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Evolutionary data driven modelling and many objective optimization of non linear noisy data in the blast furnace iron making process

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Abstract

The optimization of process parameters in modern blast furnace operations, where both control and access to large data sets with multiple variables and objectives is required, remains a challenging task. To handle such non-linear and noisy data sets, deep learning techniques have been used in recent times. In this study, an evolutionary deep neural network algorithm (EvoDN2) has been applied to derive a data driven model for a blast furnace. The optimal front generated from the deep neural network is compared against the optimal models developed from bi-objective genetic programming algorithm (BioGP) and evolutionary neural network (EvoNN). The optimization process is applied to all the training models by using a constraint based reference vector evolutionary algorithm (cRVEA).

Keywords: deep learning, reference vector, neural net, genetic programming, blast furnace

1. Introduction

In the last 20 years, the iron-making blast furnace industry has undergone remarkable changes including the modernization of technology, advanced operational strategies, and planning, design changes, modeling, and optimization etc. These technological innovations and recent modeling strategies bring challenges in multiple aspects like cost minimization, quality enhancement, productivity improvement, and process optimization etc. Controlling these specific aspects is quite difficult in such a complex reactor (*The white book...*, 2012; Geerdes et al., 2015). Numerous groups have conducted research on blast furnaces by adopting innovative modeling and optimization strategies to overcome the pertinent obstacles. In the initial phase, most blast furnace problems were tackled by analytical and mathematical modeling techniques (Fabian, 1958; Omori, 1987). Later on, the focus shifted towards comprehensive models like one dimensional, two dimensional, three-dimensional steady-state and transient models, computational fluid dynamics, and discrete elemental methods (Adema, 2014; Decastro et al., 2002; Dong et al., 2006; Hatano & Kurita, 1982; Kilpinen, 1988; Nath, 2002; Rist & Meysson, 1967; Zhou et al., 2005). These models are not efficient enough to tackle these problems, however, and findings are also not close to the operational requirements. Again these comprehensive models were exemplified by data driven strategies (Gujarathi & Babu, 2016; Pettersson et al., 2007), where the results are very close to the operational values without considering the physics of the process, as well as thermodynamics and transfer equations. Further, these techniques are enhanced by adding evolutionary strategies like neural networks, genetic programming, and support vectors

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etc. (Agrawal et al., 2010; Giri et al., 2013; Helle et al., 2006; Hodge et al., 2006; Mahanta & Chakraborti, 2018, 2019; Mitra et al., 2016; Mondal et al., 2011; Pettersson et al. 2009). These strategies have been implemented in attempts to tackle a large number of blast furnace iron making problems. EvoNN and BioGP (Agrawal et al. 2010; Giri et al., 2013) are two recently developed data driven evolutionary algorithms applied in this domain to tackle multiple conflicting objectives with a higher level of non-linearity. This strategy moves one step further by considering deep learning techniques to solve noisy data sets in a blast furnace. This novel technique can handle a large amount of non-linear data with multiple numbers of variables and objectives. A deep learning based neural network (EvoDN2) (Roy & Chakraborti, 2020; Roy et al., 2020) consists of multiple hidden layers, and each layer having different numbers of nodes. This approach can capture individual pieces of information with a higher degree of accuracy, and it might be utilized local features and predict a relation globally. The optimal training model generated from an evolutionary deep neural network is more efficient than other evolutionary models. Here, a systematic comparison is carried out between the training models, and their performance in tackling non-linear data in multi objective space is evaluated. The training models generated from these evolutionary processes are optimized using the many objective optimization algorithm stated as constraint-based reference vector evolutionary algorithm (cRVEA) (Cheng et al., 2016; Chugh et al., 2016, 2017; Mahanta & Chakraborti, 2020). The many objective problems in this domain require special attention as a larger number of conflicting objectives routinely occur in this domain. The cRVEA algorithm has played an important role in solving such multi-dimensional problems. To search Pareto solutions in a hyperspace and carry out the visualization of results is quite easy by using a reference vector based search process. This strategy is applied to resolve such complex multi objective optimization problems in a blast furnace and to evaluate results as per operational requirements. The main purpose of the work is to simultaneously optimize a large number of objectives pertinent to blast furnaces starting from noisy information and to compare the performance of different training modules for that purpose.

2. Evolutionary procedures

EvoNN: In this strategy, a population of Artificial Neural Nets (ANN) (Agarwal et al., 2010) with a flexible structure that evolves through a multi objective genetic algorithm is used to generate training models, where an optimal front is generated by considering the training error and the complexity of the networks. The complexity is determined from a number of hidden nodes and their weight distribution. The total network architecture is divided into input, hidden, and output layers. The evolution takes place at the lower part of the architecture, where a predator prey genetic algorithm (PPGA) (Mahanta & Chakraborti, 2019) is used to optimize the neural nets, and in the upper part linear transfer function is used in the optimization process. The best-suited training model is developed by using corrected Akaike information criteria (AICc) (Mahanta & Chakraborti, 2019).

BioGP: In the Bi-objective Genetic Programming algorithm (BioGP) binary trees obtained through a multi objective genetic algorithm are used to generate training models, where an optimal front is generated by considering the training error and the complexity of these GP trees (Giri et al., 2013). The maximum depth and the number of roots increase the complexity level of the GP tree. A predator prey genetic algorithm (PPGA) (Mahanta & Chakraborti, 2019) is used to develop a number of GP trees and their assembly, and the final convergence is obtained through a Linear Least Square (LLSQ) algorithm (Mahanta & Chakraborti, 2019). The least error training model is automatically selected from the number of training models available in the Pareto front.

EvoDN2: In the EvoDN2 algorithm, ANNs with multiple hidden layers and nodes evolve through a multi objective genetic algorithm are used to generate the training models (Roy & Chakraborti, 2020). Deep neural networks are preferred for larger data sets with multiple variables. Any small perturbation can easily be captured by the deep neural network. Therefore nonlinear and noisy data are handled with higher accuracy. A family of the subnet design concept is applied, where each subnet takes as its input parameter at least once. The output of the subnets is collected and mapped to the objective variable using LLSQ. EvoDN2 has a provision to change a number of subnets as well as a number of layers and nodes in the algorithm to handle complex data sets (Roy et al., 2020).

cRVEA: The constraint based reference vector evolutionary algorithm is used in the optimization process, where more than three mutually conflicting objectives are optimized simultaneously (Cheng et al., 2016; Chugh et al., 2017). A reference based evolutionary strategy is used in the evolution process to generate solutions in multi-dimensional hyperspace. The important steps which are followed during the optimization process are the generation of reference vectors in the objective space by using canonical simplex lattice design, assignment of an individual to reference vector by considering the lowest angle between the individual and the corresponding reference vector, the selection of the individual is processed by angle penalized distance and the adaption of the reference vector as per the functional requirement and uniform distribution of candidate solutions in the objective space (Chugh et al., 2016).

3. Data preparation

The operational condition and process parameters were recorded every day in an operational blast furnace. A one year record chart was generated by taking all the production data during working time. Various parameters about the blast furnace were collected regarding input materials, charging, and processes. The data sheet contains one-year operational data, which are non-linear and noisy in nature due to the complex conditions of the reactor during the operation. In this data set, the information regarding raw materials, blast components, and hot metal components came out of direct measurements, sensing reflection, and also from computing processes. The operational information consists of twelve variables and eight objectives. The input variables which are used in this reactor are iron ore, manganese, quantities of limestone and dolomite, specific flux consumption, LD slag, quartz, silicon oxide, calcium oxide, and alkali and alumina additives. The operational parameters are directly or indirectly influenced by these variables during the operation. The output parameters which depend upon these variables are known as objectives of the process. Our choice of input and output variables was restricted by the availability of industrial data and the inputs from the industrial decision-maker. The considered objectives are total flow of gas inside the blast furnace, flow velocity inside the furnace, loss of heat from the furnace, tuyere cooling heat loss, productivity, coke rate, plate cooling heat loss, and the rate of carbon flow through the shaft. The propriety items used here are reported in a dimensionless manner to protect propriety information. These objectives are of immense practical importance. For example, productivity defines furnace capacity, the optimized coke rate improves the furnace efficiency, which in turn reduces fuel loss and results in better utilization of the reducing gas. Similarly, the minimization of the heat loss terms renders the furnace energy efficient. The range of input variables and the outputs are shown in Tables 1 and 2.

Table 1. Range of input parameters in blast furnace

Input parameters	Remarks	Maximum amount	Minimum amount
Quantity of pellet used (X1) [%]	measured parameter	25.34	7.70
Specific flux consumption (X2) [kg/thm]	measured from charging	161.33	26.79
Quantity of limestone (X3) [kg/thm]	measured parameter	32.73	0.00
Dolomite (X4) [kg/thm]		24.93	0.00
LD slag (X5) [kg/thm]		45.76	0.00
Quartz (X6) [kg/thm]		97.61	14.00
Mn (X7) [%]	required alloying element	0.62	0.04
Alkali additives (X8) [kg/thm]	measured parameter	5.14	0.08
Alumina additives (X9) [kg/thm]		3.85	0.17
FeO ore (X10) [%]		8.79	0.55
SiO_2 (X11) [%]	required for slag formation	6.75	1.21
CaO (X12) [%]	reaction agent	0.44	0.04

Table 2. Range of output parameters in blast furnace

Output parameters	Remarks	Maximum amount	Minimum amount
Tuyere cooling heat loss (Y1) [GJ/hr]	measured value estimated from the tuyere cooling water flow and temperature	38.51	18.41
Total BF gas flow (Y2) [Nm^3/hr]	calculates from blast parameters calculated from blast	279588.59	177788.73
Tuyere velocity (Y3) [m/s]	estimated from blast volume, pressure and temperature	222.87	130.64
Heat loss (Y4) [GJ/hr]	measured from sensors	107.40	55.82
Corrected productivity (Y5) [t/m^3/day]	measured as output	2.91	1.99
Coke rate (Y6) [kg/thm]	calculated from charging	555.01	412.52
Plate cooling heat loss (Y7) [GJ/hr]	measured	529.22	77.2
Carbon rate (Y8) [kg/thm]		540.35	437.29

4. Metamodel generation

The above input and output variables are used in the evolution process by means of evolutionary data driven strategies like EvoNN, BioGP, and EvoDN2. The surrogate models generated by running actual operational data are quite significant in this research work. The objectives are separately trained with prescribed number generations where neural net, genetic programming, and the deep neural net play an important role in developing such surrogate models. The primary focus of this study has been to apply the EvoDN2 algorithm to mimic the blast furnace reactor and study how the results fare against existing EvoNN and BioGP. The use of the trained models to optimize the objectives by using cRVEA will be demonstrated as well, followed by a detailed analysis of the findings.

5. Formulation of many objective optimization

Many objective optimization problems have been used to tackle multiple objectives at a time. In this work, eight objectives are considered to have mutual conflicts with each other. The output process parameters are presented in Table 3 according to their functional requirements. The primary intention of this work is to control the parameters in an efficient way to find out the best possible results which directly affect the system and improve the operational condition. The performance of the plant depends upon the production of hot metal per day from tons of input material is known as the productivity of the blast furnace, which should be maximized. To make the process cost effective, it requires coke rate minimization as the coke rate directly affects the cost of the operation. It also needs to reduce the carbon rate during a reaction to generate a lesser amount of CO and CO_2 at the outer part of the furnace to avoid pollution. For the proper functioning of the blast furnace, the reduction process and the melting rate of the metal are analyzed by the minimization of heat loss from the furnace and tuyere cooling heat loss to maintain the optimum temperature in the blast furnace's operations. The optimization process is also focused on the maximization of total blast furnace gas flow and tuyere velocity at the cohesive zone to provide a better chemical reaction and reduction process to maintain the optimum temperature inside the blast furnace. These are the eight objectives that are considered and formulated according to the operational requirements.

Table 3. Formulation of objectives for the blast furnace

Objectives	Task
Carbon rate	minimize
Tuyere velocity	maximize
Coke rate	minimize
Heat loss	minimize
Productivity	maximize
Plate cooling heat loss	minimize
Total BF gas flow	maximize
Tuyere cooling heat loss	minimize

6. Results and discussion

The daily data collected from an operational blast furnace are applied in the data driven modeling and many objective optimization work. cRVEA is applied in this many objective problem to find out the optimum solutions. Training models are required in the many objective optimization process to find Pareto solutions in multi-dimensional hyperspace. The trained data generated from evolutionary data driven models like EvoNN, BioGP, and EvoDN2 are significantly important because the models are chosen according to the optimal tradeoff between the accuracy and complexity of the model. The minimum and maximum errors which are generated from these training models are shown in Table 4. In EvoNN and EvoDN2 the training model is selected from the Pareto tradeoff by using the corrected Akaike Criterion (AICc) while in BioGP the least error model belonging to the optimal tradeoff curve is considered.

Table 4. Training error evaluated from the data driven model

Objectives	Data driven models training error [%]					
	EvoNN		BioGP		EvoDN2	
	max^m error	min^m error	max^m error	min^m error	max^m error	min^m error
Tuyere cooling heat loss (Y1)	24	12	16	14	18	12
Total BF gas flow (Y2)	14	09	12	11	15	08
Tuyere velocity (Y3)	12	07	10	07	14	08
Heat loss (Y4)	25	11	13	11	18	12
Productivity (Y5)	17	10	13	11	15	09
Coke rate (Y6)	15	06	12	08	16	08
Plate cooling heat loss (Y7)	26	14	15	14	21	11
Carbon rate (Y8)	13	07	12	09	14	08

The algorithms used here combine training and testing by creating models using some overlapping partitions in the data set (Mondal et al., 2011). The models are tested on each other, and the best performing model is selected. In this case, the 'Total data' was split into three overlapping partitions, 'Partition 1', 'Partition 2' and 'Partition 3'. The respective models generated using these subsets of 'Total data' are denoted as 'Model 1', 'Model 2' and 'Model 3'; while the 'Model' is created using the 'Total data'.

The test results for all the eight objectives through EvoNN are presented in Table 5. The highlighted diagonal entries denote the original training errors of these models when they are trained using their assigned data sets, and the rest denote the errors recorded while they are tested on each other.

This procedure allows testing to continue even when there is a paucity of available data.

Table 5. Error table for the testing of models in EvoNN

	Partition 1	Partition 2	Partition 3	Total data
Tuyere cooling heat loss (Y1)				
Model 1	0.0119	0.5073	0.3895	0.369
Model 2	1.2002	0.0155	0.4516	0.7463
Model 3	0.5377	0.1651	0.0352	0.323
Model	0.1261	0.1177	0.0995	0.1126
Total BF gas flow (Y2)				
Model 1	0.0347	0.3091	0.6323	0.4119
Model 2	0.6854	0.0485	0.6676	0.5588
Model 3	0.4729	0.415	0.0389	0.3664
Model	0.054	0.0953	0.0898	0.0812
Tuyere velocity (Y3)				
Model 1	0.0288	0.1736	0.1364	0.1298
Model 2	0.4576	0.0273	0.7504	0.5139
Model 3	0.181	0.5704	0.0335	0.2535
Model	0.0608	0.0647	0.0711	0.0654
Heat loss (Y4)				
Model 1	0.0458	0.4816	1.3091	0.8164
Model 2	1.7141	0.0562	2.4674	1.7555
Model 3	0.2771	0.142	0.0773	0.1859
Model	0.0783	0.1318	0.1016	0.1055
Productivity (Y5)				
Model 1	0.0001	0.0002	0.0004	0.0003
Model 2	7.9984	0	2.9271	4.9565
Model 3	0.0006	0.0003	0.0001	0.0004
Model	0.0001	0.0001	0.0001	0.0001
Coke rate (Y6)				
Model 1	0.0432	0.0973	0.1808	0.1217
Model 2	0.2232	0.0382	0.4983	0.3199
Model 3	72.088	0.6069	0.0374	41.917
Model	0.0804	0.0773	0.0888	0.0822
Plate cooling heat loss (Y7)				
Model 1	0.0605	0.3738	0.3412	0.2965
Model 2	1.6773	0.058	7.2317	4.3455
Model 3	0.3887	0.1885	0.0718	0.2527
Model	0.1147	0.1219	0.1186	0.1181
Carbon rate (Y8)				
Model 1	0.036	0.088	0.1616	0.1085
Model 2	0.3658	0.0421	0.1986	0.2433
Model 3	0.5911	0.3788	0.0388	0.4086
Model	0.0805	0.0642	0.0741	0.0729

The outcomes of training and the corresponding correlation coefficients are evaluated from the training results. The experimental data and trained data after computation show that neither underfitting nor overfitting occurred in the metamodels. The correlation coefficient directly indicates that slope of fitting between experimental and trained data, and it is more than 60% for all the objectives. In Table 6, the correlation coefficients which evolved from various algorithms are shown with respect to their individual objectives.

Table 6. Correlation coefficient between experimental data and trained data

Objective	BioGP	EvoNN	EvoDN2
Tuyere cooling heat loss (Y1)	0.715	0.789	0.758
Total BF gas flow (Y2)	0.561	0.580	0.634
Tuyere velocity (Y3)	0.612	0.713	0.661
Heat loss (Y4)	0.688	0.746	0.771
Productivity (Y5)	0.564	0.647	0.640
Coke rate (Y6)	0.528	0.695	0.647
Plate cooling heat loss (Y7)	0.733	0.780	0.817
Carbon rate (Y8)	0.541	0.696	0.667

The exercised output results evaluated from training models clearly indicate that the model generated data are well trained and the modeled value evaluated from the three algorithms are different with respect to their genetic configurations. In most of the objectives, EvoDN2 shows better results compared to EvoNN and BioGP. The overall performance of all the training models is significantly important for the optimization purpose. The fittings with correlation coefficients are shown in Figure 1.

Many objective optimization plays a major role in evaluating the Pareto solutions from trained data of various algorithms like EvoNN, BioGP, and EvoDN2. Nature-inspired training models evolve through multi objective genetic algorithms are used in the optimization process. Here eight objectives are considered at a time. A constraint based reference vector evolutionary algorithm is applied to process all the objectives in multi-dimensional hyperspace. It means reference vectors are to be distributed uniformly in the objective hyperspace, and individuals are assigned to these objective vectors. The selection of individual and adaption processes is carried out to find out multiple numbers of solutions in multi-dimensional space. The optimized results computed from these training models consist of the optimal values of eight objectives and twelve variables. The evaluated multi-dimensional results are shown in Figures 2–4.

In this optimization work, all eight objectives were used in many objective optimization processes. If we properly examine the results from multi-dimensional figures, we realize that four dimensions are used to represent four objectives at a time in each figure. Likewise, three figures are used to present eight objectives in a systematic manner. Each point in the multi-dimensional hyperspace is an optimal solution.

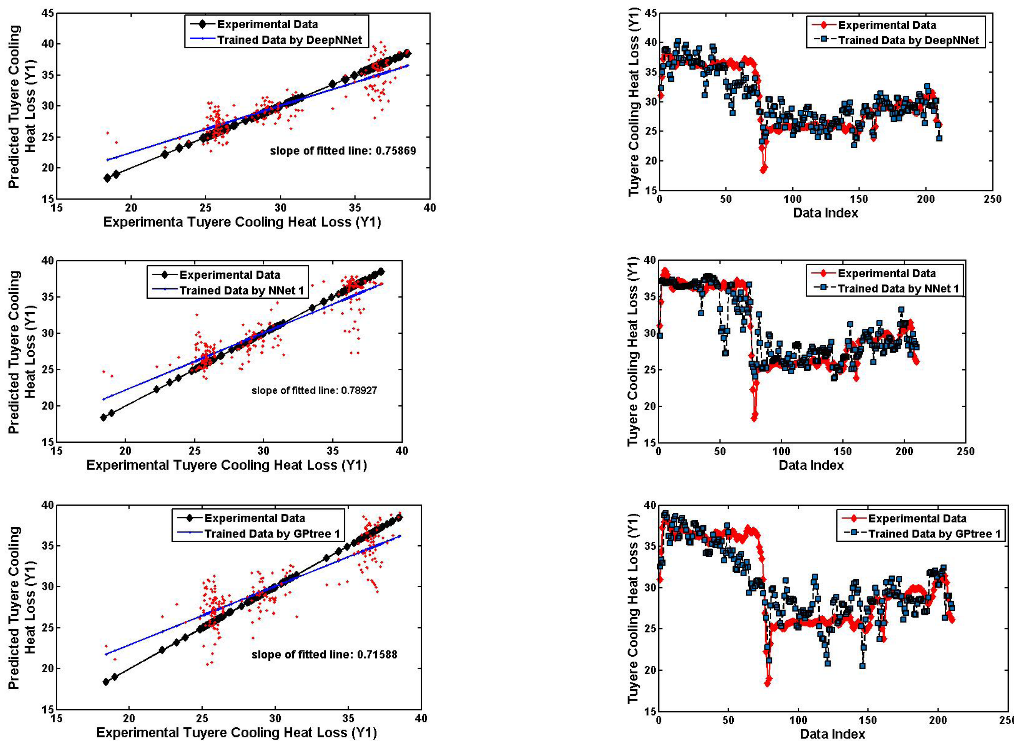

Fig. 1. Fitting and correlation coefficient figures generated for Tuyere Cooling Heat Loss (Y1)

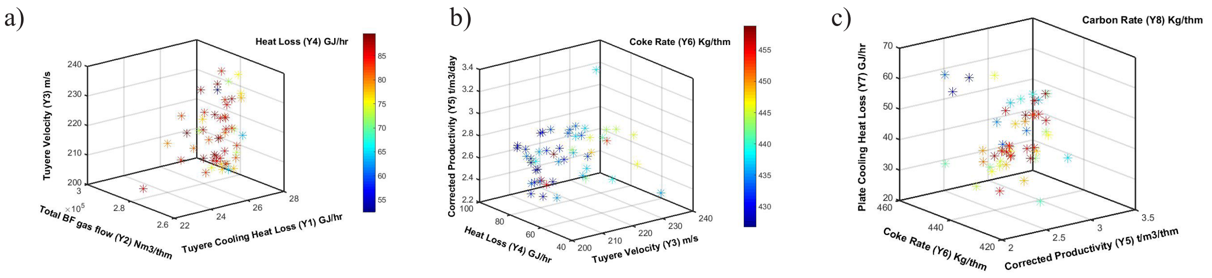

Fig. 2. cRVEA optimization results obtained from BioGP training data: a) heat loss; b) coke rate; c) carbon rate

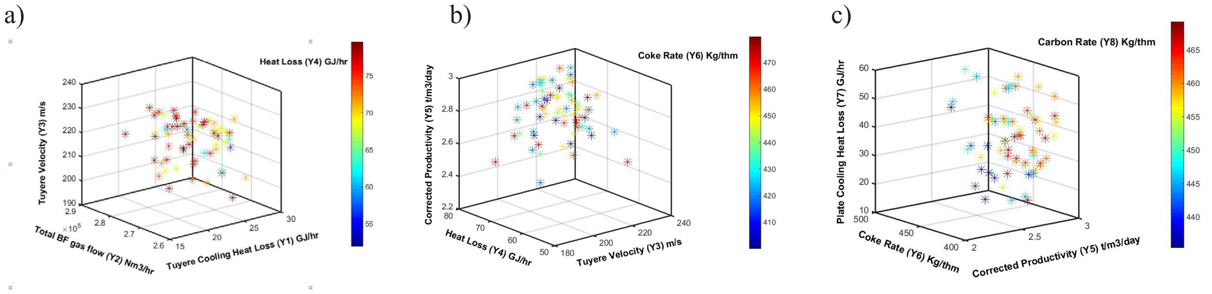

Fig. 3. cRVEA optimization results obtained from EvoNN training data: a) heat loss; b) coke rate; c) carbon rate

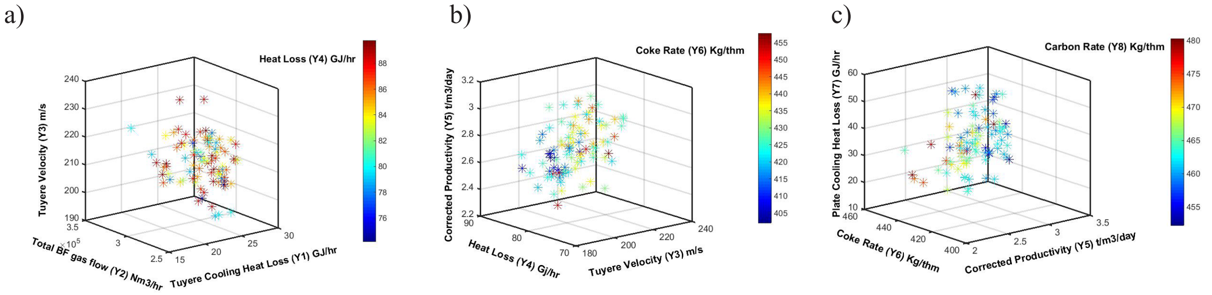

Fig. 4. cRVEA optimization results obtained from EvoDN2 training data: a) heat loss; b) coke rate; c) carbon rate

From multi-dimensional figures, we can visualize the results, but it is difficult to determine and read the exact values that exist in the solution set. To proper visualization and representation of all the solutions, a simple technique called parallel plotting is used (Li et al., 2017). In parallel plotting, the multi-dimensional space is represented in two dimensions, where each optimum solution with its objectives and variables are represented by equally spaced vertical axes, and the traces along the horizontal direction represent the candidate solutions. This is a very standard way of representing multi-objective optimum, where the solution is a set rather than a unique value. Here following one trace from end to end, we get one optimum solution. Thus, the exact candidate solution can be determined using this procedure without any difficulty. The two-dimensional parallel plotted results for this study are provided in Figures 5–7.

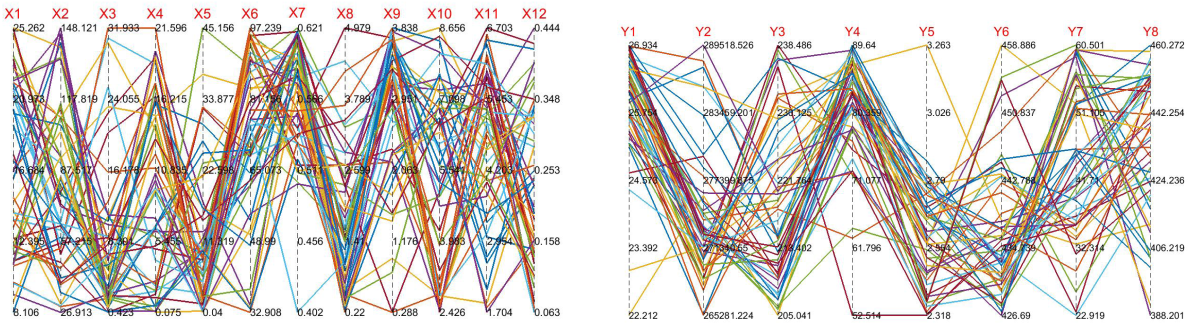

Fig. 5. Parallel plotting optimal solutions obtained from BioGP_cRVEA

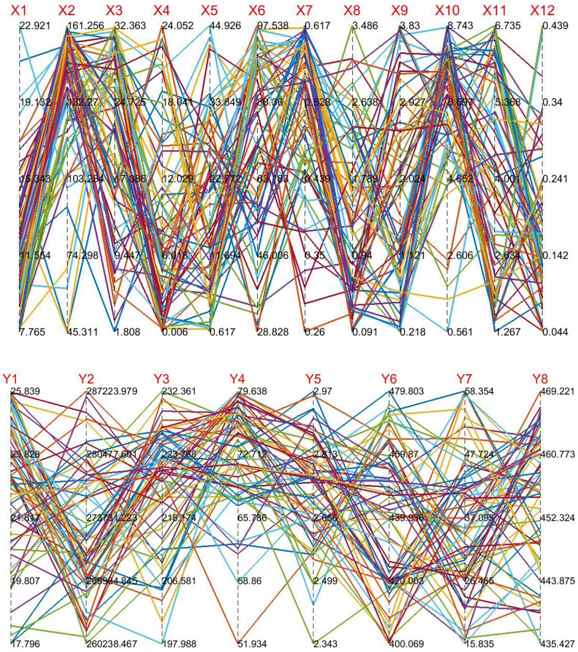

Fig. 6. Parallel plotting optimal solutions obtained from EvoNN_cRVEA

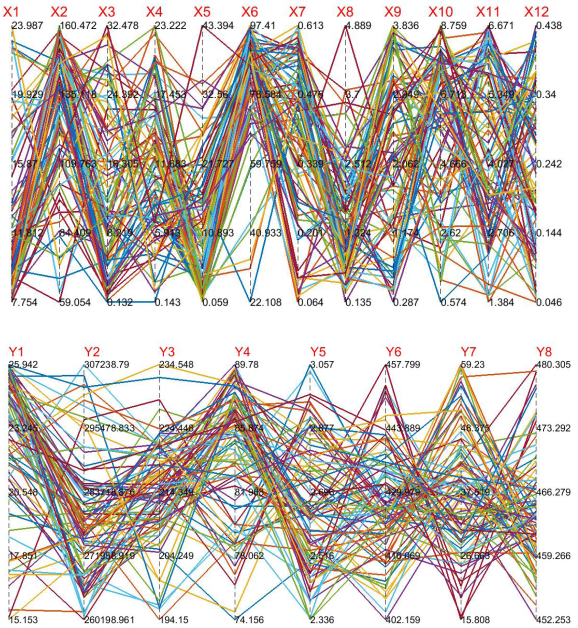

Fig. 7. Parallel plotting optimal solutions obtained from EvoDN2_cRVEA

In the optimization process, according to the formulation, the objectives are minimized as well as maximized in a many objective optimization process. The objectives which are set for minimization here are tuyere cooling heat loss (Y1), heat loss (Y4), coke rate (Y6), plate cooling heat loss (Y7), carbon rate (Y8), and objectives configured for maximization are total blast furnace gas flow (Y2), tuyere velocity (Y3), productivity (Y5). Before optimization, the data sheet information confirms that the range of data for tuyere cooling heat loss exists between minimum value 18.41 GJ/hr to maximum value 38.52 GJ/hr, total blast furnace gas flow occurs between minimum value $1.77 \cdot 10^5$ Nm³/hr to the maximum value $2.79 \cdot 10^5$ Nm³/hr, tuyere velocity falls between minimum value 130.64 m/s to maximum value 222.87 m/s, heat loss occurs between minimum value 55.82 GJ/hr to maximum value 107.41 GJ/hr, productivity arises between minimum value 1.99 t/m³/day to maximum value 2.92 t/m³/day, coke rate occurs between minimum value 412.52 kg/thm to maximum value 555.02 kg/thm, plate cooling heat loss generates between minimum value 29.22 GJ/hr to maximum value 77.36 GJ/hr and carbon rate turn out between minimum value 437.29 kg/thm to maximum value 540.36 kg/thm. Then many objective optimization processes was carried out to the above objectives. First, the cRVEA algorithm was applied to the models using BioGP training data. It was found that optimal solutions are generated between the operational limits. The computed optimized result shows that the range of solutions for tuyere cooling heat loss exists between minimum value 22.21 GJ/hr to maximum value 26.64 GJ/hr, total blast furnace gas flow occurs between minimum value $2.65 \cdot 10^5$ Nm³/hr to the maximum value $2.89 \cdot 10^5$ Nm³/hr, tuyere velocity falls between minimum value 205.04 m/s to maximum value 238.48 m/s, heat loss occurs between minimum value 52.51 GJ/hr to maximum value 89.64 GJ/hr, productivity varies between minimum value 2.31 t/m³/day to the maximum value 3.26 t/m³/day, coke rate occurs between minimum value 426.69 kg/thm to maximum value 458.88 kg/thm, plate cooling heat loss generates between minimum value 22.91 GJ/hr to maximum value 60.50 GJ/hr and carbon rate turn out between minimum value 388.20 kg/thm to maximum value 460.27 kg/thm. The EvoNN training data were also optimized by using cRVEA. The optimum solution falls within the required limits of plant operation. The computed optimized result shows that the range of solutions for tuyere cooling heat loss exists between minimum value 17.79 GJ/hr to maximum value 25.83 GJ/hr, total blast furnace gas flow occurs between minimum value $2.60 \cdot 10^5$ Nm³/hr to the maximum value $2.87 \cdot 10^5$ Nm³/hr, tuyere velocity falls between minimum value 197.98 m/s to maximum value 232.36 m/s, heat loss occurs between minimum value 51.83 GJ/hr to maximum value 79.63 GJ/hr, productivity arises between minimum value 2.34 t/m³/day to the maximum value 2.97 t/m³/day, coke rate occurs between minimum value 400.06 kg/thm to maximum value 479.80 kg/thm, plate cooling heat loss generates between minimum value 15.53 GJ/hr to maximum value 58.35 GJ/hr and carbon rate turn out between minimum value 435.42 kg/thm to maximum value 469.22 kg/thm. cRVEA was then applied to EvoDN2 training data. The results were also generated well within the required limit. The evaluated results show that the range of solutions for tuyere cooling heat loss exists between minimum value 15.15 GJ/hr to maximum value 25.94 GJ/hr, total blast furnace gas flow occurs between minimum value $2.60 \cdot 10^5$ Nm^3/hr to the maximum value $3.07 \cdot 10^5$ Nm^3/hr, tuyere velocity falls between minimum value 194.15 m/s to maximum value 234.54 m/s, heat loss occurs between minimum value 74.15 GJ/hr to maximum value 81.78 GJ/hr, productivity arises between minimum value 2.33 t/m^3/day to the maximum value 3.05 t/m^3/day, coke rate occurs between minimum value 402.15 kg/thm to maximum value 457.79 kg/thm, plate cooling heat loss was obtained between minimum value 15.80 GJ/hr to maximum value 59.23 GJ/hr and carbon rate turns out to be between minimum value 452.28 kg/thm to maximum value 480.30 kg/thm. Therefore, all the evaluated results from training models are individually well within the industrial data range. The results are computed as per the formulation of the objectives and fall within the operational range of the plant, which is one of the major requirements of this many objective optimization of the blast furnace process. The range of solutions computed from all the training models is shown in Table 7.

7. General trend analysis and decision making in many objective optimization

The parametric features associated with the Pareto optimal set are deeply studied and analyzed during this work. Each solution from the optimal set contains useful information regarding twelve variables and eight objectives. Until recently, such many objective algorithms were not tractable through evolutionary algorithms. From multi-dimensional pictures and parallel plotting figures, it was observed that each optimal point occurs within the acceptable operational limit. In multi-dimensional hyperspace, the range of solutions varied from model to model, but according to objective formulation, each objective drifted towards a higher limit or lower limit as per definition. When these solutions compared against the experimental datasheet, it clearly indicates that all the converged solutions make certain the objectives satisfy the necessary conditions required for the plant operation. The optimal solutions, including objectives and variables computed from different training models, are shown in Figures 8–10, where each variable and objectives are compared against the range in the datasheet. Figure 8 shows that the optimized range of all the eight objectives generated from different training models by using cRVEA algorithm and compared the same against that obtained from datasheet. Similarly in Figures 9 and 10 reflect the optimized ranges of all the twelve variables generated from different training models by using cRVEA and compared the same against the datasheet variable ranges.

Table 7. Results evaluated by using cRVEA algorithm

Objectives		Algorithm			
		data sheet	BioGP_cRVEA	EvoNN_cRVEA	EvoDN2_cRVEA
Y1 [GJ/hr]	min.	18.41	22.21	17.79	15.15
	max.	38.52	26.64	25.83	25.94
Y2 [Nm^3/hr] $\cdot 10^5$	min.	1.77	2.65	2.60	2.60
	max.	2.79	2.89	2.87	3.07
Y3 [m/s]	min.	130.64	205.04	197.98	194.15
	max.	222.87	238.48	232.36	234.54
Y4 [GJ/hr]	min.	55.82	52.51	51.83	74.15
	max.	107.41	89.64	79.63	81.78
Y5 [t/m^3/day]	min.	1.99	2.31	2.34	2.33
	max.	2.92	3.26	2.97	3.05
Y6 [Kg/thm]	min.	412.52	426.69	400.06	402.15
	max.	555.02	458.88	479.80	457.79
Y7 [GJ/hr]	min.	29.22	22.91	15.53	15.80
	max.	77.36	60.50	58.35	59.23
Y8 [Kg/thm]	min.	437.29	388.20	435.42	452.28
	max.	540.36	460.27	469.22	480.30

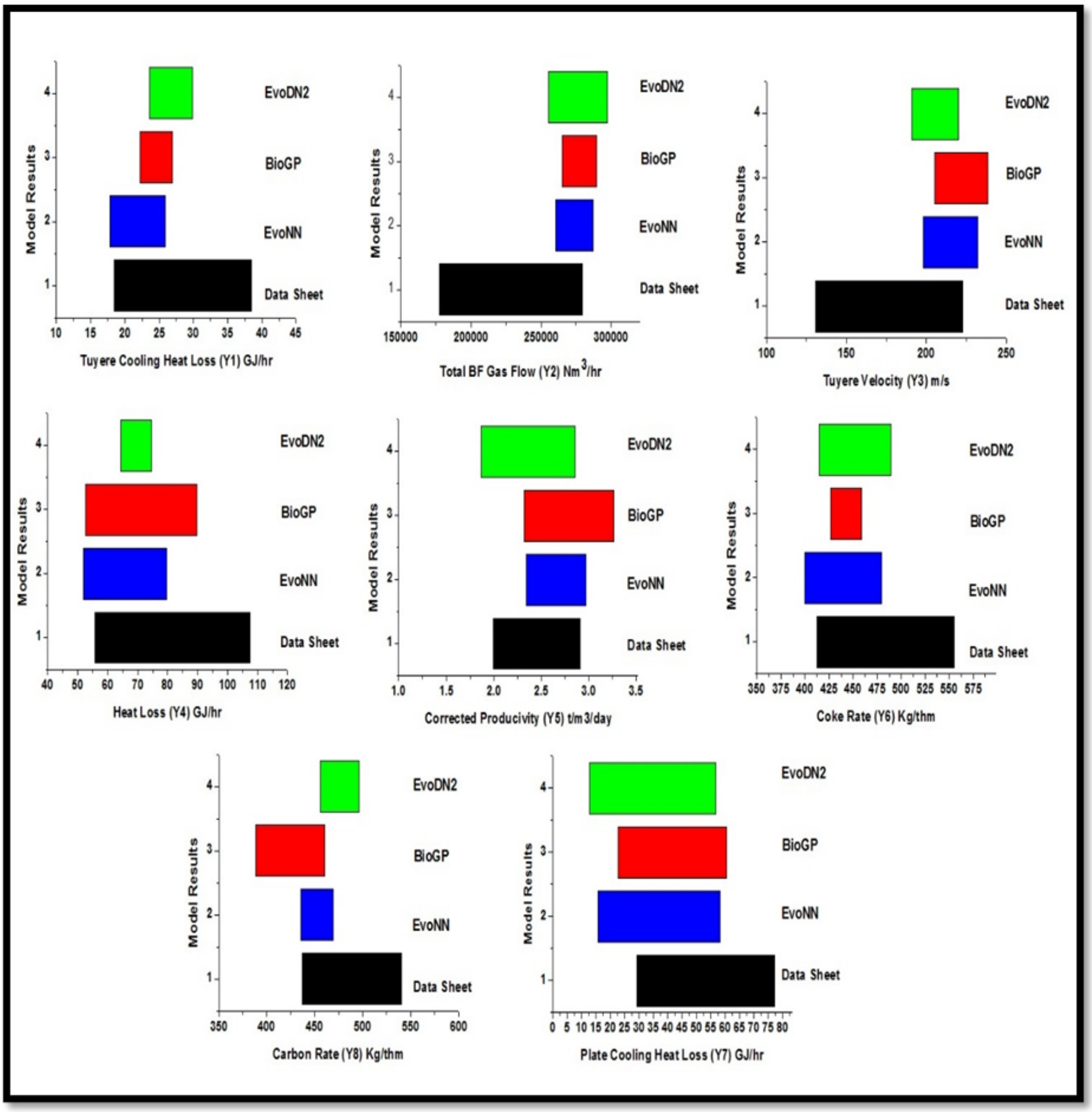

Fig. 8. Optimized solution ranges generated from training algorithms and compared against operational datasheet in objective space

Once the optimization process is completed, the implementation of optimal solutions is an important task in the many objective optimization field. The proper use of these solutions depends upon the environment, process, and working condition to take decisive action during the operation. This solely depends upon the decision making process where the most suitable option is chosen out of a number of options available in the decision set. This is a very difficult task in the blast furnace iron making process, as multiple numbers of variables and objectives are associated with one solution. A well trained operator or a decision maker can make a call by proper understanding the processes and utilized the alternatives smartly, so that plant performance and optimal condition can be achieved in a better way compared to the ongoing operations. Recently, multi-dimensional pictures and two dimensional parallel plots turned out to be immensely helpful in the early decision making process in blast furnace operation.

Since analytical models in a blast furnace are cumbersome and often of limited use, data driven models are the most viable options for the modeling and optimization of different features of this reactor. An evolutionary approach was used by Brännbacka and Saxén (2001) to study the blast furnace hearth and Mitra and Saxén (2014) optimize the charging sequence in this reactor. Gao et al. (2011b) have successfully applied a support vector strategy to study a blast furnace, and a fuzzy rule base was also added to it in another study (Gao et al., 2013). Data driven modeling for this reactor was also conducted using both Volterra series (Gao et al., 2011a) and time discrete approaches (Saxén et al., 2012) beside the conventional neural nets (Jimenez et al., 2004) and subspace concepts were also brought in (Zhou et al., 2016). Data driven approaches related to information technology were also found effective in a running plant (Spirin et al., 2016).

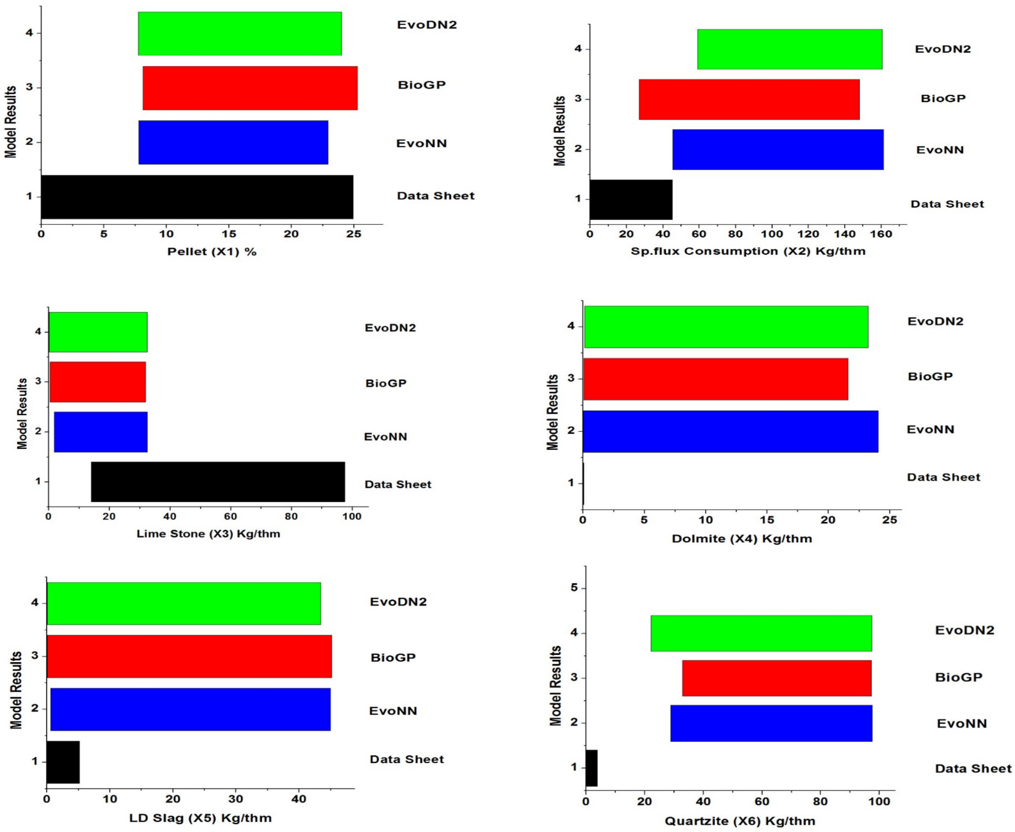

Fig. 9. Optimized solution ranges generated from training algorithms and compared against operational datasheet in variable space

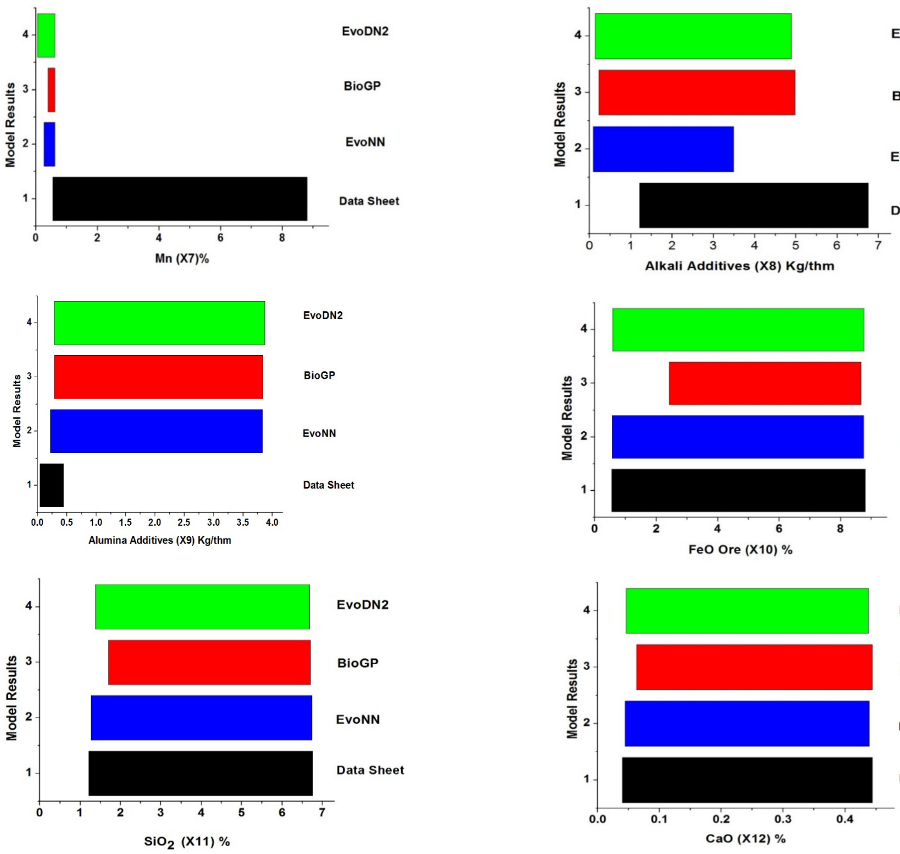

Fig. 10. Optimized solution ranges generated from training algorithms and compared against operational datasheet in variable space

8. Conclusion

In this article, data driven strategies have been discussed along with their implementation in the many objective optimization process in a blast furnace operation. The evolutionary techniques like EvoNN, BioGP, and EvoDN2 were applied to generate training models with the best possible Pareto tradeoff between accuracy and complexity. cRVEA many objective optimization process was used to handle a blast furnace problem with twelve variables and eight objectives. This technique evaluated the results in multi-dimensional hyperspace and generated the results as per the requirement and achieved within the acceptable ranges. Some significant results were achieved regarding all of the objectives by considering these intelligent techniques. This can be effectively introduced in operational strategies and planning in blast furnace operation as computed optimal solution can be helpful in the improvement of plant performance. According to the requirements, a decision maker can take the necessary action by changing the input parameters so that optimum objectives can be achieved at the output. To construct a meta model with twelve variables and eight objectives is a complex job, but in our research process, we effectively handled all these parameters and computed the optimal solutions as per the requirements of the steel plant. Globally, steel demand is increasing day by day and to achieve the demand like quality enhancement, productivity improvement, process optimization, and cost minimization etc. in blast furnace operation needs advanced optimization strategies like evolutionary techniques, where multiple objectives can be handled simultaneously to achieve the required goal.

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References

Adema, A.T. (2014). *DEM-CFD modelling of the iron making blast furnace* [doctoral thesis, Delft University of Technology]. https://doi.org/10.4233/uuid:f8cd8841-7f88-4c29-86a5-2a1c58021d96.

Agarwal, A., Tewary, U., Pettersson, F., Das, S., Saxén, H., & Chakraborti, N. (2010). Analyzing blast furnace data using evolutionary neural network and multi objective genetic algorithm. *Ironmaking and Steelmaking*, *37*(5), 353–359.

Brännbacka, J., & Saxén, H. (2001). Modeling the liquid levels in the blast furnace hearth. *ISIJ International*, *41*(10), 1131–1138.

Castro, J.A., de, Nogami, H., & Yagi, J.I. (2002). Three-dimensional multiphase mathematical modelling of the based on multi-fluid model. *ISIJ International*, *42*(1), 44–52.

Cheng, R., & Jin, Y., Olhofer, M., & Sendhoff, B. (2016). A reference vector guided evolutionary algorithm for many-objective optimizations. *IEEE Transactions on Evolutionary Computation*, *20*(5), 773–791.

Chugh, T., Jin, Y., Miettinen, K., Hakanen, J., & Sindhya, K. (2016). A surrogate assisted reference vector guided evolutionary algorithm for computationally expensive many-objective optimization. *IEEE Transactions on Evolutionary Computation*, *22*(1), 129–142.

Chugh, T., Chakraborti, N., Sindhya, K., & Jin, Y. (2017). A data-driven surrogate-assisted evolutionary algorithm applied to many-objective blast furnace optimization problems. *Materials and Manufacturing Processes*, *32*(10), 1172–1178.

Dong, X.F., Pinson, D., Zhang, S.J., Yu, A.B., & Zulli, P. (2006). Gas-powder flow in blast furnace with different shape of cohesive zone. *Applied Mathematical Modeling*, *30*(11), 1293–1309.

Fabian, T. (1958). A linear programming model of integrated iron and steel production. *Management Science*, *4*(4), 415–441.

Gao, C., Jian, L., Liu, X., Chen, J., & Sun, Y. (2011a). Data-driven modeling based on volterra series for multidimensional blast furnace system. *IEEE Transactions on Neural Networks*, *22*(12), 2272–2283.

Gao, C., Jian, L., & Luo, S. (2011b). Modeling of the thermal state change of blast furnace hearth with support vector machines. *IEEE Transactions on Industrial Electronics*, *59*(2), 1134–1145.

Gao, C., Ge, Q., & Jian, L. (2013). Rule extraction from fuzzy-based blast furnace SVM multiclassifier for decision-making. *IEEE Transactions on Fuzzy Systems*, *22*(3), 586–596.

Geerdes, M., Chaigneau, R., Kurunov, J., Lingiardi, O., & Ricketts, J. (2015). *Modern Blast Furnace Ironmaking: An Introduction*. IOS Press, Delft University Press.

Giri, B.K., Pettersson, F., Saxén, H., & Chakraborti, N. (2013). Genetic programming evolved through Bi-objective algorithms applied to a blast furnace. *Materials and Manufacturing Processes*, *28*(7), 776–882.

Gujarathi, A.M., & Babu, B.V. (2016). *Evolutionary Computation. Techniques and Application*. CRC Press.

Hatano, M., & Kurita, K.A. (1982). Mathematical model of blast furnace with radial distribution of gas flow, heat transfer and reaction considered. *Transaction of the Iron and Steel Institute of Japan*, *22*(6), 448–456.

Helle, M., Pettersson, F., Chakraborti, N., & Saxén, H. (2006). Modelling noisy blast furnace data using genetic algorithms and neural networks. *Steel Research International*, *77*(2), 75–81.

Hodge, B.M., Pettersson, F., & Chakraborti, N. (2006). Re-evaluation of the optimal operating conditions for the primary end of an integrated steel plant using multi-objective genetic algorithms and nash equilibrium. *Steel Research International*, *77*(7), 459–461.

Jiménez, J., Mochón, J., Ayala, J.S., de, & Obeso, F. (2004). Blast furnace hot metal temperature prediction through neural networks-based models. *ISIJ International*, *44*(3), 573–580.

Kilpinen, A. (1988). An on line model for estimating the melting zone in a blast furnace. *Chemical Engineering Science*, *43*(8), 1813–1818.

Li, M., Zhen, L., & Yao, X. (2017). How to read many-objective solutions sets in parallel coordinates [Educational Forum]. *IEEE Computational Intelligence Magazine*, *12*(4), 88–100.

Mahanta, B.K., & Chakraborti, N. (2018). Evolutionary data driven modeling and multi objective optimization of noisy data set in blast furnace iron making process. *Steel Research International*, *89*(9), 1–11.

Mahanta, B.K., & Chakraborti, N. (2019). Evolutionary computation in blast furnace iron making. In S. Datta & J.P. Davim (Eds.), *Optimization in Industry* (pp. 211–252), Springer.

Mahanta, B.K., & Chakraborti, N. (2020). Tri-objective optimization of noisy dataset in blast furnace iron-making process using evolutionary algorithms, *Materials and Manufacturing Processes*, *35*(6), 677–686.

Mitra, T., & Saxén, H. (2014). Evolution of charging programs for achieving required gas temperature profile in a blast furnace. *Materials and Manufacturing Processes*, *30*(4), 474–487.

Mitra, T., Pettersson, F., Saxén, H., & Chakraborti, N. (2016). Blast furnace charging optimization using multi objective evolutionary and genetic algorithms. *Materials and Manufacturing Processes*, *32*(10), 1179–1188.

Mondal, D.N., Sarangi, K., Petterson, F., Sen, P.K., Saxén, H., & Chakraborti, N. (2011). Cu–Zn separation by supported liquid membrane analyzed through multi objective genetic algorithms. *Hydrometallurgy*, *107*(3–4), 112–123.

Nath, N.K. (2002). Simulation of gas flow in blast furnace for different burden distribution and cohesive zone shape. *Materials and Manufacturing Processes*, *17*, 671–681.

Omori, Y. (1987). *Blast Furnace Phenomenon and Modelling*. Elsevier.

Pettersson, F., Chakraborti, N., & Saxén, H. (2007). A genetic algorithms based multi-objective neural net applied to noisy blast furnace data. *Applied Soft Computing*, *7*(1), 387–397.

Pettersson, F., Biswas, A., Sen, P., Saxén, H., & Chakraborti, N. (2009). Analyzing leaching data for low-grade manganese ore using neural nets and multi objective genetic algorithms. *Materials and Manufacturing Processes*, *24*(3), 320–330.

Rist, A., & Meysson, N. (1967). A dual representation of the blast furnace mass and heat balance. *Journal of Metals*, *19*, 50–59.

Roy, S., & Chakraborti, N. (2020). Development of an evolutionary deep neural net for materials research. In *TMS 2020 149th Annual Meeting & Exhibition. Supplemental Proceedings* (pp. 817–828), Springer International Publishing.

Roy, S., Saini, B.S., Chakrabati, D., & Chakraborti, N. (2020). Mechanical properties of micro-alloyed steels studied using an evolutionary deep neural network. *Materials and Manufacturing Processes*, *35*(6), 611–624.

Saxén, H., Gao, C., & Gao, Z. (2012). Data-driven time discrete models for dynamic prediction of the hot metal silicon content in the blast furnace – A review. *IEEE Transactions on Industrial Informatics*, *9*(4), 2213–2225.

Spirin, N.A., Lavrov, V., Rybolovlev, A.V., Krasnobaev, A.V., & Pavlov, A.V. (2016). Use of contemporary information technology for analyzing the blast furnace process. *Metallurgist*, *60*(5–6), 471–477.

The white book of steel (2012). World Steel Association.

Zhou, P., Song, H., Wang, H., & Chai, T. (2016). Data-driven nonlinear subspace modeling for prediction and control of molten iron quality indices in blast furnace ironmaking. *IEEE Transactions on Control Systems Technology*, *25*(5), 1761–1774.

Zhou, Z., Zhu, H., Yu, A., Wright, B., Pinson, D., & Zulli, P. (2005). Discrete particle simulation of solid flow in a model blast furnace. *ISIJ International*, *45*(12), 1828–1837.