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Research Paper

Virtual entropy generation (VEG) method in experiment reliability control: Implications for heat exchanger measurement

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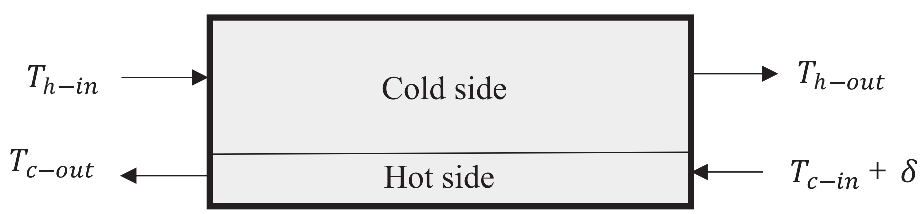
HIGHLIGHTS

- A new concept, virtual entropy generation (VEG), is defined.
- Virtual entropy generation (VEG) is a measure of error and uncertainty in experiments.
- Two virtual entropy generation (VEG) restrictions are proposed.
- The critical heat balance error for a general imbalanced heat exchanger is derived.
- Calibration models are proposed to minimize the systematic uncertainty for heat exchanger measurement.

GRAPHICAL ABSTRACT



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ABSTRACT

Heat exchangers are widely-used heat recovery devices. To evaluate their performance, reliable experimental data are necessary and important. In the present paper, a "virtual entropy generation (VEG)" method is developed to control the quality of heat exchanger measurement. Different from the real entropy generation caused by the process irreversibility, virtual entropy generation (VEG) is defined as the difference between the measured entropy generation and the theoretical entropy generation caused with no measurement error and uncertainties. The results of this paper illustrate the existence and restrictions of VEG in two forms: the error form and the uncertainty form. Based on the new analytical approach (VEG method), new techniques are developed (1) to derive a second-law obeying measurement error criterion, and (2) to regulate the measurement uncertainties with four kinds of calibration techniques. Finally, the virtual entropy generation (VEG) are illustrated and clarified by existing experimental results. Our new framework of analysis demonstrates a more reasonable way to develop the criterion of any irreversible process measurement and provides a promising way to improve experiment reliability.

1. Introduction

Entropy generation methods are a widely used second-law methods in nature and engineering problems with irreversibility [1–4]. Nowadays, more and more energy transfer and conversion processes in industry are evaluated by the analytical entropy generation methods. For example, heat exchange [5], fluid flow [6–9], chemical reaction [10,11], combustion [12], thermodynamic cycle [13], and biological process [14], etc. are all applications of entropy generation methods. Recent studies of entropy generation methods have evolved into a general design and evaluation criterion, the Constructal law [15]. Among all these applications, heat exchanger

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Nomenclature

C	specific heat at constant pressure, J/(kg K)
$C*$	thermal capacity ratio
Error(*B*)	heat balance error
$\dot{m}$	mass flow rate, kg/s
Q	heat transfer rate, W
$r(T_i, T_j)$	systematic correlation coefficient
T	temperature, K
S_{gen}	entropy generation, kJ/(kg K)
Ns	analytical entropy generation number
$(Ns)_m$	entropy generation number in experiment
$T_{c\text{-in}}$	cold side inlet temperature, K
$T_{h\text{-in}}$	hot side inlet temperature, K
$T_{c\text{-out}}$	cold side outlet temperature, K
$T_{h\text{-out}}$	hot side outlet temperature, K
ΔT_c	cold side outlet/inlet temperature difference, K
ΔT_{max}	max temperature between cold and hot side, K
U	measurement uncertainty
$U(N_S)$	uncertainty of entropy generation
UMF	uncertainty magnification factor

Greek symbols

τ	inlet temperature ratio $T_{c\text{-in}}/T_{h\text{-in}}$
δ	measurement variant
Δ	increment
ε	heat exchanger efficiency
∂	particle difference

Subscripts

m	measurement value
ave	average
in	heat exchanger inlet
out	heat exchanger outlet
h	heat exchanger hot side
c	heat exchanger cold side

evaluation is one of the most successful examples because it is more frequently studied and used by researchers and engineers [16].

When dealing with real-world evaluations, experimental studies are more broadly conducted than analytical equations because experiments are more specific and persuasive for addressing the performance of each device. Also important is that a variety of performance parameters are determined by empirical correlations through experiments [17]. From a theoretical or design standpoint, it is usually assumed that there are no data deviations (or measurement uncertainties) in parameters. When processing experiment data, researchers need to consider measurement reliability and control error. Measurement error has long been a concern since it can induce bias and lower the reliability of data. Extensive efforts have been made to improve the reliability of measurement data, taking heat exchangers as an example. However, this is not an easy task since it requires interdisciplinary research among device design, heat transfer, thermodynamics, and statistical theory.

Error and uncertainty are two of the most important considerations for heat exchanger experimental reliability. Uncertainty presented in this paper is the standard deviation of measurement parameter, which focuses on the measurement result and characterizes the dispersion of the values [18]. Two routine practices in engineering measurement are to use a constant margin of error criterion or to conduct uncertainty estimation before experiments. The measurement error is often controlled within ±5% [19]. A higher error requirement may need a larger sample size, which is reliable but expensive.

The conventional uncertainty calculation for heat exchangers are conducted for flow rate, media properties [20], and temperature measurement uncertainties [21] by zero-order uncertainty equation. Data regression can also help to obtain a more reliable analysis. To obtain highly reliable data with minimized uncertainty at the pre-test stage can achieve a low-cost measurement.

Other alternative techniques are also applied in the uncertainty study of heat exchanger experiments. For example, Monte Carlo stochastic approach is used to study the appropriate uncertainty confidence intervals of heat exchanger design to physical properties estimation at high temperatures [22]; the artificial neural network (ANN) approach [23] improves data quality on insufficient data measurement and with an upper error bound. A methodology based on global optimization techniques that include genetic algorithms, simulated annealing and interval analysis demonstrates improved accuracy with errors of only 3% [24].

Recent research has shown a great potential of applying entropy generation restriction to control measurement error within reasonable physical bounds. Zhang et al. proposed the critical heat error criterion for a balanced heat exchanger [25]. Results showed a constant heat balance error is not adequate for obtaining second law obeying measurement data. With this criterion, the filtration of negative entropy generation experiment data are possible at the efficiency rate of 82%. One merit of using this method is that this method defines the error criterion with a clear physical restriction [26].

In the present study, we are interested in improving the quality of measurement data by defining a second-law obeying error criterion. We are interested in developing a practical, reliable, and effective method to evaluate the data and exclude the invalid data at the pre-design stage. To this end, the present paper proposes a "virtual entropy generation (VEG)" method. This method controls measurement errors and uncertainties by reducing the difference between measured entropy generation (indirectly calculated) and the theoretical value. To build the analytical framework, we propose two virtual entropy generation (VEG) restrictions based on the second law of thermodynamics in measurement. In the application of this principle, we apply the VEG method to a general imbalanced heat exchanger measurement. We also explain how we minimize the uncertainty by using different calibration models. Successful application of the virtual entropy generation (VEG) method proves promising in dealing with the measurement of energy systems, irreversible processes, and devices, which could guide design measurement criteria and minimize measurement uncertainties.

2. Virtual entropy generation (VEG) method

The second law of thermodynamics states that any real-world thermodynamic process is irreversible [1]. From the entropy generation perspective, these real-world processes produce non-negative entropy generations. To evaluate these processes, experimentalists conduct experiments and expect valid and reliable data. However, each measurement contains error and uncertainties. Taking heat exchanger experiments as an example, the entropy generation is a function of four temperatures: hot/cold-side inlets/outlets, thermal properties of fluid media, and flow velocities. Each measurement of these quantities contains errors and uncertainties. All these measurement errors will propagate into the entropy generation equation and generates a "virtual irreversibility", which is the difference between theoretical entropy generation and the analytical expression. With the existence of measurement error, the entropy generation measured can be decomposed into two parts,

$$(\dot{S}_{gen})_m = \dot{S}_{gen} + \delta(\dot{S}_{gen}) \quad (1)$$

Here, $(\dot{S}_{gen})_m$ is the measurement entropy generation, calculated from analytical combination of measured parameters (includes measurement error); $\dot{S}_{gen}$ is the theoretical entropy generation induced by the process irreversibility assuming no measurement error exists. $\delta(\dot{S}_{gen})$ is the "virtual entropy generation (VEG)" caused by measurement variation (i.e. measurement error and uncertainty); VEG is the difference between the measured entropy generation (with no error and uncertainty) and the theoretical entropy generation with no measurement error. Alternatively, we can say the virtual entropy generation (VEG) we defined here is an indicator of error influence on data quality.

To make definitions clear, we tabulated and made a comparison of three similar concepts: entropy, entropy generation, and virtual entropy generation in Table 1. Rather than a measure of disorder or process irreversibility, virtual entropy generation (VEG) we defined in the present paper is a measure of error and uncertainty in the practice of experiments.

Based on the concept of virtual entropy generation (VEG) and the non-negative entropy generation requirement in experiment, we can get the following two restrictions:

(1) The first virtual entropy generation (VEG) restriction is given by an error description: since the measurement value $(\dot{S}_{gen})_m$ should follow the second law of thermodynamics, the virtual entropy generation (VEG) and the theoretical entropy generation should satisfy:

$$\delta(\dot{S}_{gen}) \geqslant -\dot{S}_{gen} \quad (2)$$

With the increase of measurement error, the virtual entropy generation becomes comparable with the theoretical entropy generation. However, the virtual entropy generation should not be greater than the theoretical entropy generation. Eq. (2) gives an upper limit of the measurement error. This restriction is a very generous criterion since we know when the virtual entropy generation approaches this limit, the measurement error reaches 100% from an entropy generation perspective.

(2) Furthermore, the second virtual entropy generation (VEG) restriction is given by an uncertainty description: the uncertainty of measured entropy generation should be smaller than a certain ratio of the theoretical entropy generation it measures.

$$U_{(\dot{S}_{gen})_m} \leqslant \frac{1}{\alpha}\dot{S}_{gen} \quad (3)$$

Eq. (3) is a flexible restriction. This ratio is determined by a designed confidence level. For very sensitive experiment cases or experiments with large measurement uncertainties, the measurement uncertainty can be comparable with the theoretical value. For these measurements, there will be a high possibility to get a second-law breaking data.

Table 1
Comparisons of three entropy-related physical quantities.

Physical quantity	A measure of
Entropy	Disorder
Entropy generation	Process irreversibility
Virtual entropy generation	Measurement error or uncertainty

Since the virtual entropy generation (VEG) is bounded by the entropy generation of the process. Based on the 3σ criterion (assuming a normally distributed error in the measurement), the probability of the measured entropy generation in the range of $\dot{S}_{gen} - 3U_{S_{gen}}$ and $\dot{S}_{gen} + 3U_{S_{gen}}$ is 99.73%. So the probability of invalid measurement, $P_{invalid} = \int_{-\infty}^{0} f(N_S)dN_S < \int_{-\infty}^{\dot{S}_{gen}-3U_{S_{gen}}} f(N_S)dN_S = 0.135\%$. Consequently, if the experiment follows this restriction, we can get a negative entropy generation measurement with a probability less than 0.135% when α = 3. By using this restriction, we can control and optimize the measurement process by selection of α.

3. Virtual entropy generation in the form of heat balance error

We claim that the data are reliable as they obey the second law of thermodynamics by following the above two restrictions. One of the challenges is how to determine virtual entropy generation and how to make it explicit and comparable with the real entropy generation. In this part, we show the process of how to make the virtual entropy generation explicit by using Taylor's expansion method for a general heat exchanger.

Heat exchangers are used in a wide variety of engineering applications in the oil and gas industry, power plant, chemical processing industry and more. Generally speaking, the heat exchanger is an important processing unit which maximizes energy recovery. Heat transfer engineers have been engaged in the design, testing and evaluation of heat exchangers since this device was invented. A one-dimension heat exchange model is illustrated in Fig. 1. One of the most important parameters to be evaluated is heat exchanger efficiency. So we will express our results in the form of heat exchanger efficiency. When measuring the efficiency of the exchanger, the most commonly measured parameters are the temperature located at the inlet/out of the cold/hot side.

3.1. Experiment reliability parameter

Experimental studies in the heat exchange process and device provide valuable data for prototype design and optimization from the early stage of heat enhancement structure selection to the following stage of prototype or even in-service device test and evaluation. We use this criterion to get the critical heat balance error of measurement of a general heat exchanger.

For large-error measurement, it has been demonstrated by example and simulation that the usual estimate of the probability can be in significant error, especially for high-risk groups [27]. Theoretically, the heat transferred from the hot side is equal to the

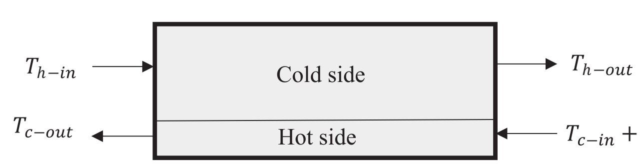

Fig. 1. A one-dimensional heat exchanger model for entropy generation evaluation. It consists of two sides: a cold side and a hot side. The model is generalized for any type of counter-flow heat exchangers with imbalanced indicator C* > 1. C* is a function of heat exchanger configuration and operation condition. δ is the measurement error.

energy gain of the cold side. However, in practice, due to measurement errors and uncertainties, there will be a non-negative heat balance error (HBE). The heat balance error, assuming the measurement error from the cold side inaccuracy, is defined by [24],

$$Error(B) = \frac{\delta Q_c}{Q_{ave} + \delta Q_c/2} = \frac{\delta(\Delta T_c)}{\Delta T_c} \tag{4}$$

This heat balance error is a data-reliability indicator in heat exchanger test. The heat balance error includes all the influence of all measurement errors and model imperfections, like thermal leakage. The inaccuracy exists in the form of temperature measurement error in a linear relation expression,

$$\delta(\Delta T_c) = Error(B) \times \Delta T_c \tag{5}$$

3.2. First-law efficiency parameter

In the design and analysis of heat exchanger, one of the most important parameters is the heat exchanger efficiency, which is defined as the ratio of the heat transferred in the actual heat exchanger to the heat transfer capability in the ideal heat exchanger,

$$\varepsilon = \frac{\max\{\Delta T_c, \Delta T_h\}}{T_{h-in} - T_{c-in}} = \frac{\Delta T_h}{T_{h-in} - T_{c-in}} \tag{6}$$

$\max\{\Delta T_c, \Delta T_h\}$ is the bigger temperature difference between the cold side outlet-inlet temperature difference ($\Delta T_c = T_{c-out} - T_{c-in}$) and the hot side inlet-outlet temperature difference ($\Delta T_h = T_{h-in} - T_{h-out}$). The thermal capacity ratio C^* is the imbalance indicator defined by, $C* = (mc)_c/(mc)_h > 1$, for a general imbalanced heat exchanger (taking cold side bigger as an example). So the temperature variance of the hot side is bigger than the cold side. Since $\dot{m} \doteq vA$, where v is the inlet flow rate and A is the cross-section of the heat exchanger flow path, we can consider C^* as an indicator of heat exchanger configuration.

Using the first law of thermodynamics, we can obtain this relation, $\Delta T_h = C * \Delta T_C$. So the heat exchanger efficiency can alternatively be expressed as,

$$\varepsilon = \frac{\Delta T_h}{T_{h-in} - T_{c-in}} = \frac{C^* \Delta T_c}{T_{h-in} - T_{c-in}} \tag{7}$$

Besides, another important parameter is the cold and hot side inlet temperature ratio defined as, $\tau = T_{c-in}/T_{h-in}$. Here, T_{c-in} and T_{h-in} are the cold and hot side inlet temperature (in Kelvin), respectively. By this definition, the following relation can be obtained, $\varepsilon(\frac{1}{\tau} - 1) = C * \frac{\Delta T_c}{T_{h-in} - T_{c-in}} \frac{T_{h-in} - T_{c-in}}{T_{c-in}} = C^* \frac{\Delta T_c}{T_{c-in}}$. Or we can get a useful non-dimensional relation for later used,

$$\frac{\Delta T_c}{T_{c-in}} = \frac{1}{C*} \varepsilon \left(\frac{1}{\tau} - 1\right) \tag{8}$$

3.3. The second- law boundary on the first-law parameter

The heat transfer irreversibility and the fluid flow irreversibility are the two main irreversibilities in the second-law heat exchanger analysis. For gas heat exchangers or low-velocity liquid heat exchangers, the fluid flow irreversibility is usually neglected [1]. In our study, heat exchangers are tested at flow velocities between 0.1 and 1 (m/s). When Estimated with the equation $\dot{S}_{gen-\Delta P} \approx \frac{\dot{m}\Delta P}{\rho T_{in}}$, the fluid flow irreversibility is less than 5% of the heat transfer irreversibility. Then fluid flow irreversibility is neglected. In the estimation formula, ΔP is the pressure drop of one side, ρ is the density of testing media (water), T_{in} is the absolute temperature of channel inlet.

After simplification, the entropy generation for a one-dimensional heat exchanger model is expressed as,

$$\dot{S}_{gen} = (\dot{m}c)_h \ln\left(\frac{T_{h-out}}{T_{h-in}}\right) + (\dot{m}c)_c \ln\left(\frac{T_{c-out}}{T_{c-in}}\right) \tag{9}$$

Here, $\dot{m}$ is the mass flow rate, c is the specific heat at constant pressure, the subscript c the cod side, the subscript h indicates the hot side. One of the simplest non-dimensional form of entropy generation (also called the entropy generation number) is calculated as dividing entropy generation by the product of mass flow rate and specific heat of test media. This form of entropy generation number is increasingly used in heat exchanger design and evaluation. Further, by introducing the thermal imbalance indicator (C^*), the entropy generation number can be expressed as,

$$N_s = ln\left(\frac{T_{h-out}}{T_{h-in}}\right) + C^* ln\left(\frac{T_{c-out}}{T_{c-in}}\right) \tag{10}$$

In the above equation, four temperatures terms can be directly measured by temperature sensors. The subscripts of each temperature T indicates each measurements source point: hot side outlet, hot side inlet, cold side outlet, and cold side inlet.

3.4. Virtual entropy generation (VEG)

Under the influence of measurement error and uncertainty, the measurement value of entropy generation number can be represented by $(N_s)_m$. Similarly, the entropy generation number measured is expressed as,

$$(N_s)_m = ln\left(1 + \frac{\Delta T_h}{T_{h-in}}\right) + C^* ln\left(1 + \frac{\Delta T_c + \delta(\Delta T_c)}{T_{c-in}}\right) \tag{11}$$

Expand the error by Taylor's expansion method,

$$\begin{aligned}(N_s)_m &= ln\left(1 + \frac{\Delta T_h}{T_{h-in}}\right) + C^* ln\left(1 + \frac{\Delta T_c}{T_{c-in}}\right) + C^* \frac{\delta(\Delta T_c)}{T_{c-in}} + \frac{1}{2} C^* \left(\frac{\delta(\Delta T_c)}{T_{c-in}}\right)^2 \\ &\approx N_s + C^* \frac{\delta(\Delta T_c)}{T_{c-in}}\end{aligned} \tag{12}$$

Considering the measurement variation relation $\delta(\Delta T_c)/T_{c-in} = \Delta T_c/T_{c-in} * \delta(\Delta T_c)/\Delta T_c$ and Relation (8), we finally got the expression,

$$(N_s)_m = N_s + \left(\frac{1}{\varepsilon} - 1\right) Error(\mathrm{B}) \tag{13}$$

The non-dimensional form of virtual entropy generation is now made explicit and expressed as follows,

$$\delta(N_S) = (N_S)_m - N_S = \varepsilon\left(\frac{1}{\tau} - 1\right) Error(B) \tag{14}$$

Eq. (14) shows that the virtual entropy generation (VEG) is proportional to the device operation condition (by heat exchanger efficiency), media temperature (by inlet temperature ratio), and the measurement error (by heat balance error).

3.5. Critical heat-balance-error criterion for a general heat exchanger

Under the control of the first virtual entropy generation restriction in Eq. (2), the non-dimensional form of entropy generation requires a positive expression, $(N_S)_m \geqslant 0$. According to this, we can derivate the analytical expression of critical heat balance error for a general imbalance error,

$$Error(B) \geqslant -\frac{N_S}{\varepsilon(1/\tau - 1)} \approx -(1 - \varepsilon)(1 - \tau) \tag{15}$$

Results in Eq. (15) shows a same criterion as the balanced heat exchanger. So, no matter what the heat exchanger configuration is (by thermal imbalance parameter C^*), the critical heat balance error is the same by using the heat exchanger efficiency (ε) and the cold-hot side temperature ratio. In sum, we applied the first restriction in developing a new heat-balance-error criterion for a general imbalanced counter-flow heat exchanger. This analytical expression stands for a measurement criterion when the entropy generation is "0". Similarly, when the error comes from hot side another criterion can be obtained as: $-(1/\varepsilon - 1)(1 - \tau)$. By comparison, we keep Eq. (15) for a better filtration.

4. Virtual entropy generation in the form of measurement uncertainty

In addition, the practice of uncertainty control has been considered as another major important consideration since it was proposed. The purpose of this section is to use virtual entropy generation to provide a reasonable uncertainty boundary. By this boundary, the uncertainty is always related to the sensor accuracy level. By a reasonable selection of sensor accuracy level, we can achieve an economic measurement.

In order to make further understanding and control measurement uncertainty, we developed an extended uncertainty model with consideration of temperature sensor calibration correlations. Based on the new model, we developed a technique to minimize the uncertainty by adjusting correlations between sensors. We also provide practical guidelines for calibration.

However, insufficient trials are engaged on the experiment reliability of the entropy generation number. The most commonly used uncertainty model is the classical no-correlation uncertainty model [14]. Based on the classical uncertainty model, the only possible guidance to decrease the uncertainty in measurement is to select higher resolution sensors, which may increase the cost of measurement.

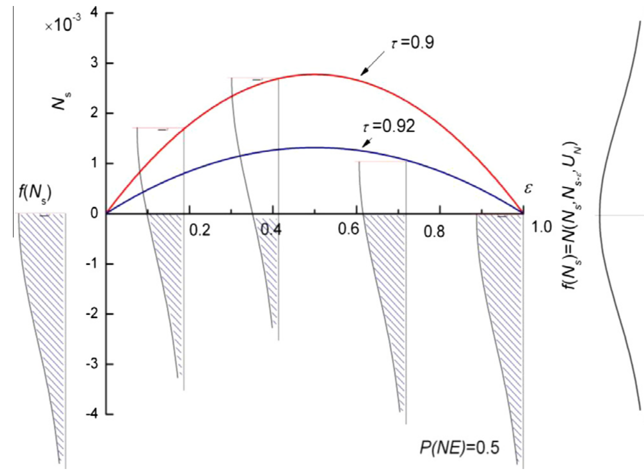

Fig. 2. Influence of uncertainty on the measurement of entropy generation at different heat exchanger efficiency. This figure shows the case when the uncertainty and the entropy generation are comparable. The uncertainty of heat exchanger efficiency (x-axis) is about 10% due to temperature inaccuracy [21]. $\tau = T_{\text{c-in}}/T_{\text{h-in}}$, is the inlet temperature ratio, which is an important parameter for heat exchange process.

Table 2
Four analytical expressions of entropy generation number uncertainty.

	Correlations adjustment	Expanded U_N^2 expression
1	$r_{(T_i,T_j)} = 0$	$\left(\frac{U_{T_{h-out}}}{T_{h-out}}\right)^2 + \left(\frac{U_{T_{h-in}}}{T_{h-in}}\right)^2 + \left(\frac{U_{T_{c-out}}}{T_{c-out}}\right)^2 + \left(\frac{U_{T_{c-in}}}{T_{c-in}}\right)^2$
2	$r_{(T_i,T_j)} = 1$	$\left(\frac{U_{T_{h-out}}}{T_{h-out}} - \frac{U_{T_{h-in}}}{T_{h-in}} + \frac{U_{T_{c-out}}}{T_{c-out}} - \frac{U_{T_{c-in}}}{T_{c-in}}\right)^2$
3	$\begin{cases} r_{(T_{h-in},T_{h-out})} = 1 \\ r_{(T_{c-in},T_{c-out})} = 1 \\ r_{(T_h,T_c)} = 0 \end{cases}$	$\left(\frac{U_{T_{h-out}}}{T_{h-out}} - \frac{U_{T_{h-in}}}{T_{h-in}}\right)^2 + \left(\frac{U_{T_{c-out}}}{T_{c-out}} - \frac{U_{T_{c-in}}}{T_{c-in}}\right)^2$
4	$\begin{cases} r_{(T_{c-out},T_{h-out})} = 1 \\ r_{(T_{c-in},T_{c-out})} = 1 \\ r_{(T_{in},T_{out})} = 0 \end{cases}$	$\left(\frac{U_{T_{h-out}}}{T_{h-out}} + \frac{U_{T_{c-out}}}{T_{c-out}}\right)^2 + \left(\frac{U_{T_{h-in}}}{T_{h-in}} + \frac{U_{T_{c-in}}}{T_{c-in}}\right)^2$

4.1. Uncertainty influence on measurement of entropy generation number

Recent research found that entropy generation is likely to be negative/invalid for certain test cases [24]. A simplified analytical expression is proposed for the filtration of invalid entropy generation measurement. According to this research, negative entropy generation measurements are found in 4% of 975 test cases. To help decrease the uncertainty in measurement in an economical way has significant contribution in further test and measurement.

There are several studies on uncertainty influence on entropy generation as previously described. The influence of temperature uncertainty on the entropy generation in this section is simplified into a model of probabilities. By this model, we can further understand the second restriction by considering uncertainty as Gaussian distributions, for each calibrated measurement, the uncertainty plays a role of ruler centered on the entropy generation line as illustrated in Fig. 2. The distribution of the measurement can be estimated by, $f(N_S) = \frac{1}{\sqrt{2\pi}U_N} \exp\left[-\frac{1}{2U_N^2}((N_s)_m - N_{s-\varepsilon})^2\right]$, where $N_{s-\varepsilon}$ is the theoretical entropy generation number at the heat exchange efficiency ε. Corresponding probability of negative entropy generation at each test condition can be estimated by the expression, $P_{invalid} = \int_{-\infty}^{0} f(N_S) dN_S$. If the uncertainty is small enough, we are less likely to get a negative entropy generation. However, if the entropy generation and the corresponding calibrated uncertainty listed in Table 2 are comparable, we need to be cautious because we are more likely to get invalid entropy generation measurement. Measurement are risky at very low/high heat exchange efficiency or at high inlet temperature ratio because entropy generation itself is small. More attention should be paid to these high-risk measurement operation conditions.

In order to decrease the possibility of invalid entropy generation in experiments, we need to minimize the uncertainty of entropy generation. Two potential solutions to minimize the uncertainty are to buy either upgrading sensors resolution or improving calibration method. Toward an economical measurement, we are developing new models of calibration to minimize the uncertainty of entropy generation based on existing sensor resolutions in the present paper.

From the entropy generation expression, we understand the uncertainties mainly come from three sources: the specific heat uncertainty contribution by $(\partial S/\partial C_P)$, the flow uncertainty contribution by$(\partial S/\partial \dot{m})$, and the temperature uncertainty contribution by $(\partial S/\partial T)$. A reasonable assumption is that there is negligible uncertainty in a fluid property such as specific heat [21]. The analysis is much simpler if we also neglect the contribution of flow uncertainty by dividing the mass flow rate at the both side of equation. Then by using the non-dimensional form of entropy generation, the classical uncertainty model tells,

$$U^2(N_S) = \sum \left[\frac{\partial N_S}{\partial T_i} \times U(T_i)\right]^2 \tag{16}$$

Here, i and j are the rotation numbers from 1 to 4. In the present paper, they also represent the rotation sequence of the hot side outlet, hot side inlet, cold side outlet and cold side inlet. T_i is the rotation of $T_{\text{h-out}}$, $T_{\text{h-in}}$, $T_{\text{c-out}}$, and $T_{\text{c-in}}$. The sensitivity coefficient

$(\partial N_S/\partial T_i)$ is the partial derivative of N_S with respect to T_i: $\partial N_S/\partial T_i = (-1)^{i+1} \times (1/T_i)$. $U(T_i)$ is the absolute uncertainty of the T_i component. These partial derivatives are appropriate for further discussion and calculation since they are continuous.

All the uncertainties in temperature measurement are propagated into the final entropy generation measurement. The uncertainty magnification factor (UMF) [28] can be described as,

$$|UMF_i| = \left|\frac{T_i}{N_S} \times \frac{\partial N_S}{\partial T_i}\right| = \frac{1}{N_S} \tag{17}$$

This indicates that the influence of the relative uncertainties of temperatures is magnified for $1/N_S$ times during propagation through data reduction equation into entropy generation, as $Ns \ll 1$.

4.2. Extended uncertainty model to minimize uncertainty

In this section, we extend the classical uncertainty model to an adjustable, dynamic uncertainty model. In this extended model, the uncertainty control becomes feasible by selection of the correlation between sensors. To expand the analytical form of the uncertainty model, we use the balanced heat exchanger for model derivation. Regarding the uncertainty of the entropy generation number, we expand it by the first-order Taylor method, with the correlations between temperature sensors (thermocouples for our experiment) expressed by:

$$U^2(N_S) = \sum \left\{ \left[\frac{\partial N_S}{\partial T_i} \times U(T_i)\right]^2 + 2 \times \frac{\partial N_S}{\partial T_i} \times \frac{\partial N_S}{\partial T_j} \times r(T_i, T_i) \times U(T_i) \times U(T_j) \right\} \tag{18}$$

Here, $r(T_i, T_j)$ is the systematic correlation coefficient between T_i and T_j, usually, $-1 \leqslant r(T_i, T_j) \leqslant 1$. Since there is nearly no negative r value in experiments, we only consider the zero and positive values. However, these correlations are difficult to determine because they always depend on the experience of the researchers involved.

4.3. Uncertainty minimization by the second entropy generation restriction

The expression in Eq. (18) was transformed into four practical cases as listed in Table 1. Considering the correlations between sensors, the square of U_N is listed in the second column. Practical calibration methods are detailed as:

In Case 1, all systematic error correlations between hot/cold sides and inlet/outlet thermocouples are neglected. This model is the commonly used first-order no-correlation model.

In Case 2, all thermocouples' systematic calibration errors are correlated. This case generates the smallest uncertainty. For perfect calibration, the uncertainty is zero.

In Case 3, all thermocouples' systematic calibration errors between inlet/outlet are linearly correlated, and there is no correlation between hot/cold sides.

In Case 4, all thermocouples' systematic calibration errors in hot/cold sides are correlated, and there is no correlation between inlets/outlets. This case generates the biggest uncertainty, which is even bigger than the totally no-correlation expression.

As seen in Table 2, for a given experiment, we can consider U_N as a constant within the following range:

$$\left(\frac{U_{T_{h-out}}}{T_{h-out}} - \frac{U_{T_{h-in}}}{T_{h-in}} + \frac{U_{T_{c-out}}}{T_{c-out}} - \frac{U_{T_{c-in}}}{T_{c-in}}\right)^2 \leqslant U_N^2 \leqslant \left(\frac{U_{T_{h-out}}}{T_{h-out}} + \frac{U_{T_{c-out}}}{T_{c-out}}\right)^2 + \left(\frac{U_{T_{h-in}}}{T_{h-in}} + \frac{U_{T_{c-in}}}{T_{c-in}}\right)^2 \tag{19}$$

The classical uncertainty model in Eq. (16) was extended into the range above in Eq. (19) by considering the correlations between sensors. By doing this, we can use the correlation adjustment to help control the uncertainty in entropy generation measurement without requesting higher resolution of sensors as guided by Eq. (16).

These calibration models can help increase the reliability of the experiments by reducing the systematic uncertainties of measurements. With better calibration using the correlation adjustment between sensors, the uncertainty can be minimized ideally with 0 systematic error. To optimized uncertainties by calibration, methods can be selected from Table 2. The occurrence of invalid (negative) entropy generation measurement will consequently decrease without any cost on higher resolution sensors.

5. Experimental comparison

To make these physical definitions clear, we compared our latest understanding with the existing measurement. Detailed experiment setup can be seen in existing Ref. [24]. In these experiments, negative entropy generation measurements were observed. Fig. 3 shows the relation of negative (invalid) entropy generation with heat exchanger efficiency and imbalance indicator (C^*). Two curves are theoretical limits at maximum with $C^* = 3.58$ and minimum with $C^* = 1$.

According to our latest understanding, the data variation between the measurement experiment and the theoretical entropy generation are the virtual entropy generation we proposed in the present paper. Under the new framework of analysis, the data below the y-axis is the intolerable experiment data which conflicts the law of physics.

The analytical criterion of critical heat balance error for a general imbalanced heat exchanger is validated with previous experiment results in Fig. 4. Rather than a balanced heat exchanger, our new contribution takes consideration of the configuration and operation (C^*) and prove that the criterion is a general expression is for any imbalanced heat exchanger.

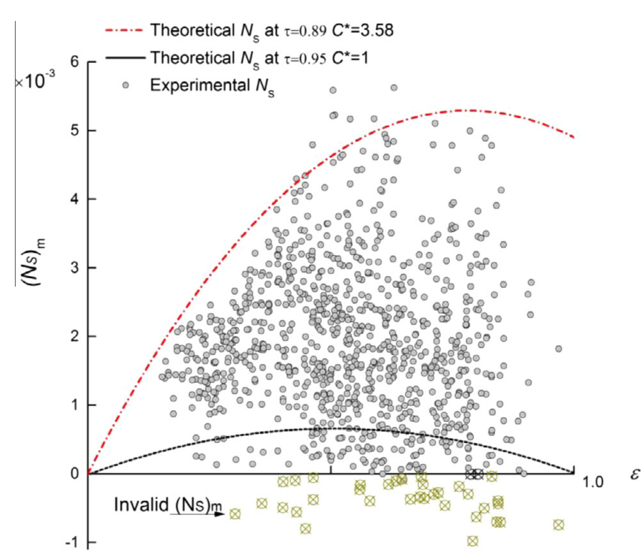

Fig. 3. The distribution of 975 cases of experimental entropy generation number. The test used water as test media. Detailed experiment setup can be seen in Ref. [25]. There are approximately 4% of whole test data. The variation of measurement error exists in the form of virtual entropy generation.

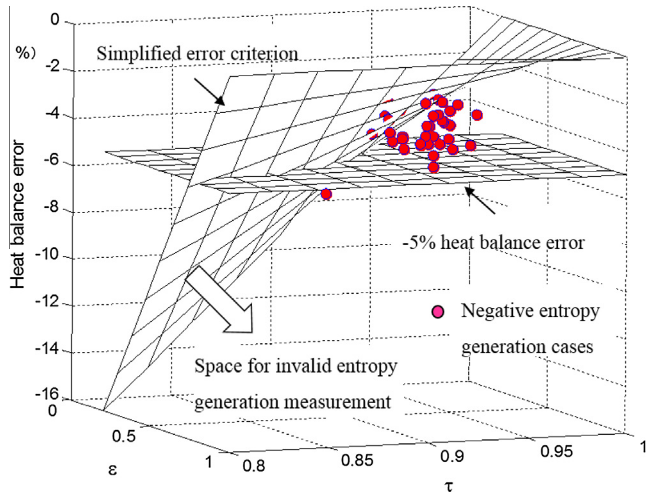

Fig. 4. Efficiency of simplified heat balance error criterion, pink points are values with negative entropy generation in Fig. 3. Space under filter is the theoretical negative entropy generation space by analytical solution in Eq. (14). The figure cited is from Ref. [25]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

6. Conclusions

In the present paper, we proposed the "virtual entropy generation (VEG)" method. It is an analytical method to control the quality of measurement data by the second-law of thermodynamics. Theoretically, it can be used to analyze the measurement of any irreversible process. We built the analytical framework of this approach with two virtual entropy generation restrictions: error form and uncertainty form. Using this method, we developed new measurement criteria, which enable the measurement data to follow the second law of thermodynamics. In the application of heat exchanger measurements, we demonstrated how to use this method to develop new criteria as well as new calibration methods to minimize measurement uncertainties. The virtual entropy generation (VEG) method we presented is a widely-applicable approach for measurement control. More research on criteria development and uncertainty control can be inspired by using the virtual entropy generation method presented here.

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