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Type A expanded uncertainty assigned to the measurand

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***Abstract*—The Monte Carlo Method was used to calculate the coverage factors for the convolution of two t-distributions laws with a different number of degrees of freedom and the ratio of standard deviations. Approximating expressions for the coverage factor of this convolution are given. The relative errors of applying these approximating expressions are calculated. The choice of an expression that provides the most accurate approximation of the obtained numerical values is substantiated. A technique for finding the number of degrees of freedom of the resulting convolution is proposed.**

Keywords—Monte Carlo Method, coverage factor, t-distribution, convolution of distribution laws, approximating expressions

I. INTRODUCTION

In metrology, measurements with repeated observations are widely used. Statistical processing of such measurements can significantly reduce the random component of the error of their result. When finding the expanded uncertainty with a limited number of observations *n*, the t-distribution law is used. In the case of multiple input quantities in a measurement model with repeated observations, it is necessary to compose several laws of t-distributions with a different number of degrees of freedom (NDF) and a different ratio of standard deviations (RMS). Estimating the NDF of such a convolution is an urgent problem.

As noted in [1] "... this problem does not have an exact solution". Approximate estimates of the effective NDF of the convolution of t-distribution laws are given in the papers of Welch B.L. and Satterthwaite F.E [2 -4]:

$$\nu_{eff} = \frac{\left[\sum_{i=1}^{m} S_i^2\right]^2}{\sum_{i=1}^{m} S_i^4 / (\nu_i + 2)} - 2\ , \qquad (1)$$

$$\nu_{eff} = \frac{\left[\sum_{i=1}^{m} S_i^2\right]^2}{\sum_{i=1}^{m} S_i^4 / \nu_i}\ . \qquad (2)$$

In these expressions S_i, ν_i are RMS and the number of degrees of freedom of the *i*-th input quantity, respectively.

The purpose of this work is to estimate the degree of approximation when using expressions (1), (2) to find the coverage factor and to find an expression that provides its best approximation.

To achieve this goal, the following tasks were solved:

1. Numerical modeling of the convolution of two t-distribution laws with different NDF ν_1 and ν_2 RMS ratio $\gamma = \frac{S_2}{S_1}$.

2. Evaluation of the NDF ν of the resulting convolution.

3. Finding reliable estimates of the coverage factors *k* and the NDF ν for the convolution of t-distribution laws.

II. DETERMINATION OF THE NDF OF THE LOWS OF T-DISTRIBUTION CONVOLUTION

Modeling of the convolution of t-distribution laws was carried out by the Monte Carlo Method (MCM) [5,6]. To implement it, we generated two samples of random variables with a volume of $5 \cdot 10^6$ each, obeying the t-distribution with a given NDF and a given RMS ratio γ. The summation of these samples gives a sample of a random variable whose distribution law corresponds to the desired convolution.

A peculiarity of t-distributions is that at $\nu \le 2$, the variance estimate of the scatter width ceases to exist [7]. The kurtosis estimate, through which the NDF can be estimated, ceases to exist already at $\nu = 4$. In view of the foregoing, the parameters of the resulting convolution can only be estimated using confidence or entropy estimates [7].

Therefore, for a prearranged confidence level (*p*=0,95), the coverage factor k_{MCM} of the resulting convolution was evaluated. To improve the accuracy of finding this estimate and determining the degree of its dispersion, the numerical experiment was carried out 10 times with subsequent averaging. At the same time, the own uncertainty of the obtained estimate of the coverage rate was no more than 0,001.

The dependence of the coverage factor of the convolution on the parameters ν_1 and ν_2 for different ratios γ is shown in the figures in Table. 1. The approximating dependences k_{app} obtained as t-coefficients $t_{p;\nu_{eff}}$ with the NDF ν_{eff} determined by expressions (1), (2) are also shown there.

Relative approximation errors calculated by the formula

$$\delta_k = 100 \cdot \frac{k_{app} - k_{\text{MCM}}}{k_{\text{MCM}}}\ ,$$

are given in Table. 2.

It can be seen from the tables that these dependences at small values of ν_1 and ν_2 differ significantly, especially when γ tending to unity.

TABLE I. THE DEPENDENCE OF THE COVERAGE FACTOR OF THE CONVOLUTION ON THE PARAMETERS ν_1 AND ν_2 AND FOR DIFFERENT RATIOS γ

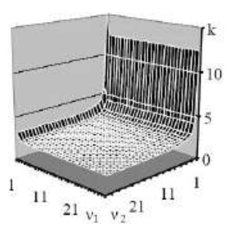
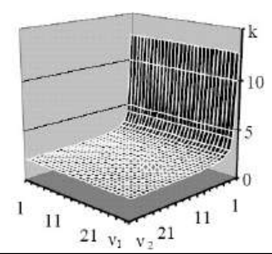
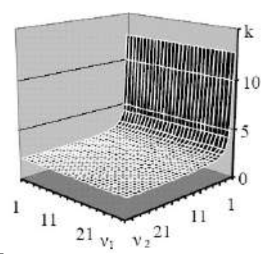
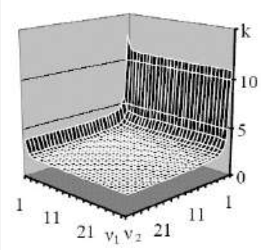
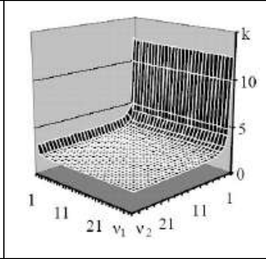
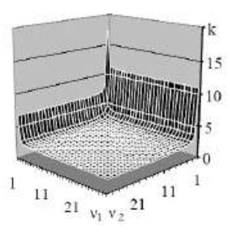
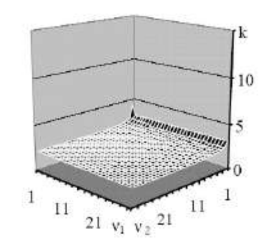
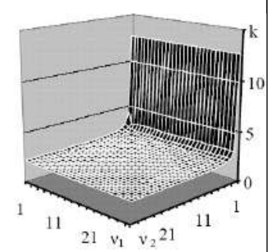
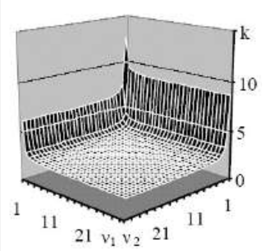
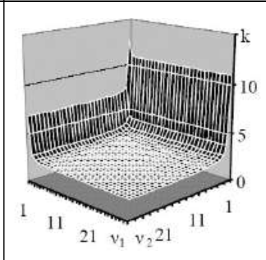
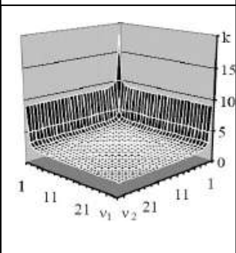
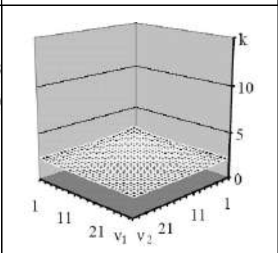
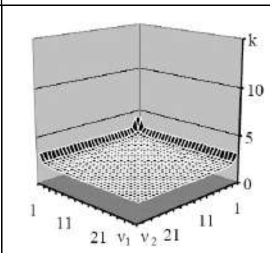
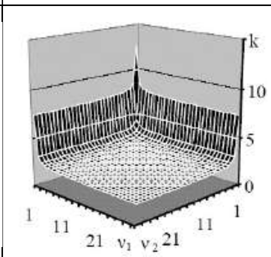
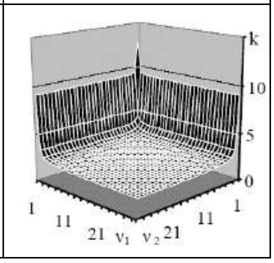
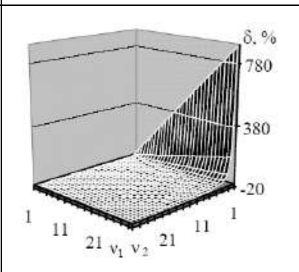
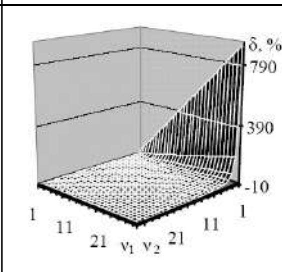
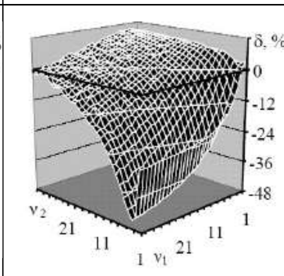
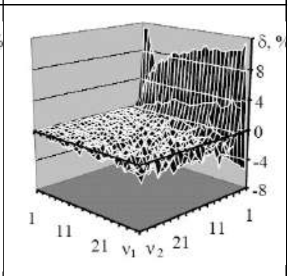
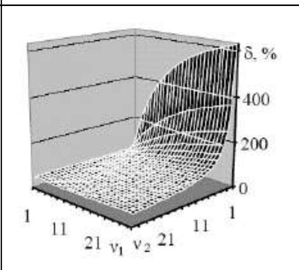
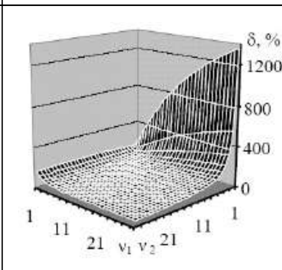
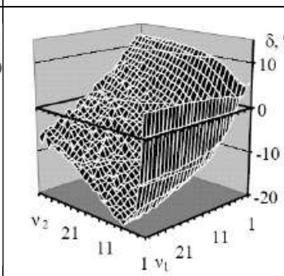
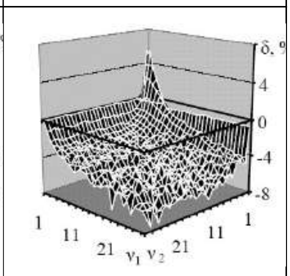
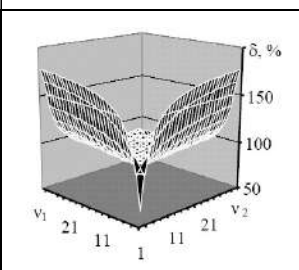
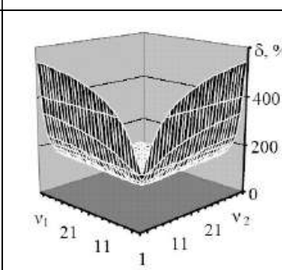
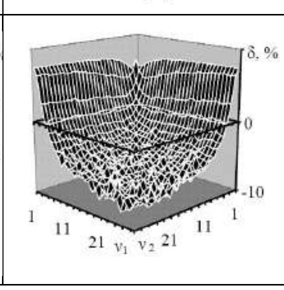
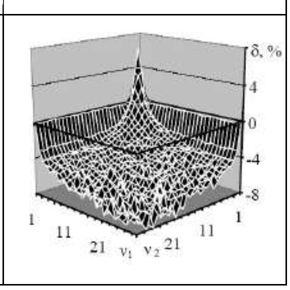
	MCM	**From formula (1)**	**From formula (2)**	**From formula (5)**	**From formula (6)**
$\gamma = 0{,}2$					
$\gamma = 0{,}6$					
$\gamma = 1{,}0$					

TABLE II. RELATIVE APPROXIMATION ERRORS δ_k , %

	From formula (1)	**From formula (2)**	**From formula (5)**	**From formula (6)**
$\gamma = 0{,}2$				
$\gamma = 0{,}6$				
$\gamma = 1{,}0$				

III. DETERMINATION OF THE NDF OF THE CONVOLUTION OF THE T-DISTRIBUTION LAWS

To estimate the NDF of the resulting convolution, it is necessary to inversely transform the t-coefficients into the number of degrees of freedom. To do this, we first found an approximation of the dependence of the t-distribution coefficients on the NDF $k(\nu)$ for the confidence level *p*=0,95:

$$t_{0,95;\nu} = t_{0,95;\infty}\left[1+\frac{1}{0{,}822\nu - 0{,}87}\right], \qquad (3)$$

where $t_{0,95;\infty} = 1{,}96$.

The approximation error for ν=2 is 4%, for $\nu \geq 3$ no more than ± 0,22%.

After that, the desired empirical dependence was obtained from expression (3):

$$\nu = \frac{1}{0{,}822}\left[\frac{1{,}96}{t_{0,95;\nu} - 1{,}96} + 0{,}87\right]. \qquad (4)$$

The dependence of the NDF of the convolution of the t-distribution laws ν_{eff} on ν_1 and ν_2 for different ratios γ, found by the proposed method, is shown in the figures Table. 3. The same table shows similar dependences obtained by formulas (1) and (2).

In Table. 4 shows the relative errors of these approximate formulas calculated by the formula:

$$\delta_\nu = 100 \cdot \frac{\nu_{app} - \nu_{\text{MMC}}}{\nu_{\text{MMC}}}.$$

From the figures in Table. 4 it can be seen that the number of degrees of freedom of the convolution obtained by formulas (1) and (2) differs from the number of degrees of freedom obtained by the MCM by almost 2 times. This difference leads to an incorrect estimate of the confidence coefficient for the convolution of the t-distribution laws.

III. RELIABLE ESTIMATION OF COVERAGE FACTOR FOR THE CONVOLUTION OF T-DISTRIBUTION LAWS

We will look for this estimate based on the expression used in the standard [8]:

$$k_{app} = \frac{t_{0,95;\nu_1}S_1 + t_{0,95;\nu_2}(\nu_2)S_2}{S_1 + S_2} = \frac{t_{0,95;\nu_1} + t_{0,95;\nu_2}\gamma}{1+\gamma} \qquad (5)$$

and the formula proposed in [9]:

$$k_{app} = \frac{\sqrt{t^2_{0,95;\nu_1}S_1^2 + t^2_{0,95;\nu_2}(\nu_2)S_2^2}}{\sqrt{S_1^2 + S_2^2}} = \sqrt{\frac{t^2_{0,95;\nu_1} + t^2_{0,95;\nu_2}\gamma^2}{1+\gamma^2}}. \qquad (6)$$

The dependences of the coverage factor k_{app} determined by formulas (5) and (6) on the parameters ν_1 and ν_2 for different ratios γ are shown in the figures Table. 1.

Relative approximation errors δ_k are given in Table. 2.

TABLE III. THE DEPENDENCE OF THE NDF OF THE CONVOLUTION OF THE T-DISTRIBUTION LAWS ON ν_1 AND ν_2 FOR DIFFERENT RATIOS γ

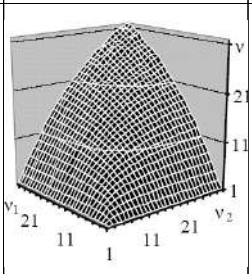
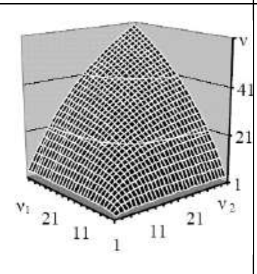
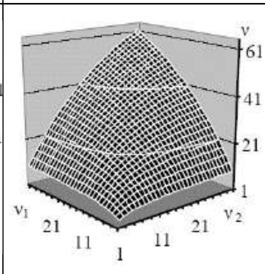
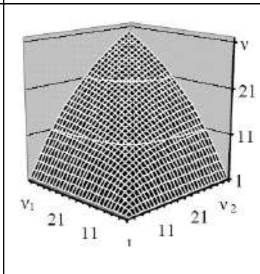
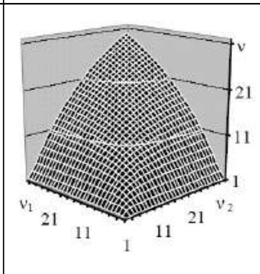
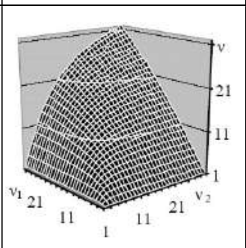
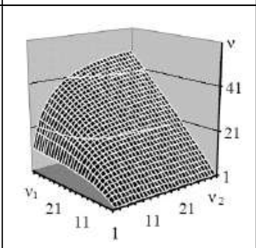
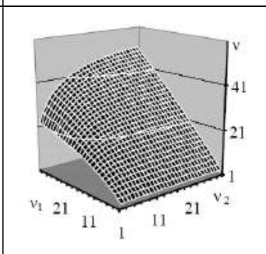
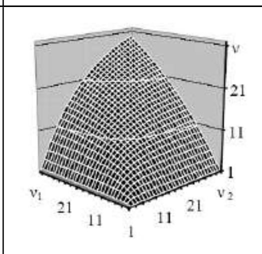
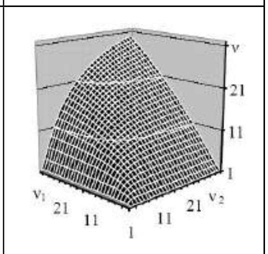
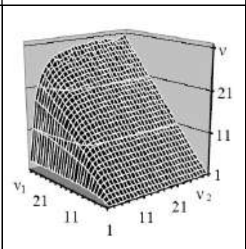
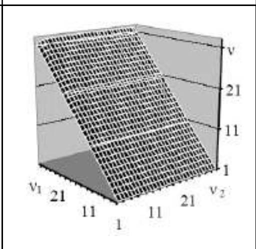
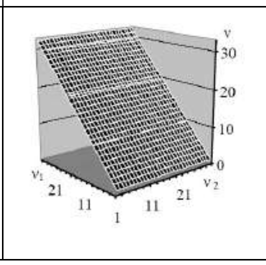
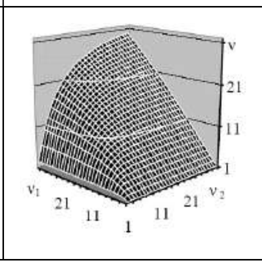
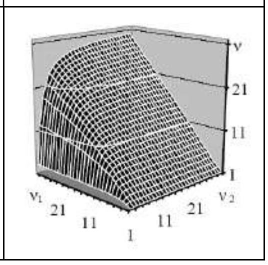
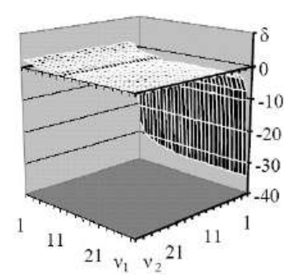
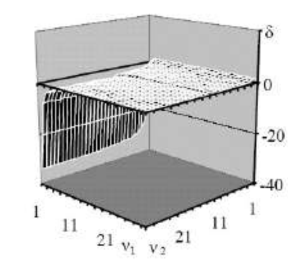
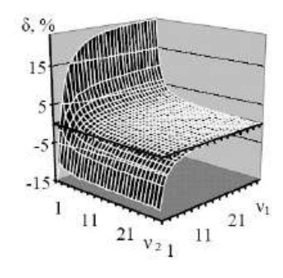
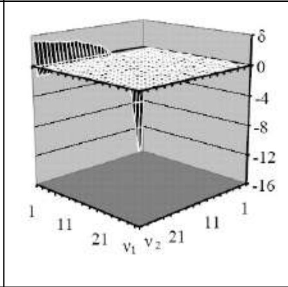
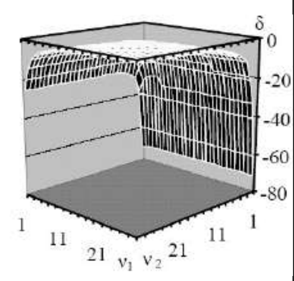
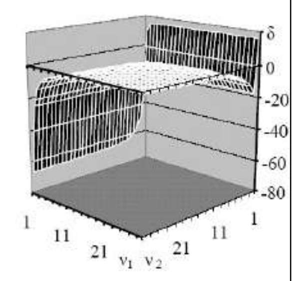
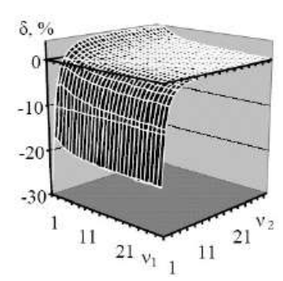
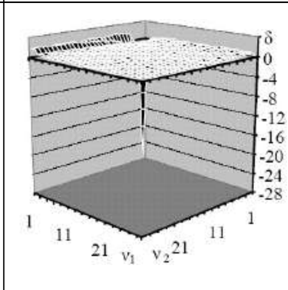
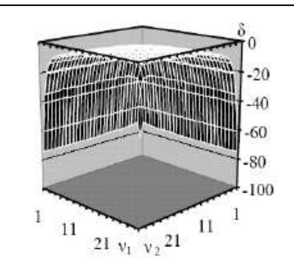
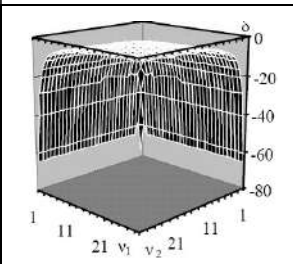
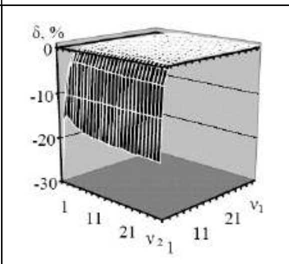
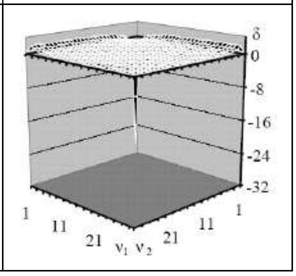
	From MCM	**From formula (1)**	**From formula (2)**	**From formula (5)**	**From formula (6)**
γ = 0,2					
γ = 0,6					
γ = 1,0					

TABLE IV. RELATIVE APPROXIMATION ERRORS δ_ν , %

	From formula (1)	From formula (2)	From formula (5)	From formula (6)
$\gamma = 0,2$				
$\gamma = 0,6$				
$\gamma = 1,0$				

From the table. 1 and 2, it can be seen that the confidence factor is approximated by these expressions better than by t-coefficients with the NDF determined by formulas (1), (2).

The best approximation is achieved by formula (6). This is also confirmed by the figures in Table. 3, 4, which show the dependences of the NDF obtained by converting expressions (5), (6) using the empirical dependence (4) as well as the relative errors of their approximation.

CONCLUSIONS

1. Composite of two laws of t-distribution with different NDF ν_1 , ν_2 and RMS ratio γ is obtained by numerical simulation.

2. An empirical expression has been obtained that approximates the dependence of the t-coefficients $t_{0,95;\nu}$ on the NDF ν , on the basis of which a method for estimating the NDF ν of the studied convolution has been developed and applied.

3. Comparison of confidence factors and NDF obtained by various methods using expressions (1), (2), (5), (6) showed that the best approximation is the use of expression (6).

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