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Optimization of Operating Parameters for Sponge Iron Production Process using Neural Network

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Abstract: In the present study, estimation of optimum input parameters corresponds to desired values of output parameters is carried out for a sponge iron production process. For this purpose two different data sets, Data-1 and Data-2, are collected from a typical sponge iron plant, which correlate the input and output parameters. Data-1 includes temperatures profiles and air inlet at positions, AT-1 to AT-3 and MF-1 and MF-2, inside the kiln whereas, flow rates of iron ore, feed coal, slinger coal and sponge iron is accounted as Data-2. Total sixteen topologies are proposed for each data set to optimize the regression coefficients (R), which are solved through ANN. These topologies are used to identify optimum value of output parameters based on value of R. The values of output parameters meet the process requirements. The % errors observed in industrial values and that predicted through ANN software fall within ±5% for Data-1 and Data-2. Further, a better option is found to compute optimum input parameters correspond to desired output. The analysis predicts optimum input parameters within 4% deviation than that are used in the process.
Keywords: Sponge iron process, Rotary kiln, ANN topologies, Optimum input parameters.

1. Introduction

Sponge iron is the metallic form of iron produced from reduction of iron oxide below the fusion temperature of iron ore (1535°C) by utilizing hydrocarbon gases or carbonaceous fuels as coal. The reduced iron having high degree of metallization exhibits a 'honeycomb structure', due to which it is named as sponge iron.

It is seen that the growth of sponge iron industry in last few years is remarkable and today India is the largest producer of sponge iron as it covers 16% of global output[1]. Sponge iron is produced primarily both by using non-coking coal and natural gas as reductant and therefore classified as coal based and gas based process respectively. Due to promising availability of coal in India the coal based sponge iron plants share the major amount of its production[2].

With the availability of raw materials, high demand of sponge iron and less payback period, sponge iron industry has emerged as a profitable venture. However, due to lack of proper integration techniques, non-optimal process parameters, high energy consumption and old running process technology, the industries are facing a setback in market. Amongst these draw backs the problem of improper integration technique and high energy consumption are addressed by many investigators[3,4,5,6,7,8,9,10,11,12]. However, the optimization of process parameters based on the desired output of the industry remains untouched. These parameters include temperature profile inside the main units of the process which is kiln and flow rate of sponge iron production. These parameters depend on air, iron ore and coal flow rate, which may be regulated to suit the desired output of the process. For this purpose one may use manual practice to see the outcome when one input parameter is varied. It is clumsy and cumbersome approach, which requires considerable experimentation to set the optimum parameters. Thus, an easy methodology to optimize the process parameters is considered in the present work with artificial neural network (ANN).

With the advancement in computer technology neural network has made notable contribution in non-linear problem estimation[13,14]. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. This modeling capability, as well as the ability to learn from experience, have made ANN superior over most traditional modeling methods. In this work, ANN based topologies are developed and discussed to know actual temperature profile in rotary kiln as well as production rate of sponge iron. It appears that no literature is available where ANN is used to optimize the operating parameters of metallurgical plants such as sponge iron process.

2. Sponge iron process

The course of the direct reduction of iron ore in rotary kiln (RK) is schematically described in Fig. 1. Iron ore and coal are fed to the kiln at controlled rates without pre-mixing and the charge moves through the kiln depending upon the rotation and inclination of the kiln. In combination with the feed charge, other successive processes such as drying, preheating and reduction are controlled by means of air which is injected along the kiln length[9]. The material discharged from the kiln is cooled in an evacuated rotary cooler (RC) with water sprayed on the shell side. The cooler discharge is then separated into sponge iron, char and ash through magnetic separator. The waste gas generated in the rotary kiln is passed through dust settling chamber (DSC) and the carbon monoxide produced through incomplete oxidation is converted to carbon dioxide by supplying excess air in the after burning chamber (ABC) as shown in Fig. 1. As waste gas is at 900^{o}C while exiting the ABC, it is passed through a waste heat recovery boiler (WHRB) to produce steam for power generation. Further, waste gas is passed through electro static precipitator (ESP) for dust removal and is then released to the atmosphere through chimney. The flow of waste gas from rotary kiln to chimney is maintained using an induced draft fan located before the chimney.

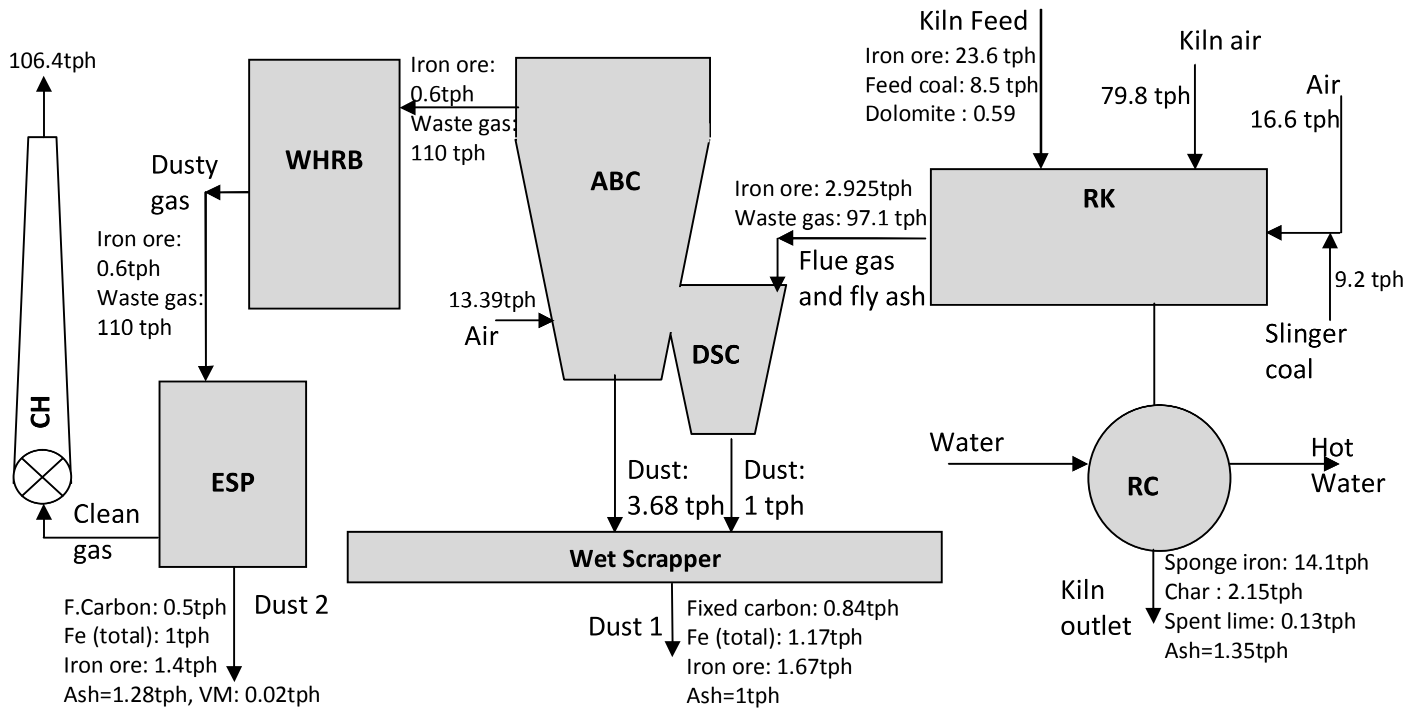

Fig. 1. Process flow diagram of sponge iron process

The process flow diagram (PFD) of sponge iron production process, shown in Fig. 1, consists of a number of equipment namely rotary kiln, rotary cooler, DSC, ABC, WHRB, ESP, wet scrapper and chimney. As the aim of the present work is to correlate input and output parameters of the sponge iron process using ANN, data of most important unit of process i.e. rotary kiln is collected. Further, it is observed that the operating parameters of rotary kiln are adjusted in such a manner so that temperature profile and Fe conversion can be maintained at desirable values. Therefore, all input and output parameters correspond to temperature profile and Fe conversion are required to be collected.

3. Data collection

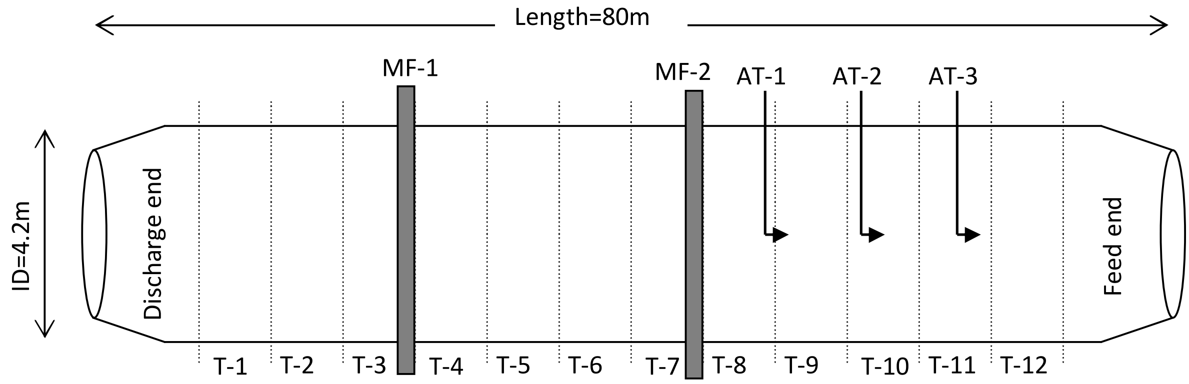

Fig. 2 Schematic of rotary kiln

The schematic of rotary kiln is shown in Fig. 2 where temperatures, T-1 to T-12, are noted through 12 thermocouples, which are placed along the length. The values measured through these thermocouples give temperature profile in the rotary kiln. Around the periphery of the kiln air is injected through positions AT-1, AT-2, AT-3, MF-1 and MF-2. At AT-1 to AT-3 one blower is attached to each position whereas, at MF-1 and MF-2 two blowers are placed to each inlet. Therefore, total seven blowers are placed which provide air along the length of the kiln. To produce sponge iron, iron ore and coal are used as raw material. In the kiln coal is injected from feed as well as discharge side, which is called feed coal and slinger coal, respectively, as shown in Fig. 1. Slinger coal is fed as fines, medium and coarse coal pneumatically; however, feed coal is fed as coarse coal. This is due to the process requirement. The sponge iron along with char, spent lime and ash are produced as kiln outlet. It further enters to rotary cooler where it cools from 1048°C to 110°C. The production of sponge iron depends on metallization of iron ore.

For the present work data of a typical sponge iron industry with production capacity of 350 tonne/day is collected on per hour basis. There are 440 data points which are collected for 24 hours for 18 days and 8 hours of 19th day. Due to limitation of the pages of journal complete data of day-1 is shown in Table A.1. Temperatures, T-1 to T-12, are in °C, flow rates of iron ore, feed coal and injected coal are in tonne/h and flow of air is in % damper opening such as 20, 19, 43, etc. Damper opening of 1% gives air flow rate around 600 m^3/h as per information collected from industry. Before using these data for analysis, these are checked with mass balance. For this purpose, mass balance is performed to all 440 data points. It is found that for these data points the maximum deviation in values is 5.4%. As all data points satisfy mass balance with ±6%, these are considered for further analysis. These data are divided in two sets: Data-1 and Data-2. Details of these data sets are discussed in subsequent paragraphs:

3.1. Data-1

The data of temperature T-1 to T-12, AT-1 to AT-3 and MF-1 and MF-2 are referred as data set, Data-1. As temperature is dependent on combustion that takes place inside the kiln, it is affected by air entered the kiln along the length. Therefore, temperature profile and flow rate of air are considered as one data set and is referred as Data-1. It consists of data of column 7 to 23 of Table A.1.

3.2. Data-2

The production of sponge iron depends primarily on the amount of iron ore and coal as reduction of iron ore is carried out with carbon available in coal. Therefore, iron ore, feed coal, slinger coal and sponge iron is accounted as another set of data which is referred as Data-2. It consists of data of column 1 to 6 of Table A.1. It should be noted in Table A.1 that slinger coal is presented in three sizes such as fines, medium and coarse. Though industrial data of day-1 is shown in this work the operating ranges of input and output parameters for Data-1 and Data-2, found for 440 data points, are summarized in Table 1.

Table 1 Operating ranges of input and output parameters for Data-1 and Data-2

Parameter	Operating range	Parameter	Operating range
Iron ore	21-23.8 tph	T-1	1002-1108 °C
Feed coal	8.2-8.8 tph	T-2	986-1098 °C
Fines	1.7-1.9 tph	T-3	976-1091 °C
Medium	2.65-4 tph	T-4	992-1092 °C
Coarse	2.9-3.9 tph	T-5	1015-1109 °C
Sponge iron	13.53-15.355 tph	T-6	1019-1102 °C
AT-1	16-20 %	T-7	1002-1097 °C
AT-2	19-21 %	T-8	1000-1098 °C
AT-3	3-14 %	T-9	862-991 °C
MF-1	43-53 %	T-10	829-955 °C
MF-2	20-23 %	T-11	764-911 °C
		T-12	700-800°C

3. The ANN model

An ANN is a parallel-distributed information processing system[15]. ANN is made up of interconnecting artificial neurons. These are distributed, adaptive, nonlinear learning machines built out of many different processing elements (PEs). Each PE receives signal from other PEs and/or itself. The interconnectivity, amongst PEs, is defined by topology. The ANN system is a collection of operators interconnected by means of one-way signal flow channels. ANN stores the samples with a distributed coding, thus forming a trainable non-linear system. The strengths of signals flowing on the connections are scaled by adjustable parameters called weights. The PEs sum all these contributions and produce an output that is a nonlinear (static) function of the sum. The PEs' outputs become either system outputs or are sent to the same or other PEs. The ANN network also includes hidden layer(s) between the input and output layers. The main idea of the ANN approach resembles with the human brain functioning. Therefore, ANN has a quicker response and higher performance than a sequential digital computer. Given the inputs and desired outputs, it is also self-adaptive to the environment so as to respond to the different inputs rationally. It has a complex internal structure, so that these imitate basic biological functions of neurons. In this study, the feature of a neural network is used in the estimating actual output parameters such as flow rate of sponge iron as well as temperature profile in rotary kiln for Data-1 and Data-2.

3.1 Development of ANN topologies

Data-1 and Data-2 are analyzed through ANN. As ANN model provides relationship between input and output parameters it affects by varying a few factors used in development of ANN topology. These are number of randomization, number of hidden layers, type of models, type of functions, number of epochs, etc. All these factors are varied to develop different topologies. For example number of randomization and hidden layer is considered as one and two. As more number of hidden layers complexes the solution, only two is considered in the present work. MLP and RBF models are used as type of models as these are most suited to handle random industrial data. Moreover, TanhAxon and SigmoidAxon are accounted as different functions through which input and output parameters are related. Considering these factors sixteen topologies are developed as reported in Table 2. For each topology 2/3rd data points (i.e. 2/3rd rows of complete data) is used as training and the rest as testing. In the present work 440 data points are used for analysis in which 295 and 145 data points are used for training and testing, respectively.

Table 2 Topologies for ANN network

S.No	Networks tested for present work	Randomization	No. of hidden layers	Model	Function
1	TOP-1	1	1	MLP	TanhAxon
2	TOP-2	1	1	MLP	SigmoidAxon
3	TOP-3	1	1	RBF	TanhAxon
4	TOP-4	1	1	RBF	SigmoidAxon
5	TOP-5	2	1	MLP	TanhAxon
6	TOP-6	2	1	MLP	SigmoidAxon
7	TOP-7	2	1	RBF	TanhAxon
8	TOP-8	2	1	RBF	SigmoidAxon
9	TOP-9	1	2	MLP	TanhAxon
10	TOP-10	1	2	MLP	SigmoidAxon
11	TOP-11	1	2	RBF	TanhAxon
12	TOP-12	1	2	RBF	SigmoidAxon
13	TOP-13	2	2	MLP	TanhAxon
14	TOP-14	2	2	MLP	SigmoidAxon
15	TOP-15	2	2	RBF	TanhAxon
16	TOP-16	2	2	RBF	SigmoidAxon

The performance of a topology is defined by two parameters: Normalized Mean Square Error (NMSE), which should be minimum and the correlation coefficient (R), which should have a value near unity[15]. These two parameters are defined as:

$$NMSE = \frac{PN(MSE)}{\dfrac{\sum_{j=0}^{P}\left[N\sum_{i=0}^{N}d_{ij}^2 - (\sum_{i=0}^{N}d_{ij})^2\right]}{N}} \tag{1}$$

$$R = \frac{\dfrac{\sum_{i=o}^{N}(y_i-\bar{y})(d_i-\bar{d})}{N}}{\sqrt{\dfrac{\sum_{i=0}^{N}(y_i-\bar{y})^2}{N}\,\dfrac{\sum_{i=0}^{N}(d_i-\bar{d})^2}{N}}} \tag{2}$$

4. Results and discussion

The detailed analyses of ANN topologies developed for Data-1 and Data-2 are discussed in subsequent paragraphs.

4.1. ANN Topologies for Data-1

For Data-1 AT-1, AT-2, AT-3, MF-1 and MF-2 are input parameters to the kiln whereas, T-1, T-2, T-3, T-4, T-5, T-6, T-7, T-8, T-9, T-10, T-11 and T-12 are considered as output parameters. For ANN analysis actual flow rates of air at different opening are considered, which are found through multiplication of 600 m^3/h to % of damper opening, shown in Col. 7 to 11 of Table A.1.

4.1.1. Regression coefficient for Data-1

Using Data-1, shown in Table A.1, topologies, TOP-1 to TOP-16, are developed and solved using software NeuroSolutions 4.0. For these networks the average values of regression coefficient, R, are shown in Table 3. The average value of R is computed using R values of individual temperatures, T-1 to T-12. In fact, this value of R is found considering constant values of iron ore, feed coal, slinger coal and sponge iron as 23.44 T/h, 8.695 T/h, 8.97 T/h and 15.022 T/h, respectively. These are average values of iron ore, feed coal, slinger coal and sponge iron and found using data shown in Table A.1. Table 3 shows that average value of R is maximum for topology, TOP-11, which is predicted as 0.7509. This value is found with 1000 epochs. When topology, TOP-11, is trained with increased number of epochs the average value of R is shown in Table 4.

Table 3 Average values of R for different ANN topologies developed for Data-1

Networks tested for present work	Randomization	No. of hidden layers	Model	Function	Average values of R
TOP-1	1	1	MLP	TanhAxon	0.7106
TOP-2	1	1	MLP	SigmoidAxon	0.5663
TOP-3	1	1	RBF	TanhAxon	0.7335
TOP-4	1	1	RBF	SigmoidAxon	0.6297
TOP-5	2	1	MLP	TanhAxon	0.7282
TOP-6	2	1	MLP	SigmoidAxon	0.6008
TOP-7	2	1	RBF	TanhAxon	0.7369
TOP-8	2	1	RBF	SigmoidAxon	0.6583
TOP-9	1	2	MLP	TanhAxon	0.7370
TOP-10	1	2	MLP	SigmoidAxon	0.4516
TOP-11	1	2	RBF	TanhAxon	0.7509
TOP-12	1	2	RBF	SigmoidAxon	0.4472
TOP-13	2	2	MLP	TanhAxon	0.7172
TOP-14	2	2	MLP	SigmoidAxon	0.3376
TOP-15	2	2	RBF	TanhAxon	0.7377
TOP-16	2	2	RBF	SigmoidAxon	0.4036

Table 4 Average values of R for different number of epochs for topology, TOP-11

Number of epochs	Average values of R
1000	0.7509
2000	0.7695
3000	0.7230
4000	0.7437
5000	0.7415

Table 5 Testing report for Data-1

Parameter	T-1	T-2	T-3	T-4	T-5	T-6	T-7	T-8	T-9	T-10	T-11	T-12
NMSE	0.197	0.199	0.205	0.548	0.432	0.828	0.359	0.360	0.461	0.539	0.426	0.281
MAE	10.58	10.37	10.8	9.22	8.4	8.58	9.64	10.82	10.77	12.8	10.9	10.15
R	0.898	0.897	0.893	0.681	0.762	0.445	0.803	0.809	0.742	0.684	0.766	0.854

Table 4 shows that for 2000 epochs TOP-11 finds best average value of R, which comes out as 0.7695. For this topology detailed report of testing is shown in Table 5, which indicates R values for individual temperatures, T-1 to T-12. The mean absolute error (MAE) and normalized mean squared error (NMSE) are 10.25 and 0.403, respectively, for TOP-11 with 2000 epochs.

In fact, for Data-1 average value of R is also not very significant, which may be due to large variation in input data. For example temperature T-1 varies from 1108 to 1002◦C, which is 9.57%, as shown in Table 1. Similarly, T-2, T-3, T-4, T-5, T-6, T-7, T-8, T-9, T-10, T-11 and T-12 vary by 10.2%, 10.5%, 9.16%, 8.48%, 7.53%, 10.1%, 13%, 13.2%, 16.1% and 12.5%, respectively. In the similar pattern variations in input parameters such as flow rate of air at position, AT-1, AT-2, AT-3, MF-1 and MF-2, are observed as 20%, 9.524%, 78.6%, 18.87% and 13.04%, respectively. It is to be noted that variation in flow rate of air at AT-3 is maximum, i.e. 78.6% where flow rate of air vary from 8400 m^3/h to 1800 m^3/h. In fact, the maximum and minimum values of % of damper opening for AT-3, reported in Table 1, are 14 and 3, respectively. These are corresponding to 8400 m^3/h to 1800 m^3/h. The combined effect of all values of air inlet causes variation in total amount of air enters to kiln by 7.44% where maximum and minimum amounts of air are 72600 m^3/h (i.e. 87.12 t/h) and 67200 m^3/h (i.e. 80.64 t/h), respectively. Further, it is observed that such large variation in input and output data of Data-1 is due to variation in quality of iron ore and coal, accretion formation in kiln, etc. As TOP-11 with 2000 epochs shows best average value of R it is used for further analysis.

4.1.2 Error analysis for Data-1

For topology, TOP-11, with 2000 epochs the values of temperatures, which are the output parameter in the present case, obtained from industry and that predicted using software NeuroSolutions 4.0 are compared. The values of temperature, T-1, found through industry and software are plotted in Fig. 3 where 145 data points are shown which are considered for testing. Fig. 3 shows that industrial data vary significantly from 1003 to 1108°C, however, the predicted values of T-1 using software shows variation from 1004.9 to 1094.9°C. The % variation in values of T-1 obtained from industry and predicted using software is 9.1% and 8.2%, respectively.

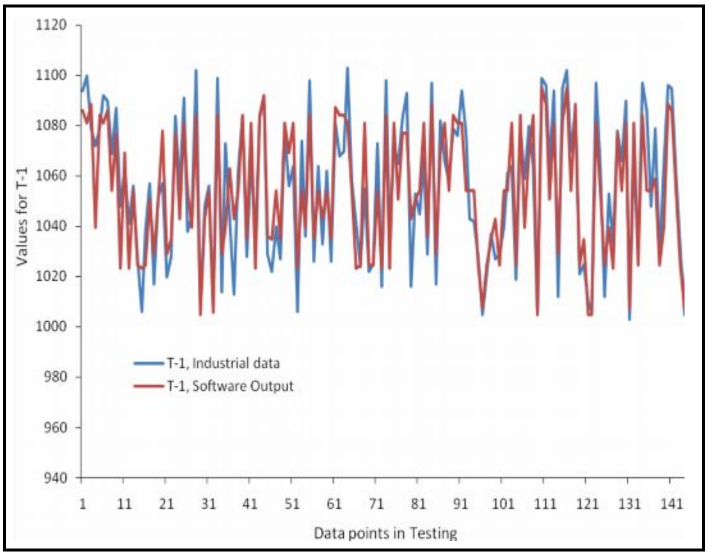

Fig. 3 Values of T-1 obtained from industry and software

The % error, E, is computed using Eq. 3, which denotes the deviation between two values of T-1 predicted using software and that collected from industry. For all 145 data points of testing, E is computed. Amongst these maximum (most positive value) and minimum (most negative value) values of E are found. This computation shows that for values of T-1 the maximum deviation, E, is found as -3.2%. It indicates that value of T-1 obtained from industry should be increased maximum by 3.2% to fall within the range predicted using software. It can be done through varying input parameter i.e. flow rate of air. Therefore, to obtain best relationship between input and output parameters the flow rate of air should be varied in such a manner so that temperature T-1 should be within the range predicted from software i.e. 1004.9 to 1094.9°C instead of 1003 to 1108°C used in sponge iron industry.

$$E = \left(\frac{Value\ predicted\ from\ software - Value\ obtained\ from\ industry}{Value\ predicted\ from\ software} \right) \times 100 \qquad (1)$$

Similarly, comparison between values for other output temperatures such as T-2 to T-12, obtained from industry and predicted using software NeuroSolutions 4.0, for topology, TOP-11, with 2000 epochs are shown in Table 6. Along with this, the variation for temperature, T-1, is also reported in Table 6 for clarity.

From Table 6 it is clear that values of E for temperature, T-1 to T-12, found from industry and computed through software are within ±10%. In fact, the value of maximum temperature in output parameters, T-1 to T-12, predicted through software is 1095.8°; however, it was 1109° in Data-1 shown in Table 1 and 6. This meets the process requirement as accretion formation inside the kiln starts at 1100°C. It is caused by low melting eutectic compounds of the FeO, SiO_2, and Al_2O_3 in combination with CaO or MgO from desulphurising agent used in the process. As the maximum temperature predicted through software is 1095.8^0C, which is less than 1100^0C, the results fall in the feasibility range of operation and satisfy the process requirement.

Table 6 Comparison of values of temperatures, T-1 to T-12

Temp.	Variation in data obtained from industry	Variation in values predicted using software	% variation in data obtained from industry	% variation in values predicted through software	Value of E (%)
T-1	1003-1108	1004.9-1094.9	9.1	8.2	-3.2
T-2	986-1092	989.3-1081.7	9.7	8.54	3.14
T-3	976-1085	982.3-1076.1	10.05	8.7	-3.08
T-4	992 -1089	1024.9-1071.6	8.9	4.36	3.86
T-5	1015-1109	1047.2-1095.8	8.2	4.43	4.5
T-6	1019-1098	1050.1-1088.6	7.2	3.5	4.6
T-7	993-1089	1000.5-1069.6	8.8	6.5	-3.8
T-8	946-1048	977.7-1031.1	9.7	5.2	3.8
T-9	890-989	918.2-960.9	10.0	4.4	3.9
T-10	830-953	865.6-921.7	12.9	6.1	-9.7
T-11	765-911	799.4-862.4	16.02	7.3	-9.9
T-12	700-800	730.2-786.9	12.4	7.2	-4.2

Further, Table 6 shows that as values of temperatures, T-10 and T-11, carry significant error such as -9.7% and -9.9%, respectively, these are to be controlled stringently to reduce the % error. For temperature, T-10, large deviation in values, obtained from industrial data and predicted using software, is mainly caused by six data points obtained from industry as indicated through drought and peaks shown in Fig. A.1. The values of temperatures at these data points are summarized in Table 7. If these points are discarded from industrial data the value of E is reduced by -4.6%. Similarly, deviation of -9.9% in value of T-11, as evident from Table 6, is observed due to three data points in industrial values as can be seen from Fig. A.2. Table 7 shows that discarding these points value of E can be decreased upto -4.3%.

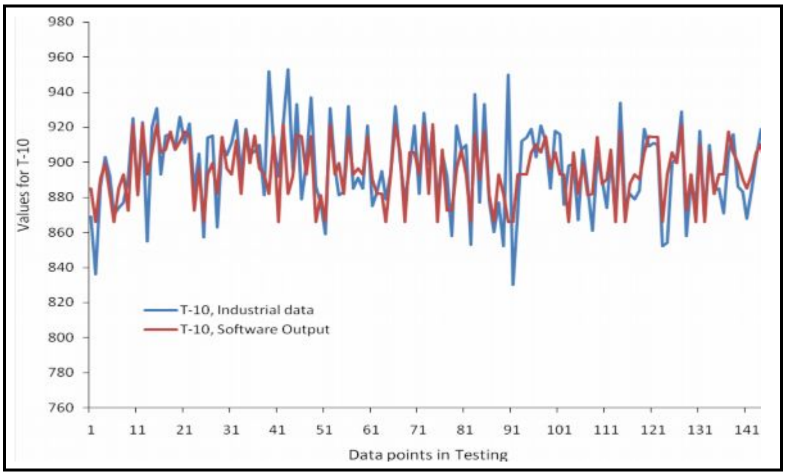

Fig. A.1 Values of T-10 obtained from industry and predicted from software

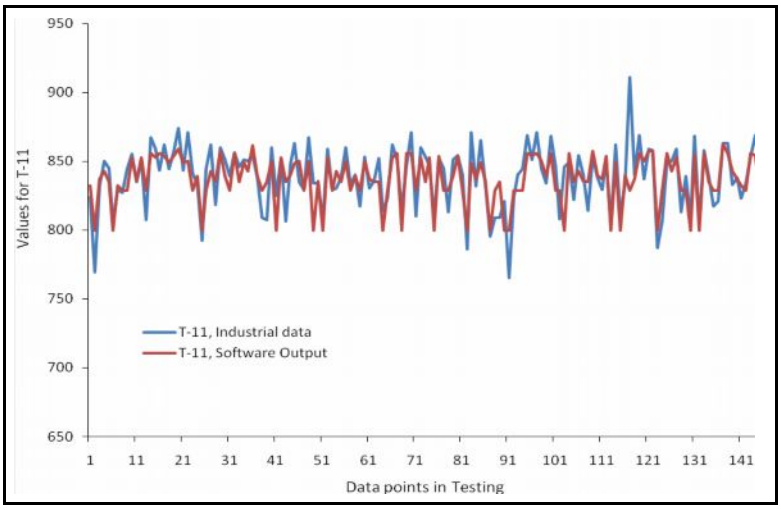

Fig. A.2 Values of T-11 obtained from industry and predicted from software

Table 7 Points discarded from industrial data

Temp	Points falling away from the predicted limits			Value of E before discarding the points	Value of E after discarding the points
	No. of points	Values	Data point		
T-10	6	836, 855, 952, 953, 950, 830	2, 13, 39, 43, 90, 91	-9.7	-4.6
T-11	3	769, 765, 911	2, 91, 118	-9.9	-4.3

It is observed from Table 6 and 7 that % errors observed in industrial values and that predicted through software are reduced from ±10% to ±4.6% by discarding a few points from industrial data. As the value of E is within ±5%, it is acceptable. These data are very less in number which may be discarded without disturbing the process performance. Further, topology TOP-11 with 2000 epochs is applied to the revised set of Data-1, where data points shown in Table 6.5 are discarded. The average value of R for the revised data is found as 0.7857, which is the improved value in comparison to that for original Data-1, which was 0.7695 as shown in Table 4.

4.2 ANN Topologies for Data-2

The flow rate of feed and product are confined to data set, which is named as Data-2. It consists of flow rate of iron ore, feed coal and slinger coal as input parameters and sponge iron as output parameters. Slinger coal contains flow rate of fine, medium and coarse coal whereas feed coal carries only coarse coal. It is due to the process requirement. Therefore, Data-2 has five input parameters such as flow rate of iron ore, feed coal, fine-, medium- and coarse-slinger coal and one output parameter as flow rate of sponge iron. These data are shown in Table A.1 for day-1. In the present section ANN analysis of Data-2 is carried out and results found are discussed:

4.2.1 Regression coefficient for Data-2

For Data-2 topologies, TOP-1 to TOP-16, are developed and solved using software NeuroSolutions 4.0. For these networks the value of regression coefficient, R, are shown in Fig. 4. This value of R is found considering constant values of temperatures, T-1, T-2, T-3, T-4, T-5, T-6, T-7, T-8, T-9, T-10, T-11 and T-12, as 1054, 1041, 1032, 1058, 1079, 1071, 1072, 1043, 942, 896, 837 and 762°C, respectively, and flow rate of air as 11401, 11877, 3539, 31154 and 12792 m^3/h at position AT-1, AT-2, AT-3, MF-1 and MF-2, respectively. Fig. 4 shows that R is maximum for topology, TOP-7, which is predicted as 0.8938. This value is found using 1000 epochs. When topology, TOP-7, is trained with number of epochs as 2000, 3000, 4000 and 5000 the values of R are found as 0.9206, 0.8815, 0.8675 and 0.8689, respectively. As a result of it, value of R is maximum for TOP-7 when 2000 epochs are considered, which comes out as 0.9206. For this topology, value of MAE and NMSE are found as 0.09 and 0.162, respectively. For Data-2, these values are considerably low in comparison to Data-1. It shows that TOP-7 relates the input and output parameters well for Data-2 than that are carried out using TOP-11 for Data-1. It is also indicated through average value of R as it is 0.9206 and 0.7695 for Data-2 and Data-1, respectively. As TOP-7 with 2000 epochs shows best average value of R it is used for further analysis of Data-2.

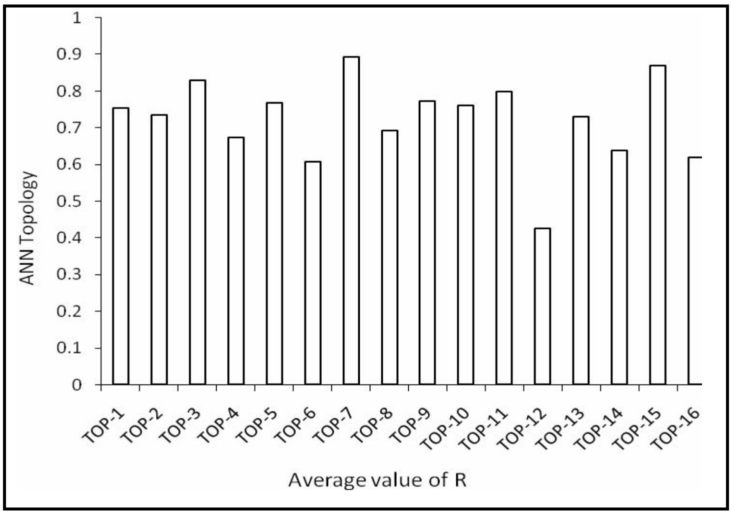

Fig. 4 Average values of R for different ANN topologies developed for Data-2

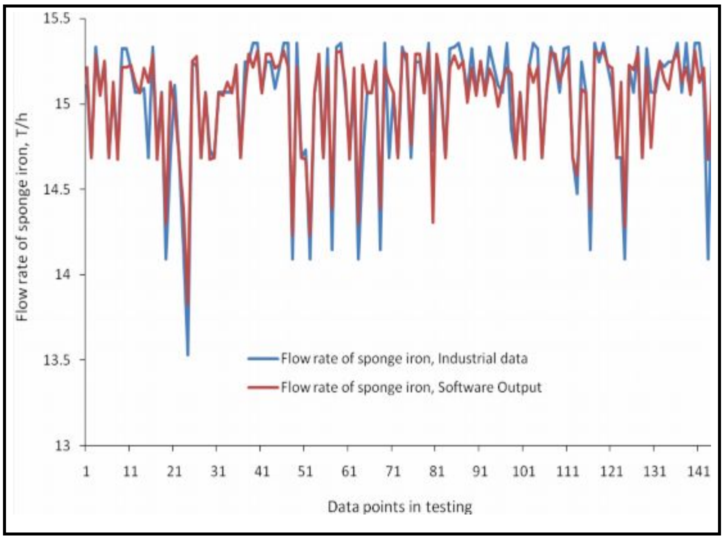

Fig. 5 Flow rate of sponge iron obtained from industry and predicted from software

4.2.2 Error analysis for Data-2

For topology, TOP-7, with 2000 epochs the flow rate of sponge iron, which is the output parameter in the present case, obtained from industry and predicted using software NeuroSolutions 4.0 is compared through Fig. 5. There are 145 data points considered for testing. This figure shows that industrial data vary from 13.53 to 15.355 T/h, however, the predicted values of flow rate of sponge iron using software shows variation from 13.83 to 15.31 T/h. The % variation in data obtained from industry and predicted from software is 11.9% and 9.7%, respectively. The % error, E, is computed using Eq. 3 for all points of testing, i.e. 145. It shows that for flow rate of sponge iron the maximum deviation, E, is found as 3.99%. As the value of E is within ±5%, it is acceptable. Therefore, to obtain best relationship between input and output parameters the flow rate of iron ore, feed coal and slinger coal should be varied in such a manner so that flow rate of sponge iron should be within the range predicted from software i.e. 13.83 to 15.31 T/h instead of 13.53 to 15.355 T/h used in sponge iron industry.

4.3. Selection of best value of input parameters

The operating range of output parameters, flow rate of sponge iron and temperatures, T-1 to T-12, predicted for Data-1 and Data-2, shown in Section 4.2.2 and Table 6, can be maintained in the process by adjusting input parameters. However, it is not known a priory that how each input parameters must be set to get actual output. For this purpose one should observe output parameters while varying values of input parameters. It is a cumbersome approach which requires considerable experimentation to set the optimum input parameters. Thus, a better option is to find out values of input parameters correspond to desired output. For this purpose parameters T-1, T-2, T-3, T-4, T-5, T-6, T-7, T-8, T-9, T-10, T-11, T-12 and flow rate of sponge iron are considered as input whereas flow rate of iron ore, feed coal, fine-, medium- and coarse-slinger coal, AT-1, AT-2, AT-3, MF-1 and MF-2 are accounted as output parameters. Further, the values of T-1, T-2, T-3, T-4, T-5, T-6, T-7, T-8, T-9, T-10, T-11, T-12 and flow rate of sponge iron considered in Data-1 and Data-2 are varied in such a manner so that all values fall within the operating range shown in Table 6 and Section 4.2.2. For example, if value of T-1 is 990°C, it is replaced with 1004.9°C. While varying in such manner values of T-1, T-2, T-3, T-4, T-5, T-6, T-7, T-8, T-9, T-10, T-11, T-12 and flow rate of sponge iron are considered to be the desired output. For these output parameters, values of input parameters are found using Neurosolutions 4.0.

For this purpose, topologies, TOP-1 to TOP-16, are developed and solved using software NeuroSolutions 4.0. For these topologies the average values of regression coefficient, R, are shown in Table 8. It shows that average value of R is maximum for topology, TOP-5, which is predicted as 0.8621 using 1000 epochs. When topology, TOP-5, is trained with number of epochs as 2000, 3000, 4000 and 5000 the average value of R is found as 0.8791, 0.7674, 0.8513 and 0.8161, respectively. Therefore, the average value of R is maximum for TOP-5 when 2000 epochs are considered, which comes out as 0.8791. For this purpose 145 data points are considered for testing. Based on this analysis the average value of output, iron ore, feed coal, fine-, medium- and coarse-slinger coal, AT-1, AT-2, AT-3, MF-1 and MF-2, is found as 23.4 T/h, 8.7 T/h, 1.8 T/h, 3.6 T/h, 3.5 T/h, 11391.9 m^3/h, 11857.2 m^3/h, 3602.2 m^3/h, 31110.9 m^3/h and 12772.7 m^3/h, respectively. The values of these parameters are found through averaging the 145 points of testing condition. As these values of operating parameters correlate the output with appreciable average value of R, these are considered as most suitable values of input parameters for desired output parameters. Thus, these values of input parameters are considered optimum for the present industrial data.

Table 8 Average value of R for different ANN topologies when T-1 to T-12 and sponge iron are treated as input parameters

Networks tested for present work	Randomization	No. of hidden layers	Model	Function	Average values of R
TOP-1	1	1	MLP	TanhAxon	0.8399
TOP-2	1	1	MLP	SigmoidAxon	0.6803
TOP-3	1	1	RBF	TanhAxon	0.8282
TOP-4	1	1	RBF	SigmoidAxon	0.4446
TOP-5	2	1	MLP	TanhAxon	0.8621
TOP-6	2	1	MLP	SigmoidAxon	0.6084
TOP-7	2	1	RBF	TanhAxon	0.8084
TOP-8	2	1	RBF	SigmoidAxon	0.5422
TOP-9	1	2	MLP	TanhAxon	0.8356
TOP-10	1	2	MLP	SigmoidAxon	0.4818
TOP-11	1	2	RBF	TanhAxon	0.7837
TOP-12	1	2	RBF	SigmoidAxon	0.3056
TOP-13	2	2	MLP	TanhAxon	0.8487
TOP-14	2	2	MLP	SigmoidAxon	0.4420
TOP-15	2	2	RBF	TanhAxon	0.7608
TOP-16	2	2	RBF	SigmoidAxon	0.4112

Table 9 Comparison of optimum values of input parameters with that are used in the process

Operating parameter	**Shown in Fig. 1**	**Optimum input parameters predicted**	**% deviation**
Iron ore	23.61 tph	23.4 tph	0.89
Feed coal	8.5 tph	8.7 tph	2.4
Slinger coal	9.2 tph	8.9 tph	3.3
Air through position, AT-1, AT-2, AT-3, MF-1 and MF-2	79.8 tph	70734.9 m^3/h (i.e. 79.223 tph)	0.72

4.4. Comparison with the published data

It appears that such type of work i.e. application of ANN on industrial data of sponge iron process is not available in the literature. Thus, it is not possible to compare the results of the present work with published literature. However, the comparison of results of ANN analysis with industrial data, shown in Table 6, 7 and Section 4.2.2, indicates that the error between two values fall within ±5%. Thus, the results of ANN analysis are compared well with the industrial data, which shows the reliability of the analysis.

However, the values of optimum operating parameters found through ANN are different in comparison to that are used in the process as shown in Fig. 1. The results of comparison are shown in Table 9. It shows that % deviation between two values is less than 4%, which indicates that to get desired values of output parameters one should change the values of input parameters slightly. In fact, these optimum input parameters also somewhat reduces the coal consumption. Further, it is noted that maintaining the input parameters at optimum values the values of temperatures, T-1 to T-12, fall with the feasible range i.e. less than 1100°C as shown in Table 6. Thus, present analysis also suits the process requirement.

5. Conclusions

In the present work the input output data of a typical sponge iron process are collected in two sets: Data-1 and Data-2. Sixteen ANN topologies are developed for each data set considering number of randomization, number of hidden layers, type of models, type of functions, number of epochs, etc. The salient features of the study are shown below:

1. For Data-1 TOP-11 with 2000 epochs finds best average value of R, which comes out as 0.7695. For this topology the MAE and NMSE are 10.25 and 0.403, respectively. The error analysis of TOP-11 shows that % errors observed in industrial values and that predicted through software are fall within ±10% which is reduced to ±4.6% by discarding very few points from industrial data.
2. The average value of R for Data-2 is maximum for TOP-7 when 2000 epochs are considered, which comes out as 0.9206. For this topology, value of MAE and NMSE are found as 0.09 and 0.162, respectively. The error analysis indicates that for flow rate of sponge iron the maximum deviation, E, is found as 3.99%.
3. For Data-2 topology, TOP-7, relates the input and output parameters well than that are carried out for Data-1 using TOP-11.
4. The tested output parameters meet the process requirements.
5. The values of input parameters correspond to desired output are found through ANN. Based on this analysis the optimum value of iron ore, feed coal, slinger coal and air at positions, AT-1, AT-2, AT-3, MF-1 and MF-2, is found as 23.4 tph, 8.7 tph, 8.9 tph and 79.223 m^3/h, respectively. These values are within 4% deviation than that are used in the process.

Nomenclature

d_i	Desired response for i^{th} exemplar
d_{ij}	Desired output for exemplar ‘i’ at processing element ‘j’
$\overline{d}$	Mean desired value for the dataset considered
N	Number of exemplars in the data set

P	Number of nodes in output layer
R	Coefficient of correlation
y_i	Network output for exemplar 'i'
$\bar{y}$	Mean network output value for the dataset considered

Abbreviations

ABC	After burning chamber
DSC	Dust settling chamber
ESP	Electrostatic precipitator
MAE	Mean absolute error
MSE	Mean square error
NMSE	Normalized mean square error
RC	Rotary cooler
RK	Rotary kiln
WHRB	Waste heat recovery boiler

Appendix A

Table A.1 Complete operating data of sponge iron process

Col.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
S. No.	Iron ore	Feed coal	Fines	Medium	Coarse	Sponge iron	AT-1	AT-2	AT-3	MF-1	MF-2	T-1	T-2	T-3	T-4	T-5	T-6	T-7	T-8	T-9	T-10	T-11	T-12
1	21	8.2	1.75	2.65	2.95	13.53	16	20	13	43	20	1091	1068	1081	1077	1076	1057	1061	1007	954	902	854	773
2	21.5	8.2	1.75	2.65	2.95	13.845	17	20	13	43	20	1094	1087	1083	1077	1068	1047	1044	1000	951	901	849	770
3	22	8.5	1.8	2.75	3	14.16	17	20	13	43	20	1081	1072	1064	1061	1064	1045	1051	1011	947	897	847	766
4	22.5	8.6	1.8	2.95	3.1	14.475	18	20	14	43	20	1079	1069	1062	1052	1077	1056	1075	1011	953	905	863	784
5	22.5	8.6	1.8	2.95	3.1	14.475	18	20	14	44	20	1055	1045	1038	1035	1080	1061	1062	1029	951	889	851	770
6	22.7	8.6	1.8	3	3.15	14.601	18	20	14	45	20	1043	1033	1026	1034	1083	1062	1070	1030	954	906	854	775
7	22.7	8.6	1.8	3	3.15	14.601	18	20	14	46	21	1064	1054	1047	1027	1085	1066	1065	1039	974	922	874	793
8	22.9	8.6	1.8	3	3.15	14.727	18	20	14	47	21	1057	1047	1040	1028	1081	1060	1074	1041	974	926	874	795
9	22.9	8.6	1.8	3	3.15	14.727	18	20	14	48	21	1080	1070	1063	1049	1092	1073	1076	1048	977	925	877	796
10	23	8.6	1.8	3	3.15	14.09	18	20	13	48	21	1089	1079	1072	1054	1103	1089	1082	1070	970	922	870	791
11	23	8.6	1.8	3	3.15	14.09	18	20	11	49	21	1103	1093	1086	1060	1102	1090	1085	1077	973	921	873	792
12	23	8.6	1.8	3	3.15	14.09	18	20	10	49	21	1099	1089	1082	1063	1094	1080	1077	1053	940	890	838	759
13	23	8.6	1.8	3	3.15	14.09	18	20	10	49	21	1108	1098	1091	1067	1089	1077	1065	1039	931	879	831	750
14	23	8.6	1.8	3	3.15	14.09	18	20	10	49	21	1106	1096	1089	1066	1084	1070	1060	1078	930	880	828	749
15	23	8.6	1.8	3	3.15	14.09	18	20	10	49	21	1102	1092	1085	1062	1090	1078	1071	1036	932	882	834	753
16	23	8.6	1.75	3	3.15	14.09	19	20	10	49	21	1097	1087	1080	1060	1092	1078	1078	1049	939	891	839	760
17	23	8.6	1.75	3.15	3.15	14.09	19	20	10	49	21	1092	1082	1075	1049	1096	1084	1089	1062	946	896	848	767
18	23	8.6	1.8	3.15	3.2	14.09	18	21	10	49	20	1079	1069	1062	1046	1109	1095	1097	1064	948	898	846	767
19	23	8.6	1.8	3.15	3.2	14.09	18	21	10	49	20	1066	1056	1049	1046	1104	1102	1092	1055	944	894	846	765
20	23	8.6	1.8	3.15	3.2	14.09	18	21	10	49	20	1059	1049	1042	1047	1104	1100	1091	1058	949	899	847	768
21	23	8.6	1.75	3.15	3.2	14.09	18	21	10	49	20	1071	1061	1054	1060	1104	1092	1087	1056	927	884	841	760
22	23	8.6	1.75	3.15	3.2	14.09	18	21	10	49	20	1105	1095	1088	1087	1088	1074	1088	1061	925	882	835	756
23	23	8.7	1.75	3.3	3	14.09	19	21	10	49	20	1104	1094	1087	1089	1101	1089	1069	1031	920	877	834	753
24	23	8.7	1.75	3.3	3	14.09	19	21	10	49	20	1099	1089	1082	1088	1102	1088	1069	1030	916	950	826	747

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