AI Application to Melting Temperature Prediction in an Electric Arc Furnace

Digital technologies are transforming industry at all levels. Steel has the opportunity to lead all heavy industries as an early adopter of specific digital technologies to improve our sustainability and competitiveness. This column is part of AIST's strategy to become the epicenter for steel's digital transformation, by providing a variety of platforms to showcase and disseminate Industry 4.0 knowledge specific for steel manufacturing, from big-picture concepts to specific processes.

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World steel producers face new challenges every day due to the need to be competitive in their markets as well as to produce high-quality products to meet the expectations of their most demanding customers.

This situation implies two things:

- Processes must be well adjusted to maintain product properties within the most stringent tolerances and reduce the dispersion range.
- It is critical to minimize operational risks that could generate machine downtimes, impacting the overall equipment effectiveness (OEE) of the processes.

For both challenges, the combination of technologies and disciplines belonging to Industry 4.0 such as big data and artificial intelligence (AI) makes it possible to have powerful platforms for prediction, exploratory analysis and descriptive analytics.

Nowadays, steel production can be done through two main routes: blast furnace and electric arc furnace (EAF). A mix of scrap and direct reduced iron (DRI) is used for the production of commercial steel that will be transformed into slabs for hot rolling. During the EAF process, a combination of scrap and DRI is melted to produce molten steel at temperatures up to 1,630°C. Electrical energy and energy from exothermic reactions are employed to perform such melting. As with many batch production processes, increasing productivity while reducing energy consumption is important to reduce operational costs, so control of process variables such as temperature in each stage in the EAF process plays an important role in process control.

Due to high temperatures in the EAF and the presence of slag covering the molten steel, it is not possible to have an on-line continuous temperature measurement system. Only a few measurements at around the end of melting are performed using a robot equipped with a thermocouple. This represents a challenge that can be addressed using mathematical models in combination with machine-learning techniques to predict the temperature of the molten steel using process variables that can be measured. Having a temperature prediction with reasonable accuracy can lead to better DRI control in the EAF because the load profile of DRI can be determined according to the amount of energy that will be used to melt the solid mass; consequently, this will save tap-to-tap time and energy consumption and will result in a better control of the goal weight of the batch.

This paper will expose the underlying physical complexities driving the melting process and how a solution to this problem was structured using AI capabilities. In addition, it will comment on the development process with the support of agile methodologies and scrum, as well as the learned lessons.

Challenges and Project Goal

Introduction — The objective of this work is to provide an introduction and present a real case of one of the disciplines of Industry 4.0, big data/analytics/AI, showing how data science can contribute to create value and business benefits for the steel production companies, through the development of predictive models to explain and predict process behaviors.

This case belongs to typical business use cases with AI, which include:

- Virtual sensors: Predictors for spots where it would be difficult or impossible to measure physically.
- Process optimization in terms of productivity, equipment efficiency and production costs.

The expected benefits of the development of these disciplines, in relation with this case, are:

- Reduction of tap-to-tap time by knowing the steel bath temperature precisely.
- Avoid the damage in firebricks that cover the internal of furnace as a consequence of overheating by having more control over temperature.
- In relation to the previous issue, reduce energy consumption by avoiding overheating.
- Save costs associated with temperature measurement cartridges.

Challenges — By analyzing the physical problem, several characteristics and challenges were found in order to develop a model for temperature prediction:

- In EAFs where metallic charge is composed of metal scrap and DRI, the mix is approximately 35% metal scrap and 65% DRI. After loading the scrap, the melting process is started by adding electrical and chemical energy.
- Once the melting process is started, the DRI is added by controlling the charging speed.
- The objective melting temperature is between 1,600°C and 1,630°C.
- The DRI charging speed is adjusted to get 100% of the melted metal at the required melting temperature.
- The temperature and O_2 ppm measurements are taken based on the percentage of the melted metal predicted by a physical model.
- The procedure foresees three measurements: the first with 90% of the melted metal, the second when approximately 15 metric tons of DRI remains, and a final one to confirm the complete melting.

Fig. 1 shows the evolution of percentage melted iron versus consumed energy, where the event of first temperature sample taken and the final one can be seen.

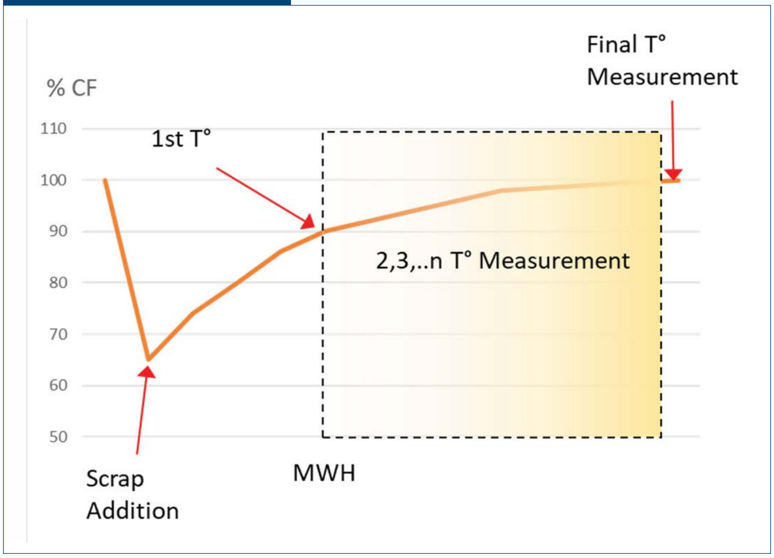
In the development process, several issues were found to develop a model. Because of the process nonlinearities and the changes in the quality of the DRI, the predictions of the percentage of melted metal by white box physical models are not always accurate. This is where machine learning could exhibit its major advantages against white box models.

These inherent uncertainties determine when the bath temperature is taken. The value will be different than expected and consequently additional temperature measurements will be required, until reaching the goal casting value.

These extra temperature measurements create a cost increase due to the additional temperature cartridges. The EAF productivity is also impacted since it generates process stoppages to allow the measurement device to enter the furnace.

Using this approach, based on the machine-learning model, the quantity of temperature measurements are limited to two, one with approximately 90% melted metal and one to verify bath temperature at the end of melting.

Figure 1



Percentage of melted iron vs. consumed energy.

Project Goal — The project goal is to predict the temperature in the last 10 minutes of the melting process, starting the prediction with the first temperature sample taken from the EAF.

The prediction error must be less than ±15°C for a standard deviation of 1σ considering a normal error distribution.

Development Process

The development process was based on agile methodology, more precisely scrum methodology. Scrum is an iterative and incremental methodology where development is broken into fixed time slots called sprints, which are 2–4 weeks in duration.

The methodology defines the following roles for the project participants:

- Product owner: Represents the interests of the customer and could be a real market customer or an internal customer of an organization. This role requires high knowledge of the domain/business where the product under development will work. This role must establish the priorities of the project activities in order for the functionalities that are incrementally built to be aligned with business priorities.
- Scrum master: Leader of the development team; responsible for project coordination. However, unlike traditional project management, the scrum master is more like a facilitator or a coach, a person focused on clearing the obstacles team faces, thinking they count as part of a team while being autonomous and self-managed, more than the traditional role of project manager.
- Team members: Self-managed developers, with an excellent communication level and capacity to do agreements quickly, and a good level of conflict resolution, focused on problem resolution, but always having in mind concepts such as business constraints and business value.

In each sprint, there is a sequence of events that take place with the participation of stakeholders of the project. These events are:

- Sprint planning meeting: In this meeting, the team agrees with the product owner on the sprint goals that will be disaggregated in what is called "user stories" (in this case, named "data science requirements") and requirements that must be fulfilled before the end of sprint.
- Mid-sprint review meeting: An informal meeting that takes place at the midpoint of the sprint, where the product owner, scrum master and team meet in order to review the project progress.
- Sprint review meeting: An informal meeting in which the development team, the scrum master, the product owner and the stakeholders must attend. The team presents the results obtained across the sprint and determine what is finished and what isn't.
- Retrospective meeting: As described in the scrum guide, the sprint retrospective is an opportunity for the scrum team to inspect itself and create a plan for improvements to be enacted during the next sprint. The sprint retrospective occurs after the sprint review and prior to the next sprint planning.

This methodology fits very well with the nature of data science projects. As its name suggests, data science projects are founded on a scientific method that sets the following sequence, called an "experiment":

- Question to be answered.
- Hypothesis to be validated.
- Design and execution of experiments.
- Outcome analysis that confirm or reject the hypothesis.
- Agree with previous step, determine next step.

As it can be seen, a data science project consists of a sequence of experiments and has an iterative nature compatible with scrum structure. The methodology fits well from the perspective of project execution as well as from the perspective of risk mitigation and investment optimization, because at the end of each sprint it's possible to continue with the project or abort it if the results are not promising. The inherent uncertainty nature of this kind of project is mitigated through multiple decision points in time.

In this case, scrum was instanced with the following characteristics:

- Sprints of 2 weeks in duration.
- Required 12 sprints to obtain a model ready to be implemented in the edge control.
- Team consisted of one scrum master, one data engineer and two data scientists.
- The project was developed simultaneously with another two data science projects.

Technical Approach

Characterization of the Physical Problem — In order to increase background knowledge that allows for enhancing the stage of "feature engineering" in the modeling process, it's convenient to analyze some aspects of the underlying physics.

In the first place, the EAF behavior is non-linear. This is because of the nature of the current and voltage of the electric arc and time-varying loads of many chemical additions. The electric arc behavior can be described with existing models, such as the Cassie-Mayr arc model, which takes into account the conductivity of electric arc in relation with voltage, current, time constant of electric arc and the cooling power of arc. From the equations, its non-linear behavior is obvious.

Second, in relation to energy balance models existing in the market, many are based on the change of the electrical energy, energy by burners, energy by chemical reactions and cooling. In real-time practice, there are not available independent measurements of all quantities. It's not possible to know the losses of exit gases, due to the lack of gas analyzer; therefore this option must be discarded.

Third, knowing the amount of oxygen in the bath would be beneficial in order to enhance model accuracy. However, nowadays the only way to know it is by taking samples of the bath to measure both temperature and ppm of oxygen. The model must go without continuous ppm oxygen measurement.

Finally, the temperature measurement occurs in the last stage of the process, around the last 10 minutes (Fig. 1), meaning the model doesn't know the real temperature until this time. With those limitations, the strategy of the model was focused on the changes of all mass fluxes (carbon, cal, gas, oxygen, metallic mass) and electric power.

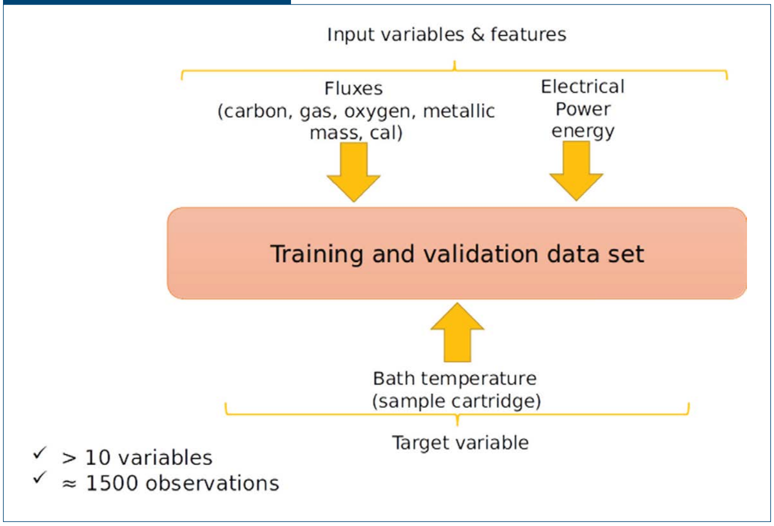
Data Collection — A significant amount of melting batches was selected to make the data set (Fig. 2), with measurements from on-line variables existing during the melting process. Only batches with the best tap-to-tap time were selected.

The variables that were taken into account represent: total metal (scrap and DRI) and chemical mass, total energy that can be measured on-line, and also the fluxes of mass and energy.

The data to be integrated comes from different data sources: structured data from relational databases and time series from data historians. The big picture is shown in Fig. 3.

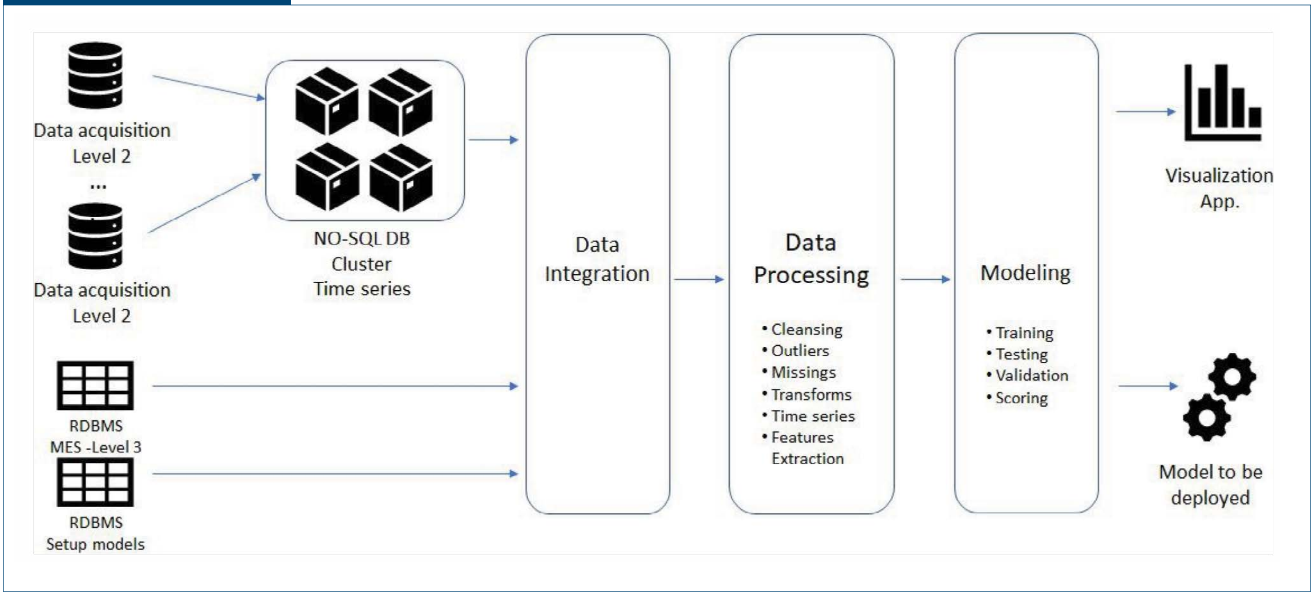
Data Characterization — The distribution of variation of temperature , $\Delta T = T_{batch[i]} - T_{batch[i-1]}$, of these melting batches is represented in Fig. 4. As it can be seen, values of ΔT appear very large in the distribution, meaning there are outliers in the registered data. In practice, the measurements begin at approximately 1,560°C and span until 1,650°C. ΔT never can be higher than 90°C.

Figure 2



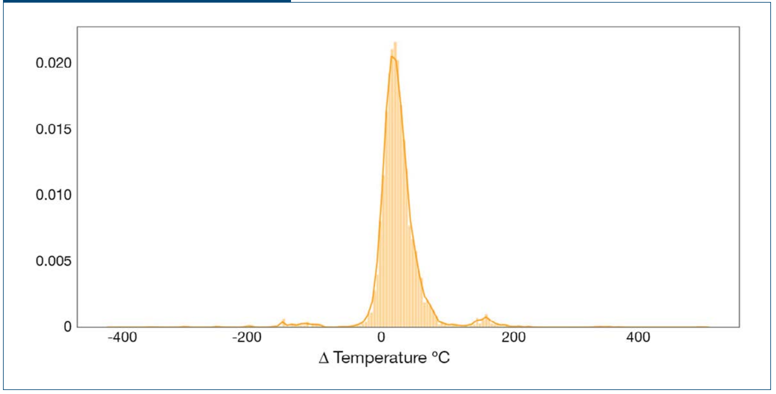
Working data set.

Figure 3



The big picture of the data processing pipeline.

Figure 4



Temperature variation between measurements on melting batches.

Figure 5

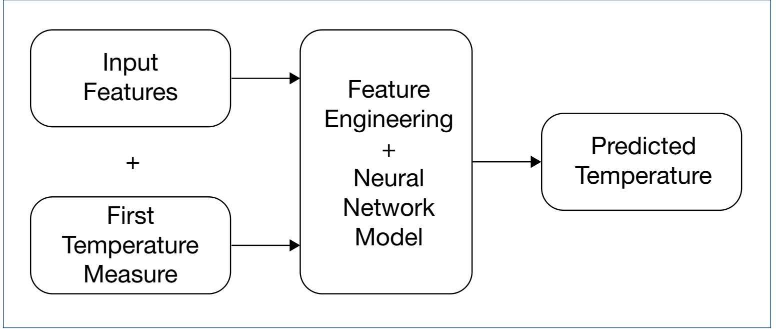
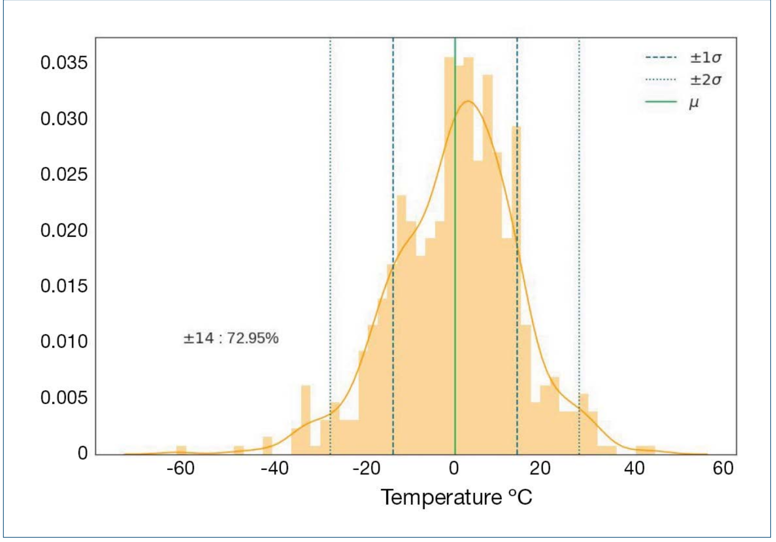


Diagram of the modeling process for prediction of the furnace temperature.

Figure 6



Distribution of the prediction error.

With this information, just batches with $0 < |\Delta T| < 85$ were considered.

The attributes considered to filter melting batches to build the data set:

- Base: Furnace production.
- Scrap loads: One load.
- Tap-to-tap time: < 63.1 minutes.
- % DRI: 66–68.
- Starting, drained and delayed melted batches were not included.

Modeling — The first approaches considered DRI because it is the most important parameter to control the metallic yield, which has an impact on plant productivity. When a DRI with low metallization (for example 87–89%) is melted, the levels of FeO at the end of a batch can reach values as high as 45–50 mass%.[1] Because the metallization of DRI is around 98% and is very constant for this case, this variable has no impact on the results, therefore it was not included in the model.

Later, a variable was constructed that represents the cooling part in order to include one part of energy losses. This "cooling variable" has the information of water temperature of panels in shells. This variable improved 4% in the performance of the model, but the result was not the expected one.

Finally, after some sprints of modeling the approach to the problem changed. The new approach focused on the change of all mass fluxes and electric power. The model inputs then were the difference of each variable with respect with their previous value. This treatment with variational quantities and not with absolute quantities gave better results.

The data set collected was split into training and testing subsets with an 80:20 ratio. It was trained and validated with the training set by cross-validation.

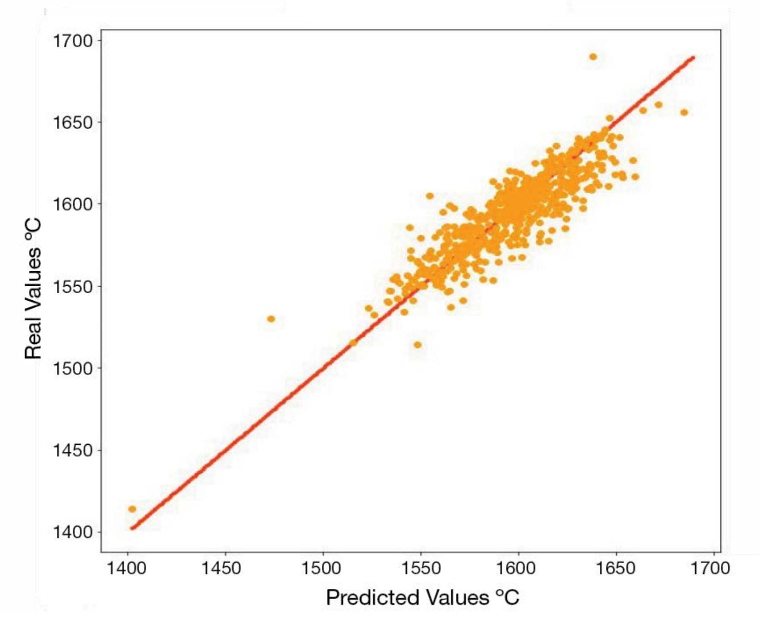
Deep-learning neural network regressor was used with five dense hidden layers of up to 256 neurons in one of them and exponential linear unit activation function.

The scheme in Fig. 5 summarizes the development of the model. The first temperature measurement is an input value.

Results — The final model based on deep learning showed the best performance. The model performance can be summarized as:

- ±14°C prediction error for 1σ of predictions.
- The comparative between predictions and real values of temperature is represented in Fig. 6.
- The distribution model error for the fixed tolerance of ±14°C can be seen in Fig. 7.

Figure 7



Predicted temperature vs. real temperature.

Conclusions

As could be seen in the examples, the use of industrial analytics to predict process behaviors is a fact, and not only a theoretical formulation. If the required conditions to develop analytical models are met, that is, historic data availability, data quality, relevant process variables of the process instrumentation, and the availability of experienced domain experts to work in a multidisciplinary team with data scientists, it is possible to create value through analytics-based innovations.

It is not an easy path, but the potential business value to be generated implies a substantial return on investment and could enable organizations to develop new differentiating strategies in the steel market.

Reference

1. R.D. Morales, H. Rodríguez-Hernández and A.N. Conejo, "A Mathematical Simulator for the EAF Steelmaking Process Using Direct Reduced Iron," *ISIJ International,* Vol. 41, No. 5, 2001, pp. 426–435. ✦

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Did You Know?

worldsteel Announces steelChallenge-15 World Championship Finalists

The Regional Championship took place online for 24 hours on 25 November 2020. This year's steelChallenge attracted more than 1,200 participants representing over 50 companies and about 90 academic institutions from 27 countries.

The top-placed people in the Industry and Student categories will be invited to the World Championship in April 2021. Also qualifying for the World Championship are the first-placed people in each of the five geographic regions.

steelChallenge-15 utilized steeluniversity's secondary steelmaking and continuous casting courses in a combined simulation. Competitors were tasked to produce a grade of steel meeting technical requirements at the lowest cost per metric ton. The simulation used a grade of steel specifically designed for steelChallenge-15. Competitors could undertake unlimited "runs" of the simulation during the 24-hour competition period. The best run of each competitor determined their score and placement in the Regional Championship.

The World Championship finalists are:

Student Category
- Andre Massaccesi Guimaraes, University of Westminster, U.K.
- Darley da Silva Lima, Universidade Federal do Ceará, Brazil
- Abdelrahman Hosny Gomma, Abu Dhabi University, United Arab Emirates
- Zhihao Zheng, Wuhan University of Science and Technology, China
- Kwon Ik Hwan, Dong-A University, South Korea

Industry Category
- Alexander Nesmeev, TMK, Russia
- Bruno Galdino Sousa, Companhia Siderúrgica do Pecém, Brazil
- Uday Kumar Bhakat, Tata Steel Ltd., India
- Xiaowei Shi, HBIS Group, China
- Jungho Choi, POSCO, South Korea