A Model for Temperature Prediction of Melted Steel in the Electric Arc Furnace (EAF)

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Abstract. A constant aspiration to optimize electric arc steelmaking process causes an increase of the use of advanced analytical methods for the process support. The goal of the paper is to present the way to predict temperature of melted steel in the electric arc furnace and consequently, to reduce the number of temperature measurements during the process. Reducing the number of temperature measurements shortens the time of the whole process and allows increasing production.

1 Introduction and Problem Statement

The electric arc steelmaking process usually consists of three main steps: melting steel scraps in electric arc furnace (EAF), refining the steel in the ladle heating furnace (LHF) and the continuous casting process (CCS) (fig.1). During the EAF phase, the main aim is to melt down metal scrap in the shortest time possible. During the LHF stage, furnace additives are injected to the liquid steel to obtain proper chemical constitution of steel. Continuous casting of steel ends the whole process. In this paper, the authors will consider the possible improvements of the first stage of the process - EAF. Steel production

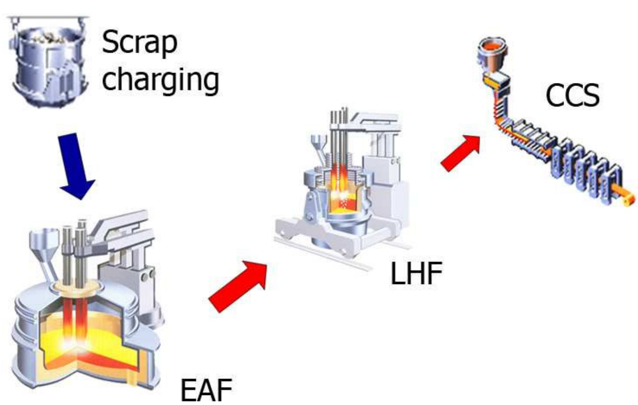

Fig. 1. Diagram of typical electric arc steelmaking process

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by the use of EAF bases only on metal scrap. That is why, EAF has become one of the world's main steel production method. The natural reserves of metal ore are still decreasing and becoming more expensive. Another advantage is the fact that the time of the EAF process is shorter than the time of any other steel production method. (e.g. than blast furnaces). The EAFs capacity and power level have steadily expanded during the last decades. Due to the fact that the main goal of the EAF stage is to melt down metal scrap in the shortest time possible, an oportunity to reduce even one minute of this process is very important.

It has been already mentioned that the metal scrap is the only charge in the EAF process which should be melted in the shortest time possible. Reducing even one minute of this period of time may be very important and may allow saving money. There are several ways to achieve the goal [10,11]: by appropriate management of the process (e.g. impedance matching of the current track and the feedstock of the furnace, chemical composition, etc.) or by reducing the time and the number of periods when the electric arc is switched off (what is not a trivial problem) [12]. The last approach is considered in this paper.

The type of scrap most frequently used is, so-called, merchant scrap, which consists of a variety of elements [4]. The industrial practice and market situation shows that there is still uncertainty about determining the melting process parameters (e.g. steel temperature). The most obvious method to identify steel temperature in the furnace is observation of the EAF process. However, because of high temperature, high dust density, flames (which are composed of a variety of combustion gases, where each of them absorbs light to varying degrees and different wavelengths) and other circumstances in the EAF, a reliable observation of the process is almost impossible. Recently, papers referring to the first tests of direct observations of the melting process in an EAF have appeared [5]. For this purpose, camera-based technology for monitoring the scrap melting process in the EAF has been developed. However, this method presently has not got any practical applications. Another way of experimental identification of the temperature in the EAF is a continuous temperature measuring. Results of the first tests appeared in the paper [6] and presented a development of temperature measuring system, which showed that there is a possibility to accurately measure temperature of steel in the furnace for the whole furnace cycle.

Currently, the temperature is measured a few times during overheating period with the use of the thermocouple. The furnace operator turns off the electric arc and manually places the disposable thermocouple in the liquid steel. This process of measurement takes at least two minutes so reducing the number of temperature measurements may reduce the time of the whole process.

Another way to identifiy temperature in the EAF, is the intelligent modeling [1,2], which is the main aim of this paper. The authors present a research concerning building the temperature prediction model. The method is based on the fact that in the last phase of the EAF process, during the overheating period, two or even three temperature samples are taken. Until this moment, there is no information about liquid steel temperature. By proper prediction of temperature of liquid steel, one can reduce the energy comsumption during the EAF process.

It is important to remember that every temperature measurement takes about two or three minutes, but in the context of a sixty minute process it is a long time and the posibility of reducing even one temperature measurement is very important. Reducing only one temperature measurement in each melting process could increase steel production nearly thousands of tones per year [8,9].

In the paper, the authors will consider aspects of data acquisition and also data preparation, which are very important factors for proper model learning.

2 Dataset

The first and one of the most important steps of building the model is data acquisition, which will be used to train the model. Accuracy of the model strongly depends on the quality of the dataset delivered to data mining tools. Appropriate data preprocessing is crucial to build a model that will have a small error rate. Understanding of real process, which is described by the data is a very important aspect during building the dataset. It allows rejecting data that is inappropriate from the technological point of view and which could be wrongly registered. By knowing technical details of data collection procedures many pieces of information can be obtained, such as possible redundancy, oversampling (which appeared in our calculations), etc. Such knowledge can be also used to preselect decision model or narrow down a problem of model selection.

In this section, the authors describe the process of gathering and preparing data for calculations and also describe the whole research environment.

2.1 Data Source

Data used for training the model came from the real metallurgical process. The data describes scrap melting process in the electric arc furnace (EAF). The data was collected in one of Polish steelworks by the use of Simatic-5 and Simatic-7 programmable logic controllers (PLC) which factory uses for process control and for recording process parameters. Over 200 variables incoming from controlers every second are recorded by *Data acquisition server* (fig.2) which communicates with all PLC's and saves values of variables into the Industrial SQL Server (InSQL).

Dataset was collected in two different periods. The first dataset was gathered after six months' work of InSQL server. That dataset was used as *training set* for building the temperature prediction model. That training set consists of 2127 samples. Then, the second dataset was collected for model validation (*validation set*). It includes description of over 1200 EAF melting processes of the last 8 months and over 3500 temperatures measurements taken during those melting processes. The collected dataset describes processes of a production of over 40 different grades of steel.

For these calculations, the most important variables were those describing weight of the first, the second and the third scrap charging basket; electric energy used for melting each basket; electric energy used during the overheating period; amount of blowed oxygen and solid carburizing and temperatures of thermocouples located in furnace bottom. The last, the 17th variable, was temperature of melted steel, whose prediction was our aim.

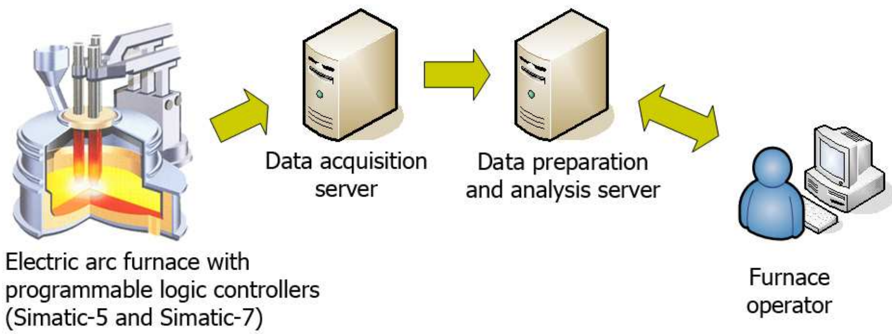

Fig. 2. Diagram of real environment data flow

Many variables not used directly in calculations were also extremely important for the process analysis, identification of particular steps of the process and for proper data acquisition. There were, amongst other things: primary and secondary voltage, primary and secondary current, transformer tap position, power coefficient, positions of electrodes etc.

2.2 Data Preparation

From data collected in the database we have selected following attributes:

- *Time* - exact data and time of the measurement
- *MeltNumber* - ID number of a melt
- $Mass_1$, $Mass_2$, $Mass_3$ - Mass of each steel scrap basket
- $Energy_1$ ... $Energy_3$ - Electric energy consumed during melting of each backet
- *CurrentEnergy* - Electric energy consumed during overheating period (from the end of melting the third basket until now)
- $TemperatureSensor_1$ ... $TemperatureSensor_6$ - Values of temperature measured by sensors placed inside the bottom of the furnace
- *Temperature* - manually measured temperature by the furnace staff

Basing on these attributes, after outlier elimination by the use of interquartile range, two different datasets were built. The first one (*dataset A*) was created for direct temperature prediction. In this dataset,the variables that are described above were taken to analysis and *temperature* was marked as the output variable. All input variables were normalized to keep its values in the range $[0, 1]$. The second dataset (*dataset B*) was defined as a difference between the current and the previous measurement of the following attributes:

- $dTime = Time_{i+1} - Time_i$ - time passed between measurements
- $dCurrentEnergy = CurrentEnergy_{i+1} - CurrentEnergy_i$ - Electric energy consumed during $dTime$ period
- $dTemperatureSensor_1 = TemperatureSensor_{1,i+1} - TemperatureSensor_{1,i}$ ... $dTemperatureSensor_6 = TemperatureSensor_{6,i+1} - TemperatureSensor_{6,i}$ - A change of temperature values measured by sensors during $dTime$ period

– $dTemperature = Temperature_{i+1} - Temperature_i$ - Changes in the temperature of the steel bath during the $dTime$ period

The final dataset was extended by the *mass* attribute.

Both datasets have its advantages and disadvantages. *dataset A* was very simple to implement in real environment however, it was sensitive to external parameters and to the behaviour of the whole process of steel scrap melting. We believe that this dataset might not be accurate enough to fulfill the desired requirements because melting process is very unstable by nature and external, unpredictable behaviour, caused by other stages of steel production (e.g. the breaks in CCS stage force breaks in EAF) might appear. In contrast to *dataset A* , *dataset B* wouldn't be useful until the first temperature is measured. In other words, it requires at least one single temperature measurement because the prediction model was able to predict only a change of the temperature, so the final temperature was calculated as the sum of the last measured temperature and the temperature change.

$$temp = temp_{last} + \Delta_{temp} \tag{1}$$

where:

– $temp$ - predicted temperature
– $temp_{last}$ - last measured temperature
– Δ_{temp} - predicted temperature change

We believe that this dataset is more stable (less sensitive to unpredictability of the process) and leads to better results because most of the attributes were calculated as the differences of their values.

3 Building the Model

The goal of the prediction model is to achieve the best possible accuracy [3], what in our case leads to the smallest temperature prediction error, measured by the use of mean square error (MSE). To find the best possible regression model, various algorithms were evaluated on the datasets described in the previous section. In our calculations, we considered following regression algorithms:

– simple linear regression (LR)
– SVM for regression with ϵ-insensitive cost function and linear (SVR_L) and Gaussian kernel (SVR_G)
– kNN regression algorithm

Both SVM algorithm and kNN require the tuning of parameters. All the parameters were selected by 10-fold cross validation test and by the use of the most common greed-search strategy. For kNN, k-value was considered as $k = [1 \ldots 10]$ while SVM required searching in quadratic for linear kernel and cubic space for Gausian kernel [7]. For SVM, the following values were tested: softness parameter $C = 2^{[-3-11,3,5,7]}$, cost function parameter $\epsilon = [15, 10, 7, 5, 3, 1, 0.1, 0.01]$ and for Gaussian kernel γ = [0.5, 0.7, 1, 1.3, 1.5].

Table 1. Comparison of the MSE error rate of LR, kNN, SVR_L and SVR_G models

	dataset A		*dataset B*	
Model	MSE	ME	MSE	ME
LR	1092.97 ± 37.96	762.10 ± 48.04	31.77 ± 2.05	25.97 ± 2.32
kNN	32.14 ± 3.48	23.97 ± 1.76	19.51 ± 1.37	15.29 ± 1.13
SVR_L	29.69 ± 2.28	21.65 ± 1.13	18.13 ± 1.72	14.02 ± 1.48
SVR_G	40.39 ± 4.68	28.93 ± 1.71	18.06 ± 1.43	14.06 ± 1.3

The obtained results for the best set of parameters are reported in the table (1).

The analysis of results presented in the table (1) proved our assumptions related to both datasets. System requirements indicated that only results obtained for *dataset B* were acceptable while the results obtained for *dataset A* were charged with too large error, not acceptable in real environment. Moreover, the value of the temperature is necessary only during overheating period to determine the proper moment for the begining of casting.

Surprisingly, linear regression in comparison with SVR_L obtained much worse results, though, both models were linear. It is worth a mention that there is a small difference in accuracy between the linear and non-linear (Gaussian kernel based) SVM model. According to this fact, SVR_L was implemented in the production system.

4 Validation in Real Environment

The best predicting model was used in the real environment. For this purpose, proper implementation for *Data preparation and analysis server (DPAS)* was prepared (fig.2). This server was running Microsoft SQL Server, where proper server jobs were responsible for: transmition of suitable data from *Data acquisition server*; identification of the particular steps of the process; collecting and preparing data for calculation model; recording answers of predicting model and sending temperature prediction to the furnace operator.

Operator, during the last step of the process (during overheating), was supported by model prediction and could make a decision whether to take or not to take another temperature measurement. Each real measurement was recorded by *DPAS* in its database and that allowed for the comparison of the results.

In the figure 3, the obtained prediction error is presented. A large majority of prediction values were in the error range from -20 to +20 $^\circ C$. However, there were over 67 cases from 3500 predictions compared with real measurements, where error was greater than 50 Celsius degrees.

Table 2. Statistics of obtain error values

	Maximum	Minimum	Mean	Standart deviation
Temperature error value $^\circ C$	154^*	1.1	4.4	21

*The maximum error occurred one time among 3500 predictions and probably was caused by wrong measurement.

The maximim, minimum, mean and standard deviation of the occurred error (in $^{\circ}C$) is presented in the table 2.

5 Conclusions and Further Research

Prediction of the liquid steel temperature during the EAF process is a very important task. The value of steel temperature determines the proper moment for the begining of casting. The results obtained in our experiments proved that it is possible to achieve much better accuracy of prediction by adequate dataset preparation. The results obtained with *dataset A* have an error rate by one-third higher from those obtained with *dataset B* . We believe that the reason is that *dataset B* was built basing on the differences of values of variables, which allows reducing significantly the impact of unstable behaviour of the initial melting phases. The best of all evaluated models was SVM model that allowed obtaining temperature error accuracy, which was 18 Celsius degrees. In our experiments both SVM models (SVR$_L$ and SVR$_G$) got similar accuracy. However, the SVR$_G$ gave slightly better results with smaller value of variance. However, in real environment the linear model (SVR$_L$) was implemented because it was much simpler and faster than the nonlinear one.

After eight months of using that model, we were able to compare the obtained results with values of real temperature measurements. The provided results proved a very good quality of our model. Several outliers appeared (fig.3), however they could be caused by inconsistence of the validation set or by the wrong real measurement. Taking consideration of the obtained results and the results presented in the table (2), we came to

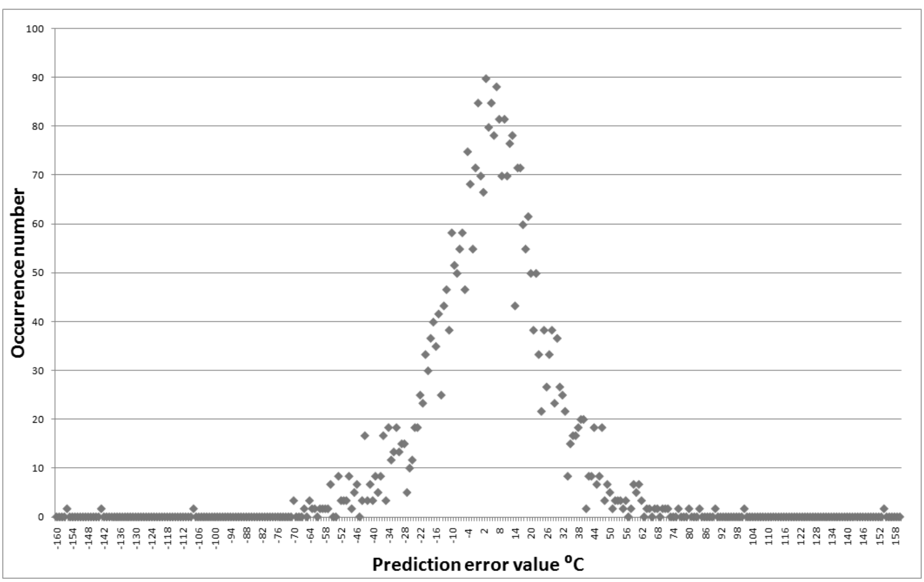

Fig. 3. Histogram of prediction error

the conclusion that mean error of our model does not equal zero. We believe that this fact is related to the *concept shift*, caused by the changes in the production procedures that appeared during the last eight months.

We believe that this model can be further improved. There are several ways to achieve this goal. Firstly, we did not take into consideration energy delivered to the furnace by the flames of the burners and the gases. Taking energy into account, may significantly improve accuracy of the model. We also plan to extend the dataset by even more variables and we plan to apply feature selection methods to determine automatically the most important variables. The last concept is to improve the data preprocessing instead of calculating the difference between the following samples and map them to another, more sophisticated space.

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