Application of Artificial Neural Network Modeling for Predicting the Ferro Alloys Furnace Output

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1. Introduction

The major input to ferroalloys industry is the natural resources (ore). Availability of consistent quality of ore is very difficult. In order to maintain consistency in the quality of output, it is necessary to predict the output quality with respect to a set of input mix. The general practice in ferroalloys manufacturing is to prepare a material balance (charge mix) for a particular quality of output and keep on fine tuning the mix based on the tapping analysis and desired output. However, in this process generation of deviated quality product takes place resulting in increase in the cost of quality.

Recent research activities in artificial neural networks (ANNs) have shown that ANNs have powerful pattern classification and pattern recognition capabilities. Inspired by biological systems, particularly by research into the human brain, ANNs are able to learn and generalize from experience. Currently, ANNs are being used for a wide variety of tasks in many different fields of business, industry and science (Widrow et al., 1994). One major application area of ANNs is forecasting (Sharda, 1994). ANNs provide an attractive alternative tool for both forecasting researchers and practitioners. Several distinguishing features of ANNs make them valuable and attractive for forecasting task.

Currently the furnace output is monitored by trial and error method. At the end of each/alternate tapping, metal and slag samples are tested against the desired chemical composition. Based on the laboratory analysis, necessary corrections are made in the charge mix on a regular basis to minimize the deviation in the quality of the product. This is a humble effort made to predict the furnace behavior parameters using ANN. Here, ANN has been developed for predicting the quality of output and other important key parameters.

3. Model Input

Following data of 295 consecutive heats (tapings) of a furnace producing Ferrochrome alloys were collected as an input to the model.

- Chemical composition of charge mix,
- Furnace operating parameters and
- Furnace output data respective to the input

The following parameters having strategic importance to the furnace operations, were taken to be the input to the ANN model.

3(a) Input Parameters.

The following nine parameters were considered as input to the model. Cr_2O_3, Chromium, SiO_2, CaO, MgO, Al_2O_3, Phosphorus, Fixed Carbon (FC), Friable Chrome ore (-5mm size),

Cr2O3 and Chromium – This is the basic input to produce chromium alloy. The input is in the form of friable or lumpy ore, sinters or briquette of chrome ore. The cost of chrome ore is about 50% of the total raw material cost. Chromium oxides, along with carbon, get reduced to chromium to form the major part of alloy and carbon oxides exhaust in the form of gas.

SiO_2, CaO, MgO, Al_2O_3 - This elemental input through chromite ore, flux and reductants forms a part of the material mix. In the process of reduction, these elements carry the impurities of Alloy and form a major part of the slag.

Phosphorus- This is one of the undesirable elements present in almost all the input materials and gets reduced to metal. Presence of this element more than 4 kg per metric ton of alloy is not accepted in the export market. Though the presence is negligible, it is one of the critical elements of alloy. Coke is the main source of input of Phosphorus to the alloy.

Fixed Carbon (FC) – Fixed Carbon is the reducing agent in the ferroalloys Manufacturing Process. Low Ash Metallurgical Coke, Anthracite coal, etc., which contains about more than 85% of fixed carbon, are used as reductant. The reductant constitutes 45% of the raw material cost. Chromium recovery and reduction process efficiency primarily depends upon the quality of reductant.

(-) 5 mm ore – Major portion of the Chrome ore is available in friable form. The friable ore cannot be fed to furnace due to its poor reactivity. Chrome ore briquettes with the lime and molasses binders are used in the furnace, but along with the briquette, some – 5mm friable ore is also used.

3(b) Output Parameters.

The following six output parameters were selected for the model as they represent the important parameters of the ferroalloys furnace operations.

- Specific Power Consumption (Mw/MT)
- MgO/Al_2O_3
- $(MgO+CaO)/SiO_2$
- Slag Volume (no. of times of metal volume)
- Cr (Chromium) Recovery (%)
- Chromium in Alloy (%)

Specific Power – Ferroalloys manufacturing is very power-intensive. Power cost is about 45% of the product cost. Power consumption depends upon many factors. The most important ones are the charge (raw material mix) conductivity and slag volume. The higher the impurity in the raw material, the higher the power consumption is.

MgO/Al_2O_3, $(MgO+CaO)/SiO_2$, Slag Volume – In ferroalloys manufacturing, slag formation and slag chemistry is as important as that of metal. The basicity of slag need more attention and is very much essential to maintain at desired level for slag metal separation. Slag volume is also a very important parameter. The higher the slag volume the higher the power consumption is, and therefore it needs to be maintained at an optimum level.

Chromium Recovery – The process efficiency of ferrochrome manufacturing is measured by the chromium recovery .Chromium recovery depends upon many factors. Few important factors include the reductant mix, charge porosity and conductivity, electrode length, etc. Recovery below 79% is considered to be poor. The cost of production increases with reduction in recovery.

Cr% in Alloy – The sales price of chromium alloy is based on the chromium content in the Alloy. The base price is based on 60% chromium content in the Alloy and the actual price of the alloy is decided by prorating the chromium content in the alloy. So this parameter is very much significant for the ferroalloys industry.

4. Model Formulation and Execution

Furnace operational data from 295 heats (7 experiments) are used for training and validation of the ANN model. The structure of the neural network is as depicted in Fig 1. Five different combination options consisting of the following parameters are made for training validation. The details of different combination options are mentioned in Table 1.

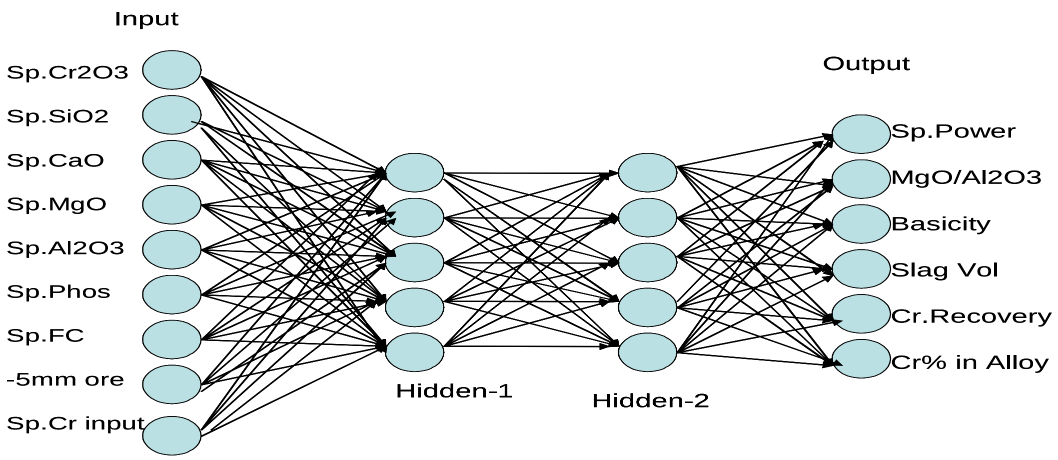

Fig.1 Structure of the neural network for predicting the furnace output

Parameters considered for ANN Network Architecture

Number of Hidden Layers (2), No of input (9), No of Output (7)

Learning parameter, Momentum, Hidden Layer sizes and Initial weight age

Training and Validation options

Present Inputs (whether in Random order or not), No. of Training cycles
Training Mode (Batch or Sequential)

Table: 1 Different combination options of ANN Network Architecture, Training options, Validation options and Other Parameters

ANN Network Architecture

	Option-1	Option-2	Option-3	Option-4	Option-5
Number of Input – 9 nos	9	9	9	9	9
Number of Outputs-7 nos	7	7	7	7	7
Momentum	0.4	0.5	0.6	0.7	0.9
Learning parameters	0.5	0.7	0.5	0.7	0.5
No of Hidden Layers	2	1	2	1	2
Hidedn Layer Size	2	4	2	4	2
Initial weight range	0.5	0.7	0.5	0.7	0.5

Training Options

Input order (Whether in random order or not)	No	Yes	No	Yes	No
No of Training Cycles	250	200	250	200	250
Training Mode (Batch or Sequential)	Sequential	Batch	Sequential	Batch	Sequential

Training and validation of the ANN was conducted in the above combination options as mentioned in Table 1. Seven experiments were conducted in the furnace in a controlled environment. The output data with respect to the input parameter to the ANN module are collected for testing the models. The details of the data collected from the experiments are given in Tables 2 to 9.

Table 2. Furnace Experiment data (295 heats)

Input to the Furnace (295 heats)

	Exp-1	Exp-2	Exp-3	Exp-4	Exp-5	Exp-6	Exp-7
Cr_2O_3	1.022	1.0567	1.028	1.047	1.046	1.049	1.049
Sio_2	0.358	0.384	0.415	0.474	0.436	0.352	0.440
Cao	0.106	0.115	0.135	0.170	0.112	0.108	0.114
Mgo	0.238	0.251	0.256	0.283	0.244	0.280	0.283
Al_2O_3	0.329	0.334	0.317	0.300	0.316	0.319	0.319
Phos	0.003	0.003	0.004	0.004	0.004	0.004	0.004
FC	0.411	0.411	0.411	0.409	0.412	0.402	0.402
-5mm ore	0.19	0.10	0.12	0.080	0.090	0.140	0.150
Cr	0.699	0.723	0.703	0.717	0.716	0.717	0.717

Furnace Output (295 heats)

Power	Mwh/MT	3.72	3.7	3.78	3.69	3.698	3.71	3.71
Mgo/Al2O3		0.84	0.75	0.81	0.95	0.84	0.88	0.89
Mgo+Cao/Sio2		1.124	1.119	1.236	1.179	1.100	1.110	1.117
Slag Volume	Mt	1.27	1.28	1.31	1.30	1.29	1.29	1.28
Cr Recovery	%	82%	82%	83%	82%	80.9%	82%	81%
Cr% in Alloy	%	59.56	60.01	59.64	59.7	59.85	60.1	60

The above actual furnace input data is fed to ANN module developed with five different combination options (table-1) and the output of the ANN module was compared with the actual furnace output to check the correctness of the prediction by ANN. The details of experiments are presented in Tables 3 to 9.

Table 3. Actual data of experiment 1 and output of ANN module having trained in different option combinations.

Experiment-1				
Input (MT/MT of FeCr)		Furnace output		
Cr_2O_3	1.022	Power	Mwh/MT	3.72
Sio_2	0.358	Mgo/Al2O3		0.84
Cao	0.106	Mgo+Cao/Sio2		1.124
Mgo	0.238	Slag Volume	Mt	1.27
Al_2O_3	0.329	Cr Recovery	%	82%
Phos	0.003	Cr% in Alloy	%	59.56%
FC	0.411			
Cr	0.699			

ANN Model output at different option

Parameters	Units	Option-1		Option-2		Option-3		Option-4		Option-5	
		ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual
Power	Mwh/MT	3.72	0%	3.357	10%	3.652	2%	3.56	4%	3.729	0%
Mgo/Al2O3		0.78	7%	1.05	-25%	0.825	2%	0.84	-1%	0.88	-5%
Mgo+Cao/Sio_2		1.09	3%	1.42	-26%	1.066	5%	1.236	-10%	1.138	-1%
Slag Volume	Mt	1.22	4%	1.581	-24%	1.274	0%	1.289	-1%	1.26	1%
Cr Recovery	%	79%	4%	76%	7%	0.799	3%	87%	-6%	81%	1%
Cr% in Alloy	%	62%	-4%	63%	-6%	0.616	-3%	60.01%	-1%	60.45%	-1%

Table 4. Actual data of experiment 2 and output of ANN module having been trained in different option combinations

Experiment-2				
Input (MT/MT of FeCr)		Furnace output		
Cr_2O_3	1.0567	Power	Mwh/MT	3.7
Sio_2	0.384	Mgo/Al2O3		0.75
Cao	0.115	Mgo+Cao/Sio2		1.119
Mgo	0.251	Slag Volume	Mt	1.28
Al_2O_3	0.334	Cr Recovery	%	82%
Phos	0.003	Cr% in Alloy	%	60.01%
FC	0.411			
Cr	0.723			

ANN Model output at different option

Parameters	Units	Option-1		Option-2		Option-3		Option-4		Option-5	
		ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual
Power	Mwh/MT	3.72	-1%	3.357	9%	3.638	2%	3.560	4%	3.712	0%
Mgo/Al2O3		0.78	-5%	1.05	-41%	0.8254	-10%	0.842	-12%	0.775	-3%
Mgo+Cao/Sio_2		1.093	2%	1.42	-27%	1.063	5%	1.232	-10%	1.13	-1%
Slag Volume	Mt	1.23	4%	1.581	-24%	1.275	0%	1.284	0%	1.261	1%
Cr Recovery	%	79%	4%	76%	7%	80%	2%	87.2%	-6%	80.80%	1%
Cr% in Alloy	%	62.10%	-3%	63%	-5%	62%	-3%	60%	0%	60.40%	-1%

Table 5. Actual data of experiment 3 and output of ANN module having been trained in different option combinations.

Experiment-3				
Input (MT/MT of FeCr)		Furnace output		
Cr_2O_3	1.028	Power	Mwh/MT	3.78
Sio_2	0.415	Mgo/Al2O3		0.81
Cao	0.135	Mgo+Cao/Sio2		1.236
Mgo	0.256	Slag Volume	Mt	1.31
Al_2O_3	0.317	Cr Recovery	%	83%
Phos	0.004	Cr% in Alloy	%	59.64%
FC	0.411			
Cr	0.703			

ANN Model output at different option

Parameters	Units	Option-1		Option-2		Option-3		Option-4		Option-5	
		ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual
Power	Mwh/MT	3.725	1%	3.357	11%	3.91	-3%	3.5901	5%	3.8834	-3%
Mgo/Al2O3		0.781	3%	1.05	-30%	0.913	-13%	0.8521	-6%	0.821	-2%
Mgo+Cao/Sio_2		1.093	12%	1.42	-15%	1.229	1%	1.2439	-1%	1.2169	2%
Slag Volume	Mt	1.228	6%	1.581	-21%	1.294	1%	1.2652	3%	1.2944	1%
Cr Recovery	%	79%	5%	77%	7%	85%	-2%	86.01%	-4%	83.81%	-1%
Cr% in Alloy	%	62%	-4%	63%	-6%	61%	-2%	60.34%	-1%	60.74%	-2%

Table 6. Actual data of experiment 4 and output of ANN module having been trained in different option combinations.

Experiment-4				
Input (MT/MT of FeCr)		Furnace output		
Cr_2O_3	1.047	Power	Mwh/MT	3.69
Sio_2	0.474	Mgo/Al2O3		0.95
Cao	0.170	Mgo+Cao/Sio2		1.179
Mgo	0.283	Slag Volume	Mt	1.3
Al_2O_3	0.300	Cr Recovery	%	82%
Phos	0.004	Cr% in Alloy	%	59.70%
FC	0.409			
Cr	0.717			

Parameters	Units	Option-1		Option-2		Option-3		Option-4		Option-5	
		ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual
Power	Mwh/MT	3.803	-3%	3.357	9%	3.692	0%	3.525	4%	3.743	-1%
Mgo/Al2O3		0.813	14%	1.05	-11%	0.815	14%	0.843	11%	0.924	2.33%
Mgo+Cao/Sio_2		1.126	4%	1.42	-20%	1.06	10%	1.223	-4%	1.145	3%
Slag Volume	Mt	1.255	3%	1.581	-22%	1.268	2%	1.284	1%	1.267	3%
Cr Recovery	%	79%	4%	76%	7%	80.20%	2%	88.30%	-8%	81.30%	1%
Cr% in Alloy	%	62.30%	-4%	63%	-6%	61.60%	-3%	59.70%	0%	60.50%	-1%

Table 7. Actual data of experiment 5 and output of ANN module having been trained in different option combinations

Experiment-5				
Input (MT/MT of FeCr)		Furnace output		
Cr_2O_3	1.046	Power	Mwh/MT	3.698
Sio_2	0.436	Mgo/Al2O3		0.84
Cao	0.112	Mgo+Cao/Sio2		1.1
Mgo	0.244	Slag Volume	Mt	1.29
Al_2O_3	0.316	Cr Recovery	%	80.90%
Phos	0.004	Cr% in Alloy	%	59.85%
FC	0.412			
Cr	0.716			

Parameters	Units	Option-1		Option-2		Option-3		Option-4		Option-5	
		ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual
Power	Mwh/MT	3.725	-1%	3.357	9%	3.637	2%	3.54	4%	3.688	0%
Mgo/Al2O3		0.781	7%	1.05	-25%	0.822	2%	0.841	0%	0.869	-3%
Mgo+Cao/Sio_2		1.093	1%	1.42	-29%	1.06	4%	1.226	-11%	1.118	-2%
Slag Volume	Mt	1.228	5%	1.581	-23%	1.273	1%	1.286	0%	1.256	3%
Cr Recovery	%	78.58%	3%	75.60%	7%	79.80%	1%	87.87%	-9%	80.42%	1%
Cr% in Alloy	%	62.11%	-4%	63.81%	-7%	61.63%	-3%	59.83%	0%	60.37%	-1%

Table 8. Actual data of experiment 6 and output of ANN module having been trained in different option combinations.

Experiment-6				
Input (MT/MT of FeCr)		Furnace output		
Cr_2O_3	1.049	Power	Mwh/MT	3.71
Sio_2	0.352	Mgo/Al2O3		0.88
Cao	0.108	Mgo+Cao/Sio2		1.11
Mgo	0.280	Slag Volume	Mt	1.29
Al_2O_3	0.319	Cr Recovery	%	82%
Phos	0.004	Cr% in Alloy	%	60.10%
FC	0.402			
Cr	0.717			

Parameters	Units	Option-1		Option-2		Option-3		Option-4		Option-5	
		ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual
Power	Mwh/MT	3.725	0%	3.357	10%	3.648	2%	3.5531	4%	3.7288	-1%
Mgo/Al2O3		0.781	11%	1.05	-19%	0.829	6%	0.84481	4%	0.8801	0%
Mgo+Cao/Sio_2		1.093	2%	1.42	-28%	1.07	4%	1.235491	-11%	1.138	-3%
Slag Volume	Mt	1.228	5%	1.581	-23%	1.277	1%	1.286158	0%	1.2644	2%
Cr Recovery	%	78.58%	4%	75.60%	8%	79.91%	3%	87.18%	-6%	81.03%	1%
Cr% in Alloy	%	62.11%	-3%	63.81%	-6%	61.63%	-3%	59.94%	0%	60.45%	-1%

Table 9. Actual data of experiment 7 and output of ANN module having been trained in different option combinations.

Experiment-7				
Input (MT/MT of FeCr)		Furnace output		
Cr_2O_3	1.049	Power	Mwh/MT	3.71
Sio_2	0.440	Mgo/Al2O3		0.89
Cao	0.114	Mgo+Cao/Sio2		1.117
Mgo	0.283	Slag Volume	Mt	1.28
Al_2O_3	0.319	Cr Recovery	%	81%
Phos	0.004	Cr% in Alloy	%	60%
FC	0.402			
Cr	0.717			

Parameters	Units	**Option-1**		**Option-2**		**Option-3**		**Option-4**		**Option-5**	
		ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual	ANN model Prediction	% Actual
Power	Mwh/MT	3.725	0%	3.357	10%	3.641	2%	3.533	5%	3.693	0%
Mgo/Al2O3		0.781	12%	1.05	-18%	0.82	7%	0.842	5%	0.87	2%
Mgo+Cao/Sio_2		1.093	2%	1.42	-27%	1.06	5%	1.227	-10%	1.12	0%
Slag Volume	Mt	1.228	4%	1.581	-24%	1.273	1%	1.288	-1%	1.257	2%
Cr Recovery	%	79%	2%	75.60%	7%	79.80%	1%	0.88	-9%	80.50%	1%
Cr% in Alloy	%	62%	-3%	63.81%	-6%	61.60%	-3%	59.7%	0%	60.40%	-1%

5. Observations

It was observed from the experiments that the neural network developed and trained with the Option-5 combinations gives the best output having less deviation from the actual furnace performance. The summary of deviations from the actual performance is presented in Table 10. The table shows the experiment wise percentage deviation of output derived from ANN developed with different options.

Table 10. Summary of deviations between ANN Model prediction and actual performance

	Experiment -1					Experiment -2					Experiment -3				
	Opt-1	Opt-2	Opt-3	Opt-4	Opt-5	Opt-1	Opt-2	Opt-3	Opt-4	Opt-5	Opt-1	Opt-2	Opt-3	Opt-4	Opt-5
Sp.Power	0%	10%	2%	4%	**0%**	-1%	9%	2%	4%	**0%**	1%	11%	-3%	5%	**-3%**
MgO/Al2O3	7%	-25%	2%	-1%	**-5%**	-5%	-41%	-11%	-13%	**-4%**	3%	-30%	-13%	-6%	**-2%**
(MgO+CaO)/SiO2	3%	-26%	5%	-10%	**-1%**	2%	-27%	5%	-10%	**-1%**	12%	-15%	1%	-1%	**2%**
Slag Volume	4%	-24%	0%	-2%	**0%**	4%	-24%	0%	0%	**1%**	6%	-21%	1%	3%	**1%**
Cr Recovery	4%	7%	3%	-6%	**1%**	4%	7%	3%	-6%	**1%**	5%	7%	-2%	-4%	**-1%**
Cr% in Prime	-4%	-6%	-3%	-1%	**-1%**	-3%	-5%	-3%	0%	**-1%**	-4%	-6%	-2%	-1%	**-2%**

	Experiment -4					Experiment -5					Experiment -6				
	Opt-1	Opt-2	Opt-3	Opt-4	Opt-5	Opt-1	Opt-2	Opt-3	Opt-4	Opt-5	Opt-1	Opt-2	Opt-3	Opt-4	Opt-5
Sp.Power	-3%	9%	0%	4%	**-1%**	-1%	9%	2%	4%	**0%**	0%	10%	2%	4%	**-1%**
MgO/Al2O3	14%	-11%	14%	11%	**2%**	7%	-25%	2%	0%	**-3%**	11%	-20%	6%	4%	**0%**
(MgO+CaO)/SiO2	4%	-20%	10%	-4%	**3%**	1%	-29%	4%	-11%	**-2%**	2%	-28%	4%	-11%	**-3%**
Slag Volume	3%	-22%	2%	1%	**3%**	5%	-23%	1%	0%	**3%**	5%	-23%	1%	0%	**2%**
Cr Recovery	4%	7%	2%	-8%	**1%**	3%	7%	1%	-9%	**1%**	4%	8%	3%	-6%	**1%**
Cr% in Prime	-4%	-6%	-3%	0%	**-1%**	-4%	-7%	-3%	0%	**-1%**	-3%	-6%	-3%	0%	**-1%**

	Experiment -7				
	Opt-1	Opt-2	Opt-3	Opt-4	Opt-5
Sp.Power	0%	10%	2%	5%	**0%**
MgO/Al2O3	12%	-18%	7%	5%	**2%**
(MgO+CaO)/SiO2	2%	-27%	5%	-10%	**0%**
Slag Volume	4%	-24%	1%	-1%	**2%**
Cr Recovery	2%	7%	1%	-9%	**1%**
Cr% in Prime	-3%	-6%	-3%	0%	**-1%**

6. Validating the prediction of ANN Model with actual Furnace output

The above data was processed in the ANN developed and trained with Option 5 parameter combinations. The predictions of the neural network compared with the parameters of the actual furnace output are reported in Table 12.

It has been observed that the prediction of the neural network is reasonably good as compared to the actual output of the furnace. The graphical presentations of ANN prediction w.r.t the actual experiment are presented in Fig 2 to Fig.7.

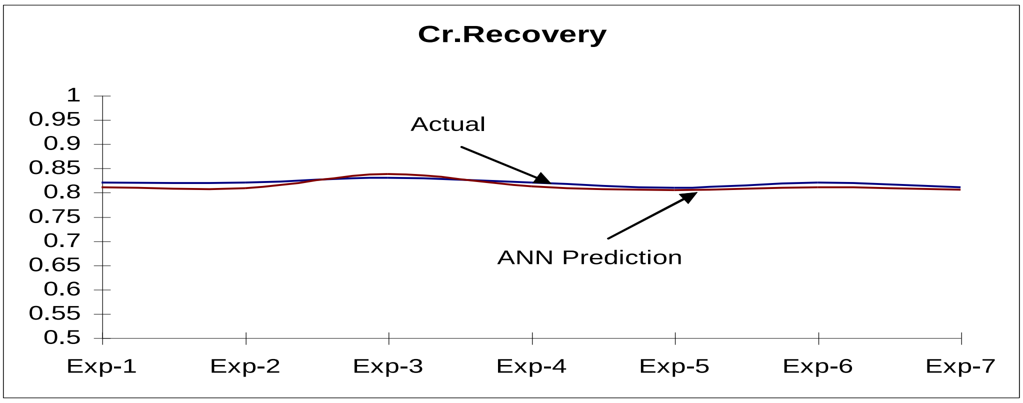

Fig 2. Prediction w.r.t the actual Experiment (Cr.Recovery)

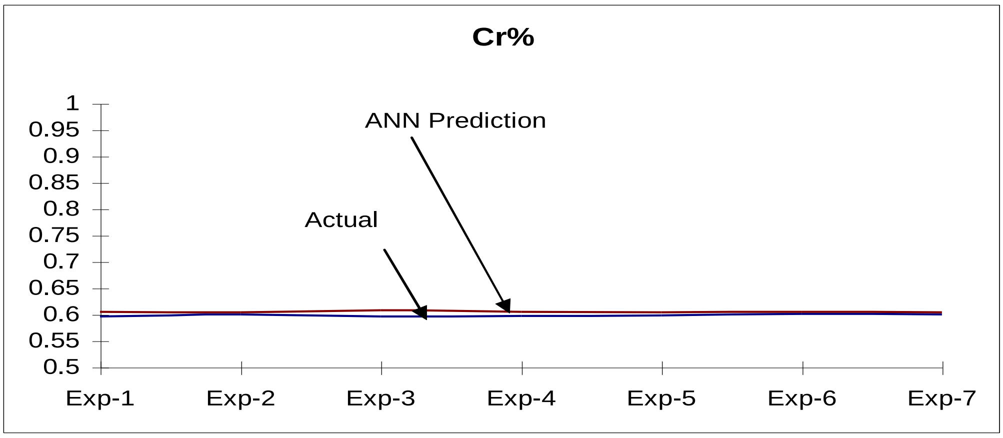

Fig 3. ANN prediction w.r.t the actual Experiment (Cr%)

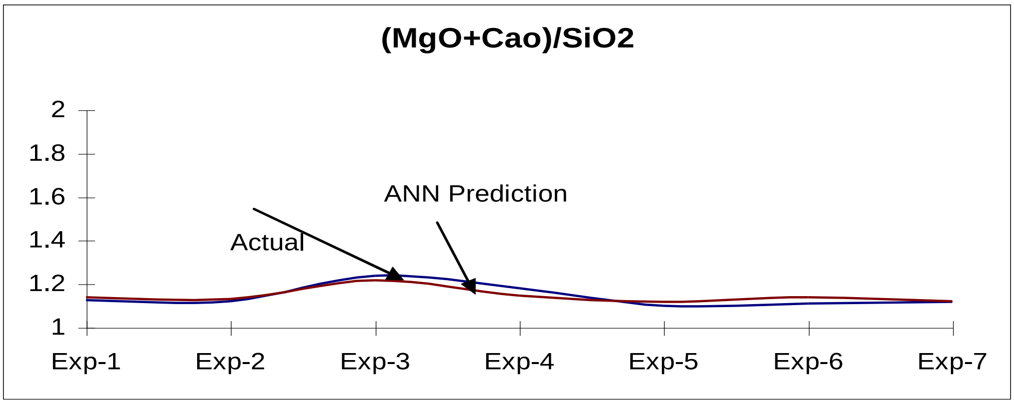

Fig 4. ANN prediction w.r.t the actual Experiment (MgO+CaO)SiO2.

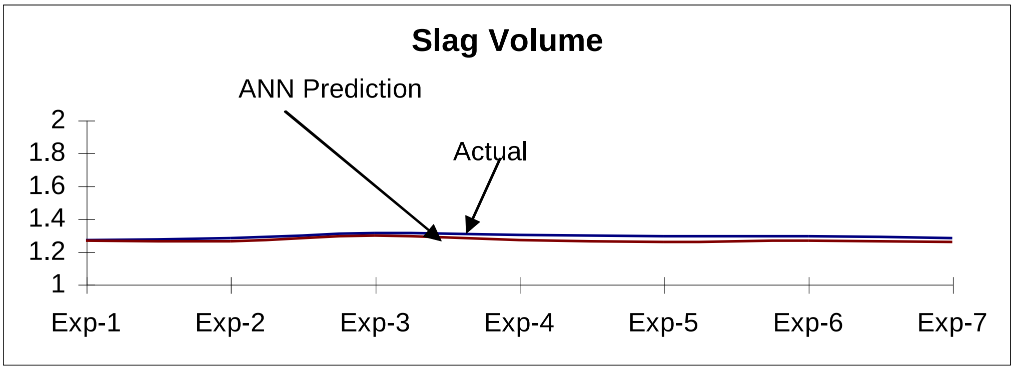

Fig 5. ANN prediction w.r.t the actual Experiment slag volume

7 Conclusions

The model has been developed using a limited number of data. The prediction can be more accurate with increase in data volume. The important findings in the implementation of ANN for predicting the furnace output with certain input can be summarized as follows:

•The unique characteristics of ANNs – adaptability, nonlinearity, arbitrary function mapping ability – make them quite suitable and useful for forecasting tasks. Overall, ANNs give satisfactory performance in forecasting.

•There are many factors that can affect the performance of ANNs. The shotgun trial-and-error methodology for specific problems is typically adopted by most researchers which is the primary reason for inconsistencies in different combinations.

The model facilitates in predicting the output of the furnace before producing the metal. This will result in

- Minimizing the off grade production
- Minimizing the quality cost
- Deciding on the raw material mix
- Predicting the furnace behaviour with given set of input.

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