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Optimization algorithms in the charge planning for the BOF Plant

M. Gawron [a,*], Cz. Adamczyk [b]
[a] Director, Support Primary Office, ArcelorMittal, Poland
[b] Support Primary Office, ArcelorMittal, Poland
* Corresponding e-mail address: marek.gawron@arcelormittal.com

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Analysis and modelling

ABSTRACT

Purpose: The purpose has been to demonstrate the possibilities of reducing the cost of steel processing in the BOF Plant by using optimization algorithms in the charge planning.
Design/methodology/approach: A lot of production factors and technological relationships impact the BOF processing costs. Practically any change in charge material parameters, like chemistry and temperature of hot metal, scraps and fluxes, as well as market prices of materials and cost of carbon dioxide emission, have to be considered to find an optimum charge mix, which generates the minimum cost and simultaneously complies with all technological and steel quality constraints. A linear optimization task including a simplified version of a BOF static model has been defined and a few examples of typical industry charge planning problem have been solved and presented.
Findings: Critical price and amount of a given charge material for current technological conditions, stocks and market situation is the basic information for the Steel Plant management as well as for the Purchase Department. The relationship between material prices, CO_2 emission price and material consumption for a given production and logistic constraints have been identified.
Research limitations/implications: The paper describes using mathematical optimization methods in a specific area of steel industry, but it is opened problem with large potential of obtaining substantial benefits in other areas.
Practical implications: The optimization model has been a base for developing the application for the Steel Plant and Purchase Department to optimize charge mix and plan the charge materials purchasing.
Originality/value: The optimization algorithms has been adapted for a specific operation problem in steel making, i.e. calculation of charge for BOF.
Keywords: Production and operations management

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1. Introduction

One of the basic problems in the Steelmaking Industry is the choice of such charge materials on particular stages of hot metal and steel production, which would permit to satisfy all quantity and quality product requirements at a minimum cost of production. Currently an important component of the production cost, which has an impact upon the optimum charge, is the cost of CO_2 emission. For some time in ArcelorMittal Poland the research on a mathematical model to be applied in a production processes in the Primary Area, including sintering, hot metal production in blast furnaces, and steel melting in convertors (BOF), has been conducted. In each of these processes, local optimization tasks for the charge selection can be specified (Fig. 1). Implementation of models for the local processes can bring about significant advantages, however a full effect can be obtained with the use of a model, which includes all production processes in a given area. The above premise is underlined by the fact that the global optimization effect is usually higher than the sum of local optimization effects.

The first stage of the research on a global optimization model for the production processes consists however in developing the local processes models, including in this case the Sintering Plant, Blast Furnaces and Converters (BOFs). The present article concentrates on the results of work on the optimization model for the BOF process charge selection. Some tasks, typical for the metallurgical process, which were solved with the use of the model have been presented.

It should be stressed that some selected project results have been presented, the project itself still being under implementation.

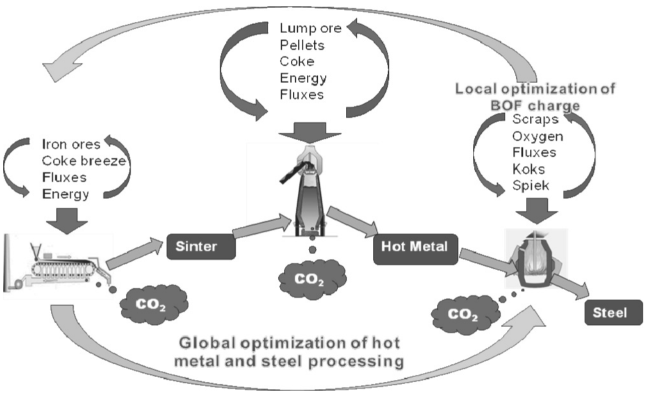

Fig. 1. The principles of a global and local optimization for the hot metal and steel production

2. Definition of the optimization problem

For a BOF process, a basic task is to calculate a selection of charge materials, i.e. the amount of hot metal, scraps, fluxes, endo- and exothermic additives and oxygen required to arrive at:

- Minimum cost of liquid steel production.
- Required parameters of steel before tapping: temperature and chemical composition - a content of C, P, S and trace elements.
- Correct run of metallurgical processes in a BOF, in particular, slag-formation processes, which impact a refractory lining life, desulfurization, dephosphorization and slag and metal slopping from the BOF.

The task can be divided in two parts:

- **Optimization model**, including:
  - *Target function* - a total cost of steel production in a given planning period.
  - *Decision variables* - amount of charge materials.
  - *Constraints* - charge materials available in a given period of time, required steel parameters.
- **Static Model for a BOF Process,** aimed at calculating the amount of charge materials and oxygen for a pre-set temperature of metal in a BOF, steel volume and slag basicity.

Taking the optimization task into consideration, the static model function is mainly to reduce the steel temperature; in such a sense, it is a part of the optimization model.

3. Characteristics of the static model

A key role in solving the problem in question is played by the static model [1,2,3,4], i.e. an algorithm to calculate the BOF charge for a pre-set temperature and other process parameters, or in an opposite mode, to calculate the temperature based on pre-set charge parameters. In a production practice both modes of operation are used.

In the first mode, charge is calculated for a pre-set temperature, before the start of heating. After the end of a charging process, the second mode is started, i.e. a forecast steel temperature is calculated for a real charge composition (which, for the operational reasons, can be slightly different from the charge calculated in the first mode), in order to check if the difference between a forecast temperature and a required temperature does not exceed a maximum value.

For the use of the optimization model, the first mode of the static model is applied.

The first problem to appear - when the static model used in a production process is attempted to be included in an optimization task - is the model complexity. The static model is a physical and chemical model, i.e. based on a mass and energy balance. Solving of the model by means of classical mathematical algorithms, such as linear programming or quadratic programming, is either impossible, or at least not effective. Heuristic algorithms, such as genetic algorithms, "tabu search", "simulated annealing", etc., often used for solving the complicated tasks, are on the other hand of a slow-convergence nature, which effects in time-consuming calculations, even if high-speed processors are available.

For that reason and for the needs of the project, a new version of a static model has been developed, based on linear statistic equations, which describe the relations between the steel temperature and a unit consumption of hot metal and other charge components, hot metal parameters and the time between the heats, namely:

$$t = a_0 + \sum_{i=1} a_i x_i \tag{1}$$

where:

t - steel temperature;

x_i - variable - hot metal parameters, unit consumption of charge materials, time between two successive heats;

a_i - regression coefficient.

Despite its simplicity, the accuracy of such a model does not differ significantly from the accuracy of a physical and chemical model and it has appeared satisfactory for the reason of the charge material purchase planning. The statistic model can however be used only for such materials and technological conditions, based on which the values of regression coefficients have been identified. It cannot be applied for new materials and together with each significant change in a heating technology, the statistic calculations need to be repeated.

4. Optimization model

Linearization of the static model through the application of regression equations has helped to use a simple and effective linear programming algorithm [5], as a method of solving the optimization task.

4.1. Objective function and decision variables

Objective function takes the form of:

$$K_{\min} = b_0 + \sum_{i=1} b_i x_i \tag{2}$$

where:
K - variable cost of liquid steel production;
x_i - decision variable with a number "i" - consumption of a material with a number "i";
b_i - the cost of consuming a given material with a number "i".

The main component of a consuming cost for a given material is its price, however this cost also includes other components, e.g. the cost of CO_2 emission, or the cost of oxygen used for refining the components brought in with this material. The costs of oxygen or CO_2 emission cannot be directly introduced to the objective function as decision variables, because they are linearly related to the charge materials consumption, and a linear programming algorithm excludes a linear relationship between decision variables.

4.2. Constraints

Defining the constraints is essentially significant for the usage of the charge optimization results. Two kinds of constraints have been introduced in the optimization model:

- *Bounds on the decision variables* - i.e. charge material consumption - are specific types of constraints. This type of constraints always refers to one decision variable. A separate defining of such variables allows an optimization algorithm (solver) to do more effective calculations. The above constraints specify a current or expected charge materials availability and refer to a status of a stock level, market situation and company policy in the field of logistics and raw materials purchasing.
- *General constraints* - are defined by formulas, which contain two or more decision variables. These are:
    - Tonnage of steel planned for production in a given period of time.
    - Average tapping temperature.
    - Slag basicity.
    - P content in steel.
    - S content.
    - Content of trace elements - Cu, Cr, Ni, Sn.

5. Examples of optimization problems in planning the BOF charge - based on a metallurgical practice

5.1. The impact of changes in a hot metal cost upon the optimum BOF charge composition

The optimum charge composition, which ensures a minimum cost of production, with all other requirements fulfilled, depends on prices and properties (chemical composition, temperature, etc.) of particular charge materials, as well as on BOF process parameters. As the cost of hot metal production in blast furnaces fluctuates month by month, depending on the price of charge materials, i.e. iron ores, coke, gas, therefore an optimum proportion of hot metal in a BOF charge also changes, especially that hot metal parameters and the prices of other materials also change. The process of planning the hot metal consumption in the next planning period (month, quarter) for a specified production of steel grades and expected prices of other charge materials is of a primary importance for the Metallurgical Plant cost optimization.

The models described above have been set up in order to solve the problem of calculating an optimum charge, with a fluctuating price of hot metal. The prices and parameters of materials in a reference period - February 2012 - have been regarded as the input data. A carburizing agent based on C and SiC and iron ore have been used to adjust a heat balance in a BOF. Calculations have been done for an average steel temperature and slag basicity in a reference period.

Bounds: For this simulation the bounds values have been assumed at +- 10% of each material consumption in a reference period. Such narrow bounds bring the simulation conditions close to a real situation, in which the changes in the availability of different charge materials are significantly limited by the market conditions. For example, a charge with a high proportion of cheap scrap may be optimum in theory, however a massive purchase of this type of scrap by such a big customer as ArcelorMittal would result in the price increase, and thus would make the calculations inadequate.

The results have been shown in Fig. 2.

The rising share of different scrap grades, together with the hot metal price increase in an optimum charge mix have been shown in the Figure 2. With a low hot metal price the consumption of iron ore is at a maximum level, in order to maximize the hot metal consumption. With high hot metal prices exothermic material is added to an optimum charge mix. The results have been presented in a Table 1 below, due to a low resolution of the graphics in Fig. 2.

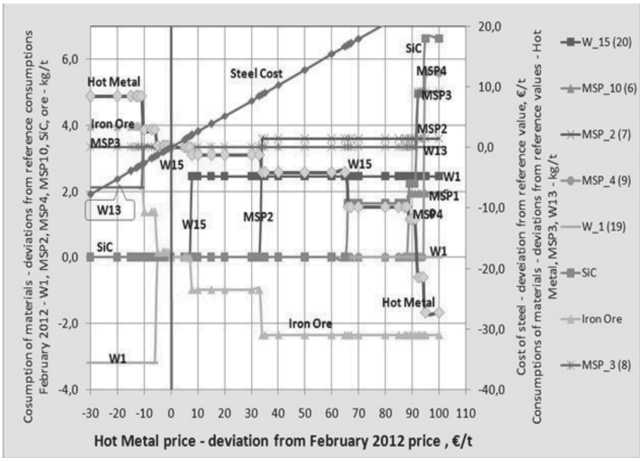

Fig. 2. Impact of Hot Metal price on the charge materials consumption in the optimum BOF charge mix returned by Linear Programming algorithm

Table 1.
Impact of Hot Metal price on the BOF charge material consumption returned by Linear Programming algorithm

H.M. price, €/t	-11,0	-10,0	-5,0	0,0	8,0	34,0	66,0	89,0	92,0	95,0
Type of material	Material consumption kg/t									
Hot Metal	**18,0**	**12,5**	**9,9**	**9,6**	**8,3**	**5,4**	**-0,3**	**-2,3**	**-11,8**	**-17,6**
W_13	-3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3
W_1	-1,6	-1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6	1,6
W_2	-0,2	-0,2	-0,2	0,2	0,2	0,2	0,2	0,2	0,2	0,2
W_15	-1,2	-1,2	-1,2	-1,2	1,2	1,2	1,2	1,2	1,2	1,2
MSP_2	-1,8	-1,8	-1,8	-1,8	-1,8	1,8	1,8	1,8	1,8	1,8
MSP_5A	-2,8	-2,8	-2,8	-2,8	-2,8	-2,8	2,8	2,8	2,8	2,8
MSP_10	-1,0	-1,0	-1,0	-1,0	-1,0	-1,0	-1,0	1,0	1,0	1,0
MSP_3	-4,5	-4,5	-4,5	-4,5	-4,5	-4,5	-4,5	-4,5	4,5	4,5
MSP_4	-2,8	-2,8	-2,8	-2,8	-2,8	-2,8	-2,8	-2,8	-2,8	2,8
MSP_6	-2,5	-2,5	-2,5	-2,5	-2,5	-2,5	-2,5	-2,5	-2,5	-2,5
SiC	0,0	0,0	0,0	0,0	0,0	0,0	**1,6**	**2,2**	**4,9**	**6,6**
Iron Ore	**4,0**	**1,4**	**0,2**	**0,0**	**-1,0**	-2,3	-2,3	-2,3	-2,3	-2,3
Lime	-0,1	-0,3	-0,4	-0,4	-0,4	-0,6	0,2	0,4	1,7	2,4
Oxygen (1000 m3)	-1,8	-1,6	-1,4	-1,4	-1,3	-1,1	0,3	0,8	3,1	4,5
CO2 (1000Nm3)	77,4	77,0	76,7	76,7	76,6	76,4	78,7	79,5	83,2	85,4
Converter Gas Recovery (1000Nm3)	0,5	0,5	0,4	0,4	0,4	0,3	-0,1	-0,2	-0,9	-1,4

While analyzing the above results, the changes in lime, oxygen and CO_2 and BOF gas emission for various charge mixes should be observed. In a conclusion it can be stated that taking into consideration a high volume of the Steel Plant production and a number of factors to be included in calculations, the use of mathematical models in planning the hot metal production level and charge materials purchases can bring significant financial effects.

5.2. Calculation of the amount and a critical price of material in the optimum charge composition

A frequently appearing business problem concerns a decision making process while considering the supply offers for various charge materials, scraps in particular. For commercial negotiations it is required to know a maximum price of a given material (critical price), above which there is an increase in the cost of steel production. It should be observed that a critical price may depend on the volume of supply. This happens when other, cheaper charge materials are available in a limited amount, and they can substitute the offered material. This means that calculating one critical price for a given offer, which would be a limit price in a process of negotiating a purchase contract, is not sufficient. On the contrary, it is required to specify **a critical price as the function of the amount of a material being offered.**

An example shown below shows how to specify a critical price for the supply of 10 000 t of a virtual MSP_x scrap, as well as the relation between the price and a volume of supply (which would be required if negotiating of the price not higher than a critical price for a whole supply of 10 000 t was not possible).

Following the previous example, the input data have been taken from a reference period, but due to the volume of supply, it was required to extend the *bounds* for the charge materials up to 22%.

A series of simulations has been done with the use of the model discussed above, taking into consideration different prices of a virtual MSP_x scrap. In Table 2 the results have been presented - deviations in the amounts of all scrap grades to be consumed in a reference period, including the increase in the MSP_x scrap price .

Table 2.
Calculation of the amount and critical price of "virtual" MSP_x scrap depending on deviations of other scraps consumptions

MSP_x price deviation, €/t (simulated)	0,00	1,00	8,00	33,00	36,00	38,00	52,00
Type of scrap	Deviation of scrap consumption t/month						
MSP_x	**10 000**	**8 842**	**7 068**	**6 432**	**3 475**	**1 653**	**0**
MSP_2	-1 180	0	0	0	0	0	0
MSP_5A	-1 855	-1 855	0	0	0	0	0
MSP_10	-636	-636	-636	0	0	0	0
MSP_3	-2 982	-2 982	-2 982	-2 982	0	0	0
MSP_4	-1 828	-1 828	-1 828	-1 828	-1 828	0	0
MSP_6	-1 644	-1 644	-1 644	-1 644	-1 644	-1 644	0

As the simulation results show, if the MSP_x scrap price increases above a critical price level, the amounts of other scrap grades rise one by one. With the price higher by 52 €/t vs. critical price none of the MSP_x scrap amounts is cost-effective, having the purchases in mind.

5.3. Critical price of replacing one scrap grade with another one

This example refers to a situation, when one scrap grade, marked here as MSP_x1, is not available on the market and the offer for MSP_x2 scrap grade supply is negotiated. A new MSP_x2 scrap is to replace MSP_x1 in the next month, at the same amount and with the same production technology. For the Purchasing Department it is important to know what is - in the current conditions - a critical price of replacing MSP_x1 scrap with MSP_x2 scrap, i.e. the price which will guarantee that the cost of steel production remains unchanged. Two options are possible, each with a different critical price:

a) **Option 1** - a contract being negotiated for the supply of MSP_x2 scrap refers to the whole amount of this scrap, which is planned to be consumed in the next month.

b) **Option 2** - a contract being negotiated refers only to a new supply of MSP_x2 scrap. Previously contracted amounts and prices of the scrap are not to be changed.

The results have been shown in Fig. 3.

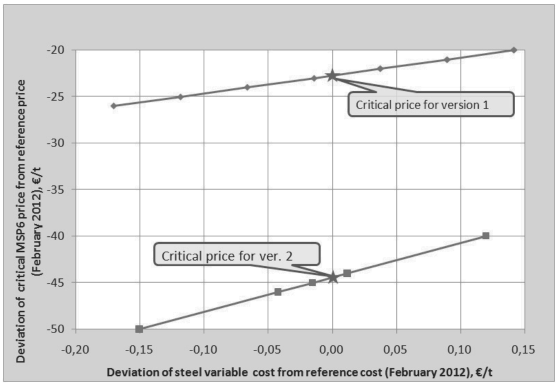

Fig. 3. Critical price of replacing the MSP_x1 scrap by MSP_x2

Additional information:

Amount of MSP5_x1 to be replaced - 28.3 kg/t

Amount of MSP_x2 that is used monthly up to now - 25.1

Results of calculations:

- ver.1 Total amount of MSP_x2, including scrap necessary for MSP_x1 replacing - 52.1 kg/t, and
- ver.2 Amount of MSP_x2, necessary for MSP_x1 replacing only - 27.1 kg/t

Remarks: amount of replacing MSP6_x2 scrap is smaller than MSP_x1 due to higher Fe content

Based on the above results, critical prices of replacement are much different in both options. In option 2, a critical price is significantly lower. This can be explained by the fact that so far the price of MSP_x2 scrap was higher than the price of MSP_x1 scrap and the price difference in this option falls to a smaller amount of material in a future contract.

6. Summary

- A critical price of BOF charge materials depends on:
  - Consumption (purchase volume) of a given material.
  - Prices and volumes of other charge materials.
  - Technological rates and parameters, such as yield, chemical composition and energy consumption.
- Due to the fact that there are many factors which influence the price, the calculations of both a critical price and an optimum amount of a given material in the charge composition should be done with the use of a mathematical model of the BOF process, with implemented cost optimization algorithms.

References

[1] S. Kimura, M. Kimura, K. Semura, R. Misumi, S. Nishina, T. Ohmori, Improvement of calculation models for BOF, Proceedings of the Steelmaking Conference, Toronto, 1998, 401-402.

[2] D.J. Buchanan, J. Fear, R.A. Gordon, Computer control of the DOFASCO No. 2 BOF meltshop, Proceedings of the 64th Steelmaking Conference, Warrendale, 1981, 203-213.

[3] J. Flavio Viana, L.F. Andrade de Castro, Converter oxygen blowing model based on neural networks, Proceedings of the Scanmet II-2nd International Conference on "Process Development in Iron and Steelmaking", Lulea, 2004, 199-206.

[4] A.B. Snoeijer, P. Mink, A. Overbosch, M. Hartwig, H. terVoort, J.P. Brockho, Improvement of converter process consistency at BOS no. 2 Corus IJmuiden, Proceedings of the 5th European Oxygen Steelmaking Conference, Aachen, 2006, 186-193.

[5] L. Schrage, Optimization modelling with LINDO, Duxbury Press, 1997, 21-48.