# Neural Network Thermal Model of a Ladle Furnace

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## Abstract

*Since the Brazilian inclusion in the global market, search for productivity and product quality improvement became essential for the companies to survive. However, due to energy costs rise, national steel industries are investing in electrical power generation in partnership with energy supply companies aiming at overall cost reduction. Therefore, actions that search for energy consumption reduction and productivity increase became priority for their research and development projects.*

*The ladle furnace of V&M is one of the largest energy consuming units in the steel plant, consuming up to 2,400 MWh on average a month. Due to process complexity, system optimization became difficult to be implemented using conventional parametric approaches. However, applications of computational intelligence have been used as important alternative approaches to process modeling. Due to the little knowledge about the ladle furnace dynamics and the high variability of specific energy consumption, the use of neural networks was applied as a non parametric approach.*

*This paper demonstrates the use of neural networks in complex industrial problems by applying it to the steel temperature prediction of the ladle furnace process. This paper shows that the neural network used yielded high generalization capability by obtaining smaller mean error on the test data than the expected error specified by the steel temperature measurement instrument. In addition, this paper shows that the use of this neural thermal model resulted in productivity increase, operational and energy cost reduction.*

## 1. Introduction

Due to productivity demand increase, the need for reduced costs and high quality in steel plants culminated in the development of a secondary steel refinement. Steel used to be refined in electric furnaces or LD converter furnaces. The creation of this new unit led to a 20% increase in productivity, making the LD converter dedicate itself exclusively to the fusion and making of primary steel.

The principle of the secondary steel refinement, now made in a ladle furnace, is the use of electric arcs to heat the steel. Although the ladle furnace was initially developed to leave LD converter with primary refining and heating, the ladle furnace proved to have additional advantages in terms of productivity, quality and cost reduction, which has made it more and more necessary in the steel industry. The great problem with the secondary refinement is the heat loss. A study conducted by the British Steel Corporation (2005) revealed that for a 7kA and 173V electric arc, around 72.5% of the heat goes to the steel bath, 14.5% to the electrodes and 13% to the walls and dome. Despite the reported losses, the use of the ladle furnace can produce steel with precise control of temperature and chemical properties. The ladle furnace also proved capable of keeping a thermal balance between the steel and the ladle brick, considered a key feature to guarantee the quality of the final product [9]. Additionally, the need for sequential production of continuous ingot casting to attain high productivity has created a demand for a "lung" unit between the LD converter and continuous ingot casting. This demand was easily met by the ladle furnace, due to the easiness with which it heats and maintains the temperature of the molten steel. However, although the ladle furnace allowed a reduction of up to 15% of energy consumption, with the removal of the refinement process of the LD converter, this particular unit accounted for most of V&M's consumption of energy, as shown in Figure 1.

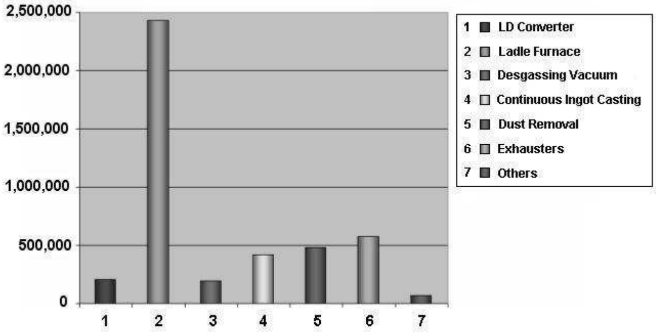


**Figure 1. Median consumption of electric power in V&M steel plant.**

In this way, the search for alternatives capable of reducing energy consumption of this furnace unit is extremely important, given the high percentage this consumption represents in the total cost of the produced steel. Apart from that, amongst all of the physical phenomena that occur during the steel production, three important phenomena have as their main variable the steel temperature. They are as follows: chemical reaction between steel and slag, liquid steel flowing and thermal exchanges of process elements, such as: ladle, dome, distributor, among others [15]. In this way, the absence of thermal control may cause the steel-making process to suffer great losses.

From a metallurgical perspective, one of the major problems at the production stage related to the lack of thermal control is the segregation of chemical elements in the steel, which may cause the product to lose in resistance and the appearance of cracks within the steel ingots. As far as operation is concerned, any degree of temperature below the specified limit may lead to a freezing effect, which is the steel solidification when its goes through the distributor valve. Overheat may lead to a break-out - a hole in the solidified surface of the billet, leading to a loss in the shaft of the ingot casting unit or a loss of casting speed, culminating in delayed production.

In this study, however, the focus was mainly on the economic side. Unnecessary overheat leads to an absurd waste of electric power, electrode and refractory. This waste is caused mainly by a lack of understanding of operators of the steel thermal characteristics, thus rendering the results of the operation dependent on the knowledge of the operating teams members.

The non-linearity and the complexity of the ladle furnace process, coupled with a lack of knowledge of its dynamics, made the use of artificial neural networks a promissing approach. The developed model was able to predict online temperature with an average error as low as the average error of the total measuring chain used to measure the steel temperature, which includes the sensors, contact blocks, compensation wires and measuring instruments.

## 2. Ladle furnace process

Steel secondary refinement may perform heating processes by means of chemical reaction or by means of electric arc. In Brazil, the ladle furnace is the equipment more often used in this process.

The ladle furnace unit under study consists basically of a metal dome with six holes, three being for electrodes, one for the alloys addition and sampling/measurement purposes, one for inspection and one for dust removal; an alloy loading system with 16 bins; an electric system whose main equipment is a 14MVA (32KA / 310V) transformer; and a transport system known as car-door panels. In Figure 2 there is a chart of the ladle furnace system.

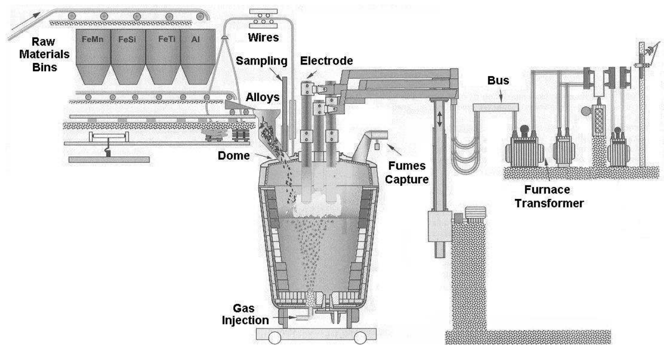


**Figure 2. Chart of the ladle furnace system.**

The process starts with pig iron and scrap metal being fed to the LD converter. Except for sulfur and oxygen, all the chemical elements are released by the LD with their values a little below the desired band of chemical analysis for the steel (primary refinement). So most of the alloys used to meet a chemical analysis are added in LD converter. In this way, only the re-refinement is done in the ladle furnace (secondary refinement).

Once the LD converter has been tipped, a crane transports the ladle with the steel to the car-door panel, which is then displaced to the ladle furnace. At the beginning of the heating process, it is necessary to add lime or synthetic slag to adjust the volume of slag, thus preventing the arc from being exposed and promoting thermal exchange. Slag is also responsible for minimizing the thermal losses of the steel and capturing existing inclusions. The heating stage lasts for about 10 minutes, depending on the steel type being produced. However, in the first minutes, since the ladle is not totally thermally soaked and there is great addition of lime (synthetic slag), the heating rate of the steel is lower.

At the end of the heating stage, the steel is sampled for the calculation correction of its chemical composition. The refinement stage begins with the addition of iron-alloys and/or pure metals as well as the remainder slag. At this stage, the heating time will depend on the temperature established for releasing the steel to the continuous ingot casting unit. The purpose of the alloys added is to reach the steel chemical band required. The argon, injected through the bottom of the ladle throughout the process of steel refinement, seeks to float the inclusions for the slag and to homogenize the temperature and the chemical composition of the steel [10]. Throughout the process the temperature is measured on a regular basis. However, so that these measurements may be performed, the electrodes will have to be raised, the little dome door opened and the temperature lance dipped in, generating around 1.5 minutes of turned-off furnace. In order to conclude the process, a steel sample is taken and the ladle is released to begin the continuous ingot casting process.

## 3. Neural network thermal model

In order to start the process of defining the thermal model variables, all factors that, according to the literature and experts on ladle furnace, would affect the variation of the steel temperature were mapped. The factors were defined as:

- Thermal loss for the ladle;
- Thermal loss for the dome;
- Thermal loss at the waiting intervals;
- Thermal gain as a result of the energy injection through the electric arc;
- Thermal effects resulting from the alloys addition;
- Thermal loss due to stirring - argon injection.

With this, an assessment was made of all process variables that had any relation with the mapped losses. The inputs were defined as soaking time index, initial steel temperature, ladle free border height, turned-off furnace time, turned-on furnace time, TAP number (switch position on the power transformer), thermal losses from the alloys addition, quality steel and liquid steel weight. In order to validate the choice of these variables, cross-correlation analyses were performed. Usually, in order to perform an analysis between temporal series, it is advisable to eliminate their trend components. The signal breakdown can de done with the use of filters such as TCS [12]. Nevertheless, the input variables series in question do not have a constant periodicity of data sampling, which renders the use of the TCS filter unfeasible. So in order to define the importance of each model's inputs, sensitivity tests were carried out. It was noted that the removal of any of the variables defined could affect its performance. Thus, all the variables selected to be inputs of the neural network (NN) model were preserved.

For the data collection on the process, a *Delphi* 7.0 © program was developed to search data in the different tables of the plant's automation system, format them and apply the pre-processing criteria to them. The initial pre-processing criteria consisted of filtering the data that were out of the operational band, such as maximum liquid steel weight of 86 tons and minimum height of free ladle brim of 10 cm. After the filter had been applied, it was observed that there were still some inconsistencies in the data related to the variation between the temperatures of the steel measured, when the time values of turned-on furnace, turned-off and thermal losses were considered. One of the hypotheses for this inconsistency is the absence of the variable argon in the neural model. The data resulting from the filters reached the 76.5% of the samples collected, which corresponds to 11431 samples in approximately 6 months of production and 2580 heats.

In order to offer a better definition of the best topology to be used, several tests were carried out. Due to the results obtained, the Levenberg-Marquardt was defined initially as the training algorithm. So, like the quasi-Newton test, the Levenberg-Marquardt method was developed to calculate an approximation of the Hessian matrix, and is capable of producing minimal point estimates that converge much faster than those produced by the gradient algorithm [4]. In order to obtain a better model generalization and avoid over fitting, the Bayesian regularization approach was used. The basis of this method is the restriction of the weight values in the net. The idea is to keep weights and biases small, which in turn enables the network output to come out smoothly [6].

The network topology was defined by the use of regularization, which provides a measure of how many network parameters are being effectively used by the network. The neural model was formed by 9 neurons in the input layer, a hidden layer with 20 neurons and an output layer with 1 neuron. The activation function for the hidden layer was the hyperbolic tangent and, for the output layer, the linear function. For the learning phase, 75% of the samples were selected, corresponding to 8573 samples, with a learning rate of 0.04. In the test phase 2858 samples were used, representing 15% of the data collected and pre-processed. The statistic results of the learning and test phases can be seen in Table 1.

In order to evaluate the performance of the online system, heat samples of June, July, August, September and October were collected in a total of 2980 and 17207 samples. The statistic results of neural model validation can be seen in Table 2.

**Table 1. Learning and test results of NN ladle furnace model.**

| NN Model Results | |
|---|---|
| Mean learning error | 2.783°C |
| Mean test error | 3.106°C |
| Minimum test error | 0.00090°C |
| Maximum test error | 49.337°C |
| Standard deviation of the test error | 4.015°C |

**Table 2. Validation results of NN ladle furnace model.**

| NN Model Results | |
|---|---|
| Mean error | 3.99°C |
| Minimum error | 0.000028°C |
| Maximum error | 129.22°C |
| Standard deviation of error | 6.42°C |

Out of the data used in the NN model validation analysis, error in 69.24% was lower than 4°C (desirable value), in 79.75% it was lower than 6°C (tolerable value) an only in 9.22% was error higher than 10°C.

In order to confirm these results, statistical tests were applied. In the linear correlation test (*Systat* 11.0 ©), the results revealed that the temperature foreseen by the NN model and the steel temperature measured were closely related ($R^2$ = 0.923 e p = 0). For the two-sample T test power analysis and sample size estimation were performed based on the minimum difference that was relevant for the steel temperature analysis [5]. The result shows that using 99,9% of power and a difference of 4°C, the sample size was 600. Then 1,000 samples were randomly collected from the database of a 4 month production. Using the two-sample T test, in the *Minitab* ©, it was not possible to reject the hypothesis that the variables are equal (p = 0.601). To confirm this result, the two-sample T test was used with all samples (15,112 samples) and the result was p = 0.115. Figure 3 shows a correlation trend of the measured temperature and the temperature foreseen by the NN.

Table 3 describes some statistical data observed in the values of the measured temperature and temperature foreseen by the NN model. The proximity of these values can be regarded as a good performance sign of the validation model.

To evaluate the likely gains from the effective use of the neural model developed, samples collected from June to October 2006 were collected. According to the data obtained, the mean value of seven measurements of steel temperature per heat was found. The number of measurements per heat varied between two and forty-five. As can be seen, there is no standardization of the number of measurements done per heat. Bearing in mind that each measurement corresponds to approximately 1.5 minutes of turned-off furnace and that each sensor used per measure costs around US$3.00, a reduction in the number of measurements would represent a significant reduction in the production cost and an increase in the ladle furnace productivity.

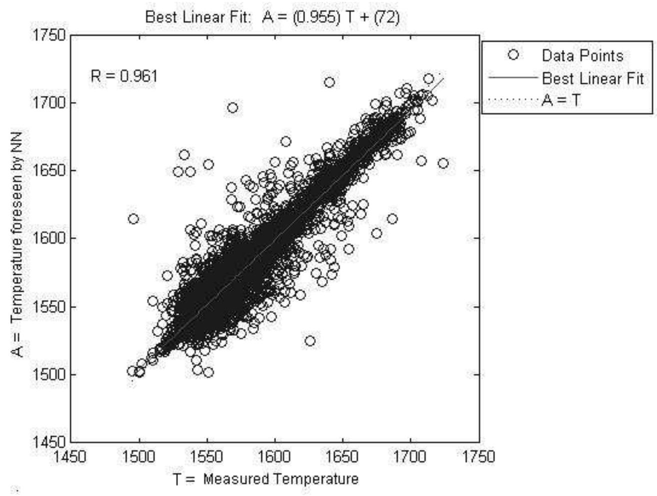


**Figure 3. Measured temperature and temperature foreseen by the NN correlation**

**Table 3. Statistical comparison of measured temperature and temperature foreseen by the NN model**

| Values | Measured Temp | NN Temp |
|---|---|---|
| Minimum | 1495 | 1501.28 |
| Maximum | 1724 | 1717.56 |
| Mean | 1571.46 | 1571.96 |
| Standard deviation | 26.96 | 26.78 |

This analysis suggests the standardization of the number of measurements to one for every 10 minutes of process. With this procedure, the mean number of thermocouples used per heat would fall to 50%, saving US$ 33,000.00 in 2930 heats, which is equivalent to a 4 month production. Applying the same analysis to the process time, there would be a 15% reduction in the total heat time.

Another advantage is the reduction in the electric power consumption. *ASEA* (1983) proposes a cost reduction calculation as a result of the reduced use of electric power. The equation considers that, with the steel temperature around 1600°C, the increase of 1°C for each ton of steel would demand approximately 0.2 kWh. However, this pre-requisite is dependent on the steel quality, serving as a parameter for an approximate calculation.

Based on the samples collected between the months of June and October 2006, a mean value of steel overheat of 7°C in 62% of the heats was found. The overheat value varied from 0.2°C to 65°C per heat. Considering a monthly production of 56,000 ton of steel and the mean value of overheat found, a mean reduction of 4°C over this overheat would result in annual savings of about US$ 125,000.00, which corresponds to 4.5% of the annual spending on electric power in the ladle furnace.

Besides productivity gains and a reduction in the productive cost, an improvement in the steel quality is expected as a result of its oxidation reduction. This effect is caused by the high agitation provoked by the argon, necessary to bring down the steel temperature.

To allow the steel temperature in the ladle furnace to be monitored online, an algorithm was implemented to calculate, at each interval time, the steel temperature in the furnace by means of the neural model obtained. This algorithm gets information from the SCADA system and stores it in the input variables to calculate the NN model. The result can be seen in the main operation screen of the ladle furnace (in the center of Figure 4), updated every 30 seconds. Apart from that, as the operator selects the drawing, he will have access to a trend diagram configured for a 40 minute span (the average time length for the ladle furnace heat) containing the measured temperature and the temperature calculated by the NN model. This way it is possible to follow the thermal evolution of the steel temperature and compare the model result with the measurements taken throughout the process.

## 4. Conclusion

The neural network model developed yielded very satisfactory results, obtaining a lower mean error than the one specified by the measurement instrument. This result reflects the generalization capability of the neural network, making its use very promising as a solution for practical application problems.

The NN model was elaborated with the aim of providing a support tool for production, by making the profile of the steel temperature behavior during the heat visible. With the effective use of the model, some gains can be expected such as the:

- reduction of electric power consumption, resulting from the losses reduction;

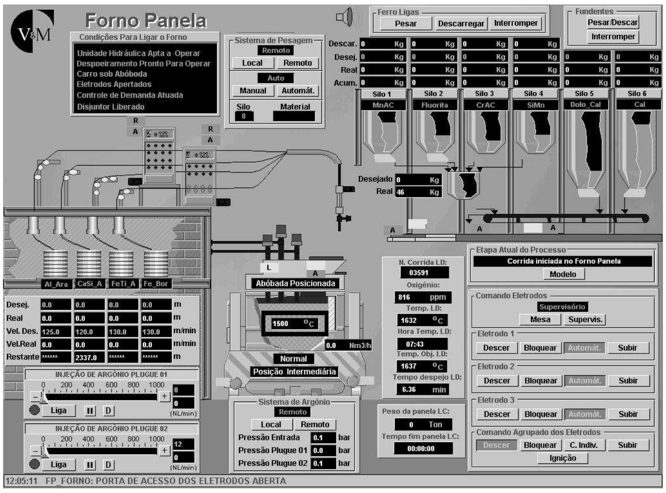


**Figure 4. Main screen of ladle furnace's automation system.**

- reduction of the variability of the steel temperature release to the continuous ingot casting, actually depending on the knowledge of each operator;
- reduction of the number of temperature measurements.

Another advantage of the neural network approach is that it offers the possibility of modeling a system without demanding deep knowledge of the process in question. However, when the variables of the model were chosen, the global knowledge of the process and the presence of specialists in secondary metallurgy were essential, once were already knew the factors that affected heat loss in the process.

Among the difficulties found in the NN model development, the stages of choice and filtering of data sampled can be regarded as one of the most serious criticisms to the construction of a model capable of transcribing the real dynamics of the process.

In order to provide process optimization, this paper suggests the use of the NN model here presented as input of specialist system will lead the production to an optimal operation with energy consumption reduction and productivity increase.

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