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Abstract: Measurement uncertainty is essential for accurate comparison and decision-making in various fields. The ISO/IEC GUM standardizes uncertainty estimation, yet traditional methods like the Law of Propagation of Uncertainties (LPU) face limitations. The Monte Carlo Method (MCM) offers a solution, especially for complex models. Our study explores MCM's application in refrigerator power measurement, overcoming challenges encountered with traditional methods. Three MCM methodologies— *a priori*, adaptive with 1 or 2 significant decimal digits—were tested. The findings reveal that while all three methods yield relatively similar results—51.3 W estimated measured power with a standard uncertainty of 1.44 W—the *a priori* method with $M = 10^6$ and the adaptive method with 2 significant decimal digits exhibit greater stability compared to the adaptive method with 1 significant decimal digit. This underscores MCM's effectiveness in handling intricate uncertainties and its potential for advancing measurement reliability and quality.

Keywords: measurement uncertainty; Monte Carlo method; ISO/IEC GUM; IEC 62552:2015; household refrigerator

1. Introduction

Measurement uncertainty serves as a pivotal quantitative indicator reflecting the quality of measurements. Its omission compromises the feasibility of comparing similar measurements, predetermined reference values, or standards[1]. Furthermore, it plays a critical role in decision-making processes[2], risk management strategies[3], tolerance level determinations[4], selection of measurement methodologies[5,6], accreditation compliance[7], hypotheses testing[8], calibration interval determinations[9], and the communication of technical variables[10]. Thus, accurate measurement prediction necessitates a realistic representation of the ongoing measurement process[11].

In the era of global development, achieving unanimous acceptance of measurement and testing results is imperative to support global free trade initiatives. Consequently, there is a pressing need for a universal procedure to predict measurement uncertainties, facilitating cross-country comparisons and metrology recognition. This necessity led to the establishment of a harmonized standard, notably realized through the ISO/IEC GUM (Guide to the Expression of Uncertainty in Measurement).

Despite its widespread adoption, the traditional method of uncertainty estimation, based on the law of uncertainty propagation (LPU)[12], has been critiqued for its inherent limitations. These limitations include the linearization of measurement models and the utilization of the t-student distribution to assess probability distribution, relying on an effective degree of freedom. Hence, to address these constraints, the ISO/IEC GUM supplement proposed the utilization of the Monte Carlo Method (MCM) [13]. The Monte Carlo approach offers an alternative means to resolve various restrictions associated with the GUM uncertainty framework, encompassing issues such as asymmetric uncertainty distribution, nonlinear models[14], multicollinearity, and systematic bias[15].

In the wake of Supplement 1 to ISO/IEC GUM, the utilization of Monte Carlo Simulation (MCS) has proliferated across diverse fields for uncertainty evaluation. Notably, some studies have employed MCS to validate uncertainties derived from the LPU GUM method[16–20], citing its advantages, including its independence from partial derivative calculations and effective degrees of freedom, particularly advantageous for complex measurement models[21]. Furthermore, this finding has been corroborated by another studies[22–25]. Regarding the determination of the number of Monte Carlo simulations (MCS), various methodologies have been employed, including the *a priori* method and the adaptive method[26,27]. However, despite this growth, the literature remains devoid of any investigation into the measurement uncertainty associated with refrigerator efficiency testing.

Meanwhile, a study on uncertainty in freezer/refrigerator consumption tests has been documented in [28]. However, it is noteworthy that the test protocol continues to reference the obsolete ISO 15502 standard, which has been superseded by the IEC 62552:2015 standard. Additionally, it is pertinent to highlight that in the assessment of measurement uncertainty, the paper does not adhere to ISO GUM principles but instead employs the standard deviation derived from the error mean square of the Analysis of Variance (ANOVA) technique.

Several scholarly works published within the past half-decade have employed the IEC 62552:2015 standard as a benchmark in their assessments, primarily concerning power and energy consumption measurements in refrigerators[29–33]. Nevertheless, these studies predominantly concentrate on appraising refrigerator performance and offer limited discussion on measurement uncertainty. Notably, only a singular study undertook an exhaustive evaluation of measurement uncertainty in refrigerator energy efficiency testing, employing the Monte Carlo Method (MCM) [34]. This study focused on assessing the energy efficiency index, calculated in accordance with the GB 12021.2-2015 standard—a directive established by the Chinese standardization administration governing the permissible electricity consumption limits and energy efficiency ratings of household refrigerators.

Diverging from prior research endeavors[28,34], our work centers on steady state power measurement data derived from refrigerator testing, adhering to the IEC 62552:2015 standard. Nevertheless, the intricacies inherent in the formula used to compute steady-state power pose challenges for estimating measurement uncertainty, particularly concerning the calculation of sensitivity coefficients. Consequently, our study aims to assess uncertainty in steady state power measurement using the MCM, anticipating that its implementation will surmount the aforementioned challenges. As the second aim, we endeavor to establish a method for determining the optimal number of Monte Carlo simulations, balancing between *a priori* and adaptive approaches, to yield stable measurement uncertainty estimation results.

2. The evaluation of measurement uncertainty using Monte Carlo simulation

The Monte Carlo is a well proven method that had been acknowledged by the Supplement 1 ISO/IEC GUM to be an alternative method to evaluate uncertainty measurement especially when the LPU faces some limitations. This is also validated by some previous papers[16–20].

The MCS procedure utilizes pseudorandom numbers generated algorithmically and forced to follow a specific probability distribution. For a normal distribution, the numbers were determined by the value of mean and standard deviation. For every input value, the MCS procedure generates a numerical value randomly assigned from each probability density function (PDF). The numerical value generated through this procedure turns input into a single numeric output using a known function. This process is repeated numerous times to produce some output simulation results. Mean and standard deviation from the output become the estimation of the measured value and its standard uncertainty of measurement result. Since the input values are randomly assigned from a probability distribution and related to each input variable, all processes can be considered a procedure for the propagation of distribution. In addition, since MCS uses random samples from PDF as inputs, this procedure also produces output probability distribution and coverage interval. While the LPU GUM only provides means and standard uncertainty of measurement, the MCS complemented it by generating an actual PDF that contains more information. GUM supplement 1[13] provides steps that are required to be conducted to implement MCS for estimating uncertainty:

a. Defining the measurand and input quantities: clearly determining what is going to be measured.
b. Modeling: a mathematical function that relates between the measurand (Y) and input quantities (X_i) that affect it. It is stated by Eq. 1 as follows:

$$Y = f\left(X_1, X_2, \ldots, X_N\right) \qquad (1)$$

c. Estimating PDF for input quantities: choosing the most appropriate PDF for each input quantity. In this case, the principle of maximum entropy in Bayesian theory can be applied. The most common distribution based on the level of information on input quantities must be considered. For example, using the rectangular distribution if the only information available on input quantity are the maximum and minimum limits.
d. Preparing and running the MCS.
e. Summarizing and presenting the result.

Steps (d) and (e) can be elaborated further as follows [35]:

1. Determining M (number of trials that will be conducted). Generally, a higher number would lead to higher result convergence. This number can be decided using a priori or adaptive method.
2. Generating a set of N input parameter $\{x_1, x_2, \ldots, x_N\}$. These are random values distributed based on the PDF of each input parameter. This process must be repeated M times for each input

quantity. One of the requirements for reliable simulations is the use of a good random number generator. Supplement 1 GUM recommends the use of the Wichmann-Hill algorithm[36].

3. Calculating Y (output quantity) using an appropriate model as expressed in Eq. 2:

$$y_j = f\left(x_{1,j}, x_{2,j}, \ldots, x_{N,j}\right),\ \text{for}\ j = 1, 2, \ldots, M \tag{2}$$

The result can be used to predict the PDF of Y.

4. Calculating the mean and standard deviation of output vector $\{y_1, y_2, \ldots, y_M\}$ as the y measurement results and the standard uncertainty $u(y)$.
5. Sorting the output vector in ascending order and determining the coverage interval $[y_L, y_H]$ in coverage probability p, using Eqs. 3 and 4 as follows[37]:

$$L = \text{round}\left(\left(M+1\right)\alpha\right) \tag{3}$$

$$H = \text{round}\left(\left(M+1\right)\left(1-\alpha\right)\right) \tag{4}$$

6. Alpha (α) is the significance level ($\alpha = 0.025$ for 95% coverage probability), and the round(x) function is used to represent the closest integer to x. In other words, y_L and y_H are the *2.5%* and *97.5%* sorted percentiles of y_i[38].

Supplement 1 GUM recommends that M, as the number of simulations, is determined to provide a reasonable representation of the expected result based on the general rule as expressed in Eq. 5:

$$M > \frac{10^4}{1-p} \tag{5}$$

If p is 0.95, for example, then the selected coverage probability is 95% (100p%), and M must be higher than 200,000. The value of 10^6 is often deemed appropriate for 95% coverage probability. However, if M is selected *a priori*, there would be no direct control over the generated result. Furthermore, the random character of the process and the probability distribution of the output quantity (Y) have an influence on determining the required M value and will vary from one case to another. Therefore, the determination of the value of M is then carried out adaptively.

When the value of M is determined using the adaptive approach, condition selection is checked after every simulation to identify the stability of the results. These checks include the mean, standard deviation, and limits of the selected output interval. A result is considered stable if two standard deviations of the result are lower than the specified numerical tolerance.

Hereby below is the MCS algorithm calculation with the adaptive approach[39]:

(a) Select the coverage probability (p) for the interval determination
(b) Select the number of significant decimal digits (n_{dig}) for uncertainty $u(y)$. Usually, the n_{dig} is either one or two.
(c) Determine the number of simulations (M) for each step in the pr ess. The standard practice is to use Eq. 6 as follows:

$$M = \max\left(\frac{100}{1-p}, 10^4\right) \tag{6}$$

These two values are smaller than the total estimated iteration (*10^6*) so that the variability of parameters after each sequence can be determined. Aside from that, the M value is a multiple of $(1-p)^{-1}$ to get the shortest coverage interval (*10^4* is the multiply of $(1-p)^{-1}$ for a common case, with $p = 0.95$ and *0.99*).

(d) Variable h calculates the number of MCS. For the first time, set $h = 1$.
(e) For every h sequence, M simulations are conducted, resulting in y_r value ($r = 1, \ldots, M$) and the estimated parameters are stated by Eqs. 7 and 8 as follows:
   - Mean as the estimation of y from Y:

$$y^{(h)} = \frac{1}{M}\sum_{r=1}^{M} y_r \tag{7}$$

   - Standard deviation as the standard uncertainty $u(y)$ related with $y^{(h)}$:

$$u\left(y^{(h)}\right) = \left[\frac{1}{M}\sum_{r=1}^{M}\left(y_r - y^{(h)}\right)^2\right]^{1/2} \tag{8}$$

   - For example, q is the part of integers from $pM + ½$. Sort the values of y_r ($r = 1, \ldots, M$) in nondescending sequence $y_{(r)}$ ($r = 1, \ldots, M$), then obtain the probabilistically symmetric coverage interval for $Y = [y_{low}^{(h)}, y_{high}^{(h)}]$. The interval limits are $y_{low}^{(h)} = y_{(r)}$ and $y_{high}^{(h)} = y_{(r+q)}$, where r is the part of integers from $(M-q)/2 + ½$. If the expected result is the shortest coverage interval, r* must be determined as $y_{(r^*+q)} - y_{(r^*)} < y_{(r+q)} - y_{(r)}$ for all values, $r = 1, \ldots, (M-q)$.

(f) Analyzing parameter variabilities needs more than one sequence, so if $h = 1$, a unit must be added, and step (e) must be repeated.
(g) After each sequence has been obtained, this last parameter mean and standard deviation must be calculated using Eqs. 9-12 as follows:
   - Estimated value:

$$\hat{y} = \bar{y} = \frac{1}{h}\sum_{i=1}^{h} y^{(i)} \tag{9}$$

$$s_{\hat{y}} = \left[\frac{1}{h(h-1)}\sum_{i=1}^{h}\left(y^{(i)} - \hat{y}\right)^2\right]^{1/2} \tag{10}$$

   - Standard uncertainty:

$$\hat{u}(y) = \frac{1}{h}\sum_{i=1}^{h} u\left(y^{(i)}\right) \tag{11}$$

$$s_{\hat{u}(y)} = \left[\frac{1}{h(h-1)}\sum_{i=1}^{h}\left(u\left(y^{(i)}\right) - \hat{u}(y)\right)^2\right]^{1/2} \tag{12}$$

- The lower limit of coverage interval is expressed in Eqs. 13 and 14:

$$\hat{y}_{low} = \frac{1}{h}\sum_{i=1}^{h} y_{low}^{(i)} \tag{13}$$

$$s_{\hat{y}_{low}} = \left[\frac{1}{h(h-1)}\sum_{i=1}^{h}\left(\hat{y}_{low}^{(i)} - \hat{y}_{low}\right)^2\right]^{1/2} \tag{14}$$

- The upper limit of coverage interval is calculated using Eqs. 15 and 16:

$$\hat{y}_{high} = \frac{1}{h}\sum_{i=1}^{h} y_{high}^{(i)} \tag{15}$$

$$s_{\hat{y}_{high}} = \left[\frac{1}{h(h-1)}\sum_{i=1}^{h}\left(\hat{y}_{high}^{(i)} - \hat{y}_{high}\right)^2\right]^{1/2} \tag{16}$$

(h) The numerical tolerance (δ) associated with $u(y)$ must be calculated to apply the stability criterion to the results. $u(y)$ is calculated as in step (e) using all the values in the $h \times M$ matrix. For computer calculation purposes, the uncertainty must be expressed as $u(y) = c \times 10^d$, where c is an integer with the same number of digits as the significant digits of $u(y)$, and d is an integer. The numerical tolerance is stated in Eq. 17:

$$\delta = \frac{1}{2}10^d \tag{17}$$

(i) Stability criteria stated that if the value of $2s_{\hat{y}}$, $2s_{\hat{u}(y)}$, $2s_{\hat{y}_{low}}$, or $2s_{\hat{y}_{high}}$ is higher than δ, a unit must be added to h, and step (e) must be repeated.

Finally, after the stability criteria have been verified, all $h \times M$ model values must be used to calculate y_{low} and y_{high} using step (e) for each sequence. The values of y and $u(y)$ have been computed in step (g).

3. Methods

3.1 Calculation of Steady State Power of Refrigerator

IEC 62552-3:2015[40] is an International standard that regulates the test method for calculating energy consumption of household refrigerators. The amount of energy consumption is calculated based on the steady state power of the refrigerator. The Annex B section of IEC 62552-3:2015 explains that there are two methods of determining the steady state condition of the refrigerator during testing, namely the SS1 and SS2 approaches. Both methods have their own stability criteria. Technically, the SS2 approach can be used as an alternative if the stability criteria with the SS1 approach are not met. Steady state power of the refrigerator is the measured power when the refrigerator has reached steady state, either through the SS1 or SS2 approaches. This value is then corrected by Eq. 18 on the basis of consideration of the difference between the measured ambient temperature during the test and the nominal ambient temperature of the test.

$$P_{SS} = P_{SSM} \times \left[1 + \left(T_{at} - T_{am}\right) \times \sum \frac{V_i}{\left(c_1 \times \left(18 + T_{it}\right) + c_2\right)} \times \left(\sum \frac{V_i \times \left(T_{am} - T_{im}\right)}{\left(c_1 \times \left(18 + T_{it}\right) + c_2\right)}\right)^{-1}\right] \times \left[1 + \left(T_{at} - T_{am}\right) \times \Delta COP\right]^{-1} \tag{18}$$

3.2 Measurement

The dataset utilized in this research stems from refrigerator testing conducted in accordance with the IEC 62552:2015 standard, a methodology akin to that employed in prior research by Kusnandar[41], particularly focusing on power measurements. The object of examination is a two-door refrigerator, characterized by specifications delineated in Table 1.

The measurand in this research is steady-state power of refrigerator (P_{ss} in Eq. 18). This value is obtained by the time the compartment temperature reaches its steady-state condition. Other quantities, T_{im} and T_{am}, are obtained by measuring the inner compartment and the ambient temperature. While V_i is determined based on the information written on the refrigerator label.

Table 1. Specification of refrigerator under test.

Specification	Value
Brand/Type	Polytron/PR-21SERI
Nominal Voltage	220 V
Current/Freq.	1.1 $A/50\ Hz$
Max Lamp Power	15 W
Heating Power	145 W
Frozen Compartment Vol.	41 L
Unfrozen Compartment Vol.	125 L
Refrigerant	R134a/90g
Climate Class	T

The experimental configuration and positioning of thermocouple sensors adhered meticulously to the guidelines outlined in the IEC standard 62552-1:2015, depicted in Fig. 1. Specifically, five thermocouple sensors were strategically deployed within the frozen compartment, while three sensors were positioned within the unfrozen compartment. Additionally, two sensors were affixed on both the left and right sides, maintaining a separation distance of 30 cm from the test specimen to capture ambient temperature variations. Temperature and power data recording was carried out simultaneously utilizing a dedicated data logger and power meter with a logging time of 10 seconds.

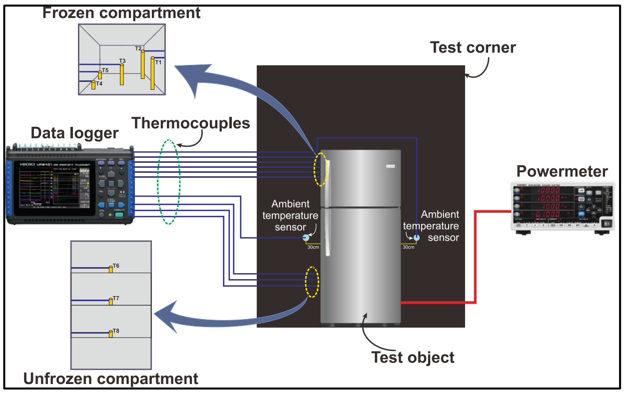

Fig 1. Measurement Set-up

The test was carried out in a temperature-controlled room at *32℃*, which is the temperature of the test room for products for a climate class T/Tropical (it is mean that the refrigerator was designed to be used in tropical area). Since the test object used was a refrigerator with a 2-star compartment type, the target temperatures for the frozen and unfrozen compartments were *−12℃* and *4℃*, respectively. The thermostat on the refrigerator was set in such a way that the temperature in the frozen and unfrozen compartments approaches the set target. Figure 2 shows a graph of refrigerator temperature and power over time, with unloaded conditions during the measurements. The spike shown in the graph indicates when the refrigerator is defrosting. Steady-state conditions are determined between two defrosts with stability criteria according to standard provisions (SS1 or SS2).

Measurement uncertainty assessment was meticulously executed employing the Monte Carlo method, wherein the number of trials (*M*) was determined through three distinct approaches:

1) A priori, by setting $M = 10^6$.

2) Adaptive, by setting the number of significant decimal digits $n_{dig} = 2$.

3) Adaptive, by setting the number of significant decimal digits $n_{dig} = 1$.

Each of the aforementioned methodologies underwent a tenfold repetition, facilitating rigorous comparison of outcomes. The simulation endeavor was orchestrated utilizing the computational capabilities of Matlab[39], a widely acknowledged software platform renowned for its robust numerical computation and visualization functionalities.

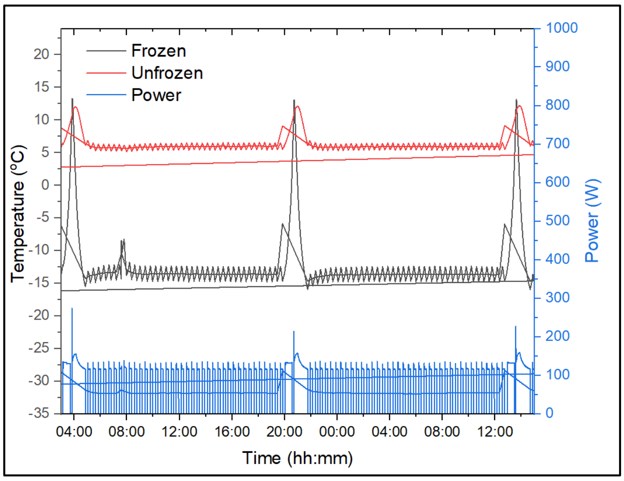

Fig. 2: Graph of refrigerator temperature and power over time

4. Results and Discussions

Table 2 provides a comprehensive breakdown of sources of uncertainty in measuring the steady-state power of a refrigerator, along with their estimated probability distribution functions (PDFs). The estimated values of the PDF parameters from each of these components of uncertainty are the inputs in conducting the Monte Carlo simulation.

For the steady-state power (P_{SSM}), sources of uncertainty include repeated measurement, power meter (PM) resolution, and PM calibration. Repeated measurement and PM calibration are modeled with a normal distribution. The mean steady-state power from repeated measurements is estimated at $53.6\ W$, with a standard deviation of $0.99\ W$. PM calibration introduces a mean deviation of $-0.05\ W$ with a standard deviation of $0.02\ W$. PM resolution is represented by a uniform distribution ranging from $-0.05\ W$ to $0.05\ W$.

Regarding ambient temperature (T_{am}), sources of uncertainty encompass repeated measurement, data logger (*DL*) resolution, DL calibration, chamber calibration, and thermocouple calibration. These sources are modeled with normal or uniform distributions. Repeated measurement of ambient temperature yields a mean of 31.8°C with a standard deviation of 0.10°C. DL calibration introduces a mean deviation of 0.6°C with a standard deviation of 0.1°C. Chamber calibration and thermocouple calibration contribute mean deviations of 0.4°C and 0.2°C, respectively, with corresponding standard deviations.

Table 2. Sources of uncertainty in measuring the steady state power of the refrigerator and its estimated distribution (PDF).

	Sources	Type	Dist.	Parameters			
				Mean	Std. Dev	Min	Max
Steady-state Power (P_{SSM})	Repeated measurement	A	Normal	$53.6\ W$	$0.99\ W$	-	-
	Power Meter (PM) resolution	B	Uniform	-	-	$-0.05W$	$0.05W$
	PM calibration	B	Normal	$-0.05\ W$	$0.02\ W$	-	-
Ambient temperature (T_{am})	Repeated measurement	A	Normal	*31.8℃*	*0.10℃*	-	-
	Data Logger (DL) resolution	B	Uniform	-	-	*−0.05℃*	*0.05℃*
	DL calibration	B	Normal	*0.6℃*	*0.1℃*	-	-
	Chamber calibration	B	Normal	*0.4℃*	*0.3℃*	-	-
	Thermocouple calibration	B	Normal	0.2℃	0.4℃	-	-
Frozen temperature (T_{2m})	Repeated measurement	A	Normal	*−13.4*℃	*0.05*℃	-	-
	Data Logger (DL) resolution	B	Uniform	-	-	*−0.05℃*	*0.05℃*
	DL calibration	B	Normal	0.6℃	0.1℃	-	-
	Thermocouple calibration	B	Normal	*−0.8*℃	0.4℃	-	-
Unfrozen temperature (T_{1m})	Repeated measurement	A	Normal	5.9℃	0.05℃	-	-
	Data Logger (DL) resolution	B	Uniform	-	-	*−0.05*℃	0.05℃
	DL calibration	B	Normal	0.6℃	0.1℃	-	-
	Thermocouple calibration	B	Normal	*−0.4*℃	0.4℃	-	-

Similarly, frozen temperature (T_{2m}) and unfrozen temperature (T_{1m}) undergo uncertainty analysis. For both temperatures, repeated measurements and DL resolution are considered, along with DL calibration and thermocouple calibration. The PDFs for these sources are also represented by normal and uniform distributions, with means and standard deviations specified accordingly.

Three approaches of determining the number of trials (M) in Monte Carlo Simulation (MCS) are presented in Appendix A. In Table A.1, with $M = 10^6$ (*a priori*), all simulations yield an estimated measured value (P_{SS}) of 51.30 W with a standard uncertainty ($u(P_{SS})$) of 1.44 W. The coverage interval spans from 48.47 W to 54.13 W. Adaptive MCS with 2 significant decimal digits (Table A.2) also maintains consistency in P_{SS} and $u(P_{SS})$, yet the coverage interval fluctuates slightly. Conversely, adaptive MCS with 1 significant decimal digit (Table A.3) exhibits slight variations in P_{SS} and $u(P_{SS})$, influencing the coverage interval.

Meanwhile, the average results from the 10 simulations are presented in Table 3. In estimating the 95% coverage interval, the three methods provide results that still vary, both for the lower and upper limits of the interval. However, the variation in the simulation results using the *a priori* method and the adaptive method with 2 significant decimal digits are relatively smaller than the results using the adaptive method with 1 significant decimal digit. On the average, there is only a difference of $0.01\ W$ between the 95% coverage interval of *a priori* method and the adaptive method with 2 significant decimal digits, both for the lower and upper limits.

Table 3. Statistics from 10 times Monte Carlo simulation with three approaches to determine of *M*.

MCS methods	Number of trials, M	Measured value, P_{ss} (W)	Standard uncertainty, $u(P_{ss})$ (W)	95% coverage interval (W)	Significant digit, n_{dig}	Numeric tolerance, δ
A priori	10^6	51.30	1.44	[48.49-54.15]	-	-
Adaptive	2.32×10^6	51.30	1.44	[48.50-54.16]	2	0.01
Adaptive	3.1×10^4	51.30	1.44	[48.47-54.13]	1	0.1

Moreover, based on the outcomes derived from the Monte Carlo simulation concerning the steady-state power measurement of the refrigerator, it is evident that both the *a priori* method ($M = 10^6$) and the adaptive method with 2 significant decimal digits yield comparable results in estimating the measured value, standard uncertainty, and 95% coverage intervals. This suggests a robustness and consistency in the methodology across multiple simulations. Conversely, the adaptive Monte Carlo simulation with 1 decimal digit demonstrates discrepancies in the obtained values upon repeated simulations, indicating its less favorable performance. Additionally, the distribution graphs generated from these three approaches are visually depicted in Fig. 3, offering further insights into the distribution characteristics of the simulated data.

Fig. 3 demonstrates that the Monte Carlo simulation (MCS) output yields a steady state power distribution closely resembling a normal distribution, particularly evident in the *a priori* method ($M = 10^6$) and the adaptive approach with two significant decimal numbers (Fig. 3-a and 3-b). The distributions align closely with the normal distribution curve line. Therefore, employing a normal distribution approach is appropriate for determining the 95% coverage interval for the estimated value of the standard uncertainty. On the other hand, the adaptive MCS method with one significant decimal digit produces an output distribution graph that deviates more from the normal curve line due to the smaller number of simulations (Fig. 3-c).

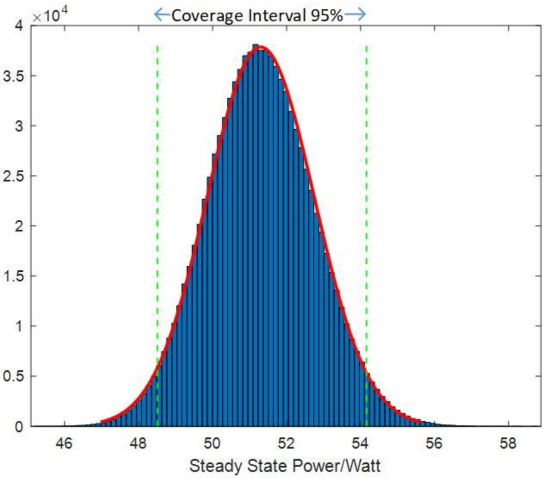

Fig. 3-a: The output distribution graph of the MCS using the a priori method ($M = 10^6$).

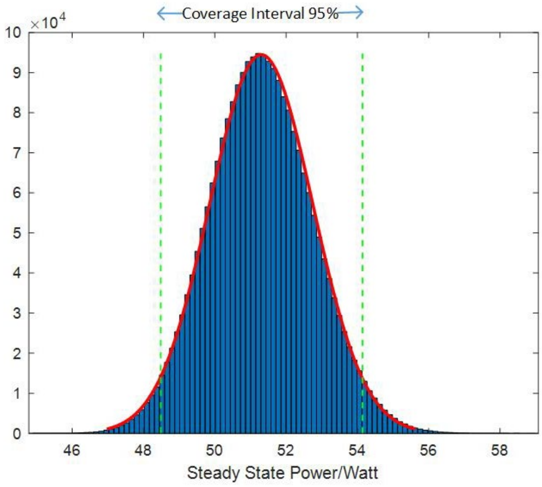

Fig. 3-b: The output distribution graph of the MCS using the adaptive method with 2 significant decimal digits.

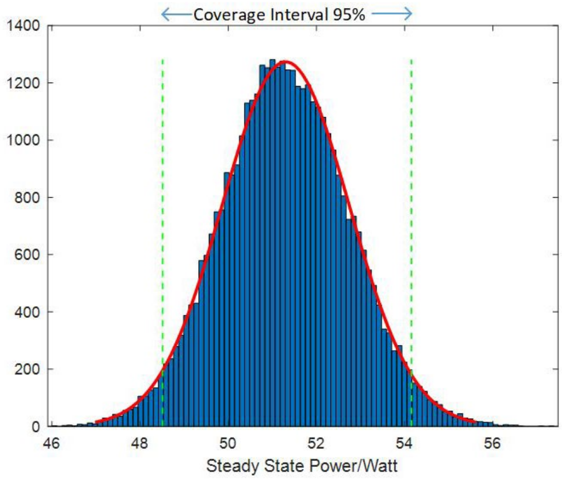

Fig. 3-c: The output distribution graph of the MCS using the adaptive method with 1 significant decimal digit.

5. Conclusions

The application of the Monte Carlo method to evaluate uncertainty in the steady-state power measurement of refrigerators, based on the IEC 62552:2015 standard, has yielded promising results. Our study produced an estimated measured value of $51.3\ W$ with a standard uncertainty of $1.44\ W$. By addressing the challenges outlined in the introduction, particularly regarding the limitations of traditional methods such as the Law of Uncertainty Propagation (LPU), the Monte Carlo method emerges as a robust alternative for uncertainty estimation in complex measurement models.

The choice between setting the number of trials (M) for the Monte Carlo simulation presents interesting insights. Both approaches, setting $M = 10^6$ and using an adaptive method with 2 significant decimal digits, yield relatively similar results. This flexibility in methodology underscores the versatility and effectiveness of the Monte Carlo method in handling intricate measurement uncertainties.

Our findings suggest that the Monte Carlo method offers a viable solution to the uncertainty calculation problem encountered with traditional methods, especially given the complexities involved in determining sensitivity coefficients in complicated measurement models. Furthermore, future research should delve deeper into investigating dominant factors of uncertainty components, exploring correlations among input quantities, and determining appropriate distributions using the Monte Carlo method.

The main challenges of using the Monte Carlo Method for uncertainty estimation in refrigerator power measurements include the computational intensity due to the need for a large number of simulations and significant processing power. Additionally, selecting appropriate probability distributions, conducting thorough sensitivity analysis to identify influential parameters, establishing convergence criteria, and ensuring result stability. The choice of software and tools also impacts the ease and effectiveness of the analysis

Nomenclature

MCM	Monte Carlo Method
MCS	Monte Carlo Simulation
LPU	Law of Propagation of Uncertainties
PDF	Probability Density Function
GUM	Guide to the Expression of Uncertainty in Measurement
P_{SS}	steady state power of refrigerator after correction
P_{SSM}	steady state power obtained through the SS1 or SS2 approach (W)
T_{at}	target ambient temperature of test chamber (°C)
T_{am}	measured ambient temperature of the test chamber during the test period (°C)
V_i	nominal volume of compartment i (L)
T_{im}	measured temperature of compartment i during the test period (°C)
T_{it}	target temperature for energy consumption of compartment i (°C)
c_1	constant value $= 0.011364$ (–)
c_2	constant value $= 1.25$ (–)
ΔCOP	adjustments given are in accordance with the type of product and test conditions (based on the standard, the value is set at -0.014)

Greek symbols

δ	numerical tolerance (–)

A. MCS results with three approaches of determining the number of trials (*M*)

Table A1. MCS results with $M = 10^6$ (*a priori*)

Simulation No.:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Estimated measured value, P_{ss} (W)	51.30	51.30	51.30	51.30	51.30	51.30	51.30	51.30	51.30	51.30
Standard uncertainty, $u(P_{ss})$ (W)	1.44	1.44	1.44	1.44	1.44	1.44	1.44	1.44	1.44	1.44
Lower limit of *95%* coverage interval (W)	48.47	48.48	48.51	48.50	48.50	48.47	48.51	48.49	48.50	48.50
Upper limit of *95%* coverage interval (W)	54.13	54.14	54.17	54.16	54.15	54.13	54.16	54.14	54.15	54.14
Number of trials, M	10^6	10^6	10^6	10^6	10^6	10^6	10^6	10^6	10^6	10^6

Table A2. Adaptive MCS with 2 significant decimal digits

Simulation No.:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Estimated measured value, P_{ss} (W)	51.30	51.30	51.30	51.30	51.30	51.30	51.30	51.30	51.30	51.30
Standard uncertainty, $u(P_{ss})$ (W)	1.44	1.44	1.44	1.44	1.44	1.44	1.44	1.44	1.44	1.44
Lower limit of *95%* coverage interval (W)	48.51	48.50	48.50	48.48	48.50	48.51	48.48	48.50	48.51	48.52
Upper limit of *95%* coverage interval (W)	54.17	54.16	54.16	54.13	54.16	54.15	54.14	54.15	54.16	54.18
Number of trials, M	1.98×10^6	2.38×10^6	2.41×10^6	2.19×10^6	2.25×10^6	2.21×10^6	2.69×10^6	2.41×10^6	2.15×10^6	2.57×10^6

Table A3. Adaptive MCS with 1 significant decimal digit

Simulation No.:	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Estimated measured value, P_{ss} (W)	51.30	51.29	51.29	51.30	51.30	51.31	51.31	51.30	51.31	51.31
Standard uncertainty, $u(P_{ss})$ (W)	1.44	1.44	1.45	1.45	1.44	1.44	1.45	1.44	1.45	1.45
Lower limit of *95%* coverage interval (W)	48.46	48.52	48.49	48.52	48.38	48.43	48.37	48.52	48.51	48.52
Upper limit of *95%* coverage interval (W)	54.11	54.16	54.15	54.18	54.05	54.07	54.06	54.14	54.16	54.21
Number of trials, M	2×10^4	2×10^4	2×10^4	6×10^4	4×10^4	4×10^4	2×10^4	4×10^4	2×10^4	3×10^4

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