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Comparison of GUM and Monte Carlo Methods for Measurement Uncertainty Estimation of the Energy Performance Measurements of Gas Stoves

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Abstract: The paper presents the comparison of uncertainty measurement estimations of the energy performances of gas stoves. The Guide to the Expression of Uncertainty in Measurement (GUM) framework and two Monte Carlo Simulation (MCM) approaches: ordinary and adaptive MCM were applied for the energy performance uncertainty: thermal energy and efficiency measurement uncertainties. The validation of the two MCMs is performed by comparing the MCM estimations to the GUM estimations for the thermal energy and efficiency measurement results. A test method designed in Indonesia National Standard SNI 7368:2011 was employed for the thermal energy and efficiency determinations. The results of the GUM and two MCM methods are in good agreement for the estimation of the thermal energy value. Significant differences of the uncertainty estimations for the thermal energy and efficiency results are observed for both GUM and MCM methods. Both the ordinary and adaptive MCM estimations give larger coverage interval compared to the GUM method. The adaptive MCM can give similar estimations with a much lower number of iterations compared to the ordinary MCM. From the estimation difference between the GUM and MCM methods, suggestions are needed for the improvement in measurement models for thermal energy and efficiency of the standard.

Keywords: measurement uncertainty, national standard, GUM framework, Monte Carlo, thermal energy, efficiency.

1. INTRODUCTION

The government of Indonesia introduced a national energy program called Kerosene Conversion to Liquefied Petroleum Gas (LPG) for household sector in 2007 [1]. As part of the program, the government also introduced an Indonesian National Standard (SNI) to govern the quality assurance of the conversion packages consisting of a gas stove, hose, and gas regulator. For the gas stove, the quality assurance should meet the SNI standard either for domestic use or commercial use. In terms of the energy performance, every single gas stove intended for domestic use in Indonesia should meet a minimum efficiency of 50 % [2] and a minimum of 35 % for commercial use [3]. As the thermal energy and efficiency value should be confidently and reliably evaluated to the minimum criteria mentioned in the standard, estimating the uncertainty value attributed to the obtained thermal energy and efficiency is essential.

Harmonization of universal procedures for estimating measurement uncertainty has been achieved by the Guide to the Expression of Uncertainty in Measurement (GUM), first published in 1993 [4]. The uncertainty estimation in the GUM is based on the Law of Propagation of Uncertainty (LPU). This approach has been successfully applied to a variety of different measurement results obtained from different measurement processes. However, LPU requires that the mathematical model of a measurement is available and can be mathematically derived. Due to these reasons, very often, the GUM method is not practically applicable to estimate measurement uncertainties.

Due to the limitations of the GUM mentioned above, the application of the Monte Carlo (MCM) method for propagation of the full probability distribution of a measurement has been discussed in the ISO / IEC GUM, Supplement 1 [5]. The MCM method can cover a broader range of measurement uncertainty problems where GUM is difficult, if not impossible, to be implemented. This MCM approach can be used even without the requirement of a mathematical model and derivation of the model and is flexible to be used for many complex measurements. In addition, the MCM approach can be also used when the mathematical model is available.

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The distribution of uncertainty propagations, involving the convolution of the probability distribution of input quantities, can be carried out by numerical simulations of the MCM. Thus, the evaluation of uncertainty using the MCM is an alternative approach to solve many uncertainty estimation problems compared to the GUM uncertainty framework. The MCM advantages also include the uncertainty estimation for measurements with variables having asymmetric distribution of measurement uncertainty, non-linearity in the measurement system, interdependence between inputs and systematic bias [6]. The MCM method should be validated by GUM following the ISO / IEC GUM [7].

Since being introduced as an alternative method for uncertainty estimation, the applications of the MCM method for measurement uncertainty have inspired many researchers. In calibration, the applications of MCM have been applied for mass, length, and temperature calibration [8], gauge block calibration [9], compact prover calibration [10], and coordinate measuring machine calibration [11]. Comparative studies of the GUM method and MCM in testing field have been reported for cadmium content determined by graphite furnace atomic absorption spectrometry [12], and gross heat of combustion measured by a calorimetric bomb [13]. In mechanical measurement, the GUM and MCM were applied for tensile strength, torque, Brinell hardness and Vickers Hardness [14]-[16], flatness [17], acoustic magnitudes [18], and thermal balance and efficiency [19], pressure standard [20], cylindricity error [21], and precision centrifuge [22] measurements.

The estimations of uncertainty obtained by the MCM are found to have insignificant differences compared with GUM for studies as mentioned earlier [8]-[11], [14]-[19], [22]. The absolute differences of the respective endpoints of the coverage intervals between GUM and MCM approach are found to be less than 0.00023 % [10] and smaller than or equal to numerical tolerance [11]. Nevertheless, the MCM method does not always agree with the GUM method. Some studies reported that the uncertainty estimation by the MCM method was significantly lower than that by the GUM method [12]-[13], [20]-[21]. The difference may be due to the non-linearity of the measurement model and different assumptions and approximations applied in both methods [12]-[13]. A study on pressure balance uncertainty suggests that a single correction factor may be identified to compensate for the difference between GUM and MCM results [20].

According to the author' knowledge, from the aforementioned literatures, very few, if not none at all, reports present the use and comparison of uncertainty estimation by using the GUM and MCM methods for applications on the calculation of thermal energy and efficiency. Particularly in the case of the test method for the energy performance of gas stoves, there are no reports and discussions with regard to the uncertainty estimation using the GUM and MCM methods.

Limited studies regarding the thermal energy and efficiency of the gas stove have been observed, especially studies related to thermal energy assessments and the evaluation of the energy test method. A comparative study of the thermal energy test was carried out to study the effect of test duration in double burner gas stoves. The experimental study was carried out by varying the test duration into three different durations: 20 minutes, 40 minutes, and 60 minutes following a report elsewhere [23].

Another study was undertaken for the evaluation of thermal energy and efficiency test method of a single burner gas stove through comparative tests. A test method of a single burner gas stove constituted in SNI 7638:2011 has been evaluated in this study [24].

This paper presents the uncertainty estimation and comparison for the measurement of the thermal energy and the efficiency of the gas stoves by using the GUM, ordinary MCM and adaptive MCM methods. In addition, this paper also aims to validate the uncertainty estimation using the MCM method with respect to the GUM method and to find proposal for the SNI 7368:2011 standard improvement. The test method constituted in the SNI standard is followed and applied to determine the thermal energy and efficiency of the single gas stove.

2. THERMAL ENERGY AND EFFICIENCY MODEL

The determinations of thermal energy, in terms of heat input, and efficiency of the gas stove are carried out according to the SNI 7368:2011 standard, ‘‘Kompor gas bahan bakar LPG satu tungku dengan sistem pemantik“, that applies to both mechanic and electric lighter systems for low-pressure gas stove [25]. The standard test method states that the thermal energy test should be determined before performing the efficiency test. The value of the thermal energy is used to be the basis for determining the dimensions of the vessel and the mass of water for efficiency measurement.

Table 1. gives the information regarding the thermal energy value corresponding to the vessel's diameter and the water's mass inside the vessel for efficiency measurement.

Table 1. The diameter of vessel and mass of water correspond to the thermal energy value [25].

Thermal Energy (kW)	Diameter of Vessel (mm)	Height of Vessel (mm)	Minimum Water Mass (kg)
1.16 ~ 1.64	220	140	3.7
1.65 ~ 1.98	240	150	4.8
1.99 ~ 4.20	260	160	6.1

Fig.1. shows the experimental setup for the measurement of the gas stove energy performance. From Fig.1., the single burner gas stove with a mechanic ignition system was used in this experiment. The gas stove has a burner's diameter of 85 mm, with 42 holes circulating the burner. A commercial LPG is used as the fuel source for thermal energy and efficiency determination. A mechanical pressure gauge was used to measure the input pressure of the LPG to the gas stove. The pressure gauge has a resolution of 20 mmH$_2$O and is capable to measure pressure up to 1000 mmH$_2$O. A commercial gas regulator with adjustable valve pressure was plugged in the LPG tube to ensure that the inlet pressure of the LPG is as per the standard requirement. In order to quantify the measured LPG during the test, a digital mass scale was used. This digital scale can quantify mass up to 15 kg.

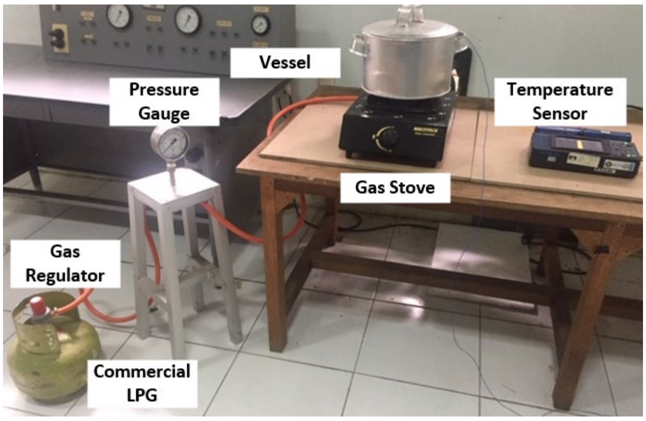

Fig.1. Experimental set-up for the energy performance (thermal energy and effciency) measurements.

According to the standard test method in SNI 7368:2011, the thermal energy and efficiency for LPG gas stove are calculated as

$$\mathrm{Q_n} = \frac{1000 \times \mathrm{M_n} \times \mathrm{H_s}}{3600}, \tag{1}$$

$$\eta = \frac{4.186 \times 10^{-3} \times \mathrm{M_e} \times (\mathrm{t} - \mathrm{t_1})}{(\mathrm{M_c} \times \mathrm{H_s})} \times 100\ \%. \tag{2}$$

By referring to (1) and (2), the quantities involved in the equations are explained in Table 2. These input and output quantities will contribute to the uncertainty estimation of the thermal energy and efficiency measurements.

Table 2. List of quantities related to thermal energy (1) and efficiency (2).

Quantity	Unit	Definition
Q_n	kW	Thermal energy
M_n	kg/hr	Mass flow rate
H_s	MJ/kg	Calorific value
1000	kW/MW	Conversion factor
3600	s/hr	Conversion factor
η	%	Efficiency
4.186×10^{-3}	MJ/kg/°C	Specific heat capacity of water
M_e	kg	Total mass of water inside the vessel, the vessel's mass, and the vessel lid
M_c	kg	The total of consumed gas
t	°C	The final temperature of water
t_1	°C	The initial temperature of water

Note: H_s value is 49.14 MJ/kg.

The initial $(\mathrm{t_1})$ temperature of the water is (20 ± 1) °C, the final temperature (t) is the highest temperature observed after the burner's extinction, this being carried out once the temperature of the water in any of the vessels reaches (90 ± 1) °C. It has to be noted that the wire thermocouple with a diameter of 0.3 mm was used for temperature sensing. The thermocouple was prepared according to the Committee of Testing Laboratories-Operational Procedure (CTL-OP) [26]. Since the position of temperature sensing inside the vessel is not mentioned clearly in the SNI 7368:2011, the thermocouple was positioned at the middle of the volume of water for temperature measurement in this test case.

3. UNCERTAINTY ESTIMATION

A. *GUM uncertainty framework*

The estimation of uncertainty measurement using the GUM approach mainly consists of the determination of estimates of standard uncertainty, and coverage interval associated with measurement results [27]. The initial step of the GUM is to define the measurement model by specifying the measurand Y (output quantity) and its relation with the input quantities $(X_1, X_2, \dots, X_n)$.

The measurement model consists of all relevant parameters that contribute to the measurement results of the thermal energy and efficiency of the gas stove. In addition to the relevant parameters, correction factors for systematic effects are also considered when relevant. In the case of energy performance for the gas stove, the relationship of thermal energy and efficiency to their relevant contributors as formulated in (1) and (2), respectively can be defined and can be mathematically derived. The models involve one and three input quantities measured directly for thermal energy and efficiency. The function can be represented as

$$Q_n = f(M_n), \tag{3}$$

$$\eta = f(M_c, t, t_1, M_e). \tag{4}$$

The uncertainties of constant quantities appearing in (1) and (2) are considered to be negligible in both cases. The combination of standard uncertainties of the input estimates $x_1, \dots, x_N$, denoted by $u(x_1), \dots, u(x_N)$ results in the combined standard uncertainty of y, denoted by $u_c(y)$. This determination is based on the first-order Taylor series approximation by implementing the propagation of uncertainty and formulated as [12]:

$$u_c(y) = \sqrt{\sum_{i=1}^{N} c_i^2 \cdot u^2(x_i)}, \tag{5}$$

where c_i:

$$c_i = \frac{\partial f}{\partial x_i}. \tag{6}$$

The sensitivity coefficient c_i describes how the estimate y varies with changes in the values of the input estimates $x_1, \dots, x_N$. This coefficient is obtained using partial differentiation of the measurement models in (1) and (2) [28]. Table 3. presents sensitivity coefficients derived from (1) and (2) for the thermal energy and efficiency measurement model, respectively. Note that the calorific value H_s of gas stated in Table 2. is the constant value specified in the SNI. Therefore, in this case, the measurement of the value of H_s is not carried out, and hence the contribution of the uncertainty from the calorific value is negligible.

Standard uncertainties can be determined either from independent repeated observations called Type A uncertainty or can be generated from scientific or expert judgement called Type B uncertainty [28].

For an input quantity X_i determined from n independent repeated measurements, the Type A evaluation requires the standard uncertainty $u(x_i)$ estimation to be calculated from the basis of the standard deviation $s(x_i)$ of the mean, which can be formulated as

$$u(x_i) = s(\overline{x_i}) = \frac{s(x_i)}{\sqrt{n}}. \tag{7}$$

The degrees of freedom v_i of standard uncertainties $u(x_i)$ associated with Type A equal to $n - 1$ [28].

Table 3. Sensitivity coefficients for the mathematical models in (1) and (2).

Variable	Sensitivity coefficient
$\mathrm{M_n}$	$c_1 = \frac{\partial Q_n}{\partial M_n} = \frac{Q_n}{M_n}$
$\mathrm{M_e}$	$c_2 = \frac{\partial \eta}{\partial M_e} = \frac{\eta}{M_e}$
t	$c_3 = \frac{\partial \eta}{\partial t} = \frac{\eta}{(t - t_1)}$
$\mathrm{t_1}$	$c_4 = \frac{\partial \eta}{\partial t_1} = -\frac{\eta}{(t - t_1)}$
$\mathrm{M_c}$	$c_5 = \frac{\partial \eta}{\partial M_c} = -\frac{\eta}{M_c}$

For Type B evaluation, an estimate x_i of an input X_i that has not been obtained from repeated observations, the evaluation of associated standard uncertainty $u(x_i)$ is determined through a scientific judgement. This judgement is based on the available information on the possible variability of input quantity X_i such as previous measurement data, experience with or general knowledge of the behavior and properties of relevant materials and instruments, manufacturer's specifications, data provided in calibration and other certificates as well as uncertainties assigned to reference data taken from handbooks.

It has to be noted that the Type B evaluation requires information regarding the distribution and the degrees of freedom of estimate quantities in order to determine the coverage interval. In the case of no specific information about the possible values of X_i within an interval, a rectangular distribution can be considered, and an infinite value could be taken as degrees of freedom [12], [28].

The importance of determining expanded uncertainty, denoted by U, is to provide the confidence interval of measurement results. The expanded uncertainty is determined by multiplying the combined standard uncertainty $u_c(y)$ by a coverage factor k as [5]

$$U = k \cdot u_c(y). \tag{8}$$

The complete expression of the measurement result then can be stated as $Y = y \pm U$, in which y is the best estimate of the value attributable to the measurand Y. Following this expression, it may be expected that the interval of $y - U$ to $y + U$ must encompass a significant fraction of the distribution of values that could reasonably be attributed to Y.

Together with the confidence level, the interval of $y - U$ to $y + U$ will determine the selection of coverage factor, denoted by k. Generally, the coverage factor will be in the range 2 to 3, corresponding to an interval having a confidence level of approximately 95 % to 99.7 % considering a Gaussian family distribution, respectively [5]. However, in some cases of Type A standard uncertainty, the t-distribution will not describe the distribution of the variable if combined standard uncertainty may not be based on the large sums of standard uncertainty.

This case could lead to the inaccurate coverage factor k being selected to its coverage probability. The t-distribution with n degrees of freedom, denoted by v_{eff} may be used to approximate the distribution of that variable. These effective degrees of freedom are obtained through the Welch-Satterthwaite (W-S) formula, calculated as [5], [12]:

$$v_{eff} = \frac{u_c^4(y)}{\sum_{i=1}^{N} \frac{u_i^4(y)}{v_i}}. \tag{9}$$

Equation (9) gives now the effective degree of freedom to obtain a more accurate coverage factor. The value of k_p allows the expanded uncertainty U_p to maintain the coverage probability at approximately the required confidence level p [5], [12]. Then, an expanded uncertainty can be calculated as $U_p = k_p u_c(y) = t_p(v_{eff}) u_c(y)$ providing an interval $Y = y \pm U_p$.

B. Probabilities Propagation of the Monte Carlo Method (MCM)

The Monte Carlo method (MCM) is aimed as an alternative method for uncertainty estimation for cases where it is difficult to model a measurement and calculate its partial derivative required by the GUM approach. This problem arises when a developed mathematical model is complex [29].

The MCM method involves the propagation of the distributions of the input sources of uncertainty by using the model to provide the output distribution. The input quantities' propagation distributions mainly consist of the appropriate probability distribution, such as rectangular, normal, or triangular [5], [15]. Similar to the GUM framework, the framework of MCM consists of determining an estimate of the output quantity Y associated with standard uncertainty $u(x_i)$ and determination relates to a coverage interval [29].

The application of the MCM method for measurement uncertainty evaluation is implemented using an algorithm that can be summarized as follows: [15], [30]

1. Defining the measurand Y and establishing the measurement model of the measurand;
2. Identifying the probability density functions corresponding to each input quantity X_i;
3. Selecting the number of trials M. This number can be chosen as a priori or by using an adaptive method. When choosing *a* priori trials, the GUM Supplement 1

recommends the selection of a number of trials. Following is a general rule of selection M in order to provide a reasonable representation of the expected result

$$M > \frac{10^4}{1-p}, \tag{10}$$

where $100p$ % is the selected coverage probability. For instance, when the chosen coverage probability is 95 %, $p = 0.95$ and M should be at least higher than 200,000;

4. Generating a set of N input parameters, (M_n, M_e, t, t_1, M_c), random variables are distributed according to a probability density function (PDF) assigned to each input parameter. This process should be repeated M times for every input quantity;
5. Calculating the corresponding value of measure quantity Y using model as

$$y_j = f\left(x_{1.j}, x_{2.j}, \dots, x_{n.j}\right), for\ j = 1,2, \dots, M. \tag{11}$$

6. Calculating the mean and the standard deviation from output vector, $(y_1, y_2, \dots, y_M)$, as the measurement result y for Y and its associated standard uncertainty $u(y)$ as

$$y = \frac{1}{M}\sum_{j=1}^{M} y_j, \tag{12}$$

$$u(y) = \sqrt{\frac{1}{M-1}\sum_{j=1}^{M}\left(y_j - y\right)^2}. \tag{13}$$

7. Sorting the output vector in ascending order and determining a coverage interval $[y_L, y_H]$ at coverage probability p:

$$L = round\big((M+1)\alpha\big), \tag{14}$$

$$H = round\big((M+1)(1-\alpha)\big), \tag{15}$$

where α is significance level with $\alpha = 0.025$ for 95 % coverage probability, and the function $round(x)$ is used to represent the nearest integer to x [30].

When the skewness value for the distribution of the output quantity Y approaches zero, the expanded uncertainty can be evaluated using coverage interval resulting from (14) and (15) as

$$U = \frac{y_H - y_L}{2}. \tag{16}$$

C. Validation of the MCM method

The GUM Supplement 1 presents a procedure for comparing the LPU approach addressed by the GUM with the MCM results. The validation is accomplished by comparing the low and high endpoints obtained from both methods. Thus, the absolute differences d_{low} and d_{high} of the respective endpoints of the two coverage intervals are calculated by (17) and (18) as follows

$$d_{low} = |y - U - y_L|, \tag{17}$$

$$d_{high} = |y + U - y_H|, \tag{18}$$

where y is the measurand estimate, U is the expanded uncertainty obtained by the GUM approach, and y_L and y_H are the low and high endpoints of coverage interval of the PDF obtained by the MCM for a given coverage probability, respectively.

The numerical tolerance δ of uncertainty can be obtained by expressing the standard uncertainty as $c \times 10^l$, where c is an integer with the number of digits equal to the number of significant digits of the standard uncertainty and l is an integer. δ is calculated as:

$$\delta = \frac{1}{2}10^l. \tag{19}$$

If both d_{low} and d_{high} are lower than δ, the GUM and MCM methods are in good agreement (comparable) [13].

4. RESULTS

Type A uncertainty is caused by random errors emerging during the measurement process. The characterization of random error is based on the statistical approach through repeated measurement. In this study, the measurement of thermal energy and efficiency of the gas stove was carried out by six repetitions of measurement. The quantification of standard uncertainty $u_i(x)$ is therefore obtained by (7).

On the other hand, the evaluation of Type B is based on a non-statistical approach. The source of uncertainty is associated with systematic error and therefore it cannot be reduced through repeated measurement. In this study, the evaluation of Type B is derived from the manufacturer's specifications provided in calibration of instrumentation used in the measurement.

According to (1) and(2), parameters which affect the gas stove's thermal energy and efficiency were measured by the same instrument for both measurement types. The Type B uncertainty is obtained from the instrument's resolution and the calibration data from traceability to the higher standard. The measurement of input pressure during the test was maintained to avoid the fluctuation of input pressure as suggested in a previous study [22]. Therefore, the uncertainty contribution is assumed to be negligible in this case.

The digital scale used to quantify the mass flow rate of consumed gas and water has the resolution of 0.1 g and traceability to the higher standard of 0.1 g. Meanwhile, the temperature sensor used for temperature measurement during the efficiency test has the resolution of 0.1 °C and calibration to its higher standard of (1.66 + 0.06 %t) °C.

Table 4. shows the uncertainty budget for thermal energy and efficiency, respectively, using the GUM method. According to Table 4., the Type A contribution coming from repeatability is more dominant than the uncertainty contribution compared with Type B (instrument and traceability). The repeatability gives the estimated thermal energy of 2.62 kW and efficiency of 69.59 %.

The standard uncertainty $u_i(x)$ due to resolution of the measuring instruments is obtained from the manufacturer's specification and, thus, it can be assumed that the resolution provides symmetric bonds. Therefore, the distribution due to resolution can be assumed as rectangular distribution and, hence, the standard uncertainty is derived from half-width of the resolution divided by coverage factor of 3 ($k=\sqrt{3}$).

Table 4. Uncertainty budget for thermal energy and efficiency measurements.

Source	Value	Standard Uncertainty	Sensitivity Coefficient
Thermal Energy			
M_n	**g**	**g**	**kW/kg**
Rep.	192	1.7992	1.366 x10^{-2}
Inst.	0.1	2.89x10^{-2}	1.366 x10^{-2}
Trace.	0.1	5x10^{-2}	1.366 x10^{-2}
Efficiency			
M_e	**g**	**g**	**°CMJ^{-1}**
Rep.	6676.5	8.33 x10^{-2}	1.042x10^{-4}
Inst.	0.1	2.89 x10^{-2}	1.042x10^{-4}
Trace.	0.1	5x10^{-2}	1.042x10^{-4}
t	**°C**	**°C**	**kgMJ^{-1}**
Rep.	91.14	0.120	9.805x10^{-3}
Inst.	0.1	2.89 x10^{-2}	9.805x10^{-3}
Trace.	1.715	0.857	9.805x10^{-3}
t_1	**°C**	**°C**	**kgMJ^{-1}**
Rep.	20.16	0.121	-9.805x10^{-3}
Inst.	0.1	2.89 x10^{-2}	-9.805x10^{-3}
Trace.	1.672	0.836	-9.805x10^{-3}
M_c	**g**	**g**	**°CMJ^{-1}**
Rep.	58	0.483	-0.0120
Inst.	0.1	2.89 x10^{-2}	-0.0120
Trace.	0.1	5x10^{-2}	-0.0120

Rep. = Repeatability
Inst. = Instrument's resolution
Trace = Traceability of instrument to the higher standard

Furthermore, the degree of freedom v_i due to rectangular distribution is obtained to have infinite result as the input quantity lying outside this interval is zero [27]. The standard uncertainty due to traceability is obtained by the calibration certificate. It is stated that the uncertainty measurement is expressed at a 95 % confidence level by the coverage factor $k = 2$ with normal distribution. The confidence level of 95 % gives the probability of value lying outside the interval equal to 5 %. Therefore, the degree of freedom v_i due to normal distribution with 95 % confidence level is obtained at 200 [27].

The contribution of uncertainty type in Table 4. is given in Fig.2. and Fig.3. for thermal energy and efficiency, respectively. The calculations of the contributions result in combined uncertainty u_c equal to 2.46×10-2 kW and 1.32 % for thermal energy and efficiency, respectively.

Fig.2. and Fig.3. also give information that the repeatability is a dominant source for thermal energy uncertainty, while the traceability of instrument to the higher standard is a major source for efficiency uncertainty. The dominant contribution of this traceability comes from the temperature sensor used in measuring water temperature in measuring efficiency. The uncertainty due to the traceability of the temperature sensor is 1.66 °C.

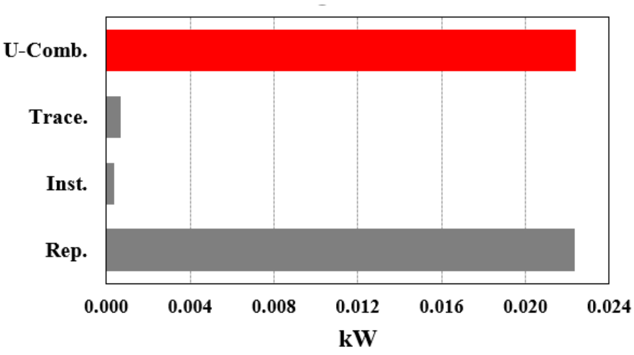

Fig.2. Combined uncertainty and uncertainty contributions of thermal energy.

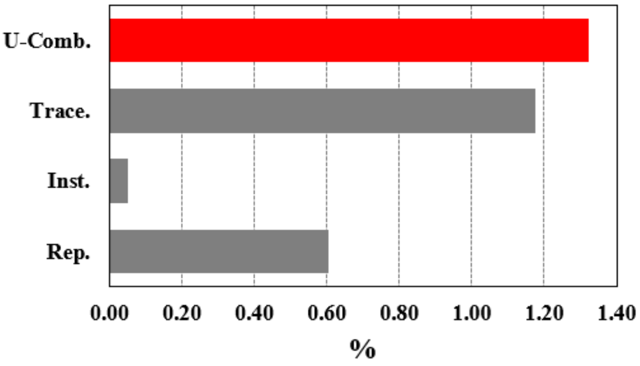

Fig.3. Combined uncertainty and uncertainty contributions of efficiency.

Meanwhile, the repeatability of the LPG flow rate during the thermal energy measurement is the most significant source. The standard deviation produced in six measurements is 4.023 Kg/hr. This significant value indicates that the mass flow rate of the consumed LPG from the six measurements is very dispersed. Similar to thermal energy, the standard deviation resulting from the six repetitions of mass flow rate measurement of LPG in efficiency measurement is 1.18 Kg/hr. This standard deviation is the most considerable compared to the standard deviation produced by repeating the measurements of water mass (0.204 g) and water temperature (0.297 °C for initial temperature, and 0.283 °C for initial temperature) for the efficiency measurement. This contribution makes repeatability the second-largest contribution after traceability on the uncertainty value of efficiency. In this case, the digital mass scale used to determine the mass flow rate of LPG could be a factor that causes variations in LPG mass readings.

Another factor contributing to this significant Type A contribution is a method for determining the gas mass flow rate in SNI 7368:2011. In this standard, the determination of flow rate of consumed LPG is carried out using the gas cylinder mass method by calculating the difference between the initial and final mass of the LPG cylinder. Unfortunately, the method does not mention the limitation on the use of LPG volume during the measurement. This consideration is essential due to the possibility of gas temperature effect on the quality of the LPG gas mixture when using the one LPG gas for several consecutive measurements. It is important to note that the method of determining the LPG flow rate and the mathematical formula for thermal energy and efficiency have not changed in the latest edition of SNI 8660:2018, *"Kompor gas LPG dan LNG/NG tekanan rendah untuk rumah tangga* (Gas stove with low pressure of LPG and LNG/NG for household)" [2].

The expanded uncertainty U is obtained by applying (8), with coverage factor calculated through determination of effective degrees of freedom in (9). The Welch-Satterthwaite formula results in effective degrees of freedom equal to 5.0103 and 135.520, which corresponds to a coverage factor of 2.57 and 1.98 for thermal energy and efficiency at 95 % confidence level, respectively. The calculation gives expanded uncertainty equal to 0.063 kW for thermal energy and 2.62 % for efficiency. Therefore, the measurement result of thermal energy and efficiency can be stated as 2.62 kW ± 0.063 kW and 69.59 % ± 2.62 %, respectively.

Table 5. Input parameters to run MCM for thermal energy and efficiency measurement.

Source	PDF	Parameter			
		Mean	Std-dev	Min	Max
Thermal Energy					
Rep. (kg)	Gauss	0.192	4.4×10^{-3}	-	-
Inst. (g)	Uni	-	-	-0.05	0.05
Trace. (g)	Gauss	0.02	0.05	-	-
Efficiency					
Me					
Rep. (kg)	Gauss	6.6765	2×10^{-4}	-	-
Inst. (g)	Uni	-	-	-0.05	0.05
Trace. (g)	Gauss	0.57	0.05	-	-
t					
Rep. (°C)	Gauss	90.94	0.29	-	-
Inst. (°C)	Uni.	-	-	-0.05	0.05
Trace. (°C)	Gauss	0.2	1.71	-	-
t_1					
Rep. (°C)	Gauss	19.88	0.30	-	-
Inst. (°C)	Uni	-	-	-0.05	0.05
Trace. (°C)	Gauss	0.28	1.67	-	-
Mc					
Rep. (kg)	Gauss	0.058	1.2×10^{-3}	-	-
Inst. (g)	Uni	-	-	-0.05	0.05
Trace. (g)	Gauss	-0.09	0.05	-	-

The MCM was then carried out to calculate thermal energy and efficiency in (1) and (2) by using the input parameters presented in Table 5. The table also specifies the probability density function (PDF) of each component (Gauss = Gaussian, Uni = uniform) as the basis for generating random numbers during the simulation.

In this study, simulation was carried out with two approaches in determining the number of trials, namely a priori (for the ordinary MCM) ($M = 10^6$) and adaptively (for the adaptive MCM). The algorithm of MCM was implemented in MATLAB [31]. The results are shown in Table 6. for thermal energy and efficiency measurement.

The two MCM approaches gave precisely the same results in estimating the value of thermal energy and efficiency along with their uncertainties. In this case, at one significant digit, the adaptive method could achieve this result with trials smaller than $M = 10^6$ for the normal MCM.

Table 6. Comparison between the GUM and MCM for thermal energy and efficiency measurement.

Method		GUM	MCM	Adaptive MCM
Thermal Energy				
MCM trials			1×10^6	3.4×10^5
Estimate (kW)		2.62	2.62	2.62
u-Std. (kW)		0.02	0.06	0.06
y_L (kW)	95% coverage	2.56	2.50	2.50
y_H (kW)	interval	2.68	2.74	2.74
Significant digits		-	1	1
Numerical tolerance, δ		-	0.005	0.005
d_{low}		-	0.054	0.056
d_{high}		-	0.056	0.053
Efficiency				
MCM trials			1×10^6	1.4×10^5
Estimate (%)		69.6	69.7	69.7
u-Std. (%)		1.3	2.8	2.8
y_L (%)	95% coverage	67.0	64.3	64.3
y_H (%)	interval	72.2	75.2	75.2
Significant digits		-	1	1
Numerical tolerance, δ		-	0.5	0.5
d_{low}		-	0.675	0.721
d_{high}		-	0.657	0.707

5. DISCUSSION

The uncertainty estimation results from both GUM and MCM results for all cases are summarized in Table 6. Both the GUM and MCM approaches give comparable estimation for thermal energy and efficiency measurement results. However, appreciable differences exist regarding the estimated standard uncertainty between MCM and GUM results. The estimated standard uncertainties of thermal energy and efficiency from GUM are approximately 33 % and 46 % of that generated by MCM, respectively. This difference also causes differences in 95 % coverage intervals produced by the two methods.

The assumed PDFs of the GUM approaches are shown in Fig.4. and Fig.5. for thermal energy and efficiency, respectively. These approaches provide the histogram of scaled frequency distribution obtained by MCM and the endpoints of the probabilistically symmetric 95 % coverage interval. It can be seen that the 95 % coverage provided by the GUM when assuming a Gaussian distribution is narrower than that obtained by the MCM.

Furthermore, the results obtained from the GUM and MCM methods were compared using the numerical tolerance method proposed in the GUM Supplement 1. From the results, the uncertainty estimation differences between the GUM and MCM are significantly large, since the magnitudes of the coverage interval endpoint differences d_{low} and d_{high} were more significant than the numerical tolerance δ, associated with the uncertainty of the measurand.

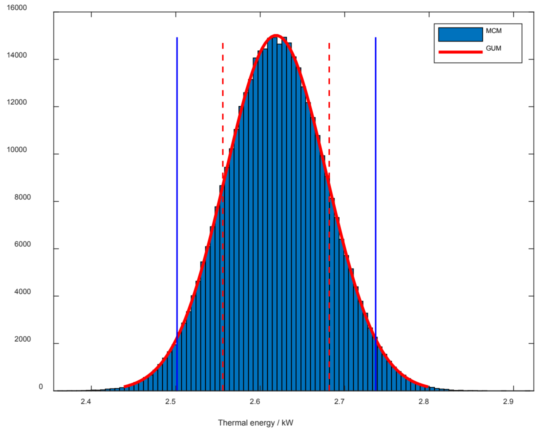

Fig.4. Histogram representing the resulting PDF the thermal energy estimated by Adaptive MCM and GUM.

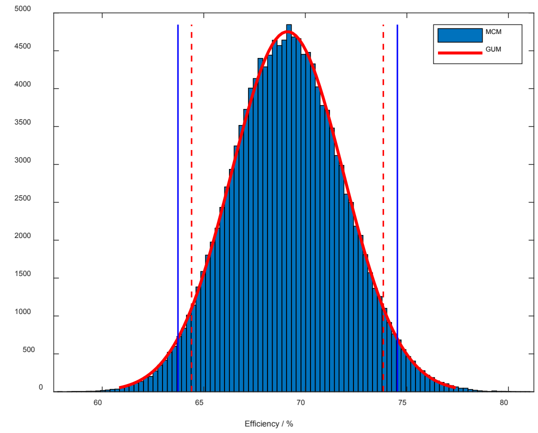

Fig.5. Histogram representing the resulting PDF for efficiency estimated by Adaptive MCM and GUM.

The significant differences for the estimations between the GUM and MCM can be caused by the accuracy of the mathematical model used to represent the thermal energy and efficiency. The accuracy of the models is reduced because, at the current models, second-order (non-linear effect) quantities affecting the energy performance are not considered. In this paper, the correlations among input quantities are negligible. In addition, there is some noise on the sensor that affects the estimation of input quantities distributions used to apply the MCM and GUM methods.

From these results, two proposals for the improvement of SNI 7368:2011 and SNI 8660:2018 are in the mathematical model of the thermal energy and efficiency by considering more factors, such as gas composition. Secondly, the improvement can be carried out through the more defined LPG volume in order to reduce the uncertainty of the gas flow rate.

6. CONCLUSION

This paper aims to estimate and compare the measurement uncertainty of thermal energy and the efficiency measurements of a single gas stove. The uncertainty estimations obtained from the propagation law described by the GUM framework were compared to ordinary and adaptive MCM methods following the GUM Supplement 1.

The energy performance estimation procedure designed in Indonesia National Standard for gas stove, SNI 7368:2011, is applied for thermal energy and efficiency calculations.

From the comparison of uncertainty estimation between the GUM and MCM methods, significant differences in uncertainty estimation are obtained. The difference of the estimation is 33 % for thermal energy measurement and 46 % for efficiency between the GUM framework and MCM. The GUM and MCM methods give the same results for estimation of the thermal energy value. For estimation of the efficiency value, a similar value is obtained up to one significant digit.

In addition, two types of MCM were applied: a priori (normal) MCM and adaptive MCM. Both a priori and adaptive MCM give estimation in very good agreement despite the adaptive MCM having much smaller number of iterations than the a priori MCM.

The significant difference between the estimation by the GUM and MCM can emerge from several reasons: inaccurate measurement models, sensor noises and the variation of gas flow measurement to determine the input quantities distribution. These aspects can be an important suggestion to improve the SNI standard.

Future work will focus on improving the mathematical model of thermal energy and efficiency measurement. Possible ways, for example, are to investigate the gas composition during the test in the measurand model. The possibilities of changes in the quality of the gas composition during measurement can affect the combustion quality of the gas stove. The method for determination of fractional evaporation or distillation of the gas during consumption can be proposed for improvements of the standard and considered in the mathematical model for thermal energy and efficiency measurements. In addition, the improvement could be on defining the LPG volume for the gas flow determination. In terms of temperature measurement for efficiency, the investigation of thermocouple position could contribute to the uncertainty.

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