Understanding the behavior of an effluent generation indicator throughout uncertainty analysis

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Abstract

This paper addresses the impact of uncertainty evaluation on the analysis of an environmental performance indicator for the process industry. As an industrial case study, the analysis concerns an indicator of the effluent generation of a Brazilian petrochemical industry. The uncertainty evaluation results from the Guide to the Expression of Uncertainty in Measurement (GUM) and its Supplement 1 (GUM-S1) revealed that the current company target to reduce the effluent generation indicator by 5% is unfeasible. This is because the worst-case uncertainty scenario of the indicator has a value of 5.4%. The analysis also demonstrated that the effluent flow rate is the major source of uncertainty in the indicator, and the uncertainty associated with the measurement apparatus (Parshall flume) is the most meaningful factor with respect to this uncertainty. Before establishing any target reduction concerning this indicator, the measurement system of the effluent flow rate should be improved.

Keywords Environmental performance · Effluent generation indicator · Measurement uncertainty · Uncertainty of indicators

Introduction

Indicators have been widely used in the analysis of the environmental performance of organizations (Haffar and Searcy 2018). The literature reports a myriad of application around the world since many industrial approaches, for example, production of ceramic tiles (Bovea et al. 2010) and clay ceramics (Sani and Nzihou 2017), production of banana (Coltro and Karaski 2019), cultivation of sustainable rice (Devkota et al. 2019), evaluation of oyster norovirus outbreaks in coastal waters (Chenar and Deng 2017), until urban road traffic scale analysis (Liu et al. 2017) and use in the building sector (Maslesa et al. 2018), including also theoretical issues as composite indicator (Mangili et al. 2019). In fact, the International Standard for Environmental Performance Evaluation (EPE-ISO 14031) proposes a method to measure environmental performance in terms of definitions, working structure and different types of quantitative indicators. Although there are some definitions and

characteristics of indicators in the literature, the essential idea of an indicator is a tool to depict in a comprehensive and concise manner the vast quantity of data.

On the other hand, environmental performance indicators are carried out from measurements such as flow, temperature, pressure, level and so on. However, any measurement, in turn, is subject to uncertainty, either due to imperfections in the dimensions of meters and materials, limitations in the installation, technology and measurement systems or due to the variability of the process itself (e.g., external disturbances, changes in the characteristics of the process over time, starting and stopping the plant, load changes and turbulence). As a result, there will always be uncertainties associated with measurements and, consequently, these will also affect the environmental performance indicators and their associated decision-making, in according to works of Burgassa et al. (2017), Latan et al. (2018), which qualitatively address the uncertainty importance on performance indicators. Contrary to what one might think, the presence of uncertainty does not imply unreliable information concerning the environmental indicators. Rather, it characterizes the possible values that could be attributed to the indicators, which allows for more assertive decision-making in an industrial scenario than one which simply neglects it. In

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other words, decisions taken without any knowledge of uncertainty might be easy to take; however, such decisions may be based on incorrect information and have misleading consequences.

Unfortunately, the task of including uncertainties related to environmental performance indicators still remains an open issue. In fact, evaluating the impact of modeling uncertainties concerning to performance indicators seems to be in a mature stage, since the seminal work of Bertrand-Krajewski et al. (2002), whose efforts are associated with the design and the operation of urban drainage systems, until recent developments, for instance, Chen et al. (2016), which focuses on the evaluating of impacts of the uncertainties associated with the water assimilative capacity in conventional effluent trading system, and Azadeh et al. (2017), which deals with a multi-objective mathematical model for integrating upstream and midstream segments of crude oil supply chain in the context of environmental indicators. Nonetheless, the explicit inclusion of measurement uncertainties following the internationally recognized framework, Guide to the Expression of Uncertainty in Measurement—GUM (BIPM et al. 2008a) and its Supplement 1—GUM S1 (BIPM et al. 2008b), is still incipient in this area of knowledge. As far as we know only Perotto et al. (2008) and Mendes et al. (2011) have reported the measurement uncertainty evaluation toward these types of indicators. The former analyzes the role of the uncertainty of measurement in indicators associated with municipal wastewater discharges based on the GUM S1 approach, whereas the latter focuses on energy indicators typical of a petrochemical industry through the GUM method.

Another important reason for characterizing the uncertainty of the indicator is the fact that it can become a valuable tool to identify the major components that influence the final quality of the indicator. Based on the knowledge of the uncertainty associated with each component of the indicator, it is possible to systematically categorize the main uncertainty sources and therefore act directly to reduce them. This is one of the contributions of the present work since such a task was not explored by Perotto et al. (2008), Mendes et al. (2011). Moreover, this work aims to emphasize the importance of the uncertainty evaluation of an industrial indicator in order to support the definition of environmental performance targets in a situation where the number of data available is limited and the probability distribution function of the data is unknown, a very common situation in most industrial sites. As a case study, the analysis focuses on an effluent generation indicator of the largest petrochemical industry located in the Industrial Complex of Bahia, Brazil. The two major methods for evaluating the measurement uncertainty, GUM and GUM S1, are properly used in a novel methodological context for supporting the decision-making process.

Evaluation of uncertainty in measurement

The term uncertainty is closely related to doubt. From a statistical point of view, it is expressed as a parameter that characterizes the dispersion of values that could reasonably be assigned to a measured (inferred) quantity, based on all the information available (BIPM et al. 2008c).

Although there are several methods for evaluating measurement uncertainty, the most widely used method and internationally recognized is the one based on the GUM framework (BIPM et al. 2008a). The idea behind the GUM approach is to propagate the first (best estimate) and second (square standard uncertainty) statistical moments associated with the input quantities through the linearized measurement function by Taylor series expansion. Then, the best estimate and associated standard uncertainty of the output quantity (or measurand - variable measured indirectly, e.g., environmental indicators) are obtained. The expanded uncertainty is associated with the symmetric coverage interval of the measurand and is obtained by multiplying the standard uncertainty by a coverage factor. This factor is determined by considering a *t*-distribution to the measurand with the effective degree of freedom computed using the restrictive Welch–Satterthwaite formula (BIPM et al. 2008a, Annex G). Several papers touch on the theoretical and practical relevant details of this uncertainty evaluation scheme, e.g., Willink (2005), Kacker (2006), Lira (2006), White and Saunders (2007), Kacker et al. (2007) and Martins et al. (2010).

The necessary linearization of the measurement function from the GUM method, as well as its assumption that all the quantities are Gaussian in the calculation of the coverage interval, is constrained issues for its use. To work around this, Supplement 1 of GUM (BIPM et al. 2008b) was developed to provide wider applicability to the GUM framework in the task of evaluating measurement uncertainty. GUM S1 considers the evaluation of the measurement uncertainty of a given measurand on the basis of probability distribution functions (PDFs) assigned to input quantities along with the direct use of the measurement function (a nonlinear model, a priori). In fact, this approach involves a Monte Carlo method that approximates the probability distribution of the measurand by applying a known function to sampled randomly values of the PDFs attributed to the input quantities. The GUM S1 procedure may yield better results than those from GUM in the following situations: (1) when the functional relationship between the output quantity and input quantities is strongly nonlinear (Cox and Siebert 2006; Herrador et al. 2005; Martins et al. 2011) and (2) when the PDFs of the input and output quantities are not necessarily Gaussian and may be asymmetric (Cox and

Siebert 2006; Wubbeler et al. 2008). The only shortcoming of this approach is its computational burden which may become costly as the complexity of the measurement model increases (e.g., the number of variables and degree of nonlinearity). The application of both methods to an indicator of industrial effluent generation illustrates as the uncertainty assessment reliably supports decision-making in an industrial scenario.

Methods

Case study

Increasing environmental concern has led many companies to promote industrial effluent minimization at Camaçari Industrial Complex, state of Bahia, Brazil, since its installation in the late 1970s. At that time, petrochemical production required 5400 m³/h of water to produce 380,000 t/year of ethylene, its main petrochemical product. In 1989, the duplication of the Industrial Complex led to the introduction of a significant number of water disposal regulations in terms of quality and quantity, and this forced the industries to treat or reduce the pollutants within their plants and to adopt new policies of pollution control and water reuse (Oliveira-Esquerre et al. 2011).

Time series of the effluent flow rate and its relationship with petrochemical production mass has been used to monitor the environmental performance of the largest petrochemical industry located in this complex. The descriptive statistics of mean and variance help to analyze the process stability over time, according to Oliveira-Esquerre et al. (2009). The authors demonstrated that the highest production mass and lowest effluent generation occurred under normal process operation. The same variance profile of both variables is also associated with process stability.

The goal of the petrochemical industry is to reduce the effluent generation rate by 5%, with investments in projects and personnel. This reduction has the following benefits: (1) reduction in the costs of effluent treatment (2) reduction in raw materials and input flows resulting from the minimization of discharges and leaks (3) reduction in burdensome fines for releasing high amounts of contaminants that exceed the levels permitted by environmental regulations.

With the purpose of ensuring that a reduction of 5% in the effluent generation rate is a truly feasible goal, the uncertainty evaluation of its associated indicator is essential to be able to make reliable decisions about the process and data reliability.

The GUM and GUM S1 methods

The effluent generation indicator (IGE) considered in this study is the ratio of the volume of effluent (VE) to the production mass (P),

$$\text{IGE} = \frac{\text{VE}}{P}. \quad (1)$$

VE corresponds to the accumulated value of the average daily volumetric flow rate of the generated effluent (Q_j) over 30 days, or

$$\text{VE} = \sum_{j=1}^{30} 24Q_j, \quad (2)$$

where factor 24 converts the quantity of hour into day. In the company, six measurements of effluent flow rate are available per day using a Parshall flume, which is a primary element of measurement developed from the principle of Venturi tubes for use in open channels. Each daily volumetric flow rate Q_j is obtained by calculating the average of these measurements and P is given by the sum of mass flow rates of 23 petrochemicals produced monthly (F_k) i.e.,:

$$P = \sum_{k=1}^{23} F_k. \quad (3)$$

Applying the GUM method in this case study consists of propagating the standard uncertainties related to the input quantities VE and P , which are obtained from both the Type A and Type B evaluation of measurement uncertainty so as to evaluate the standard uncertainty of IGE.

According to the GUM framework, the Type A evaluation of measurement uncertainty of a given quantity x_i ($u_A(x_i)$) is represented by the experimental standard deviation of the mean ($s(x_i)$). However, as stated by Martins et al. (2010), this representation is only valid when the number of independent observations is equal to or greater than twenty-three samples ($n \geq 23$). In this case, when the number of observations of the input quantity lying the interval ($4 \leq n \leq 22$), the Bayes correction factor (f_B) for Type A evaluation of measurement uncertainty is recommended. For the present case study, the Type A evaluation of measurement uncertainty of each quantity Q_j is then calculated with six daily measurements:

$$u_A(Q_j) = f_B s(Q_j) = \left(\frac{\sqrt{6-1}}{\sqrt{6-3}} \right) \frac{\sqrt{\frac{\sum_{d=1}^6 (Q_{j,d} - \bar{Q}_j)^2}{6-1}}}{\sqrt{6}}, \quad j = 1, \dots, 30, \quad (4)$$

where each $\bar{Q}_j$ represents the average daily volumetric flow rate of the generated effluent.

The Type B evaluation of measurement uncertainty is carried out by scientific judgment based on all the available

information on the quantity. In this study, the Type B uncertainty associated with each Q_j is evaluated through “Minimum Requirements for the Self-Monitoring of Effluent Flow”, Environment Agency (2014). This establishes a typical uncertainty of 4% for Parshall flume discharge of industrial effluents.

With the available information about the Type A and Type B uncertainties related to each Q_j , their combined standard uncertainty can be evaluated by the following expression:

$$u_c(Q_j) = \sqrt{u_A(Q_j)^2 + u_B(Q_j)^2}, \quad j = 1, \dots, 30. \quad (5)$$

The degrees of freedom corresponding to the Type A evaluation of standard uncertainty is obtained from the data, i.e., $\nu_A(Q_j) = n - 1 = 5$. With regard to the sources of the Type B uncertainty, the approach presented by Martins et al. (2010) was adopted. In this approach, the quality of information is used to estimate the degrees of freedom instead of simply assuming a value infinite as suggested by the GUM framework. In this case, $\nu_B(Q_j) = 10$ is assigned in order to accommodate the quality of information of the real system. Considering that the quantities $Q_{j=1,\dots,30}$ are Gaussian and independent, the effective degrees of freedom ($\nu_{\text{eff}}(Q_j)$) from the combination of the Type A and Type B evaluation are calculated by the Welch–Satterthwaite (W-S) formula:

$$\nu_{\text{eff}}(Q_j) = \frac{u_c^4(Q_j)}{\frac{u_A^4(Q_j)}{\nu_A(Q_j)} + \frac{u_B^4(Q_j)}{\nu_B(Q_j)}}, \quad j = 1, \dots, 30. \quad (6)$$

The uncertainty associated with the quantities $F_{k=1,\dots,23}$ was based on a priori judgments provided by the engineers and technicians of the company. They thought that the Type B uncertainty is the most significant source of uncertainty concerning the petrochemicals involved in this case. The assumed measurement uncertainty follows the manufacturer's recommendations of the instruments, whose value of 0.8% for a monthly measured value (F_k^*) fulfills the highest confidence degree of the measurement instruments. Then the measurement uncertainty of each quantity F_k can be described by:

$$u_c(F_k) = \sqrt{(0.008F_k^*)^2} \quad k = 1, \dots, 23. \quad (7)$$

The standard uncertainties of the quantities $Q_{j=1,\dots,30}$ and $F_{k=1,\dots,23}$, are used to evaluate the uncertainties of the quantities VE and P . This assessment is also based on the law of propagation of uncertainties, namely:

$$u_c(\text{VE}) = \sqrt{\sum_{j=1}^{30} \left[\frac{\partial \text{VE}}{\partial Q_j} \right]^2 u_c^2(Q_j)}, \quad (8)$$

$$u_c(P) = \sqrt{\sum_{k=1}^{23} \left[\frac{\partial P}{\partial F_k} \right]^2 u_c^2(F_k)}. \quad (9)$$

The effective degrees of freedom of VE and P are then obtained by using the W–S formula again:

$$\nu_{\text{eff}}(\text{VE}) = \frac{u_c^4(\text{VE})}{\sum_{j=1}^{30} \frac{\left[\frac{\partial \text{VE}}{\partial Q_j} \right]^4 u_c^4(Q_j)}{\nu_{\text{eff}}(Q_j)}}, \quad (10)$$

$$\nu_{\text{eff}}(P) = \frac{u_c^4(P)}{\sum_{k=1}^{23} \frac{\left[\frac{\partial P}{\partial F_k} \right]^4 u_c^4(F_k)}{\nu_{\text{eff}}(F_k)}}, \quad (11)$$

where $\nu_{\text{eff}}(F_k)$ represents the degrees of freedom of each quantity F_k . In this study, $\nu_{\text{eff}}(F_k) = 10$ was assigned to represent the quality of information related to each petrochemical product. Therefore, the combined standard uncertainty of the indicator IGE and its effective degrees of freedom $\nu_{\text{eff}}(\text{IGE})$ are obtained as follows:

$$u_c(\text{IGE}) = \sqrt{\left[\frac{\partial \text{IGE}}{\partial \text{VE}} \right]^2 u_c^2(\text{VE}) + \left[\frac{\partial \text{IGE}}{\partial P} \right]^2 u_c^2(P)}, \quad (12)$$

$$\nu_{\text{eff}}(\text{IGE}) = \frac{u_c^4(\text{IGE})}{\frac{\left[\frac{\partial \text{IGE}}{\partial \text{VE}} \right]^4 u_c^4(\text{VE})}{\nu_{\text{eff}}(\text{VE})} + \frac{\left[\frac{\partial \text{IGE}}{\partial P} \right]^4 u_c^4(P)}{\nu_{\text{eff}}(P)}}. \quad (13)$$

When there is a need to express the measurement uncertainty as an interval, it is necessary to evaluate the expanded uncertainty. It is evaluated by multiplying the combined standard uncertainty and a coverage factor.

$$U(\text{IGE}) = k u_c(\text{IGE}) \quad (14)$$

The value of k is obtained through an inverse t -Student distribution assumed to the measurand, with a given coverage probability and effective degrees of freedom rounded to the nearest lower integer. The coverage probability is often assumed to be equal to 95%, but as industrial data are susceptible to high levels of uncertainty, one recommends a probability of 90% to avoid physically infeasible values for the measurand (Martins et al. 2010).

As proposed by Kessel et al. (2006), the coefficients of contribution for the effluent flow rate ($h(\text{IGE}, \text{VE})$) or production mass ($h(\text{IGE}, P)$), respectively, on a relative scale (%), were estimated to evaluate their contribution to the uncertainty of IGE, i.e.

$$h(\text{IGE}, \text{VE}) = \left[\frac{\left(\frac{\partial \text{IGE}}{\partial \text{VE}} \right) u_c(\text{VE})}{u_c(\text{IGE})} \right]^2, \quad (15)$$

$$h(\text{IGE}, P) = \left[\frac{\left(\frac{\partial \text{IGE}}{\partial P} \right) u_c(P)}{u_c(\text{IGE})} \right]^2. \quad (16)$$

Furthermore, the contributions of the Type A and Type B components on the uncertainty associated with the input quantities are an important factor in the uncertainty analysis, namely

$$h(\text{VE}_A) = \left[\frac{\sum_{j=1}^{30} \left(\frac{\partial \text{VE}}{\partial Q_j} \right) u_A(\overline{Q}_j)}{u_c(\text{VE})} \right]^2, \quad (17)$$

$$h(\text{VE}_B) = \left[\frac{\sum_{j=1}^{30} \left(\frac{\partial \text{VE}}{\partial Q_j} \right) u_B(\overline{Q}_j)}{u_c(\text{VE})} \right]^2. \quad (18)$$

On the other hand, when the mathematical model of the measurand is nonlinear or when some PDFs of the input quantities are not Gaussian or both, the GUM method may fail. In such cases, the use of the more general method based on the propagation of probability density functions (GUM S1) is recommended. Indeed, at a first moment, it is

interesting to evaluate the uncertainty using both the GUM and GUM S1 methods because if there are any discrepancies in the results, the GUM method will not be valid and, therefore, in a future uncertainty evaluation only the GUM S1 method should be used.

The two terms in the ratio IGE, the numerator (VE) and denominator (P), are linear, so the results from the GUM and GUM S1 methods for these input quantities are identical to each other. However, due to the lack of knowledge of PDFs associated with the quantities VE and P, a sensitivity analysis is performed varying the probability distributions as Gaussian (G), triangular (T) and uniform (U) for each quantity so as to learn about the impact of these variations on the estimate of IGE and its associated uncertainty. The realization of this analysis focuses then on several execution of the GUM S1 method, which numerically propagates PDFs from VE ($g_{\text{VE}}(\xi_{\text{VE}})$) and P ($g_P(\xi_P)$) through the measurement function (Eq. 1) in order to empirically obtain PDF from IGE ($g_{\text{IGE}}(\eta)$), where ξ_{VE} , ξ_P and η represent the possible value to be assigned to quantities VE, P and IGE, respectively. The procedure associated with the GUM S1 method treated here is summarized in Fig. 1.

An important step in implementing GUM S1 is the correct choice of the number of Monte Carlo trials (M). For this purpose, a sensitivity analysis of the approach also is carried out to verify if the standard uncertainty results have stabilized in a statistical sense, as recommended in BIPM et al. (2008b, clause 7.9).

Fig. 1 The procedure of the GUM S1 method applied to the effluent generation indicator

Results and discussion

In order to effectively support the decision-making process, a sensitivity analysis was carried out to evaluate four scenarios of the Type B uncertainty associated with the Parshall flume. Variations in the Type B uncertainties ($Q_{j=1,\dots,30}$) from 4 to 15% of actual flow rate were considered. In fact, the first scenario is at the lower boundary because the technical

Table 1 Scenarios for the assessment of the uncertainty of IGE for a volume of generated effluent of $3.0 \times 10^5 \text{ m}^3/\text{month}$ and a total production of petrochemicals of $2.4 \times 10^5 \text{ t/month}$

Uncertainty	Scenarios			
	1	2	3	4
Combined $u_c(\text{VE})$ (m^3)	5.7×10^3	6.9×10^3	7.7×10^3	9.9×10^3
Combined $u_c(P)$ (t)	8.6×10^2			
Combined $u_c(\text{IGE})$ ($\text{m}^3 \text{ t}^{-1}$)	2.3×10^{-2}	2.8×10^{-2}	3.2×10^{-2}	4.1×10^{-2}
Expanded $U(\text{IGE})$ ($\text{m}^3 \text{ t}^{-1}$)	3.9×10^{-2}	4.7×10^{-2}	5.3×10^{-2}	6.8×10^{-2}
Relative $U(\text{IGE})$ (%)	3.1	3.7	4.2	5.4
Value of the IGE ($\text{m}^3 \text{ t}^{-1}$)		1.25		

Note 1: Scenario 1—Type B uncertainty of 4% on the average hourly flow of effluent generated

Note 2: Scenario 2—Type B uncertainty of 8% on the average hourly flow of effluent generated

Note 3: Scenario 3—Type B uncertainty of 10% on the average hourly flow of effluent generated

Note 4: Scenario 4—Type B uncertainty of 15% on the average hourly flow of effluent generated

norm considered here establishes a minimum uncertainty of 4% on the measured value associated with the measuring device. Meanwhile, scenarios 2–4 are, in turn, more realistic because the apparatus is actually old and has not been calibrated with the correct periodicity. In this analysis, one considers an uncertainty value of 15% as a worst-case measurement uncertainty by virtue of being the maximum value registered for this Parshall flume before its maintenance and corrective actions.

Table 1 summarizes the application results from the GUM method for this sensitivity analysis. From the practical point of view and for the sake of conservativeness with regard to the decision-making process associated with the indicator under study, scenario 4 should be adopted. Thus, the measurement result of the effluent generation indicator (IGE) can be presented as:

$$\text{IGE} = (1.25 \pm 0.07) \cdot \text{m}^3 \text{ t}^{-1}, \quad (19)$$

where the number following the symbol $\pm$ is the numerical value of the (expanded uncertainty), with U determined from (a combined standard uncertainty) $u_c = 0.04 \text{ m}^3 \text{ t}^{-1}$ and (a coverage factor) $k = 1.67$ based on t -distribution for $\nu_{\text{eff}} = 260$ degrees of freedom. This uncertainty defines an interval for the best estimate of IGE with a coverage probability of 90%.

The conservative scenario 4 will now be assumed to apply the GUM S1 method. To do this, Fig. 2 shows the standard uncertainty of IGE ($u(\text{IGE})$) as a function of the number of Monte Carlo trials (M), which varies from 10^2 to 10^7 . It can be seen that when M is equal to 10^6 the values of the standard uncertainties resulting from variations in the PDFs [Gaussian (G), triangular (T) and uniform (U)]

Fig. 2 Sensitivity analysis of the number of Monte Carlo trials for Gaussian (G), triangular (T) and uniform (U) distributions

Table 2 Measurement results for the measurand IGE using the GUM S1 method

PDFs		Mean	Standard uncertainty	Coverage interval	T_{int}
VE	P	($\text{m}^3 \text{t}^{-1}$)	($\text{m}^3 \text{t}^{-1}$)	($\text{m}^3 \text{t}^{-1}$)	($\text{m}^3 \text{t}^{-1}$)
G	U	1.253	0.029	[1.206,1.300]	0.094
G	T	1.253	0.029	[1.206,1.300]	0.094
G	G	1.253	0.029	[1.205,1.302]	0.097
U	G	1.253	0.029	[1.208,1.297]	0.089
U	T	1.253	0.029	[1.209,1.298]	0.089
U	U	1.253	0.029	[1.209,1.298]	0.089
T	U	1.253	0.029	[1.205,1.300]	0.095
T	G	1.253	0.029	[1.205,1.301]	0.096
T	T	1.253	0.029	[1.205,1.301]	0.096

T_{int} Amplitude of the coverage interval

converge at $0.029 \text{ m}^3 \text{t}^{-1}$, whose estimated value of IGE converges at $1.253 \text{ m}^3 \text{t}^{-1}$. When comparing the GUM and GUM S1 results, no difference can be seen between the values of the IGE estimate, although there is a slight discrepancy in terms of standard uncertainty. Therefore, it is necessary to evaluate the coverage intervals (or expanded uncertainty) such that more reliable decision is taken on which approach should be chosen.

Table 2 presents the corresponding coverage intervals of IGE for all the possible combination pairs of PDFs assigned to the input quantities VE and P, when a coverage probability of 90% is assumed. These results show that the coverage interval of the indicator is shorter when uniform PDFs are assigned to input quantities while it is larger for Gaussian PDFs. As a further result of this analysis, Fig. 3 shows the empirical PDFs of IGE obtained from the GUM S1 method, when PDFs assumed to input quantities are Gaussian and uniform, respectively. For comparison, the coverage intervals estimated from the GUM and GUM S1 approaches are also presented in this figure. It can be observed that there is no clear difference between the coverage intervals from both approaches for the Gaussian case. In this case, as the empirical PDF of the measurand behaves like a Gaussian, the results from both methods are quite close to each other (Fig. 3b), thus corroborating the application of the GUM method with its adopted assumptions. On the other hand, there is a slight difference between the coverage intervals for the case in which PDFs assigned to the input quantities are uniform (Fig. 3b). Such a discrepancy can be explained by the fact that the empirical PDF of IGE resulting from the application of the GUM S1 method does not behave as a Gaussian. However, the coverage intervals estimated from this U–U combination are shorter than those from

(a) Gaussian PDFs for VE and P.

(b) Uniform PDFs for VE and P.

Fig. 3 PDF generated by the GUM S1 method for the measurand IGE. Coverage interval obtained from the GUM method (—), and the GUM S1 method (---)

the G–G combination. Therefore, following a conservative way, which adheres necessarily to the highest uncertainty scenario, it would be a most assertive decision to assume that the G–G combination would represent a realistic scenario by turning out to be a largest coverage interval of the indicator IGE. Such a decision implies, in turn, that any of the GUM and GUM S1 methods could be chosen for further analysis of the environmental performance of the industrial unit. Due to its numerical simplicity, the GUM method is thus recommended for the underlying decision-making process.

In fact, it is clear that if the company aims to reduce the indicator of effluent generation by 5%, first it must take steps to minimize the uncertainty corresponding to this indicator because the relative uncertainty associated with IGE is 5.4% (Table 1). In other words, a reduction of 5% of the indicator means its value will be about $1.19 \text{ m}^3 \text{t}^{-1}$,

which belongs to the coverage interval $[1.18 \quad 1.32] \text{ m}^3 \text{ t}^{-1}$ and it is therefore a target unfeasible.

In an attempt to mitigate the problem, the major sources of uncertainty associated with the indicator should be identified, and in this sense, the coefficients of contribution seem to be a comprehensive mechanism to this analysis. These coefficients of contribution, denoted here as $h(IGE, VE)$ and $h(IGE, P)$, whose values on a relative scale (%) are 92% and 17%, respectively, reveal that the component that most influences to the uncertainty of IGE is the volume of generated effluent. More specifically, by comparing the contribution analysis of the Type A and Type B uncertainties from the volume of generated effluent, namely $h(VE_A) = 28\%$ and $h(VE_B) = 72\%$, it is possible to detect that the Type B uncertainty is the most significant for a possible reduction in the uncertainty of IGE, even though if one adopts operating policies to stabilize the process the reduction in the effluent generation can be reached, thus resulting in a lower operating variability and as a consequence the Type A uncertainty will turn out to be a less meaningful source of uncertainty. This indicates that any effective reduction in the indicator to track the industrial target should be made only after an improvement in the measurement system of the effluent flow rate, i.e., the Parshall flume.

Conclusion

In this work, we have presented the effectiveness of the uncertainty analysis in the making-decision process associated with an environmental performance indicator. In particular, it was demonstrated, in the industrial case study analyzed here, that the current company target to reduce effluent generation by 5% is an unfeasible goal because of the most realistic relative uncertainty of the associated indicator, IGE, is 5.4%. Within this analysis, it was also possible to identify the volume of generated effluent as the most important contributor to the uncertainty of the indicator owing to the Type B uncertainty, that is, its measurement system. Under these circumstances, it can be concluded that a more trustworthy analysis of the profile or tendencies of the indicator can be obtained only if significant improvements in the measurement system of the Parshall flume are performed.

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