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Research Article

In-Depth Analysis of Municipal Solid Waste's Heating Value for Green and Clean Renewable Energy in the context of Way of Live

K. Laohalidanond[1]
T. Wiangthong[2,*]
S. Kerdsuwan[1]
[1] *The Waste Incineration Research Center, Department of Mechanical and Aerospace Engineering, Faculty of Engineering, Science and Technology Research Institute, King Mongkut's University of Technology North Bangkok, Bangkok, 10800, Thailand*
[2] *Department of Mechanical Engineering, Faculty of engineering, Rajamangala University of Technology Phra Nakhon, Bangkok, 10800, Thailand*

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Abstract:
The increase in global waste levels and the decrease in fossil energy sources are major concerns around the world. Waste-to-Energy (WtE) technologies have been used to transform Municipal Solid Waste (MSW) into energy and minimize concerns about global waste levels and fossil energy. However, MSW presents a number of challenges when used as a feedstock for energy production due to its heterogeneous composition, low energy content, and high moisture. To design waste incineration power plants, it is necessary to measure the Higher Heating Value (HHV) and the composition characteristics of MSW. Therefore, this paper proposes a most suitable correlations based on ultimate analysis to accurately estimate the HHV of MSW. The correlations consider all parameters that influence the HHV of MSW. MSW was collected from both urban and rural areas. Ultimate analysis was performed to characterize the chemical composition of MSW from both areas, and the HHV was also determined to compare the differences in the chemical properties of MSW from different areas. This work helps save experimentation costs and assists in the design and management of waste incineration plants.

Keywords: *Municipal Solid Waste (MSW), Higher Heating Value (HHV), Ultimate analysis, Correlation*

1. Introduction

The increase of global waste levels presents a pressing worldwide issue, including the decline of fossil fuels, which has led to a rise in resource crisis. According to a report from the World Bank, it is projected that by 2050, the world will produce about 3.40 billion tons of waste. The major methods for handling municipal solid waste (MSW) are landfills and open dumps, but these are far from being ultimate solutions for waste management. This is because some components of waste are non-degradable and persist in landfills for extended periods. Recycling and composting processes currently recover only 19 percent of these wastes, with a mere 11 percent being utilized in modern incineration facilities [1]. In addition to the challenges posed by waste management, the world is also grappling with an escalating energy crisis and ecological concerns. In the near future, a key challenge for the global community will be to identify reliable sources of renewable energy. Utilizing MSW as a source of renewable energy emerges as one potential solution to address both the waste disposal predicament and the global energy crisis. Waste-to-energy (WtE) plays an important role in waste management systems. From an energy system perspective, WtE contributes to the advancement of a low-carbon society. Incineration stands out as an efficient method for reducing waste volume and the demand for landfill space. By locating incineration plants in proximity to the center of waste generation, transportation costs can be reduced. Additionally, the utilization of ash from MSW incinerators in environmentally responsible construction not only provides a cost-effective aggregate but also reduces the necessity

* Corresponding author: T. Wiangthong
E-mail address: thanaphon.w@rmutp.ac.th

for landfill capacity. One of the most interesting aspects of the incineration process is its capability to reduce the original volume of combustibles by 80 to 95 percent. Waste incineration becomes particularly advantageous when a landfill cannot be sited because of a lack of suitable sites or extensive transportation distances, which result in elevated costs [2].

In the design of MSW incineration systems, a crucial requirement is to accurately determine the energy content of the waste. However, it's worth noting that the process of determining the energy content of MSW can be time-consuming and can lead to increased project costs. To avoid these drawbacks, correlations or models can be utilized to estimate the energy content of the waste. Currently, there are three primary types of models employed for this purpose, each based on one of the following types of analyses: physical composition [3, 4], ultimate analysis [5, 6] and proximate analysis [4, 7]. Each of these analysis methods provides insights into the energy content of MSW and can be used to design MSW incineration facilities. The choice of which analysis to use depends on the available data and the specific requirements of the incineration project. The study primarily focused on utilizing ultimate analysis-based correlations to assess the HHV of MSW.

In general, there has been extensive development of HHV estimation models based on elemental composition, as reported by Olatunji et al. [5]. For instance, Shi et al. [8] employed a dataset of 193 experimental observations to create and validate a novel equation. Janna et al. [3] established a correlation to estimate the HHV of MSW by linking it to the physical composition of MSW in two scenarios, namely wet MSW and dry MSW. Their findings indicated that models relying on dry MSW yielded greater accuracy. Meanwhile, Zhu and Yang [9] applied artificial neural network (ANN) models for HHV prediction of MSW, and they observed that models based on proximate analysis exhibited lower precision in HHV estimation, whereas those based on ultimate analysis demonstrated superior predictive performance.

Nevertheless, MSW comprises a heterogeneous mixture of materials, which makes predicting HHV challenging, and some proposed models may not be universally applicable to all waste categories. In this study, the objective was to determine the most suitable correlations based on ultimate analysis for each type of MSW gathered from both urban and rural areas. We conducted experimental tests to determine the moisture content, the ultimate analysis and HHV of the MSW samples. Then eight correlations for HHV calculation based on ultimate analysis were selected from literature. The results of HHV calculation were subsequently compared to the experimentally measured HHV values. To identify the best correlation, the mean absolute error (MAE) was employed as the selection criterion. Moreover, an optimal predictive model for predicting the HHV of different MSW samples will be chosen to precisely anticipate outcomes using ultimate analysis data, resulting in cost savings related to experimentation and establishing a theoretical foundation for modeling MSW combustion, pyrolysis processes, and thermal conversion to enhance energy security. These results also provide quick and effective guidance for the MSW's incineration process.

2. Methodology

This study aimed to determine the most suitable correlations based on ultimate analysis for MSW from urban and rural areas, the work procedures was shown in Fig. 1.

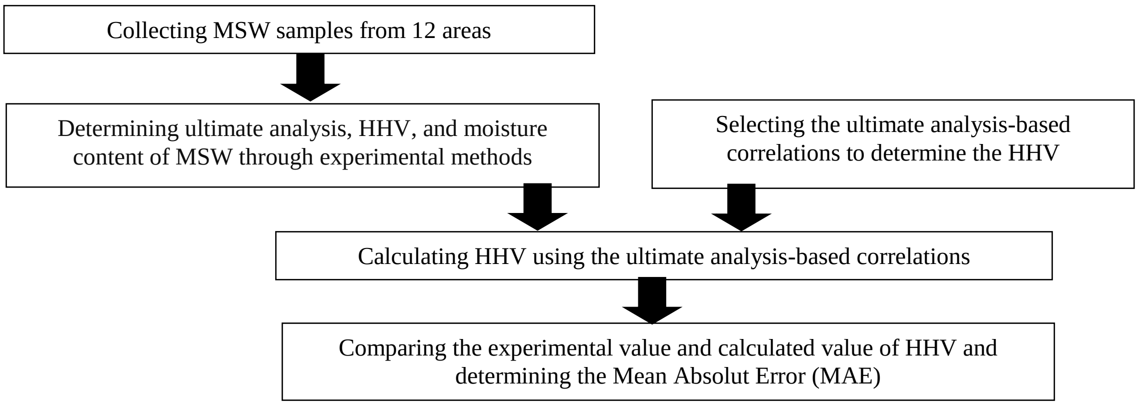

Fig. 1. Work procedures

2.1 Sample Collection

The goal of this study is to identify the appropriate correlation for estimating the Higher Heating Value (HHV) of Municipal Solid Waste (MSW) based on data from ultimate analysis. To achieve this objective, MSW samples were gathered from various locations in both urban and rural areas across Thailand. Totally 12 samples were obtained from 8 provinces to represent MSW from urban areas, which are referred to as MSW_U. Additionally, 8 samples of MSW were collected from 3 provinces to serve as representatives of rural areas, and these are denoted as MSW_R throughout the manuscript, as shown in Table 1.

2.2 MSW Characteristics

Therefore, the moisture content, the ultimate analysis of MSW_U and MSW_R, as well as the HHV of MSW were investigated according to ASTM, as shown in Table 2.

Table 1: Locations for MSW Collection

Area	Province	Location	
Urban	Songkhla	Songkhla city	MSW_{U1}
		Hat Yai	MSW_{U2}
	Bangkok	Sathorn	MSW_{U3}
		Prawes	MSW_{U4}
	Chonburi	Pattaya	MSW_{U5}
		Chonburi city	MSW_{U6}
	Udonthani	Udonthani city	MSW_{U7}
	Nonthaburi	Nonthaburi city	MSW_{U8}
		Pak Kret	MSW_{U9}
	Phuket	Phuket city	MSW_{U10}
	Tourist Acttractions	Ko Lipe	MSW_{U11}
		Ko Pha-ngan	MSW_{U12}
Rural	Songkhla	Ban Phru	MSW_{R1}
		Bor Tru	MSW_{R2}
		Cha Na	MSW_{R3}
	Udonthani	Na Ngua	MSW_{R4}
		Nong Han	MSW_{R5}
	Krabi	Ao Nang	MSW_{R6}
		Nuea Khlong	MSW_{R7}
		Ao Luek	MSW_{R8}

Table 2: ASTM for determination of MSW characteristics

Properties	Standard
Moisture content (%wt, as received)	ASTM D3173-87
Ultimate analysis (%wt, dry basis)	
Carbon	ASTM D3178-89
Hydrogen	ASTM D3178-89
Nitrogen	ASTM D3178-89
Sulfur	ASTM D4239-85c
Chlorine	ASTM D2361-91
Oxygen	By Difference
HHV (kJ/kg, dry basis)	ASTM D3286-91

2.3 Selection of Correlation

The correlations employed in this study were empirical correlations that have been mathematically validated by numerous researchers for determining HHV [5, 6, 8, 10]. This work used 8 ultimate analysis-based correlations to determine the HHV of MSW_U and MSW_R, as presented in Table 3.

Table 3: Correlations for the prediction of HHV

Modelers	Empirical correlations	Unit	Reference
Boie	HHV = 0.3517C + 1.1626H - 0.1047S - 0.111O	MJ/kg	[5]
Dulong	HHV = 81C + 342.5(H - O/8) + 22.5S	kcal/kg	[6]
Modified Dulong	HHV = 80.5C+ 338.6H - 42.3O + 22.2S + 5.55N	kcal/kg	[6]
Vandralek	HHV = 85C + 270H + 26(S - O)	kcal/kg	[10]
Khuriati et al.	HHV = -2762.68 + 114.63C + 310.55H	kcal/kg	[6]
Shi et al.	HHV = -1.46 + 0.361C + 1.05H - 0.160N + 1.24S - 0.0658O	MJ/kg	[8]
Scheurer&Kestner's	HHV = 81(C–3/4(O))+342.5H+22.5S+57(3/4(O))-6(9H+W)	kcal/kg	[6]
Steuer's	HHV = 81(C–(3/8)O)+57((3/8)O)+345(H-O/16)+25S-6(9H+W)	kcal/kg	[6]

The HHV calculated using the ultimate analysis-based correlations were compared with the experimental data. The relative error (RE) [9] was also determined using the following equation.

$$RE_i = \frac{\mathrm{HHV_{Cal}} - \mathrm{HHV_{Exp}}}{\mathrm{HHV_{Exp}}} \times 100 \qquad (1)$$

Where,
RE_i is relative error (%)
HHV_{Cal} is HHV calculated using ultimate analysis-based correlation (MJ/Kg)
HHV_{Exp} is experimentally HHV value (MJ/Kg)

The RE was used to access the mean absolute error (MAE) [9] of each correlation which used to determine the optimal correlation for each MSW from urban and rural area. The MAE essentially measures the degree of proximity between predicted HHVs and experimental values by taking the average of the dataset. A lower MAE signifies greater accuracy for a specific correlation [11].

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |RE_i| \qquad (2)$$

Where,
MAE is mean absolute error (%)
RE_i is relative error (%)

3. Results and Discussion

3.1 Ultimate Analysis and Experimentally HHV Value

The ultimate analysis of MSW_U and MSW_R are shown in Table 4 and Table 5, respectively. According to world bank report [1], the composition of MSW demonstrates notable variations based on income levels. As income levels increase, there is a decrease in the proportion of organic matter in the waste. Additionally, higher-income countries use more paper and plastic in consumed goods compared to lower-income countries. The granularity of data regarding waste composition, including rubber and wood waste, also increases by income level. This observed trend contributes to an understanding of the differences in MSW composition between urban and rural areas, influencing the calorific value of MSW.

Nguyen et al. [12] also indicated that the composition of MSW varies significantly from one municipality to another and from area to area, influenced by factors such as human activities, consumption patterns, population behavior, economic conditions, waste management regulations, and also industrial makeup. The amount and composition of MSW play a crucial role in determining the suitable methods for handling and managing these wastes. This information is vital for establishing solid waste-to-energy conversion facilities within municipalities. The ultimate analysis also plays a vital role in predicting the HHV of MSW. It serves as a crucial parameter for making informed decisions when establishing effective waste processing and disposal facilities within urban and rural areas.

The findings revealed that the carbon content in MSW_U ranged from 31.12% to 52.85%, whereas in the case of MSW_R, the range was higher, spanning from 39.80% to 51.03%. The hydrogen content fell within the range of 3.52% to 7.62% for MSW_U and 4.58% to 7.89% for MSW_R. Another significant chemical component, oxygen, exhibited variation between 23.85% and 37.03% for MSW_U and 15.98% to 32.22% for MSW_R. These values for chemical content will be employed in the calculation of HHV using correlations based on ultimate analysis.

The HHV of MSW, as determined experimentally using a bomb calorimeter, was presented in Tables 4 and 5 and demonstrated a range from 14.69 to 24.37 MJ/kg for MSW_U. Similarly, the HHV of MSW_R fell within the range of 15.40 to 23.78 MJ/kg. It's important to note that the variation in HHV for MSW can be attributed to differences in population behavior within each area.

3.2 HHV Calculated Using Ultimate Analysis-Based Correlation

Following the experimental determination of the ultimate analysis, the data presented in Table 4 and Table 5 was employed to calculate the HHV using correlations based on ultimate analysis. These calculated HHV values for MSWU were then compared with the experimentally obtained HHV values, as shown in Table 6. Additionally, the relative error and mean absolute error for each correlation were computed and are provided in Table 7. For MSWR, the comparison of HHV values, both calculated and experimental, is shown in Table 8, and the relative error and mean absolute error for each correlation are provided in Table 9.

The MAE offers a measure of the error in the same unit as the physical quantity being analyzed. In this study, the correlation with the lowest MAE value has been regarded as the optimal correlation. As a result, it's important to note that the predicted HHV values may not align precisely with the experimentally-measured data. This approach of analyzing estimation errors and selecting correlations with lower MAE values is a common practice in various studies focused on developing empirical correlations for predicting the HHV of biomass and coals [9]. The MAE for MSW_U ranged from 13.30% to 17.48%, which was notably higher than the MAE for MSW_R, spanning from 3.24% to 6.44%. The variation in MAE between the two sample groups could be attributed to differences in the behavior of the populations as well as variations in the physical composition of the waste materials.

Based on the MAE results, it can be concluded that the correlation developed by Shi et al. [8] is well-suited for predicting the HHV of MSW_U, while the correlation by Scheurer & Kestner [6] appears to be more suitable for MSW_R. However, it's important to note that the accuracy of these correlations relies on the quality and representativeness of the raw data from the ultimate analysis. Therefore, before relying on these correlations for predictions, it's crucial to perform validation to assess their accuracy and reliability.

Table 4: MSW_U characteristics

Characteristics	Songkhla		Bangkok		Chonburi		Udonthani	Nonthaburi		Phuket	Tourist Acttractions	
	MSW_{U1}	MSW_{U2}	MSW_{U3}	MSW_{U4}	MSW_{U5}	MSW_{U6}	MSW_{U7}	MSW_{U8}	MSW_{U9}	MSW_{U10}	MSW_{U11}	MSW_{U12}
Moisture (%wt, as received)												
	51.83	52.59	56.47	66.67	53.57	44.5	61.95	64.20	60.20	46.34	64.75	65.38
Ultimate analysis (%wt, dry basis)												
Carbon	52.85	49.2	39.61	41.76	51.93	55.55	43.6	31.12	39.56	46.1	47.73	39.2
Hydrogen	7.45	4.22	5.35	5.38	7.28	7.62	6.34	3.52	4.23	6.23	6.11	5.05
Oxygen	25.67	27.25	30.8	37.03	30.32	23.85	30.4	30.05	29.08	27.54	26.41	26.31
Nitrogen	2.05	0.86	1.17	1.18	1.9	0.33	1.46	1.04	1.33	1.1	1.75	0.12
Sulfur	0.26	0.25	0.18	0.19	0.16	0.09	0.22	0.19	0.16	0.12	0.2	0.14
Chlorine	1.78	1.39	0.98	0.74	1.1	1.4	5.72	0	0	0	2.99	2.1
Ash	9.94	16.83	21.91	13.72	7.31	11.16	12.26	34.08	25.64	18.91	14.81	27.08
Total	100	100	100	100	100	100	100	100	100	100	100	100
HHV (MJ/kg, dry basis)												
	23.29	22.88	14.69	16.1	24.37	19.84	19.63	19.5	18.31	21.61	18.73	20.13

Table 5: MSW_R characteristics

Ultimate analysis	Songkhla			Udonthani		Krabi		
	MSW_{R1}	MSW_{R1}	MSW_{R1}	MSW_{R1}	MSW_{R1}	MSW_{R1}	MSW_{R1}	MSW_{R1}
Moisture (%wt, as received)								
	61.6	55.65	59.17	58.3	65.05	27.12	63.44	50.14
Ultimate analysis (% at dry basis)								
Carbon	50.36	51.03	50.46	48.14	51.65	50.8	47.6	39.8
Hydrogen	6.82	7.34	6.46	6.2	7.45	7.89	6.38	4.58
Oxygen	20.82	28.09	15.98	28.78	22.4	28.75	28.11	32.22
Nitrogen	1.19	0.75	1.67	1.12	1.99	0.42	0.94	0
Sulfur	0.35	0.3	0.48	1.36	0.3	0.98	0.19	0.13
Chlorine	1.19	1.2	1.54	3.58	3.88	0	2.53	5.77
Ash	19.27	11.29	23.41	10.82	12.33	11.16	14.25	17.5
Total	100	100	100	100	100	100	100	100
HHV (MJ/kg, dry basis)								
	22.66	23.52	23.78	19.13	23.51	22.37	20.04	15.4

Table 6: HHV calculated using ultimate analysis-based correlation of MSW_U

Modeler	HHV (dry basis, MJ/kg)											
	Songkhla		Bangkok		Chonburi		Udonthani	Nonthaburi		Phuket	Tourist Attractions	
	MSW_{U1}	MSW_{U2}	MSW_{U3}	MSW_{U4}	MSW_{U5}	MSW_{U6}	MSW_{U7}	MSW_{U8}	MSW_{U9}	MSW_{U10}	MSW_{U11}	MSW_{U12}
Experiment	**23.29**	**22.88**	**14.69**	**16.10**	**24.37**	**19.84**	**19.63**	**19.50**	**18.31**	**21.61**	**18.73**	**20.13**
Boie	24.37	19.16	16.71	16.81	23.35	25.74	19.31	11.68	15.59	20.39	20.94	16.72
Dulong	24.01	17.86	15.59	15.25	22.62	25.48	18.44	10.23	14.27	19.63	20.22	15.82
Modified Dulong	23.88	17.77	15.51	15.18	22.50	25.30	18.34	10.19	14.22	19.52	20.12	15.72
Vandralek	24.45	19.33	16.80	16.92	23.41	25.78	19.38	11.80	15.70	20.45	21.03	16.80
Khuriati et al.	23.47	17.52	14.39	15.46	22.81	24.98	17.59	7.94	12.91	18.65	19.27	13.80
Shi et al.	23.76	19.29	16.68	16.96	22.83	25.17	19.09	11.96	15.63	20.06	20.56	16.75
Scheurer&Kestner's	23.86	18.48	16.25	16.30	22.94	25.14	18.72	11.02	14.94	20.01	20.10	15.77
Steuer's	22.43	17.03	14.60	14.31	21.26	23.95	17.08	9.40	13.34	18.54	18.63	14.44

Table 7: Relative error and MAE of MSW_U's HHV

Modeler	Relative error (%)												MAE (%)
	Songkhla		Bangkok		Chonburi		Udonthani	Nonthaburi		Phuket	Tourist Attractions		
	MSW_{U1}	MSW_{U2}	MSW_{U3}	MSW_{U4}	MSW_{U5}	MSW_{U6}	MSW_{U7}	MSW_{U8}	MSW_{U9}	MSW_{U10}	MSW_{U11}	MSW_{U12}	
Boie	4.67	-16.25	13.74	4.45	-4.19	29.71	-1.65	-40.10	-14.87	-5.65	11.77	-16.94	**13.66**
Dulong	3.13	-21.91	6.10	-5.27	-7.18	28.42	-6.09	-47.56	-22.04	-9.15	7.94	-21.41	**15.52**
Modified Dulong	2.57	-22.32	5.57	-5.70	-7.67	27.50	-6.58	-47.74	-22.36	-9.68	7.39	-21.93	**15.58**
Vandralek	4.99	15.51	14.33	5.13	3.91	29.92	1.26	39.51	14.24	5.35	12.24	16.56	**13.58**
Khuriati et al.	0.79	23.41	2.07	3.95	6.40	25.91	10.40	59.28	29.49	13.70	2.88	31.44	**17.48**
Shi et al.	2.03	-15.66	13.53	5.40	-6.32	26.84	-2.75	-38.65	-14.65	-7.16	9.74	-16.81	**13.30**
Scheurer&Kestner's	2.48	-19.23	10.62	1.24	-5.86	26.70	-4.63	-43.50	-18.42	-7.39	7.31	-21.67	**14.09**
Steuer's	-3.69	-25.54	-0.64	-11.07	-12.75	20.68	-13.02	-51.81	-27.12	-14.21	-0.53	-28.26	**17.44**

Table 8: HHV calculated using ultimate analysis-based correlation of MSW_R

Modeler	HHV (dry basis, MJ/kg)							
	Songkhla			Udonthani		Krabi		
	MSW_{R1}	MSW_{R2}	MSW_{R3}	MSW_{R4}	MSW_{R5}	MSW_{R6}	MSW_{R7}	MSW_{R8}
Experiment	**22.66**	**23.52**	**23.78**	**19.13**	**23.51**	**22.37**	**20.04**	**15.40**
Boie	23.29	23.33	23.43	20.80	24.31	23.75	21.02	15.73
Dulong	23.14	22.81	23.54	20.17	24.20	23.47	20.26	14.29
Modified Dulong	23.00	22.66	23.40	20.06	24.06	23.30	20.14	14.20
Vandralek	23.39	23.42	23.56	21.14	24.38	23.96	21.10	15.84
Khuriati et al.	21.46	22.45	21.04	19.59	22.89	23.06	19.56	13.48
Shi et al.	22.88	23.08	22.97	21.74	23.65	24.16	20.78	16.01
Scheurer&Kestner's	22.30	22.71	22.37	20.27	23.36	23.93	20.21	15.33
Steuer's	21.20	21.27	21.49	18.86	22.11	22.57	18.73	13.70

Table 9: Relative error and MAE of MSW_R's HHV

Modeler	Relative error (%)								MAE (%)
	Songkhla			Udonthani			Krabi		
	MSW_{R1}	MSW_{R2}	MSW_{R3}	MSW_{R4}	MSW_{R5}	MSW_{R6}	MSW_{R7}	MSW_{R8}	
Boie	2.78	-0.81	-1.46	8.74	3.39	6.16	4.87	2.18	**3.80**
Dulong	2.12	-3.03	-1.01	5.45	2.91	4.91	1.08	-7.18	**3.46**
Modified Dulong	1.48	-3.66	-1.59	4.84	2.33	4.17	0.47	-7.75	**3.29**
Vandralek	3.19	0.44	0.94	10.52	3.69	7.11	5.28	2.86	**4.25**
Khuriati et al.	5.33	4.54	11.54	2.38	2.64	3.08	2.40	12.45	**5.55**
Shi et al.	0.94	-1.89	-3.40	13.62	0.59	8.01	3.68	4.01	**4.52**
Scheurer&Kestner's	-1.62	-3.44	-5.95	5.98	-0.63	7.00	0.85	-0.43	**3.24**
Steuer's	-6.46	-9.56	-9.64	-1.40	-5.97	0.90	-6.53	-11.03	**6.44**

4. Conclusion

This study aimed to identify the most appropriate ultimate analysis-based correlations for estimating HHV of MSW from both urban and rural areas. Eight correlations from existing literature to calculate HHV have been performed and compared the results with experimental data, also to assess the relative error and mean absolute error (MAE) as selection criteria.

For MSW from urban areas (MSW_U), the correlation developed by Shi et al. [8] yielded the lowest MAE at 13.30%. In contrast, for MSW from rural areas (MSW_R), the correlation by Scheurer & Kestner resulted in the lowest MAE at 3.24%. Based on these findings, it can be concluded that the Shi et al. [8] correlation, equation 3, is well-suited for predicting the HHV of MSW_U, while the Scheurer & Kestner correlation, equation 4, appears to be more suitable for MSW_R.

$$HHV = -1.46 + 0.361C + 1.05H - 0.160N + 1.24S - 0.0658O \quad (3)$$

$$HHV = 81(C - (3/4(O))) + 342.5H + 22.5S + 57(3/4(O)) - 6(9H+W) \quad (4)$$

Applying these correlations is uncomplicated through manual calculations, necessitating only information on ultimate analysis data (both expressed as %wt. dry basis).

This research has the potential to address challenges and inconveniences in the design of MSW incineration systems, especially when knowledge of the energy content of waste is needed. Furthermore, the suitable predictive model for the HHV of various MSW samples was selected to accurately forecast using ultimate analytical data, thereby reducing the expenses associated with experimentation and establishing a theoretical basis for modeling MSW combustion, pyrolysis processes, and thermal conversion to enhance energy security. The findings also offer rapid and efficient guidance for operating MSW incineration processes.

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