters including all the annealing neurons. The creation of SOM has been improved by means of a better quality of the training data and so a successful classification of annealing stainless steel has been got.

At the moment we have centred on the global classification of coils but we can't characterize what kind of abnormality it is affected for. Additional work is necessary to do in this field and a supervised neural network is proposed to use it in future investigations. This study will be continued in a thesis with a more detailed analysis and we will contrasted SOM method with other techniques that could also be employed in this scenario.

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