Real-Time Testing of Steel Strip Welds based on Bayesian Decision Theory

Julio Molleda, Daniel F. García, Juan C. Granda, and Francisco J. Suárez

***Abstract*—**One of the main trouble in a steel strip manufacturing line is the breakage of whatever weld carried out between steel coils, that are used to produce the continuous strip to be processed. A weld breakage results in a several hours stop of the manufacturing line. In this process the damages caused by the breakage must be repaired. After the reparation and in order to go on with the production it will be necessary a restarting process of the line. For minimizing this problem, a human operator must inspect visually and manually each weld in order to avoid its breakage during the manufacturing process. The work presented in this paper is based on the Bayesian decision theory and it presents an approach to detect, on real–time, steel strip defective welds. This approach is based on quantifying the tradeoffs between various classification decisions using probability and the costs that accompany such decisions.

***Keywords*—**Classification, Pattern Recognition, Probabilistic Reasoning, Statistical Data Analysis.

I. Introduction

IN the steel industry many manufacturing lines need a continuous strip for their permanent operation. Steel coils are welded in the input section of these lines in order to obtain the strip needed.

A concrete manufacturing line in which this kind of operation is used is a galvanizing line. The aim of these installations is to provide protection against corrosion to the steel processed in it. Protecting process is done in two steps. Firstly, a thin layer of zinc is applied to the steel strip. Secondly, a thin layer of chrome can be applied to the steel strip if it is required by the customer.

The building scheme of a galvanizing line, shown in Fig. 1, is divided into three operational sections: input section, process section and output section. The unions to obtain the continuous strip from steel coils are carried out by welding processes at the input section of the line. Between the input section and the process section there is installed a steel strip accumulator. The purpose of this accumulator is to provide the necessary strip to the next section of the line, the process section, while the strip is stopped into the input section to carry out the weld.

The weld between two coils obtained in the input section is carried out by a critical welding process. It is a critical process for two reasons.

Firstly, the time available to carry out the weld: This time is defined by the capacity of the accumulator. The welding process should be done before the entire strip in this accumulator is consumed. In other case, the continuous steel strip processed must be stopped and, from that moment, the protection quality against corrosion of the steel strip will not fulfil the expected galvanizing requirements. Stopping the strip while it is in the process section provokes that the galvanizing layer applied to the strip will not be even in the entire strip which will generate irregularities in manufactured final product.

Secondly, the reliability of the obtained weld: The welds must have a high quality to ensure that they can pass through all the components of the galvanizing line (clean electrolytic baths, warm–up furnace and galvanizing bath) without breaking. Furthermore, the welds must be able to support the strains to which they will be exposed in each roller of the line.

A. Welding Process

The welding process used at the input section of the galvanizing line is sheave electrical welding. This welding process is autogenous, that is, contribution of external material is not necessary. The weld is basically carried out by an electrical current that flows through the parts of the material to be welded. The coils to be welded are transversally overlapped over the welding machine chassis. In the welding process, the Joule effect of an electrical current applied to the steel is used to raise the temperature of the overlapped area of the coils until welding temperature. The electrical current is applied to the coils by means of two sheaves, called welding sheaves. After these two sheaves, another pair of sheaves, called flattening sheaves, apply pressure to both sides of the overlapped area of the coils to ensure the weld.

All the adjustable parameters of a welding process in the galvanizing line are defined by different welding machine control programs. Each welding program is determined by the class of the two coils to be welded and the thickness of each of those. The range of the steel thickness that the line can process is divided into small intervals in order to determine the correct welding parameters for them. The welding control

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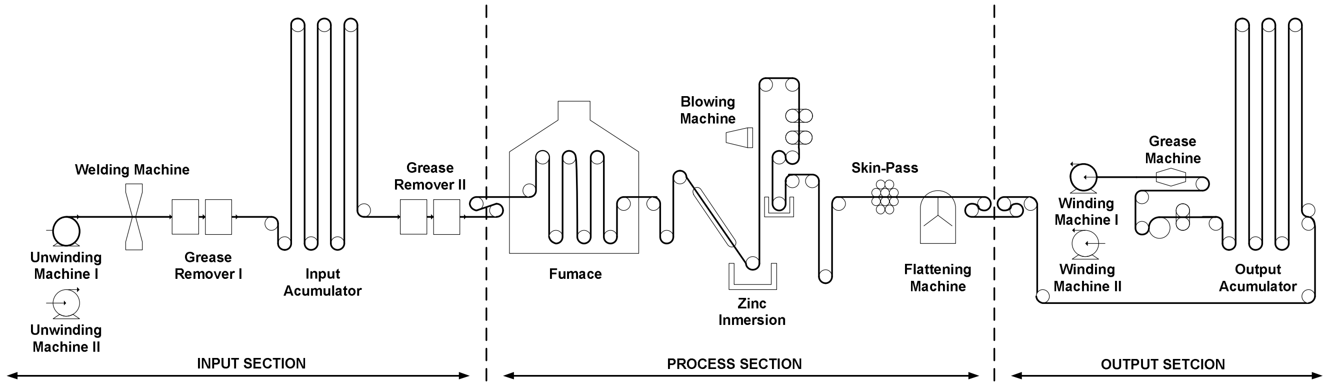

Fig. 1 Galvanizing Line

program defines the voltage applied to the welding sheaves, the overlapping area of the coils to be welded and the pressures to be applied to the welding area by means of the welding sheaves and the flattening sheaves.

B. Current Nondestructive Tests

The aim of this work is to provide a technique for predicting the quality of each weld carried out in the galvanizing line and, therefore, for suppressing the manual and visual inspection of the human operator.

A first technique for replacing the human operator inspection consists in acquiring images of the welding area with an artificial vision system that automatically emulates his inspection process [1] [2]. These techniques only obtain acceptable results in welds with external defects.

Techniques which do not use visible spectrum for detecting defects in welds, either internal or external, are based on X–Ray [3] [4] and ultrasound [5] [6] technologies. The cost of the techniques based on these systems is very high. Furthermore, their implementation and installation are difficult in industrial lines that have not previewed their utilization in the design phase, as it is the case of the galvanizing line in which this work is developed.

As an alternative to the high cost methods referenced above, other approaches were developed. The analysis of a weld can be made by several physical variables of the welding process easy to measure, such as, the voltage and current applied to the steel during the electrical welding process. The defective welds in these cases are detected by a statistical processing of the evolution of the acquired variables [7]. Instead of a statistical approach, the processing of the variables can use other classical computational intelligence techniques, such as classification and regression tress [8] [9], neural–networks [10] [11], fuzzy–logic [12] [13], and data–mining techniques [14].

In some steel manufacturing line in which the installation of X–Ray or ultrasound testing systems can not be installed because of the limitations of the line design, cheap sensors besides the indispensable sensors for the control of the welding process can be installed, such as, temperature sensors.

The work presented in this paper follows this approach: a statistical processing of the measurements provided by basic and complementary sensors.

II. Architecture of the Welding Defects Detection System

The detection system needs to know information about each weld carried out in the line in order to classify it as defective or non–defective. This classification is made on real–time and it is shown to the human operator of the input section of the galvanizing line.

The components of the developed detection system are shown in Fig. 2.

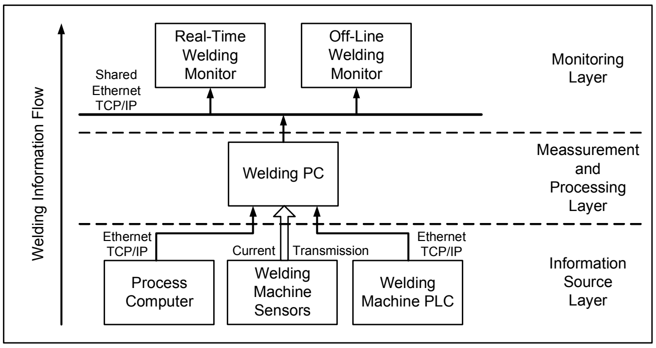

Fig. 2 Architecture of the Welding Defects Detection System

The architecture of the system is organized in three layers: Information Source Layer (low level), Measurement and Processing Layer (intermediate level) and Monitoring Layer (high level). The information about each weld carried out in the line flows from the bottom layer to the top layer.

The low level layer and its interface with the intermediate level layer contain the hardware implementation of the system. They provide information about the processes to the upper layer. This layer is composed by the following components: Process Computer, a computer which stores data about each coil processed in the line (identification, steel class, length, weight, width, thickness...); Welding Machine PLC, a programmable logic controller which controls all the actions of the welding machine by the welding control programs; and Welding Machine Sensors, a set of basic and complementary sensors that measure the welding process physical variables. These variables are: the welding machine header speed, the voltage applied to the steel coils by means of the welding sheaves, the electrical current that flows through the welding area, the welding area temperature, the welding sheaves pressure and flattening sheaves pressure.

The intermediate level layer acquires, stores and processes the information. This layer is composed by the Welding PC, a computer which is the core of the system. The set of sensors connected to the welding machine transmit data to the Welding PC by means of current loops to avoid interferences produced by the high electromagnetical noise of the line. This computer has an analogical acquisition system which acquires Welding Machine Sensor measurements in real–time. Welding PC is also connected to the other two subsystems of the lower layer. Using a dedicated TCP/IP link it receives from Process Computer identification, physical characteristics and chemical composition of each coil processed in the line. Using another dedicated TCP/IP link, Welding PC receives from Welding Machine PLC the specific welding control program for each welding process and indications about the starting and finishing of the process. This computer stores, for each weld carried out in the line, a binary file containing the identification, physical characteristics and chemical composition of the welded coils, the welding control program and the evolution of the signals measured during the welding process.

The top level layer provides two ways of monitoring the welding process. This layer is composed by Real–Time Welding Monitor and Off–Line Welding Monitor. These are computers connected with the Welding PC by means of a shared TCP/IP link. Real–Time Welding Monitor displays, in real–time, the evolution of the welding process signals measured by the lower layer. Off–Line Welding Monitor provides a remote access point to the entire information of each weld carried out in the galvanizing line stored in Welding PC.

III. Defective and Non–Defective Welds Classification

As a defect detection strategy, the system uses a classifier to separate the two possible kinds of a weld carried out in the line: defective, when a weld is unacceptable for the rest of the galvanizing process, and non–defective, when a weld is considered valid for the process.

The developing process of this classifier is based on the empirical knowledge obtained after carrying out many welds with different steel classes and different thickness intervals, and the expert knowledge on welding processes of the qualified staff of the manufacturing line. A wide testing set of welds, obtained during six month work of the galvanizing line, is used (seven thousand welds) to build this classifier. Each weld of this set was classified by a group of human operators of the line.

A pattern recognition system [15] is used and it can be divided into four different components as is shown in Fig. 3. The *input* of the pattern recognition system is a natural pattern and the result provided by it is a category for the pattern.

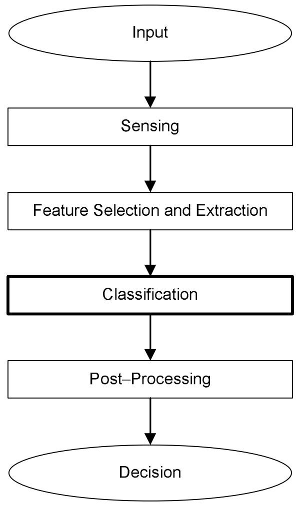

Fig. 3 Components of the Pattern Recognition System

A. Sensing

The *input* of the pattern recognition system is provided by the lower layer of the architecture (Fig. 2). Process Computer data, Welding Machine Sensors measurements and Welding Machine PLC data are combined for each weld carried out in the line in order to obtain an input to the system.

An *input* of the pattern recognition system, X, is a random variable composed by *n* components, $X = \{x_1, x_2, ..., x_n\}$. For a specific combination of steel classes to be welded and a specific thickness interval, the input pattern is defined as X = {*Voltage, Current, Temperature, Welding Machine Header Speed, Welding Sheaves Pressure, Flattening Sheaves Pressure*}, where x_i is a statistical value of each analogical signal.

B. Feature Selection and Extraction

The goal of this stage is to characterize a weld to be recognized by measurements whose values are very similar for welds in the same category (defective or non–defective) but very different for welds in other category. The relevant information for the classification, $Y = \{y_1, y_2, ..., y_d)$, must be extracted (Fig. 4) from the original pattern, $X = \{x_1, x_2, ..., x_n\}$, where $d \leq n$.

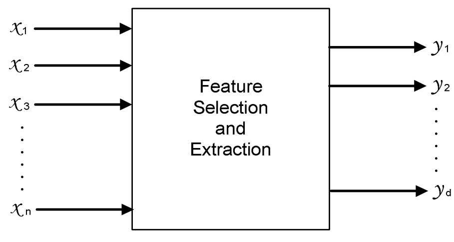

Fig. 4 Feature Selector and Extractor

A study with the testing weld set was done and it determined that it is no necessary to work with all measured values of the analogical signals acquired because defects in one weld can be identified by significant variations in the average values of the signals, with regard to average values obtained from non–defective welds for the same combination of steel classes to be welded and the same thickness interval.

This study also determined that there are two variables acquired that do not show variations between defective or non–defective welds: the welding machine head speed and the voltage applied to the welding sheaves. The reason for no variations in header speed is that, in all welding processes, speed is always set by the welding machine controllers and they can support the same speed during the entire process, independently of the quality of the weld obtained. The voltage applied to the welding sheaves is controlled by a transformer which can support the set–point fixed by the welding control program during the entire welding process. In this way, the variations can be observed in the electrical current that flows through the welding area due to the steel resistivity of each coil to be welded.

The important information for classification is the set *Y* = {*Current, Temperature, Welding Sheaves Pressure, Flattening Sheaves Pressure*}.

C. Classification

The task at this stage is to use the feature vector provided by the feature selection and extraction stage, *Y*, to assign the weld to a category, or more specifically, to determine the probability for each of the possible categories.

Following the decision theory terminology, a steel coil weld is in one of these two possible states: either the weld is defective or it is non–defective. These two categories defined the Ω set: $\Omega = \{\omega_1, \omega_2\}$ = {*Defective, Non–Defective*}.

With all the population of the welds acquired in the testing set, prior probabilities can be calculated for each category in the Ω set, *Defective* (1) and *Non–Defective* (2).

$$P(\omega_1) = P(\mathit{Defective}) = 0.085 \qquad (1)$$

$$P(\omega_2) = P(\mathit{NonDefecti\ ve}) = 1 - P(\mathit{Defective}) = 0.915 \qquad (2)$$

For each particular feature of *Y*, its probability density function is calculated, $p(y|\omega_j)$. These functions show the probability density of measuring a particular feature value: *Current*, *Temperature*, *Welding Sheaves Pressure* or *Flattening Sheaves Pressure*, given the pattern is in the category *Defective* or *Non–Defective*. Fig. 5 shows the two curves which describe the difference in Current of the population of two kinds of quality weld. Fig. 6 describes the difference in Temperature of the same population. Fig. 7 and Fig. 8 describe the difference in Welding Sheaves Pressure and Flattening Sheaves Pressure in the same population, respectively. Density functions are normalized, thus the area under each curve is 1.0.

The two first probability density functions show that there are significant differences in *Current* and *Temperature* between the two weld quality categories. The two last functions show that there are no significant variations in Welding Sheaves Pressure and that there is no any variation in Flattening Sheaves Pressure between both categories. Therefore, *Current* and *Temperature* are the two variables selected for the classification process.

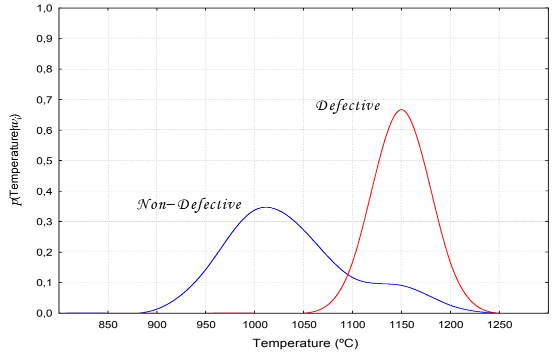

Fig. 5 Current Probability Density Function

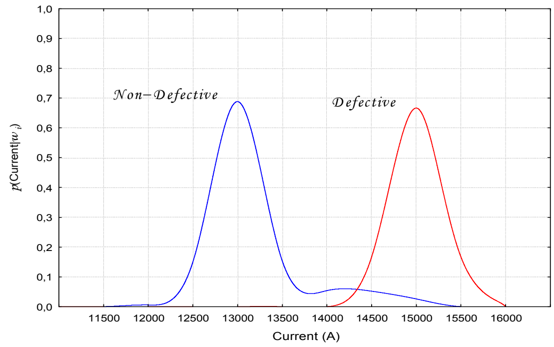

Fig. 6 Temperature Probability Density Function

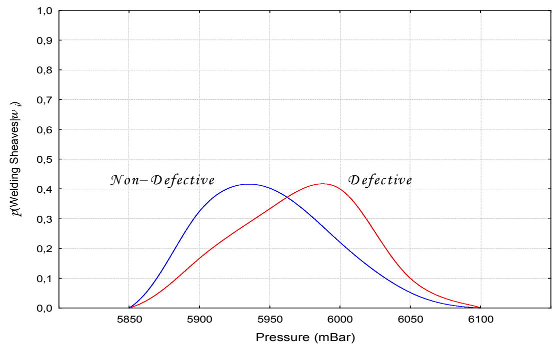

Fig. 7 Welding Sheaves Pressure Probability Density Function

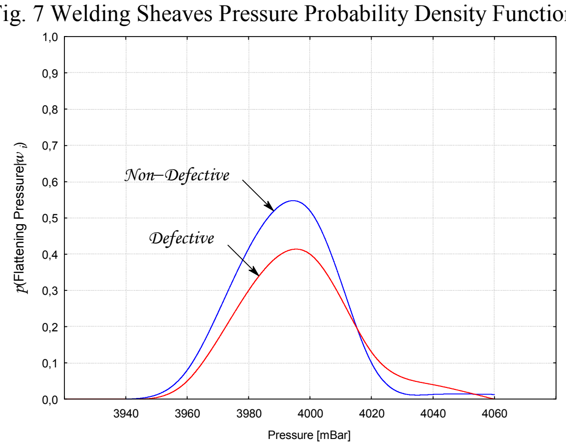

Fig. 8 Flattening Sheaves Pressure Probability Density Function

Weld classifier uses the feature vector *z*, which is a

2−dimensional space called feature space, defined as $\boldsymbol{z} = \{z_1, z_2\} = \{Current, Temperature\}$, and it is based on the *Bayes formula* (3).

$$\mathrm{P}(\omega_j \mid z) = \frac{p(z \mid \omega_j)\mathrm{P}(\omega_j)}{p(z)} \tag{3}$$

where

$$p(z) = \sum_{j=1}^{2} p(z \mid \omega_j)\mathrm{P}(\omega_j) \tag{4}$$

and $\mathrm{P}(\omega_j|z)$, the posterior probability, is the probability of the state of nature being ω_j given that feature vector $\boldsymbol{z}$ has been measured.

Particularizing, *Bayes formula* is applied as (5) and (6).

$$\mathrm{P}(Defective \mid z) = \frac{p(z \mid Defective)\mathrm{P}(Defective)}{p(z)} \tag{5}$$

$$\mathrm{P}(NonDefective \mid z) = \frac{p(z \mid NonDefective)\mathrm{P}(NonDefective)}{p(z)} \tag{6}$$

where, being z_1 and z_2 conditionally independent random variables,

$$\begin{aligned} &p(z \mid Defective) = p(\{z_1, z_2\} \mid Defective) = \\ &p(z_1 \mid Defective)\, p(z_2 \mid Defective) = \\ &p(Current \mid Defective)\, p(Temperature \mid Defective) \end{aligned} \tag{7}$$

$$\begin{aligned} &p(z \mid NonDefective) = p(\{z_1, z_2\} \mid NonDefective) = \\ &p(z_1 \mid NonDefective)\, p(z_2 \mid NonDefective) = \\ &p(Current \mid NonDefective)\, p(Temperature \mid NonDefective) \end{aligned} \tag{8}$$

and

$$\begin{aligned} p(z) = \;& p(z \mid Defective)\mathrm{P}(Defective) + \\ & p(z \mid NonDefective)\mathrm{P}(NonDefective) \end{aligned} \tag{9}$$

After calculating $\mathrm{P}(Defective|\boldsymbol{z})$ and $\mathrm{P}(Non\text{−}Defective|\boldsymbol{z})$ for a specific weld, $\boldsymbol{z}$, the simplest decision to classify it in one of the two categories, *Defective* or *Non−Defective* weld, is (10), but it is not always the best decision in this system. The problem is that all errors have not the same cost. An error in classifying a defective weld as non−defective ("*Real D, Predicted ND*") is more expensive than classifying a non−defective weld as defective ("*Real ND, Predicted D*"). The first error provokes that a low quality weld pass through the rest of the galvanizing line having a high probability of breaking. The second error provokes that a good quality weld is repeated by the welding machine. The cost of one welding process is much lower than a stopping process of the entire galvanizing line (Table I).

$$Decide \quad \omega_1 \quad if \quad \mathrm{P}(\omega_1 \mid z) > \mathrm{P}(\omega_2 \mid z) \quad else \quad decide \quad \omega_2 \tag{10}$$

TABLE I
CLASSIFICATION COSTS

		Real	
		D	ND
Predicted	D	0 €	2.500 €
	ND	50.000 €	0 €
D = Defective		ND = Non−Defective	

D. Post−Processing

The post−processor subsystem uses the output of the classifier to decide on the action to recommend to the human operator of the input section of the galvanizing line. There are two actions depending on the quality of the weld carried out. If the weld is classified as defective, the recommended action is "*repeat welding process*". Otherwise, the recommended action is "*continue galvanizing process*".

Classification errors "*Real D, Predicted ND*" must be avoided, so, it is necessary to define a decision rule to minimize the probability of this error.

Let $\{\alpha_1, \alpha_2\} = \{repeat, continue\}$ be the set of possible actions to recommend to a human operator. A loss function [16], $\lambda(\alpha_i|\omega_j)$, is defined, in (11) based on the error classification cost shown in Table I. $\lambda(\alpha_i|\omega_j)$ describes the loss incurred for recommending action α_i to a human operator when the state of the weld is ω_j. If action α_i is recommended to an operator and the true state of the weld is ω_j then the decision is correct if i = j and is in error if i ≠ j. This function penalizes the classification error "*Real D, Predicted ND*".

$$\begin{aligned} &\lambda(repeat \mid Defective) = 0 \\ &\lambda(repeat \mid NonDefective) = 0.05 \\ &\lambda(continue \mid Defective) = 1 \\ &\lambda(continue \mid NonDefective) = 0 \end{aligned} \tag{11}$$

An expected value of "loss" when taking action α_i is calculated applying (12). Then, the conditional risk of each action recommended in the galvanizing line is (13).

$$R(\alpha_i \mid z) = \sum_{j=1}^{2} \lambda(\alpha_i \mid \omega_j)\mathrm{P}(\omega_j \mid z) \tag{12}$$

$$\begin{aligned} &R(continue \mid z) = \lambda(continue \mid Defective)\mathrm{P}(Defective \mid z) \\ &R(repeat \mid z) = \lambda(repeat \mid NonDefective)\mathrm{P}(NonDefective \mid z) \end{aligned} \tag{13}$$

The final decision is to select a choice that minimizes the conditional risk (14).

$$\begin{aligned} &Decide \quad Defective \quad if \quad R(repeat \mid z) < R(continue \mid z) \\ &\qquad else \quad decide \quad NonDefective \end{aligned} \tag{14}$$

IV. DEFECTS DETECTION SYSTEM INTERFACES

The top level layer of the architecture of the welding defects detection system is composed by two computers, as is shown in Fig. 2.

One computer receives, on real−time, the data of each weld carried out in the line. The interface developed allows human operators to monitor each weld and to receive, from the core of the system, the recommended action about the welding process just finished. This interface is shown in Fig. 9. It provides visualization of physical variables of the welding process in real−time.

Users of this interface are operators of the input section of the galvanizing line, specifically, welding machine operators.

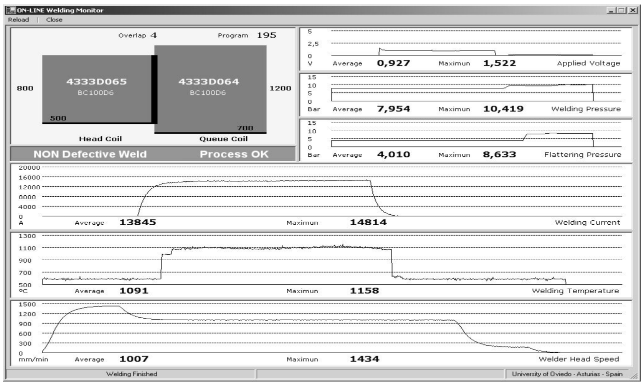

Fig. 9 Real–Time Welding Monitor

The other computer is an access point to the data stored by the system. The interface developed allows galvanizing line engineers to monitoring each welding process carried out in the line previously. This interface is shown in Fig. 10. It provides a navigation tool for each welding binary file stored in Welding PC (intermediate level of the architecture of the system) and allows monitoring all welding parameters, physical characteristics and chemical compositions of the welded coils.

Users of this interface are maintenance engineers and quality engineers of the galvanizing line. They will be able to calculate, analyzing the data stored the unavailability of the manufacturing line due to defective welds.

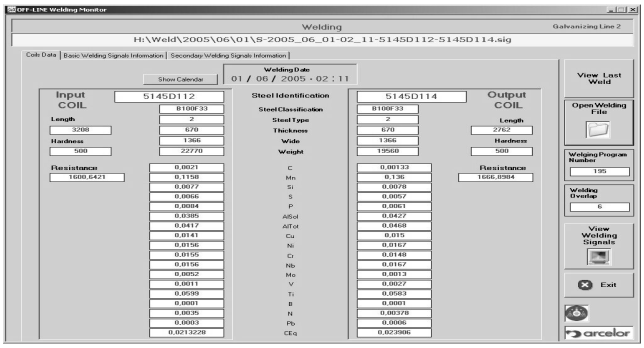

Fig. 10 Off–Line Welding Monitor

V. Results

A system that allows detection of defective steel strip welds in real–time has been developed based on the strategy shown in this paper. The system is installed in a galvanizing line of Arcelor Group in Avilés (Spain). About eighty steel strip welds are manufactured each day. The entire data of these welding processes are on–line monitored and stored by the system.

Based on the classification strategy described and the cost of each possible action, the system is able to indicate to the human operators of the input section of the galvanizing line, the recommended action for each weld carried out in the line.

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