Soft-computing approach to predict cost and performance of natural gas combined cycle (NGCC) plants using carbon dioxide capture

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Abstract Coal is the backbone of the Indian power sector with more than 60 % of the net installed electricity capacity being coal-based. Among other fossil fuels, natural gas also contributes significantly to the power sector in India. This contribution may increase in the future with exploration of new reserves of unconventional gases, more stringent climate norms and so on. Concurrently, the global climate change problem also becomes more enhanced if larger dependence on fossil fuels remains. In some scenarios, carbon dioxide (CO₂) capture and storage (CCS) with natural gas combined cycle (NGCC) may be a feasible technological alternative. Such a scenario is manifested by some critical factors such as low natural gas prices and high carbon tax, among others. Nevertheless, several parameters remain highly uncertain if CCS is to be introduced in NGCC plants. As a result, modern computational techniques such as soft-computing approaches may be used to generate predictive models for cost and performance in such plants. This paper utilizes one such technique, multi-gene genetic programming (MGGP) to generate predictive models for cost of electricity (with coefficient of determination, $R^2 > 95$ %), CO₂ emission factor and net plant efficiency ($R^2 > 98$ %). The sensitivity analysis carried out for these parameters show results which are expected in real situations. Subsequently, the calculation of the CO₂ avoidance cost and energy penalty for a hypothetical case is demonstrated. The results show that MGGP can be successfully used in such applications.

Keywords NGCC · Genetic programming · Carbon capture and storage · Fossil fuel · Climate change

Introduction

India is heavily reliant upon coal for meeting its electricity demands, with more than 60 % of its installed power capacity being coal based. However, a significant portion of the installed capacity (~8.5 %) also comprises of natural gas fired power plants (CEA 2016). These plants, which work using combined cycle operation, provide cleaner electricity with less environmental impacts. However, because of India's low natural gas reserves, such power has never dominated the national scene.

The future electricity market in India may have a slightly larger role of natural gas, with the following considerations:

1. Natural gas prices in India have been steeply falling for the past few years because of the falling gas prices internationally. If such a decline continues, it may provide a slight boost to gas based power in India.
2. Post the Paris climate agreement, coal use in India and China has come under a lot of scrutiny. If international pressure rises, then natural gas may fill in the demands where renewable sources of electricity cannot be deployed.
3. Exploration for shale gas, coal-bed methane and underground coal gasification may help bridge the gas deficit in India.
4. Imported natural gas was used mostly as liquefied natural gas (LNG). However, with the inception of the Turkmenistan–Afghanistan–Pakistan–India (TAPI) pipeline, imported natural gas may also be utilized for power generation purposes.

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If natural gas comes to occupy a substantial chunk of the Indian power market in the future, then decarbonisation options associated with NGCC plants will have to be explored. This is so because Sathaye and Shukla (2013) have projected that there will be no single technology, which can play an overwhelming role in resolution of the climate change crisis. As a result, carbon dioxide (CO₂) capture in natural gas plants is an area which needs to be studied at least for techno-economic assessment. This area has not been explored by other researchers, since coal remains the single largest source of electricity in India. Thus, while many works have focussed on CO₂ capture and storage (CCS) in coal-fired power plants (Karmakar and Kolar 2013; Rao and Kumar 2014; Singh and Rao 2014a, b), none have estimated the cost of avoidance associated with carbon-dioxide capture and storage (CCS) in Indian NGCC plants.

In this paper, we initially simulate a natural gas combined cycle plant, based on current Indian financial parameters. Subsequently, the parameters are varied on hypothetical basis, but values are selected to be suitable in real plant conditions. On the basis of these realistic values, simulations are carried out to estimate the cost, emissions and performance of the plants. The system is then translated into a soft-computing domain using multi-gene genetic programming (MGGP) technique. The reader may refer to Garg et al. (2014a) for details on MGGP. Subsequently, parametric analysis is carried out and models for calculating the cost of CO₂ avoidance are generated.

Implementing NGCC with CCS in India offers different challenges than elsewhere (say, USA, which has a greatly increasing shale gas reserve). A large volume of natural gas in India is imported and this trend is likely to increase in light to the inauguration of the TAPI pipeline. This renders the gas price to a high volatility. Also, O&M costs in India are different, which have been compiled in Table 1 and included in this paper. Other parameters such as debt-equity ratio also vary depending on the country and legal framework.

Context of this Paper

The global climate change crisis has been identified as one of the major problems across the world. For countering this, our recent dependence on fossil fuels will have to decrease. However, unconventional sources of energy have not been developed in a cost-effective way so far to completely replace fossil fuels in the power sector. Thus, CO₂ capture and storage (CCS) is commonly identified as a transition technology en-route to an energy mix with lower dependence on fossils (Maroto-Valer 2011).

India has a high degree of reliance on coal. This, coupled with the fact that coal based power plants have a

higher CO₂ emission factor (mass of CO₂ emitted per unit of electricity generated), has meant that most of the research carried so far for CCS in India has been based on coal based power. Several works have identified the implications of CCS on the economics, costs, gaseous and particulate emissions, resource consumption and the overall energy sector of India. However, majority of these works (listed in Table 1) deal with coal based CCS on the capture front. Other works, of course pertain to source-sink matching and CO₂ storage.

Garg et al. (2014b) utilized a multi-model comparison which looked at several conventional and rigorous strategies for greenhouse gas (GHG) abatement. They have concluded that in a carbon constrained scenario, natural gas based energy will play a considerable role in India due to its lower carbon content and because it can supply electricity during peak hours. Also, in some models such as the TIAM-ECN model and the WITCH model, the composition of CCS based power is higher for gas based plants than coal based plants, under specific scenarios. As a result, we need to understand the implications of CO₂ capture on natural gas combined cycle (NGCC) plants in India.

Many international studies have studied how CCS would affect costs and performance of NGCC plants (Rubin et al. 2007; Rubin and Zhai 2012; Grande et al. 2009; Berstad et al. 2011). In India however, even if CO₂ capture is integrated into NGCC plants, it will be met with a large degree of uncertainty in the parameters on account of being a new technology. Thus, this paper will develop predictive models to understand the functioning of NGCC plants with CO₂ capture. It is also sought to understand if a soft-computing technique (viz, multi-gene genetic programming or MGGP, used in this paper) can suitably predict the cost and performance parameters and also represent the uncertainty encountered in such applications. The advantage of MGGP compared to other soft-computing techniques is its ability to generate predictive equations without assuming any prior relationship between the parameters (Kaydani et al. 2014). Thus, it helps in de-linking of the operating parameters which is of use to the present application, as shown in the sensitivity analysis in “Results and Discussion”.

Many other researchers have also utilized soft-computing techniques such as fuzzy algorithms and neural networks to CCS based applications. Zhou et al. (2010) developed a neuro-fuzzy predictive model for predicting of CO₂ production rate and other output parameters from four input parameters such as CO₂ concentration in flue gas, steam flow rate, sorbent concentration and sorbent flow rate. They found out that such processes had an accuracy of greater than 90 % for predicting the output. Zhou et al. (2011) compared neural network and neuro-fuzzy analysis for predicting CO₂ capture process parameters. They suggested that the rule-base developed in neuro-fuzzy

Table 1 Year-wise O&M costs for the gas power plants in India

Plant	Year	Net generation (MU)	O&M cost (Rs in lakh)	O&M cost (M\$) ^a	O&M (\$/MWh) ^b
Anta	2008–2009	2456.19	6695.5	10.30	4.19
	2009–2010	2933.49	6043.5	9.30	3.17
	2010–2011	2420.77	7561.4	11.63	4.80
	2011–2012	2420.77	6758.5	10.40	4.30
	2012–2013	2125.08	9015.3	13.87	6.53
Kawas	2008–2009	3429.6	9622.14	14.80	4.32
	2009–2010	4253.5	10,218.7	15.72	3.70
	2010–2011	3808.5	11,385.18	17.52	4.60
	2011–2012	3540.6	11,042.4	16.99	4.80
	2012–2013	2839	12,918.67	19.87	7.00
Dadri gas	2008–2009	5153.9	13,525.39	20.81	4.04
	2009–2010	5475	9373.39	14.42	2.63
	2010–2011	5271.2	9214.63	14.18	2.69
	2011–2012	5247.1	9875.78	15.19	2.89
	2012–2013	4311.6	9418.88	14.49	3.36
Gandhar ^c	2009–2010	4423.7	9365.47	14.41	3.26
	2010–2011	3990.3	10,605.95	16.32	4.09
	2011–2012	3618.9	12,710.18	19.55	5.40
	2012–2013	3414.3	10,666.38	16.41	4.81
Faridabad	2008–2009	2317.94	5753.25	8.85	3.82
	2009–2010	3143.33	5144.91	7.92	2.52
	2010–2011	3087.51	9323.05	14.34	4.64
	2011–2012	3002.82	11,517.7	17.72	5.90
	2012–2013	1608.49	7250.93	11.16	6.94

Source: CERC, <http://www.cercind.gov.in/NTPC.html>

^a Using exchange rate of US\$ = Rs. 65

^b 1 MU = 1000 MWh

^c The O&M cost for Gandhar plant was taken only for 4 years because the figure for the year 2008–2009 was abnormally high

technique can help in optimizing the process. Tan et al. (2010) developed crisp and fuzzy programming models in optimal planning of CO₂ capture retrofitting in the power sector.

Several technical and financial factors are likely to affect the prospects of NGCC based CCS in India. Some of them include the plant load factor, type of capture technology, turbine inlet temperature etc. Another major instrument, which is likely to give CCS a push, is tax on CO₂ (Shukla et al. 2010; Shukla and Chaturvedi 2013). The natural gas prices, which have been on a declining trend for some time, now, are also a crucial factor. Government of India released the *New Domestic Natural Gas Pricing Guidelines* which made the gas prices in India highly dependent on the natural gas pricing. This creates an inherent uncertainty in the gas pricing. Nevertheless, Shukla et al. (2009) have projected that at a price of less than US\$ 4/MBtu, gas compares favorably against coal as a base-load option.

The above factors are likely to result in a dynamic scenario, with wide ranging economic aspects of technologies and numerous operating parameters. Due to this, policymakers may desire a tool which accounts for uncertainty while also reducing estimation times. A modern soft-computing technique such as MGGP can result in meeting both these objectives. For instance, the equations and graphic results developed in “[Results and Discussion](#)” can help in calculating deviation in overall COE and efficiency, if operating parameters change by a certain degree. As a result, soft-computing techniques help in dual intertwined advantages for NGCC plants i.e. reduction in estimation times and accounting of uncertainty. Similar approaches using other intelligent techniques such as artificial neural networks (ANN) and multivariate regression analysis (MVRA) have been used in prediction of CO₂ adsorption isotherms for Indian geologic formations (Verma and Sirvaiya 2016a, b).

Methodology

The methodology for the above study involves four basic steps. The methodological framework for the study is shown in Fig. 1.

Simulating a typical Indian NGCC plant

Firstly, a typical NGCC plant in India is simulated using the cost assumptions for capital investments and average operation and maintenance (O&M) costs. The simulation has been performed using the Integrated Environmental Control Model (IECM v8.0.2, <https://www.cmu.edu/epp/iecm/>). The model offers a software framework to allow a multi-parameter, multi-output simulation of a power plant. Assumptions can be made with regards to various components of the power such as power block, turbine, fuel, general financing options and so on. The methodology followed in the model is sufficiently well-documented (Berkenpas et al. 1999) and we will not mention it here for the sake of brevity.

Most performance parameters at this stage are kept as IECM defaults. Using the estimates given in Indian Energy Security Scenarios (IESS) 2047 model (indiaenergy.gov.in/), the capital cost is estimated as Rs. 3586.5/GW. The O&M costs are found by taking the median of the O&M costs of five running gas plants in India, viz. Anta, Kawas, Dadri, Gandhar and Faridabad (refer to Table 1). This leads us to a median O&M cost of US\$ 4.24/MWh. The gas cost is taken as US\$ 4.2/MBtu (=US\$ 152.2/mscm), representative of the current gas prices in India. The fuel escalation rate is taken as the median of the rates during April 2011 to October 2015, available from the website of the Central Electricity Regulatory Commission (CERC 2016) and calculated as 5.02 %. Other assumptions made in simulating the plant are shown in Table 2. Some of the assumptions stem either from the Government of India policy, such as the debt-equity ratio of 70:30 (Ministry of Power 2014) and has been considered in several other works as well (Singh and Rao 2015; Soni et al. 2016). Other assumptions have been taken in accordance with the industry norms (such as the gas turbine of GE 7FB make).

Table 2 Assumptions used to simulate reference plant

Parameter	Unit	Value
Plant life	Years	30
Real bond interest rate	%	5.83
Debt—equity ratio	Ratio	70:30
Gas properties		
Methane (CH ₄)	vol %	93.1
Ethane (C ₂ H ₆)	vol %	3.2
Propane (C ₃ H ₈)	vol %	1.1
Carbon dioxide (CO ₂)	vol %	1
Nitrogen (N ₂)	vol %	1.6
Density	kg/m ³	0.76
Gas turbine model		GE 7FB
Turbine inlet temperature	K	1644
Turbine back pressure	MPa	1.38×10^{-2}
HRSG outlet temperature	K	394

Remaining parameters have been assumed as IECM defaults.

Generating the dataset for MGGP

After simulation of the reference plant, some key parameters are varied within the IECM v8.0.2 software framework to generate the basic dataset. In this process, CO₂ capture is also incorporated within the dataset. The varied parameters take hypothetical but realistic values within the range of those parameters specified in the model. The range taken by each parameter is shown in Table 3.

By varying the above parameters for 240 hypothetical cases, we obtain the outputs as cost of electricity, net plant efficiency and CO₂ emission factor for each case. 180 sets of data are selected as training data and 60 as testing data. A sample dataset is shown in Table 4 for 50 sample sets of data.

MGGP Approach

Genetic programming (GP) is a mathematical tool that develops models or programs to solve regression problems (Garg et al. 2014a, c). The technique uses structure optimization method to search through the program space to provide solutions as a combination of multiple models or weighted sum of coefficients (Gandomi and Alavi 2012). Multi-gene genetic programming (MGGP) is a variant of GP where the output from a set of simple, fixed-depth GP models is used to produce a single program that develops a linear model culminating into a low-order non-linear term (Garg et al. 2014a, c). This enables the mutation and crossover of a variety of multi-gene individuals. The methodology uses GPTIPS 2.0 toolbox

Fig. 1 Methodological framework for the study

Table 3 Ranges for variation of each parameter

Parameter	Symbol	Unit	Range
CO ₂ capture technology ^a	<i>a</i>		None/amine/ammonia
Plant load factor*	<i>b</i>	%	25–80
CO ₂ tax	<i>c</i>	\$/t-CO ₂	10–80
Natural gas price	<i>d</i>	\$/mscm	120–235
Turbine inlet temperature	<i>e</i>	K	1373–1713
HRSG temperature	<i>f</i>	K	353–413
CO ₂ capture efficiency ^{b,**}	<i>g</i>	%	50–90

* Plant load factor is an annual average value, which represents the percent of equivalent full load operation during a year (Berkenpas et al. 1999)

** CO₂ capture efficiency indicates the percentage of the CO₂ which the system is able to capture (Berkenpas et al. 1999)

^a Since the variables in an MGGP expression can only take numerical values, therefore No Capture has been input as 0, amine based capture as 1 and ammonia based capture as 2

^b CO₂ capture efficiency is always 0 % when the CO₂ capture technology assumes a value none or 0

(Searson 2015) for implementing MGGP that is independent of the interpretation of multi-gene individuals. The toolbox has two distinct modules for performing MGGP as well as multi-gene regression. The program uses high level crossover as a probabilistically selective substitute with a crossover rate parameter (CR) of 0.5. This is termed as rate based high-level crossover where one or more genes are exchanged with any other selected individual. Additionally, the toolbox allows one to visualise the genes obtained by the model and facilitates the identification of those genes that can be further processed (either eliminated or modified) to reduce the complexity of the model. Table 5 shows the parameter setting used for MGGP approach in this study while Fig. 2 illustrates formulation of a multiple gene model resulting from a least mean square error algorithm.

Results and Discussion

A predictive model was developed for cost of electricity (COE), net plant efficiency and CO₂ emission factor, with the parameters listed in Table 4 as input parameters. A high degree of correlation of more than 95 % is noted between the predicted values and the actual values. The relative error (RE) for each case is calculated as less than 10 % using the following formula:

$$RE (\%) = \frac{RMSE}{Average\ value} \times 100,$$

where RMSE or the root mean square error is given by (Garg et al. 2014c):

$$RMSE = \sqrt{\frac{\sum_{i=1}^N |G_i - A_i|^2}{N}}.$$

Here, G_i is the predicted value for i th data point generated using MGGP technique, A_i is the actual value and N is the number training samples. RMSE is selected as the critical parameter because it is defined as the fitness of a MGGP function in most cases (Muduli and Das 2014). Table 6 enlists the accuracy of the results obtained for each of the three output parameters.

The fitness function of the MGGP is used to determine which of the evolved expression best predicts the output parameter with minimum error. We will now see the correlation and sensitivity of each parameter towards the calculation of individual outputs.

Results for Cost of Electricity

Figure 3 shows the value of $1 - R^2$ against the increasing expressional complexity for the population model of COE. A total of 500 population models are generated. As we can see in the figure, most of the values correspond to a small value of $1 - R^2$ and therefore an R^2 value of close to 1. An expressional complexity of around 140 gives the best model, with the following equation:

$$\begin{aligned} COE = & 0.8319d - 1.94b - 0.5572a - 0.05687e - 0.2654f \\ & - 0.08319ac + 0.02632af + 1.578ag \\ & + 0.001963df - 0.00005448cg^2 + 0.00001013dg^2 \\ & + 0.0002791c(2d + e - f + g) + 0.01316b^2 \\ & - 0.001963g^2 + 0.0007475ag(d - e) \\ & - 0.005779abg + 0.00002026bcg + 196.6 \end{aligned}$$

The degree of correlation for the training and testing data, with respect to COE is shown in Fig. 4. Both display an R^2 value of greater than 95 %, which is considerably high.

Table 4 Sample inputs and outputs for dataset containing 50 hypothetical parametric values

Sl. no.	Input parameters							Output		
	Capture type	Load factor (%)	CO ₂ tax (\$/t)	Natural gas cost (\$/mscm)	Turbine inlet temperature (K)	HRSG temperature (K)	Capture efficiency (%)	COE (\$/MWh)	CO ₂ emission factor (kg/kWh)	Net plant efficiency (%)
1	Amine	41	72	141	1137	145	71	141.6	0.13	39.99
2	None	45	21	210	1361	112	0	105.1	0.36	50.53
3	Ammonia	49	78	203	1376	108	71	154.6	0.12	42.85
4	Amine	31	71	199	1380	148	64	155.6	0.15	44.51
5	Ammonia	74	75	167	1225	143	85	145.4	0.08	36.16
6	Ammonia	65	24	145	1230	132	87	137.4	0.06	36.34
7	Ammonia	75	31	149	1169	143	87	144	0.07	34.09
8	Ammonia	55	45	159	1324	137	84	141.2	0.08	38.8
9	Ammonia	34	28	127	1140	157	84	216.9	0.09	33.22
10	None	64	65	192	1228	85	0	110.3	0.36	50.18
11	Ammonia	38	26	149	1140	99	65	173.3	0.16	40.09
12	Amine	79	57	159	1373	121	84	96.03	0.07	43.92
13	None	43	33	170	1102	86	0	107	0.38	48.55
14	None	62	74	181	1387	101	0	106.1	0.36	51.08
15	Amine	34	73	159	1202	132	66	151.1	0.15	42.27
16	Amine	66	67	145	1379	120	90	95.52	0.04	43.54
17	Amine	76	74	141	1386	97	62	91.37	0.15	46.36
18	None	68	66	235	1262	106	0	125.3	0.36	49.78
19	Amine	39	52	138	1382	139	80	114.8	0.08	43.75
20	None	76	77	235	1123	85	0	132	0.37	48.9
21	None	69	79	232	1348	96	0	124.8	0.36	50.92
22	Ammonia	38	41	181	1192	154	81	209	0.10	35.63
23	Amine	69	10	232	1181	145	74	142.1	0.12	40.73
24	Ammonia	76	24	138	1293	104	88	113.9	0.06	38.78
25	None	61	66	232	1216	85	0	126.3	0.36	50.05
26	Amine	26	31	210	1365	124	80	169	0.08	44.02
27	Ammonia	55	65	127	1348	119	62	116.7	0.16	43.24
28	Ammonia	67	41	192	1260	145	73	147.6	0.12	39.08
29	Amine	76	66	145	1216	142	81	103.5	0.08	40.99
30	Ammonia	53	54	156	1357	148	72	135.1	0.12	40.85
31	Ammonia	39	49	199	1321	111	71	172	0.12	41.94
32	Ammonia	37	24	159	1231	135	75	178.7	0.12	38.61
33	Ammonia	74	16	159	1286	125	63	114.1	0.16	41.94
34	Amine	53	77	163	1176	132	66	130.2	0.15	41.77
35	Amine	38	71	170	1211	140	81	148.7	0.08	40.98
36	None	62	64	138	1266	87	0	90.25	0.36	50.49
37	None	34	29	170	1253	88	0	104.8	0.36	50.32
38	None	50	13	181	1256	131	0	94.45	0.37	48.81
39	Ammonia	32	16	192	1303	130	65	184.4	0.15	41.71
40	None	33	12	141	1123	139	0	96.55	0.39	46.54
41	Ammonia	74	16	217	1136	128	85	179.9	0.08	34.38
42	Amine	70	47	141	1159	80	64	100.8	0.15	43.83
43	Ammonia	77	63	196	1316	140	81	141.4	0.08	39.06
44	None	80	27	225	1389	141	0	103.2	0.36	49.87
45	Amine	34	56	207	1109	111	61	169.5	0.17	41.66
46	Amine	42	30	235	1206	88	60	155	0.16	44.54

Table 4 continued

Sl. no.	Input parameters							Output		
	Capture type	Load factor (%)	CO ₂ tax (\$/t)	Natural gas cost (\$/mscm)	Turbine inlet temperature (K)	HRSG temperature (K)	Capture efficiency (%)	COE (\$/MWh)	CO ₂ emission factor (kg/kWh)	Net plant efficiency (%)
47	Amine	26	43	174	1345	139	61	156.3	0.16	44.55
48	Amine	52	34	207	1263	141	88	139.5	0.05	41.29
49	Ammonia	58	46	130	1158	146	88	158	0.06	33.30
50	None	43	17	141	1284	101	0	82.55	0.36	50.17

Table 5 Parameter settings for MGGP used in GPTIPS 2.0 toolbox

Parameter	Value
Population size	250
Number of generations	150
Number of runs	2
Maximum tree depth	4
Tournament size	20
Tournament type	Pareto
Elite fraction	0.3

Further, sensitivity analysis is performed for cost of electricity. In this process, two sets of data are taken. For the first set of data, each variable is increased by 10 % one at a time, keeping other variables constant. For the second set, each variable is decreased by 10 % one at a time, keeping other variables constant. It is found that the COE is

most sensitive to turbine inlet temperature. Natural gas cost is the second most important parameter affecting the COE. On the other hand, CO₂ tax and HRSG temperature are the parameters to which the COE is least sensitive to. It may be noted that although CO₂ tax is a highly essential tool for controlling the large CO₂ emissions, it does not show any major effect here because we are assuming the same capture technology in all the cases. As a result, the CO₂ emission factor does not change considerably. The sensitivity analysis for COE is shown in Fig. 5.

The different degrees of sensitivity to capture efficiency in the two cases is seen because Case-I is a case of ammonia based capture at default capture efficiency of 65 %, while the second case represents amine based capture at capture efficiency of 80 %. The two solvents behave differently at different capture rates as shown in Fig. 6 with IECM simulations. It can be noted that the slope of COE

Fig. 2 Formulation of MGGP model using least squares algorithm (Garg et al. 2014c). Reproduced with permission

Table 6 Correlation and errors for each of the output parameters

	COE	Net plant efficiency	CO ₂ emission factor
Coefficient of determination, R ²	0.9502	0.9944	0.9999
Root mean square error	7.2576	0.3480	0.0010
Relative error (%)	5.44	0.79	0.51
Mean absolute error	4.0850	0.1322	6.85×10^{-4}
Maximum absolute error	34.5494	4.1891	0.0079

Fig. 3 Population models with varying expressional complexity. The *red circle* depicts the best model for COE (color figure online)

Fig. 4 Correlation of predicted value against the actual value of cost of electricity for **a** training data and **b** testing data

versus capture rate is significantly higher for ammonia based capture than amine based capture and as a result they show different levels of sensitivities to capture rate in Fig. 5.

Results for Net Plant Efficiency

For net plant efficiency, the population diagram is shown in Fig. 7. A larger number of points are seen with $(1 - R^2)$ value close to 0, as compared to the COE. The best fit is obtained for an expressional complexity of nearly 350, with the following equation:

$$\begin{aligned} \text{Net plant efficiency, } \eta = & -0.00009888a^4g^2 - 0.00000006814a^2df^2 \\ & - 0.00000006814ba^2df - 0.00106a^2e + 0.00009877aeg \\ & + 0.4472a - 0.00000005627d^2e - 0.00000005627d^2f \\ & + 0.02917d - 0.00002149e^2 - 0.00002149eg \\ & + 0.06729e - 0.03348f - 0.1574g + 0.0002296. \end{aligned}$$

The correlation between predicted and actual values of net plant efficiency is displayed in Fig. 8. The R^2 value for both the training and testing sets of data is greater than 99.4 %, which shows a very high degree of correlation.

While a high R^2 value gives a good indication of the ability of MGGP to predict the net plant efficiency, a major test relies upon its ability to perceive the parameters. MGGP, as an artificial intelligence technique, should be able to understand some critical factors, like; carbon tax should have no effect on the net plant efficiency. Whether this criterion is being satisfied by the model developed by us can be understood by carrying out sensitivity analysis. As in “[Simulating a Typical Indian NGCC Plant](#)”, we vary each parameter by 10 % one-by-one, keeping other parameters constant.

The results of the sensitivity analysis for net plant efficiency are shown in Fig. 9. It is quite evident that parameters such as CO_2 tax, plant load factor and natural gas cost show no major effect on the plant efficiency. In fact, the percentage variation in efficiency due to 10 % variation in CO_2 tax is of the order 10^{-6} %, which is negligible. Thus, the model developed using MGGP not only shows a high R^2 value but is successful in identifying important input parameters affecting a particular output parameter.

Fig. 5 Sensitivity analysis displayed as percentage change in COE due to 10 % variation in input parameters

Fig. 6 Variation of cost of electricity with capture efficiency for amine and ammonia based capture

Results for CO₂ Emission Factor

Similar results are obtained for CO₂ emission factor using MGGP. The best fit model developed by the tool follows the equation,

$$\begin{aligned}
 CO_2 \text{ emission factor} = & 0.009785a - 0.0000009561b \\
 & + 0.000003206d - 0.00004482e + 0.0007321f \\
 & - 0.003595g - 0.00002712ae - 0.00002712af \\
 & - 0.000003142ag - 0.0000003869ef + 0.0000009561eg \\
 & - 0.000003142fg + 0.00000007179af^2 - 0.000008259a^2g \\
 & + 0.009792a^2 + 0.0000001305f^2 - 0.000008259g^2 \\
 & + 0.0000000aef - 0.0000003869afg + 0.3954.
 \end{aligned}$$

Figure 10 shows a high degree of correlation between the predicted values and the actual values for both training and testing data. The R^2 value in both the cases is obtained to be greater than 98 %. The blue dots towards the right side of the curves depict the plants with no CO₂ capture and those on the left represent plants with CO₂ capture. Since, we have assumed that CO₂ capture rate is always greater than 50 %, we find no data points in the middle of the curve.

The sensitivity analysis for CO₂ emission factor is shown in Fig. 11. It is evident that capture efficiency, as expected, is the most dominant parameter affecting the CO₂ emission factor. Again, parameters like plant load factor do not affect the mass of CO₂ emitted per unit

Fig. 7 Population models with varying expressional complexity. The red circle depicts the best model for net plant efficiency (color figure online)

Fig. 8 Correlation of predicted value against the actual value of net plant efficiency for **a** training data and **b** testing data

Fig. 9 Sensitivity analysis displayed as percentage change in net plant efficiency due to 10 % variation in input parameters

Fig. 10 Correlation of predicted value against the actual value of CO₂ emission factor for **a** training data and **b** testing data

electricity generation. This is manifested well within the MGGP model. Thus, we can safely state that the models generated sufficiently match the expected results for all the three output parameters.

Calculation of Cost of CO₂ Avoidance and Energy Penalty

The cost of CO₂ avoidance is defined as the average cost of avoiding a unit mass of CO₂ emissions to the atmosphere, while still generating the same amount of electricity (Rubin 2012). Mathematically,

$$\text{Cost of CO}_2 \text{ avoidance} = \frac{COE_{CCS} - COE_{ref}}{EF_{ref} - EF_{CCS}},$$

where EF is the CO₂ emission factor and the subscripts ref and CCS denote the reference plant and the plant with CCS respectively.

Another major aspect of CO₂ capture is that it decreases the net plant efficiency substantially, as it requires additional power to run the CO₂ capture and compression equipment. The energy penalty represents the additional energy requirement to run a plant with CO₂ capture and is given as (Rubin et al. 2007):

$$\text{Energy penalty} = \frac{\eta_{ref}}{\eta_{CCS}} - 1,$$

where η denotes the net plant efficiency and the subscripts ref and CCS denote the reference plant and the plant with CCS respectively.

Fig. 11 Sensitivity analysis displayed as percentage change in CO₂ emission factor due to 10 % variation in input parameters

Table 7 Assumptions for S1 (high push) and S2 (low push) scenarios

Parameter	S1	S2
Plant load factor (%)	75	30
CO ₂ tax (\$/t-CO ₂)	65	15
Natural gas price (\$/mscm)	150	220
Turbine inlet temperature (K)	1400	1100

Table 8 Results for reference and CCS plants in the S1 (high push) and S2 (low push) scenarios

	S1		S2	
	Ref	CCS	Ref	CCS
Cost of electricity (\$/MWh)	84.73	88.03	130.82	190.73
Net plant efficiency (%)	50.48	44.63	47.05	39.64
CO ₂ emission factor (kg/kWh)	0.35	0.08	0.39	0.09
Cost of CO ₂ avoidance (\$/t-CO ₂)		12.22		199.7
Energy penalty (%)		13.11		18.69

Since, we have already developed models for COE, net plant efficiency and emission factor in “Results for Cost of Electricity”, “Results for Net Plant Efficiency” and “Results for CO₂ Emission Factor”, we can easily replace the values in the aforementioned equations to calculate the cost of CO₂ avoidance and the energy penalty. For this, we assume two cases, a high push scenario favourable to CCS (S1) and low push (S2), with the assumptions as shown in Table 7. Both scenarios assume amine based capture at a capture efficiency of 80 %.

The results for the two scenarios are shown in Table 8.

Thus, the results obtained for the two scenarios match the expected results i.e. the high push scenario shows a lower cost of CO₂ avoidance and energy penalty. Using the equation in “Results for Cost of Electricity” for COE and varying the values for various parameters as shown in Table 7, we arrive at the results shown in Table 8. In fact, keeping other parameters in the S1 scenario same and

changing the CO₂ tax to US\$ 80/t-CO₂, we find that the cost of avoidance becomes zero. In other words, at this rate, CCS in the natural gas power plants becomes financially and environmentally feasible. This is so because the cost of electricity with CCS becomes less than that without CCS, thereby increasing the incentives to use the technology.

Conclusion

In this paper, we began by discussing why CO₂ capture and storage (CCS) in the natural gas based power sector could be seen as a favourable alternative. Nonetheless, considerable uncertainties exist in the various important parameters affecting this technology. As a result, predictive models can be developed to predict cost and performance of such power plants, which may be further refined and used as the uncertainties decrease. The present paper has utilized one particular technique, namely, multi-gene genetic programming (MGGP) to generate predictive models for cost of electricity, CO₂ emission factor and the net plant efficiency. It was found that the R² value for cost of electricity is greater than 95 %, while for the other two parameters it is substantially higher than 98 %, thereby showing a considerably high correlation. The sensitivity analysis carried out on such models also show expected results. Lastly, we have created two hypothetical scenarios to calculate the cost of CO₂ avoidance and energy penalty for the CCS process and the results follow the expected trend. It is also observed that at typical operating ranges and a natural gas price of around US\$ 4/MBtu, a carbon tax of US\$ 80/t-CO₂ makes CCS in the NGCC power plants a viable option.

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