Implementation of a virtual sensor on a hot dip galvanizing line for zinc coating thickness estimation

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Virtual sensors allow the measuring of variables for which no physical sensor is available using indirect measurements of related variables.

In this work we describe the implementation of a virtual sensor for the zinc coating thickness in a hot dip galvanizing line from related process variables such as blowing pressure, knives-to-strip distance, knives-to-pot distance, based on artificial neural networks (multilayer perceptrons - MLP) that model nonlinear dynamical relationships (NARX models).

The virtual sensor is currently working on Avilés (Galvanizing 2) and encouraging results have been achieved that suggest future developments.

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■ INTRODUCTION

Coating thickness control is a very important issue in a galvanizing process. Producing coating thicknesses lower than required may lead to product rejection by quality control checks or by the customer, while higher coating thicknesses, on the other hand, lead to unaffordable costs, due to the high cost of zinc. Accurate control of zinc coating thickness in hot dip galvanizing lines, however, is a difficult issue. First, we often lack an accurate model of the process, due to the highly complex and nonlinear nature of the hot-dip coating process that involves tightly coupled chemical, mechanical and thermal phenomena. Besides this, in many cases thickness sensors (X-ray gauges) are not installed in the same point where the coating thickness is being controlled but several meters away downstream (typically about a hundred meters). A typical hot-dip galvanizing line is depicted in *figure 1*.

Two important problems can arise in the control of the coating thickness:

- A transport delay is introduced by the misplacement of the X-ray gauge *(fig. 2)*. This degrades thickness control performance as a result of delayed control actions, leading to slow transient behaviours, overshot and even instability.
- In addition, the X-ray sensor can fail to give measurements to the control system due to damages in the transmission line or in the sensor. When this happens, the technicians who supervise the process have to turn off the automatic control system and work in manual mode (open loop), assigning presets for the control variables from preconfigured tables, but without having into account the actual coating thickness that is being obtained. This obliges them to set higher objective coatings to ensure the required tolerances.

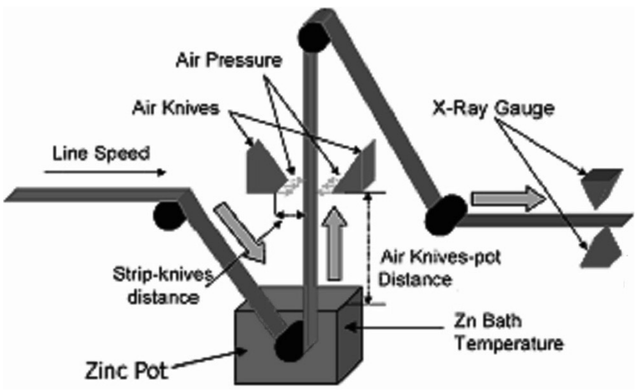

Fig. 1 - Schematic diagram of the hot-dip galvanizing line.

Fig. 1 - Schéma d'une ligne de galvanisation à chaud.

Installation d'un capteur virtuel sur une ligne de galvanisation pour l'évaluation de l'épaisseur du revêtement

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Les capteurs virtuels permettent la mesure de variables pour lesquelles il n'existe pas de capteur physique ; ils utilisent la mesure indirecte de variables connexes. Le texte décrit l'installation d'un capteur virtuel de l'épaisseur du revêtement de zinc en ligne de galvanisation à partir de variables process : pression du gaz, position des buses par rapport à la bande et au bain. La méthode est fondée sur des réseaux neuronaux (MLP) qui modélisent des relations non linéaires dynamiques (NARX).

Le contrôle de l'épaisseur du revêtement est un enjeu majeur du procédé de galvanisation. Les épaisseurs trop faibles peuvent conduire à un litige avec l'utilisateur et les épaisseurs trop fortes entraînent des coûts supplémentaires par consommation excessive de zinc. Le contrôle précis de l'épaisseur du revêtement de zinc est difficile, à cause de la nature non linéaire du process de revêtement par immersion à chaud. De plus, la plupart des jauges d'épaisseur (RX) ne sont pas situées dans la zone même où est déterminée l'épaisseur. Le délai qui en résulte peut introduire des régimes de transition lente, des dépassements de consigne ou même de l'instabilité. D'autre part, les jauges RX peuvent être défaillantes par suite d'endommagements divers ce qui rend nécessaire le pilotage manuel de la ligne sans retour d'information.

Un capteur virtuel a été développé pour le contrôle de l'épaisseur de zinc en ligne de galvanisation. Il utilise des variables connexes du process qui ont un effet établi sur la détermination de l'épaisseur du revêtement : position des buses d'essorage, pression du gaz, température du bain, vitesse de la ligne,…Le développement du capteur est fondé sur l'acquisition et l'analyse de données pertinentes avec des techniques de data mining, de visualisation, de matrices de corrélation (SOM).

Différents modèles, statiques ou dynamiques, linéaires ou non, ont été testés en vue de leur apprentissage. Le modèle finalement mis en service est du type non linéaire dynamique. Les estimations de l'épaisseur du revêtement donnent des résultats satisfaisants sur la ligne de galvanisation 2 d'Avilés.

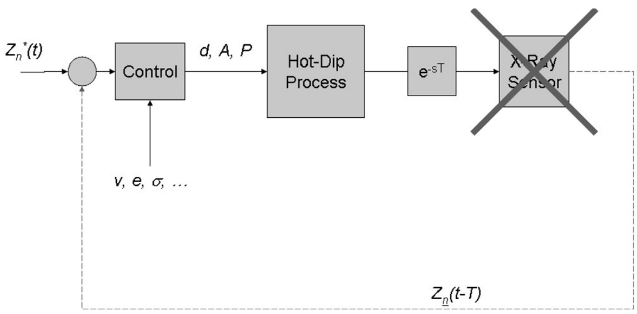

Fig. 2 - Simplified block diagram of the coating thickness control.

Fig. 2 - Diagramme simplifié du dispositif de contrôle d'épaisseur.

In this work we describe the design and implementation of a virtual sensor to provide an estimation of the coating thickness in a hot-dip galvanizing line that Arcelor has in the factory of Avilés, based on other related process variables which have a proven influence on this parameter, such as those related to the position of knives (distance to the strip, skew, vertical height, etc.), pressure of the air jet, temperature of the zinc pot, line speed, etc. The produced estimation, on one hand, corresponds to the point where the control process takes place and, on the other hand, has into account not only the controllable variables but also other measured process variables, thus providing a coating value that could be potentially used for control and supervision.

■ VIRTUAL SENSOR DESIGN

A virtual sensor provides an estimation of an unavailable process variable using available measurements and a model of the process. As seen in *figure 3*, it can be considered as a single sensor that provides an estimation of the desired variable

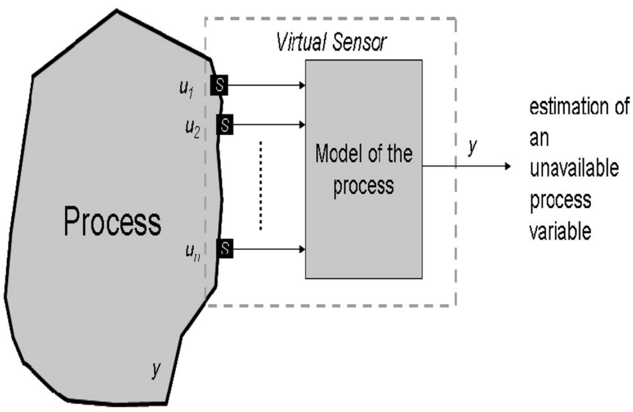

Fig. 3 - Block diagram of a virtual sensor.

Fig. 3 - Diagramme simplifié d'un capteur virtuel.

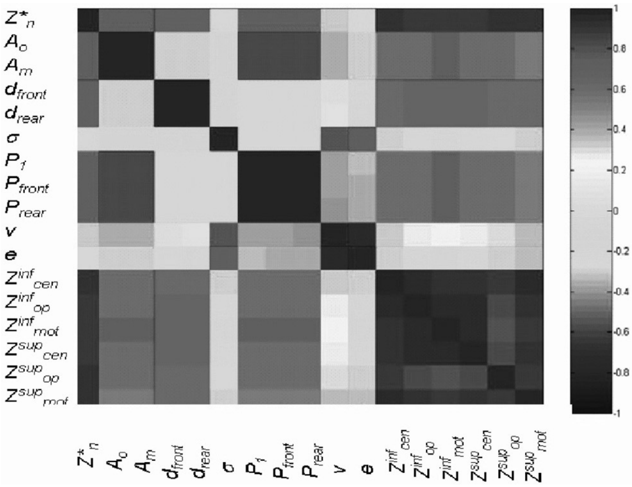

Fig. 4 - Unsorted correlation matrix, as a visual aid for feature selection.

Fig. 4 - Matrice de corrélation non triée, visualisation pour la sélection des paramètres.

from indirect but related physical measurements. The success of a virtual sensor design relies on an adequate selection of the variables (features) that are used to compute the estimation, a proper choice of the model structure and an adequate estimation of the model parameters.

Feature selection

The first step for the virtual sensor design is feature selection. Feature selection is an indispensable part of the design process with two main objectives:

- To reduce complexity of the sensor by excluding redundant or useless variables.
- To maximize the information input to the sensor, by selecting those input variables that convey the largest amount of information regarding the estimated variable.

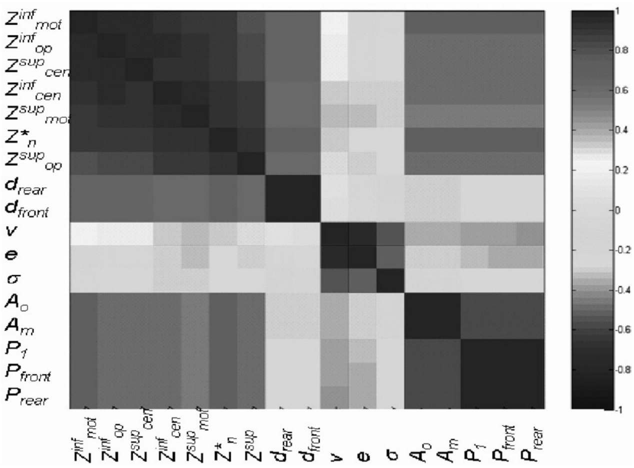

Fig. 5 - Sorted correlation matrix, as a visual aid for feature selection.

Fig. 5 - Matrice de corrélation triée, visualisation pour la sélection des paramètres.

TABLE I: Input variables obtained after the feature selection process.

TABLEAU I: Données d'entrée retenues après l'étape de sélection des paramètres.

Z^*_n	reference value for coating thickness
A_o	height from knives to pot (operator side)
A_m	height from knives to pot (motor side)
d_o	distance from knives to strip (operator side)
d_m	distance from knives to strip (motor side)
σ	strip tension
P_1	main pressure on the knives
P_f	knives pressure (frontal)
P_r	knives pressure (rear)
e	strip thickness
v	line speed

We used two main approaches to carry out the feature selection process:

Prior knowledge

First we relied on prior knowledge about the process, which involved the study of the process physics and meetings with plant staff to exploit the expert knowledge they had in selecting the most useful variables. Despite the complexity of the hot dip coating process, theoretical models (10, 11) reveal that information about the coating thickness is present in certain process variables, such as those related to the position of the knives (distance to the strip, skew, vertical height etc.), pressure of the air jet, temperature of the zinc pot, line speed, strip thickness, line speed, strip tension. Also, other variables can be considered such as, for instance, air pressure at different points of the knives (primary pressure, or the value of pressure at front or rear sections), or the height of each individual knife with respect to the pot (both at operator and motor side).

Visual data mining techniques

Once a set of feasible variables is obtained, statistical methods that make few assumptions about the problem allow determining the most related variables. We used mainly a visual data mining approach (2) using advanced data visualization methods such as correlation matrix visualization and self organizing maps (SOM). Correlation matrix visualization *(fig. 4, 5)*, consists of visualizing using a colour code the elements of the correlation matrix of the set of variables under study, showing up in a visual way the correlations (values and signs) existing between all the variables. Sorting the rows and columns of this matrix by means of a similarity preserving algorithm (1D versions of SOM or MDS algorithms can be used for this) so that similar variables are positioned adjacently (3) provides an additional insight on the most relevant relationships as well as groups of related variables that show up in a visual way the main relationships between the involved variables. Self organizing maps *(fig. 6)* can be used to determine in a visual way the most important clusters of states of the process. As correlation matrix visualization, the SOM also allows to find correlated variables by looking at similar component planes that reveal variables that behave in a similar way for all the process states and in consequence, are redundant. Moreover, SOM allows determining in a visual way whether correlations between two given variables hold for all process states or if they only hold under certain circumstances. *Table I* displays the variables that were selected as inputs for the virtual sensor after the feature selection process.

Dynamical models of the process

After the feature selection stage, the hot-dip galvanizing process can be modelled by means of a functional relationship between the selected variables, and the coating thickness:

$$Z_n = f(d,\sigma,A,P,T,v, ...) \qquad [1]$$

where Z_n denotes the zinc coating thickness. If we denote the vector of known process variables as $u = [d, s, A, P, T, v, ...]^T$, the problem can be stated in a more compact form as finding a functional relationship f(.), such that:

$$\mathbf{y} = f(\mathbf{u}) \quad [2]$$

The problem so posed can be regarded as a regression or function approximation problem. However, expression [2] represents a static model, where the process inputs immediately affect the process outputs. In complex processes that involve dynamical phenomena such as the hot dip zinc coating, inputs can affect internal states that evolve according to some dynamics and determine the outputs (8). This requires, therefore, having into account this dynamical behaviour in the model. To implement the virtual sensor, a nonlinear autorregresive with exogenous variable (NARX) model was considered:

$$\mathbf{y}(k) = f(\mathbf{y}(\tilde{k}-1),\ldots,\mathbf{y}(\tilde{k}-n),\mathbf{u}(\tilde{k}-d),\ldots,\mathbf{u}(\tilde{k}-\tilde{m}-d)) \qquad [3]$$

where n and m are the autorregresive and exogenous model orders and d is the pure delay. Vector y(k) is a 3 element vector containing the upper, lower and mean Zn coating thickness:

$$\mathbf{y} = (Z^{(up)}{}_n, Z^{(lo)}{}_n, Z^{(me)}{}_n)^T \qquad [4]$$

and u(k) is a vector containing the 11 related process variables obtained after the feature selection process, that are the inputs

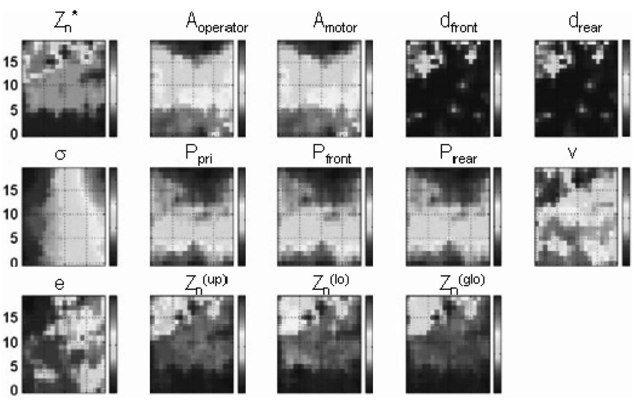

Fig. 6 - SOM planes of the main variables.

Fig. 6 - Projections planes SOM des variables principales.

to the virtual sensor:

$$\mathbf{u} = (Z^*{}_n, A_o, A_m, d_o, d_m, \sigma, P_1, P_f, P_r, e, v)^T \qquad [5]$$

The NARX model described in (3) involves a nonlinear relationship between the current output $\mathbf{y}$(k), and delayed versions of the outputs (autorregresive part) and the inputs (exogenous part). Artificial neural networks and particularly multilayer perceptrons have been extensively used for nonlinear function approximation. There exists a broad amount of literature related to the problem of function approximation and learning from examples and, particularly in the field of neural networks (NN). Neural networks (1, 4) can learn a function mapping $\mathbf{y} = f(\mathbf{x},W)$ relating a set of points $\mathbf{x}_i$ in a given input space to a set of corresponding points $\mathbf{y}_i$ of an output space in a rather simple way.

Most widely used neural networks for function approximation are multilayer perceptrons (MLP) and radial basis functions (RBF). Both types of neural networks are classes of functions of the type $f(\mathbf{x},W)$ with the property of universal function approximation, i.e. provided a sufficiently high number of parameters W is used they can approximate any function with arbitrary low error. Another key factor in the success of neural networks in the process industry is that there exist methods (backpropagation, conjugate gradient, Newton and quasi-Newton methods such as Levenberg-Marquardt, and many others variants of these (1, 4, 9) which allow determining an optimal, in a least square sense, set of weights W which minimizes the cost function J from a set of input-output examples. In other words, neural networks allow performing nonlinear regression over a set of examples to estimate the coating thickness in the strip given a set of available data which have a proven relationship.

While both MLP and RBF neural networks are universal approximators, MLP neural networks have the advantage of making global approximations and require substantially less parameters to achieve a similar accuracy. Also, despite MLP's with one hidden layer already have universal approximation ability, those with two or more hidden layers require fewer parameters for a similar accuracy. On the other hand, MLP architectures with three or more layers however, do not suppose a substantial gain in efficiency. Thus, an MLP with two hidden layers was chosen *(fig. 7)*.

A crucial part in the design of the virtual sensor is the training procedure as well as the model order determination. We proceeded through a systematic training-validation-test procedure that integrates both tasks whose pseudo-code is presented in *figure 8*:

First, we fix the parameters of the model that will be changed on each individual training. These may be (we may choose all or some of them) model order parameters *(m,n,d)* and the MLP parameters (N_1,N_2).

Then we fix a set of values for each parameter that will define all the training-validation iterations to be carried out for all possible combinations.

Train N times for each combination of the parameters (because the MLP training algorithm starts with random weights) and save the model with the smallest validation error (mean

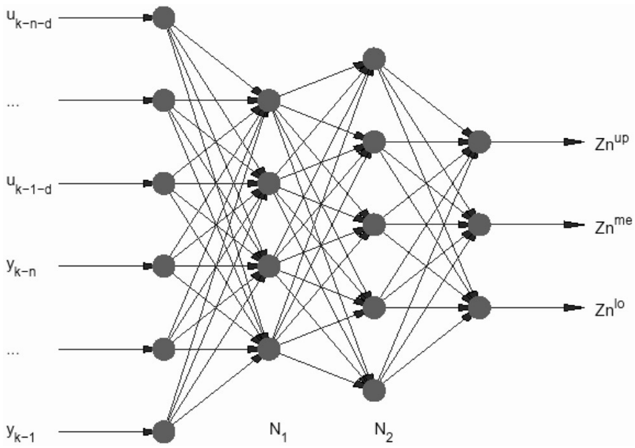

Fig. 7 - MLP architecture for the NARX model.

Fig. 7 - Architecture MLP du modèle NARX.

STEP 1

Fix the parameters to be changed. These may be

a) Model order parameters (m, n, d)
b) MLP parameters (N1, N2)

STEP 2

Fix a set of possible values for each parameter

STEP 3

For each combination (m,n,d,N1,N2) do:
–Train N times using a validation set
–Save the best MLP (less validation RMSE) of the N trainings end

Fig. 8 - Pseudo-code summarizing the training procedure.

Fig. 8 - Pseudo code résumant la procédure d'apprentissage.

absolute error, MAE, or root mean squared error, RMSE, can be used) from the N trainings for each combination. An optimized backpropagation algorithm [7] was used for training.

Finally, test the saved models against one or more test sets and take the best performing model according to a predefined performance index (MAE or RMSE).

Despite all this process takes time (since it may require many training runs) it is done from time to time (in a fixed periodical schedule or when the process is suspected to have changed) offline in a fully automated way, and does not require to be supervised.

■ VIRTUAL SENSOR IMPLEMENTATION

The virtual sensor was installed on a modern and fully automated galvanizing plant, where measurements of all the required variables coming from different automation-level-1 computers, PLC's, and acquisition systems, are sent to level 2 alpha stations where a comprehensive database integrates all the information.

Learning of the models

The learning of the models is performed off-line. All the process data (input and output variables) are obtained from the level-2 database. This database is easily accessible by standard queries from different terminal computers to retrieve the required variables for training of the virtual sensor, such as different knives position parameters given by high resolution encoders, strip temperature, zinc pot temperature, strip speed, coating thickness measurements at hundreds of points along the strip width given by a X-ray scan system as well as many other related process variables.

The systematic iterative training-validation-test process described in the previous section is done off-line over the data retrieved from the database using specialized numerical software (a toolbox of functions developed under MATLAB environment). Once this process is finished, the resulting best performance model can then be saved for future use or converted into a configuration file, which contains the parameters and structure of the model, and loaded into the real time application that runs in the process computer.

Execution of the virtual sensor

The virtual sensor, which runs in real time on the process computer, proceeds in the following steps *(fig. 9, fig. 10)*:

1- Reads the configuration file stored in the process computer. This file contains the virtual sensor parameters such as weights, numbers of neurons in both hidden layers (N_1,N_2), model order parameters and delays *(m,n,d)*, etc. required to completely define the model.

2- Then, a C++ function is called on regular intervals by the operating system of the process computer and performs the following actions:

a. It reads the process parameters from the so called common memory space (a memory space in the process computer where the process variables are stored as they come from the automation level) stored as a typical C structure.

b. Performs all needed calculations from the process data obtained from the fields of the C structure reserved for the input variables.

c. Stores the results on the fields of the C structure reserved for the output variables (estimations).

d. Stores also the required information (e.g. inputs and estimations of the virtual sensors) as a row on a log file for debugging purposes.

3- Finally, the level-2 database is updated so that the estimations are made available through standard queries from plant-wide terminal computers for being displayed or to be used as an aid for manual control in case of X-ray gauge malfunction.

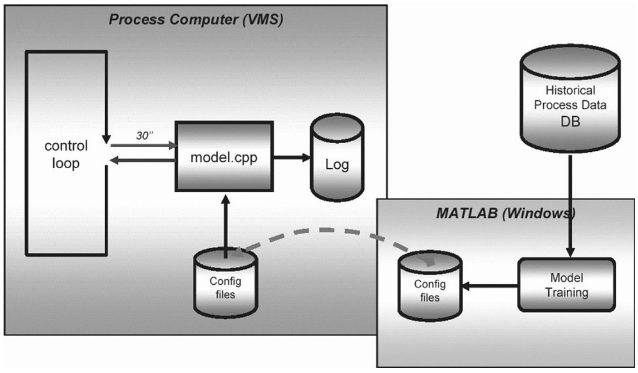

Fig. 9 - Flow grams of the virtual sensor implementation.

Fig. 9 - Architecture de l'installation du capteur virtuel.

■ RESULTS

For comparison purposes, apart from the previously described MLP-based NARX model, an ARX model (linear version of the NARX model), and a SOM-based regression model were implemented:

ARX model

The ARX model is a particular case of NARX model [3] where f() is restricted to be linear:

$$\mathbf{y}(k) = a_1\, \mathbf{y}(k-1)+\dots+a_n\, \mathbf{y}(k-n) + b_0\, \mathbf{u}(k-d) + \dots + b_m \mathbf{u}(k-m-d)$$

Parameters a_i and b_i, were obtained using standard least squares.

SOM based regression

A 42x42 SOM was trained using the standard batch algorithm (5, 6), on vectors containing both the input and output values, (u(k), y(k)) resulting in 42x42 prototypes $m(i)=(m_u,m_y)$ where m_u and m_y are the coordinates that represent the input and output data respectively. The best matching unit is obtained by comparing the input coordinates to the actual input vector u:

$$\text{bmu} = \text{argmin}_i\, |\mathbf{u}-\mathbf{m}_u(i)|$$

and the estimation is readily obtained from the output coordinates of the winner prototype

$$\mathbf{y}_{est} = \mathbf{m}_y(\text{bmu})$$

The comparative results using RMSE (Root mean squared error), MAE (mean average error) and % error (a percent mean average error) for the three approaches are summarized in *table II*.

MAE $\quad \frac{1}{N}\sum_{i=1}^{N}|\hat{y}_i - y_i|$

RMSE $\quad \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2}$

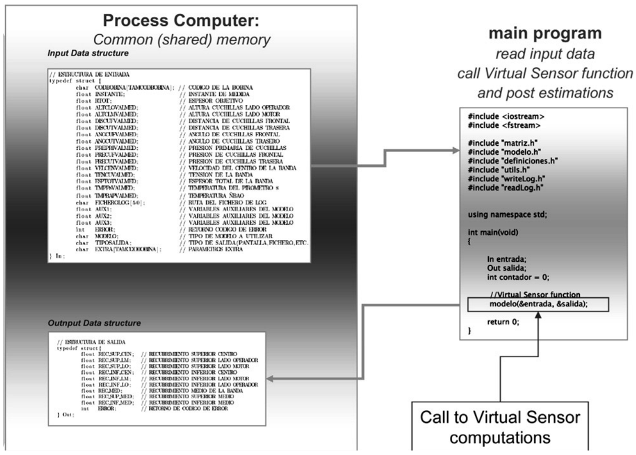

Fig. 10 - Schematic flow gram of the computer implementation of the algorithm.

Fig. 10 - Schéma de l'implantation de l'algorithme.

E [%] $\quad \frac{1}{N}\sum_{i=1}^{N}\frac{|\hat{y}_i - y_i|}{y_i} \times 100$

As seen, the MLP-based NARX model gives the best global results, being especially good in the RMSE. Since RMSE error is more susceptible to large errors than MAE, the much better behaviour of MLP-NARX method with respect to RMSE reveals better prediction ability especially in cases where coatings deviate substantially from nominal values, typically in abrupt changes of thickness (peaks). The results are encouraging with mean absolute errors (MAE) lower than 5 g/m^2 for the best predictor (MLP-NARX).

The performance of MLP is exemplified in *figure 11*. The plot displays several different coils with different coating target and the response of the virtual sensor. Dotted line, representing model results, follows very precisely the continuous line, representing the X-Ray gauge measurement. Also, two zoom zones are shown for better representation.

Figure 12 shows a screenshot of the information that is available on site for the technical staff. Both measured and estimated coating thicknesses for upper and lower side of the strip are plotted showing, a good approximation of the virtual sensor to the measured coatings. The estimators show up a good dynamical performance upon changes on the coatings, with a good tracking of the measured values.

■ CONCLUSIONS

In this work a nonlinear dynamical model (MLP based NARX) has been used to implement a virtual sensor of the zinc coating thickness on a galvanizing line from a set of available process variables that are known to be related. A highly flexible approach based on a virtual sensor function programmed in C++ in the process computer that loads the parameters obtained from a MATLAB based design process and implements the proposed model is presented. The estimations provided by the implemented virtual sensor have given encouraging results up to the moment and are currently being monitored at plant terminals. This brings the following benefits. First, the estimation of the coating thickness as well as preset values can be obtained even when the X-ray gauge is damaged or inoperative, allowing the technical staff to improve the production quality in this situation. Second, the redundant measurements provided by the virtual sensor give a mechanism to quickly detect possible X-ray gauge malfunction by observing the differences (residuals) between the measured and estimated coatings.

Finally, an estimation of the coating thickness is obtained in the same place where the control actions are taking place. This might allow in the future the design of control algorithms that use the estimation provided by the virtual sensor to take immediate corrective actions on the process parameters thus improving the coating thickness control system performance.

■ REFERENCES

(1) BISHOP (C.-M.) - Neural networks for pattern recognition, Oxford University Press, 1995.

(2) CUADRADO (A.), DÍAZ (I.), DIEZ (A.), OBESO (F.), GONZALEZ (J.) - Visual data mining and monitoring in steel processes, proceedings of the 37th IEEE industry applications conference, Pittsburgh, PA, USA, 2002.

(3) FRIENDLY (M.) - Corrgrams: exploratory displays for correlation matrices. *American Statistician,* 56 (4), p. 316-324, 2002.

(4) HAYKIN (S.) - Neural networks, a comprehensive foundation. Prentice-Hall, Inc., 1999.

(5) KOHONEN (T.) - Self-Organizing Maps, Springer-Verlag, 1995.

(6) KOHONEN (T,) ERKKI OJA, OLLI SIMULA, ARI VISA, JARI KANGAS - Engineering applications of the self-organizing map, proceedings of the IEEE, 84 (10), p.1358-1384, October 1996.

(7) LE CUN (Y.), BOTTOU (L.), ORR, (G.-B.), MÜLLER (K.-R.) - Efficient backprop neural networks: tricks of the trade, 1998.

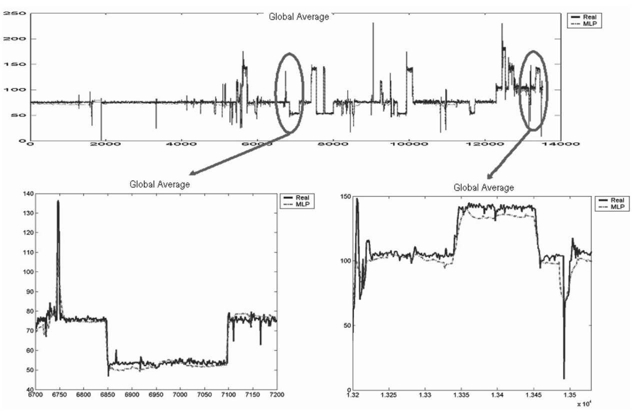

Fig. 11 - Example of performance of virtual sensor with MLP.

Fig. 11 - Exemple de performance du capteur virtuel avec MLP.,

TABLE II: Comparative results for three different algorithms of the virtual sensor: SOM, ARX, NARX (MLP).

TABLEAU II: Comparaison des résultats des trois différents algorithmes du capteur virtuel : SOM, ARX, NARX (MLP).

		MAE	RMSE	E (%)
SOM	$Z^{(up)}$	5.37 g/m²	16.30 g/m²	10.02 %
	$Z^{(lo)}$	4.18 g/m²	8.64 g/m²	5.27 %
	$Z^{(me)}$	3.45 g/m²	7.58 g/m²	7.35 %
ARX	$Z^{(up)}$	4.77 g/m²	15.76 g/m²	10.03 %
	$Z^{(lo)}$	4.42 g/m²	15.12 g/m²	3.97 %
	$Z^{(me)}$	3.68 g/m²	15.02 g/m²	6.78 %
MLP-NARX	$Z^{(up)}$	4.28 g/m²	6.45 g/m²	7.87 %
	$Z^{(lo)}$	4.46 g/m²	7.10 g/m²	5.04 %
	$Z^{(me)}$	3.68 g/m²	5.81 g/m²	5.35 %

(8) MORRIS (A.-J.), MARTIN (E.-B.) - Neural networks: panacea or pragmatic solution, ECSC Workshop, Application of artificial neural networks systems in the steel industry, p. 9-42, Brussels, January 1998.

(9) RIEDMILLER (M.), BRAHUN (H.) - A direct adaptive method for faster back propagation learning: the Rprop algorithm. IEEE International Conference on Neural Networks,1993.

(10) THORNTON (J.-A.), GRAFF (H.-F.) - Analytical description of Jet finishing process for hot-dip metallic coatings on strip, *Metallurgical Transactions B-Process Metallurgy,* 7, 4, p. 607-618, 1976.

(11) KIM (J.-K.), KIM (S.), KIM (H.), LIM (K.) - Development of dynamic air knife system (DAK) in continuous galvanizing lines, *CAMP-ISIJ,* vol 9, p. 939, 1996.

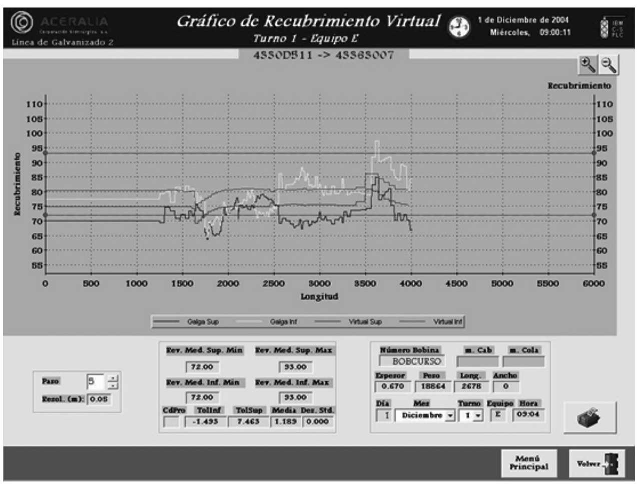

Fig. 12 - Screenshot of the information available on site; measured and estimated coatings for the upper and lower side of the strip are shown.

Fig. 12 - Vue d'écran des informations affichées en ligne ; les revêtements mesurés et estimés des faces supérieure et inférieure de la bande sont présentés.