

Optimisation of Ferrochrome Addition Using Multi-Objective Evolutionary and Genetic Algorithms for Stainless Steel Making via AOD Converter

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Abstract: This paper describes a new approach towards optimum utilisation of ferrochrome added during stainless steel making in AOD converter. The objective of optimisation is to enhance end blow chromium content of steel and reduce the ferrochrome addition during refining. By developing a thermodynamic based mathematical model, a study has been conducted to compute the optimum trade-off between ferrochrome addition and end blow chromium content of stainless steel using a predator prey genetic algorithm through training of 100 dataset considering different input and output variables such as oxygen, argon, nitrogen blowing rate, duration of blowing, initial bath temperature, chromium and carbon content, weight of ferrochrome added during refining. Optimisation is performed within constrained imposed on the input parameters whose values fall within certain ranges. The analysis of pareto fronts is observed to generate a set of feasible optimal solution between the two conflicting objectives that provides an effective guideline for better ferrochrome utilisation. It is found out that after a certain critical range, further addition of ferrochrome does not affect the chromium percentage of steel. Single variable response analysis is performed to study the variation and interaction of all individual input parameters on output variables.

Keywords: Stainless steel making, Optimisation, Genetic algorithm, Ferrochrome

1. Introduction

AOD steel making is a complex metallurgical process which involves intricate interplay of multiphase reactions, turbulent reacting flow, mass, momentum & heat transfer as well as numbers of heterogeneous chemical reactions among slag, metal, gas and solid phases. So under extreme operating conditions, it is hard to accurately predict the operating parameters and complex interaction between them in real time. Random fluctuations combined with statistical variations in the composition and properties of various input material and various controlling parameters even add to further complexity. In order to overcome this problem, data-driven approaches on the noisy and clumsy data are increasingly being leveraged to analyse and optimise the steel making process [1-2]. Removal of impurity element from molten steel to maximum extent is desirable in steel making process. Addition of chromium in stainless steel above 12% produces a thin layer of stable and passive surface film of chromium oxide. This oxide protective film passivates the metal and prevents corrosion in extreme corrosive media. With increase in percentage of chromium, stability of that oxide film increases resulting in higher corrosion resistance and wear resistance [3-4]. Kim, Jeong Kil, et al reported that for Ti-stabilized ferritic stainless steels, Increase in Chromium content improved inter granular resistance even with temperature and time for the sensitization becomes higher [5]. In addition to chromium, other alloying elements are also added in order to obtain required chemical and mechanical properties of the final products. Since all types stainless steel grade contain some amount of chromium, it is economical to use chromium containing raw materials such as stainless steel scrap or ferrochrome for production of stainless steel. Because of the availability and suitability, Ferroalloys



are primary choice of addition for Stainless steel making. As occurrence of raw materials of ferrochrome is quite limited on a global scale, production cost of ferroalloy and price of low carbon ferrochrome is high [6-7]. Chromium percentage of stainless steel is augmented by the amount of ferrochrome added during initial stages of oxygen blowing. As ferrochrome addition increases, cost per ton of steel production also increases which makes selling of the product unviable in competitive commercial market. Also with decrease in ferrochrome addition, chromium percentage also decreases which is undesirable since it affects the mechanical properties of stainless steel. So obtaining high chromium content in stainless steel with minimum ferrochrome addition is an industrial problem related to optimising the system and such problems are difficult to solve in conventional way [8-10]. Simultaneous optimisation of the above two competing and incommensurable objective is required to find a pareto optimal solution as uniformly as possible for which evolutionary computing techniques are being leveraged efficiently these days [11-12]. Normally there is error in the neural network model as the under fitted network does not capture the trends in the dataset due to large bias and those over fitted network does not generalise to the training data due to large variation [13]. To overcome this problem, Concept of multi objective genetic algorithm based on Evolutionary Neural Network (EvoNN) was developed by Pettersen et al [14]. Since AOD converter steel making data are very noisy and nonlinear, EvoNN generates several neural network meta models that tends to eliminate the arbitrary noisy data. Here the optimised neural network models are created by multi objective predator prey algorithm through arbitrarily generated population of neural nets. Multi objective algorithm selects the best model corresponds to an optimal trade-off between training error and neural network complexity [15-16]. Scope of data driven modelling and optimisation processes based on evolutionary technique has numerous application in the field of steel making as these processes are involved in large number of input as well as output parameters making it extremely difficult to evaluate pareto optimality in an effective manner [17-18].

In the present investigation, an attempt has been made to achieve the optimisation of two conflicting objectives simultaneously in presence of multiple constraints imposed on the system. The two conflicting objectives are

1. Minimisation of ferrochrome addition in AOD converter stainless steel making
2. Maximisation of end blow chromium content of stainless steel in AOD converter

The input variables used to optimise above two conflicting objective functions are 1st stage blowing rate, 2nd stage blowing rate, 3rd stage blowing rate, reduction stage nitrogen blowing rate, reduction stage argon blowing rate, initial bath temperature, time of ferrochrome addition, initial carbon and chromium percentage and different time period of blowing.

2. Methodology

In this study, by training the dataset obtained from the mathematical model through Evolutionary Neural Network (EvoNN), bi-objective optimisation task has been carried out. Evolutionary Neural Network is a process of neural network construction that tends to create an optimum trade-off between training error and complexity of the models developed from a population of dataset without the risk of under-fitting or over-fitting. The trade-off curve between these two criterion deals with a flexible architecture from which a suitable one is chosen by using the Corrected Akaike Information Criterion (AICC) [19].

Multi-layer Neural Networks are commonly applied machine learning algorithm that converts predictive models by learning the patterns in the obtained dataset. The architecture of neural networks are composed of input layer, output layer and hidden layer. The input layer is partitioned into number of input cells which receive the input signal and multiply them as per their own weight. A set of hidden nodes called as hidden layer receive their input from input layers and feedforward it to the output layers. Each nodes of the hidden layer respond multiple nodes of previous layer to different extent and is multiplied by their connection strength to a unique weight and added directly with a bias value. The total is processed by an activation function and leaves the nodes as output. This process continues until these responses combine to generate a final response at the output layer and leaves as prediction for input variable. The network then compares against the actual dependent variable during the iterative learning process. If any standard error exists between these values, the weights are recalibrated between the hidden nodes and input nodes to better learn the process. Iteration is repeated until neural network is able to estimate accurate prediction for

most of the observations [20-21].

Using meta models generated from training of dataset by EvoNN, pareto optimality between the conflicting objectives is calculated by predator prey algorithm. This algorithm consists of a small numbers of preys chosen from the dataset. They are arranged in an interconnected two dimensional network. The algorithm works as the predator population swallows the weakest prey in its neighbourhood. The prey is allowed to breed indiscriminately but the predator is restricted for breeding. The annihilation mechanism is governed by some sets of hunting rules present in a Moore's neighbourhood. The population grows exponentially in absence of predator and predator starves in absence of prey population. As the predator continues to consume the weakest prey by moving around the lattice, prey population surviving after several generation of predator attack evolves with stronger attributes which leads to generation of Pareto frontier [22-23]. The pareto frontier generated by EvoNN algorithm does not help to predict the effect of each individual variables on the objective function. So Single variable analysis is required for investigating relationship amongst the clinical input variable. To examine the conclusiveness of a response variable towards the input variable, a simple and intuitive procedure is followed. In this approach, systematic variation of the output variable has been examined with the concerned input variable keeping other independent variables constant. If response of output variable is synchronised as a qualitatively similar pattern of variation as the nature of the input variable, then they are considered to be correlated by a direct relationship. If the input variable has negative response towards the output variable, then they are assumed to inversely correlated. If one part of the response is towards the positive side and remaining part is in the negative side, then the response is assumed to be of mixed type in nature [24]. Various parameters used in predator prey algorithm and EvoNN are listed in **Table 1**.

Table 1. Parameters defined in learning module of EvoNN and PPGA during optimisation

Training	Values
Probability of node exchange	0.8
Probability of mutation	0.1
Maximum no of nodes	5
Initial prey population	500
Preferred prey population	500
Predator population size	30
Number of generations	100
Probability of prey movement	0.5
Lattice dimension	50 x 50
Number of hidden nodes	3
Optimization	
Initial prey population	500
Preferred prey population	500
Predator population size	30
Number of generations	100
Probability of prey movement	0.8
Probability of mutation	0.1
Lattice dimension	50 x 50

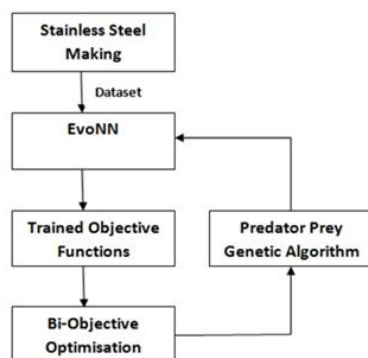


Figure 1: Flow chart of overall process.

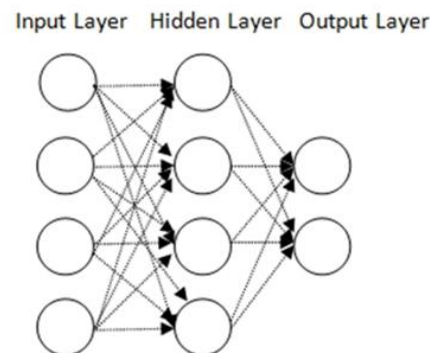


Figure 2: Simplified model of neural Network

Referring the mathematical model developed in the research paper of Patra et al., 2016 [25] for 204Cu grade stainless steel for predicting Final composition of stainless steel in reference to blowing time in an AOD converter. Using collection of input variables constrained to values within certain ranges given in **Table 2**, multiple simulations are run programmatically. 100 dataset is generated using those input

data ranges. Using different combination of input values, final carbon content is varied in between 0.0003 wt% to 0.19751 wt%. The chromium percentage is varied between 14.47 wt % to 26 wt%.

Table 2. Range of variables for optimising Ferrochrome content and chromium percentage of stainless steel

Sl. No	Input Parameter	Unit	Lower Boundary	Upper Boundary
1	1st stage Oxygen Blowing rate	Nm3/minute	90	130
2	Initial bath Temperature	°C	1510	1570
3	2 nd stage blowing rate	Nm3/minute	15	25
4	3 rd Stage blowing rate	Nm3/minute	5	10
5	Silicomanganese addition	MT	2.51	4.98
6	Nitrogen blowing rate	Nm3/minute	0	25
7	Argon blowing rate	Nm3/minute	0	35
8	Initial Carbon content	wt %	1.49	2
9	Initial Chromium content	wt %	15	16.1
10	Time of ferrochrome addition	Minute	2	8
11	1 st stage blowing time	Minute	10	13
12	2 nd stage blowing time	Minute	10	14
13	3 rd stage blowing time	Minute	12	14
14	Nitrogen blowing time	Minute	0	4
15	Argon blowing time	Minute	0	5
16	Ferrochrome addition	MT	2.5	7.98
17	End blow Carbon content	wt%	0.0003	0.19751
18	End Blow Chromium content	wt%	14.47	26

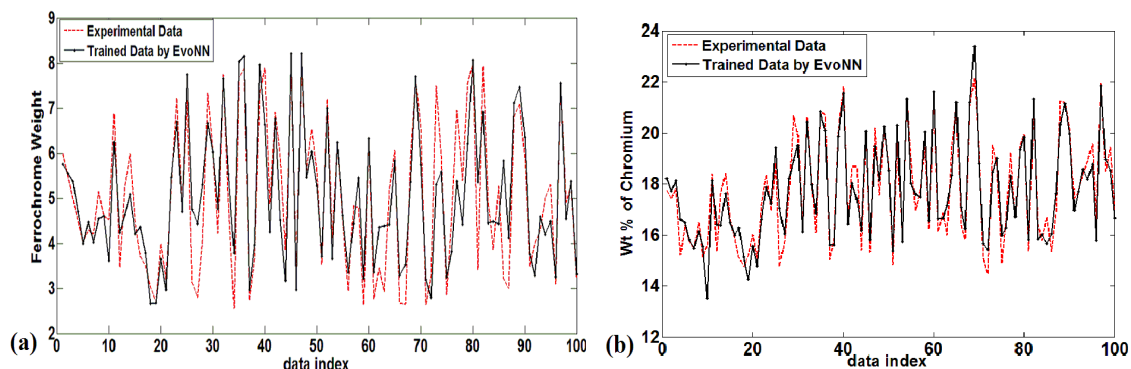


Figure 3. Setlog files of two objectives trained through data training module using predator prey algorithm for (a) amount of ferrochrome added during steel refining (b) end blow chromium content of stainless steel

The flowchart depicted in **Figure 1** illustrates the step by step procedure used in the optimisation process named as minimisation of Ferrochrome addition and maximisation of end blow chromium content of stainless steel by EvoNN. The generated dataset are trained and meta-models are created using EvoNN algorithm. With proper parameter setting, the same input parameter is run twice individually for each objective function to create two meta models through data training modules. **Figure3** represents the optimised meta models with lowest error after training the original experimental dataset. Optimisation study is carried out between the two conflicting objective functions using predator prey genetic algorithm.

3. Result and Discussion

In the current work, end blow chromium content of stainless steel has been maximised resulting minimisation of ferrochrome addition during refining of molten metal. First part of the dataset was used for neural network training purposes. The data is optimised using EvoNN and pareto front is generated by resolving tradeoffs between the two selected objectives. The pareto front in **Figure 4**

translates a complete set of unique optimal solution into intuitive visual representation and each point of the curve precisely approaches a single pareto optimal solution between two concerned objectives in a constrained design search space. All the pareto points evaluated by Multi EvonNN are optimised to have their individual set of sixteen input variables and majority of the points are positioned in the user's area of interest on the pareto frontier. Each point of the pareto front leads to an optimum potential solution

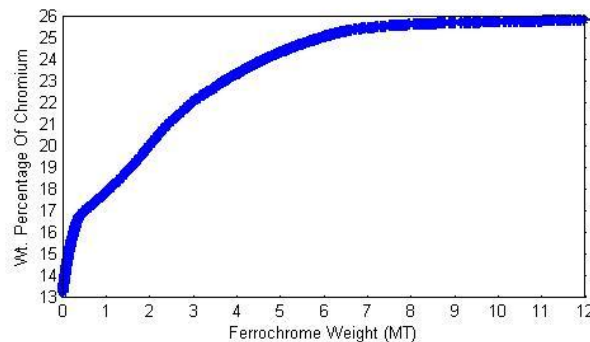


Figure 4. Pareto Fronts between weight of ferrochrome addition and end blow chromium content computed using Evolutionary Neural Network

between ferrochrome addition and end-blow chromium percentage for which any improvement in one objective function leads to impairment of the other objective function. It is observed from the plot of pareto set that increase in weight of ferrochrome addition up to 7 MT results increase in end blow chromium percentage of steel till 25% and after that chromium content becomes gradually constant even if more ferrochrome is added to the molten metal.

Table 3. Single variable response of individual input variables on objective functions

Sl. No	Variable/Output	Ferrochrome Weight	Chromium Content
1	1st stage Oxygen Blowing rate	Direct	Direct
2	Initial bath Temperature	Nil	Nil
3	2 nd stage blowing rate	Direct	Inverse
4	3 rd Stage blowing rate	inverse	Nil
5	Silicomanganese addition	Nil	Inverse
6	Nitrogen blowing rate	Direct	Direct
7	Argon blowing rate	Nil	Nil
8	Initial Carbon content	Inverse	Inverse
9	Initial Chromium content	Inverse	Direct
10	Time of ferrochrome addition	Inverse	Nil
11	1 st stage blowing time	Direct	Nil
12	2 nd stage blowing time	Nil	Nil
13	3 rd stage blowing time	Nil	Nil
14	Nitrogen blowing time	Direct	Direct
15	Argon blowing time	Direct	Direct
16	End blow Carbon content	Direct	Direct

The single variable response analysis in **Table 3** suggests that increase in first stage oxygen blowing rate increases consumption of ferrochrome during refining and subsequently increases chromium content of stainless steel. Initial bath temperature has no effect on both the objective functions. Second stage blowing rate has direct relation with ferrochrome weight but has inverse relation on the final chromium content. With increase in blowing rate during third stage of refining, ferrochrome consumption decreases. But it has no effect on final chromium content of steel. Initial carbon and chromium content has inverse relation with the ferrochrome addition. But higher initial chromium content leads to high end blow chromium content. Increase in ferrochrome addition time requires less amount of ferrochrome during refining but has no effect on final chromium content. First stage blowing time proportionally affects the utilisation of ferrochrome but has no effect on chromium content of steel. Similarly Second stage and third stage blowing time has no effect on both the

objective functions. Nitrogen blowing time and argon blowing time has a positive response on both the concerning objective function as increase in blowing time of requires more ferrochrome addition and subsequently increase the chromium content of stainless steel.

4. Conclusion

Effective utilisation of ferrochrome during stainless steel making in an AOD converter has been investigated using the principle of multi objective evolutionary and genetic algorithm. Constructing data-driven models, optimisation work has been conducted to minimize the ferrochrome addition and simultaneously maximize the end blow chromium content of stainless steel, satisfying some conflicting requirements. A set of input operating variables considered in this investigation are 1st stage blowing rate, initial bath temp, 2nd stage blowing rate, 3rd stage blowing rate, silicomanganese weight, nitrogen blowing rate, Argon blowing rate, Initial carbon %, initial chromium %, time of ferrochrome addition, 1st stage blowing time, 2nd stage blowing time, 3rd stage blowing time, Nitrogen blowing time, Argon blowing time and end blow % C. Using the data collected from the mathematical model, two meta models has been developed for two objective functions. Using predator prey algorithm, the meta models has been used to construct a pareto frontier where each point on the pareto curve leads to a best fitness solution. The optimisation work confirms that first and second stage blowing rate, nitrogen blowing rate, nitrogen blowing time & argon blowing time are most important influential parameters among all parameters inspected here. The pareto frontier reveals that with increase in ferrochrome addition, chromium content of stainless steel increases up to 25 wt% .After that, further addition of ferrochrome does not affect the chromium content of stainless steel. This study provides an insight towards the impact of important process parameter for determining the effective utilisation of Ferrochrome during stainless steel making.

5. References

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