STUDY OF THE INFLUENCE OF THE CHARGING MATERIALS ON THE METALLIC LOSS OF A CONTINUOUS CHARGING ELECTRIC ARC FURNACE BY MULTIPLE LINEAR REGRESSION

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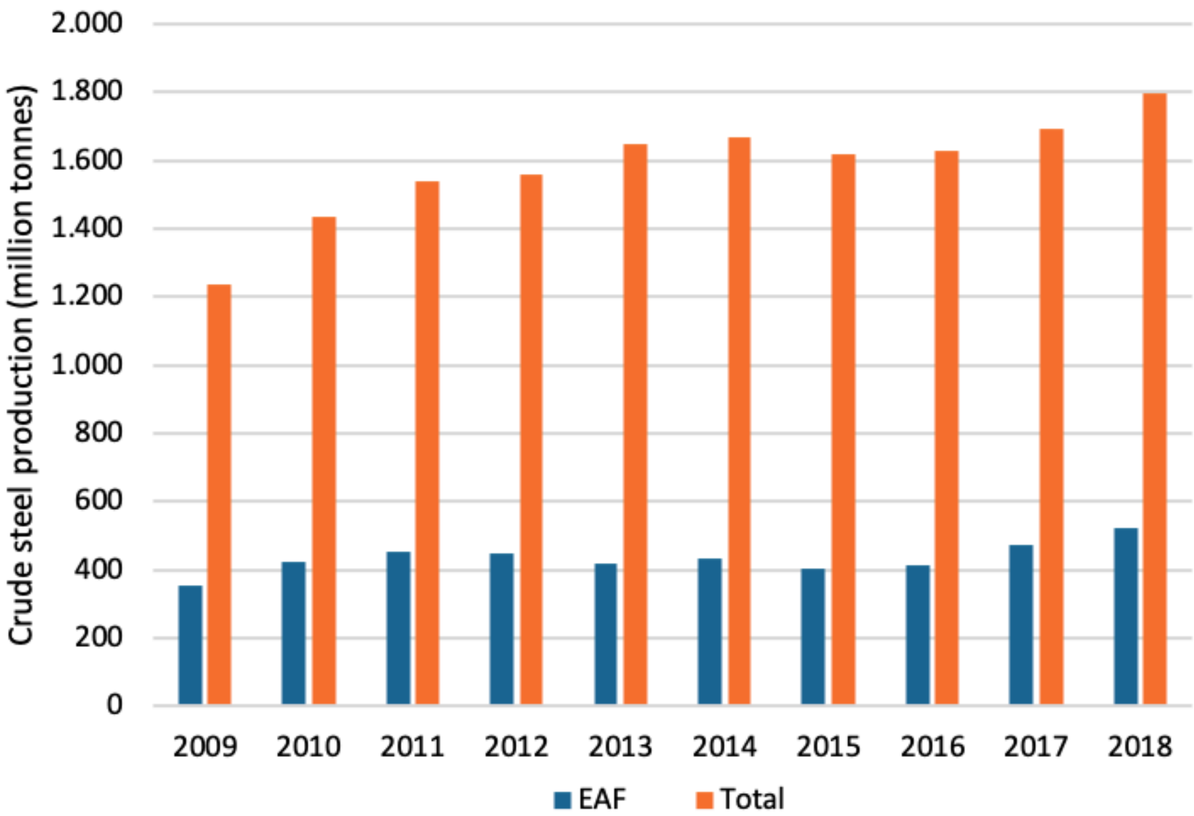
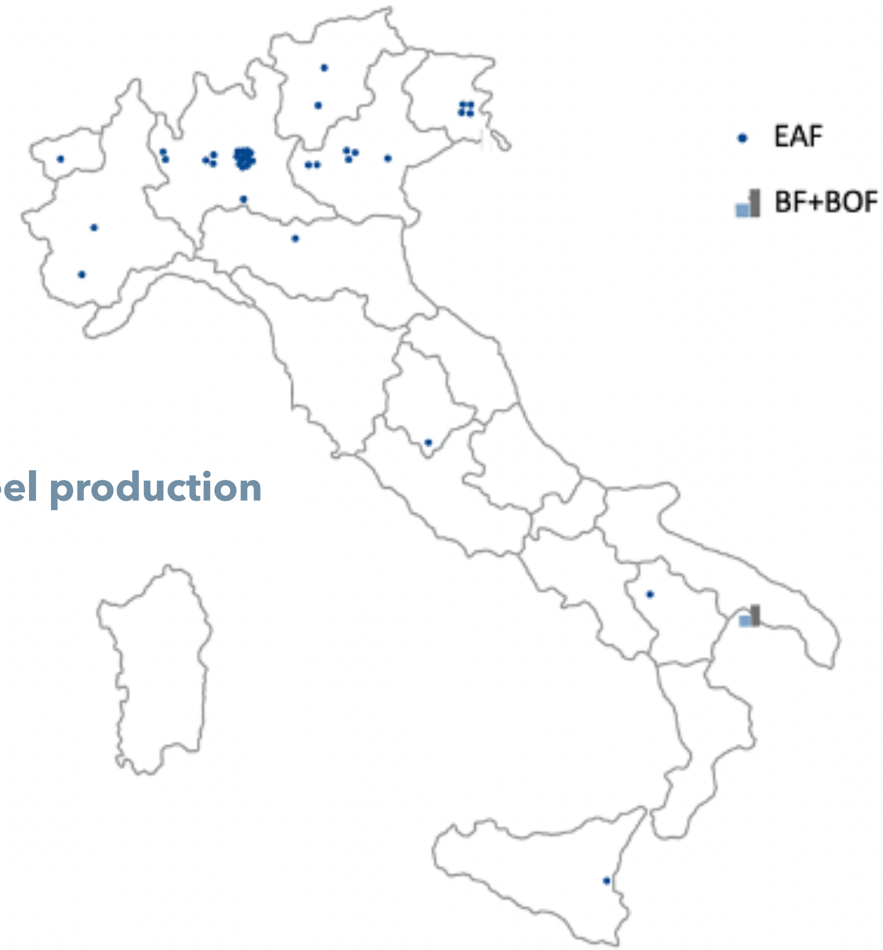
Steelmaking in Numbers



Country	Production [million ton]
China	928.3
India	106.5
Japan	104.3
USA	86.6
Russia	72.8
Korea R.	72.5
Germany	42.4
Turkey	37.3
Brazil	34.7
Italy	24.5

World Steel Association. World steel in figure 2020

Steelmaking in Italy

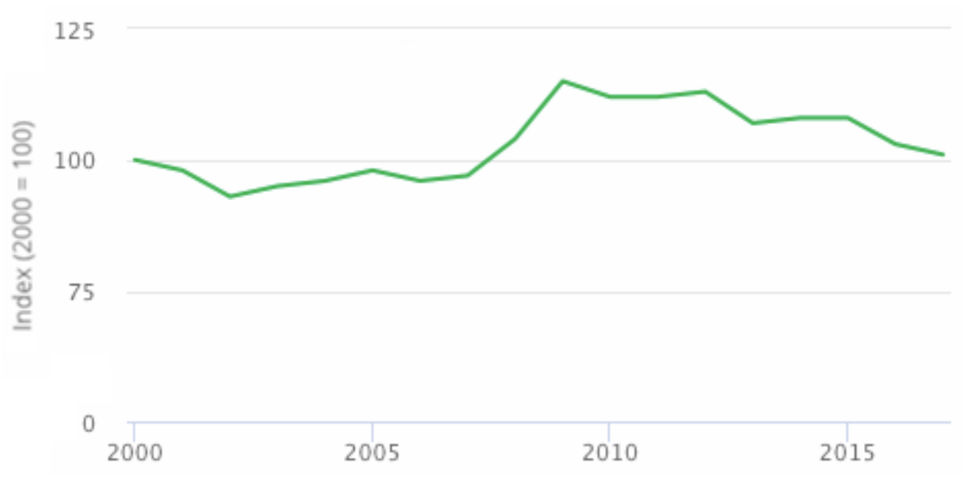


37 EAF production sites

82% of the total crude steel production

Federacciai, Assemblea annuale 2020: la siderurgia in cifre

Enviromental Impact

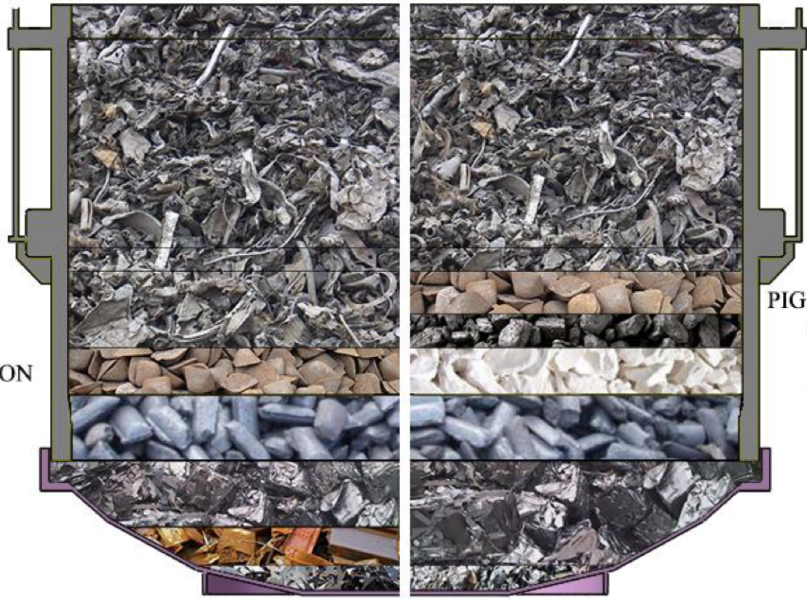


It is supposed that in the next years at least 40% of the world crude steel production will be performed by EAF thanks to its **lower emission**

The consequent **increase in scrap consumption** requires the **improvement of sorting methods** and **more conscious use** of the charging material

International Energy Agency. Iron and steel - tracking clean energy progress, 2020. [Online; accessed 26-January-2020].

Charging Materials



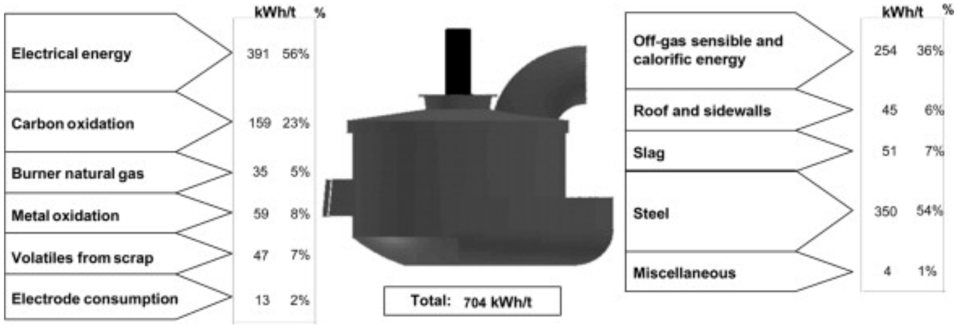
Composed by: metallic charge, slag formers, iron ore and coke

Scrap classification based on origin, chemical composition, dimensions and density

The presence of **tramp elements** (in particular Cu) in the scraps decreases the overall quality

Clean iron sources (HBI/DRI, pig iron…) diluite the pollutants but increase the total heat cost

Energy Balance



A correct balance between electrical and chemical energies leads to a **yield increase** and **cost decrease**

Scrap price responsible of the **70 ÷ 80%** of the **transformation cost**

The **control of the metallic loss** (Δ) is **fundamental** for the competitiveness of the process

Mathematical Modelling

$$\frac{W_R}{kWh/t} = 300 + 900\left[\frac{G_E}{G_A} - 1\right] + 1600\frac{G_Z}{G_A} + 0.7\left[\frac{T_A}{{}^\circ C} - 1600\right]$$
$$+0.85\frac{t_S + t_N}{min} - 8\frac{M_G}{m^3/t} - 4.3\frac{M_L}{m^3/t}$$

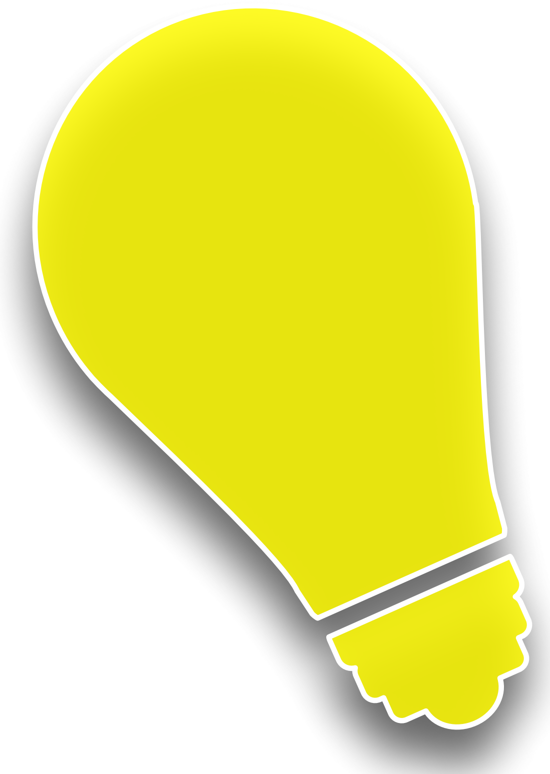
W_R	specific electric energy consumption	t_s	power-on time
G_E	weight of ferrous materials	t_N	power-off time
G_A	furnace tapping weight	M_G	specific burner gas
G_Z	weight of slag formers	M_L	specific lance oxygen
T_A	tapping temperature		

Static and **dynamic empirical models** are used in order to **study**, **predict** and **optimize** the EAF performances

In the main models based on energy and mass balance the **scraps are considered as one single variable**

The relationship between metallic loss and specific type of charing material has to be further investigated

Aim of the Proposed Work



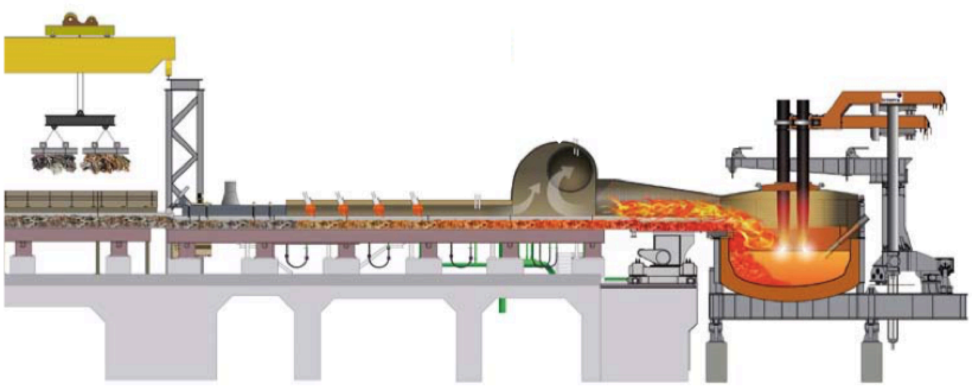
The influence of each several charging materials on the metallic loss has been studied trough the development of two regression models:

Multiple Linear Regression (MLR) without variable interactions

Multiple Linear Regression (MLR) with variable interactions

The regression models were made by the statistical analysis software **Minitab**

Electric Arc Furnace Configuration



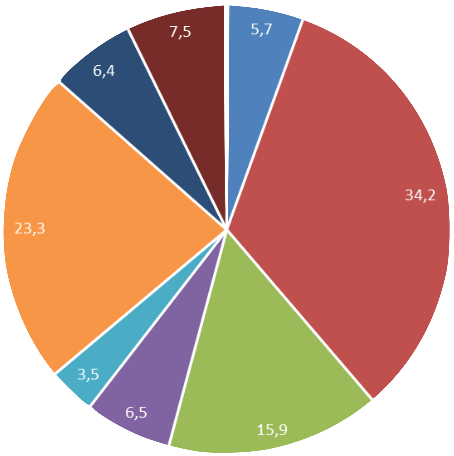
Continuous casting furnace (Consteel)

Nominal capacity of **250 tonnes**

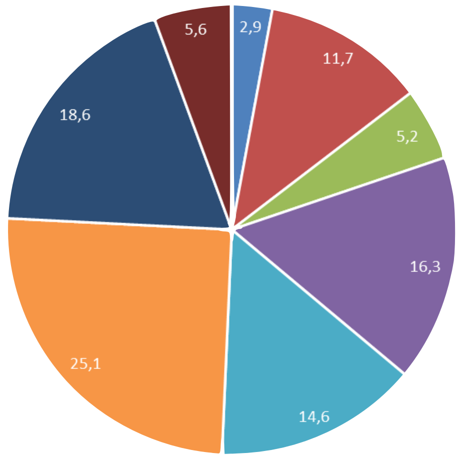
Production of **mild steel** (C=0.018÷0.022 wt%.)

Data Supplied

DATA SET A



DATA SET B



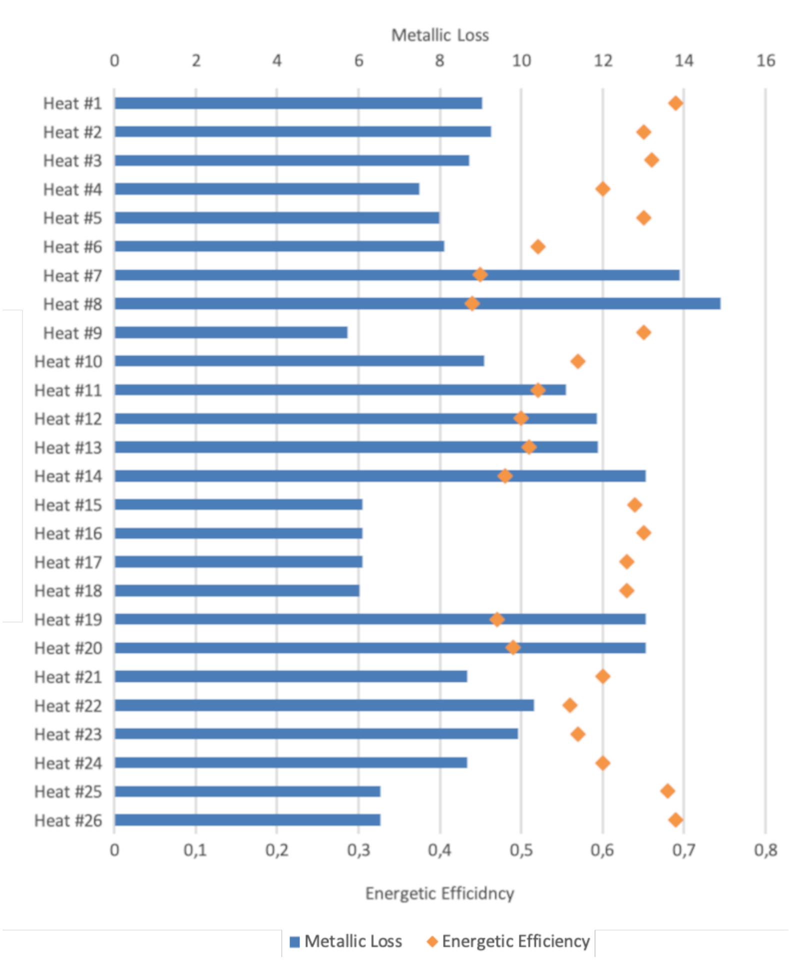
CES	Cut metal scrap from industrial demolition
HBI	Hot briquetted iron
LAPS	Sheet metal scrap of lower dimensions
RP	Internal scrap

PI	Pig iron
LAMM	Sheet metal scrap
PROLER	Shredded scrap
P53	Bales

Two data set regarding the EAF process parameters and charging materials weights of **56 monthly heats**

The main differences regarded the percentages of charged **PI, HBI, LAMM, RP** and **LAPS**

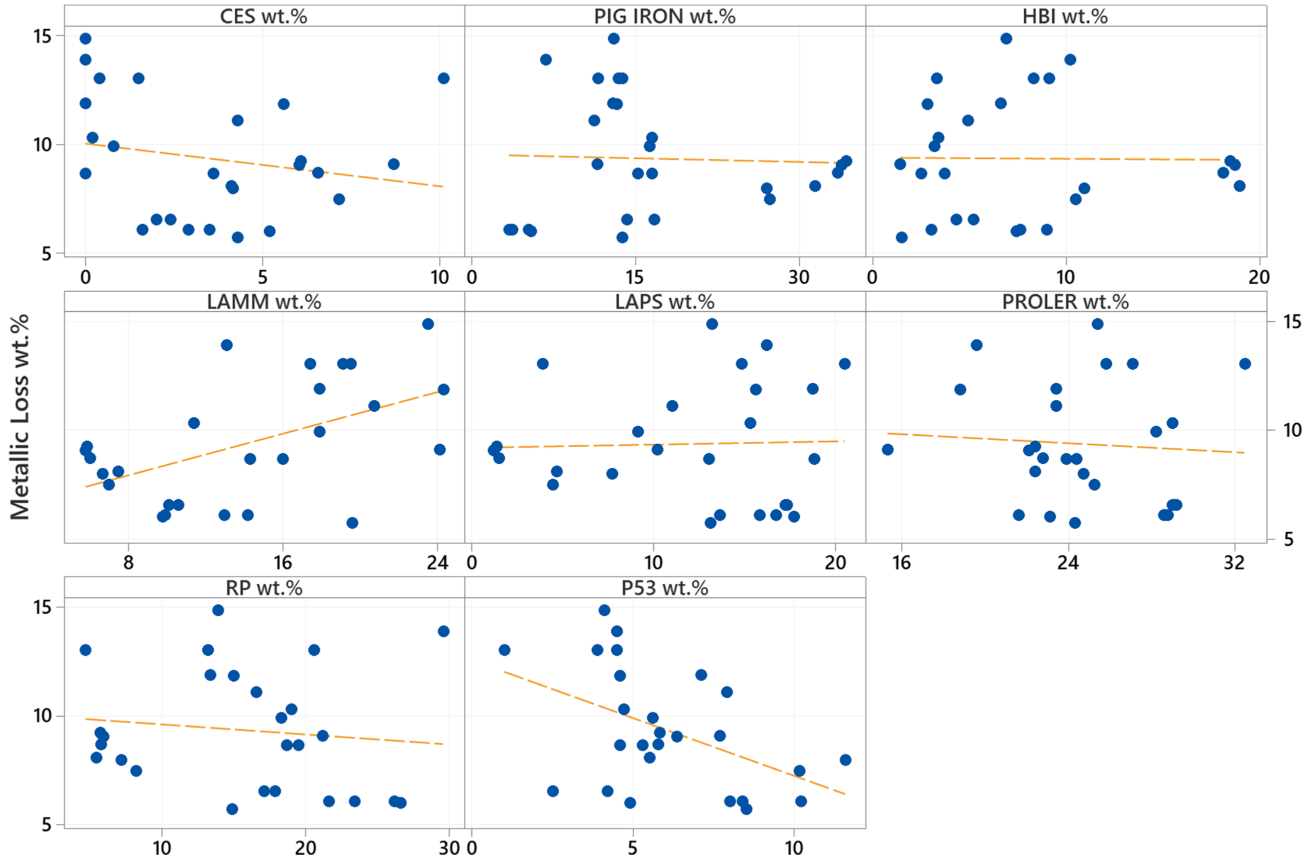
Preliminary Analysis and Data Elaboration



The furnace performances and parameters were **comparable with the state of the art** ones

The **metallic loss showed different values based on the charge mix blend**

MLR Models Development



MLR Models Development

Observations, Physical boundaries & Assumptions

- Scatterplots → No evidence of quadratic (higher order) relationships
- Hot heel → Constant
- Furnace parameters → Constant (mild steel production)
- Charging materials → Ideal condition absence of oils

↓

Exclusion of the Constant Term

MLR Models Development

Source	Adj SS	Adj MS	F-Value	P-Value	Coefficient
HBI	9.89	9.907	4.85	0.043	**0.16**
LAMM	113.04	113.106	55.33	0.000	**0.42**
PROLER	19.67	19.673	9.62	0.007	**0.16**
RP	11.32	11.360	5.56	0.008	**-0.12**

Model Summary

R-sq	R-sq(adj)	R-sq(pred)
98.20%	97.75%	97.21%

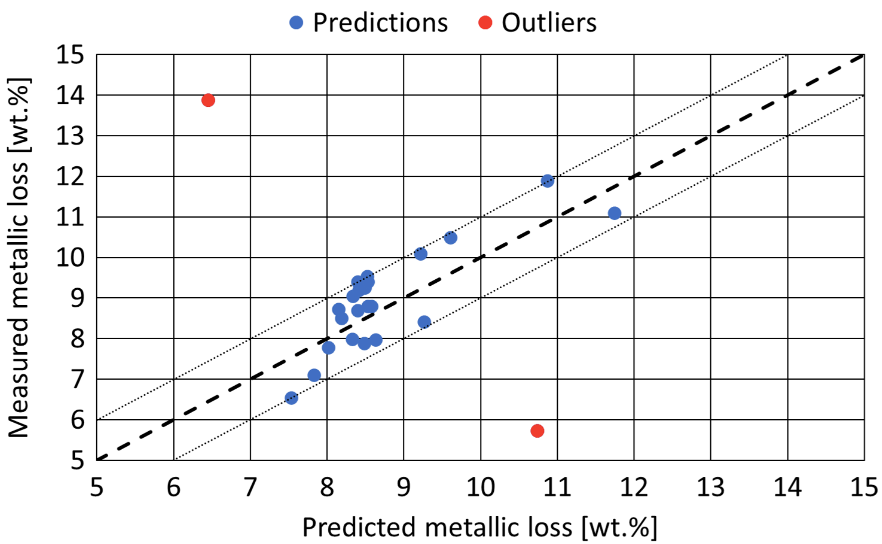
MLR Models Development

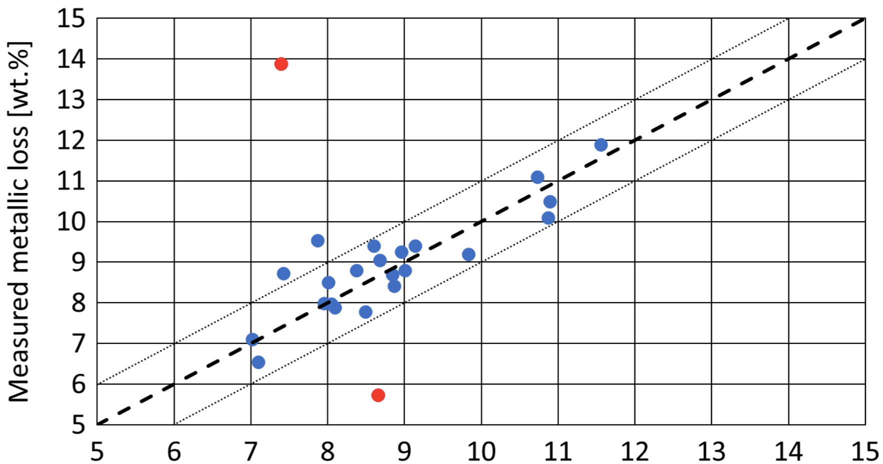
Source	Adj SS	Adj MS	F-Value	P-Value	Coefficient
LAMM	36.92	36.924	33.31	0.000	**0.3334**
CES x HBI	9.46	9.457	8.53	0.011	**0.1051**
CES x PROLER	5.74	5.741	5.18	0.039	**-0.0233**
PI x HBI	5.88	5.875	5.30	0.037	**-0.0101**
PI x LAPS	30.92	30.921	27.90	0.000	**0.0187**
HBI x LAMM	15.19	15.193	13.71	0.002	**0.0377**
HBI x LAPS	7.24	7.243	6.53	0.023	**-0.0204**

Model Summary

R-sq	R-sq(adj)	R-sq(pred)
98.20%	97.75%	97.21%

MLR Models Validation





The **model validation** performed using **25 heats** not used in the calibration

High model **reliability and prediction** for **7÷12% metallic loss** values

Conclusions

The aim of the work was the analysis and description of how the different scrap types influences the metallic loss of a continuous casting EAF, the main results can be summarized as follows:

- Charging materials **regression coefficients** were **physically coherent**
- **Predicted metallic losses close to the experimental ones**
- **Metallic losses are influenced mainly by** some specific charging materials (**LAMM, PROLER** and **HBI**)
- **Second order interactions between the charging materials** during the melt are **present** and affects the metallic losses
- The **predictive ability** of the statistical method can be **increased** by adding as **individual variables** the different categories of **scraps** used as charging materials

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Thanks for your attention!

For any further information:

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