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# Modelling of electrical energy consumption in an electric arc furnace using artificial neural networks

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ABSTRACT

The objective of this research was to use state-of-the-art artificial neural network approach to estimate the extent and effect of fluctuations in the chemical composition of stainless steel at tapping of an electric arc furnace, and thus scrap and alloy weights in the charge material mix, on the specific electrical energy consumption. Such an estimation would help to further evaluate process control strategies and optimize overall operation of the electric arc furnace. The multilayer perceptron architecture 5-5-1 with hyperbolic tangent function in the hidden layer and linear function in the output layer was used as an optimal neural network model. The model was built, tested and validated based on experimental melts of the electric arc furnace at a melt shop in Italy. The proposed model was presented as an adequate one based on the coefficient of determination ($R^2$) which was above 0.9 as well as other error parameters calculated. The highest effect on the electrical energy consumption has carbon content.



## 1. Introduction

Stainless steel plays a very important role in the economic development and its consumption per capita has been considered as an index of relative prosperity of a community. Stainless steel is also recognized as a reference for sustainable development because it is 100% recyclable at the end of its life. On the other hand the stainless steel industry is among the most energy-intensive industries where energy has a major share of operating costs and energy savings initiatives play very important role from both economic and environmental point of view [1]. Over the past few years the stainless steel market has become highly competitive. As a result, the highest priority of the latest research work on stainless steel production has been to develop the most advanced models and techniques to produce a given quantity of stainless steel at the lowest possible cost in a stainless steel plant.

The main raw material for production of stainless steel is recycled steel scrap, mostly stainless steel scrap [2]. Around 70–80% recycled scrap is used in the production [3]. The rest is virgin material in the form of different ferro-alloys. To handle such big volumes of scrap, rigorous purchase routines are needed. At arrival, before entering the melt shop site, scrap is tested to ensure that no radioactive components are present. Scrap is then tested, analyzed and sorted according to its alloying element content to ensure that as little virgin material as possible is needed to get the right chemical composition of stainless steel [4]. Melting of scrap and ferro-alloys in the EAF (electric arc furnace) shown in Fig. 1 is the first step in the production of stainless steel. Scrap and ferro-alloys are charged into the furnace using large baskets. The lid is closed and the electrodes are lowered when powerful electric arcs start to melt the charge material mix. During the melting process, the arcs reach temperatures up to 3500 °C, and the molten steel can reach up to 1800 °C [5]. The power needed for this process varies between 50 and 80 MW depending on the EAF capacity. Additional injection of chemical energy in the form of carbon, oxygen or natural gas speeds up the melting process. After

*Abbreviations:* EAF, electric arc furnace; AOD, argon oxygen decarburization; VOD, vacuum oxygen decarburization; LF, ladle furnaces; MLP, multilayer perceptron; ANN, artificial neural network; BFGS, Broyden–Fletcher–Goldfarb–Shanno algorithm; SSE, sum of squares for error; MSE, mean squared error; RMSE, root mean squared error; MAE, mean absolute error; $R^2$, coefficient of determination.

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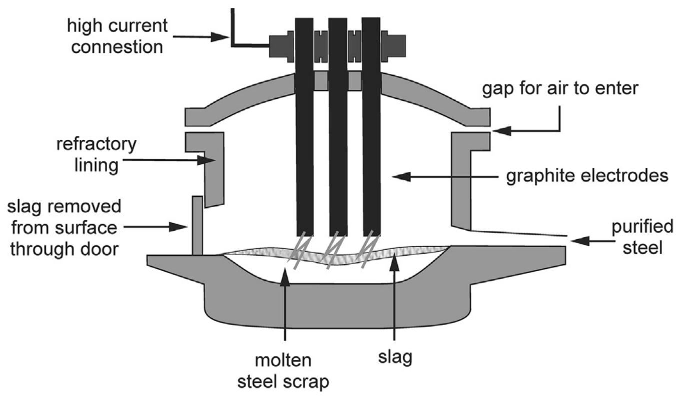


**Fig. 1.** Schematic representation of an electric arc furnace.

samples have been taken to check the chemical composition of the molten steel, the EAF is tilted to allow the slag, which is floating on the surface of the molten steel, to be poured off. The EAF is then tilted in the other direction and the molten steel poured (tapped) into a ladle. Final chemical composition of stainless steel is adjusted in the subsequent production stages by the AOD (argon oxygen decarburization), the VOD (vacuum oxygen decarburization) and the LF (ladle furnaces) to meet the standard quality requirements. The melting process in the EAF as the most energy-intensive step in the production of stainless steel has been investigated in a number of studies using various approaches with the goal to better understand the effect of various process parameters and thus further decrease the specific electrical energy consumption. For example, an optimal operating strategy can be determined taking into account different melting stages and electrodes position [6]. Understanding the influence of both gas burners [7] and direct reduced iron [8] on energy efficiency is also very important. Preheating of the charge material mix before its loading using off-gasses is among the most promising solutions for further reduction of energy consumption in the EAF [9].

The decision about the charge material mix composition is solely based on chemical composition, availability and price of different scrap materials. This study shows how the chemical composition of the charge material mix affects the specific electrical energy consumption and how electrical energy costs, as the second largest part of EAF operating cost, could be further lowered by taking into account such an impact as well when choosing an optimal charge material mix.

Nowadays, application of evolutionary algorithms such as ANNs (artificial neural networks) is broadly used to define a mathematical relationship between process inputs and outputs [10,11] as well as an efficient use of available resources [12]. This approach is based on the passing the inputs through the ANN and their transformation into the outputs using adequate activation function. The ANN consists of neurons that are classified in the input, hidden and output layers (Fig. 2). The hidden layer may have more than one layer.

The neurons are connected with neighboring neurons using the varying coefficients of connectivity, i.e. weights, which are optimally adjusted during training of ANN. The role of an artificial neuron is to activate the weighted sum of inputs from preceding layer of neurons including the bias neuron as given by the following equation:

$$y = f\left[\sum_{i=1}^{n} x_i w_i + b\right] \tag{1}$$

where $b$ is the bias, $x_i$ the input and $w_i$ the weight from the $i$th neuron in the preceding layer and $f$ the activation function. If necessary, the bias neuron may allow a shift of the activation function. The activation function typically falls into one of three categories: linear (or ramp), threshold and sigmoid.

In order to train a neural network, it is necessary to choose adequate activation function and adjust all the weights in such a way that the error between the desired output and the actual output is minimized. The training process also requires computation of the error derivative of the weights, i.e. how the error changes as each weight is increased or decreased slightly. The backpropagation algorithm is the most widely used method for determining the weights which are optimized moving from layer to layer in a direction opposite to the way activities propagate through the network. It uses the first-order techniques such as the gradient-descent method to optimize the weights in an iterative procedure. Quasi-Newton methods which use the second-order derivatives to find the optimal solution converge much faster. The second order derivatives are computed in a Hessian matrix, $H$, while the weight update is a product of the inverse Hessian matrix and the direction of the steepest descent. However, the computation of a Hessian matrix with all the second-order partial derivatives is time consuming. Therefore, approximations to the Hessian matrix are used to increase speed. In this work the BFGS (Broyden-Fletcher-Goldfarb-Shanno) algorithm [13] as the most efficient way of computing weight updates is used.

ANNs have been already proven as a suitable approach to various challenges related to the EAF operation such as temperature prediction [14,15] as well as simulation of its power load [16,17]. Olabi et al. [18] employed the backpropagation ANN and the Taguchi approach to design and to find out the optimum levels of the welding speed, the laser power and the focal position for $CO_2$ keyhole laser welding of medium carbon steel butt weld. Actually, the aim of the backpropagation algorithm is to reduce difference between actual and expected results, until the ANN learns the training data. The backpropagation algorithm send the signals forward, and then the errors are propagated backwards. Unlike the previous studies, the aim of this study was to use the feedforward ANNs, i.e. the MLP (multilayer perceptron), for modelling the relation between the specific electrical energy consumption and the chemical composition of the molten steel.

## 2. Experimental

### 2.1. Melts

Experimental melts used to build, test and validate our MLP model were run in the EAF at a melt shop in Italy, which is one of the global leaders in the manufacturing of stainless steel products. Its melt shop is based on modern technologies including the EAF, the AOD and VOD converters, the ladle furnaces and the continuous casters. In total 46 experimental melts were run with various chemical composition of the charge material mix during a couple of days in the summer 2014. Other important properties such as scrap type and density, injection of chemical energy as well as final temperature of the molten steel were kept as much as possible at a constant level during the melts in order to minimize their effect on the specific electrical energy consumption. The chemical composition of the molten steel was determined using the standard procedures in the melt shop laboratory.

### 2.2. Multilayer perceptron model

The feedforward ANNs were trained in order to construct the optimal network for estimation of the effect of the chemical components in the molten steel on the specific electrical energy consumption in the EAF. The content of carbon, chromium, nickel,