Modelling of temperature in the aluminium smelting process using Neural Networks

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Modelling of Temperature in the Aluminium Smelting Process using Neural Networks

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***Abstract*— Industries are aiming to become more competitive and enlarge their profits. A good management is a key factor to accomplish the company's target, however all management decisions are supported by tools that provide good information on the process. Soft Sensors have been applied in industries and its use has been growing lately. It can be adapted to any application regarding variable measurement, therefore reducing operational costs without compromising process information. In some cases, better results can be obtained. The key of its success is the intelligent computing it uses, which has been heavily used in nonlinear and highly complex process modeling. This work exploits its use with Neural Networks in a chemical process in an important Brazilian Aluminum Smelter whose process is very complex and whose measurements consume operational resources due to corrosive nature of the plant. The usage of soft sensors may reduce costs and measures' delays drastically. A case of use of the soft sensor for temperature measure is presented on this work, its design through implementation, according to a researched methodology.**

I. INTRODUCTION

SOFT SENSORS have lately been heavily used in the industry [1]. Because of its software basis, soft sensors are able to estimate variables whose measurements are difficult, costly and require some hard work, such as laboratory analysis [2]. Soft Sensors usually have a short response time and a good precision, according to a knowledge base. [1, 3]. Its use has been exploited mainly in the chemical processes, which presents most of the challenges in process control and identification. Figure 1 shows the principle of soft sensor.

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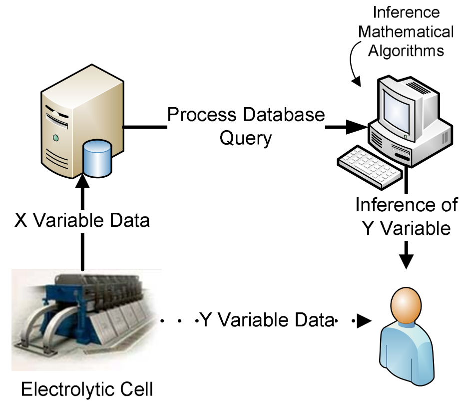

Fig. 1. Soft Sensor operating principle.

For the industry, soft sensors have some advantages such as:

1) Expensive hardware Substitution: Soft Sensors are based on Software, thus they can replace process expensive hardware and reduce maintenance costs;

2) Deployment Flexibility: As mathematical algorithms, soft sensors can be implemented in any device provided with a processing unit, such as controllers, microprocessors and computers;

3) Variable Trends in real time: Soft Sensors allow plant experts to simulate the process, regardless of delays that usually occur with analog or hardware sensors;

4) For process, they work as real sensors: Soft Sensors can be integrated to the automation plant in a transparent way.

This work shows a practical use of a soft sensor in the aluminium smelting industry. The indirectly estimation of the cell temperature is the desired objective, but in order to achieve this, one should follow a methodology described in detail in [1]:

--Identify behavior patterns among process variables, in order to choose which dataset should be used in the model.

--Select and filter real process data, so the noisy and outlier data are removed and a process simplified analysis is permitted.

--Build an inference model, having input and output variables, allowing its implementation in any programming language.

--Validate the soft sensor estimations and implement it in software.

In addition, a research on the subject regarding aluminium smelting process has been done. Likewise, one has good theoretical support for variable and data selection. An interaction with the process team is also highly recommended, since they are expert in the process control and therefore a good source of knowledge.

This paper follows the structure:

1) Introduction: It introduces an overview of the subject and the methodology used in this paper;

2) Aluminium Smelting Process: It presents the Aluminium smelting process at a glance, regarding the problem concerned in the paper, which motivated the soft sensor modeling;

3) Soft Sensor Design Methodology: The methodology used in this paper is detailed in this section, including how the data filtered, variable selection and so on;

4) Model Structure: The model structure and its design are presented in this section, including the neural network and its training;

5) Results and Validation: In this section some results are discussed and how some challenges are treated within the soft sensor usage;

6) Conclusion: The work findings are shown and a suggestion for future works derived from this approach is given.

II. ALUMINIUM SMELTING PROCESS

This section provides some background of the Aluminium Smelting Process needed for this paper. Aluminium is produced through the Hall-Héroult process, in which there are basically three control systems: electrical resistance control, heat and mass balance control and alumina (Al2O3) feeding control [4].

The main input of this process is refined alumina, which is distributed in pots or cells containing a chemical or electrolytic bath mainly composed of cryolite (Na3AlF6) under a high electrical current, where electrolysis occurs. The alumina molecule is broken into aluminum (Al2+) and carbon dioxide (CO2) by the electrolysis [3]. The electrolytic cells have two electrodes: the anode (negative pole) in its upper part and the cathode (positive) on the bottom. A current of about 180 kA is conducted through these electrodes, resulting in a heating of the electrolytic bath, raising the temperature close to 960ºC. Figure 2 shows the side view of an aluminium reduction cell.

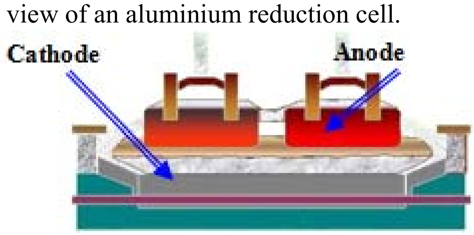

Fig. 2. The side view of an aluminium reduction cell.

The aluminum production is strongly affected by heat and mass balance, thus it is desirable to maintain stability on heat and mass variables, since such variations could even result in pot destruction [5,6]. Others additive components like Aluminum and Calcium Fluorite are added to the bath in order to keep the stability of the heat and mass balance [5]. The heat and mass variables are collected daily to weekly [6], and some laboratory analysis or manual instrumentation are needed. Such measurements are desirable to be online, but it cannot due to the corrosive nature of the smelting plant. The primary aluminum industries, aiming to achieve levels of quality and increasing production, invest in computational intelligence techniques for process control. In this context, the indirect measurement of the cell temperature via Artificial Neural Networks is implemented as an alternative source for the heat balance control. Its implementation is based on the soft sensor design methodology described in detailed in the next section.

III. SOFT SENSOR DESIGN METHODOLOGY

Fortuna et al. shows a good methodology to design a soft sensor [1]. There are basically four steps to follow in designing of a soft sensor:

1) Historical Data Selection and Filtering: The process database is a useful source of information on the process dynamics and should be used for modeling. However, attention should be paid regarding variables and data selection. Noisy and outlier data should be left out. Data for both model construction and model validation should be selected;

2) Model Structure Definition: The core part of the soft sensor should be chosen, which can be any nonlinear (or even linear) model (NARMA, Box-Jenkins, ANN, Neuro-Fuzzy Strategy and so on);

3) Model Estimation: This is the part when a parameter estimation algorithm is chosen. For instance, in the case of Neural Network, one should choose the training algorithm, and train the network;

4) Model Validation: The model is validated through comparisons with real data and its performance may be evaluated with a MSE or RMSE error.

An early cooperation between soft sensor designers and plant experts is highly recommended, in order to select only relevant variables with good noiseless data to build the model [1].

A. Variable Selection

The concerned aluminum reduction process maintains a database with more than 200 variables from 4 potlines of 240 cells each, for all control systems, not only heat balance control. These data have different samplings, varying from 0.5 s to 7 days. In order to obtain a plain database, an average of each variable was taken for a sampling time of 32 hours, which is the average sample time of most of the heat and mass balance variables, and is the base time for heat balance control cycle.

From the 200 available variables, only 40 variables were investigated. According to literature and the process team, the remained variables have absolutely no influence in the cell temperature [5]. A linear correlation analysis is done, in order to early detect the variables with the strongest correlations with cell temperature [1]. The correlation charts are shown in Figures 3(a), 3(b) and 3(c).

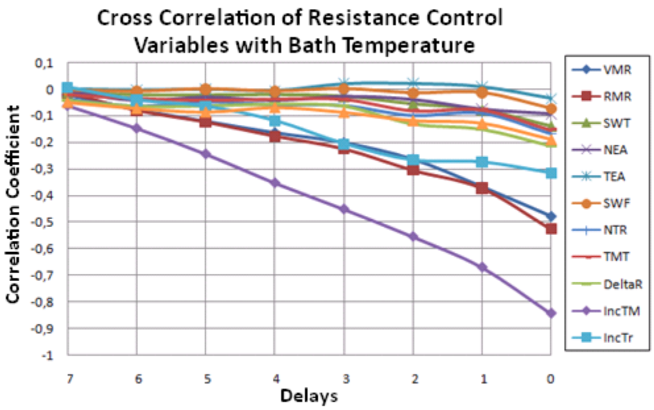

Fig. 3(a) Cross Correlation Chart of resistance control variables with temperature. Best scores: IncTM (Temperature Increase by Resistance), RMR(Cell Resistance) and VMR (Cell Voltage)

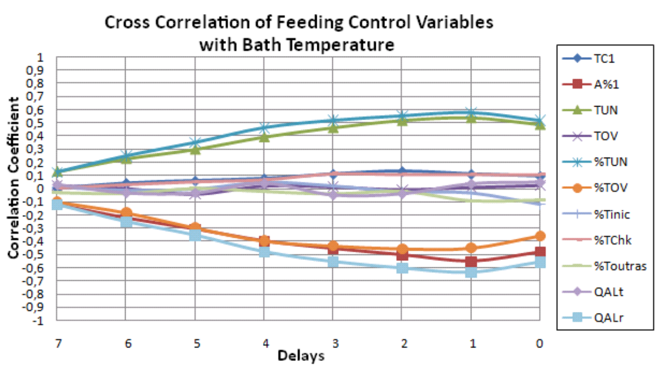

Fig. 3(b) Cross Correlation Chart of alumina feeding control variables with temperature. Best scores: TUN(Time Under Feeding), %TUN(% of Time Under Feeding), %TOV (% of Time Over Feeding), A%1 (% of Alumina Feeding) and QALr (Total amount of Alumina fed).

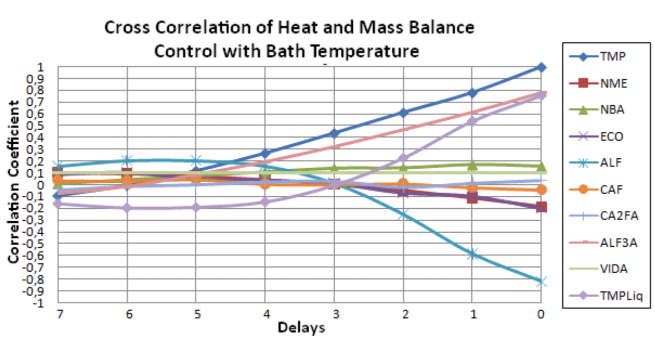

Fig. 3(c) Cross Correlation Chart of heat and mass balance control variables with temperature. Best scores: TMP (Temperature), ALF (% of Aluminium Fluoride), ALF3A (Amount of Aluminium Fluoride added) and TMPLiq (Liquidus Temperature)

After the correlation analysis, variables whose correlation coefficient is greater than 0.4 or less than -0.4 were selected for the soft sensor model structure. One should mention that some variables that match this requirement are correlated such as TMPLiq and TUN, which are correlated with TMP and %TUN respectively, and then can be replaced by the latter. Some delays were taken into account for the model structure, regarding the fact that some measurements are not available online and they have a strong correlation with the current temperature. Table I shows the variables with some delays and its correlation with temperature.

TABLE I
SELECTED VARIABLES FOR SOFT SENSOR MODELLING

Variable	Description	Correlation Coefficient at instant ^{k}
VMR[k]	Cell Voltage	-0.52082
RMR[k]	Cell Resistance	-0.47877
IncTM[k]	Temperatue Increase by Resistance	-0.84635
IncTM[k-1]	Last Temperature Increase by Resistance	-0.66902
%TUN[k]	Percentage of Time in Under Feeding	0.5368
%TOV[k-1]	Last Percentage of Time in Over Feeding	-0.4581
QALr[k-1]	Amount of Alumina fed in the pot	-0.6353
A%1[k]	Percentage of Alumina Feeding	-0.5299
TMP[k-1]	Last Value of Temperature	0.7799
TMP[k-2]	Penultimate Value of Temperature	0.6155
ALF[k-1]	Last Percentage of Aluminium Fluoride in the Bath	-0.58523
ALF3A[k-1]	Last Amount of Fluoride Added to the Bath	0.61355
ALF3A[k-2]	Penultimate Amount of Fluoride Added to the Bath	0.4638

^{k}The sampling time here considered is 32 hours or 1.33 days

B. *Data Collection and Filtering*

The selected variable data were collected from two potlines in a period of seven months from June/2007 to January/2008, resulting in a total of 62,657 records. The data were filtered in 2 stages: 3σ rule, and outliers' rejection [1]. The 3σ edit consists of eliminating the records whose data exceeds a weighted distance of 3 from the mean, as determined by the formula:

$$d_i = \frac{x_i - E[x]}{\sigma_i} \tag{1}$$

where x_i is value of x variable at a given time $_i$, E[x] is the variable mean, σ_i is the standard deviation and d_i is the weighted distance from the point x_i to the variable mean, according to the standard deviation.

Thus, table II shows the variable limits defined by the 3σ rule:

After filtering the outliers, there remained 60,191 records. In this filtering, a total of 408 cells is queried, but only 30% of these have its records fully within the limits, that is, its data series have no gaps. Figure 4 shows the gap of a data serie of a cell whose record was beyond the limit established by the 3 sigma rule.

TABLE II
SELECTED VARIABLES LIMITS

Variable (SI Unit)	Minimum Value[1]	Maximum Value[1]	Percentage of original records in this range (%)
VMR(mV)	3.25	5.33	99.86
RMR(μΩ)	13.77	16.47	99.03
IncTM(μΩ)	-0.42	0.41	99.91
%TUN(%)	14.87	60.33	97.2
%TOV(%)	18.28	77.56	99.2
QALr(Kg)	2009.47	3018.97	99.67
A%1(%)	79.26	133.08	99.37
TMP(ºC)	929.41	997.81	99.94
ALF(%)	2.79	17.61	99.94
ALF3A(Kg)	0	100.79	99.97

[1]According to the 3 sigma rule

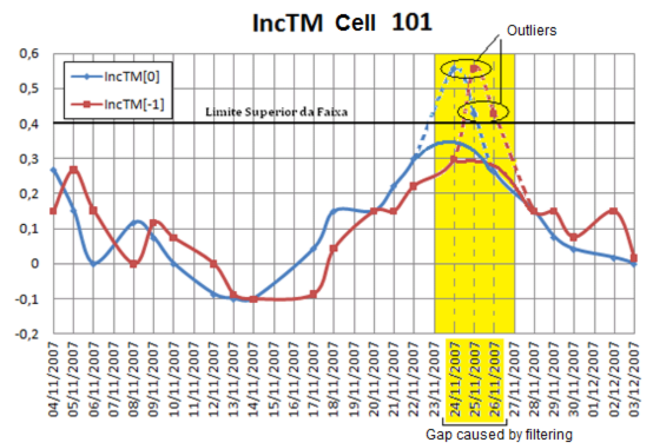

Fig. 4 Data Serie with a gap caused by outlier filtering

In addition, one fact should be mentioned about cell stability. Prasad and Welch state that there are cells whose dynamics is unpredictable and its variables are often beyond the stability border, therefore those cells are not a good data source for modeling [4,7]. Thus, in this work, it was taken into account that cells in which outliers were detected contains noisy data, and then their data were excluded from the dataset. This filtering reduced the dataset to 22460 records.

C. *Separation of the training, test and validation sets*

Following the rules recommended in [3], the data should be organized in three sets, which are:

--Training Dataset: 65% (about 14,600 records)

--Test Dataset: 15% (about 3,370 records)

--Validation Dataset: 20% (about 4,490 records)

Since the final data series are full, and have the same length, which is seven months or 140 records for each cell, some cells were chosen to be in the training set, others for the test set and others for the validation set. The recommendation is to use a different dataset for test and validation, and this is achieved by randomly selecting cells for composing each set.

IV. MODEL STRUCTURE

The model structure includes the modeling algorithm, which can be any modeling technique, including computational intelligence technique. The choice of the model depends on the problem studied. For most nonlinear problems, the use of Artificial Neural Networks have been applied [1]. In this work, an artificial neural network of type multilayer perceptron was used. Its use has proven to have a good generalization ability [2]. Since generalization is a basic requirement for this kind of sensor, initially the MLP was chosen as a model for the soft sensor. A schematic diagram of the model is shown in figure 5.

In the model figure, it is worth noting that the temperature prediction by the network is fed back to itself, but when training the network, real data are used instead of the delayed feedbacks.

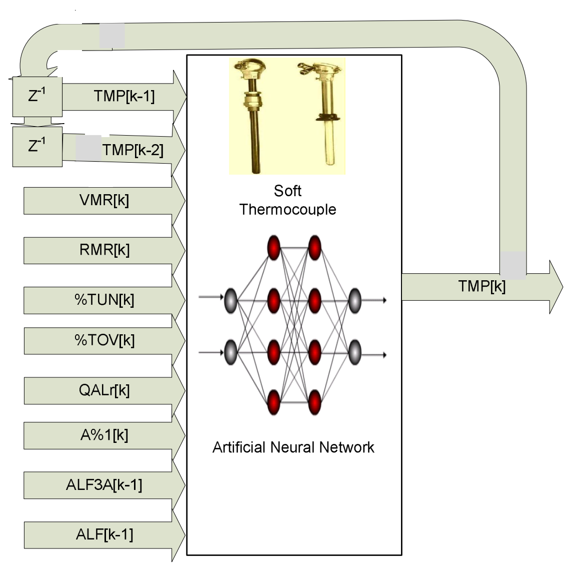

Fig. 5. Model Structure of Soft Sensor for Temperature Inference.

Initially, two layer networks with a small quantity of neurons were considered, then as an improvement of the results was demanded, the size of the network was increased, up to four layers networks.

A. *Training*

For model training, the Levenberg-Markvardt algorithm was chosen [3], which is quite fast and find a solution in the first few epochs of training. This option becomes interesting, as the number of records increases. The configuration for training algorithm parameters should lead to faster training and good solutions [2,8]. Table III shows the range used for algorithm parameters.

B. *Data Normalization*

The data normalization is an important step for training. Since data have different scales, it is highly recommended to normalize them to the same scale. Therefore, the Neural Network will never receive very high or very low data, which could delay or even derail the training. Normalization is done using the min-max scale, as shown in the equation 2 and graphically in figure 6.

$$x' = \frac{x - \min_x}{\max_x - \min_x}(\max_{x'} - \min_{x'}) + \min_{x'} \quad (2)$$

where x' is the normalized variable, $\min_x$ and $\max_x$ are the minimum and maximum values of x variable and $\min_{x'}$ and $\max_{x'}$ are minimum and maximum values of the normalized variable.

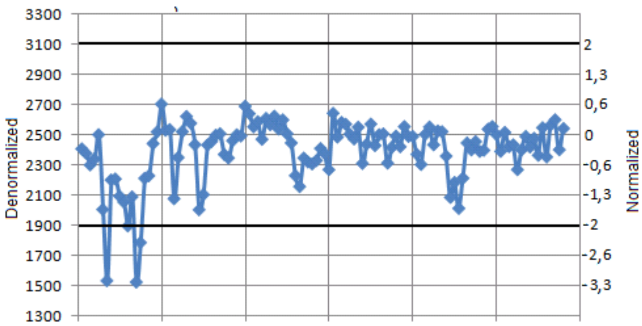

Fig. 6. Graphical representation of min-max normalization in a variable

V. Results and Validation

The neural model was consisted of four layers and was trained in parts, in order to evaluate its performance with known data and how it responds to new data. Table IV shows the configuration of final Neural Networks used to achieve the best results.

The training set was divided into nine groups, named T1 to T9. Each group has 1653 records. First the model was trained with T1 only, and then the T2 set was added in the network training and so forth. Table V shows the results of training for each stage of training for each Neural Network.

It can be seen through the table V, that the ANN3 had achieved the better result, despite its number of neurons. The training results for this ANN are shown in the figures 7(a), 7(b), 7(c) and 7(d) for two pots which were chosen for training and test, respectively.

TABLE IV
Neural Networks Configuration used

ANN Name	Layer	Neurons	Transfer Function
ANN1	1	10	Hyperbolic Tangent
	2	12	Sigmoid
	3	6	Hyperbolic Tangent
	4	1	Linear
ANN2	1	10	Hyperbolic Tangent
	2	24	Sigmoid
	3	12	Hyperbolic Tangent
	4	1	Linear
ANN3	1	12	Hyperbolic Tangent
	2	144	Hyperbolic Tangent
	3	12	Hyperbolic Tangent
	4	1	Linear

TABLE V
MSE Error after partial training for each ANN

Training Set	MSE Error ANN1	MSE Error ANN2	MSE Error ANN3
T1 (1,653 records)	$5.632e^{-2}$	$4.324e^{-2}$	$2.5791e^{-2}$
T1-T2 (3,310 records)	$5.872e^{-2}$	$4.8412e^{-2}$	$3.2263e^{-2}$
T1-T3 (4,964 records)	$6.287e^{-2}$	$5.2981e^{-2}$	$3.3487e^{-2}$
T1-T4 (6,624 records)	$6.397e^{-2}$	$5.6213e^{-2}$	$3.4898e^{-2}$
T1-T5 (8,824 records)	$6.5534e^{-2}$	$5.9923e^{-2}$	$3.8575e^{-2}$
T1-T6 (9,927 records)	$6.5432e^{-2}$	$6.0017e^{-2}$	$4.0274e^{-2}$
T1-T7 (11,581 records)	$6.5834e^{-2}$	$6.0872e^{-2}$	$4.0471e^{-2}$
T1-T8 (13,234 records)	$6.5223e^{-2}$	$6.0832e^{-2}$	$4.0328e^{-2}$
T1-T9 (14,633 records)	$6.5287e^{-2}$	$6.0815e^{-2}$	$4,0534e^{-2}$

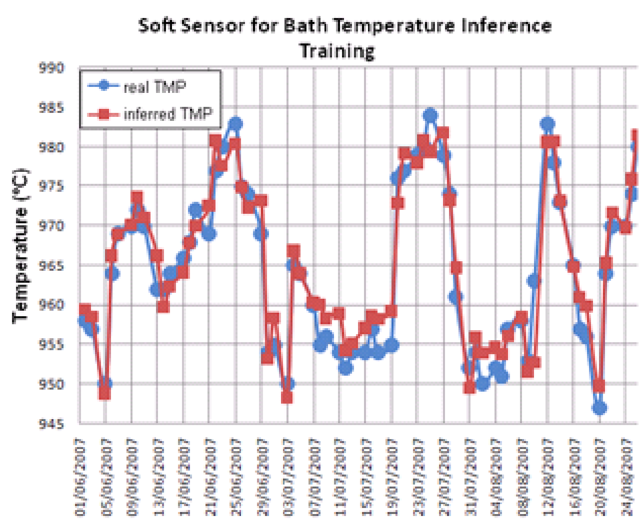

Fig. 7(a) Result of Training for one cell

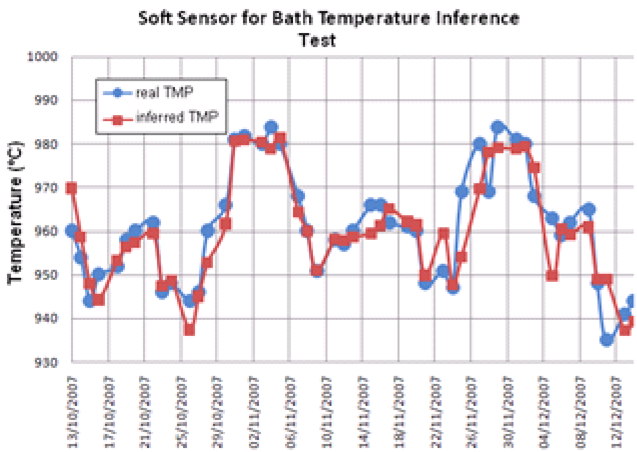

Fig.7(b) Result of Test for one cell

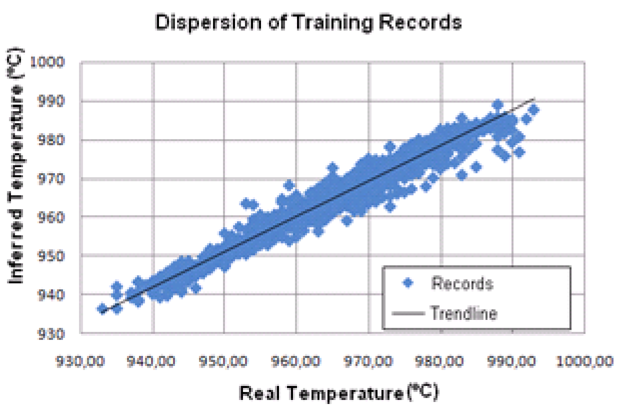

Fig.7(c) Dispersion of Training Records

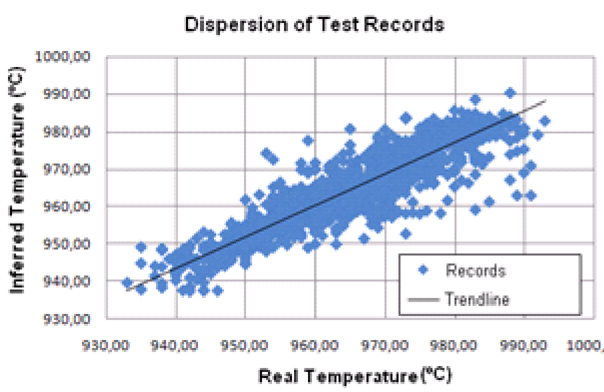

Fig.5(d) Dispersion of Test Records

For the validation, the model uses its inferred temperature delayed in the input. The effect of this is that if there is some error in the inference, it is propagated through the following inferences, as can be seen in figures 8a and 8c. To avoid this, the temperature was measured every 4 days (3 cycles of 32 hours), instead of the normal frequency, and the results were satisfactory. These two cases are shown in the figure 8a, 8b and 8c.

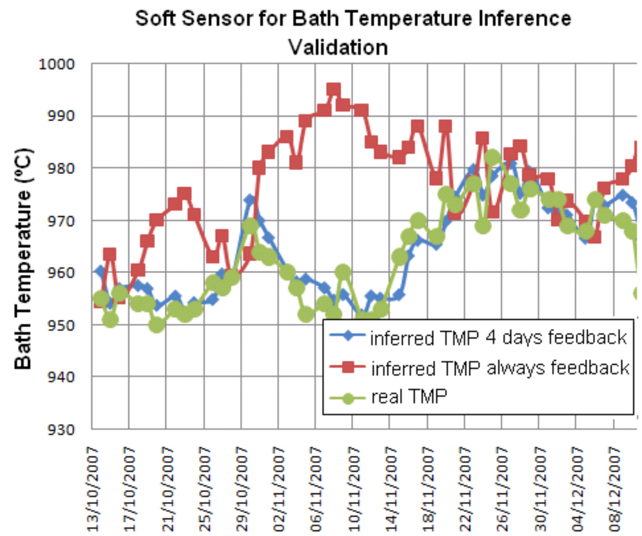

Fig.8(a) Validation of Soft Sensor with feedback

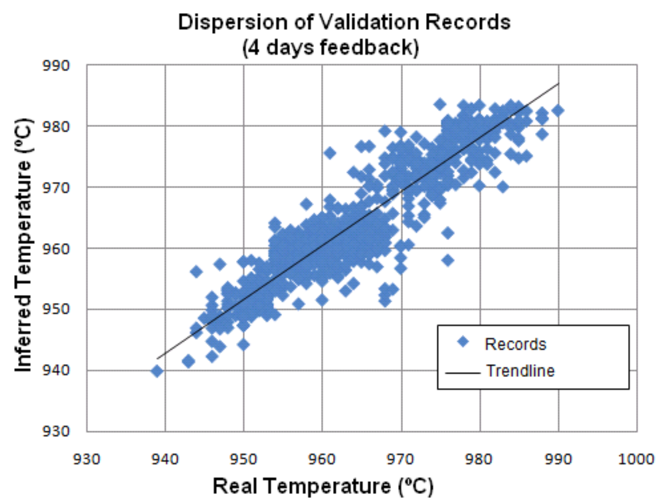

Fig.8(b) Dispersion of Validation Records inferred by soft sensor when using temperature measurements every 4 days

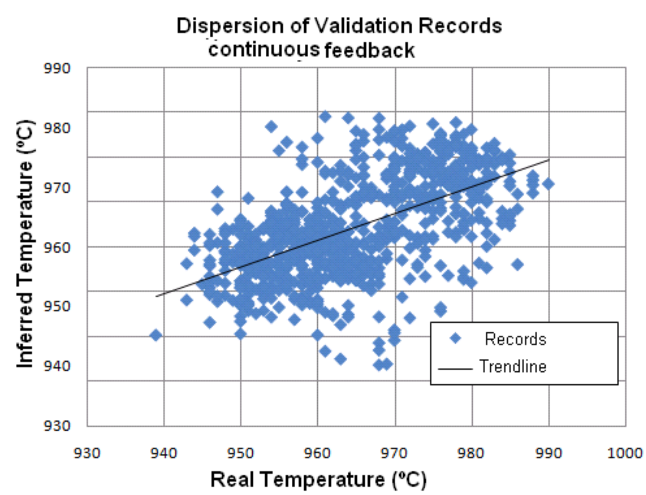

Fig.8(c) Dispersion of Validation Records inferred by soft sensor without any temperature measurements

It can be seen in figures 8a and 8c that the validation fails when it comes to the situation that no measurement will be done anymore. Since the temperature inference may fail, because of pot instabilities, the soft sensor is not yet able to fully substitute the thermocouples, but when there is a real or errorless last measurement value, it works satisfactorily. Table VI shows the MSE error, after validation.

TABLE VI
ERROR AFTER VALIDATION

Strategy used	Error ANN1	Error ANN2	Error ANN3
Soft Sensor without feedback	15.905ºC	6.881ºC	4.9143ºC
Soft Sensor with Feedback and Temperature measurements every four days	16.881ºC	12.304ºC	8.7612ºC
Soft Sensor with full feedback, no real measurement is performed	19.632ºC	19.43ºC	17.951ºC

VI. CONCLUSION

This work presented a practical approach for the use of soft sensors in the aluminum reduction process. Although the soft sensor is not yet able to fully substitute the thermocouples, good results can be achieved through its application. With the obtained results, it is possible to simulate heat balance control strategies, allowing plant operators to early detect trends in temperature and take actions to prevent strong variations in the heat balance. An improvement for the model would be the use of other learning algorithms or model structures.

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