



Determination of Calorific Values from Municipal Solid Waste as a Potential for Electricity Generation using Artificial Neural Network

Akpoiyibo, O.F.¹, Ogbeide O.O.², and Aliu, S.³

¹Department of Production Engineering, University of Benin, Benin City, Nigeria

²Department of Production Engineering, University of Benin, Benin City, Nigeria

³Department of Mechanical Engineering, Federal Polytechnic, Auchi, Edo State, Nigeria

¹felixak967@gmail.com, ²osarobo.ogbeide@uniben.edu, and ³polytechnics2009@gmail.com

Abstract One option of utilizing municipal solid waste is energy recovery. Municipal solid waste management low electric energy supplied is major problems affecting the development of Nigeria. In order to evaluate the feasibility of energy recovery as an integral part of a solid waste management system, it is of great importance to determine the energy content or calorific value (CV) of the solid waste. This work aimed at determination of heat energy from municipal solid waste and its potential for electricity generation. Hence, the municipal waste streams were characterized into four parameters to determine the heating value of the various municipal waste components with Dulong's model. Predict and optimize the heat energy response using Artificial Neural Network. Solid waste sampling and analysis from the characterized waste components food waste, wood waste, plastic waste, and cotton waste in the Benin municipality were carried out to determine the waste composition and proximate analysis (moisture, content, volatile matter, ash content and fixed carbon) according to the random sampling method based on the American society of Testing and Materials (ASTM) standard. (2) Grams sample of the various municipal waste component were prepared for laboratory experimentation for energy estimation. Central composite design matrix version (13.0.5.0) for 30 experimental runs was applied for optimization and prediction of Heat Energy response from with Artificial Neural Network model. The result of the study shows that the Dulong's model produced calorific value for heat energy of 22,354.7195kJ/kg. While the Central composite design matrix produces Heat Energy value of 29,897.8kJ/kg. A regression plot showing the correlation between the input and output is produced with R-values of 97% for the training, 87% for the validation, 98% for testing and 97% for the overall. Reliability was produced to test the networks adequacy a reliability plot of 89.8% was obtained for Artificial Neural Network. As municipal solid waste is a potential energy source, the analysis shows heat values ranging from 10024.1kJ/kg to 29897.8kJ/kg which indicate the feasibility of waste to energy plan to produce electricity. The study established the calorific values for energy potential of the municipal waste components in the area.

Keywords Municipal waste, Energy potential, Calorific value, Artificial Neural model

Background to the Study

The electricity problem and environmental degradation are currently vital issues for national sustainable development; load shedding is now impractical as living standards are becoming a great barrier in socio-economic growth (Guilherme *et. al.*, 2017). The standards measure of the energy content of a fuel is its heating value (HV), sometimes called the calorific value or heat of combustion. In fact, there are multiple values for the HV, depending on whether it measures the enthalpy of combustion, the internal energy of combustion, and whether for a fuel containing hydrogen, product water is accounted for in the vapor phase or the condensed (liquid) phase (Ayhan and Hilal, 2021). The Higher Heating Value (HHV) at constant pressure measures the



enthalpy change of combustion with water condensed. The Dulong's formulae (Perry and Chilton, 2017) define the HHV as a function of the carbon, hydrogen, oxygen, and sulphur contents:

In the last few decades municipal solid waste has been on the increase due to the increase in population and expansion of human activities. Rapid urbanization, industrialization and population growth have led to severe waste management problems in several cities of developing or under developed world like Nigeria (Aliu and Ogbeide, 2021). The uncontrolled urbanization has left many Nigerian cities devoid of many infrastructural services such as water supply, sewerage and municipal solid waste management. Most of urban centers in Edo State are overwhelmed by severe problems related to solid waste due to lack of grave efforts by town/city authorities, garbage and its management. Great increase in the amount of municipal solid waste has been reported in the cities due to an improved lifestyle and social status (Rasi and Rintala, 2018).

Statement of the Problem

The problem of energy and environmental degradation are currently vital issues for sustainable development of the nation. Rapid industrialization and population explosion in Nigeria has led to the migration of people from villages to cities, which generate thousands tons of municipal solid waste daily, which is one of the important contributors for environmental degradation at national level. These wastes pose a very serious environmental problem. Mechanisms and management systems are almost nonexistent. Consequently the Benin City has serious problem of electricity, load shedding is now impractical as living standards and become a great barrier in socioeconomic growth.

Purpose of the Study

Recovering energy from municipal solid waste is feasible by means of a number of energy generation processes such as combustion, pyrolysis and gasification.

Aim and Objectives of the Study

The aim of this work is to determine the calorific values from municipal solid waste properties as a potential for an alternative source of electricity generation.

In order to fulfill the aim of this study, the following objectives were pursued. They include to:

- i. carry out site-specific study to determine waste disposal points
- ii. characterize the generated municipal solid waste samples and determine the weight and the range of input parameters using simple weighing balance method;
- iii. determine ultimate analysis of the chemical composition from the various municipal solid waste samples
- iv. estimate the calorific value for energy potential of various waste samples for electricity generation using modified Dulong's model; and
- v. optimize and predict target responses of the classified wastes using Artificial Neural Network model

Relevance of the Study

The successful planning of waste management system strongly depends on an accurate projection and prediction of municipal solid waste quantities, keeping in mind that the future predictions of municipal solid waste generation serve as a basis in the development of the existing waste management, infrastructure connections, municipal solid waste quantity optimization and sustainable development. Inaccurate predictions could lead to numerous problems, such as inadequate infrastructure for the collection, transportation, landfilling or MSW processing. In recent years, mathematical models in the form of Artificial Neural Network have gained popularity, as evidenced by its use in the study of models for predicting the MSW generation. Moreover, the ANN approach is well known for its suitability in estimating nonlinear functions for optimization and prediction of Heat energy for electricity estimation that will serve as an alternative option for a sustainable electric power generation in the area of studied. Before computation, the observed database should be normalized to improve the functionality of the network.



Methodology

In pursuance of these research objectives with a view to achieving the aim, adequate literature survey was conducted to gain insight into the waste management system in the metropolis. To this end, various areas of waste generation and disposal function were examined. From the examined area, suitable places were adapted to suit the purpose of the research work in Benin metropolis.

Research Design

For the purpose of electric energy determination, the waste was classified into four (4) components due to their chemical composition; food wastes, wood waste, plastics wastes, and cotton waste were determined from the collection and the disposal points.

Method of data collection

This study was carried out in Benin metropolis. Municipal solid waste samples (kg) were considered in the chosen solid waste parameters for the determination of the chemical composition of the various municipal solid waste compositions.

To determine the chemical composition of the municipal waste components, the range of input parameters of the various solid waste compositions as depicted in Table 1 were prepared for laboratory experimentation. The samples were blended to powder with blending machine and sundried and weighed using analytical balance as shown in Figure 1, to determine 2gram weight for various waste samples. Ash content was determine from the waste with a temperature of 450⁰C to 550⁰C using a Muffle Furnace as depicted in Figure 2. Nitrogen was also determined by digesting the waste samples to liquid content using digester as depicted in Figure 3, and the results of the ultimate analysis is depicted in Table 2.



Figure 1: Analytical Balance



Figure 2: Muffle furnace



Figure 3: waste digester

Data Presentation (Experimentation)

Ultimate Analysis: this is an elemental quantitative evaluation of the total carbon (C), hydrogen (H), nitrogen (N), sulphur (S), oxygen (O), and percentages after removal of the moisture and Ash. This analysis was performed using classic oxidation, decomposition, and reduction technique to determine, carbon (C) content, hydrogen (H) content, nitrogen (N) content, and sulphur (S) content, and oxygen (O) was calculated by difference.



Determination of Carbon and Hydrogen: The amount of water and carbon dioxide were calculated by difference using Equation 1 and 2.

$$\%C = \frac{a \times 0.2727}{\text{Wt of sample}} \times \frac{100}{1} \quad (1)$$

$$\%H = \frac{b \times 0.1117}{\text{Wt of sample}} \times \frac{100}{1} \quad (2)$$

Where a = quantity of CO₂ recorded

b = quantity of H₂O recorded

Ash Content: The ash content was determined by measured sample of 2g into a pre tarred and weighed crucible. This was heated in a muffle furnace as depicted in appendix B, at 550°C for four (4) hours. The residue obtained was used to calculate the ash content using equation 3.

$$\%ASH (AC) = \frac{\text{weight of residue}}{\text{Weight of sample}} \times \frac{100}{1} \quad (3)$$

Determination of Nitrogen: Samples were analyzed chemically according to the official methods of analysis described by the Association of official Analytical Chemist (A.O.A.C., 18th EDITION, 2005). This consists of three techniques of analysis namely Digestion, Distillation and Titration.

Determination of Sulphur: 1g of sample was weighed into a 100 volumetric flask; 40ml of distilled water was added to make a solution of the sample. The result was determined using Equation 4.

$$\%Sulphur = \frac{\text{weight of filter paper plus residue} - \text{weight of empty filter paper}}{\text{Weight of sample}} \times \frac{100}{1} \quad (4)$$

The Oxygen content (% O) was obtained by difference using Equation 5.

$$\% O = 100 - \% (C + S + N + H + AC) \quad (5)$$

The results of the chemical composition of the various municipal solid wastes in the metropolis are depicted in Table 2.

Results and Discussion

Results Presentation

In the course of this research work, a research on the municipal solid waste composition in Benin metropolis was determined in a scaling method (weighed and record). The range of municipal solid waste components considering the maximum and minimum weight were also determined that represent; food waste of 11 – 14kg, wood waste of 18 – 26kg, plastics waste of 140 – 170kg, and cotton waste of 130 – 170kg respectively as shown in Table 1. A sample of 2g of weight were measured for Laboratory experiment to determine the amount of carbon, hydrogen, oxygen, nitrogen, sulfur, and ash content for each type of waste in the metropolis. These analyses were carried out in the Department of Chemistry, Federal University of Technology, Akure, Ondo State.

Table 1: The range of process Input parameters

| Categories | Parameter | Units | Minimum | Maximum |
|------------|---------------|-------|---------|---------|
| A | Food waste | Kg | 11 | 14 |
| B | Wood waste | Kg | 18 | 26 |
| C | Plastic waste | Kg | 140 | 170 |
| D | Cotton waste | Kg | 130 | 170 |

Source; field survey, Benin 2023

To determine heat energy generated by whole Benin metropolis solid waste, Dulong's formula was applied. Dulong's model as described in Equation 6.

$$\text{Heat Energy (kJ/kj)} = 337 C + 1428 (H - \frac{O}{8} + 9S) \quad (6)$$

Table 2: Ultimate Analysis for Chemical composition of the various waste components

| Components | %C | %N | %S | %H | %Ash | %O | Total |
|---------------|---------------|--------------|--------------|---------------|---------------|----------------|-------|
| Food waste | 49.22 | 3.577 | 0.464 | 5.265 | 5.233 | 36.241 | 100 |
| Wood waste | 69.83 | 0.075 | 0.084 | 9.89 | 1.55 | 18.571 | 100 |
| Plastic waste | 49.75 | 0.205 | 0.186 | 4.263 | 25.03 | 20.566 | 100 |
| Cotton waste | 51.68 | 0.305 | 0.228 | 6.337 | 2.061 | 39.389 | 100 |
| Total | 220.48 | 4.162 | 0.962 | 25.755 | 33.874 | 114.767 | |

Source Chemistry Lab. FUTA, 2023



Putting percent by mass value from Table 2 into Dulong's model, the Calorific values generated from municipal wastes samples in Benin metropolis is determined using Equation 6.

$$\text{Calorific Value (Benin) kJ/kg} = (337 \times 220.48) + 1428 \left(25.755 - \frac{114.767}{8} + 9 \times 0.962 \right)$$

$CV_{Total}(\text{Benin}) = 74,301.76 + 28,655.8545 = 102,957.62 \text{ kJ/kg}$. This show that reasonable amount of heat energy can be generated for electricity estimation on the municipal solid wastes that will increase electricity supply in Nigeria.

Modeling and Optimization

For the purpose of modeling and optimization, statistical software was used.

This statistical tools help in categorizing the solid waste factors into four units for central composite design and design of experiments.

Modeling and Optimization using (ANN): Artificial Neural Network Response is an optimization prediction statistical tool to determine the best possible combination of variables for a specific response to a phenomenon. It's particularly useful to understand the relationship between multiple input variables with one or response variables. The technique is popular in industries where process and statistical optimization plays a key role.

To generate the experimental data for the optimization process;

- i. Statistical design of experiment (DOE) using the central composite design method (CCD) was done .Central composite design (CCD) is unarguably the most acceptable design for response surface methodology (RSM). The design and optimization was done using statistical software and for this particular problem, Design Expert 13.0.5.0 was employed as presented in Table 3.
- ii. Experimental design matrix having six (6) center points, six (6) axial points and eight (8) factorial points to generate 30 runs for the experiment.

Table 3: Build information for the CCD design having a quadratic behavior

| File Version | 13.0.5.0 | | |
|-----------------|-------------------|---------|------------|
| Study Type | Response Surface | Subtype | Randomized |
| Design Type | Central Composite | Runs | 30 |
| Design Model | Quadratic | Blocks | No Blocks |
| Build Time (ms) | 2 | | |

The Central Composite Design and Design of Experiment for the range of process input parameters of the municipal waste components with coded responses to determine the optimum value of each input variable namely: food waste, wood waste, plastic waste, and cotton waste that will minimize the rate of solid waste disposal and generate heat energy from the municipal waste in the metropolis under investigation resulting to about 30 experimental runs was generated. The real values are presented in Table 4.

Table 4: Central Composite Design and Design of Experiment for the municipal waste

| | Factor 1 | Factor 2 | Factor 3 | Factor 4 |
|-----|--------------|--------------|-----------------|----------------|
| Run | A:Food waste | B:Wood waste | C:Plastic waste | D:cotton waste |
| | Kg | Kg | Kg | Kg |
| 1 | 14 | 20 | 170 | 140 |
| 2 | 12 | 20 | 150 | 140 |
| 3 | 14 | 20 | 150 | 160 |
| 4 | 14 | 24 | 150 | 160 |
| 5 | 14 | 20 | 170 | 160 |
| 6 | 13 | 22 | 160 | 150 |
| 7 | 13 | 26 | 160 | 150 |
| 8 | 11 | 22 | 160 | 150 |
| 9 | 12 | 24 | 170 | 140 |
| 10 | 14 | 24 | 170 | 160 |
| 11 | 12 | 24 | 150 | 140 |



| | | | | |
|----|----|----|-----|-----|
| 12 | 12 | 24 | 170 | 160 |
| 13 | 12 | 20 | 150 | 160 |
| 14 | 14 | 20 | 150 | 140 |
| 15 | 12 | 20 | 170 | 140 |
| 16 | 12 | 24 | 150 | 160 |
| 17 | 12 | 20 | 170 | 160 |
| 18 | 14 | 24 | 170 | 140 |
| 19 | 14 | 24 | 150 | 140 |
| 20 | 13 | 22 | 140 | 150 |
| 21 | 13 | 22 | 160 | 170 |
| 22 | 13 | 22 | 160 | 130 |
| 23 | 13 | 22 | 160 | 150 |
| 24 | 13 | 18 | 160 | 150 |
| 25 | 13 | 22 | 160 | 150 |
| 26 | 13 | 22 | 160 | 150 |
| 27 | 13 | 22 | 160 | 150 |
| 28 | 13 | 22 | 160 | 150 |
| 29 | 13 | 22 | 160 | 150 |
| 30 | 13 | 22 | 160 | 150 |

Modeling and prediction using Artificial Neural Network Analysis (ANN)

One of the fundamental challenges with artificial neural network (ANN) is the inability to accurately predict the response variables without design of experiment. It means therefore that the performance of ANN is dependent on the beauty of experimental design. Therefore, to predict the response variables beyond the scope of experimentation, predictive model such as artificial neural network (ANN) was employed. Thirty (30) experimental data generated by replicating the design matrix from the CCD was used for the neural network modeling. The experimental data were first normalized to avoid the problem of weight variation that may consequently results in overtraining which is a major limitation in neural network modeling.

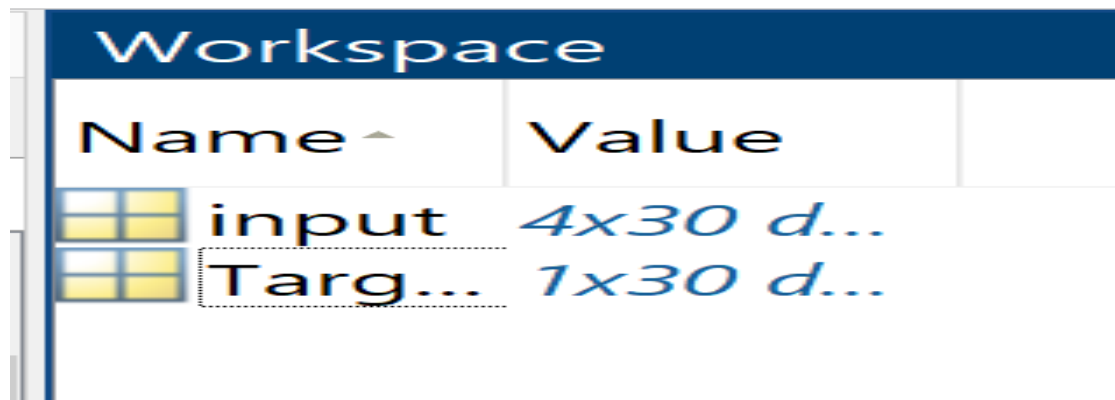


Figure 4: Workspace for input and response data

To train a neural network for predicting surface heat energy, a feed forward back propagation algorithm was used. The input layer of the network uses the hyperbolic tangent (tan-sigmoid) transfer function to determine the layer output from the network input while the output layer uses the linear (purelin) transfer function. The number of hidden neuron was set at 10 neurons per layer and the network performance was monitored using the mean square error of regression (MSEREG). Using these parameters, an optimum neural network architecture was generated as presented in Figure 5. The same network architecture was generated to predict the four response variables.



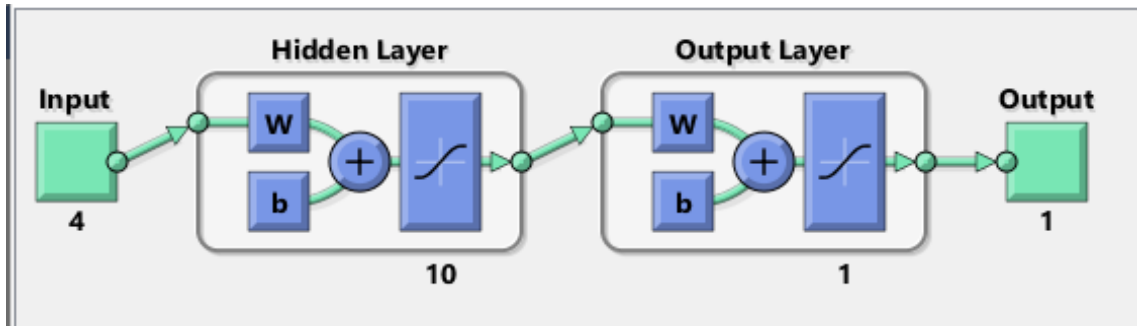


Figure 5: Neural network architecture

The network training diagram generated for the prediction of heat energy responses using back propagation neural network is presented in Figure 6.

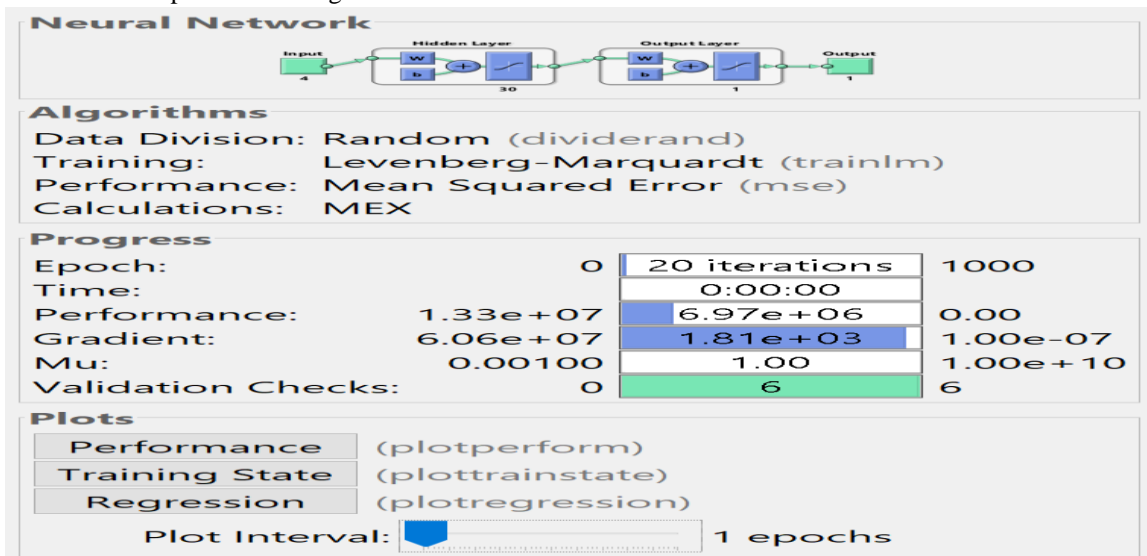


Figure 6: Network training diagram for predicting heat energy responses

Based on the computed values of the correlation coefficient (R) as observed in the network training, it was concluded that the network has been accurately trained and can be employed to predict the heat energy. To test the reliability of the trained network, the network was thereafter employed to predict its own values of heat energy response using the same sets of input parameters (food waste, wood waste, plastic waste, and cotton waste) and three response variables designated as EXP, ANN, and error representing: Heat energy (J) as presented in Table 5 for the 30 experimental run.

Table 5: ANN prediction results for the generated heat energy from municipal waste

| Run | Factor 1 A:Food waste | Factor 2 B:Wood waste | Factor 3 C:Plastic waste | Factor 4 D:cotton waste | EXP Heat energy (J) | ANN Heat energy (J) | Error Heat energy (J) |
|-----|--------------------------|--------------------------|-----------------------------|----------------------------|------------------------|------------------------|--------------------------|
| | Kg | Kg | Kg | Kg | | | |
| 1 | 13 | 22 | 160 | 150 | 10324 | 12157.3348448519 | -1833.33484485187 |
| 2 | 13 | 22 | 160 | 150 | 10326 | 12157.3348448519 | -1831.33484485187 |
| 3 | 13 | 22 | 160 | 150 | 10323 | 12157.3348448519 | -1834.33484485187 |
| 4 | 13 | 22 | 160 | 150 | 10324 | 12157.3348448519 | -1833.33484485187 |
| 5 | 13 | 22 | 160 | 150 | 10325 | 12157.3348448519 | -1832.33484485187 |
| 6 | 13 | 22 | 160 | 150 | 10323 | 12157.3348448519 | -1834.33484485187 |
| 7 | 13 | 26 | 160 | 150 | 10021 | 10024.0501226721 | -3.05012267208804 |
| 8 | 11 | 22 | 160 | 150 | 29899 | 29897.7648803372 | 1.23511966282604 |

| | | | | | | | |
|----|----|----|-----|-----|-------|------------------|---------------------|
| 9 | 13 | 22 | 140 | 150 | 22015 | 22014.9202852721 | 0.0797147278535704 |
| 10 | 13 | 22 | 160 | 170 | 20005 | 20004.8344664777 | 0.165533522296755 |
| 11 | 13 | 22 | 160 | 130 | 28765 | 28764.9722602965 | 0.0277397035206377 |
| 12 | 13 | 22 | 160 | 150 | 21325 | 12157.3348448519 | 9167.66515514813 |
| 13 | 13 | 18 | 160 | 150 | 16534 | 18893.5257201205 | -2359.52572012050 |
| 14 | 13 | 22 | 160 | 150 | 20873 | 12157.3348448519 | 8715.66515514813 |
| 15 | 12 | 20 | 170 | 140 | 27276 | 28582.4284518679 | -1306.42845186788 |
| 16 | 12 | 24 | 150 | 160 | 15454 | 20308.6740523843 | -4854.67405238429 |
| 17 | 12 | 20 | 170 | 160 | 23843 | 22131.7110791980 | 1711.28892080201 |
| 18 | 14 | 24 | 170 | 140 | 23438 | 23438.2310660214 | -0.231066021377046 |
| 19 | 14 | 24 | 150 | 140 | 21037 | 21036.7680169095 | 0.231983090503491 |
| 20 | 12 | 24 | 170 | 140 | 21552 | 21552.1169976798 | -0.116997679753695 |
| 21 | 14 | 24 | 170 | 160 | 16371 | 16370.7385524895 | 0.261447510483777 |
| 22 | 12 | 24 | 150 | 140 | 19965 | 19965.0643942310 | -0.0643942310052807 |
| 23 | 12 | 24 | 170 | 160 | 26262 | 26261.9547436768 | 0.0452563231519889 |
| 24 | 12 | 20 | 150 | 160 | 25862 | 22733.5954297333 | 3128.40457026671 |
| 25 | 14 | 20 | 150 | 140 | 22322 | 22321.9858621282 | 0.0141378718471969 |
| 26 | 14 | 20 | 170 | 140 | 24315 | 24314.7357006995 | 0.264299300528364 |
| 27 | 12 | 20 | 150 | 140 | 23981 | 23202.9418063460 | 778.058193653960 |
| 28 | 14 | 20 | 150 | 160 | 18693 | 18693.2152935256 | -0.215293525623565 |
| 29 | 14 | 24 | 150 | 160 | 10677 | 11607.3766971278 | -930.376697127780 |
| 30 | 14 | 20 | 170 | 160 | 10621 | 10422.5067441323 | 198.493255867697 |

The generated results presented in the Table 5, shown the Heat energy from the four input variables designated as factor 1, factor 2, factor 3, and factor 4 representing food waste, wood waste, plastic waste, and cotton waste for ANN in comparison with the Experimental results of Heat energy (J).

A regression plot of output between the experimental values of heat energy and the predicted values of heat energy was generated using ANN. Coefficient of determination (r^2) was determined for ANN that predicted heating values as presented in figure 7. The rule of higher the better was employed to select the best model for predicting the heat energy.

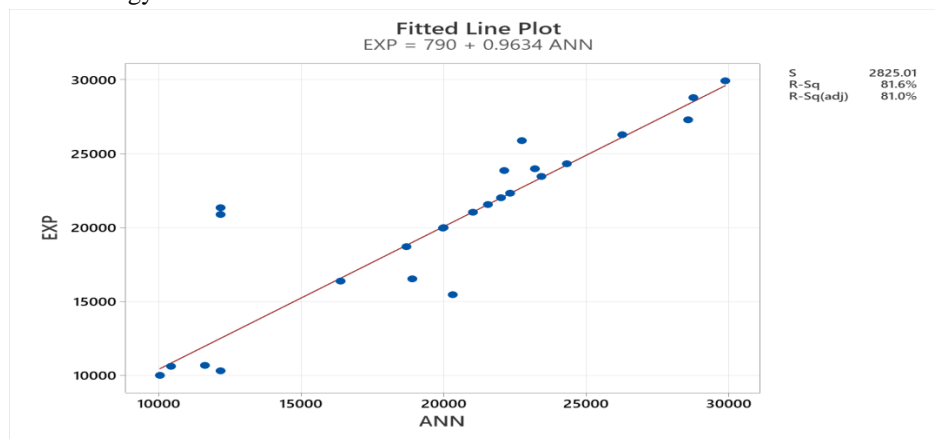


Figure 7: Fitted line plot for ANN against EXP

From figure 7 above, ANN with r-square on a fitted linear line plot having 89.8% provided an excellent prediction of Heat energy for electricity estimation from municipal solid waste.

Discussion

The determination of municipal solid waste composition on the range of input parameters from the generated municipal solid waste were characterized to be food waste of 11 – 14kg, wood waste of 18 – 26kg, plastics



waste of 140 – 170kg, and cotton waste of 130 – 170kg respectively. Experimentally, 2g sample of the various waste component were measure for laboratory experiment to determine the ultimate analysis for chemical composition of each waste element and the amount of carbon, hydrogen, oxygen, nitrogen, sulfur, and ash content for each type of waste. The ultimate analysis experimental values were subjected to Dulong’s model for the determination of Heat Energy on the characterized municipal solid waste been generated in Benin metropolis that resulted to 22,354.7195kJ/kg. The artificial neural network was also used to optimize the input parameters such as food waste, wood waste, plastics waste and cotton waste. The ANN model was also employed for prediction; the data was normalized before generating the network. A regression plot of training, validation, and testing for heat energy responses produced with R-values of 93% for the training, 91% for the validation, 81% for testing and 90% for the overall. Reliability was produced to test the networks adequacy a reliability plot of 89.8% was obtained for the ANN network.

Findings

Arising from the outcome of this study, the following are the findings.

1. The average composition of the municipal solid waste for maximum and minimum range of waste parameters of food waste of 11 – 14kg, wood waste of 18 – 26kg, plastics waste of 140 – 170kg, and cotton waste of 130 – 170kg respectively were determined.
2. Ultimate analysis to determine the amount of carbon, hydrogen, oxygen, nitrogen, sulphur, and ash content from the municipal solid waste properties in the metropolis were performed.
3. Dulong’s model was suitable for the determination of heat energy value of 22,354.7195kJ/kg for electricity estimation in the metropolis.
4. The overall performances of the developed models for heat energy estimation from the municipal solid waste disposal problem shows R^2 value of 93% for training, 91% for validation, 81% for testing, and 90% for overall with a reliability plot of 89.8% for the artificial neural network (ANN).

Conclusion

Waste to energy solves the problem of municipal solid waste disposal while recovering the energy from the waste materials with the significant benefits of environmental quality, increasingly accepted as a clean source of energy. Statistical design of experiment (DOE) using central composite design (CCD) matrix was employed to determine the optimum value from the waste parameters that will minimize the rate of solid waste disposal as well as generating heat energy to boost the electric power supply in the metropolis using ANN model. Reliability was produced to test the networks adequacy. A reliability plot of 89.8% was obtained for the ANN network. The study established the heating values for energy potential of the municipal waste components in the area. The results of this research showed that energy recovery is a feasible option as part of an integrated municipal solid waste management plan in Benin City, Edo State.

Recommendations

Arising from the results of this study the following recommendations are made for further studies.

- i. Further work on the use of other optimization and prediction models such as Response Surface Methodology, Fuzzy Logic, and the generic algorithm to understand the performance of their model when compared to the expert system on ANN utilized here
- ii. Chemical composition on Liquid waste should be performing experimentally for heat energy for electricity estimation in comparison to solid waste heat energy analysis.

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