Statistical modeling of heat exchange coefficient evolution during quenching

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In the premium steelmaking industry, the heat treatment of steel products is a key process in order to obtain the good final properties and in a correct range of values.
In general, the heating processes are well managed as the modeling and the piloting algorithms for the furnaces are today widespread in many production plants. Industry 4.0 target is a complete management of things inside the plants. To do that it is important to model all the processes in a sufficiently accurate way.
One of the most complex processes in steelmaking heat treatment is quenching. Fast convective phenomena are always complex to model, in particular, if the model is strictly linked to the process set up. The literature is not very rich in models that can be used in real production processes; each case has his own particularities that imply the associated model is in general unique. A way to understand a quenching process is to create a large database of trials with a variation of the process set up. The first point is how large this trials database could reasonably be, considering all the constraints of measuring a real production process and how to optimize the creation of DOE (Design of Experiment) considering all the possible process parameters.
The basic idea is to combine the database trials with a statistical tool in order to predict the HTC (Heat Transfer Coefficient) during quenching with each particular set up. We tried different regressions analysis in order to optimize the combination of parameters to obtain the smallest possible error. Our first idea was to use the simplest tool to have quickly the dimension of the complexity of the quenching HTC, so Multiple Linear Regression was used. To improve the first results Local Regression (LOESS) and Random Forest Regression were tested in the second moment. To validate all models we used Leave-one-out cross-validation method and Determination Coefficient techniques.

KEYWORDS: QUENCH, IMPINGING JET, HEAT EXCHANGE COEFFICIENT (HTC), DATA ANALYSIS, STATISTICAL MODEL, MULTIPLE LINEAR REGRESSION, LOESS, RANDOM FOREST, LEAVE-ONE-OUT

NOMENCLATURE

MHF: Leidenfrost point (minimum heat transfer)
CHF: maximum heat transfer
HTC: heat transfer coefficient
T: temperature
v: speed of the steel product
P: pressure
LOESS: LOcal RegrESSion
RF: random forest
K: number of samples
DOE: design of experiment

INTRODUCTION

A good understanding of the quenching industrial processes behaviour needs a modelling of heat exchange coefficient that takes into account the effects on cooling of each process set up variation. Today it is no more sufficient on a heat treatment line to consider only the starting and finishing temperature on quench process: what is happening in between is also important. The choice of the process set up is very often done with « try and learn » technique in particular in quench; for sure this is not the best way and more than that this is not ensuring to have chosen the better set up for obtaining our target product without cracks or bending.
The literature shows many heat exchange coefficient models in the different cooling phases defined by Nukiyama [1]. This description of cooling was developed since the beginning of last century and it is still the basis of quenching analysis.

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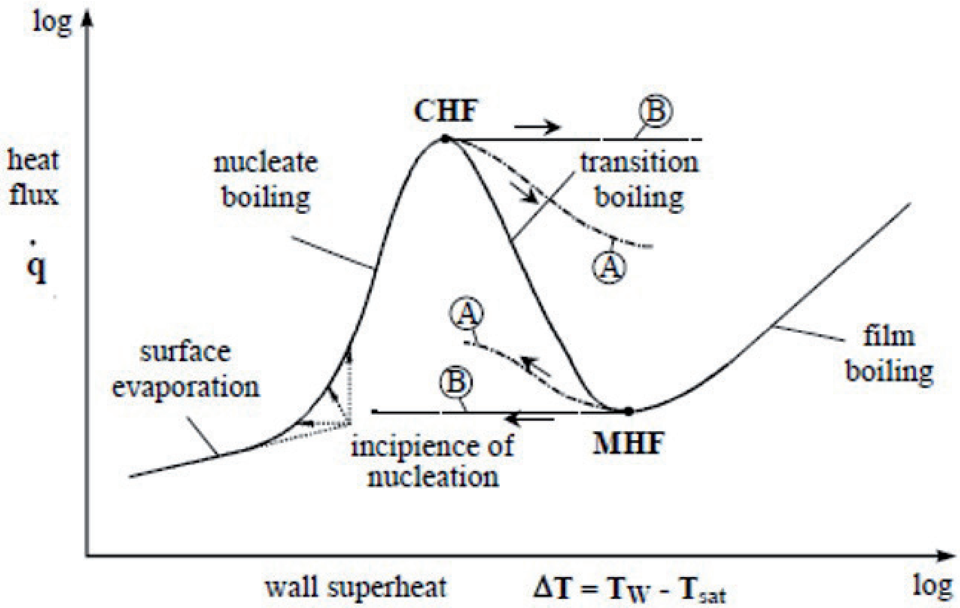


Fig. 1 – Nukiyama curve

In terms of heat flux, 4 main phases are defined in the temperature decreasing direction: film boiling, transition boiling, nucleate boiling and surface evaporation. This could be translated in four heat exchange phases dependent on steel surface temperature with 2 main transition points: MHF or "leidenfrost" point that corresponds to minimum heat flux and CHF that corresponds to maximum heat exchange. These two points can "move" changing the shape of the curve if the quench set up changes ([2] [3]). Also, the slopes of the curves in between each changing phase point could be of variable shapes, depending on the speed of the product, the rotation frequency and so on [4].

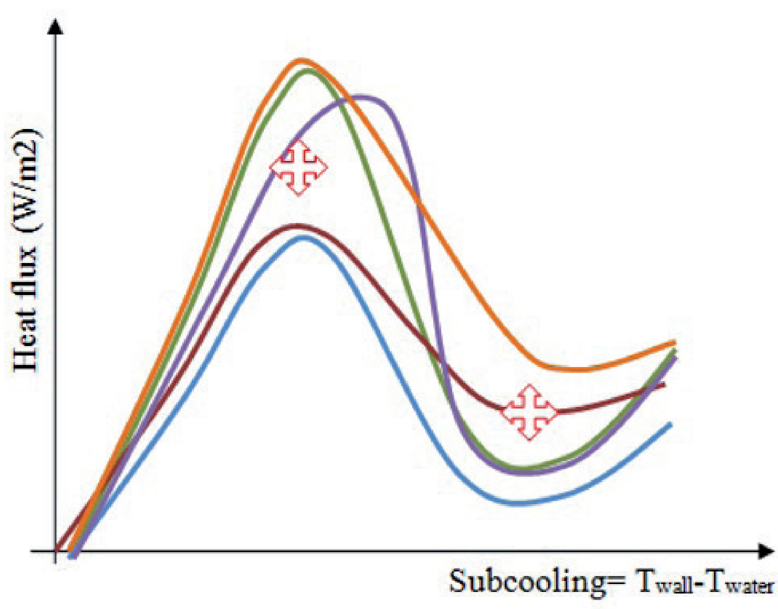


Fig. 2 – Influence of set up on heat exchange coefficient

At the end of the day, it is not possible to found a general model that could be applied to real cooling cases without passing from a strong characterization test matrix, covering as much as possible the whole multi-dimension space determined by the variation of the setup parameters.
The last point is critical, as the set up possibility space in our case is at least 7 or 8 dimensions made, if we consider starting temperature of the steel, water flow distribution per quench module, nozzle angle, product speed, distance from the nozzle, product rotation frequency, water temperature, water cleanness and product surface state. Trying to work in a so big space is not so easy, it is important at first to choose a good Design of Experiment (DOE) in order to choose the better dataset as possible.
Once the dataset exists the following problem is how to combine the data in order to have a model predicting the "empty" zones between a trial and another trial. Classically the problem is solved searching functional equations depending on set up parameters [5], very often this is applied on simplifications of the process, making a hypothesis on some parameters that are in general neglected. In this paper, we tried with another technique that is more statistically based.

QUENCHING BY IMPINGING JETS

The impinging jet quench category includes many types of quench characterized by the fact that the water impacts on the hot surface with a certain speed, geometry of jet, flow, pressure and the hot surface travels through the quench with a movement of translation, rotative or both (that gives a helicoidal movement of each point of the hot surface). Four many families of industrial impinging jet quench have been detected in the industry.

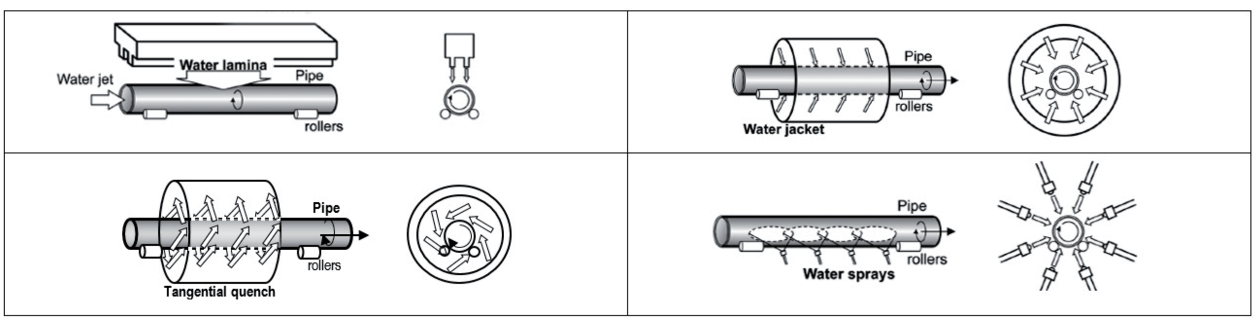


Fig. 3 – Industrial impinging jet quench types

The advantages of this type of quenching are the high productivity and the possibility to work on the parameters in order to obtain the desired cooling speed. Nevertheless, the complete control of this production tools needs big efforts of thermal characterization.

QUENCHING BY IMPINGING JETS

The aim is to find a mathematical model in order to be able to predict the HTC, starting from a dataset generated by trials on the real process devices. We want an HTC model as a function of the surface temperature of the product for each possible set up in a specific quench process.
The possibilities are 2: one is the classical research of a deterministic function of the HTC depending on the setup values; the other (that we choose for this work) is to use statistical tools. In the second option two mathematical choices are again possible:

1. The first is to establish a function determined by constant predictors. We can refer to that as to "functional data analysis".

$$HTC_{v,flow,angle,\dots}(T)$$

2. The second is to predict a value in function of the others variables including the surface temperature in the form:

$$HTC\ (T, v, flow, angle\dots)$$

The first one is the best choice when the dataset is huge; in our case, we have an 8-D space, it is very difficult to generate enough test in order to have a dataset considered sufficient for functional analysis. More than that the literature on that technique is poor and not sufficiently explicit for our needs [11].
The second choice allows us to build models with statistical techniques with a more limited dataset. However, we must make a strong mathematical hypothesis: each measurement point is independent of the others.

To limit the previous hypothesis, the idea is to create a "basis" structure for the function HTC in the dependence of temperature. The choice of the basis type is the first step. Three possibilities have been taken into account: Lagrange basis, Fourier basis and B-spline basis. As we had not a periodic function (as you can see in Nukiyama curve behaviour) we choose the B-spline basis. This is a linear combination of positive splines that doesn't need a periodic function as Lagrange or Fourier series.

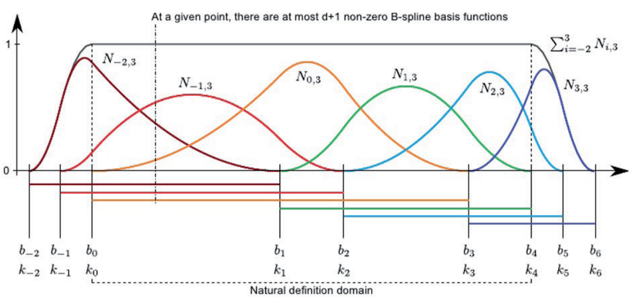


Fig. 4 – Example of B-spline decomposition on a simple problem

The idea is to decompose our function in single HTCj(T) with a B-spline basis in order to obtain something of the form :

$$HTC_j(T)=\Sigma i(a_{\_i} * B_i)$$

After this B-spline decomposition, the regression analysis has a bigger number of parameters because of the inclusion of the B-spline basis parameters. That helps in the solution of our multiple dimensions problems.
The following step is to test and choose a statistically relevant method; after a bibliographic ([6], [7]) research we focused on three methods: Multiple Linear Regression, LOESS and Random Forest.
The criteria we used for ranking the most accurate model is the K-fold cross-validation methods ([6], [7]). This method allows checking the performance of a statistical model used in practical cases. The principle is simple: the dataset is cut randomly into K groups. One part J of the sample is extracted and the model is built with the "K-J" remaining data. The extracted samples are used for the comparison with the model (that is used for simulating the extracted samples set up) and so the error is estimated. This is repeated for the "K-J" possible combinations. In our case we chose to use the "leave one out cross validation", that means that J=1.
To give a performance indicator of the model we used as an indicator the average error on the HTC.

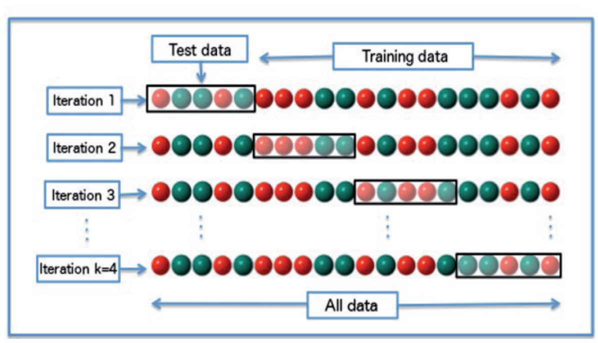


Fig. 5 – "Leave one out" technique

The last point in order to create an efficient model is to use a stepwise regression process for adjusting the model parameters. We adjust our model by adding and removing one of the 8-D parameters: at each step, we're using leave one out to have an idea of the accuracy of the model. As we have D=8 parameters, we build 2D-1 models for our optimization. As the number of parameters increase, the time to find the best model, can increase dramatically.
In this condition, other methods can be useful like forward or backward stepwise regression (see the graphic below), this methods are quicker but this doesn't guarantee to find the best model.

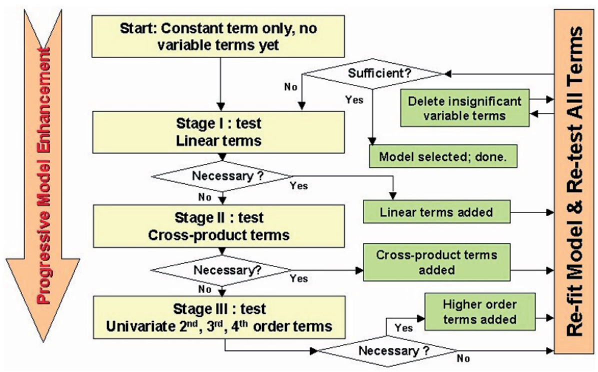


Fig. 6 – Forward or backward stepwise regression scheme

Multiple linear regression
This is the classical method to represent the relationship between the response variable and the predictors by a simple formula.

$$Y = X\beta + \varepsilon$$

Where Y is the sample, X the variables, β the weight and ε the residuals

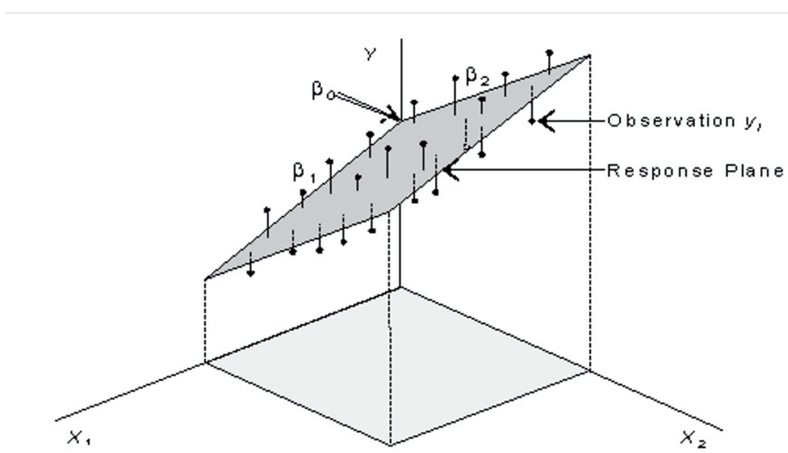


Fig. 7 – Example of multiple linear regression

It is the simplest statistical method and had several advantages: it is simple to use, it expresses the HTC with a mathematical formula and it is not necessary to have a big data set. The drawbacks are the fact of not taking into account the non-linearity, there is no functional aspect and it may be affected by outliers, which is sometimes the case with measurement.

LOESS
The LOESS method was first developed in 1979 by Cleveland [9]. The aim is to approximate the HTC in a local point of view. Several polynomial regressions are made and we join them together. The main advantage is to take into account the local peaks, that is not possible with a linear regression. It is a way to model the non-linearity of the function. The main disadvantage is the fact that you have to make a lot of regression for each point and you need a substantial data set.

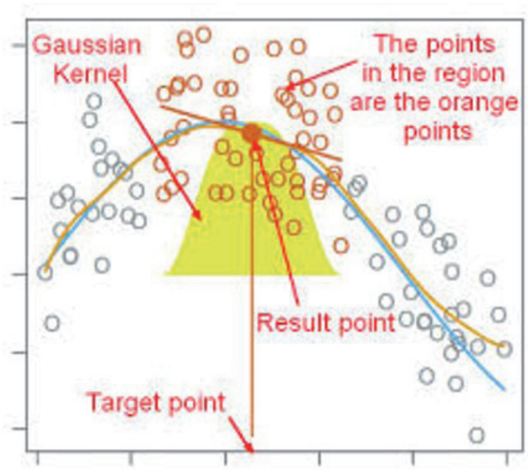


Fig. 8 – Example of LOESS regression

Random Forest

The classical machine learning methods need normally a big set of data as it is well known for neural networks. In our case the dataset was limited. Random Forest is also a machine learning method but it needs fewer data compared to the others for reaching a good precision. But for sure the more data we get the more precision we have.

The Random Forest method is based on decision tree technique. Decision trees are better known for the classification, nevertheless, regression as in our case is also possible.

In the CART method (Classification and Regression Tree) proposed by Breiman [7], the main idea is to split the sample into two or more homogeneous sets. Each time we split a branch into 2 leaves, we try to get the smallest error in each decision node. The CART method is a binary tree (we only split our branch into 2 leaves).

However, a disadvantage of the decision tree technique is the instability of the method: Random Forest method creates and makes a mean of several trees for improving the stability. That's the main idea of the Random Forest method invented by Breiman in 2001. Making a mean prediction of a lot of decision trees, it reduces the variance of the method, and that implies automatically the reduction of the error.

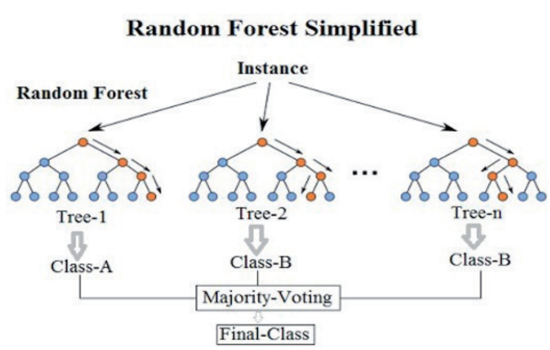
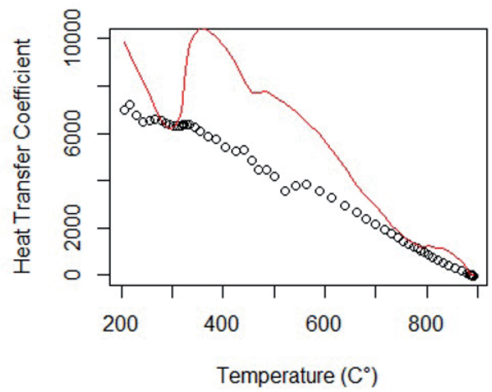


Fig. 9 – Random Forest example

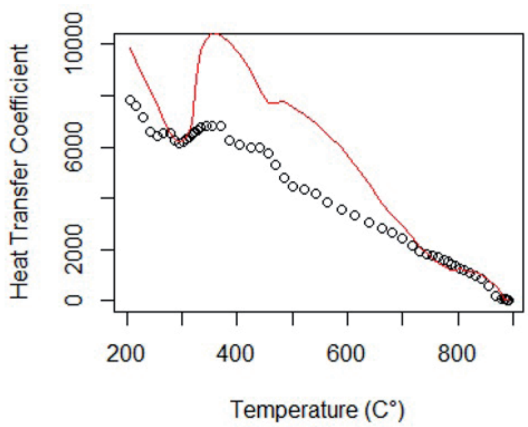
This method as the other statistical method has the disadvantage of being a non "functional" method. To keep him stable and avoid non-linearity it needs an idea of the shape of the curve we want to predict. So finally, some physical knowledge of the phenomena we want to predict, has to be introduced in the "box" if we want to have a good accuracy.

CONCLUSIONS

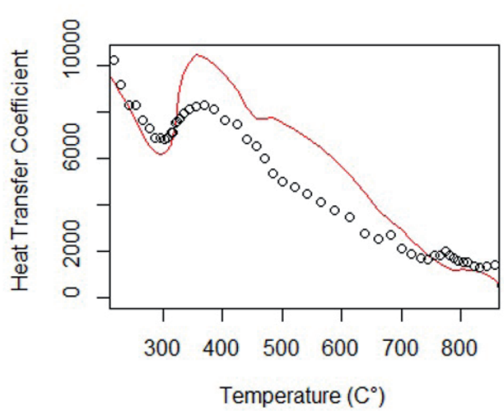
The three methods have been tested on a set of 20 trials in order to evaluate the efficiency. The meter for the evaluation is the average of the difference between the model generated by the statistical method and the real measurement using the leave-one-out technique.



Multiple regression



Local regression



Random Forest

Fig. 10 – Test of the three methods on one case measured by trial

The better precision evaluated on the set of 20 trials has been estimated for random forest technique. The comparison gives 11% of estimated error on RF that is a quite good result considering the precision that is common in "convective" heat exchange measurement, considering the error propagation from temperature measurement to inverse method for evaluating the HTC. If we compare this result with other correlations that we can found in the literature [13], the error given by RF is comparable.

Method	Multiple Regression	Local Regression	Random Forest
Estimated error	25%	18%	11%

Fig. 11 – Evaluation of the error on a dataset of 20 trials

For sure improvements can be done on the size of the dataset and on the DOE, nevertheless, this first trial gives good perspectives on statistical techniques applied to physical measurement as heat exchange coefficient.
In particular, when there are a lot of parameters influencing the physical phenomena, as in this case 8, it's not so easy to build a model in a classical way with a deterministic equation taking in account every parameter influence on the result.
If well managed and checked, a statistical method, as in this case RF, gives an alternative to classical physical methods with errors that can be kept at the same level as measurement errors.

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