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DETERMINATION OF THE FUEL WOOD PROPERTIES OF SELECTED NIGERIAN WOOD TREES

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Abstract

Wood has originally and primarily been the source of energy for many industrial and domestic processes. Certain properties of wood such as moisture content, density, ash content, fuel value index and calorific value determine the fuel value of each wood tree species. In this research , fuel wood properties for six selected Nigerian wood trees were determined; *Peltophorum pterocarpum, Terminalia catappa, Psidium guajava, Azadirachta indica, Gmelina arborea* and *Mangifera indica*. Standard empirical procedures were used to determine the moisture content, density, ash content and volatile content while net calorific value and fuel value index were determined by using analytical calculations. The results obtained for moisture content, density, volatile content, ash content, net calorific value and Fuel value index are as follows: *Peltophorum pterocarpum* 66.97%, 0.4108 g/cm^3, 67 %, 4.5 %, 4.4765 KJ/g and 40.86 , *Terminalia catappa,* 69.37%, 0.3263 g/cm^3, 65%, 4%, 3.9739 KJ/g and 32.41, I *Psidium guajava*, 42.21%, 0.6491g/cm^3, 69%, 7%, 9.6612KJ/g and 89.59, *Azadirachta indica*, 40.99%, 0.6813g/cm^3, 52%, 10.5%, 9.9167KJ/g and 64.35, *Gmelina arborea,* 36.62%, 0.44 g/cm^3, 68%, 2.5%, 10.8318 KJ/g and 190.64 and *Mangifera indica* ,36.02%, 0.6652g/cm^3, 59%, 5.5%, 10.9574KJ/g and 132.53 respectively. *Gmelina arborea* produces the best fuel value index irrespective of its low density because of its low ash content and moisture content while *Peltophorum pterocarpum* has the least. Kendall tau shows strong similarity in rank between net calorific value and the fuel value index (Kendall tau = 0.7333, p-value = 0.0388).

Keywords: Wood trees, Fuel wood Fuel value index, Rank coefficient, Net calorific value

Introduction

Wood fuels have always played an important role in the sourcing of energy by mankind. It is an ageless energy source known for its ergonomics. It has been at the forefront for combustible fuels because of its availability, renewability and ease of conversion into energy (Tillman, 1978). Mankind's utilization of heat from wood fires to cook and keep warm was one of the early applications of wood fuels in human history. Although the uses of wood have expanded as science and technology grows, its main application in the world today is as a fuel for both domestic and industrial heating. Wood is used as a building and construction material for houses and bridges. It is used as a raw material for producing equipment, weapons, tools and implements like bows, arrows, shovels, spears, hoes, wheel barrows etc. It can be used for making clothing materials and can be even used as food. Yet amongst all these use cases, wood fuels make up more than half of the consumption of wood in the world according to the Food and Agricultural Organization of the United Nations (Trossero, 2002).

The use of wood as a fuel has been in decline for years now because of the oil boom of the 20th century (Tillman, 1978). However, it has seen a recent resurgence because of the issues facing fossil fuels today. Also, the environmental consequences have been an additional concern in the fossil fuel energy discourse today. Fossil fuels are not recyclable. They produce waste products like carbon dioxide which they do not take back. Oil spills and entire cities enveloped in smog are not making the situation look good at all, both in real life and on paper. Wood, on the other hand is making a comeback because of its availability. Wood is also cheap. It is the primary energy source in developing countries today. Even developed countries are working around the inefficiencies of wood fuels by building more robust combustion systems for energy recovery. Trees, the primary source of wood, are known for their carbon sequestration. Trees soak up tons of carbon dioxide from the atmosphere and trap carbon in their tissues. Wood burning is just a part of the self-recycling process. Biodegradability of wood and wood products makes it an excellent choice as fuel (Krajnc, 2015). Unused wood, partially combusted wood and charcoal are all biodegradable organic materials.

The importance of wood as a fuel today has driven research into ways to better select wood fuel species and optimize the entire combustion process for maximal release of energy. Wood properties such as moisture content, calorific value, ash content, density and specific gravity have been obtained mostly by empirical means in order to possess better knowledge to decipher which wood species make better fuels. Some properties such as fuel value index and combustion efficiency have been developed with the aid of numerical calculations to help in ranking these species. The fuel value index incorporates multiple properties considering the fact whether each property is a negative or positive factor. There are some characteristics that define the choice of a species for wood and these includes: the kind of flame, the length of the flame, the amount and duration of coal, the type of smoke produced, the ease of ignition, the flavor to food and the quantity of ash left.

The Pearson correlation coefficient, spearman's rank correlation coefficient and the one way ANOVA has been primarily been used to determine the correlation, interrelation and disassociation of the studied wood properties by most wood fuel researchers. These calculations have been done manually or with software, such as SPSS. These techniques perform excellently well but little or no work is found using alternate techniques like the Kendall tau rank coefficient. . Most of the contemporary works done on the fuel wood properties of Nigerian wood trees are quite few and most of the wood trees in Nigeria are yet to be studied. Estimation and prediction models for the wood fuel properties have rarely been documented algorithmically

The aim of this paper is to determine the fuel wood properties of selected Nigerian wood trees and to develop a representative estimation model for wood sample properties using linear regression techniques.

Materials and Methods

Wood sample collection and preparation

The wood samples for this research were obtained from the Niger Delta region specifically, Choba, Port Harcourt ,Nigeria (4.893365^{0}N, 6.908341^{0}E) and its environs. These wood fuel species are well distributed all over Nigeria. Hence, they are representative of the wood tree biosphere in Nigeria.

Table 1: Selected wood fuel trees for Sampling

Sample	Scientific name	Common name	Family
A	*Peltophorum pterocarpum*	Flamboyant yellow	*Fabaceae*
B	*Terminalia catappa*	Indian almond	*Combretaceae*
C	*Psidium guajava*	Guava	*Myrtaceae*
D	*Azadirachta indica*	Neem	*Meliaceae*
E	*Gmelina arborea*	Beechwood	*Lamiaceae*
F	*Mangifera indica*	Mango	*Anacardiaceae*

The wood samples were obtained in early-November; just after the decline of the late October rains. The table below contains the weather data for Port Harcourt obtained from the Nigerian Meteorological Agency (NIMET) and Weather Underground for four days leading to the sampling day.

Table 2: Weather data for Port Harcourt for Four days leading to sampling day

Weather Variable	Day One	Day Two	Day Three	Day Four
Mean temperature (^{0}C)	27	28	27	28
Max temperature (^{0}C)	31	30	32	33
Min temperature (^{0}C)	24	25	23	24
Dew Point (^{0}C)	24	24	24	24
Average humidity (^{0}C)	82	90	88	81
Maximum Humidity (^{0}C)	94	95	100	94
Minimum Humidity(^{0}C)	66	74	66	59
Precipitation (mm)	0.00	4.06	3.05	0.00

Source: Weather Underground and NIMET

The collected wood samples from each species were sawed to about 140 grams each with the aid of a paring knife the entire inner and outer bark was removed exposing the inner living sapwood. The branches had relatively few growth rings and hence, were young compared to their respective trees. When all the bark was removed, the stripping continued until 100 grams non-uniform cylindrical wood samples were obtained.

Determination of moisture content

The procedure for determination of the moisture content of the wood fuel samples was obtained from "Standard Test Methods for Direct Moisture Content Measurement of Wood and Wood-Base Materials" (ASTM D4442-92, 1992).

Procedure: 100 milligram samples were immediately dried on the trays of the forced convection oven maintained at 105^0C. The end point is reached when the mass loss in a 3 hour drying interval is equal to or twice the analytical balance sensitivity (10 milligram).

Calculations: Moisture content was calculated as follows:

$$MC, \%, oven - dry\ basis = \frac{A - B}{B} \times 100 \qquad (1)$$

$$MC, \%, wet\ basis = \frac{A - B}{A} \times 100 \qquad (2)$$

Where: A = original mass, g and B = oven-dry mass, g

Determination of density/specific gravity

The procedure for determination of the specific gravity of the wood fuel samples was obtained from "Standard Test Methods for Specific Gravity of Wood and Wood-Based Materials" (ASTM D2395-07, 2007). The sample was cut and weight determined with the aid of the analytical balance. The specimen was treated by dipping in a solution of paraffin wax in carbon tetrachloride (1 gram of paraffin wax in 150 cubic centimeter of carbon tetrachloride). Before immersion, the carbon tetrachloride was allowed to evaporate for a few minutes. The gain in weight due to the thin film of wax is negligible. The water level in the tube was read to an even graduation mark before immersion. The specimen was immersed and kept submerged with a slender pointed wire and the water level determined again. The difference in water level is equal to the volume of the specimen.

Calculations: The specific gravity is calculated as follows:

$$sp\ gr = \frac{K * W}{V} \qquad (3)$$

Where K = constant whose value is determined by the units used to measure weight and volume (1 for gram and cubic centimeter, 1000 for gram and cubic millimeter), W = weight of oven-dry specimen, V = volume of oven-dry specimen.

Determination of ash content

The procedure for determination of the ash content of the wood fuel samples was obtained from "Standard Test Methods for Ash in Wood" (ASTM D1102-84, 1984). Calculations: The percentage of ash for oven-dry wood was calculated as follows:

$$Ash, \% = \frac{W_1}{W_2} \times 100 \quad (4)$$

Where: W_1 = weight of ash, and W_2 = weight of oven-dry sample

Determination of volatile content

The procedure for determination of the ash content of the wood fuel samples was obtained "Standard Test Methods for Volatile Matter in the Analysis of Particulate Wood Fuels" (ASTM E872-82, 1982).

Calculations: The volatile matter percentage was calculated as follows:

$$Volatile\ matter, \% = \frac{W_i - W_f}{W_i - W_c} \times 100 \quad (5)$$

Where W_c = weight of crucible and cover, g, W_i = initial weight, g and W_f = final weight, g.

Determination of net calorific value

The net calorific value of each wood fuel sample was calculated analytically using the following formula (Valter Francescato, 2008):

$$NCV_M = \frac{NCV_0 \times (100 - M) - 2.44 \times M}{100} \quad (6)$$

With NCV_0 = 18.5 KJ/g (the oven-dry calorific value of different wood species varies within a very narrow interval; 18.5 -19 KJ/g) (Valter Francescato, 2008)

Determination of fuel value index

The fuel value index of each wood fuel sample was calculated using the following formula (Nirmal,2011 and Samuel, 2015

$$Fuel\ value\ index = \frac{Calorific\ value\ \left(\frac{KJ}{g}\right) \times Density(\frac{g}{cc})}{Ash\ content\ \left(\frac{g}{g}\right)} \tag{7}$$

Statistical Analysis

For the statistical analysis of the fuel wood properties of the samples, the Pearson, Spearman and Kendall rank correlation is employed. . The Kendall rank correlation is a measure of the ordinal association between the properties. It is the difference between the number of concordant pairs and the number of discordant pairs divided by half of the product of the number of samples and one less than the number of samples.

Linear Prediction Models

Linear prediction models were setup for the fuel wood properties using regression models. These models can be used to predict with a certain degree of accuracy fuel wood properties using other properties that are highly correlated with it. These models were written with the aid of Python and scikit-learn. The linear regression was setup using the ordinary least square method with alternate improved techniques such as the Huber, Ridge and Lasso linear models..

The experimental results obtained were used as the dataset for this computation. The data set was randomly split into training and test data in the ratio (2:1). This amounts to the training data having about 4 samples and test data 2 samples. The training data was then fitted into the specified model's technique and the predicted y-values of the x-values of the test data obtained.

Results and Discussions

Table 3: Fuel wood Properties of the Selected Wood Trees

Sample	Moisture content dry basis (%)	Moisture content wet basis (%)	Density (g/cm^3)	Volatile content (%)	Ash content (%)	Net calorific value (KJ/g)	Fuel value index	Rank
A	202.7551	66.97	0.4108	67	4.5	4.4765	40.8622	5
B	226.4773	69.37	0.3263	65	4	3.9739	32.4123	6
C	73.0403	42.21	0.6491	69	7	9.6612	89.5914	3
D	69.4628	40.99	0.6813	52	10.5	9.9167	64.3456	4
E	57.7785	36.62	0.44	68	2.5	10.8318	190.6392	1
F	56.2988	36.02	0.6652	59	5.5	10.9574	132.5325	2

Note: A = *Peltophorum pterocarpum*, B= *Terminalia catappa*, C = *Psidium guajava*, D = *Azadirachta indica*, E = *Gmelina arborea*, F = *Mangifera indica*

Table 3: The Pearson and Spearman correlation coefficients and Kendall tau rank correlation along with their respective p-values for pairwise correlation evaluation of the obtained fuel wood properties of the selected wood tree species

Properties	Pearson Correlation		Spearman Correlation		Kendall rank correlation	
	coefficient	**p-value**	**coefficient**	**p-value**	**Tau**	**p-value**
Density and Ash content	0.7534	0.0837	0.7714	0.0724	0.6	0.0909
Density and Moisture content	-0.7587	0.0803	-0.7143	0.1108	-0.6	0.0909
Density and Volatile content	-0.5545	0.2534	-0.4286	0.3965	-0.2	0.5730
Density and Net Calorific value	0.7587	0.0803	0.7143	0.1108	0.6	0.0909
Density and Fuel Value Index	0.2220	0.6725	0.4857	0.3287	0.3333	0.3476
Ash content and Moisture content	-0.2859	0.5828	-0.1429	0.7872	-0.2	0.5730
Ash content and volatile content	-0.7391	0.0932	-0.3714	0.4685	-0.3333	0.3476
Ash content and Net calorific value	0.2859	0.5828	0.1429	0.7872	0.2	0.5730
Ash content and Fuel value index	-0.3500	0.4964	-0.08571	0.8717	-0.0667	0.8510
Moisture content and Volatile content	0.2988	0.5652	0.2	0.704	0.0667	0.8510
Moisture content and Net calorific value	-1.0	0.0	-1.0	0.0	-1.0	0.0048

Moisture content and Fuel value index	-0.7873	0.06307	-0.8857	0.0188	-0.7333	0.0388
Volatile content and Net calorific value	-0.2988	0.5652	-0.2	0.704	-0.0667	0.8510
Volatile content and Fuel value index	0.1492	0.7779	0.2571	0.6228	0.2	0.5730
Net calorific value and Fuel value index	0.7873	0.06307	0.8857	0.0188	0.7333	0.0388

The moisture content, density, volatile content ash content, net calorific value and fuel value index of the selected fuel wood properties are presented in table 1. The moisture content varies from 36.62% (*gamelina arborea*) to 69.37% (*terminalia catappa*), density, 0.3263 g/cm^3 (t*erminalia catappa*) to 0.6813g/cm^3 *(azadirachta indica*), volatile content, 52% (*azadirachta indica*) to 69% (*psidium guajava*), ash content, 2.50 % (*gmelina arborea*) to 10.5% (azadirachta indica), net calorific value, 3.9739 KJ/g (terminalia catappa) to 10.9574KJ/g (*magifera indica*) and fuel value index 32.4123 (*terminalia catappa*) to 190.6392(*gamelina arborea*) .

Moisture content is the amount of water present in wood sample. All other wood properties are greatly dependent on water content; hence water content affects the choice of wood fuels and industrial applications of wood .The moisture content of freshly cut wood varies between species and also between portions of the tree. Wood density is dependent on a multiple of growth and physiological factors such as age, height and tree diameter. The density also plays an important role in the determination of fuel properties. The results shows that t*erminalia catappa* is suspected to have higher energy per unit volume when compared to other species. A higher wood density increases the calorific value and tends to slow the burning rate (Abbot and Hofi, 1997). Volatile content is the amount of volatile matter produced upon carbonization. As carbonization is prolonged, more volatile matter is produced. The high volatile content of a biomass material indicates that during combustion, most of it will volatize and burn as gas in the cookstove (Akowuah, et al, 2012). Ash content is the remaining inorganic part of wood fuels that cannot be combusted. Wood fuels in with high ash content are less desirable as fuel because a considerable amount of the wood matter cannot be converted to energy (Joseph and Shadrach, 1985). The high ash content of *(azadirachta indica)* indicates that the species has high mineral matter. The value index fuel is a composite parameter that is based on certain properties of wood that helps determine how much fuel value the wood has. The results from the six examined wood fuel species shows that *Gmelina arborea* provided the best wood fuel value. Although it has a relatively low density when compared with others, it compensates with low moisture content and ash content.

Net calorific value decreased linearly and significantly with increase in moisture content as expected (Pearson r = -1.0, p = 0.0). A coefficient of -1.0 was expected as net calorific value was calculated from a formula with moisture content being the singular variable involved. Density showed strong negative correlation with moisture content (Pearson r = -0.7587, p= 0.0803) and strong positive net calorific value (Pearson r = 0.7587, p = 0.0803). The p-values showed strong significance just shy of less than 0.05. Density and Ash content showed a strongly positive correlation (Pearson r = 0.7534) just like net calorific value and fuel value index which is moderate (Pearson r =0.7873) with p-values relatively small. Volatile content showed little correlation with fuel value index (Pearson r = 0.1492); though with a relatively high p- value (0.7779). This shows the likelihood of a true null

Fuel value index has a strongly monotonic relationship with net calorific value and moisture content (Spearman r = 0.8857 and r= -0.8557 respectively, p = 0.0188) irrespective of its weaker linear relationship. Volatile content has a weak monotonic relationship with the rest of the other properties (Spearman r ranging from -0.4286 to 0.2571)

Kendal tau test shows dissimilarity in rank between moisture content and net calorific value (Kendall tau = -1.0, p-value = 0.0048) and also strong similarity in rank between the net calorific value and the fuel value index (Kendall tau = 0.7333, p-value = 0.0388). Volatile content shows an absence of association with moisture content and net calorific value (Kendall tau = 0.0667 and -0.0667 respectively)

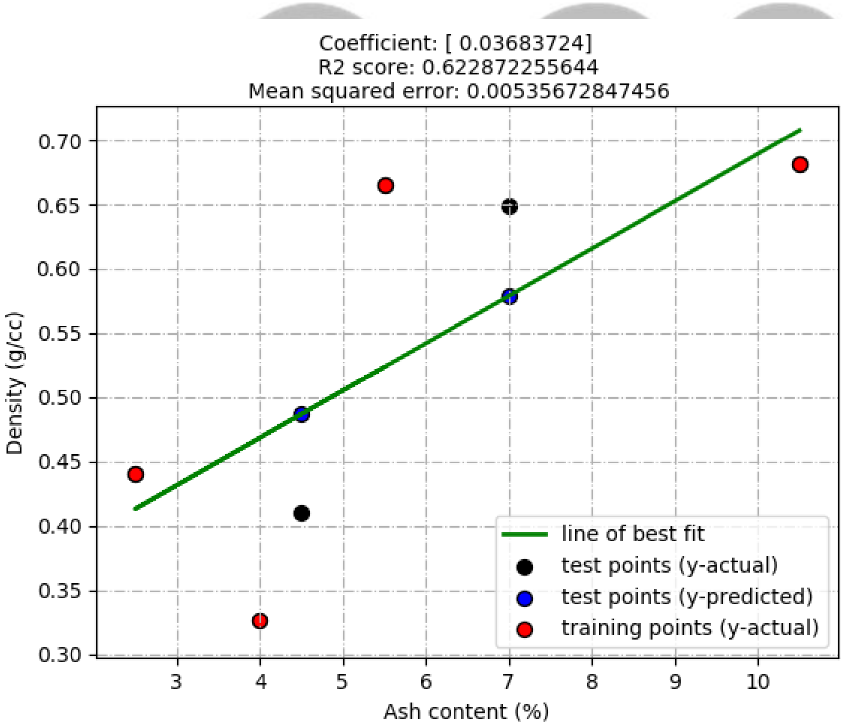

Figure 4 Graph of Density (g/cc) against Ash content (%)

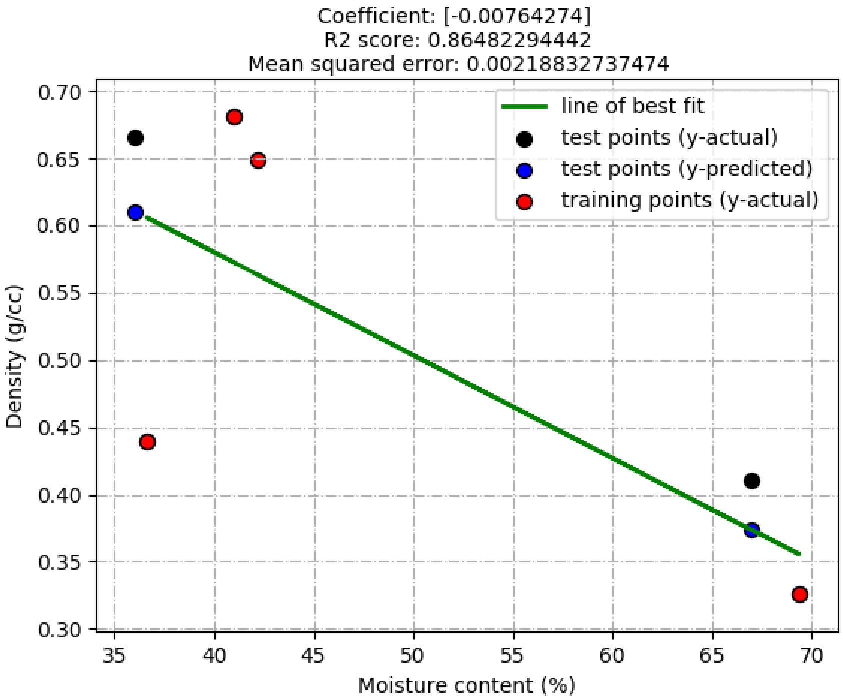

Figure 5 Graph of Density (g/cc) against Moisture content (%)

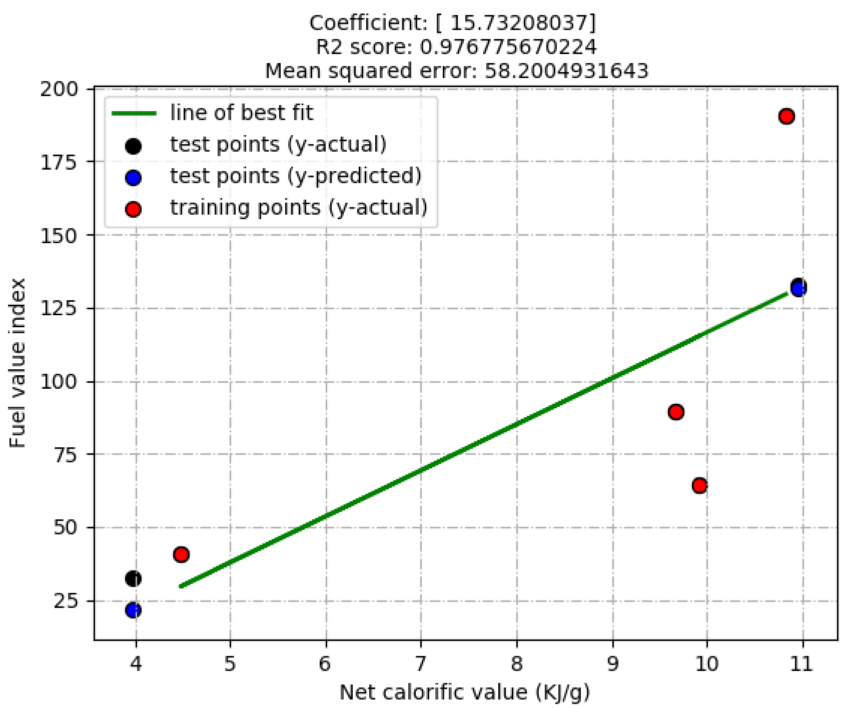

Figure 6: Graph of Fuel value index against Net calorific value (KJ/g)

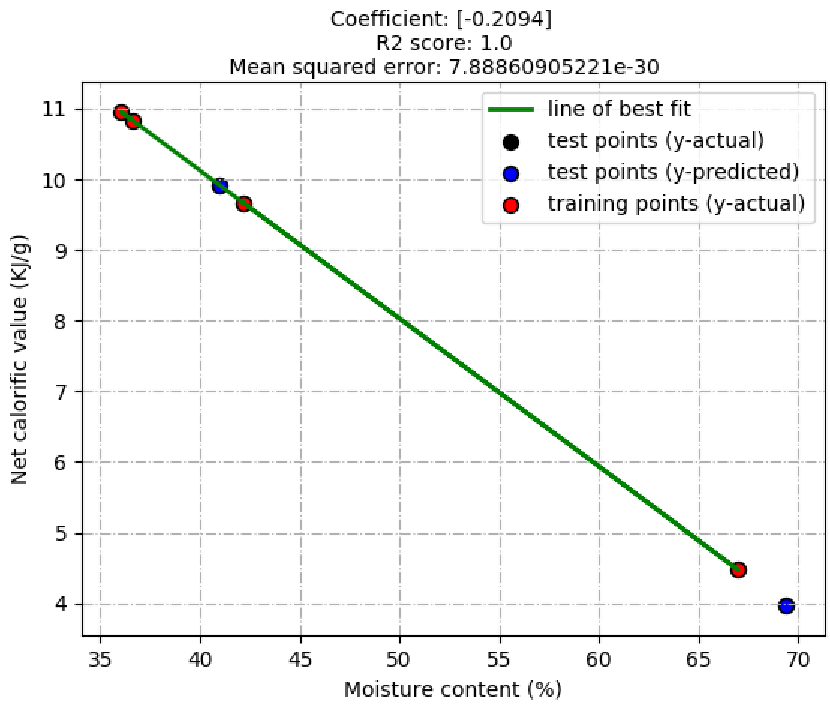

Figure 7: Graph of Net Calorific Value (KJ/g) against Moisture Content

PYTHON IMPLEMENTATION FOR STATISTICAL ANALYSIS AND REGRESSION

```
import csv
import matplotlib.pyplot as plt

from numpy import array
from scipy.stats.stats import pearsonr, spearmanr, kendalltau
from collections import OrderedDict
from sklearn.linear_model import LinearRegression, HuberRegressor, Lasso, Ridge
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn import datasets

def load_csv(file_path):
    names = {'Common name':[], 'Scientific name':[], 'Family name':[]}
    properties = {'Moisture content':[], 'Ash content':[], 'Density':[],
                  'Volatile content':[], 'Net calorific value':[],
                  'Fuel value index':[]}
    with open(file_path) as csv_file:
        csv_data = csv.DictReader(csv_file)
        for row in csv_data:
            for key in names.keys():
                property = row.get(key)
                if property is None: property = "UNDEFINED"
                names[key].append(property)
            for key in properties.keys():
                property = row.get(key)
                if isinstance(property, str):
                    property = float(property)
                properties[key].append(property)
    return names, properties

def make_dataset(requested_properties, properties):
    dataset = []
    count = None
    for property in requested_properties:
        if property in properties.keys(): pass
        else: raise ValueError(property + ' requested is not in loaded properties')
        if count is None:
            count = len(properties[property])
            for cell in properties[property]:
                dataset.append([cell])
        else:
            if len(properties[property]) != count:
                raise ValueError('properties do not have equal row count')
            i = 0
            for cell in properties[property]:
                dataset[i].append(cell)
                i = i + 1
    return array(dataset);

def stat_analysis(named_dict_dataset):
    while(len(named_dict_dataset) > 1):
        name, dataset = named_dict_dataset.popitem(False)
        for nxt_name, nxt_dataset in named_dict_dataset.items():
            print("CORRELATION BETWEEN " + name + " AND " + nxt_name)
            coef, p = pearsonr(dataset, nxt_dataset)
            print('Pearson correlation: coefficent = ' + str(coef[0]) + ', p-value = '+ str(p[0]))
            coef, p = spearmanr(dataset, nxt_dataset)
            print('Spearman correlation: coefficent = ' + str(coef) + ', p-value = ' + str(p))
            coef, p = kendalltau(dataset, nxt_dataset)
            print('Kendall rank correlation: tau = ' + str(coef) + ', p-value = ' + str(p))
```

```python
def linear_regression_fit_predict(train_x, train_y, test_x):
    regr = LinearRegression(normalize=False).fit(train_x, train_y)
    return regr.predict(test_x), regr.predict(train_x), regr.coef_

def huber_regression_fit_predict(train_x, train_y, test_x):
    regr = HuberRegressor().fit(train_x, train_y)
    return regr.predict(test_x), regr.predict(train_x), regr.coef_

def lasso_regression_fit_predict(train_x, train_y, test_x):
    regr = Lasso(normalize=False).fit(train_x, train_y)
    return regr.predict(test_x), regr.predict(train_x), regr.coef_

def ridge_regression_fit_predict(train_x, train_y, test_x):
    regr = Ridge(normalize=False).fit(train_x, train_y)
    return regr.predict(test_x), regr.predict(train_x), regr.coef_

def regression(dataset_x, dataset_y, type):
    train_x, test_x, train_y, test_y = train_test_split(dataset_x[1], dataset_y[1], test_size=0.33)
    if type == "linear":
        test_pred_y, train_pred_y, coef = linear_regression_fit_predict(train_x, train_y, test_x)
    elif type == "huber":
        test_pred_y, train_pred_y, coef = huber_regression_fit_predict(train_x, train_y, test_x)
    elif type == "ridge":
        test_pred_y, train_pred_y, coef = ridge_regression_fit_predict(train_x, train_y, test_x)
    elif type == "lasso":
        test_pred_y, train_pred_y, coef = lasso_regression_fit_predict(train_x, train_y, test_x)
    else:
        raise ValueError("Undefined regression type")
        return
    m_sq_error = mean_squared_error(test_y, test_pred_y)
    r2 = r2_score(test_y, test_pred_y)
    regr_plot(dataset_x[1], dataset_y[1], test_x, test_pred_y, train_x, train_y,
              train_x, train_pred_y, coef, r2, m_sq_error, dataset_x[0], dataset_y[0])


def regr_plot(x1, y1, x2, y2, x3, y3, x4, y4, coef, r2, m_sq_error, xlabel, ylabel):
    fig = plt.figure()
    fig.suptitle('Coefficient: ' + str(coef[0]) + "\n R2 score: "+ str(r2) +"\n Mean squared error: "
                 + str(m_sq_error), fontsize = 10)
    axes = plt.gca()
    axes.grid( linestyle='-.')
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    original_pts = plt.scatter(x1, y1, color = 'black', s =50, label = "test points (y-actual)")
    plt.scatter(x2, y2, color='blue', edgecolors='black', s= 50, label = "test points (y-predicted)")
    plt.scatter(x3, y3, color='red', edgecolors="black", s= 50, label= "training points (y-actual)")
    plt.plot(x4, y4, color='green', linewidth=2, label="line of best fit")
    plt.legend()
    plt.savefig("image.png")

def main():
    names, properties = load_csv('results.csv')
    named_dict_dataset = OrderedDict([("Density", make_dataset(['Density'], properties)),
                                      ("Ash content", make_dataset(['Ash content'], properties)),
                              ("Moisture content", make_dataset(['Moisture content'], properties)),
                            ("Volatile content", make_dataset(['Volatile content'], properties)),
                            ("Net calorific value", make_dataset(["Net calorific value"], properties)),
                            ("Fuel value index", make_dataset(["Fuel value index"], properties))])
    regression(("Ash content (%)", named_dict_dataset["Ash content"]), ("Volatile content (%)",
                named_dict_dataset["Volatile content"]), "linear")
    stat_analysis(named_dict_dataset)

main()
```

Conclusion

The quality of fuel wood depends on quantitative and qualitative properties of wood such as density, moisture content, ash content , volatile content, calorific value and fuel value index. The results from the six examined wood fuel species shows that *Gmelina arborea* provided the best wood fuel value. Although it has a relatively low density when compared with others, it compensates with low moisture content and ash content. The fuel index value is actually a good way of ranking wood because it puts the economic value into perspective such as. drying costs of wood (moisture content), incombustible mass of wood (ash content), cost considerations of bulk mass transported per volume (density), cost considerations of transporting green wood and also maintenance costs from combustion systems. Kendall tau shows strong similarity in rank between net calorific value and the fuel value index (Kendall tau = 0.7333, p-value = 0.0388).

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