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MODELING OF HEATING VALUE OF MUNICIPAL SOLID WASTE BASED ON ULTIMATE ANALYSIS USING MULTIPLE STEPWISE REGRESION LINEAR IN SEMARANG

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ABSTRACT

This study is aimed at developing an empirical model to estimate the heating value of municipal solid waste as a function of its element content (C, H, N, S, O). A correlation was developed using multiple stepwise regression analysis based on 29 samples of municipal solid waste that were randomly selected and gathered from 29 different areas in Semarang. Experimental results show that carbon and hydrogen are statistically significant predictors of the heating value. The model is HHV= -2762.68+114.63C+310.55H kcal/kg (R^2= 0.99 and Adj R^2 =0.98). Furthermore, this work also indicates that if only the C content is known, the heating value can be estimated by HHV= -1737.55+143.33C kcal/kg (R^2= 0.94 and Adj R^2 =0.94). These results show that the new correlations using regression method give accurate and excellent results that are closer to measured values.

Keywords: heating value, MSW, stepwise multiple regression, ultimate analysis.

INTRODUCTION

Municipal solid waste (MSW) has been a major environmental issue in urban areas. Population growth, urbanization, economic development, and rising living standard have apparently contributed to by-product to the environment in the form of a burgeoning amount of MSW (Akdag *et al*., 2016). MSW becomes a serious problem when it comes to its disposal as the volume may exceed environmental capacity. One of the solutions commonly adopted to minimize waste volume is burning and converting it into energy in the form of heat or steam or electricity (EIA, 2007). Thermal conversion processes available for the thermal treatment of solid wastes are combustion, gasification, and pyrolysis. The most important parameters affecting thermal processing were its composition and higher heating value (HHV) (Zhou *et al*., 2014). HHV is a measure of the chemical energy bound in a feedstock; this energy is released during combustion (Erol *et al.*, 2010). There are three methods to determine the HHV of MSW, i.e. full-scale boiler as a calorimeter, laboratory bomb calorimeter, and calculation via empirical models (Ogwueleka, 2010). Researchers have developed many empirical models. Previous studies documented three empirical models to estimate the heating value of waste based on its physical components (Liu *et al*., 1996, Lin *et al*., 2013, Lin *et al*., 2015, Khuriati *et al*., 2016), ultimate components (Tchobanoglous *et al.*, 1993, Liu *et al*., 1996, Kathiravale *et al*., 2003, Meraz *et al*., 2003, Akkaya *et al*., 2009, Komilis *et al*., 2012, Shi *et al*., 2016), and proximate components (Kathiravale *et al*., 2003, Chang *et al*., 2007). To the current day, the most popular method used to predict HHV/LHV has been linear regression. Developing an empirical model to predict the heat value is considered easier and more economical by using regression analysis Lin *et al*., 2007). A good prediction of the heating value of waste to be burnt is important during the arrangement of the burner and afterburner chambers (Lin *et al*., 2007). Table-1 contains the modelling to predict the MSW energy content using multiple regression based on ultimate analyse.

MSW is a complex material, differ from one place to another, from one country to another (Lin *et al*., 2015). Waste composition greatly depends on social-economic status, lifestyle, and climate of a particular country (Lin *et al*., 2015, Kathiravale, 2003). MSW can be categorized as combustible and noncombustible material combination (Zhou *et al*., 2014, Meraz et al., 2003). Traditionally, combustible waste fraction can be divided into six groups, i.e. food residuals, wood, paper, textile, plastic, and rubber wastes (Zhou *et al*., 2013).

Lack of information about MSW in the landfill in Indonesia relates to high cost of sampling and chemical analysis. This study has the following objectives: a) to determine the elemental content of MSW in Semarang, (b) to measure the heating values of MSW as a dependent variable to develop a new correlation as a function of element content, c) to develop an empirical correlation to estimate the heating value of municipal solid waste as a function of its elemental content (C, H, N, S, O) using multiple stepwise linear regression.

Table-1. Models/equations for estimating the energy content of municipal solid waste as a function ultimate analysis.

Empirical correlations	**Country**	**Equation**	**Unit**	**Reference**
HHV = 1558.80 + 19.96C + 44.30O - 671.82S - 19.92W	Taiwan	1	kcal/kg	Liu *et al.*, 1996
Dulong's Equation			kcal/kg	Liu *et al.*, 1996
$HHV = 81C + 342.5\left(H - \frac{O}{8}\right) + 22.5S(9H - W)$		2	kcal/kg	Liu *et al.*, 1996
Steuer's equation				
HHV = 81(C-3xO/8) + 57x3x0/8 + 345(H-O/16) + 25S - 6(9H+W)		3	kcal/kg	Liu *et al.*, 1996
Scheurer-Kestner's equation				
HHV = 81 (C-3xO/4) + 342.5H + 22.5S + 57x3x0/4 - 6(9H+W)		4	kcal/kg	Liu *et al.*, 1996
Modified Dulong Equation				
HHV = 80.5C + 338.6H-42.3O + 22.2S + 5.55N		5	kcal/kg	Tchobanoglous et al. 1993
HHV = 416.638C – 570.017H + 259.031O +598.955N – 5829.078 kJ/kg	Malaysia	6	kJ/kg	Kathiravale *et al.*, 2003
$HHV = \left(1 - \frac{H_2O}{100}\right)\left(-0{,}3517(C) - 1{,}1625(H) + 0{,}1109(O) + 0{,}0242(N) - 0{,}0928(S)\right)$		7	MJ/kg	Meraz *et al.*, 2003
$HHV = \left(1 - \frac{H_2O}{100}\right)(0{,}327C + 1{,}241H - 0{,}089O - 0{,}26N + 0{,}074S)$	Turkey	8	MJ/kg	Akkaya and Damir, 2009
$HHV = 244{,}7(979{,}9) + 70{,}4(11{,}9)C - 64{,}2(63{,}7)N + 577{,}2(798{,}6)S + 298{,}1(46{,}6)H - 46{,}7(9{,}63)0 + 8{,}07(13{,}3)OM$	Greece	9	kcal/kg	Komilis *et al.*, 2012
$HHV = -1.46 + 0.361C + 1.05H - 0.160N + 1.24S - 0.0658O$ $HHV = 0.349C + 1.01H - 0.174N + 0.886S - 0.0812O$ $HHV = 0.350C + 1.01H - 0.0826O$	Canada	12 13 14	MJ/kg	Shi *et al.*, 2016

MATERIALS AND METHODS

Site characteristics and sampling

This study took place in Semarang, Metropolitans in Indonesia and capital of Central Java Province. Semarang covers 373.70 km^2 (Bappeda kota Semarang, 2014). The total population according to the Municipal Office of Population and Civil Record of Semarang (2016) was 1,629,691 (Disdukcapil kota Semarang, 2016). MSW is produced on a daily basis, exceeding 1, 200 tons/day, in which only 800 tons of them is sent to the final disposal site (TPA). The current final disposal site is situated in Jatibarang, the only one provided by the municipal government. The limited capacity of the municipality to collect the MSW causes the community to manage waste by themselves with methods that generally do not fulfill any health requirements and are not environmentally safe (Damanhuri *et al*., 2009). The community usually performs waste management by burning, disposing to open areas or to the rivers or even to disposal tracts, only a small amount of the waste is left unmanaged to be collected by scavengers (Damanhuri *et al*., 2009).

MSW samples were collected from 29 dump trucks from different places in Semarang using a random sampling technique according to the requirements of the ASTM D 5231 – 92 (2003). The landfill was selected for sampling (4-samples/day) for one week (7 days). The number of samples is determined based on ASTM D 5231-92 (2003) calculation. The minimum sample calculation was 28 dump trucks. Samples were randomly picked from arriving trucks that have a capacity of 102 kg per MSW dump truck. The 102-kg MSW was then remixed, coned, quartered to get 2 kilograms of the final samples to be examined in the laboratory. The remaining (100kg) was disaggregated according to the selected classification. Samples of inert materials (non-combustible) were not collected. MSW is a very physically heterogeneous material. For chemical analysis, only a few grams were needed and it represented one truck of MSW. Therefore, it is collected as individual components, rather than an entire MSW.

Heating value measurement and ultimate analysis of MSW samples were performed at tekMIRA (Center for Study and Technological Development of Mineral and Coal of the Ministry of Energy and Mineral Resources, Bandung, Indonesia). Table-2 summarizes testing methodology used in this study (Pasek *et al*., 2013). The ultimate analysis was performed to Figure out the percentage weight of C, H, N, O, and S (Vargas-Moreno *et al*, 2013). The heating values of MSW were measured using a bomb calorimeter,

Table-2. Testing standards at TekMIRA.

Component	Standard
Moisture	ISO 11722ASTM D.3173
Ash	ISO 1171 ASTM D.3174
Carbon	ISO 625 ASTM D.3178
Hydrogen	ISO 625 ASTM D.3178
Nitrogen	ISO 332 ASTM D.3179
Sulfur	ASTM D.4239
Oxygen	100%-C-H-N-S-Ash
Calorific value	ASTM D.5865

Stepwise Multiple Regression Linear (SMLR) analysis

A multiple regression analysis was applied to obtain new correlations between heating value as the dependent variable and C, H, N, S, and O components as the independent variables. A stepwise regression was applied to obtain the most appropriate regression model due to its relative advantage of possessing a reversible valuation towards explanatory variables to be included in the regression equation.

To detect heteroskedastic, multicollinearity, autocorrelation, and normality, Spearman Rank Correlation, variance inflation factor (VIF), Durbin-Watson, and Kolmogorov-Smirnov test were used to analyze residuals respectively.

Evaluation of estimated model

The evaluation of the estimated result was performed by Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R^2 determination coefficient methods. These methods performed calculations of the differences between measured and estimated data. The differences were proven using randomized data and/or less accurate data obtained. MAPE expresses accuracy as an error percentage. Since these numbers are percentages, they can be understood easier than the other form of statistics.

$$MAPE = 1/n \sum_{i=1}^{n} \left|\hat{Y}_i - Y_i\right| / Y_i \times 100 \quad (15)$$

Model performance is said to be excellent if MAPE <10, while MAPE = 10 -20 is good. MAPE = 20 - 50 is acceptable, whereas MAPE > 50 is unacceptable (Chang *et al*., 2007). Using the MSE, the error denotes the extent of differences between estimated and obtained results

$$MSE = 1/\text{n} \sum_{i=1}^{n} \left(\hat{Y}_i - Y_i\right)^2 \quad (16)$$

$$RMSE = \sqrt{1/n \sum_{i=1}^{n} \left(\hat{Y}_i - Y_i\right)^2} \quad (17)$$

Smaller values of RMSE denote better estimation to be performed.

$$R^2 = 1 - \left[\sum_{i=1}^{n} \left(\hat{Y}_i - Y_i\right)^2\right] / \left[\sum_{-=1}^{n} (\hat{Y}_i - Y_i)\right] \quad (18)$$

The R^2 statistical test is one of the indicators most frequently applied. It provides a very high weight for a largely absolute error. The R^2 exact value is indefinite. The R^2 explains that the variables have been correctly selected. The closer a value to 1 of R^2, the more accurate the model is.

RESULTS AND DISCUSSIONS

Chemical characteristics of municipal solid waste

Ultimate analysis is an important aspect to be applied to the theoretical calculation of combustion and heating value (Akdag *et al*., 2016). It comprises the analysis of carbon (C), hydrogen (H), oxygen (O), nitrogen (N), and sulfur (S) represented in weight percent on a dry basis (wt. % on a dry basis). Table 3 contains ultimate analysis and heating value of MSW. Samples analyses proved that carbon became the most dominant component, followed by oxygen. The average percentage of hydrogen and nitrogen contents in the samples was lower than 10%. Hydrogen and oxygen are contained in MSW not as gasses, but they are bound by the other substances (Meraz *et al*., 2003). Oxygen is eight times lighter than hydrogen. Hence, more oxygen is required to burn hydrogen to form H_2O (Komilis *et al*., 2012). Table-4 shows the ultimate analysis and HHV of substances that make up MSW on dry basis. Plastic has the highest carbon content (80% wt.), while the lowest carbon content goes to animal bones (33.84% wt.). Wood mostly contains oxygen (44.43 wt. %), whereas plastic has the lowest oxygen content (3.98% wt.). Meanwhile, the highest H is contained in plastic. In a combustion process, C and H are oxidized by the exothermic reaction to form of CO^2 and H_2O (Obernberger *et al*., 2006).

Table-3. Chemical characteristics of urban solid waste in Semarang in dry basis.

Items analisis ultimate	Range	Average
C (%wt)	54.09-40.81	44.22 ± 3.29
H (%wt)	6.72-8,25	7,39 ± 0.38
N (%wt)	0.33-2.33	1,89 ± 0.38
S (%wt)	0,09-0,66	0,39 ± 0.1
O (%wt)	32,05- 40.38	37,66 ± 2.15
Ash(%wt)	5.18-10.08	9.05±0.97
Heating value		
HHV (kcal/kg)	3930,46-5937,78	4552.23 ±416.58

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Despite the fact that only a small fraction of nitrogen was detected in samples analysis, it may have a significant effect in air pollution by forming NOx. NOx directly contributes to global warming via acid rain and ozone depletion (Yang *et al*., 2014). Plastic has the lowest content of N, the highest concentration found in bones (4.89% wt.).

Sulfur was also present in small amount. The process of S burning results SO^2 gas. Together with NOx, SO^2 contributes to the growth of photochemical fumes, the rise in greenhouse effect and ozone depletion in the stratosphere (Akdag *et al*., 2016, Tang *et al*., 2012). SO^2 has also been proven to efficiently inhibit the formation of PCDD/F (Aurell *et al.*, 2009). Rubber contains the highest amount of sulfur, but its amount is negligently small for all other items.

Knowing the amount of ash is essential prior to choosing the proper combustion method. Fuels with lower ash content are always a better option. Higher content of ash reduces combustion efficiency and prolongs combustion time for waste (Sun *et al*., 2016). Plastic contains considerably low ash, while significantly higher contents are yard waste and bones. The average of heating value of the samples is 4552.23±416.58 kcal/kg.

Table-4. Ultimate Analysis and HHV of MSW Components on dry basis.

Items	**C** (wt%)	**H** (wt%)	**N** (wt%)	**S** (wt%)	**O** (wt%)	**Ash** (wt%)	**HHV kcal/kg**
Yard Waste	40.78	6.16	0.85	0.2	38.59	13.42	3827
Styrofoam	58.25	8.02	0.7	0.08	30.79	2.16	6699
Textile	49.29	5.86	0.29	0.15	42.38	2.03	4292
Aluminium foil	57.05	9.08	0.56	0.04	23.32	9.95	8032
Paper	42.94	6.85	0.14	0.07	44.22	5.78	3949
Absorbent hygiene product	39.96	7.22	0.88	0.18	43.28	8.48	5531
Bone	33.84	6.17	4.89	0.24	24.86	30	3494
Plastics	79.81	14.41	0.01	0.02	3.98	1.77	10332
Organics waste	37.74	6.79	2.73	0.53	41.41	10.8	3527
Rubber	65.72	6.93	0.3	1.57	11.97	13.51	6759
High Density Plastics	61.4	4.63	0.07	0.03	33.85	0.02	5402
Wood	47.72	6.67	0.14	0.03	44.43	1.01	4296
Coconut coir waste	44.02	6.36	0.55	0.07	43.97	5.03	3838

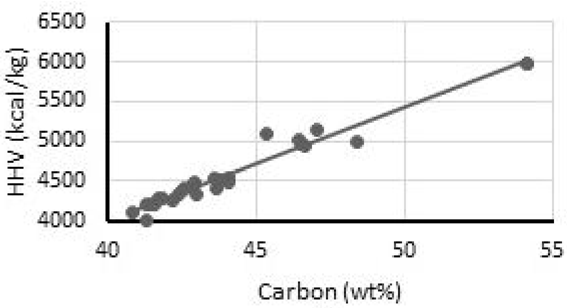
Stepwise Multiple Regression Linier (SMRL) model based on dry base

Modeling was realized using Matlab Statistics Toolbox 2013 (Matlab, 2015) with the use of experimental data provided in Table-4. This study performed multiple regression analysis applied to 29 data sets. The full model is given by

$$HHV = 5751.94 + 52.67C + 75.9H - 4.14N - 1044.03S - 97.68O \quad (19)$$

Eq. (19) shows that C and H positively contribute to HHV (as depicted in Figure-1a and b). These are also observed in Table-1, except for Eq. (6) and (7), in which carbon is the most significant predictor. Eq. (19) also shows that oxygen, nitrogen, and sulfur lower the values of HHV (as depicted in Figure-1c-d). Oxygen negatively contributes to HHV, which is also observed in Table-1, except for Eq. (6-8). The performance of this model is considered very satisfactory (R^2 = 0.99) because R^2 is in the range of 0.9 and 1 (Ogwueleka *et al.*, 2010). According to multiple regression analyses, the O, N, and S are not significant predictor statistically (p> 0.05). By using multiple stepwise regressions is obtained

$$HHV = -2762.68 + 114.63C + 310.55H \quad (20)$$



(a)

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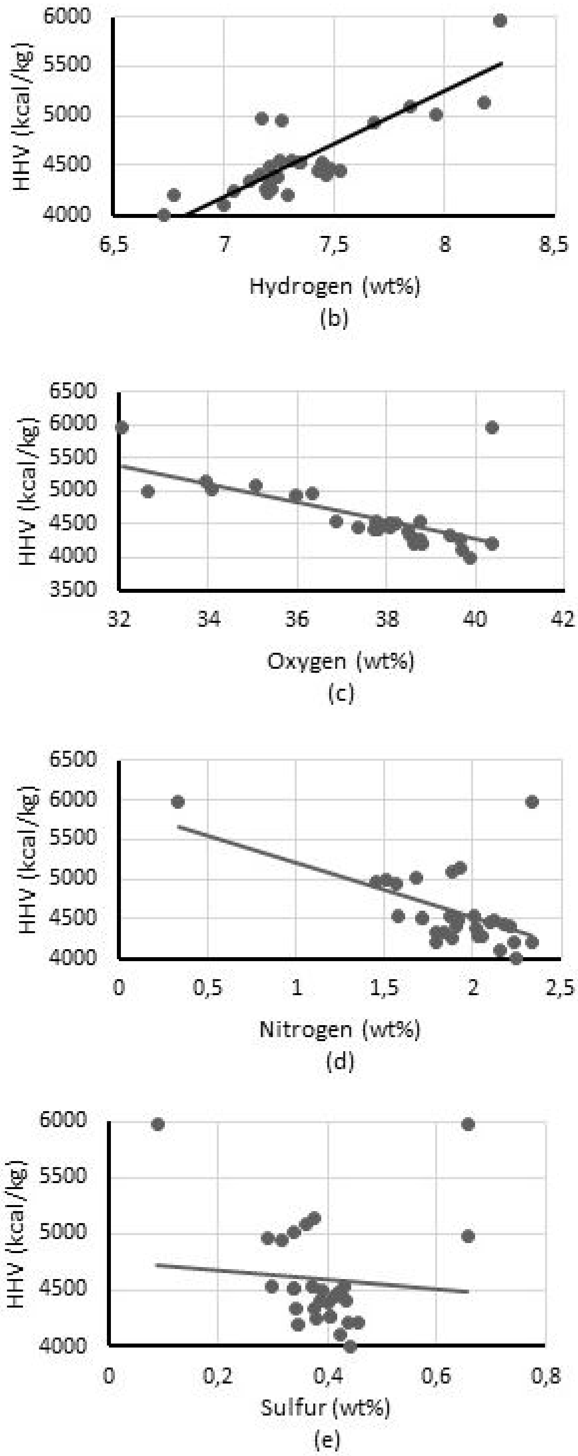

Figure-1. Correlations HHV to (a) Carbon (b) Hydrogen (c) Oxygen (d) Nitrogen (e) Sulfur.

Based on these works, only C and H which are significant predictor statistically to determine the heating value of MSW (RMSE = 65, MAPE = 0.85%, R^2 = 98, and adj R^2 = 0.98). Equation (20) also shows that the C and H contribute positively to HHV (as depicted Figure-1(a) and (b)). Knowing only the value C allows the determination of heating value satisfactorily ((RMSE = 99, MAPE = 1.35%, R^2 = 94, dan adj R^2 = 0.94). Equation (20) becomes simpler,

$$HHV = -1737.55 + 143.33C \tag{21}$$

Equation (20)-(21) are eligible. They are normal distributed to residual data. No significant problems in multicollinearity and autocorrelation were found. Whereas, carbon was the most significant predictor. Correlation of the three models (Equation (19)-(21)) to measured heating values graphically is shown in Figure-2.

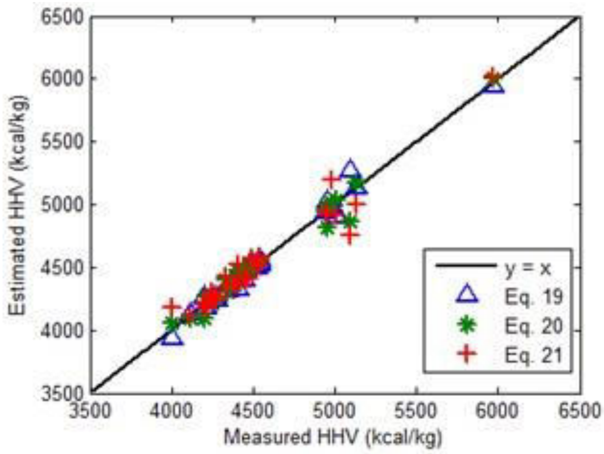

Figure-2. Comparison between measured HHV and Estimated.

The Dulong formula, Modified-Dulong formula, Steuer formula, and Scheurer-Kestner formula are widely used and have been proven to be quite precise for different kinds of wastes. Therefore, we compared the performance of the models to that of those equations. Comparisons between Equation (19) to Equation (2) (MAPE= 2.5%) and Equation (5) (MAPE=2.1%) are shown in Figure-4. Figure-5 illustrates the comparison between measured values and new models, Steuer (MAPE = 8.1%), and Scheurer-Kestner (MAPE= 2.7%). Models performance are said to be excellent (MAPE < 10%) [16].

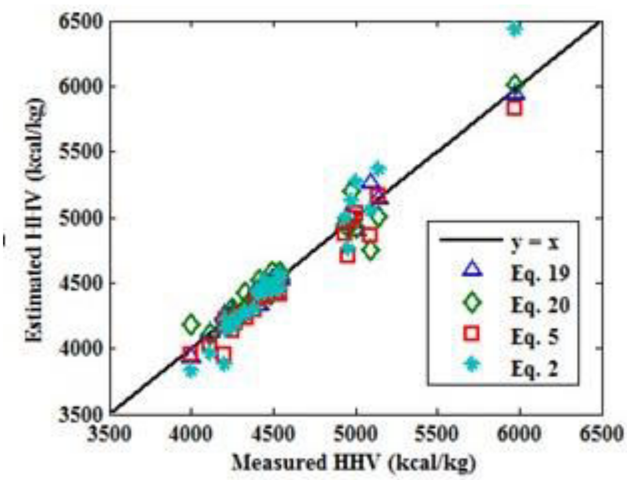

Figure-3. Comparison between measured HHV to Equation (20), Equation (21), Modified-Dulong's equation, and Dulong's equation.

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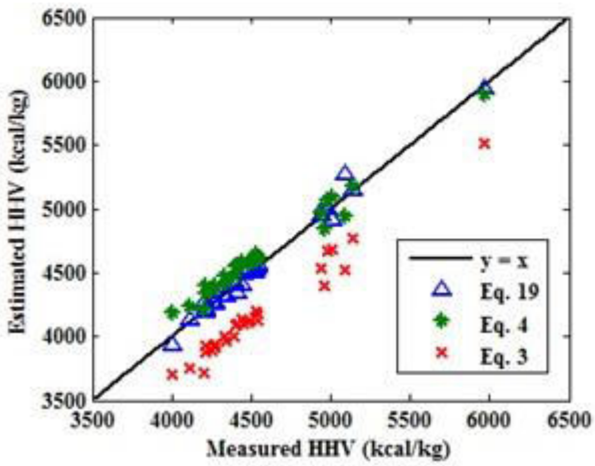

Figure-4. Comparison between measured HHV to Scheurer Kestner's and Steuer's equation.

CONCLUSIONS

The new models using regression method seems to give a satisfactory result. highly accurate and closer to the Dulong formula. Modified-Dulong formula. and Scheurer-Kestner formula. while Steuer formula tend to underestimate.

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