UNCERTAINTY EVALUATION OF THE CONDUCTED EMISSION MEASUREMENTS

by

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For the evaluation of measurement uncertainty in measuring the conduction emission, in this paper we propose a new model which uses mixed distribution. Evaluation of probability density function for the measurand has been done using Monte Carlo method and a modified least-squares method (combined method). In addition, the number of data *n* and the number of classes of histogram *k* which were used for simulation, were varied.

Key words: measurement uncertainty, conducted emission, probability density function, mixed distribution, modified least-squares method, Monte Carlo method

INTRODUCTION

The Guide to the Expression of Uncertainty in Measurement (GUM) [1] is the internationally accepted master document for the evaluation of uncertainty. In addition, for measurement uncertainty assigning for linear or linearized models, the GUM suggests one standard procedure which is known as the GUM uncertainty framework (GUF) [2]. The GUM Supplement 1 [2] is based on one general concept of propagating the probability density functions (PDF), where in order to obtain PDF for the measurand using of the Monte Carlo method (MCM) was suggested. Consequently, the law of propagation of uncertainties is based on a construction of a linear approximation of the model function [3].

One of the common problems that we face when examining electromagnetic compatibility (EMC) is an inconsistent approach to adjusting various specified or standardized tests. Consequently, some of the standardized EMC measurements are included within the precisely defined ways for evaluating uncertainty in measurement [4]. EMC tests and measurements typically have large uncertainties of at least several decibels [5]. Today, electronic equipment is considered to be the critical project element of armament and military equipment means and systems. So, for example, modern telecommunication devices are characterized, on one hand, by the great power of ultra broadband transmitters, and on the other, by sensitivity of receivers [6]. Many uncertainty sources in the domain of EMC measurements were not studied well and need further studying.

This paper presents a new model which uses mixed distribution for uncertainty evaluation of conducted emission measurement [7, 8]. Namely, evaluation of PDF for the measurand (output quantity) has been done using a MCM and a modified least-squares method. Consequently, the MCM required numerical calculation of approximate PDF values [7-10].

MODEL AND METHODS

Mixed distribution

As a model for determining the density function of a mixed distribution, two independent input quantities and one output quantity were taken (see fig. 1).

Consequently, each one of the input quantities is determined by expectation which is equal to the given estimate x_i, as well as to corresponding standard deviation which is equal to the given standard uncertainty $u(x_i)$. The output quantity (measurand) Y is determined by the best evaluation y, which is assigned by the standard uncertainty $u(y)$.

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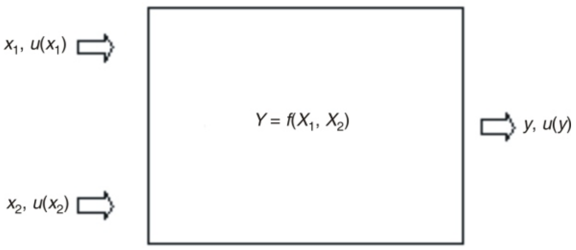

Figure 1. Illustration of the law of propagation of uncertainty for a linear model

Probability density function of the output quantity $f(x)$ (density function of a mixed normal-normal distribution) of two independent input quantities that are determined by two normal PDF is given with eq. (1)

$$f(x) \quad \varepsilon f_1(x) \quad (1 \quad \varepsilon) f_2(x), \quad 0 \quad \varepsilon \quad 1 \tag{1}$$

Consequently, probability density functions for the input quantities, $f_1(x)$ and $f_2(x)$, are given by eqs. (2) and (3), respectively

$$f_1(x) \quad \frac{1}{s_1\sqrt{2\pi}} \exp \quad \frac{1}{2} \quad \frac{x \quad m_1}{s_1} \quad ^2 \qquad \infty \quad x \quad \infty, \; s_1 \quad 0 \tag{2}$$

$$f_2(x) \quad \frac{1}{s_2\sqrt{2\pi}} \exp \quad \frac{1}{2} \quad \frac{x \quad m_2}{s_2} \quad ^2 \qquad \infty \quad x \quad \infty, \; s_2 \quad 0 \tag{3}$$

where m_1 and s_1 are the parameters that represent the mean and standard deviation of the first normal distribution, respectively, and m_2 and s_2 – the parameters that represent the mean and standard deviation of the second normal distribution. ε is the mixed coefficient of these distributions which indicates the proportion of the first distribution in the mixed distribution. The value of this coefficient is an interval from 0 to 1, ε, so that the proportion of the second distribution in the mixed distribution equals $1 - \varepsilon$.

In the fig. 2 the propagation of distributions for two independent input quantities assigned by the normal distributions are illustrated.

The mixed normal-normal distribution function for the output quantity, $F(x)$, is given with eq. (4)

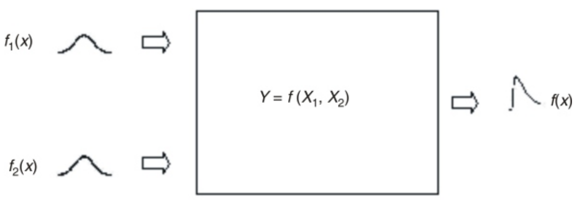

Figure 2. Illustration of the propagation of distributions

$$F(x) \quad \varepsilon F_1(x) \quad (1 \quad \varepsilon) F_2(x), \quad 0 \quad \varepsilon \quad 1 \tag{4}$$

Consequently, distribution functions for the input quantities, $F_1(x)$ and $F_2(x)$, are given by eqs. (5) and (6), respectively

$$F_1(x) \quad \frac{1}{s_1\sqrt{2\pi}} \; ^{x}_{\infty} \exp \quad \frac{1}{2} \quad \frac{x \quad m_1}{s_1} \quad ^2 \qquad \infty \quad x \quad \infty, \; s_1 \quad 0 \tag{5}$$

$$F_2(x) \quad \frac{1}{s_2\sqrt{2\pi}} \; ^{x}_{\infty} \exp \quad \frac{1}{2} \quad \frac{x \quad m_2}{s_2} \quad ^2 \qquad \infty \quad x \quad \infty, \; s_2 \quad 0 \tag{6}$$

Pseudorandom numbers that belong to the first and the second normal distribution are determined by the eqs. (7) and (8), respectively

$$x_i \quad m_1 \quad s_1 u_i, \quad i \quad 1, 2, \ldots, N_1 \tag{7}$$

$$x_j \quad m_2 \quad s_2 u_j, \quad j \quad 1, 2, \ldots, N_2 \tag{8}$$

where N_1 and N_2 are the pseudorandom numbers total of the first and the second normal distribution, respectively, r_i, r_j – the pseudorandom numbers, r_i, r_j (0, 1), and u_i, u_j – the lower quantiles of standardized normal distribution, N(0, 1).

The lower quantile of standardized normal distribution, u_i, that has the mean equal to 0 and the standard deviation equal to 1, it is determined by generating the pseudorandom number r_i (0, 1), which represents the lower quantum $r_i \quad F_1(u_i)$, and then the appropriate value for u_i is determined. For determining the values for u_i special subprogram was used here, and they can be found in statistic tables, *i. e.* the inverse function of standardized normal distribution [11].

The lower quantile of standardized normal distribution, u_j, is obtained in an identical way using the pseudorandom number r_j (0, 1), which represents the lower quantum $r_j \quad F_2(u_j)$.

When the obtained values of pseudorandom numbers x_i and x_j are mixed, *c. f.* eqs. (7) and (8), a mixed normal-normal distribution which has n values (n – pseudorandom numbers total of the mixed distribution, $n = N_1 + N_2$) is obtained.

Density function of a mixed normal-rectangular distribution is given with the eq. (1), and the appropriate probability density functions for the input quantities, $f_1(x)$ and $f_2(x)$, are given by eqs. (9) and (10), respectively

$$f_1(x) \quad \frac{1}{s\sqrt{2\pi}} \exp \quad \frac{1}{2} \quad \frac{x \quad m}{s} \quad ^2 \qquad \infty \quad x \quad \infty, s \quad 0 \tag{9}$$

$$f_2(x) \quad \frac{1}{b \quad a}, \quad a \quad x \quad b, \; b \quad a \tag{10}$$

where m and s is the parameters that represent the mean and standard deviation of the normal distribution, respectively, and a and b are the parameters that represent lower and upper limits of a rectangular distribution.

As in the previous case, mixed normal-rectangular distribution function, $F(x)$, is given by eq. (4). Consequently, distribution functions for the input quantities, $F_1(x)$ and $F_2(x)$, are given by eqs. (11) and (12), respectively

$$F_1(x)=\frac{1}{s\sqrt{2\pi}}\int_{-\infty}^{x}\exp\left[-\frac{1}{2}\left(\frac{x-m}{s}\right)^2\right], \quad -\infty<x<\infty, \ s>0 \tag{11}$$

$$F_2(x)=\frac{x}{b-a}-\frac{a}{b-a}, \quad a\le x\le b, \ b>a \tag{12}$$

Pseudorandom numbers that belong to the first normal distribution and the second rectangular distribution are determined by eqs. (13) and (14), respectively

$$x_i=m+su_i, \quad i=1,2,\ldots,N_1 \tag{13}$$

$$x_j=a+(b-a)r_j, \quad j=1,2,\ldots,N_2 \tag{14}$$

When the obtained values of pseudorandom numbers x_i and x_j are mixed, *c.f.* eqs. (13) and (14), a mixed normal-rectangular distribution which has n values (n – pseudorandom numbers total of the mixed distribution, $n = N_1 + N_2$) is obtained.

Density function of a mixed normal-triangular distribution is given by eq. (1), and the corresponding probability density functions for the input quantities, $f_1(x)$ and $f_2(x)$, are given by eqs. (15) and (16), respectively

$$f_1(x)=\frac{1}{s\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{x-m}{s}\right)^2\right], \quad -\infty<x<\infty, s>0 \tag{15}$$

$$f_2(x)=\begin{cases}\dfrac{4(x-a)}{(b-a)^2}, & a\le x\le c,\\[2mm] \dfrac{4(b-x)}{(b-a)^2}, & c\le x\le b,\end{cases} \tag{16}$$

where m and s are the parameters which represent the mean and standard deviation of the normal distribution, respectively, a and b – the parameters which represent the lower and upper limits of a symmetric triangular distribution, and $c = (a + b)/2$ is the parameter mode of the symmetric triangular distribution.

Mixed normal-triangular distribution function, $F(x)$, is given by eq. (4). Consequently, the distribution functions for the input quantities, $F_1(x)$ and $F_2(x)$, are given by eqs. (17) and (18), respectively,

$$F_1(x)=\frac{1}{s\sqrt{2\pi}}\int_{-\infty}^{x}\exp\left[-\frac{1}{2}\left(\frac{x-m}{s}\right)^2\right], \quad -\infty<x<\infty, \ s>0 \tag{17}$$

$$F_2(x)=\begin{cases}\dfrac{2(x-a)^2}{(b-a)^2}, & a\le x\le c,\\[2mm] 1-\dfrac{2(b-x)^2}{(b-a)^2}, & c\le x\le b,\end{cases} \tag{18}$$

Pseudorandom numbers that belong to the first normal distribution and the second triangular distribution are determined in the eqs. (19) and (20), respectively

$$x_i=m+su_i, \quad i=1,2,\ldots,N_1 \tag{19}$$

$$x_j=\begin{cases}a+(b-1)\sqrt{\dfrac{r_j}{2}}, & 0\le r_j\le 0.5,\\[2mm] b-(b-a)\sqrt{\dfrac{1-r_j}{2}}, & 0.5\le r_j\le 1,\end{cases} \quad j=1,2,\ldots,N_2 \tag{20}$$

When the obtained values of pseudorandom numbers x_i and x_j are mixed (cf eqs. (19) and (20)), a mixed normal- triangular distribution which has n values (n – pseudorandom numbers total of the mixed distribution, $n = N_1 + N_2$) is obtained.

Point estimates parameters of a mixed distribution

Point estimates parameters of the probability density function for the output quantity (density function of a mixed distribution) are obtained by the combined method which consists of the MCM and the modified least-squares method [7, 8]. Consequently, the MCM can be used to approximate the PDF for the output quantity [12-16].

Also, point estimates parameters of density function of a mixed distribution can be obtained in the analytical procedure, but it is more complicated, and sometimes difficult to execute.

Point estimates parameters of density function of a mixed normal-normal distribution are determined using eqs. (21)-(24)

$$\hat{m}_{1i}=1.05x_{\min}+0.95(x_{\max}-x_{\min})r_{m1;i}, \quad i=1,2,\ldots,N \tag{21}$$

$$\hat{s}_{1i}=0.1s+1.25sr_{s_1;i} \quad i=1,2,\ldots,N \tag{22}$$

$$\hat{m}_{2j}=1.05x_{\min}+0.95(x_{\max}-x_{\min})r_{m2;j}, \quad j=1,2,\ldots,N \tag{23}$$

$$\hat{s}_{2j}=0.1s+1.25sr_{s_2;j} \quad j=1,2,\ldots,N \tag{24}$$

where $x_{\min}$ and $x_{\max}$ are the minimum and maximum values which were taken by the random variable x of a mixed distribution, respectively, s is the empirical standard deviation of a mixed distribution, N – the total number of trials (iterations), $r_{m_1;i}, r_{s_1;i}, r_{m_2;j}, r_{s_2;j} \in (0,1)$ – the pseudorandom numbers, respectively.

Mixed coefficient is determined using eq. (25)

$$\varepsilon_l = r_{\varepsilon;l}, \quad l = 1, 2, \ldots, N \tag{25}$$

where $r_{\varepsilon;l} \in (0,1)$ is the pseudorandom number.

Point estimates parameters expressions of mixed distributions, eqs. (21)-(25), are obtained by experimental and numerical calculations, in order to obtain more realistic intervals for the parameters of distribution, and corresponding to the real situation.

The procedure of determining point estimates parameters of density function of a mixed normal-normal distribution consists of several steps.

First, one determines minimum and maximum values, $x_{\min}$ and $x_{\max}$, which were taken by the random variable x of a mixed normal-normal distribution *c. f.* eqs. (7) and (8), and then, according to the generated pseudorandom numbers $r_{m_1;i}, r_{s_1;i}, r_{m_2;j}, r_{s_2;j}$, and $r_{\varepsilon;l}$, respectively, which belong to the interval (0, 1) and using eqs. (21)-(25), the *i*-th, *j*-th, and *l*-th values are determined for these parameters. These values are put in eqs. (1)-(3), and function values of a mixed normal-normal distribution, $f(x_j)$ – estimated density function of mixed normal-normal distribution, are determined for every value of random variable x which belongs to midpoint of each class histogram. If histogram has k classes, then there are k values of this density function of a mixed distribution. Also, the empirical values of this function are determined for each one of these classes using eq. (26)

$$f_j = \frac{n_j}{nh}, \quad j = 1, 2, \ldots, k \tag{26}$$

where n_j is the number of values which fall under j-th class of histogram, n – the total number of values which were taken by the random variable x, and h – the class width of histogram. The function f_j in eq. (26) is the empirical density function of mixed normal-normal distribution that describes the histogram of random variable x. Class width of histogram h is determined according to eq. (27)

$$h = \frac{x_{\max} - x_{\min}}{k} \tag{27}$$

The number of classes of histogram k are determined according to eqs. (28)-(30), respectively,

$$k_1 = \sqrt{n} \tag{28}$$

$$k_2 = 1 + \frac{1}{2}\sqrt{n} \tag{29}$$

$$k_3 = [1 + 3.3\log_{10} n] \tag{30}$$

Consequently, that k_i, $i = 1, 2, 3$, is taken as an integer value [11].

When the midpoint of each class histogram, x_j, values f_j and $f(x_j)$ are determined, then one determines the sum of the squared deviations of these functions according to classes, using the eq. (31)

$$S_i = \sum_{j=1}^{k} [f(x_j) - f_j]^2, \quad i = 1, 2, \ldots, N \tag{31}$$

where N is the total number of trials (iterations).

When the first value of the S_1 sum is determined, then for the second generated pseudorandom numbers $r_{m_1;i}, r_{s_1;i}, r_{m_2;j}, r_{s_2;j}$ and $r_{\varepsilon;l}$, respectively, the same procedure determines the parameters of the density function of mixed normal-normal distribution and the sum S_2, and then, the values of the sums are compared. The parameters of density function of a mixed normal-normal distribution, are determined in this way randomly, the ones retained are those in which the minor sum of the squared deviations of these functions is obtained. The procedure continues and the new sum S is determined, and the parameters with which this sum is the least, are retained. The procedure must be repeated from 10^5 to 10^6 times (a value of N), and even more.

The procedure for determining point estimates parameters of density function of a mixed normal-rectangular distribution and a mixed normal-triangular distribution is described in the previous procedure which refers to density function of a mixed normal-normal distribution [7, 8].

EVALUATION OF MEASUREMENT UNCERTAINTY

Measurement model

This paper observes conducted emissions measurements in power leads of military telecommunication devices in Faraday cage according to the method CE102 from the standard MIL-STD-461E [17].

For determining of the measurand value, the standardized measurement method is used [17]. Consequently, the possibility of variations of obtained measurand values becomes smaller, which influences the reducing of measurement uncertainty.

Equation model for the evaluation of the Measurement Instrumentation Uncertainty – MIU is given in [18], in the eq. (32)

$$V = V_{\mathrm{r}} + L_{\mathrm{c}} + L_{\mathrm{LISN}} + \delta V_{\mathrm{sw}} + \delta V_{\mathrm{pa}} + \delta V_{\mathrm{pr}} + \delta F_{\mathrm{step}} + \delta Z + \delta M \tag{32}$$

Equation (32) represents one purely additive linear model, whose terms are independent. Information about terms of an expression in the model equation is given in tab. 1. Measurement uncertainty comprises, in general, many components. Some of these may be

Table 1. Uncertainty budget according to the GUM for the conducted emission measurements

Input quantity	X_i	Estimate X_i (x_i)		Standard uncertainty $u(x_i)$ [dB]	Sensitivity coefficient c_i	Contribution to the standard uncertainty $u_i(y) = c_i u(x_i)$
		Value [dB]	Probability distribution function			
Receive reading	V_r	0.1	Rectangular k_p = 1.732	0.058	1	0.058
LISN-receiver attenuation	L_c	0.1	Normal k_p = 2.000	0.050	1	0.050
LISN voltage division factor	L_{LISN}	0.2	Normal k_p = 2.000	0.100	1	0.100
Receiver sine wave voltage	δV_{sw}	1.0	Normal k_p = 2.000	0.500	1	0.500
Receiver pulse amplitude response	δV_{pa}	2.0	Rectangular k_p = 1.732	1.155	1	1.155
Receiver pulse repetition rate response	δV_{pr}	2.0	Rectangular k_p = 1.732	1.155	1	1.155
Frequency step error	δF_{step}	0.0	Rectangular k_p = 1.732	0.000	1	0.000
LISN impedance	δZ	+2.60 –2.70	Triangular k_p = 2.449	1.082	1	1.082
LISN-receiver mismatch	δM	+0.676 –0.734	U-shaped k_p = 1.414	–0.519	1	–0.519

evaluated by Type A evaluation of measurement uncertainty from the statistical distribution of the quantity values from series of measurements and can be characterized by standard deviations. The other components, which may be evaluated by Type B evaluation of measurement uncertainty, can also be characterized by standard deviations, evaluated from probability density functions based on experience or other information.

Values of input quantities

Table 1 presents uncertainty budget, a Type B evaluation for the case of conducted emission measurements. The given data are obtained from the manufacturer's specifications and calibration certificates, and they are used for the evaluation of the Measurement Instrumentation Uncertainty, according to the ISO-GUM [1].

This also constitutes Type A evaluation, but this paper will not consider the contribution of type A evaluation.

The standard uncertainty $u(x_i)$ is calculated by dividing the value of the uncertainty associated with x_i by the coverage factor k_p, whose value depends on the choice of PDF and confidence level which is associated to the given value.

Evaluation of the measurement instrumentation uncertainty

The previous section presents the uncertainty budget according to the GUM for the case of conducted emission measurement according to the method CE102 from the standard MIL-STD-461E [17]. Consequently, the model equation for the evaluation of the MIU is given with eq. (32). The MCM and the modified least-squares method (combined method) are applied in three cases for two independent input quantities from the given expression. Namely, the combined method is used for the evaluation of probability density function for the output quantity (mixed distribution) according to probability density function from two independent input quantities, and *i. e.*: two independent input quantities assigned by the normal distributions, two independent input quantities where the first quantity is assigned a normal distribution and the second is assigned a rectangular distribution, two independent input quantities where the first quantity is assigned a normal distribution and the second is assigned a triangular distribution [7-10].

The Monte Carlo simulations for obtaining mixed distributions are done by the procedure which was described in the previous sections. In addition, the number of classes of histogram k_i, i = 1, 2, 3, which was used for simulation is varied and the values are used from tab. 1. A value of N, the total number of trials was 10^6. The number of data which was used for simulation is n = 5000. Risk conformity was α = 0.05, that is the confidence level $(1 - \alpha)$ was 0.95. One more data that is important for our simulation was the mixed coefficient ε which was 0.5. The results obtained by the combined method are compared to the corresponding results when applying the GUM.

In figs. 3-5 a mixed normal-normal distribution (the first example) is shown. In addition, the estimated values are $x_1 = x_2$ = 0 dB, and standard uncertainties $u(x_1)$ = 0.05 dB and $u(x_2)$ = 0.1 dB, respectively, (see tab. 1).

It is noticeable that the estimated curve fitting (line 2) in histogram (line 3) is very good, regardless of the choice of k_i (the number of histogram classes), which indicates that the unknown parameters of this distribution are estimated well. It should be men-

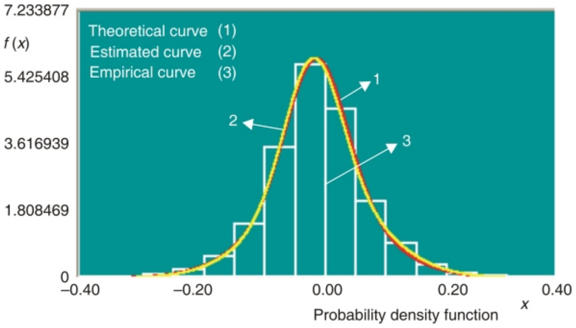

Figure 3. Mixed normal-normal distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_3 and the number of data which was used for simulation is n = 5000

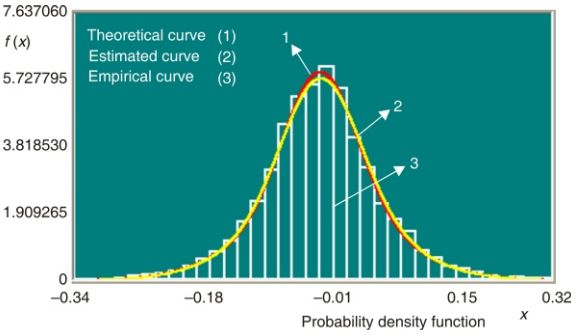

Figure 4. Mixed normal-normal distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_2 and the number of data which was used for simulation is n = 5000

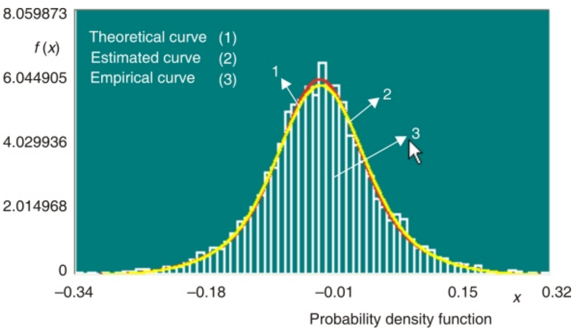

Figure 5. Mixed normal-normal distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_1 and the number of data which was used for simulation is n = 5000

tioned, that coming of the curve through the mid-point of each class histogram is considered to be the best fitting. Also, it is evident that the estimated curve (line 2) differs slightly from the theoretical curve (line 1). Consequently, the theoretical curve represents the results obtained according to the GUM. This difference was the evaluation result of the mixed distribution parameters (whose values are pseudorandom) and the number N of iterations (the total number of trials).

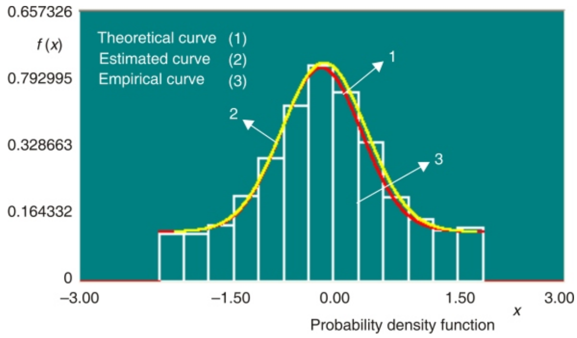

Figure 6. Mixed normal-rectangular distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_3 and the number of data which was used for simulation is n = 5000

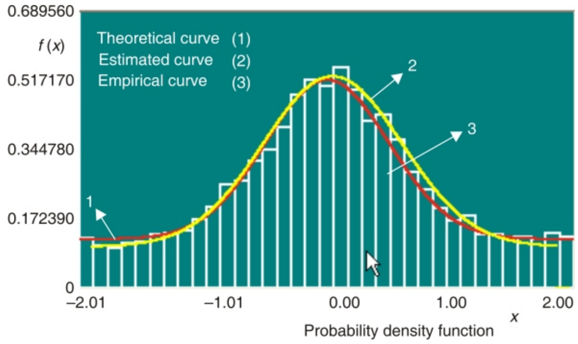

Figure 7. Mixed normal-rectangular distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_2 and the number of data which was used for simulation is n = 5000

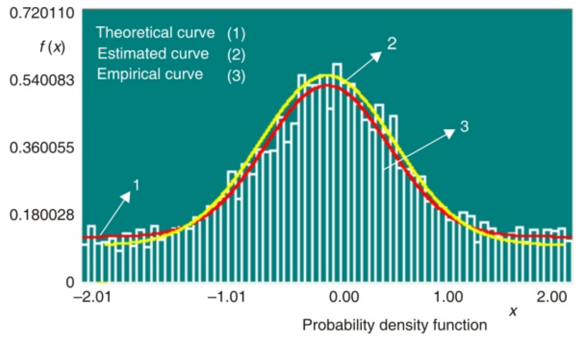

Figure 8. Mixed normal-rectangular distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_1 and the number of data which was used for simulation is n = 5000

In figs. 6-8 a mixed normal-rectangular distribution (the second example) is shown. In addition, the estimated values are $x_1 = x_2 = 0$ dB, and standard uncertainties $u(x_1) = 0.5$ dB and $u(x_2) = 1.155$ dB, respectively, (see tab. 1).

It is noticeable that fitting of the estimated curve (line 2) in histogram (line 3) is very well and does not deviate a lot from the theoretical curve (line 1), regardless of the choice of k_i. This difference was the result of evaluation of parameters of the mixed distribution (whose values are pseudorandom) and the number N of iterations.

In figs. 9-11 a mixed normal-triangular distribution (the third example) is shown. In addition, the estimated values are $x_1 = 0$ dB and $x_2 = -0.05$ dB, and the standard uncertainties $u(x_1) = 0.5$ dB and $u(x_2) = 1.082$ dB, respectively (see tab. 1).

It is noticeable that fitting of the estimated curve in a histogram is very well and does not deviate a lot from the theoretical curve, regardless of the choice k_i.

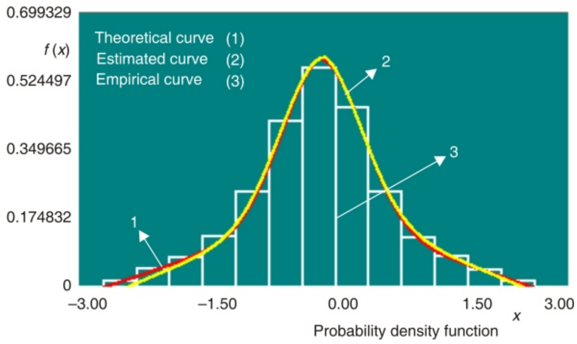

Figure 9. Mixed normal-triangular distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_3 and the number of data which was used for simulation is n = 5000

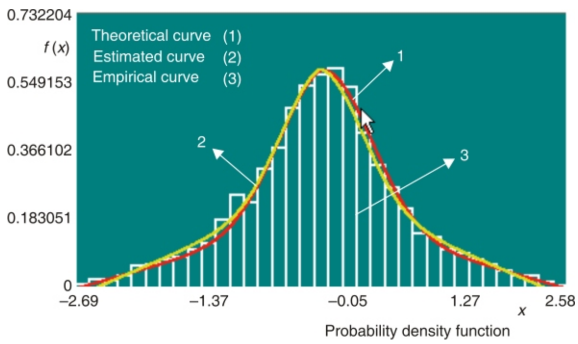

Figure 10. Mixed normal-triangular distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_2 and the number of data which was used for simulation is n = 5000

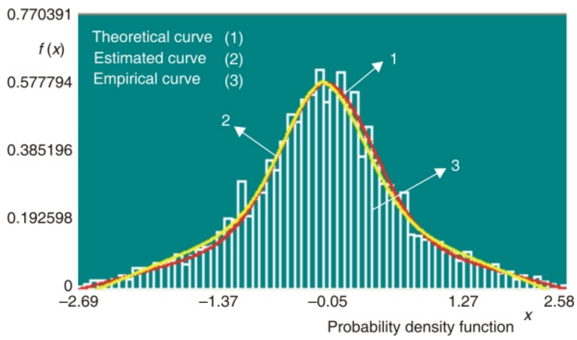

Figure 11. Mixed normal-triangular distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_1 and the number of data which was used for simulation is n = 5000

This difference was the result of evaluation of parameters of the mixed distribution (whose values are pseudorandom) and the number N of iterations.

In the figs. 12-14 a mixed normal-normal distribution where the number of data which was used for simulation is $n = 10000$ is shown. In addition, the estimated values are $x_1 = x_2 = 0$ dB, and standard uncertainties $u(x_1) = 0.05$ dB and $u(x_2) = 0.1$ dB, respectively (see the first example).

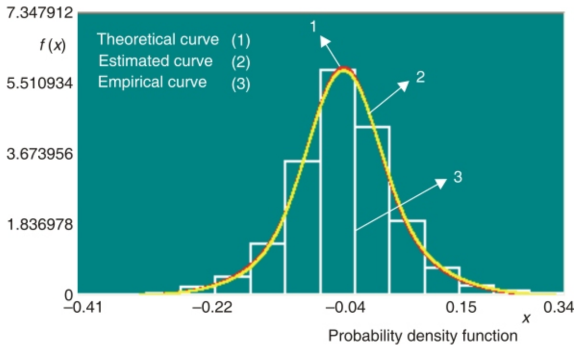

Figure 12. Mixed normal-normal distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_3 and the number of data which was used for simulation is n = 10000

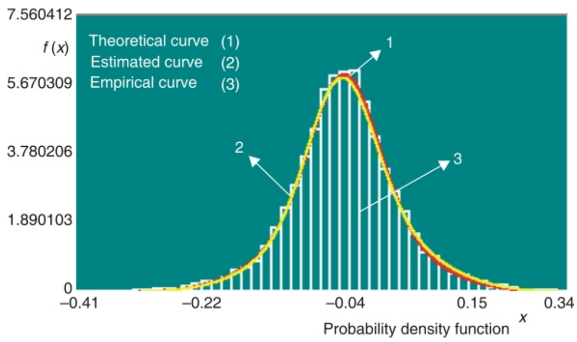

Figure 13. Mixed normal-normal distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_2 and the number of data which was used for simulation is n = 10000

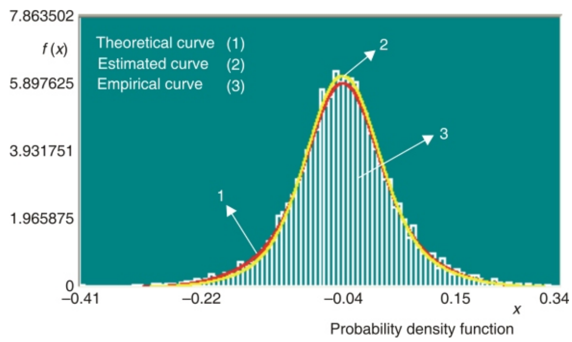

Figure 14. Mixed normal-normal distribution obtained by the combined method and GUM, respectively. The number of classes of histogram is k_1 and the number of data which was used for simulation is n = 10000

As in the first example, it is shown that fitting of the estimated curve in histogram (the empirical curve) is very good and differs slightly from the theoretical curve, regardless of the choice k_i and the increasing number of data n. This difference was the result of evaluation of parameters of the mixed distribution (whose values are pseudorandom) and the number N of iterations.

CONCLUSIONS

In this paper the Monte Carlo method (MCM) and the modified least-squares method, are presented for the estimate of the output quantity (measurand), which is interrelating with two input quantities. As a representative equation model for the evaluation, of the Measurement Instrumentation Uncertainty is used, and it is also used for the conducted emission measurement according to the method CE102 from the standard MIL-STD-461E. The MCM and the modified least-squares method (combined method) are applied in three cases, for two independent input quantities, which were associated with PDF. In addition, the number of data n and the number of classes of histogram k, which were used for simulation, are varied. It was shown that the combined method gives valid results with regard to physical accuracy of the presented model, which refers to the input and output quantities. Namely, applying the combined method produces a mixed distribution, *i. e*. PDF for the output quantity, which fits well (the estimated curve) in histograms and differs slightly from the produced results according to the GUM (the theoretical curve), regardless to the choice of k and n.

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AUTHOR CONTRIBUTIONS

Theoretical analysis and experiments were carried out by A. M. Kovačević. Literature research was carried out by A. M. Kovačević, K. Dj. Stanković, and A. V. Kovačević. The manuscript was written by A. M. Kovačević, with the suggestion of all authors. The figures were prepared by A. M. Kovačević. All authors analysed and discussed the results.

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ПРОЦЕНА МЕРНЕ НЕСИГУРНОСТИ ПРИ МЕРЕЊУ КОНДУКЦИОНЕ ЕМИСИЈЕ

У раду је предложен један нови модел за процену мерне несигурности при мерењу кондукционе емисије, који користи мешовиту расподелу. Монте Карло метода и модификована метода најмањих квадрата (комбинована метода) коришћене су за процену функције густине расподеле мерне величине. При томе, вариран је број података *n* и број класа хистограма *к* који су коришћени за симулацију.

Кључне речи: мерна несигурност, кондукциона емисија, функција густине расподеле, мешовита расподела, модификована метода најмањих квадрата, Монте Карло метода