

Development of a skin pass preset model by using artificial intelligent methods*

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The main objective of this paper is to present a model based on advanced intelligent techniques to determine the roll force preset to be applied on the temper mill of a galvanizing line. This model will pre-set both the roll force needed for the required material and the necessary tension preset. The new method also makes it possible to predict the roughness of the strip.

■ INTRODUCTION

To obtain the desired final mechanical and roughness characteristics for galvanized steel sheets, ACERALIA uses a skin-pass + tension leveller configuration, placed at the exit section of the galvanizing line. The control of this equipment is done by the operators who, taking into consideration the strip properties requirements, manually calculate the strip tension and the forces to be applied. Indeed, these parameters determine the roughness of the finished material.

In view of the various problems caused by the manual control of the equipment, an automation system is required to obtain as much strip length as possible in the prescribed range of quality.

This paper presents a description of a system based on intelligent techniques that, using the available variables, allows a good roll force adjustment, while providing continuous and accurate estimation of the final roughness.

■ FACILITY DESCRIPTION

The skin-pass that is considered here, is part of a galvanizing line belonging to ACERALIA in Avilés (Spain). This line has the possibility to work with a wet 4-high skin pass alone or joined to a tension leveller.

The material processed on this line is galvanising material with a maximum yield stress of 500 MPa, with a thickness in the range of 0,4 to 2 mm and a maximum width of 1,600 mm. The maximum line speed is 150 m/min.

Before implementation of the model, presetting was carried out only by manual operation. Initial work was made in order to present the operator with a tension preset, based on its own tables but extrapolated by means of a spline approach.

Automation of facility has a database Oracle and another dedicated to operator type MS-ACCESS. A model was developed, based on data stored in both databases. Initial data taken from databases included around 650 variables.

■ METHODOLOGY

Based on the information contained in the process database, a KDD (Knowledge Discovery and Data Mining) methodology is applied (*fig. 1*).

* Subject of a presentation at the 2002 ATS International Steelmaking Conference (Paris, December 11-12, 2003, Session 15).

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Développement d'un modèle d'intelligence artificielle pour le pré-réglage au skin-pass

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L'objectif principal de cet article est de présenter un modèle fondé sur les techniques d'intelligence artificielle en vue d'optimiser le pré-réglage du skin-pass d'une ligne de galvanisation. Il s'agit de déterminer automatiquement, pour chaque nuance d'acier, les efforts et les tensions à appliquer en respectant les impositions en termes de rugosité.

Le process et le développement du modèle

Le modèle est développé pour la ligne de galvanisation d'Aceralia à Avilès, équipée d'un skin-pass quarto et d'une planeuse en traction. Le skin-pass était, avant le modèle, pré-réglé manuellement par les opérateurs.

Une première étape du développement du modèle consiste en une analyse critique des bases de données existantes en vue de leur utilisation optimale. Le modèle est structuré en quatre variantes, correspondant à quatre groupes de nuances. Il utilise l'algorithme de projection de Sammon, les réseaux de neurones et le paramètre de Mahalanobis pour éliminer les points aberrants.

Les principaux paramètres du modèle sont :

- les propriétés mécaniques et la géométrie de la bande ainsi que les conditions de laminage et la rugosité visée,

- la largeur de la bande,
- la longueur laminée cumulée.

Le modèle en déduit la tension et l'effort différentiel à appliquer à la bande en vue d'obtenir la rugosité recherchée.

Les résultats

Le modèle d'intelligence artificielle permet d'obtenir :

- des valeurs de rugosité correspondant aux impositions pour 98 % de la production ;
- une plus grande souplesse d'adaptation du process aux différentes nuances ;
- une stabilité accrue du process, indépendante de l'habileté des différents opérateurs ;
- une augmentation de la durée de vie des cylindres et une réduction de la consommation d'énergie ;
- une réduction de la charge de travail des opérateurs.

Compte tenu de ces résultats très positifs, le modèle a été intégré au process.

Basically, the method relies on an initial pre-selection of variables from those existing in the database. To discard initial variables, statistical methods and experience from the technical staff are taken into account.

Then, a pre-processing of the data is carried out. Variables are deeply studied and treated in order to obtain a reliable data set. Further work is performed to get the feature extraction, looking for relations among variables and discarding those giving the same information to the model. Finally, the model is developed and contrasted. Arrows in *figure 1* indicate the iterating process : If the contrasts taken are not good enough, the previous step must be repeated.

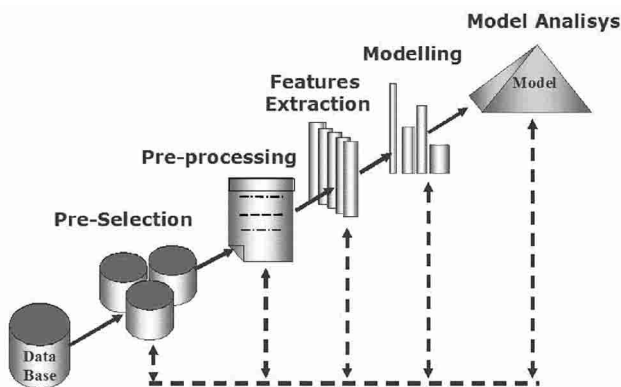


Fig. 1 – Knowledge discovery and data mining (KDD) methodology.

Fig. 1 – Méthode d'apprentissage et d'exploitation de données.

■ PRELIMINARY ANALYSIS

Tools, used for preliminary analysis, are basically two: XDPM (owned by the University of Oviedo) and R (freeware downloadable at <http://www.r-project.org/>). Among other analysis, data are studied through box-plots considering different types of materials, as shown in *figure 2*.

This preliminary analysis proves to be very useful when detecting anomalous phenomena or situations.

As an example, it can be appreciated in *figure 2* that multiple samples fall outside the 1.5 times the interquartile range, which can be accounted for by any of the following assumptions :

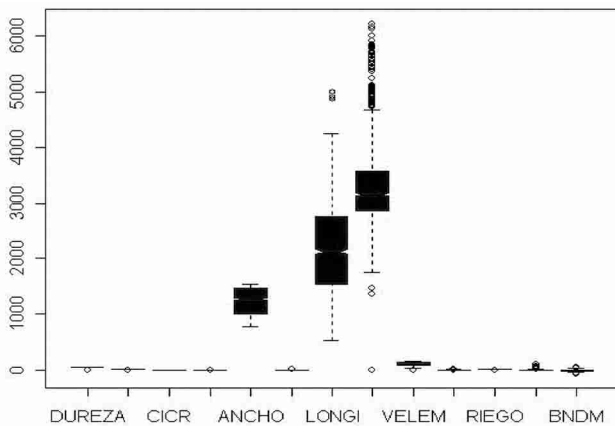


Fig. 2 – Box-plot representation of the basic statistical parameters for grade B100 data.

Fig. 2 – Représentation graphique des paramètres statistiques élémentaires pour la nuance B 100.

- Points outside the space delimited by the whiskers are considered out-liers, and are identified and isolated for a specific detailed analysis of their nature. The analysis of the rest of the points pertaining to the general pattern continues on a separate basis.
- The existence of a high number of samples that lie far from the central zone can be considered as an indication of the existence of multiple sub-populations that are still to be identified and examined individually.

Very likely, the underlying reason is a combination of both options.

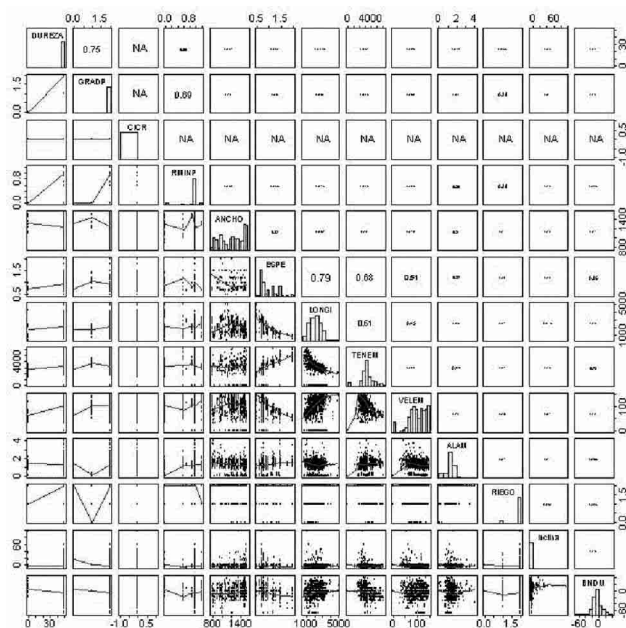


Fig. 3 – Combined graphic for grade B100.

Fig. 3 – Graphique matriciel pour la nuance B100.

After the preliminary data analysis and the elimination of those registers that, a priori, could be considered as erroneous, the following steps consist in the analysis of variable histograms, correlation between variables and the different types of fit (linear or non-linear) required by pairwise combination of variables.

Figure 3 presents a box matrix where the function histogram of the variable density (representing the range and frequency of occurrence) is represented in the main diagonal, while the rest of the boxes include the correlation coefficient, if any, and other types of linear or non-linear fits that occur between variable pairs.

It can be seen, from histograms, that the data do not follow a normal distribution and that the behaviour of data is not always continuous with particular variables.

After initial study, a detailed study of variables correlation is made. Figures 4 and 5 indicate the correlation matrix and

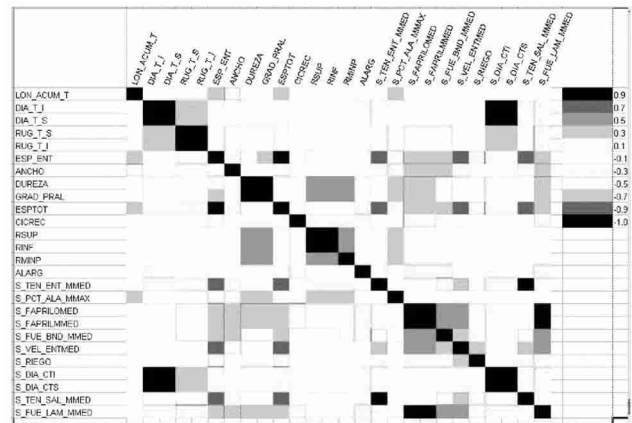


Fig. 4 – Lineal correlation among process variables.

Fig. 4 – Corrélation linéaire entre les variables de process.

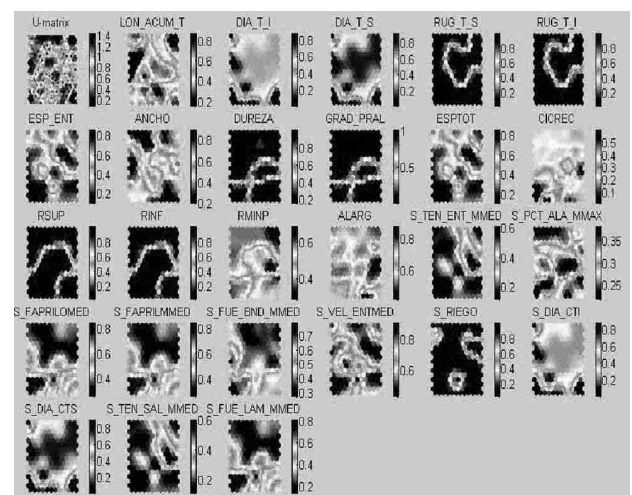


Fig. 5 – Non linear correlation among process variables.

Fig. 5 – Corrélation non-linéaires entre les variables de process.

SOM used for that purpose. Establishing which variables are lineal combinations, some of them can be discarded because information given was the same.

■ PRE-PROCESSING

Considering these preliminary results, the model strategy selected is to create separated models depending on the kind of material to be rolled. Thus, four groups of materials are considered : three for grades B100F55, B011F97 and B102G55 respectively and one for the rest of the working set grades.

Several projection methods are taken into account. For pre-processing purposes, the most efficient method is the Sammon projection. Such a method is of a great help for data structure pre-visualization. It allows visualizing high dimensional structures in the plane (2-D) thus, it identifies different varieties and patterns contained in it. More specifically, it constitutes a very helpful tool for cluster structure detection and out-lier identification.

Sammon's algorithm projects our n-dimensional universe (where n is the number of variables contemplated) to a two-dimensional plane by taking into account the Euclidean distances between variables.

The results from this filtering process are presented in the following graphics (fig. 6 - 10) accompanied by a short description of the main conclusions that can be obtained from them.

Figure 6 shows the Sammon representation of the whole data without considering any separation by type of materials. Different zones can be visualized. This projection was elaborated in parallel with neural network models, facilitating the out-liers rejection.

For interpretation, the line marks the so-called "normal" behaviour zone :

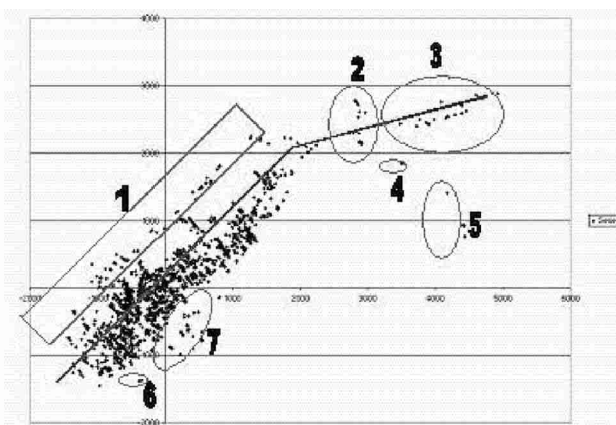


Fig. 6 – Graphic plot of the results returned by Sammon's algorithm applied to the available data.

Fig. 6 – Présentation graphique par l'algorithme de Sammon des données du process.

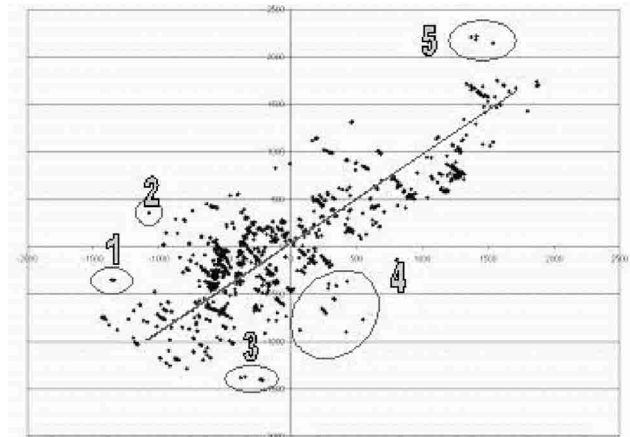


Fig. 7 – Graphic plot of the results returned by Sammon's algorithm applied to steel grade B100F55.

Fig. 7 – Résultats obtenus avec l'algorithme de Sammon pour la nuance B100F55.

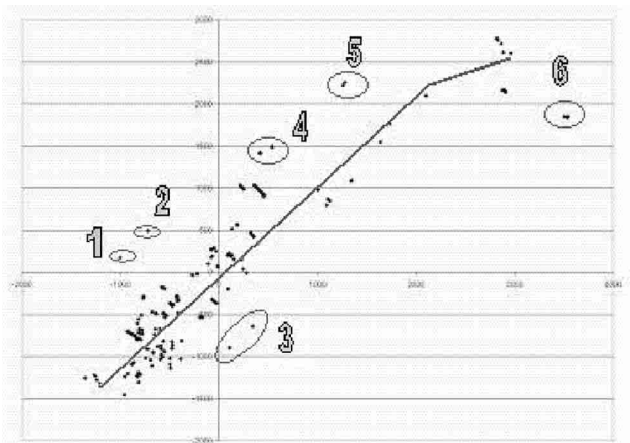


Fig. 8 – Graphic plot of the results returned by Sammon's algorithm applied to steel grade B011F97.

Fig. 8 – Résultats obtenus avec l'algorithme de Sammon pour la nuance B011F97.

- *Group 1* : It appears to be a separate zone ; thus its behaviour should not be the desired one. Nevertheless, the group presents a normal behaviour and its removal does not imply an improvement in training results. This lack of continuity between the data from group 1 and the "normal" zone seems to be accounted for by the particular final roughness specifications rather than by any anomalous behaviour.
- *Groups 2 and 3* : Even though they are located at a certain distance from the main data group, these zones present a reasonable behaviour and do not lead to errors during training. Thus this can be considered as similar to the previous situation.
- *Groups 4 and 5* : These quite distant zones show an unusual behaviour and represent an error source for training purposes. Their removal allows a slight improvement in the results obtained.

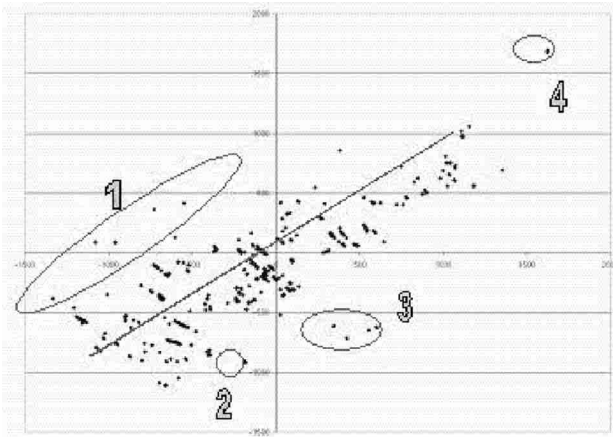


Fig. 9 – Graphic plot of the results returned by Sammon's algorithm applied to steel grade B102G55.

Fig. 9 – Résultats obtenus avec l'algorithme de Sammon pour la nuance B102G55.

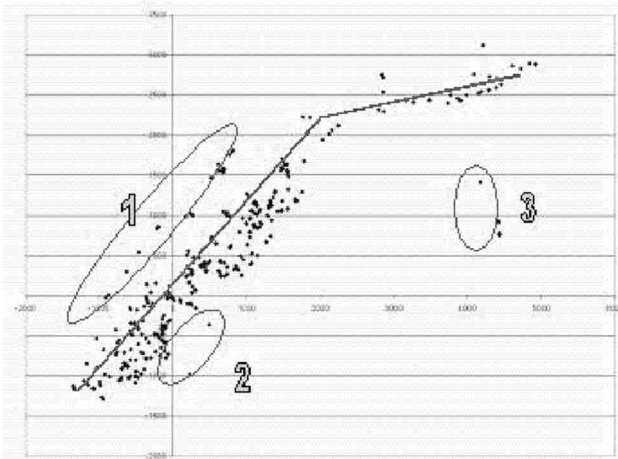


Fig. 10 – Graphic plot of the results returned by Sammon's algorithm applied to the other steel grade families.

Fig. 10 – Résultats obtenus avec l'algorithme de Sammon pour les autres nuances.

- *Groups 6 and 7* : Although their locations are not too distant from the so-called "normal behaviour" zone, it is considered that they fall outside the possible specifications and behaviours. Results improve substantially after their removal

After this initial global study, it is decided to evaluate a Sammon projection considering only data pertaining to specific types of materials. Thus, four new projections are studied.

Grade B100F55

Six different zones can be distinguished in *figure 7*. Although slightly separated from the rest, zones 1, 2 and 5 present a "normal" behaviour and correspond to extreme roughness values. Thus, the corresponding data sets can be incorporated

to the subsequent neural training process. Zones 3 and 4 show an anomalous or abnormal behaviour. This is confirmed by assessing the variable sets to which they refer and detecting some contradictions or impossible situations. On the basis of these results, these zones are excluded for network training.

Grade B011F97

The number of data, available for this grade, is more reduced (*fig. 8*) and the identification of the items to be eliminated becomes a critical issue since correct network training requires a large number of data. Therefore, only zones 3 and 6 are eliminated, and zones 1, 2, 4 and 5, although distant from other points, are taken into consideration. No anomalous behaviour is identified after a detailed analysis and the discontinuity of the points can be put down to lower data density.

Grade B102G55

Again, the evaluation of the results of the Sammon's algorithm allows to identify three minor zones (i.e., zones 2, 3 and 4) with some degree of anomalous behaviour. These are removed, whereas the remaining data are fully integrated to the training process (*fig. 9*).

Other grades

This group encompasses all the other steel grades that do not fall into any of the previously discussed categories (*fig.10*). There is no data excess. In spite of being a separate zone, zone 1 would not introduce any error. Zones 2 and 3 are removed.

■ ALGORITHM BASED ON MAHALANOBIS DISTANCE

The presence of multiple outliers can be easily seen on the Sammon plots. In a second stage, identification of outliers could be improved by using an algorithm based on the Mahalanobis distance. Given a sample X , the statistical function :

$$D = (x - \bar{x})S^{-1}(x - \bar{x})^T$$

with D Mahalanobis distance and S standard deviation,

represents the Mahalanobis distance of the sample points to its centre.

This statistic method follows a chi-square distribution with degrees of freedom equal to the number of dimensions of the samples. This property was used to detect and isolate the outliers.

Figure 11 shows the values obtained with this statistical algorithm. The plot contains the Mahalanobis distance against each considered coil. The line shows the confidence border. Above this line data are considered as outliers.

Figure 12 shows a specific zone of the Sammon's projection applied to steel grade B100. The points that by the multiva-

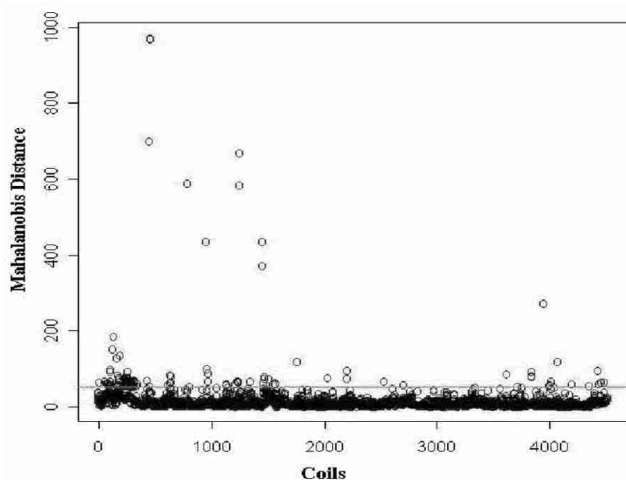


Fig. 11 – Mahalanobis distance.
Fig. 11 – Distance de Mahalanobis.

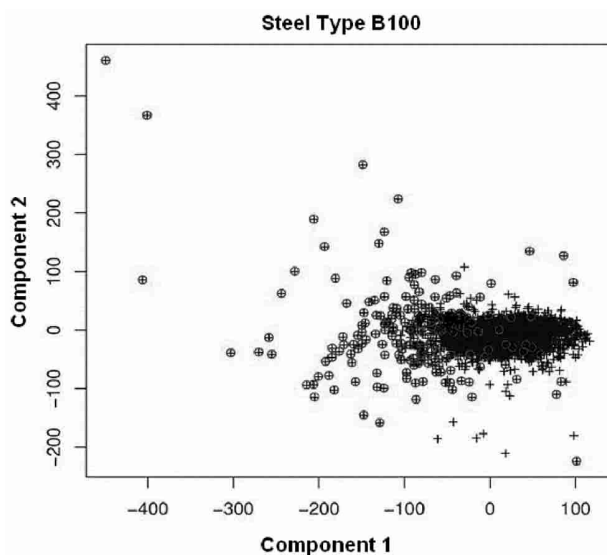


Fig. 12 – Graphic plot showing the outliers in a limited zone of Sammon's plot for steel grade B100.

Fig. 12 – Zone partielle d'une projection de Sammon, avec les points anormaux, nuance B100.

riable Mahalanobis algorithm can be considered as outliers, are shown as rounded points. It appears that a more selective trimming of outliers can be done with this method than with the Sammon projection.

■ NEURAL NETWORK MODEL

As a consequence of these treatments of data, the most suitable variables, for the different steel grades, appeared to be :

- hardness, steel grade, target roughness, thickness, elongation, speed, roll bending and type of emulsion ;

- cycle : This variable is related to the hardness and the steel grade ; it will be used as a criterion for classifying the different steel grades ;
- width : This value is directly related to the total roll force value applied ;
- cumulative rolled length : This variable, together with elongation, is a measurement of the wearing of the rolls. The greater the length rolled, the greater the wear of the rolls.
- strip tension : The strip tension is calculated as a function of the width and thickness of the strip to be rolled ;
- differential roll force : This variable is calculated as the difference in force between the drive and operator side.

In spite of not being a numerical data, the annealing cycle is used by as a numerical input to the networks. For this purpose, a number is assigned to each annealing cycle included in the available data (as example cycle A1 is referred to as 1, A2 as 2, B1 as 3, K1 as 10 and so on).

After performing several tests with neural networks, based on the conclusions reached after applying these algorithms, the final configuration of the four networks that finally constitute the model is as follows :

B100F55 NETWORKS and B102G55 NETWORK (Topology 10-21-1)

The cycles used are 3, 4, 5, 6.

Inputs :

- [0] = Annealing cycle
- [1] = Minimum target roughness
- [2] = Strip width
- [3] = Strip thickness
- [4] = Accrued length rolled by the rolls
- [5] = Strip tension at the skin pass mill
- [6] = Line speed
- [7] = Elongation
- [8] = Type of emulsion used in the skin pass mill
- [9] = Differential roll force
- [10] = Roll-bending.

B011F97 NETWORK (Topology 8-17-1)

Inputs :

- [0] = Strip width
- [1] = Strip thickness
- [2] = Accrued length rolled by the rolls
- [3] = Strip tension at the skin pass mill
- [4] = Line speed
- [5] = Elongation
- [6] = Type of emulsion used in the skin pass mill
- [7] = Differential roll force
- [8] = Roll-bending.

“OTHERS” NETWORK (Topology 12-24-1)

It encompasses all the other steel grades processed in the line. The cycles used are 1,3,4,5,8,10.

There are 2 additional variables : hardness and main grade.

Inputs :

- [0] = Hardness
- [1] = Main grade
- [2] = Annealing cycle
- [3] = Minimum target roughness
- [4] = Strip width
- [5] = Strip thickness
- [6] = Accrued length rolled by the rolls
- [7] = Strip tension at the skin pass mill
- [8] = Line speed
- [9] = Elongation
- [10] = Type of emulsion used in the skin pass mill
- [11] = Differential Roll Force
- [12] = Roll-bending.

For all networks, Roll Force preset is the output. In order to monitor roughness, an additional neural network with topology 8:18:3 is added, supervising each group. The outputs are top and bottom roughness. The inputs are :

- [0] = Roll Force estimated by model as pre-set
- [1] = Line speed
- [2] = Minimum target roughness
- [3] = Roll-bending
- [4] = Strip width
- [5] = Strip thickness
- [6] = Accrued length rolled by the rolls
- [7] = Strip tension at the skin pass mill.

A representation of the final model can be seen in *figure 13*. The variables used in the model are connected to neural networks across a commutation based on steel type. This commutation permits to introduce, in each neural network, the only variables that have been previously defined. The initial roll force together with the other input variables is introduced into the neural network. The final roll force and top and bottom roughness are obtained through this validation network.

Tables I to IV show the results obtained after training. Tolerance is defined as the percentage of target (roll force) considered satisfactory for the model. Each table refers to a different neural network, used for a different steel grade or steel grades set.

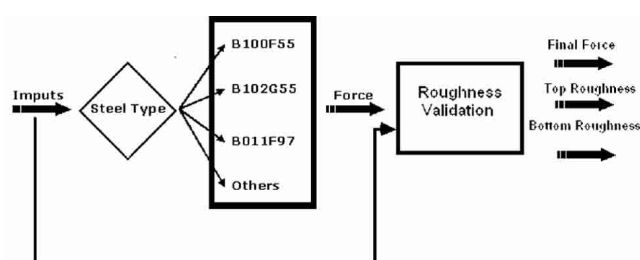


Fig. 13 – Representation of neural network mode.

Fig. 13 – Diagramme du réseau de neurones.

The first outstanding result is that a 5 % tolerance can be applied in the model, this accuracy being good enough for the skin-pass mill. Improved accuracy would be extremely difficult to obtain and, in view of the above, would not provide noticeable improvements in the process.

TABLE I : Results obtained with the grade B100F55 network.

TABLEAU I : Résultats obtenus avec le réseau de la nuance B100F55.

Tolerance : 20 %	Hits : 100 %	Misses : 0 %
Tolerance : 15 %	Hits : 100 %	Misses : 0 %
Tolerance : 10 %	Hits : 96.5 %	Misses : 3.5 %
Tolerance : 5 %	Hits : 83.6 %	Misses : 16.4 %
Tolerance : 1 %	Hits : 34.4 %	Misses : 65.6 %

TABLE II : Results obtained with the grade B102G55 network.

TABLEAU II : Résultats obtenus avec le réseau de la nuance B102G55.

Tolerance : 20 %	Hits : 100 %	Misses : 0 %
Tolerance : 15 %	Hits : 99.13 %	Misses : 0.87 %
Tolerance : 10 %	Hits : 94.21 %	Misses : 5.79 %
Tolerance : 5 %	Hits : 80.20 %	Misses : 19.89 %
Tolerance : 1 %	Hits : 29.30 %	Misses : 70.79 %

TABLE III : Results obtained with the grade B011F97 network.

TABLEAU III : Résultats obtenus avec le réseau de la nuance B011F97.

Tolerance : 20 %	Hits : 100 %	Misses : 0 %
Tolerance : 15 %	Hits : 98.1 %	Misses : 1.9 %
Tolerance : 10 %	Hits : 93.4 %	Misses : 6.6 %
Tolerance : 5 %	Hits : 81.6 %	Misses : 18.4 %
Tolerance : 1 %	Hits : 29 %	Misses : 71 %

TABLE IV : Results obtained with the grade B102G55 network.

TABLEAU IV : Résultats obtenus avec le réseau de la nuance B102G55.

Tolerance : 20 %	Hits : 100 %	Misses : 0 %
Tolerance : 15 %	Hits : 99.2 %	Misses : 0.8 %
Tolerance : 10 %	Hits : 88.2 %	Misses : 12.8 %
Tolerance : 5 %	Hits : 74.7 %	Misses : 25.3 %
Tolerance : 1 %	Hits : 16.1 %	Misses : 81.9 %

The second relevant result is the progress achieved by this neural network, compared with previous neural network trials, by using the current elongation as an additional discrimination parameter. A significant further improvement may be obtained when the new variable “cumulative length rolled by the rolls” can be used as an input variable. The introduction of new variables, such as the differential roll force and roll-bending values, lead to a more sturdy model and to a significant improvement of the hit rate achieved by the networks.

Another important benefit is in the robustness and reliability of the implemented model, resulting from the careful data validation process and the subsequent revision of the set of variables to be considered in the various components of the model.

Thus, the model has been implemented in the facility process computer in order to initiate a final stage of start up and on line validation.

Some time was dedicated to look for operator activities and to fix any difficulty that may arise when applying the model for special operations. In such circumstances, the model is running in stand by and supervised by the operators. After some period of adjustment, the model is able to run by itself without any supervision.

■ DISCUSSION OF RESULTS

The data obtained from the model of roughness and roll force, when compared with current data manually introduced by the operators, establish that the following progress have been achieved by Aeralia :

- The neural model is stable (*fig. 14*). Rude peaks due to roughness preset changes or dimension changes are absorbed more progressively than they can be by the operator. This avoids the transient period that the operator needs to adjust the process, a step that is foreseen by the model for presetting.

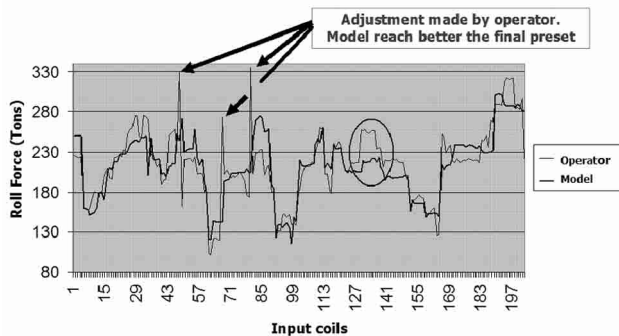


Fig. 14 – Comparison of previous and new force model.

Fig. 14 – Comparaison de l'ancien et du nouveau modèle de force.

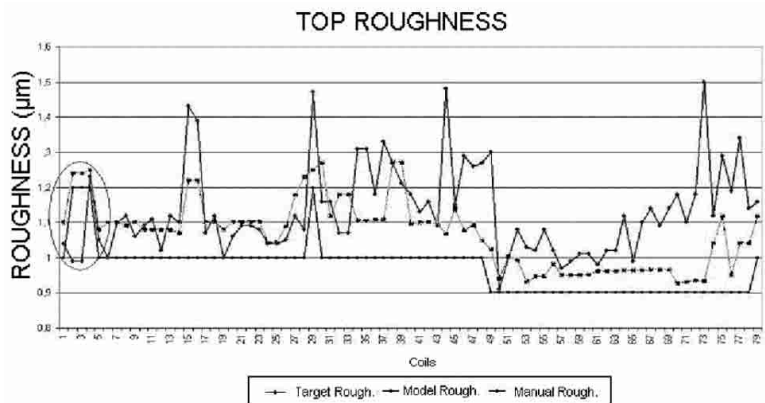


Fig. 15 – Comparison of previous and new roughness models at the topside.

Fig. 15 – Comparaison de la rugosité avec et sans le modèle, en face supérieure.

In *figure 14*, there are three peaks that correspond to adjustments to compensate for inadequate preset by the operator. Indeed, when drastic changes in incoming coils occur the operator cannot react quickly enough. Eventually, after several trials the preset of the operator matches the one predicted by the model.

Also, the model may react faster than the operator to variations of the process variables, for instance in the zone marked with a circle in *figure 14*. It corresponds to a moment when the obtained roughness meets the requested target. After few coils, the operator changes the preset for the one that is indicated by the model.

- The model tries to get a more uniform response, minimising drastic variations of roughness. It must be reminded that a high roughness is usually the consequence of process parameters that are adopted to meet other quality requirements. A comparison of model and operator preset evolutions against the targeted roughness can be drawn (*fig. 15 and 16*).

With the manual preset, the actual strip roughness may be inferior to the one requested by the customer (zones marked by an ellipse in *figures 15 -16*). With the developed model, this cannot happen, as it always tries to obtain a strip roughness equal or higher than target.

This phenomenon occurs when variations in the input conditions make the operator to decrease or increase the roll force, thus yielding a strip roughness lower than requested. It can be seen in *figures 15 and 16* that the developed model reacts in a similar way, increasing or decreasing roll force as necessary to control strip roughness, but never allowing it to go below the requested level.

Automating pre-sets of forces and tension with the new developed model makes it possible to keep a uniform production of similar strips. Without the model it is not possible to achieve a uniform strip roughness.

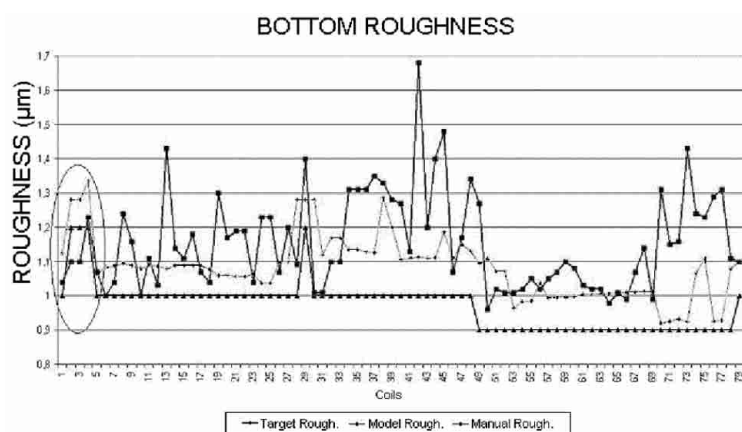


Fig. 16 – Comparison of previous and new roughness models at the bottom side.

Fig. 16 – Comparaison de la rugosité avec et sans le modèle, en face inférieure.

Further qualitative improvements can be obtained, such as :

- avoiding the frequent manual roughness measurements by quality supervisors, as the actual roughness is usually close to the one predicted by the model ;
- increasing rolls life, not only because of a reduction of rolling forces, but also because of less variation of the rolling force, thus avoiding high stresses in transient conditions ;
- training the model with new materials that will be processed in the future.

■ CONCLUSIONS

The neural-network model obtained offers the following advantages :

- It facilitates the operator's work, who is not longer in charge of calculating the rolling forces and tensions and who can concentrate on other necessary operations.
- Roll life is improved and energy consumption is reduced, as a more uniform force is applied, while, at the same time, maintaining the minimum roughness value.
- As force calculation is not operator-dependant, the process quality is not affected by the skills of the operator working in each shift.
- To a large extent, better results are obtained from the differentiated treatment given to the various coating and mechanical properties of the strip as compared to the previous generalized treatment. Such an improvement is also reflected in the increased system reliability.

- The connectionist model predicts the values for the force to be applied with a hit rate of 96 % (for a 5 % tolerance). As for the roughness model, the hit rates are nearly 98 %, with an error margin of 0.2 µm

With these results, the manual operation mode was substituted for the new model. The new configuration yields a significant improvement in process uniformity, better roll performance and lower energy consumption rates.

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