Journal of Physics: Conference Series

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# Prediction of Emissions and Profits from a Biomass, Tyre, and Coal Fired Co-Gasification CHP Plant Using Artificial Neural Network: Nigerian and South African Perspectives

To cite this article: M. Ozonoh *et al* 2019 *J. Phys.: Conf. Ser.* **1378** 022021

# Prediction of Emissions and Profits from a Biomass, Tyre, and Coal Fired Co-Gasification CHP Plant Using Artificial Neural Network: Nigerian and South African Perspectives

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## Abstract

The local sourcing of feedstock for energy generation will reduce costs in the power plant, and promote energy sustainability. Most times, potential investors in this area show interest about understanding the profitability of the business because, the information boosts the confidence of the investors in the project, and gives them the opportunity of making a short and long term plans about the business. The emissions arising from the energy plant is an important aspect of the venture that requires proper attention, otherwise the costs of emission control may consume a greater part of the profit, hence rendering the business un-viable. Nigeria and South Africa (SA) have abundant biomass (e.g. corn cob, sugarcane bagasse, & pine saw dust) coal and tyre that can be used as fuel in an energy plant. A 10 MW CHP plant was fired with coal and biomass, and tyre obtained from Nigeria and South Africa (SA) respectively, at ratios of 1:1, 3:2, and 4:1 to study the emissions and profits in the plant. An empirical model was employed to estimate the annual amount of feedstock and feed rate required for the plant, after which, an artificial neural network (ANN); LevenbergMarquardt algorithm was used to predict the emissions and profits in the plant for 20-year-investment period with feedstock costing (WFC) and without feedstock costing (WOFC). The profit obtained from the South African feedstock, WFC and WOFC; produced about 45.18 % and 36.83 % ($3,900,000.07 and $3,179,184.49) higher profits than the Nigerian feedstock, but the CO, NOX, & SO2 emissions from Nigerian feedstock were lower than that of SA. The findings from this study could be used as a platform for decision making by potential investors and stake-holders, and further research and development in the area.

**Keywords:** Artificial Neural Networks; Biomass; Coal; Emissions; Profit; Cogasification; Tyre.

## 1. Introduction

Constant electric power supply is needed by every nation to enhance economic growth. All domestic, industrial, public and private sectors depend on the available power for sustainable economic growth. There are several technologies employed for energy production such as combustion, pyrolysis, and gasification. Also, different feedstocks can be used as fuels to operate the systems such as the non-renewables (e.g. coal and petroleum) and renewable fuels (e.g. biomass), solar, wind, hydro, etc. Each of the resources and sources has its own merits and de-merits [1].

South Africa and Nigeria have large deposits of coal available for energy generation. In South Africa (SA) for example, around 95 % of electric power is generated from coal, and the country has an estimated reserve of about 32 million metric tons [2], while the Nigerian estimated coal reserve is around 2.5 Gt [3]. Nigeria with her huge reserve still depends a lot in petroleum as the major source of fuel for energy production. Coal and petroleum have peculiar drawbacks as fuels for power production. They deplete fast and emit gases that are hazardous to the environment.

Nigeria and South Africa also have abundant biomass (e.g. sugarcane bagasse (SCB), corn cob (CC), pine sawdust (PSD). Suberu et al [4] reported that South Africa, Nigeria, and Egypt are the largest producers of corn (corn cob) in Africa. Gasification of blends of these agro wastes and coal will help to reduce fuel (coal and petroleum) depletion and gas emissions. As reported by the International Energy Agency (IEA), the waste sector was responsible for one-fifth of the global climate change due to about 140 billion metric tons of waste producing GHG which leads to climate change [5]. In this regard, the aforementioned agro-wastes can be well managed by using them as fuel for energy production.

In South Africa, electricity consumers benefit from the constant power supplies and low tariff of about \$0.1408 c/kWh [6]. This is attributed to the abundance feedstock (coal) used for its generation. Furthermore, the regular power supply in the country contributions significantly in the nation's economic growth, but most importantly, the emissions from the thermal power plants in the country, constitutes a huge threat to the environment.

In Nigeria, epileptic power supply is very common, irrespective of the exorbitant bills paid by consumers. There is lack of confidence in supplies, and it undermines the overall economy of the country. Different kinds of fuels as mentioned earlier are available in the country to produce electricity. Understanding the feedstocks and emission characteristics of the fuels from both countries therefore, are essential to solving the problems.

Meanwhile, the feedstocks can be fed in a gasifier such as Integrated Gasification Combined Cycle (IGCC) or Combined Heat and Power (CHP) plant. Other technologies (though is for clean coal) which may be used are Ultra-Supercritical Combustion (USC), SupercriticalFluidized Bed Combustion (FBC), and Coal Bed Methane (CBM) [3]. The technologies are efficient in powering communities once the feedstocks are available. A 5 MW capacity CHP plant had been reported by Caputo et al [7] & Bridgwater et al [8]. The authors argued that such capacity was feasible for a fluidized bed gasifier. Malek et al [9] also studied the technoeconomic of a 10 MW CHP plant using biomass as fuels. According to the authors, the investment is profitable. Other authors including Searcy & Flynm [10], Bridgwater [8] and

Mitchell et al [11] have carried out studies using IGCC. They inferred that the technology is viable for power production and can provide around 45 – 50 % energy conversion efficiency. Demirbas [12] also reported that around 20 MWe capacity could be provided by a biomass Integrated Gasification Combined Circle (BIGCC).
Generally, the conversion efficiency of a typical co-gasification plant is about 40 % - 50 %, and the cost of feedstock used for heat and electricity production could equally decrease if a cogasification technology was employed [9]. In another studies carried out by Ahmadi et al [13] it was observed that the overall system efficiency of a typical co-generation system is within the range of 35 % - 40 %. This observation is in affirmation with the findings of Demirbas [12] and Ahmadi et al [13], thus; implying that co-gasification is an efficient process for energy production.
However, emissions and profits are the two crucial factors that must be well understood in an energy generating plant. This is because the amount of gases emitted in the plant determines the environmental impact, and it may affect the overall profit because of the cost of gas cleaning. In this study, the emissions and profits from a biomass, tyre, and coal fired co-gasification CHP co-gasification plant are studied using ANN model. The outcome of the study will assist potential investors and stake-holders in the area in decision making.

## 2. Methodology

### 2.1. Material processing

Coal, biomass (e.g. Sugarcane bagasse (SCB), Corn cob (CC), Pine sawdust (PSD)) and Wastetyre (WT) were the feedstocks used in the study. The South African coal was obtained from Matla mine, while the Nigerian coal was obtained from Onyeama mine, in Enugu state. The South African biomass and WT were collected from the Hill-brow market Berea, Johannesburg and waste tyre recycling plant in Johannesburg, South Africa, respectively, while the biomass and WT from Nigeria was collected at Enugu-Ogbete Main market, Ngwo. The feedstock pretreatment process (by milling and sieving) followed the procedure described in Ozonoh et al [14].

### 2.2. Emission and Profit Estimation

The annual feedstock and feed-rate needed to operate the 10 MW electric power plant were determined from an empirical equation employing the aforementioned feedstocks at coal-tosolid waste ratios of 1:1, 3:2, and 4:1, respectively. Further estimations were carried using different model equations described in our previous work [14] to determine the profitability of the feedstocks for power generation in terms of their economic (profits) and environmental (emissions) viabilities.

### 2.3. Artificial Neural Network (ANN)

ANN is a branch of artificial intelligence with information processing structure that allows it to simulate the functions of neurons employing the artificial neurons that behaves like the human brain [15]. A detailed concept of ANN and procedure for training the model can be found in Pandey et al [15]. In this study, Levenberg-Marquardt (L-M) algorithm with Multiple InputSingle Output (MISO) layer networks were employed to model the profits and emissions from the Nigerian and South African feedstocks for a period of 20 years, respectively. The range of the input and output variables used for the evaluation (emissions and profits) are presented in Table 2 and Table 5. The model was developed from the twenty calculated datasets for South African and Nigerian feedstocks in a MATLAB environment using the neural network toolbox (nntool), and 80 %, 10%, and 10 % of the dataset were employed for the training, validation and testing.

Meanwhile, Figure 1 illustrates the feedforward neural network for the model development.

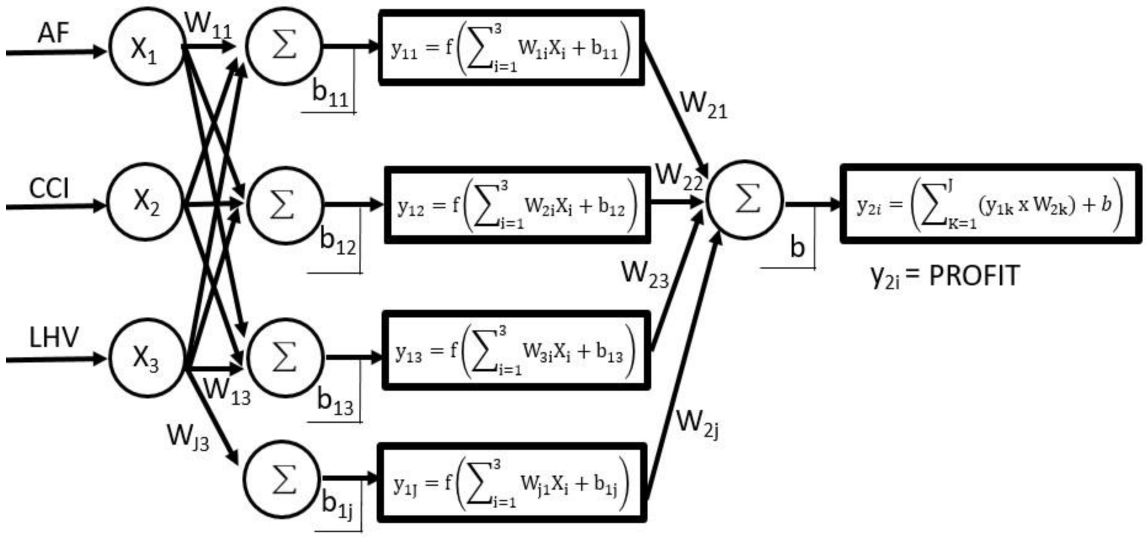


Figure 1: ANN Model Equation development: Feedforward network (MISO layer).

### 2.4. Emission and Profit estimation

#### 2.4.1. Emission estimation

To determine the emissions from the power plants, three categories of emissions were considered. It includes effective emission reduction, emission reduction by displaced energy, and emissions from transportation of fuels expressed in Equation (1) – Equation (3) [9]:

$$\varphi\varphi = \xi\xi - \varepsilon\varepsilon - \lambda\lambda \tag{1}$$

$$\xi\xi = \varpi\varpi \times [(\alpha\alpha^1 \times \tau\tau^1) + (\alpha\alpha^2 \times \tau\tau^2)] + \cdots\cdots\cdots\cdots \alpha\alpha^{nn} \times \tau\tau^{mm} \tag{2}$$

$$\lambda\lambda = \frac{AA_{FFFF} \times \gamma\gamma \times \omega\omega)}{TT_{LLLLLL}} \tag{3}$$

### 2.4.2. Profit estimation

The annual profit made from the plant is determined based on the Net Present Value (NPV) of the investment. It is expressed in Equation 4. Details of the profits and emission calculation can be found in Ozonoh et al [14]:

$$NNNNNN = -\beta\beta + \sum_{jj=1}^{LL} \left(\frac{\phi\phi_{jj}}{1 + IIIII}\right)_{jj} = 0 \qquad (4)$$

## 3. Results and Discussion

Table 1 shows the feedstock characteristics of the Nigerian and South African fuels. A detailed characterization of the South African feedstocks used in this study in terms of the proximate and ultimate analysis can be found in Ozonoh et al [14]:

Table 1: Feedstock Characterization: LHV and MC

| South African Feedstocks | | | | |
|---|---|---|---|---|
| | Feedstocks: Ratio: 1:1 | | | |
| Parameters | Coal + SCB | Coal + CC | Coal + PSD | Coal + WT |
| LHV [MJ/kg] | 17.58 | 17.15 | 19.72 | 23.57 |
| MC [%] | 6.35 | 5.34 | 4.65 | 2.06 |
| | Feedstocks: Ratio: 3:2 | | | |
| LHV [MJ/kg] | 17.65 | 17.30 | 18.68 | 22.87 |
| MC [%] | 5.84 | 5.03 | 4.48 | 2.41 |
| | Feedstocks: Ratio: 4:1 | | | |
| LHV [MJ/kg] | 17.77 | 17.60 | 18.28 | 20.16 |
| MC [%] | 4.82 | 4.41 | 4.14 | 3.10 |
| Nigerian Feedstocks | | | | |
| | Feedstocks: Ratio: 1:1 | | | |
| LHV [MJ/kg] | 24.72 | 24.01 | 26.16 | 29.42 |
| MC [%] | 5.49 | 5.52 | 6.32 | 1.77 |
| | Feedstocks: Ratio: 3:2 | | | |
| LHV [MJ/kg] | 26.20 | 25.63 | 26.48 | 30.06 |
| MC [%] | 4.98 | 5.02 | 5.66 | 2.02 |
| | Feedstocks: Ratio: 4:1 | | | |
| LHV [MJ/kg] | 29.15 | 28.86 | 29.29 | 31.03 |
| MC [%] | 4.01 | 4.03 | 4.34 | 2.53 |

MC: Moisture content; LHV: Lower Heating Value

### 3.1. ANN modelling of South African & Nigerian feedstock

### 3.1.1. South African feedstock: Profit model

Table 2 presents the calculated input and output variables used for the prediction of profits in the plant.

Table 2: Input and Output variables employed in the ANN: Profit prediction

| Variables | Coal + SCB | Coal + CC | Coal + PSD | Coal + WT |
|---|---|---|---|---|
| | | Nigerian Feedstock | | |
| AF [Ton/Yr.]* | 2.91 – 2.47 | 2.99 – 2.49 | 2.75 – 2.47 | 2.45 – 2.30 |
| CCI [$/Yr.]* | 3,518,484.32 – 4,009,387.15 | 3,631,819.66– 4,051,936.75 | 3,214,742.69 – 3,932,879.03 | 3,278,624.54 – 3,888,706.27 |
| LHV [MJ/kg]* | 24.72 – 29.15 | 24.01 – 28.86 | 26.15 – 29.29 | 23.57 – 31.03 |
| PROFIT [$/Yr.]** | 1,571,641.42 – 2,062,544.25 | 1,529,091.83 – 1,949,208.91 | 1,648,149.54 – 2,366,285.88 | 1,692,322.30 – 2,302,401.28 |
| | | South African Feedstock | | |
| AF [Ton/Yr.]* | 4.05 – 4.09 | 4.09 – 4.20 | 3.65 – 3.95 | 3.06 – 3.57 |
| CCI [$/Yr.]* | 1,296,657.80 – 1,433,141.60 | 1,309,316.99 – 1,432,594.93 | 1,259,943.24 – 1,277,626.45 | 947,129.23 – 1,085,625.97 |
| LHV [MJ/kg]* | 17.58 – 17.77 | 17.15 – 17.60 | 19.72 – 18.27 | 23.57 – 20.16 |
| PROFIT [$/Yr.]** | 7,515,429.86 – 7,651,913.64 | 7,479,547.93 – 7,639,254.43 | 7,479,547.93 – 7,670,945.00 | 7,862,945.36 – 8,001,442.21 |

*: Input Variable; **: Output Variable; CCI: Capital Cost Investment; LHV: Lower Heating Value; AF: Amount of Feedstock; NGN: Nigerian Naira; ZAR: South African Rand; CC: Corn Cob; PSD: Pine Sawdust; SCB: Sugarcane Bagasse; WT: Waste-Tyre

The results of the MISO layer network employed for the prediction of profits from the South African feedstock are depicted in Table 3. To train the networks for Coal + SCB, Coal + CC, Coal + PSD, and Coal + WT, 6, 7, 7, and 6 number of neurons in the hidden layer were used WFC and WOFC, respectively. Two performance evaluation of the efficiency of the model were employed, and it includes the Mean Square Error (MSE) and the coefficient of determination (R2); for training, validation and testing. The MSE obtained from the South African feedstocks, WFC were between 0.02 – 0.11, while the R2 were between 90 - 98 %, and the epochs which describe the stability in the convergence characteristics of the model were between 4 -12. An MSE that tends to zero (0) and R2 tending to 1 indicates better fitting of a model. Similarly, the MSE obtained for the same feedstocks, WOFC were between 0.10 – 0.41 except Coal + WT whose MSE was 2.06. The R2 in this case, were between 91 - 97 % excluding Coal + WT with an R2 of 88 - 89 % for training, validation and testing. The implication of the overall result obtained from the SA feedstock was that the ANN model has the ability of predicting the profit in the plant. Figure 2a through Figure 2d presents the convergence characteristics performance of the model for Coal + CC, Coal + SCB, Coal + PSD, and Coal + WT, respectively.

Table 3: ANN model result on profits: 10 MW CHP co-gasification power plant

| Feedstock | Blend Ratio* | Algorithm | Neurons** | MSE | Epoch | Training* | Validation* | Testing* |
|---|---|---|---|---|---|---|---|---|
| South African Coal [Matla Mine]: WFC | | | | | | | | |
| Coal +SCB | | | 6 | 0.02 | 3 | 0.98 | 0.97 | 0.95 |
| Coal + CC | 1:1 | L-M | 7 | 0.03 | 12 | 0.96 | 0.93 | 0.91 |
| Coal + PSD | | [MISO] | 7 | 0.02 | 4 | 0.98 | 0.96 | 0.98 |
| Coal + WT | | | 6 | 0.11 | 3 | 0.95 | 0.94 | 0.90 |
| Nigerian Coal [Onyeama Mine - Enugu] WFC | | | | | | | | |
| Coal + SCB | | | 6 | 0.03 | 2 | 0.96 | 0.95 | 0.96 |
| Coal + CC | 1:1 | L-M | 7 | 0.05 | 5 | 0.94 | 0.97 | 0.93 |
| Coal + PSD | | [MISO] | 7 | 0.03 | 11 | 0.97 | 0.98 | 0.95 |
| Coal + WT | | | 6 | 0.01 | 6 | 0.90 | 0.92 | 0.90 |
| South African Coal [Matla Mine]: WOFC | | | | | | | | |
| Coal + SCB | | | 6 | 0.18 | 6 | 0.97 | 0.96 | 0.94 |
| Coal + CC | 1:1 | L-M | 7 | 0.10 | 8 | 0.92 | 0.91 | 0.90 |
| Coal + PSD | | [MISO] | 7 | 0.41 | 3 | 0.96 | 0.95 | 0.96 |
| Coal + WT | | | 6 | 2.06 | 5 | 0.88 | 0.89 | 0.92 |
| Nigerian Coal [Onyeama Mine - Enugu] WOFC | | | | | | | | |
| Coal + SCB | | | 6 | 0.20 | 3 | 0.94 | 0.95 | 0.97 |
| Coal + CC | 1:1 | L-M | 7 | 0.12 | 5 | 0.96 | 0.97 | 0.95 |
| Coal + PSD | | [MISO] | 7 | 0.66 | 12 | 0.97 | 0.95 | 0.96 |
| Coal + WT | | | 6 | 2.48 | 6 | 0.87 | 0.88 | 0.89 |

L-M: Levenberg Marquardt; MISO: Multiple Input-Single Output; *: Correlation Coefficient ($R^2$); MSE: Mean Square Error: **: Number of neurons; WOFC: Without Feedstock Costing WFC: With Feedstock Costing.

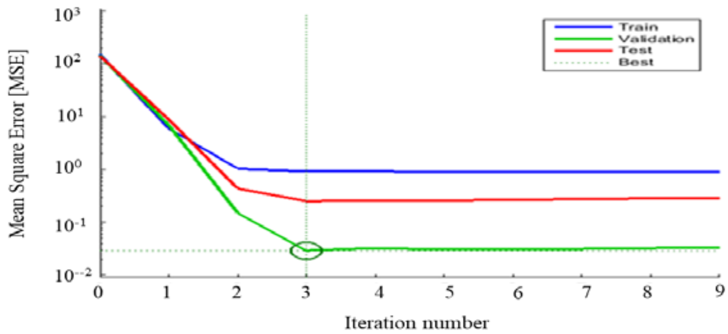


Figure 2a: Convergence characteristics for SA Coal + SCB: MISO network: Profit

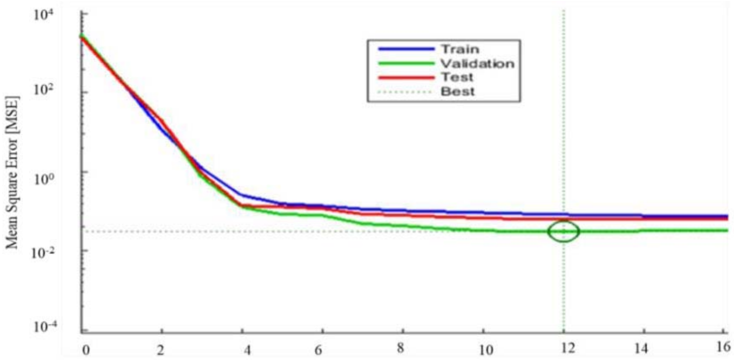


Figure 2b: Convergence characteristics for SA Coal + CC: MISO network: Profit

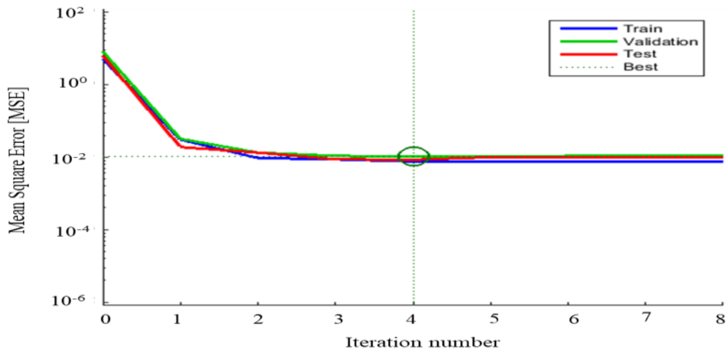


Figure 2c: Convergence characteristics for SA Coal + PSD: MISO network: Profit

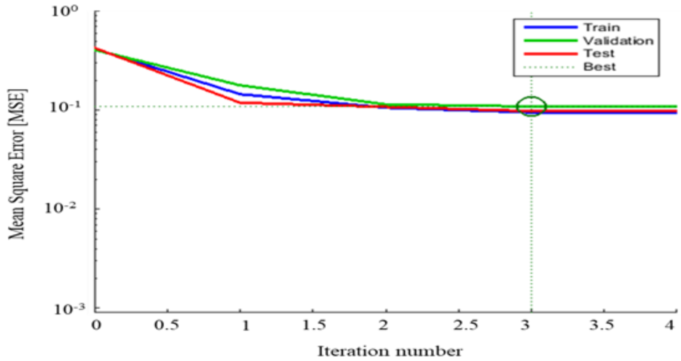


Figure 2d: Convergence characteristics for SA Coal + WT: MISO network: Profit

### 3.1.2. Nigerian feedstock: Profit Model

The same training conditions employed for the South African feedstocks were used for the Nigerian feedstocks. Figure 2e through Figure 2f displays the convergence characteristics performance of the fuels; Coal + SCB and Coal + WT, WFC respectively. The model performance in terms of the convergence behavior is stable, and this was evidenced in the epochs recorded by each of the fuels as contained in Table 4. The $R^2$ and MSE obtained from all the fuels were between 90 - 98 % and 0.01 – 0.05 indicating a better fitted model. From Table 5, WOFC, it can be seen that apart from Coal + WT that has an $R^2$ and MSE of 87 - 89 % and 2.48, the MSE and $R^2$ of other fuels were between 0.12 – 0.66, and 94 - 97 %, hence; revealing that the model has the capacity of predicting the profits from Nigerian feedstocks for the 10 MW power production.

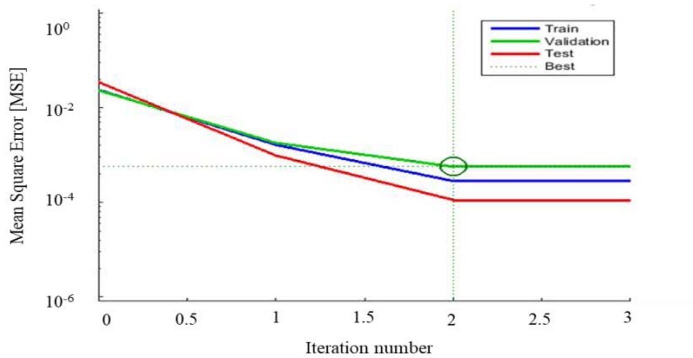


Figure 2e: Convergence characteristics for Nigerian Coal + SCB: MISO network: Profit

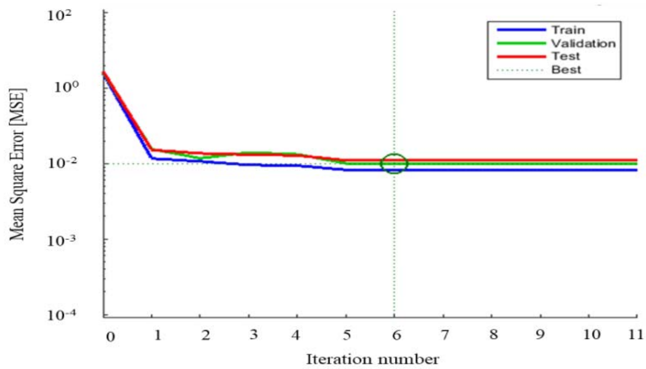


Figure 2f: Convergence characteristics for Nigerian Coal + SCB: MISO network: Profit

**3.1.3. Comparison of South African and Nigerian feedstock: Profit prediction**

The profits accrued from the power plant using South African and Nigerian fuels are compared as shown in Table 4. The comparison is carried out based on the highest and lowest profits obtained in the plant from the four feedstocks studied, WFC and WOFC, respectively. The use of South African feedstock to generate 10 MW of electricity produced about 45.18 % and 36.83 % ($3,900,000.07 and $3,179,184.49) profits higher than the Nigerian feedstock, WFC and WOFC, and the feedstocks that yielded the profits were Coal + PSD and Coal + WT, respectively. The SA fuels yielding the higher profit may be attributed to the higher cost of the Nigerian coal. The details of the evaluation are presented in Table 4.

Table 4: Predicted profits from the CHP plant using MISO layer network

| Feedstock | South African Fuel [WFC]* | | Nigerian Fuel [WFC]** | |
|---|---|---|---|---|
| | Highest Profit [US $] | Lowest Profit [US $] | Highest Profit [US $] | Lowest Profit [US $] |
| Coal + SCB | | | | |
| Coal + CC | | 5,677,056.10 | | 1,949,208.91 |
| Coal + PSD | 6,266,285.95 | | 2,366,285.06 | |
| Coal + WT | | | | |
| | South Africa Fuel [WOFC] | | Nigerian Fuel [WOFC] | |
| Coal + SCB | | | | |
| Coal + CC | | 7,479,547.93 | | 4,531,369.71 |
| Coal + PSD | | | | |
| Coal + WT | 8,001,440.06 | | 4,822,257.71 | |

*: Exchange rate of $1.00 = ZAR14.00 **: Exchange rate of $1.00 = NGN350.00; WOFC:

Without Feedstock Costing; WFC: With Feedstock Costing; CC: Corn Cob; SCB: Sugarcane Bagasse; PSD: Pine Sawdust; WT: Waste-Tyre

### 3.2. ANN Modelling of South African fuel: Emission model

Table 5 presents the calculated input and output variables used for predicting the emissions in the plant.

Table 5: Input and Output variables used in the ANN: Emission Prediction

| | Coal + SCB | Coal + CC | Coal + PSD | Coal + WT |
|---|---|---|---|---|
| | | Nigerian Feedstock | | |
| | | Range: Input Variables | | |
| AF [Ton/Yr.] | 2.91 – 2.47 | 2.99 – 2.49 | 2.75 – 2.47 | 2.45 – 2.30 |
| LHV [MJ/kg] | 24.72 – 29.15 | 24.01 – 28.89 | 26.15 – 29.86 | 29.42 – 31.03 |
| | | Range: Output Variables | | |
| CO [kg] | -33.62 – (-40.52) | -33.97 – (-41.75) | -33.45 – (-38.26) | -31.40 – (-33.90) |
| $CO_2$ [kg] | 5837.36 – 9386.87 | 5837.36 – 9386.34 | 5840.78 – 9387.13 | 5847.35 – 9390.08 |
| NOx [kg] | -111.36 – (-154.36) | -110.61 – (-159.70) | -110.61 – (-144.51) | -101.90 – (-125.07) |
| $SO_2$ [kg] | 69.28 – 111.01 | 69.28 – 111.01 | 69.29 – 111.01 | 69.31 – 111.02 |
| | | South African Feedstock | | |
| | | Range: Input Variables | | |
| AF [Ton/Yr.] | 4.05 – 4.09 | 4.09 – 4.20 | 3.65 – 3.95 | 3.06 – 3.57 |
| LHV [MJ/kg] | 17.58 – 17.77 | 17.15 – 17.60 | 19.72 – 18.27 | 23.57 – 20.16 |
| | | Range: Output Variables | | |
| CO [kg] | -56.94 – (-57.35) | -56.57 – (-58.81) | -51.03 – (-54.51) | -42.55 – (-49.30) |
| $CO_2$ [kg] | 5811.95 – 9352.86 | 5809.75 – 9352.02 | 5821.50 – 9355.33 | 5834.29 – 9363.20 |
| NOx [kg] | -209.29 – (-227.53) | -233.88 – (211.74) | -200.03 – (202.19) | -162.69 – (-179.32) |
| $SO_2$ [kg] | 69.21 – 110.91 | 69.21 – 110.91 | 69.24 – 110.92 | 69.27 – 110.94 |

AF: Amount of Feedstock; LHV: Lower Heating Value; SCB: Sugarcane Bagasse; CC: Corn Cob; Coal + WT; PSD: Pine Sawdust.

Levenberg-Marquardt (L-M) algorithm MISO layer network was used to evaluate the emissions from a 10 MW capacity co-gasification energy plant employing Coal +CC, Coal + PSD, Coal + SCB, and Coal + WT as fuels respectively. CO, CO2, NOX, and SO2 were the major environmental pollutants that were considered. In terms of CO2 and SO2 emissions, Coal + WT produced the highest amounts of around 9363.20 kg and 110.94 kg, respectively. The result was expected (SO2 emissions) because the fuel has higher Sulphur content when compared to other fuels studied, while the lower amounts of SO2 were emitted from Coal + SCB, Coal + CC and Coal + PSD because of little or no Sulphur content in the biomass. The amounts of CO and NOX generated from all the feedstocks were insignificant, with Coal + SCB having the highest of about -57.35 kg and -227.53 kg respectively.

The result of the MISO layer network assessment is presented in Table 6. It can be observed that the MSE obtained from all the fuels, WFC were low except that of the Coal + WT that produced 1.22. The more the value of the MSE tends to zero, the better. The effect has reflected in the correlation coefficient (R2) of training, validation, and testing for all the fuels investigated where the R2 were above 90 % excluding the R2 of Coal + WT. This may be attributed to the dataset used for training the network which has wider data range compared to others. Similarly, Coal + WT has the lowest epoch of 3 while Coal + SCB, Coal + CC, and Coal + PSD have 4, 7, and 9 epochs respectively, implying that the convergence characteristics performance of the fuels are more stable than that of Coal +WT. However, the ANN model is capable of predicting the four major pollutants emitted from the power plant using South African feedstocks.

Table 6: ANN model results on emissions: 10 MW CHP Co-gasification power plant

| Feedstock | Emissions | Algorithm | Neurons** | MSE | Epoch | Training* | Validation* | Testing* |
|---|---|---|---|---|---|---|---|---|
| South African Coal [Matla Mine]: WFC | | | | | | | | |
| Coal + SCB | CO | | 6 | 0.19 | 4 | 0.96 | 0.94 | 0.96 |
| Coal + CC | $CO_2$ | L-M | 5 | 0.24 | 7 | 0.97 | 0.95 | 0.94 |
| Coal + PSD | $NO_x$ | [MISO] | 7 | 0.09 | 9 | 0.99 | 0.97 | 0.96 |
| Coal + WT | $SO_x$ | | 6 | 1.22 | 3 | 0.89 | 0.85 | 0.89 |
| Nigerian Coal [Onyeama Mine - Enugu] WFC | | | | | | | | |
| Coal + SCB | CO | | 6 | 0.06 | 6 | 0.94 | 0.97 | 0.95 |
| Coal + CC | $CO_2$ | L-M | 5 | 0.15 | 5 | 0.97 | 0.95 | 0.96 |
| Coal + PSD | $NO_x$ | [MISO] | 7 | 0.04 | 8 | 0.98 | 0.98 | 0.99 |
| Coal + WT | $SO_x$ | | 6 | 1.13 | 4 | 0.90 | 0.89 | 0.88 |

L-M: Levenberg Marquardt; MISO: Multiple Input-Single Output; *: Correlation Coefficient ($R^2$); MSE: Mean Square Error: **: Number of neurons in the hidden layer; WFC: With Feedstock Costing.

### 3.3. ANN Modelling of Nigerian Feedstock: Emission model

The same condition used for training the South African emission dataset was also employed for the training of Nigerian emission datasets. The MSE from blends of Coal and biomass (i.e. Coal + SCB, Coal + CC, and Coal +PSD) were lower than that of the MSE of Coal + WT. It is shown Table 7. Similar result was obtained from the South African feedstock. Furthermore, the epoch obtained from Coal + WT was the lowest, while Coal + PSD have the highest epoch amongst the fuels investigated. Secondly, all the epochs obtained from other fuels are higher than the epoch obtained from Coal + WT. The implication is that Coal + WT has lower convergence performance characteristic when compared to the other fuels studied. The reason had been explained in section 3.2. More so, the $R^2$ obtained from the validation and testing of Coal + WT were 89 % and 88 %, respectively. This is in the same trend with that of South African feedstock, thus indicating that the dataset employed for the training of the networks were similar. Meanwhile, all the $R^2$ obtained from the fuels except Coal + WT were far above 90 %, and with Coal + PSD having the highest $R^2$ of 98%, 98 %, and 99 % for training, validation and testing, respectively.

### 3.3.4. Comparison of South African and Nigerian feedstock: Emission prediction

The emission assessment was carried out with the South African and Nigerian feedstocks based on the feedstock that generated the lowest or highest amounts of CO, $CO_2$, $NO_X$, and $SO_2$ in the plant. The model result shown in Table 7 effectively describes the emissions from the feedstocks of the two countries. It can be observed that the results of the emission from both countries followed similar trend in terms of the highest and lowest amounts of emissions from each of the fuels, but the exact values the emitted gases varies slightly. For example, the $CO_2$ emitted by the South African fuel (Coal + WT) was 9363.20 kg, while it was 9390.08 kg for the Nigerian Coal + WT; about 1.36 % higher than the $CO_2$ emitted from the plant using the South African fuel. The variation of the result is attributed to the difference in the physiochemical properties of the fuels due to different geographical regions. The details of the emissions analysis are displayed in Table 7.

Table 7: Predicted emissions from the CHP plant using MIMO layer network

| South African Fuel | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Feedstock | CO [kg] | $CO_2$ [kg] | $NO_X$ [kg] | $SO_2$ [kg] | CO [kg] | $CO_2$ [kg] | $NO_X$ [kg] | $SO_2$ [kg] |
| | Highest Emissions | | | | Lowest Emissions | | | |
| Coal +CC | -58.81 | | -233.88 | | | 5809.75 | | 69.21 |
| Coal + WT | | 9363.20 | | -110.94 | -42.55 | | -162.69 | |
| Coal + SCB | | | | | | | | 69.21 |
| Coal + PSD | | | | | | | | |
| Nigerian Fuel | | | | | | | | |
| Feedstock | CO [kg] | $CO_2$ [kg] | $NO_X$ [kg] | $SO_2$ [kg] | CO [kg] | $CO_2$ [kg] | $NO_X$ [kg] | $SO_2$ [kg] |
| | Highest Emissions | | | | Lowest Emissions | | | |
| Coal + CC | -41.75 | | -159.70 | | | 5837.36 | | 69.28 |
| Coal + WT | | 9390.08 | | 111.02 | -31.40 | | -101.90 | |
| Coal + SCB | | | | | | 5837.36 | | 69.28 |
| Coal + PSD | | | | | | | | |

PSD: Pine Sawdust; WT: Waste-Tyre; SCB: Sugarcane Bagasse; CC: Corn Cob

### 3.3.5. Results compared with literature

In this study, an assessment of emissions and profit produced from different solid fuels was carried out using a co-gasification CHP plant. A few studies have been reported on emissions and profits using different feedstock and operating conditions [9-11,7-14] but most of these works were focused on experimental and empirical model estimations. The capacities of the plant studied by the aforementioned authors were in the range of 5 – 20 MW using biomass and blends of biomass and coal as fuels. The energy conversion efficiency of the plants was between 35 – 50 %. For instance, Malek et al [9] employed the NPV, IRR, and PBP models to determine the emission reduction in a 10 MW biomass based CHP plant in Malaysia. According to the authors, 50,130.00 t $CO_2$/y, 750.00 t $SO_2$/y, 218.65 t $NO_X$/y, and 22.83 t CO/y emissions were produced from the plant when compare to the existing energy mix, and empty fruit bunch was the optimum feedstock amongst the fuels studied. Ozonoh et al [14] used a 5 MW CHP and feedstock of South African origin to study the emissions from the energy plant. About 2910.74 kg $CO_2$/y, -25.58 kg CO/y, 34.60 kg $SO_2$/y, and -100.04 kg $NO_X$/y were produced using a blend of Coal + PSD as fuel, and it was the optimum fuel for all the fuels investigated.

Comparing the works of Malek et al [9] and Ozonoh et al [14] with the current study, an ANN model was employed to predict the emissions and profits from the power plant for the current study, as against an empirical model that was used by the aforementioned authors. Furthermore, biomass and blends of biomass were used by the previous authors respectively, but in the current work, blends of coal and biomass was employed. From the present study, about 5840.78 kg $CO_2$/y, -33.45 kg CO/y, 69.29 kg $SO_2$/y, and -110.61 kg $NO_X$/y emissions were obtained from Nigerian feedstock, while 5821.50 kg $CO_2$/y, -51.03 kg CO/y, 69.24 kg $SO_2$/y, and -200.03 kg $NO_X$/y were produced from South African feedstock. The findings obtained by the previous researchers were quite interesting, but a commercial modelling tool could be better.

Consequently, ANN was employed in this article to estimate the emissions and profits in the plant. However, the performance efficiency of the ANN model was attractive when compared to the empirical models and experimental methods used by the previous researchers based on the performance evaluation results.

## 4. Conclusions

The prediction of emissions and profits from biomass, tyre, and coal fired co-gasification CHP Plant using Artificial Neural Network (ANN) was carried out for 20-year-investment period using South Africa and Nigeria as case studies. In this study, twenty datasets with emissions and profits from both countries were employed in the model development using Coal + CC, Coal + SCB, Coal + PSD, and Coal + WT blended at a ratio of 1:1, 3:2, and 4:1, respectively. A MISO layer network was used. The following conclusions were made:

- The profit obtained from the South African feedstock were about 45.18 % and 36.83 % ($3,900,000.07 and $3,179,184.49) higher than the Nigerian feedstock, WFC and WOFC.
- The CO, $NO_X$, & $SO_2$ emissions from Nigerian feedstock were lower than that of SA; indicating the variations in the physio-chemical properties of the feedstock due to different geographical locations.
- The MSE for the profit earned from Nigerian fuels was lower than the MSE obtained from SA fuels, while the $R^2$ from Nigerian fuel was higher when compared to the SA fuel. Considering the emissions from the plant, the MSE for the emissions from SA fuels was higher than that of Nigeria, while the same range of result was obtained for the $R^2$ for both countries, but the emissions generated from Coal + WT was the highest for all the fuels studied.

Furthermore, further studies should consider improving the physio-chemical properties of the fuels via chemical pre-treatment method. If the quality of the fuel is enhanced it may reduce the amount of emissions and increase the profitability of the plant. Additionally, other commercial software such as Aspen Plus and General Algebraic Method should be employed to study the profits and emissions from the power plant.

## Acknowledgement

Ozonoh acknowledges Mr. Nonye Ozonoh & Mrs. Angela Ozonoh for their financial and moral support.

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