Calorific value predicting based on moisture and volatile matter contents using fuzzy inference system

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Abstract. The calorific value is one of the most important characteristics of fuel and it determines the energy content of fuel. In this study, we developed the calorific value predicting program based on proximate analysis of moisture and volatile matter contents using the fuzzy inference system with Tsukamoto method. The moisture and volatile matter contents are used as input and the calorific value as an output. Every fuzzy variable is divided into two linguistic values of fuzzy set i.e. low and high. By evaluation on fuzzy inference rules output, it is found that moisture content has more dominant influence on the calorific value. We also found that the calorific value predicting program has prediction error of about 0 to 1.80 %.

1. Introduction

The living thing such as biogas, wood, and agricultural waste can produced the biological material which is known as biomass. The biomass is usually used as a source of alternative energy to fossil fuels [1]. In the past decade, many countries has been exploited the possibility of biomass to the provision of energy. And it makes the biomass as a promising option for renewable energy resources [2]. The energy coming from biomass material is potential for reducing the greenhouse gas emission from fossil fuels [3][4]. Many researchers have observed that the biomass material can produce qualified biomass fuels. The quality of the fuels is characterized by proximate analysis of moisture content, ash content, volatile matter, and fixed carbon and the measured calorific value [5][6][7].

Moisture content is significantly influencing the calorific value. High moisture content causes the difficulty for igniting and many losses of energy were required for water evaporation during combustion [7][8][9]. Volatile matter in biomass consist of carbon, hydrogen and oxygen and it becomes vapor when it is heating [10]. High volatile matter content doesn’t always increase calorific value because CO₂ and H₂O are noncombustible gases [11]. High volatile matter content indicates easily in ignition and high combustion rate [12][13]. The calorific value is heat energy content of fuel that released during the complete combustion of unit mass of biomass [9][14]. Experimentally the calorific value is measured with a bomb calorimeter.

It seems that there is a significant correlation between proximate analyses data with calorific value. Many attempts have been done the for analyzing this correlation by using the soft computing techniques such as regression, artificial neural network, genetic algorithm and fuzzy logic to simulate relationship between proximate analysis data with calorific value [15][16][17]. Fuzzy logic theory was introduced by Lotfi Zadeh in 1965 and nowadays numerous applications of
fuzzy logic can be found in many engineering and scientific works [18]. In this research, the calorific value predicting based on moisture and volatile matter content is done by using Fuzzy Inference System (FIS) of Tsukamoto method [19].

2. Methods
In this work, the fuzzy variables are moisture and volatile matter contents used as an input and caloric value as an output. Every fuzzy variable was divided into two linguistic value of fuzzy set i.e. low and high. The range of fuzzy set domain was selected from minimum and maximum values of each fuzzy variable data. The fuzzy logic has three steps i.e. fuzzification, inference and defuzzification steps. In this fuzzy logic, we used Tsukamoto method.

2.1. Fuzzification
Fuzzification convert crisp inputs to fuzzy input in accordance with its linguistic values based on membership function [19][20]. Shoulder curves were chosen as membership function. Left shoulder of membership function is used to represent membership grade of linguistic value “low” and right shoulder to represent membership grade of linguistic value “high”. It is given by the following equations

\[
\mu_L(x, a, b) = \begin{cases} 
1, & x \leq a \\
\frac{b-x}{b-a}, & a < x < b, \\
0, & x \geq b 
\end{cases} 
\]  

(1)

\[
\mu_H(x, a, b) = \begin{cases} 
1, & x \geq b \\
\frac{x-a}{b-a}, & a < x < b \\
0, & x \leq a 
\end{cases} 
\]  

(2)

In equation (1) and (2), parameter \(a, b, x\) are the crisp values. And \(\mu_L\) and \(\mu_H\) are the membership grade of low and high.

2.2 Fuzzy Inference System Tsukamoto
Fuzzy inference system is a method for translating the input values to output values by using some rules. The rules involve membership functions i.e., fuzzy logic operator, and if-then rules [22]. One type of fuzzy inference is Tsukamoto method. Evaluation rules in FIS Tsukamoto uses min function implication to determine \(\alpha\)-predicate value (\(a_1, a_2, a_3 \ldots a_n\)) for each rule and then counted crisp value as output for each rule (\(z_1, z_2, z_3 \ldots z_n\)) [23].

In this research, four rules are applied to set up relationship between antecedent and consequent as shown on Table 1. The output of every fuzzy inference rule will be adjusted in order to obtain a predictive calorific value with smallest prediction error. According to the research results of the relationship between proximate data and calorific values, some researchers had concluded that moisture content gives negative affect on calorific value while volatile matter content gives positive affect. We then assumed that the calorific value will be
high if the moisture content is low while the volatile matter content is high, and vice versa. This assumption is then applied in second and third fuzzy rules. Unfortunately, when moisture content and volatile matter content have same linguistic value, the percentage of dominate role between them still has not been known yet. Therefore, the linguistic value in the output of the first and fourth of the fuzzy inference rules is then counted on both high and low. So there are four possibilities output of the fuzzy inference rules. In the evaluation step, the composition of linguistic value with smallest prediction error will be chosen as the most suitable composition for the calorific value predicting program.

Table 1. Fuzzy inference rule of the calorific value predicting program

| Rule | Antecedent | Antecedent | Consequent | Output |
|------|------------|------------|------------|--------|
| 1    | IF         | Moisture content low AND Volatile Matter content low THEN Calorific value * high, low | z₁ |
| 2    | IF         | Moisture content high AND Volatile Matter content low THEN Calorific value low | z₂ |
| 3    | IF         | Moisture content low AND Volatile Matter content high THEN Calorific value high | z₃ |
| 4    | IF         | Moisture content high AND Volatile Matter content high THEN Calorific value * high, low | z₄ |

* It will be further investigated for each linguistic value

2.3 Defuzzification

Defuzzification transfer fuzzy inference rule results into a crisp output. FIS Tsukamoto uses the center average defuzzied method which is given as [19]

$$Z = \sum a_i z_i \sum a_i$$  \hspace{1cm} (3)

$Z$ is FIS Tsukamoto output. In our program, $Z$ is a predicting value.

3. Result and discussion

![Figure 2](image.png)

Figure 2. Example of composition evaluation process of our program.

We used experimental data as shown in Table 3 for composition evaluation and program prediction testing. First, we run composition evaluation process to determine the linguistic value of fuzzy inference rule output for the calorific value predicting program. As an example in Figure 2, we shown the evaluation process of the linguistic value composition of fuzzy inference rule output where only one data set is being used. The results of our analysis by using
several experimental data (14 data sets) is shown in Table 2.

The HLHL composition appears 13 times which has the smallest prediction error from 14 data sets. This indicates that the HLHL composition can represent the majority event that occurs in biofuels. Therefore we conclude that the moisture content has more dominant influence on calorific value than volatile matter content. This is consistent with the results of Refs. [12][13] where volatile matter content only influences easiness of fuel samples to ignite and combustion rate. This can be seen also in linguistic values based on the biggest membership grade of each fuzzy variable, as shown in Table 2.

Table 2. The evaluation result of composition of the fuzzy inference rules output

| Experimental data | Linguistic value on the biggest membership grade | The smallest prediction error on composition : $z_1$, $z_2$, $z_3$, $z_4$ |
|-------------------|-----------------------------------------------|-----------------------------------------------|
|                   | MC    | VM    | CV    | HLHH  | HLHL  | LLHH  | LLHL  |  |
| Sabindo L.O et.al. [6] | 1     | High  | Low   | Low   | 0 %   | 0 %   | 0 %   | 0 % |
|                    | 2     | High  | Low   | Low   | 0.07 %| 0.07 %| 0 %   | 0 % |
|                    | 3     | Low   | High  | High  | 0 %   | 0 %   | 0 %   | 0 % |
| Nurhilal O et.al. [5] | 1     | Low   | Low   | High  | 0 %   | 0 %   | 0 %   | 0 % |
|                    | 2     | Low   | High  | High  | 0.71 %| 0 %   | 0 %   | 0 % |
|                    | 3     | 0.5   | High  | 0.5   | 1.39 %| 1.39 %| 0 %   | 0 % |
|                    | 4     | High  | High  | Low   | 1.80 %| 1.80 %| 0 %   | 0 % |
|                    | 5     | High  | High  | Low   | 0 %   | 0 %   | 0 %   | 0 % |
| Sunardi et.al. [7] | 1a    | Low   | High  | High  | 0 %   | 0 %   | 0 %   | 0 % |
|                    | 2a    | Low   | 0.5   | High  | 1.52 %| 1.52 %| 0 %   | 0 % |
|                    | 3a    | High  | High  | Low   | 0 %   | 0 %   | 0 %   | 0 % |
|                    | 1b    | Low   | Low   | High  | 0 %   | 0 %   | 0 %   | 0 % |
|                    | 2b    | High  | High  | Low   | 0.88 %| 0 %   | 0 %   | 0 % |
|                    | 3b    | High  | High  | Low   | 0 %   | 0 %   | 0 %   | 0 % |

Notes: MC=Moisture Content, VM=Volatile Matter, CV=Calorific Value, H=High, L=Low

From the results as shown in Table 2, the composition HLHL was chosen as the linguistic value of fuzzy inference rule output on the calorific value predicting program, i.e., $z_1$=High, $z_2$=Low, $z_3$=High and $z_4$=Low and it was used to test the performance of the program.
The percentage of difference between the calorific value of experimental data and the calorific value predicting result is defined as prediction error.

| Experimental data | MC (%) | VM (%) | CV (Cal/gram) | CV prediction (Cal/gram) | Prediction error (%) |
|-------------------|--------|--------|---------------|--------------------------|----------------------|
| Particle size 20 mesh | 11.62 | 12.78 | 5292.24 | 5292.24 | 0 |
| 30 mesh | 10.84 | 12.92 | 5568.73 | 5572.37 | 0.07 |
| 40 mesh | 8.45 | 13.28 | 6118.49 | 6118.49 | 0 |
| Composition 90% : 0 % | 5.39 | 32.40 | 6211 | 6211 | 0 |
| 80% : 20% | 5.61 | 33.15 | 5999 | 6073.85 | 1.25 |
| 70% : 30% | 5.84 | 33.17 | 5935 | 6017.50 | 1.39 |
| 60% : 40% | 6.11 | 33.36 | 5911 | 6017.50 | 1.80 |
| 50% : 50% | 6.29 | 33.45 | 5824 | 5824 | 0 |
| Pressure 22.42 kg/cm² 40 mesh | 6.91 | 21.28 | 5571.22 | 5571.22 | 0 |
| 50 mesh | 7.82 | 21.30 | 5426.40 | 5343.66 | 1.52 |
| 60 mesh | 8.95 | 21.32 | 5091.72 | 5091.72 | 0 |
| Pressure 44.80 kg/cm² 40 mesh | 6.18 | 21.30 | 5691.15 | 5691.15 | 0 |
| 50 mesh | 7.22 | 21.33 | 5570.41 | 5619.41 | 0.88 |
| 60 mesh | 8.12 | 21.35 | 5553.20 | 5553.20 | 0 |

The results of program prediction testing shown in Table 3. It is shown that the calorific value predicting program can reproduced the calorific values of the experimental data quite well with prediction error of about 0 to 1.80 %. The difference between the experimental data of calorific value and predicting result might be due to only two parameters of proximate analysis used in the analysis.

4. Conclusion
We have developed a program for predicting the calorific value based Fuzzy inference rules of Tsukamoto method. In our analysis we only use the experimental data of moisture and volatile matter contents. We have shown that our program can explained the experimental data of the calorific value quite well. We also found that the influence of moisture content to the calorific value is more dominant compared to volatile matter content. Unfortunately, our results still have an error then the more improvement of predicting program by using other experimental data such as fixed carbon and ash content in addition to moisture and volatile matter contents.

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