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Prediction of global warming potential and carbon tax of a natural gas-fired plant

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Abstract

Industrial activities, including the process of power generation from thermal plants, are inevitably associated with the generation of gaseous wastes and particulate matters. Industrial activities, therefore, contribute largely to the emission of environmental pollutants. In addition to causing environmental degradation, the emission of pollutants, particularly greenhouse gases, have far-reaching social negative externalities, mainly in the area of unconducive temperature rise and adverse climatic impact. The unintended impacts of industrial emissions have motivated the development of plans and strategies for their abatement. In this study, predictive models of the global warming potential and carbon tax of the gaseous emission at various fuel consumption levels and different air–fuel ratio for the combustion process in a thermal power plant were developed. It is expected that the models serve as a veritable tool for projecting the environmental & economic costs of natural gas burning and optimizing the process of the fuel combustion for lower greenhouse gas emissions.

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Keywords: Industrial activities; Energy conversion; Global warming; Emission reduction; Carbon tax; Artificial intelligence; Forecast

1. Introduction

Global development, the industrial revolution, and population increase have led to massive consumption of goods and energy. Without doubt, the applications of scientific and engineering knowledge have been valuable in harnessing

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fossil fuels to create energy for the growing world population. Burning of fossil fuels for the generation of energy and goods which supports modern living and economic buoyancy is, however, not without its demerits. It is saddled with the production of greenhouse gases (GHGs), criteria air pollutants and particulate matters which are damaging to human health, the environment and the ecosystem at certain levels of concentration [1–6]. Although there is an ever-growing demand for energy to support modern development and economic growth, the quest to maximize the benefit and minimize the drawbacks of available energy sources is gaining more relevance [7–13]. Several researches are ongoing on the creation of innovative alternatives to fossil fuels. While cutting edge breakthrough in terms of sufficiency and sustainability of the green fuels emerging from these researches is much anticipated, in the meantime, concerted effort in terms of result-oriented researches on ways of abating deleterious emissions from burning of fossil fuels is also pertinent.

The prediction and mitigation of environmental impacts of anthropogenic greenhouse gases emissions (which usually attends industrial activities and fossil fuel burning) are considered to be characterized by a high level of intricacies owing to their inherent global attributes. Scientific bodies, however, have developed various emission metrics for estimating possible climate impact of various greenhouse gases. Each of the metrics that have been developed has its merits and shortcomings in estimating the contribution of various gases [14,15]. Having a general basis for comparing contributions of greenhouse gases permits ease of monitoring overall patterns in greenhouse emission; evaluation and comparison of different sources; and determination of economic trade-offs between reducing different greenhouse gases. Since approaches that permit flexibility in multi-gas abatement tend to be more cost-effective than single—gas abatement strategies, carbon dioxide (which dominates annual anthropogenic greenhouse gas emissions) generally serves as the standard for comparing the contributions of other greenhouse gases in various metrics [16].

Presently, global warming potential (GWP) is the most commonly used metric for comparing the impact of various greenhouse gases [17]. The values of GWP are strongly subject to the timespan over which it is calculated. The typical timeframe for calculating GWP is benchmarked at a period ranging from 20 to 100 years. Each benchmark is connected with a multiplier which is used to determine the influence of each greenhouse gas with respect to carbon dioxide. A sizeable number of regulatory agencies in the globe adopt the 100-year benchmark. One primary reason for this is that it is opined that 100 years is sufficiently long to obtain a more representative climatic change which aggregates all atmospheric cycling on timescales and thus gives better emission calculations. Whereas carbon dioxide can remain in the atmosphere for thousands of years, many other greenhouse gases are much short-lived in the atmosphere. The emphasis on reducing the concentration of short-lived climate pollutants has frequently been presented as a reason to lower the timeframe. Still, this proposition is rarely presented as an alternative way of addressing long-lived emissions such as carbon dioxide [17,18].

The global temperature change potential (GTP) is an emission metric that estimates the potential surface temperature response to various gaseous emissions. The estimate of the temperature response is not spread over several years, but rather it targets a definite future year. Advocates of the GTP metric posit that the approach better relates to the objective of international policies because it is linked to a temperature target. The metric can be used to achieve target based climate policies, like keeping the temperature change below 2 °C [19]. Similar to GWP, GTP values are likewise based on the radiative forcing effects of various gases. The heat-trapping characteristics of various gases primarily drive changes in atmospheric energy balance and climate change effects. With GTP values, estimates of the surface temperature change attributable to various gases are compared to that resulting from the same mass of CO_2. In calculating GWP and GTP values, a single time pulse emission of gas into the atmosphere is assumed. As shown in Table 1, IPCC provides updated values for both GWP and GTP, which are used in academic and scientific studies [20]. Fuels or technologies can be compared to each other based on GHG benefit using the total CO_2 equivalent emissions which have been obtained by summing the total emissions of each fuel or technology at a specified time horizon using either the GWP or GTP method.

GWP and GTP methods have mainly been criticized because they are purely physically based metrics and do not reveal the cost required to eliminate specific greenhouse gas emissions. In the interim, the United Nations have projected that the cost of keeping rising temperatures to safe levels will reach 4% of economic output by 2030 [21]. Some of the new metrics have thus, been developed to incorporate economic perspectives. Global Cost Potential (GCP) and Global Damage Potential (GDP) metrics account for economic factors such as damage costs, cost of mitigation, and discount rates. The two metrics are determined within an integrated climate–economy model because both the response of the climate system and economic factors affects them. However, regardless of every criticism

Table 1. Global warming and temperature potential of some greenhouse gases.

Chemical	Global warming potential		Global temperature potential	
	GWP_{20}	GWP_{100}	GTP_{20}	GTP_{100}
Methane (CH_4)	84	28.5	67	4
Carbon Dioxide (CO_2)	1	1	1	1
Nitrous Oxide (N_2O)	264	264.8	277	234

[20,24]

and various alternatives suggested, the GWP appears to retain its prevalent use, chiefly because of the absence of complications in its definition and the relative simplicity of calculation, compared to a number of the alternatives. In the same vein, GTP retains part of the attractions of the GWP, such as unambiguous formulation and dependence on comparatively few parameters [17,22,23].

In this study, the focus is to develop models which predict the global warming potential and the carbon tax due to greenhouse gas emission from the combustion of fossil fuel. A case study of a thermal power plant located in Nigeria which is designed to primarily fire natural gas to generate $220MW$ of electricity at full capacity is considered. The study which aims at achieving a cleaner environment employs thermodynamic and artificial intelligence (AI) tools to develop predictive models using the plant's boiler data at full and below the installed capacity. It is expected that the model will be handy in identifying the best combination of natural gas flowrate and air–fuel ratio (AFR) for generating the required heat in the steam power plant.

2. Methodology

The primary materials used for this study were the fuel flowrates & air–fuel mass ratios (AFRs) employed in a steam power plant in Nigeria, Aspen HYSYS 8.8, GaBi 8.0, GMDH Shell DS 3.8.9, and Microsoft Excel software. The typical composition of the natural gas, which serves as the primary fuel in the power plant is as given in Table 2. The air which supports the combustion process is considered to be 79 mole % nitrogen and 21 mole % Oxygen. The simulation of the fuel combustion at varied AFR and fuel flowrates was carried out with the aid of the Aspen HYSYS simulation software. The Peng Robinson fluid package was selected in HYSYS to obtain reasonably accurate data on the combustion process, and the combustion data at full plant's capacity is as presented in Table 3. The quantities and compositions of the flue gases which were obtained from HYSYS simulation were fed into GaBi software to determine the environmental impact of the flue gases. The CML impact assessment method, which classifies, characterize and normalize based on IPCC factors, was used for the evaluation of the global warming potential. In addition to Carbon Dioxide, Methane and Nitrous Oxide, the potential contributions of Ethane (C_2H_6), Propane (C_3H_8) and Carbon monoxide (CO) to global warming was considered. Considering 100-year benchmark, the potential global warming impact of C_2H_6, C_3H_8, CO was 1.46, 0.19 and 1.9, respectively where that of CO_2 was taken to be 1 [25]. Having obtained the global warming potential, the carbon tax that is due to the emission of the flue gas into the environment was computed at the rate of $8\,\$/\text{tonne}\,CO_2-equivalent$ [26] using Microsoft Excel. The predictive modelling of the global warming potential and carbon tax of emission from the power plant was carried out with the neural network functionality of the GMDH Shell DS software. The data on the global warming potential (obtained from GaBi simulation) and the associated carbon tax (obtained through Excel computation) at the corresponding natural gas flow rate and AFR were supplied to the GMDH Shell DS software for the predictive modelling to generate models depicting the relationship between the input variables (natural gas flow rate and AFR) and each of the output variable (GWP and Carbon tax) was thus obtained.

Table 2. Natural gas composition.

Component	CH_4	C_2H_6	C_3H_8	CO_2	N_2
Mole fraction	0.894	0.086	0.004	0.006	0.010

Table 3. Typical combustion data at full capacity.

Stream	Mass flow (kg/h)	Temperature (°C)	Pressure (kPa)
Air	1330356	30	865
Natural gas	50190	27	243
Combustion product	1380537	1432.172	243
Flue gas	1380537	387.87	241

3. Results and discussion

3.1. Composition of flue gas

The simulation result typifying the composition of the flue gas from the boiler when the plant operates at full capacity is as summarized in Table 4. The result shows that at AFR of about 26.51, most of the organic components of the natural gas have been combusted and converted to carbon dioxide and water. In addition to this, there is the formation of oxides of nitrogen. The amount of each oxide of nitrogen formed is due to the presence of nitrogen in the combustion air, the flame temperature and the amount of oxygen present to support the reactions leading to the formation of these compounds. Both the flame temperature of combustion gas and the amount of oxygen available to support the formation of oxides of nitrogen are related to the amount of air supplied for the combustion process in terms of the AFR. Hence, the amount of each oxide of nitrogen formed and the completeness of fuel combustion vary with the AFR values. As shown in Table 4, Nitrous oxide (N_2O) is the only oxide of nitrogen present in the flue gas which is a greenhouse gas, and its concentration is much lower than the other two oxides of nitrogen. From the Table, it is revealed that at the plant's full capacity, carbon dioxide is the dominant greenhouse gas in the flue gas in terms of mass flow rate. However, the weighted impact of each of the greenhouse gas will differ from their numeric mass flowrate based on their equivalent contributions relative to carbon dioxide.

Table 4. Compositional mass flow rate of the flue gas [kg/h].

CH_4	C_2H_6	C_3H_8	CO_2	N_2	H_2O	CO	NO_2	NO	N_2O	O_2
4.20E−20	1.89E−33	7.73E−40	135644.3	1020016	105638.9	14.83219	11.11101	2694.483	0.278843	116517.3

As expected, the simulation result of global warming potentials of the emissions at various fuel flowrates and AFR indicated that GWP was higher when the fuel consumed for heat generation in the plant is higher (see Table 6 in Appendix). This observation substantiates the need to operate the process of energy conversion efficiently to obtain maximum energy derivable from a source in meeting a specific amount of need. Maximizing energy derivable from a source will not only reduce the amount spent on fuel; it will prolong the lives of the dwindling fossil fuels and also reduce the negative impact of on the environment and ecosystem. The result also shows that at AFR below 16.1, the GWP was quite high, and this may be due to incomplete combustion, making the contributions of CO and the unburnt organic content of the fuel to be significant. The reduction in GWP at AFR above 24 was not as numerically appreciable as when AFR was increased to about 24. The carbon tax which was computed at a modest rate of 8 \$/tonne $CO_2 - equivalent$ for a Nigerian scenario followed the same trend as the GWP.

3.2. Predictive modelling

For the prediction of the global warming potential and the carbon tax, the maximum layer for the GMDH neural network was fixed at 33, while the initial layer width was 1000. The k-fold validation technique was employed for the modelling, and the dataset hold-out was uniformly programmed. To obtain predictive mathematical models which are plausible and reliable, the GMDH Shell software used the input–output datasets which were fed into it for supervised training of the self-organizing network and the software gradually complicated model approach if the historical values do not fit the model within the specified threshold. In other words, the GMDH Shell program employs more complex approximation techniques (linear, polynomial, Gaussian etc.) if a model gives poor prediction and every new model was tested against past data values until a model resulting in the most precise forecast was obtained. Presented in Figs. 1 and 2 is the comparison between the actual data, the model fit data and predictions

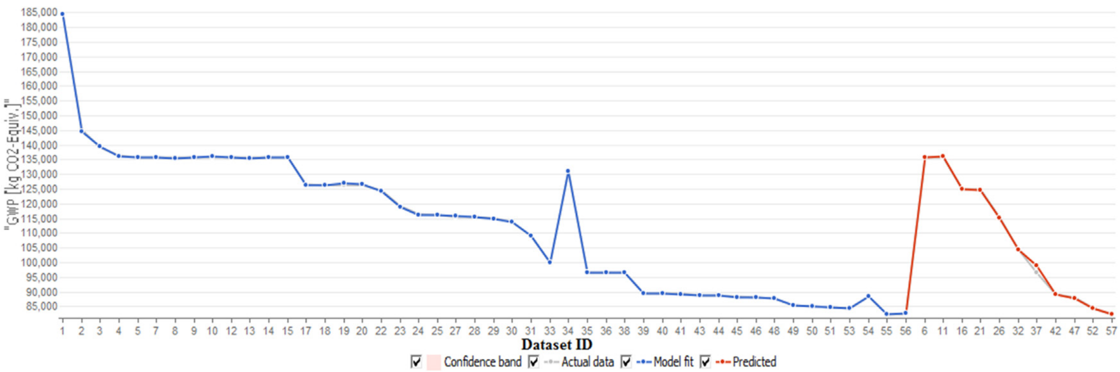

Fig. 1. Global warming potential prediction plot.

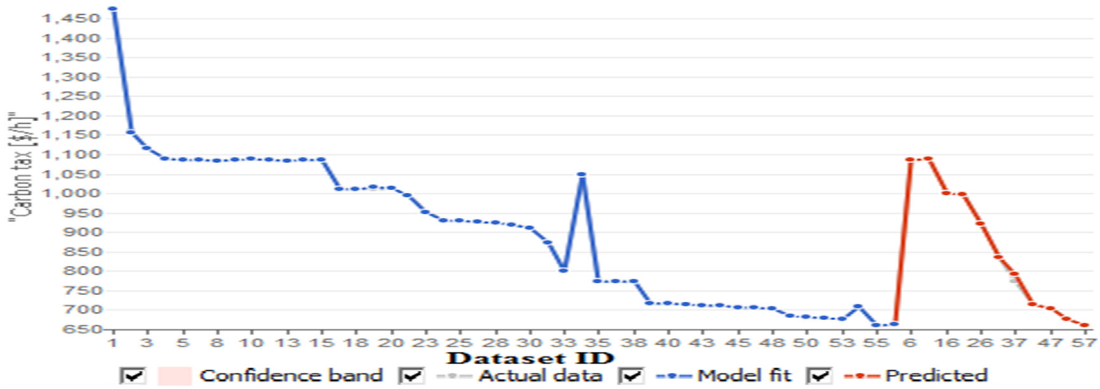

Fig. 2. Carbon tax prediction plot.

of the global warming potential and the associated carbon tax at various fuel flowrates and AFRs using 2-fold cross-validation technique. 80% of the entire datasets have been used for model fit using the 2-fold cross-validation technique while the balance was used for prediction to evaluate the model generated. The grey lines represent the actual data, the blue lines represent the model fit values, and the red lines represent the predicted values. The results of the predictive modelling summarized with these figures show that the data are well predicted with a tiny deviation from the actual data.

3.3. Model accuracy

The statistical data used in evaluating the goodness of models are presented in Table 5. The Table generally reveals that better performance is recorded at the model fit stage. At the model fit phase, the maximum negative error and maximum positive error is about −0.648% and 0.671% respectively. The equivalent values at the prediction phase were −0.17% and 2.38%, which also fall within an acceptable low range percentage error. The evaluation of the models using normalized root mean square error (NRMSE) ranged from 0.22–0.70% while the percentage error using the normalized mean absolute error (NMAE) showed that error in both model fitting and prediction phases ranged from 0.15–0.31%. The abridged raw model of the GWP and the carbon tax is given in equation 1 and 2 (full details appear in the Appendix). The validity of the raw predictive mathematical models is further substantiated by the values of correlation and the coefficient of determination, which ranged from 0.999345–0.999907. The high values of correlation indicate that there is a strong relationship between the environmental indices (global warming potential and carbon tax) and the selected process variables (fuel flowrates and AFR). The high coefficient of

Table 5. Model evaluation and performance.

Environmental index	Global warming potential		Carbon tax	
Post-processed results	Model fit	Predictions	Model fit	Predictions
Max. negative error	−0.647651%	−0.167665%	−0.647629%	−0.167643%
Max. positive error	0.67084%	2.37684%	0.670832%	2.37682%
Normalized mean absolute error (NMAE)	0.149583%	0.311828%	0.149584%	0.311814%
Normalized root mean square error (NRMSE)	0.218423%	0.729433%	0.218426%	0.729424%
Residual sum	5.72194E−13%	2.08862%	3.28285E−12%	2.08862%
Standard deviation of residuals	0.218423%	0.704287%	0.218426%	0.704278%
Coefficient of determination (R^2)	0.999907	0.99858	0.999907	0.99858
Correlation	0.999954	0.999345	0.999954	0.999345

determination values are also indications that not less than 99% of the changes in the global warming potential, and carbon tax values can be predicted from fuel flowrates and AFR.

$$\mathrm{Y1} = 0.115163 - \mathrm{N17}{*}0.137562 + \mathrm{N5}{*}1.13756$$
$$Y2 = 0.000921196 - N34 * 0.137552 + N6 * 1.13755$$

where Y1 and $Y2$ represents the global warming potential and the carbon tax, respectively. Details/nomenclatures of other variables are presented in the Appendix.

4. Conclusion

In this study, ANN-based models of global warming potential and carbon tax due to the emission of flue gas in a thermal power plant have been developed. A motivation factor for the development of the predictive models is the fact that it is established in the literature that incorporating ANN-based data-driven model into the monitoring system of the plant can provide real-time anomaly detection in affected sections of the plant [27]. Based on several statistical metrics, the models developed in this study using GMDH Shell DS 3.8.9 software were considered valid for the prediction of global warming potential and carbon tax at a given flow rate of natural gas and air–fuel flow rate. With the ultimate goal of obtaining a cleaner environment, it is expected that the models will be found useful in the area of optimizing the process of fuel combustion, establishing necessary economic trade-offs in emission handling, and early fault detection in energy conversion systems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Raw model for global warming potential for the gas-fired power plant

$$\mathrm{Y1} = 0.115163 - \mathrm{N17}{*}0.137562 + \mathrm{N5}{*}1.13756$$
$$N5 = -808.564 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N12 * 2.12888e - 07 + N12 * 1.01618$$
$$N12 = -352.608 - N85\hat{}2 * 2.62381e - 08 + N33 * 1.00621$$
$$N33 = -17.8172 + N84 * 0.50759 + N79 * 0.492568$$
$$N79 = -398.786 - N133 * 0.910859 - N133 * N86 * 5.44201e - 05 + N133\hat{}2 * 3.01652e - 05$$

$$+ N86 * 1.92105 + N86\char`^2 * 2.41878e-05$$

$$N86 = 4894.34 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N123 * 0.000118576 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\char`^2 * 0.0001828 + N123 * 0.905718 + N123\char`^2 * 1.92947e-05$$

$$N123 = -10181.9 + N146 * 1.19171 - N146 * N140 * 9.04277e-06 + N140\char`^2 * 8.16194e-06$$

$$N17 = 2.74632e-10 + N35 * 0.480392 + N36 * 0.519608$$

$$N36 = -17.8172 + N83 * 0.50759 + N80 * 0.492568$$

$$N83 = 3643.55 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * 1.13139 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N133 * 0.000142544 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\char`^2 * 0.000205721 + N133 * 0.516516 + N133\char`^2 * 2.48646e-05$$

$$N35 = -17.8172 + N84 * 0.50759 + N80 * 0.492568$$

$$N80 = -398.786 - N133 * 0.910859 - N133 * N85 * 5.44201e-05 + N133\char`^2 * 3.01652e-05 + N85 * 1.92105 + N85\char`^2 * 2.41878e-05$$

$$N85 = 4894.34 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N121 * 0.000118576 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\char`^2 * 0.0001828 + N121 * 0.905718 + N121\char`^2 * 1.92947e-05$$

$$N121 = -10181.9 - N140 * N144 * 9.04277e-06 + N140\char`^2 * 8.16194e-06 + N144 * 1.19171$$

$$N133 = -2.77131e-05 + N140 * 1$$

$$N140 = -8117.07 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * 7.29876 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N146 * 0.000573841 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\char`^2 * 0.000747404 - N146 * 1.52314 + N146\char`^2 * 0.000109007$$

$$N84 = 3643.55 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * 1.13139 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N142 * 0.000142544 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\char`^2 * 0.000205721 + N142 * 0.516516 + N142\char`^2 * 2.48646e-05$$

$$N142 = -8117.07 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * 7.29876 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N144 * 0.000573841 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\char`^2 * 0.000747404 - N144 * 1.52314 + N144\char`^2 * 0.000109007$$

$$N144 = -2.21422e-08 + N146 * 1$$

$$N146 = 55969.8 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * 2.79919 - \text{“}AFR\text{”} * 3712.6 + \text{“}AFR\text{”}\char`^2 * 53.2243$$

Carbon tax raw model for the gas-fired power plant

$$Y2 = 0.000921196 - N34 * 0.137552 + N6 * 1.13755$$

$$N6 = -6.46838 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N12 * 2.12884e-07 + N12 * 1.01618$$

$$N12 = -2.82062 - N84\char`^2 * 3.27948e-06 + N33 * 1.00621$$

$$N33 = -0.142534 + N82 * 0.507594 + N80 * 0.492563$$

$$N82 = 29.1473 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * 0.00905128 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N142 * 0.000142544 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\char`^2 * 1.64577e-06 + N142 * 0.516511 + N142\char`^2 * 0.00310808$$

$$N142 = -64.9374 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * 0.0583902$$

$$- \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N144 * 0.000573841$$
$$+ \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\hat{}2 * 5.97923e-06 - N144 * 1.52314$$
$$+ N144\hat{}2 * 0.0136258$$

$$N84 = 39.1557 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N123 * 0.000118576$$
$$+ \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\hat{}2 * 1.4624e-06 + N123 * 0.905716$$
$$+ N123\hat{}2 * 0.00241185$$

$$N123 = -81.456 - N139 * N144 * 0.00113035 + N139\hat{}2 * 0.00102024 + N144 * 1.19171$$

$$N144 = -1.69231e-10 + N146 * 1$$

$$N34 = -0.142534 + N83 * 0.507594 + N80 * 0.492563$$

$$N80 = -3.18748 + N85 * 1.92105 - N85 * N134 * 0.00680194 + N85\hat{}2 * 0.00302319$$
$$- N134 * 0.910863 + N134\hat{}2 * 0.00377038$$

$$N134 = -2.214e-07 + N139 * 1$$

$$N85 = 39.1557 - \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N124 * 0.000118576$$
$$+ \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\hat{}2 * 1.4624e-06 + N124 * 0.905716$$
$$+ N124\hat{}2 * 0.00241185$$

$$N124 = -81.456 + N146 * 1.19171 - N146 * N139 * 0.00113035 + N139\hat{}2 * 0.00102024$$

$$N83 = 29.1473 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * 0.00905128$$
$$- \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N139 * 0.000142544$$
$$+ \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\hat{}2 * 1.64577e-06 + N139 * 0.516511$$
$$+ N139\hat{}2 * 0.00310808$$

$$N139 = -64.9374 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * 0.0583902$$
$$- \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * N146 * 0.000573841$$
$$+ \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”}\hat{}2 * 5.97923e-06 - N146 * 1.52314 + N146\hat{}2 * 0.0136258$$

$$N146 = 447.759 + \text{“}Natural\ Gas\ Flow\ Rate\ [kg/h]\text{”} * 0.0223935 - \text{“}AFR\text{”} * 29.7008$$
$$+ \text{“}AFR\text{”}\hat{}2 * 0.425794$$

Table 6. GaBi-based simulation outcomes for GWP and carbon tax prediction.

ID	Natural gas flow rate [kg/h]	AFR	GWP [kg CO_2-Equiv./h]	Carbon tax [$/h]
1	50190	12.0000	184298.0	1474.380
2	50190	15.0000	145322.0	1162.580
3	50190	16.1000	139241.0	1113.930
4	50190	18.0000	136446.0	1091.570
5	50190	21.0000	135867.0	1086.940
6	50190	24.0000	135773.0	1086.180
7	50190	26.5064	135746.0	1085.970
8	50190	27.0000	135743.0	1085.940
9	50190	30.0000	135725.0	1085.800
10	50190	33.0000	135712.0	1085.690
11	50190	36.0000	135701.0	1085.610
12	50190	39.0000	135693.0	1085.550
13	50190	42.0000	135687.0	1085.500

(*continued on next page*)

Table 6 (*continued*).

ID	Natural gas flow rate [kg/h]	AFR	GWP [kg CO_2-Equiv./h]	Carbon tax [$/h]
14	50190	45.0000	135683.0	1085.460
15	50190	48.0000	135679.0	1085.430
16	46280	27.1449	125167.0	1001.330
17	46780	21.0000	126636.0	1013.090
18	46780	27.1230	126519.0	1012.150
19	46780	33.0000	126491.0	1011.930
20	46780	39.0000	126474.0	1011.790
21	46190	27.0132	124924.0	999.394
22	46080	26.9964	124627.0	997.015
23	44080	26.5619	119221.0	953.765
24	43090	26.2337	116545.0	932.362
25	42700	18.0000	116084.0	928.669
26	42700	26.2611	115490.0	923.922
27	42700	30.0000	115470.0	923.761
28	42700	42.0000	115438.0	923.506
29	42550	26.2327	115085.0	920.678
30	42100	26.4265	113866.0	910.930
31	40360	25.8502	109164.0	873.312
32	38650	25.7841	104539.0	836.315
33	36950	25.4137	99943.8	799.551
34	35690	12.0000	131054.0	1048.430
35	35690	24.0000	96547.9	772.383
36	35690	25.1371	96537.7	772.302
37	35690	36.0000	96496.9	771.975
38	35690	48.0000	96481.2	771.849
39	33090	24.6493	89508.6	716.069
40	33060	24.5732	89428.1	715.425
41	33040	24.8665	89371.7	714.974
42	32980	24.6598	89211.0	713.688
43	32892	24.6789	88972.8	711.783
44	32890	24.5395	88968.5	711.748
45	32670	24.5528	88373.3	706.987
46	32660	24.7316	88344.9	706.759
47	32540	24.6136	88021.2	704.169
48	32490	24.4824	87887.0	703.096
49	31600	24.1455	85482.4	683.859
50	31540	24.4917	85317.1	682.537
51	31410	24.4451	84965.8	679.727
52	31270	24.3568	84587.8	676.703
53	31190	24.138	84373.3	674.987
54	30530	15.0000	88397.7	707.182
55	30530	24.2737	82586.8	660.694
56	30530	27.0000	82570.7	660.566
57	30530	45.0000	82534.2	660.274

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