DOR: 20.1001.1.25383620.2021.5.2.7.3

Numerical Investigation of the Mutual Influence of Materials and Energy in the Electric Arc Furnace: A Case Study in Khorasan Steel Complex

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Received 20 September 2021 - Accepted: 08 December 2021

Abstract

Knowledge of the measurable parameters in an electric arc furnace can effectively increase efficiency while declining energy consumption, hence leading to positive environmental consequences. This issue has been frequently addressed in various studies, but the extent of these effects and their cause-effect relationships have been rarely explored. In decision-making procedures that depend on various factors, the extent of the effect could be also effective in addition to the priority. The optimization and the effect intensity, as well as affectability of some effective parameters of an electric arc furnace, can dramatically influence the quality of the produced steel, energy consumption of the process, and consumption of electrode and refractory substances. The aim of this study is thus to examine the mutual effects of various carbon injection contents, electrical power consumption levels, slag, and other effective parameters of the electric arc furnace during different charges including material and energy consumption, volume and quality of the slag, and pollutant emission using the DEMATEL mathematical model. To this end, calculations of some of the recorded parameters of a 110-ton electrical arc furnace in the Khorasan steel complex were studied and compared.

Keywords: Electric arc Furnace, Modeling, Extractive Metallurgy, Pairwise Comparison Method, DEMATEL Method.

1. Introduction

Electrical arc furnaces are employed to directly produce raw steel from sponge iron, iron scrap, and blast furnace cast iron. Advantages of this method include relative reduction of energy consumption, the possibility of steel production from recycled materials such as melting the casting tundish residuals, and iron scrap, and a significant reduction in the environmental contamination compared to other blast furnaces/convector methods [1]. In electric arc furnaces, it is possible to adjust and chemically balance the molten bath by adding carbon from the top of the furnace and oxygen through a lance embedded in the furnace design, as well as regulating the slag volume by incorporating lime and dolomite from the top [2].
The carbon content of the sponge iron (if charged), the carbon injected into the molten bath, and the carbon introduced into the molten content can react with the oxygen of the molten content through graphite electrodes, forming carbon monoxide bubbles which move to the slag, giving rise to puffy slag. As one of the influential factors in the performance of electric arc furnaces, electric energy is one of the main sources of energy for a melting cycle along with chemical energy obtained from the chemical reactions of carbon monoxide production (exothermic) and iron oxide production (endothermic) [3].
At the temperature of the molten bath (usually about 1600 °C) the carbon and oxygen contents must be in equilibrium concentration. Carbon and oxygen concentrations are shown by Eq. 1. [4]:

$$[\%C] \times [\%O] = 0.0025 \qquad \text{Eq. (1).}$$

Following a decrease in carbon content and an increment in oxygen concentration, the oxidation of pure iron in the molten phase begins and increases rapidly. On the other hand, the decline in the oxygen content below the equilibrium level will reduce the production of carbon monoxide, leading to unsuitable slag [4].
The carbon in the molten bath reacts with residual Wüstite oxygen (FeO) and converts it into Fe iron. The carbon residues from sponge iron can remain in the bath [5]. The excess carbon in the bath can help reduce the required electrical energy as a source of energy from its reaction with residual oxygen.
The most important measurable parameters affected by injected carbon are the slag volume, the iron oxide content of the slag, injected lime and oxygen, electrical energy, and carbon dioxide gas emitted into the environment.
In addition to the mentioned parameters, several other effective factors are either unmeasurable or their access is limited. Regarding the extent and diversity of instant data obtained from furnace mass and energy control software, values higher or lower than the standard range should be controlled and reviewed by designers and experts. The need for knowledge of required materials and empirical information, including defects and unused materials can be addressed by a decision-making process. Instant recording of raw material data is of

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crucial significance to achieve an optimal design with minimal risk and loss [6]. Since the arc furnace is fed from various sources of iron ore as well as recycled steels with diverse compositions, their carbon and acidic waste contents can be highly variable. Therefore, the optimal performance of an electric arc furnace can be only achieved by instant measuring and recording the parameters and their examination using mathematical algorithms [7]. The wide fluctuations in the parameters affecting the performance of electric arc furnaces can be assigned to the uncertainty of conditions as well as the effect of other non-measurable parameters such as climatic conditions [8].
Decision models have been rarely used in iron and steel production. Multi-criteria decision-making models (MCDM) can be a proper choice when several effective criteria with uncertainty are involved in a problem.
MCDM models have been already employed in various fields of engineering, especially material selection. In 2008 [8], Rong applied a linear model to optimize scrap charge in an electric arc furnace. This study was based on fuzzy theory under uncertain conditions. Moreover, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was used by Jee et al. [9] in selecting the optimal materials for the idler wheel, in which, fatigue strength and fracture toughness were considered as the study criteria. Another new model was introduced in 2010 by Maniya et al [10]. According to that research, three models of Preference Selection Index, Graph Theory and Matrix Approach (GTMA), and TOPSIS were employed to select optimal material. In 2014, several multi-criteria decision-making methods were utilized to select pipe materials in the sugar industry [11]. In the same year, a multi-objective instruction was used in Russia by Viktorovich et al. [12] to select the input charge material for a 180-ton electric arc furnace. In 2014, Liu et al. [13] also presented an MCDM hybrid model for one type of two-component round bearing. A year later, Kumar et al. [14] used a hybrid model comprising AHP and TOPSIS for the selection of power generation materials. In 2017, a hybrid model of relative composite evaluation and TOPSIS was introduced by Mousavi Nasab et al. for the selection of spare tool materials [15]. In 2016, Reyhanizadeh et al. adopted the FHTOPSIS fuzzy hybrid method to determine the ratio of input raw metallic to nonmetallic materials to the electric arc furnaces [16]. They also successfully employed this model to determine the optimal ratio of input scrap iron to sponge iron for a 110-ton electric arc furnace in the Khorasan Steel Complex [16].
In this study, due to the presence of different iron ore mines in Iran and as a result, the diverse chemical composition of primary iron ore, sponge iron pellets used in these units have diverse chemical compositions. As the charge mixture consisting of sponge iron and scrap iron is not based on a specific principle, the effect of charging furnaces on their efficiency and performance is ignored. However, the role of charge components and their chemical composition is very important and effective and requires separate research.

2. Materials and Methods

DEMATEL model for investigation of the mutual effect of factors In 1971, Gabus and Fontela [18] introduced the Decision Making Trial and Evaluation (DEMATEL) method, which presents the casualty relationship of the factors by applying the principles of directed graph theory and hierarchical structure (of factors in the system) (Fig 1). It determines the intensity of the effect of the mentioned relations in the form of a numerical score. This method has been used to analyze complex problems in the real world. The combination of this method with decision models based on direct relationships of criteria has been utilized in several articles. Various approaches have been employed in the study of highly complex problems in which the criteria affect each other in pairs or more; among which, the method of decision-making based on error and laboratory evaluation (DEMATEL) can be mentioned.
When complex factors are involved in the choice of options, it is important to explore the mutual relationships between the criteria. In various models, including the network analysis model, there is a network of mutual relationships between the variables. Modeling these mutual relationships is one of the fundamental issues. In this method, unlike the hierarchical analysis method, the criteria mutually affect each other, which is denoted by a network. The DEMATEL method is another approach to evaluate the mutual relationship and causality between the criteria. The pairwise comparison matrix of this method is directional; that is, an index such as A has an effect on B but the index B has no effect on A, or an index such as D has no effect on any index but is affected by criteria A and B (Eq. 2).

$$\begin{bmatrix} Criteria & a & b & c & d \\ a & 0 & 1 & 0 & 1 \\ b & 0 & 0 & 0 & 1 \\ c & 0 & 1 & 0 & 0 \\ d & 0 & 0 & 0 & 0 \end{bmatrix} \quad \text{Eq. (2).}$$

The directional matrix can be represented as a graph to further illustrate the effects as presented in Fig. 1. which shows the intensity of mutual relations between each factor [19].

This model is implemented through the following steps:
Step 1: formation of the matrix of the direct relationship of the criteria and their dimension (Z):
The internal relationship matrix of criteria is formed by experts that indicated as the form of Table. 1. In this way, the value must be zero if there is no relationship between the criteria and otherwise if there is a logical relationship, a value between 1 and 4 must be adopted. This number indicates the intensity of the effect of the criterion on other criteria (Table. 1).

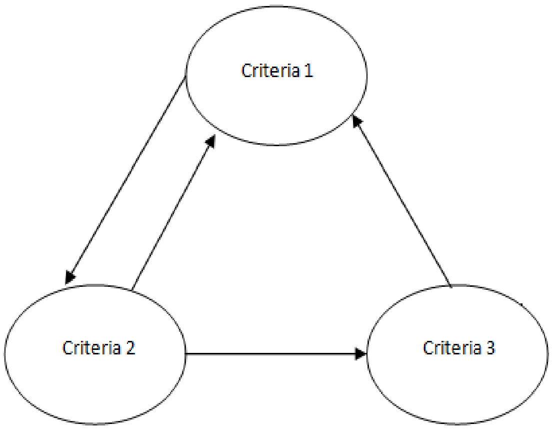

Fig. 1. directional graph of the causality relationship of the criteria.

Step 2: normalization of the direct relationship and dimension matrix (X):

$$X = \frac{Z}{s} \qquad \text{Eq. (3).}$$

$$s = \max\left[\max_{1\le i\le n}\sum_{j=1}^{n}|z_{ij}|, \max_{1\le j\le n}\sum_{i=1}^{n}|z_{ij}|\right];\ 0\le x_{ij}<1,\ \ 0\le\sum_{i=1}^{n}z_{ij}\le 1,\ \ 0\le\sum_{j=1}^{n}z_{ij}\le 1$$

Eq. (4).

Such that at least one of the rows or columns (not all) equals one.
Step 3: extraction of the total relationship matrix (T):

$$= \boldsymbol{X}(\boldsymbol{I}-\boldsymbol{X}^{k})(\boldsymbol{I}-\boldsymbol{X})^{-1}$$

$$\boldsymbol{X}(\boldsymbol{I}+\boldsymbol{X}+\boldsymbol{X}^{2}+\ldots+\boldsymbol{X}^{k-1})(\boldsymbol{I}-\boldsymbol{X})(\boldsymbol{I}-\boldsymbol{X})^{-1}$$

$$\boldsymbol{T} = \boldsymbol{X}+\boldsymbol{X}^{2}+\ldots+\boldsymbol{X}^{k} = \qquad \text{Eq. (5).}$$

Therefore:

$$;\ \lim_{k\to\infty}\boldsymbol{X}^{k} = [0]_{n\times n} \quad \boldsymbol{T} = \boldsymbol{X}(I-\boldsymbol{X})^{-1} \qquad \text{Eq. (6).}$$

Step 4: determination of the criteria priority and plotting the effective relationship diagram (IRM):

$$\boldsymbol{r} = (r_i)_{n\times 1} = [\sum_{j=1}^{n} t_{ij}]_{n\times 1} \qquad \text{Eq. (7).}$$

$$\boldsymbol{c} = (c_j)_{n\times 1} = (c_j)'_{1\times n} = [\sum_{i=1}^{n} t_{ij}]'_{1\times n} \qquad \text{Eq. (8).}$$

3. Results and Discussions

The calculations were performed as follows:
Step 1 - Formation of the matrix of the direct relationship of criteria and dimensions:
The matrix of the internal relationship of the criteria is formed as presented in Table. 1. If there is no relationship between the criteria, the value is set to zero otherwise, a number between 1 and 4 is adopted which indicates the intensity of the effect of the criterion on the other ones.

Table. 1. Matrix of the internal relationship between the criteria affecting the performance of the electric arc furnace.

Z= Direct influence Matrix								
Criteria	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**	**∑Zj (1≤j≤10)**
C_1: Inj. C	0	2	3	2	4	4	4	19
C2: Lime (Kgr)	2	0	4	0	3	1	3	13
C_3: Slag (Kg)	2	2	0	0	2	3.5	4	13.5
C_4: FeO in slag	2	1	4	0	3	1	3	14
C_5: Inj. O_2 (Nm^3)	4	3	4	3	0	4	4	22
C_6: Ex. Gas $\times 10^3$ (Nm^3)	0	0	0	0	0	0	0	0
C_7: Electrical E (Kwt/t)	1	0	2	2	1	1	0	7
∑Zi (1≤i≤10)	11	8	17	7	13	14.5	18	∑Zi (1≤i≤10)

Step 2 - Normalization of the matrix of direct relationships and dimensions (X):
At this stage, the internal relationship matrix was normalized using Eq. (3). and Eq. (4). (Table. 2).
In the diagram of Fig. 2., the horizontal axis shows the extent of the effect and dependence of the factors on each other. The higher the R+C value of one criterion, the higher its interactions with other criteria and the more important its role in the decision-making process.
The vertical vector also indicates the type of cause or effect of the criteria.
Step 3 - Extraction of the total relationship matrix (T):

In this stage, the matrix T showed be calculated by Eq. (5). and Eq. (6). which is a part of the presented model (Table. 3.). The importance and intensity of influencing each other is presented in Table. 4.
For positive R-C values, the criterion will be the cause; otherwise (R-C<0), the criterion will be the effect.
According to these explanations, oxygen is a cause with the highest interaction rate with other criteria, while exhaust gas exhibits the lowest rate of interaction with other factors.

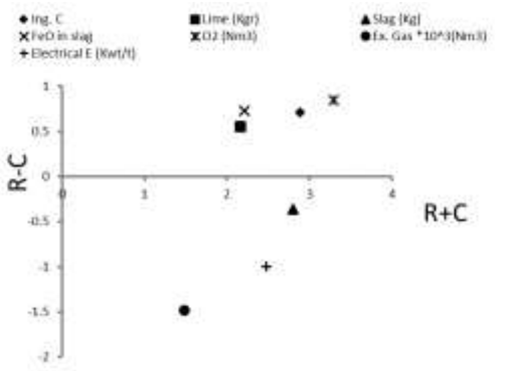

Fig. 2. Map of the importance and intensity of impact (IRM) of criteria affecting the performance of electric arc furnaces on each other.

Table. 2. The normalization matrix of internal relationships between the criteria affecting the performance of the electric arc furnace (× 10-2).

Z= Direct influence Matrix								
Criteria	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**	**$\sum Z_j$ (1≤j≤10)**
C_1: Inj. C	0	9.0909	13.6364	9.0909	18.1818	18.1818	18.1818	86.3636
C2: Lime (Kgr)	9.0909	0	18.1818	0	13.6364	4.5455	13.6364	59.0909
C_3: Slag (Kg)	9.0909	9.0909	0	0	9.0909	15.9091	18.1818	61.3636
C_4: FeO in slag	9.0909	4.5455	18.1818	0	13.6364	4.5455	13.6364	63.6364
C_5: Inj. O_2 (Nm^3)	18.1818	13.6364	18.1818	13.6364	0	18.1818	18.1818	1
C_6: Ex. Gas ×10^3 (Nm^3)	0	0	0	0	0	0	0	0
C_7: Electrical E (Kwt/t)	4.5455	0	9.0909	9.0909	4.5455	4.5455	0	31.8182
$\sum Z_i$ (1≤i≤10)	50	36.3636	77.2727	31.8182	59.0909	65.9091	81.8182	$\sum Z_i$ (1≤i≤10)

Table. 3. Matrix of total relationship between criteria affecting the performance of electric arc furnace.

Z= Direct influence Matrix							
Criteria	**C_1**	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**	**C_7**
C_1: Inj. C	0.13107	0.17942	0.30638	0.17665	0.29861	0.34142	0.36420
C2: Lime (Kgr)	0.18807	0.07987	0.3042	0.07509	0.23249	0.19051	0.28927
C_3: Slag (Kg)	0.16561	0.14341	0.11881	0.06542	0.17364	0.26251	0.29358
C_4: FeO in slag	0.19662	0.12895	0.31803	0.07851	0.24306	0.19917	0.30242
C_5: Inj. O_2 (Nm^3)	0.30608	0.23143	0.37334	0.22354	0.16973	0.36651	0.39825
C_6: Ex. Gas ×10^3 (Nm^3)	0	0	0	0	0	0	0
C_7: Electrical E (Kwt/t)	0.09825	0.04343	0.1615	0.12218	0.10462	0.11960	0.08884

Step 4 - Determining the priority of criteria and forming an effective relationship diagram (IRM):

Table. 4. Importance and intensity of influencing each other.

Criteria	r	C	R+C	R-C
C_1: Inj. C	1.797782	1.085721	2.883502	0.712061
C2: Lime (Kgr)	1.359534	0.806547	2.166081	0.552988
C_3: Slag (Kg)	1.223015	1.582313	2.805328	-0.3593
C_4: FeO in slag	1.466786	0.741416	2.208201	0.72537
C_5: Inj. O_2 (Nm^3)	2.06891	1.222181	3.291091	0.846729
C_6: Ex. Gas ×10^3 (Nm^3)	0	1.479738	1.479738	-1.47974
C_7: Electrical E (Kwt/t)	0.738468	1.736579	2.475047	-0.99811

It can be said that oxygen, carbon, and iron oxide contents of the slag are relatively the “cause” factors, whereas electrical energy and exhaust gas are relatively the “effect”. As it can be seen from the chart above, using an optimum amount of carbon and oxygen will lead to energy efficiency. On the other hand, supplying the carbon from DRI can be a good alternative for injection carbon which is an advantage from environmental point of view. The main reason of high intensity of energy consumption is mostly related to iron ore composition as source material in reduction stage. The more impurities in ore, the more slag. Then to have a proper quality of slag with lime injection will lead to more energy consumption. Which the Impact and effectiveness between lime, slag and energy can be seen from the results.

4. Conclusion

The intensity of the effect and dependence of different parameters of an electric arc furnace was different which can affect their importance in the decision-making process. Separate pairwise calculations and the DEMATEL modeling indicated that the injected oxygen and carbon involved in exothermic chemical reactions and chemical energy production are of relatively higher importance. On the other hand, DEMATEL calculations consider the two-way relationship between the criteria and the intensity of their effect on each other; leading to higher accuracy. These calculations showed that in addition to oxygen and carbon contents, the FeO concentration of slag is also in a relative relationship with other factors due to energy loss and changes in the alkalinity and chemical nature of slag.

It could be easily derived that the rising of carbon alongside the oxygen will promote each other. A balance of concentration between these two participates is very important due to prevention of re-oxidation of iron or forming the iron carbides and causes a desirable foamy slag.

Based on the results, Carbon is the preferred parameter affecting on performance of furnace and quality of product. It should be noted that the result could be contributed to all resource of input carbon entered to the molten bath such as graphite electrode, DRI exceed carbon; scrap carbon and oxy-fuel torches. These resources can be used in supplying of the part of energy.

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