The methods of obtaining and elaborating classified data in intellectual measurement systems

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Abstract - In this paper the methods of constructing a classification scale, according to which the degrees of belonging the measurement results to the established equivalence classes are obtained, are considered. By establishing this classification scale, the number of equivalence classes and their boundaries are determined, as well as the form of membership functions of individual classes, if the classification is fuzzy. In this regard, the methods of establishing the membership functions form of individual equivalence classes are analyzed, taking into account the measurement uncertainty, the appropriate recommendations for the use of fuzzy classifier algorithms are developed. Based on the use of the information criterion, it is proposed to use the consistency measure of classified data, which can be used when equivalence classes in the determining field of the classification scale are uneven placed. Examples of the obtained results practical application for the classification of soils by mobil phosphorus content are considered. This application is based on a sample of classified data in order to optimize the rate of fertilizer application. By classifying soils, a scale of fuzzy classification was constructed taking into account the results of theoretical research on the number of equivalence classes and the form of membership functions. The consistency measure of the obtained experimental data of soil samples was checked to assess the correctness of the sampling method. By assessing the level of garbage filling of the underground bins group, a classification scale was constructed taking into account the measurement uncertainty. To characterize the reliability of decision-making is proposed the use of a correspondence matrix of the classification scale.

Keywords - classification scale, classified data, measurement uncertainty.

1. INTRODUCTION

Modern intelligent measuring systems are used in conjunction with decision-making systems by performing various production tasks. In this case, for traditional operations that are the part of measurement procedure, a classification operation is added, the operation of which is ensured by the classification scale. Therefore, it is believed that a feature of intelligent measuring systems is polymorphism, which consists in displaying the measured value by several scales, namely the metric scale and the classification scale.

The main features of the classification procedure are:

- the presence of a classification scale that covers the entire population and which is developed in advance or in the classification process;
- the presence of rules developed in the classification process, based on the conditions of distinction;
- the presence of synthetic relationship that characterize the objects of classification (the relationship of equivalence or tolerance, the relationship of order);
- the possibility of forming training samples;
- information on equivalence classes;
- purpose of the classification procedure;
- methods used in classification.

In this paper the application of the classification procedure by one measurand and ordered equivalence classes, i.e. the so-called "metric" classification, is considered. It is necessary to take into account the measurement uncertainty of the quantity to be classified, or uncertainty by constructing a classification scale, or by conducting the classification itself.

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2. Analysis of literature data and problem statement

The most commonly classification scale is used with ordered equivalence classes, which is a quasi-order scale (sometimes called "semi-quantitative" [1,2]). In general, it is a scale with a fuzzy linguistic variable, which provides the ability to obtain data used in calculations based on fuzzy logic [3].

By establishing a scale with fuzzy linguistic variable is used a semantic rule, which corresponds to each element of the term set $T = \{T_1, T_2, ..., T_n\}$ a fuzzy subset from the domain of measurement [4]. The semantic rule can be a computational operation that establishes the membership function (MF) or include operators that change the fuzzy index of the set MF. Since the measurement results are accompanied by uncertainty, there is a need to analyze ways to take into account the uncertainty of measurement by establishing the MF of the term set of a linguistic variable [5]. Therefore, one of the tasks of this paper is the analysis and development of methods for constructing a classification scale, i.e. determining the MF of individual classes, taking into account the uncertainty of the measurement results.

A fuzzy classifier is used for the obtained classified data [4]. In general, the task of classification is to determine the degree of object properties belonging to individual classes or the object itself by a set of properties. In the presence of one property use one-dimensional MF. One-dimensional MFs are the most commonly used in fuzzy logic. In measuring systems, based on the measurement result of the property x_i, the classifier calculates the degree of its belonging to term sets $T_1, T_2, ..., \mathrm{T}_n$. The largest value of the degree of affiliation (which can take values in the range from 0 to 1) indicates to which term set the attribute of the object belongs, i.e. how it should be classified.

If one class of equivalence or one of the terms of the set is selected, the quality characteristic is the probability of correct classification. If the result of the classification is presented as a fuzzy subset, i.e. the scattering of degrees of affiliation by equivalence classes is taken into account, and then the representation of the result of the classification takes the form:

$$T_1 \mid \mu_i(T_1); T_2 \mid \mu_i(T_2); ... T_n \mid \mu_i(T_n)$$

Thereby obtained classified data can be used further in fuzzy calculations and inferences to make certain decisions. But this paper is considered the methods of elaborating classified data for two areas, which are most common in intelligent measuring systems, namely:

- replicate measurements of the object property with the subsequent classification of the current state of the object;
- classification (definition) of the generalized characteristic of the object according to the vector of measurement results of separate properties.

3. Research objectives

The article is devoted to the analysis of ways to solve the following problems:

- construction of a classification scale taking into account the measurement uncertainty both in determining the number of distinguishable equivalence classes and in determining the form of membership functions of individual equivalence classes or linguistic variable terms;
- obtaining classified data according to the fuzzy classifier and their further processing when determining the general state of the object and when using them in fuzzy calculations.

4. Materials and methods of research.

4.1. Establishing a fuzzy classification scale taking into account measurement uncertainty

It is possible to offer the following sequence of establishment stages or reproduction the linguistic scale: definition of terms set quantity and their borders; analysis of semantic rule ambiguity and measurement uncertainty components; taking into account the measurement uncertainty influence on the index of fuzzy subjects, which are element of the linguistic variable term set; approbation (in the presence of reference elements) or modeling of fuzzy inference using the established linguistic scale.

It is proposed to calculate the number of equivalence classes based on the measurement uncertainty. For this an information approach based on the entropy uncertainty interval is used [3]. According to this approach, the number of distinguishable gradations of the scale is determined by the boundaries of the measurement range x_1, x_2 (lower and upper, respectively) and the entropy uncertainty interval d, as $N = (x_2 - x_1)/\mathrm{d}$.

The entropy interval of uncertainty is found taking into account the error distribution. The value N is the upper limit of the number of equivalence classes. Therefore, by establishing a classification scale, their number may be smaller based on the resolution of the qualitative assessment of different classes of equivalence. After that, the names or codes or symbols of equivalence classes and their boundaries are set, which are clear at the first stage. But the presence of measurement uncertainty is the reason for the appearance of a zone of uncertainty at the boundaries between individual classes of equivalence.

Linguistic scales consist of qualitative estimates of the physical quantities, state of objects and systems. The formalization of qualitative assessments is complicated, first, by the linguistic uncertainty of concepts (for example, "small", "not large"), and secondly, by the subjectivity of these concepts perception by different experts. By creating a mathematical apparatus that can provide an adequate description and formalization of uncertainty of this kind, fuzzy linguistic variable are used, the fuzzy index of membership functions of which depends on the fuzzy semantic rule [4].

If certain agreed norms are used in setting the boundaries of terms, then the boundaries are clear, and further consideration of the ambiguity is associated with components of uncertainty that may affect the change of boundaries. And the first component of such uncertainty is the uncertainty of incomplete identification of the object when setting the scale. That is, it is possible to refine the scale for complete object identification, but this opportunity is not always used because unwillingness to increase the number of rules of the knowledge base.

If we turn to [6], the uncertainty from the incomplete identification of the object corresponds to the definitional measurement uncertainty, which arises due to the limited number of details in the determination of the measured value.

This is followed by an analysis of the uncertainty components that accompany the measurement result on a metric scale.

The next step is to establish the form of MF individual gradations of the classification scale or previously defined equivalence classes. The study was conducted for a scale of one property, i.e. MF of equivalence classes create a scale of fuzzy classification, and the fuzzy index of individual classes as fuzzy sets depends on the measurement uncertainty. The study of the relationship between the fuzzy index of the equivalence class and the measurement uncertainty was performed for the trapezoidal shape of the MF, and for example, the equivalence class "small" was chosen, ie the initial term of the equivalence classes set with the analytical representation of the MF:

$$\mu_{T_1}(x) = \left\{ \begin{array}{l} 1,\ if\ \ 0 \le x \le a_1 \\ \dfrac{a_2 - x}{a_2 - a_1},\ \ if\ \ a_1 \le x \le a_2 \\ 0,\ \ if\ \ a_2 < x \end{array} \right\} \tag{1}$$

The clear upper bound of the equivalence class was set at $x_{L} = (a_1 + a_2)/2$. Due to the measurement uncertainty with a boundary Δ equal to $(a_2 - a_1)/2$ the shape of the MF from a rectangular becomes trapezoidal.

To estimate the degree of blur in the work, the fuzzy index based on the relative Euclidean distance for a continuous set $U = [a,b]$ is chosen:

$$I^{E}_{\underset{\sim}{A}} = \frac{2}{\sqrt{b-a}}\sqrt{\int_{a}^{b}(\mu_{\underset{\sim}{A}}(x)-\mu_{\underset{=}{A}}(x))^{2}dx}, \qquad (2)$$

where $\mu_{\underset{\sim}{A}}(x)$ - MF fuzzy set $\underset{\sim}{A}$, $\mu_{\underset{=}{A}}(x)$ - MF of a clear set closest to $\underset{\sim}{A}$.

In accordance with formula (2) taking into account (1) we obtain the fuzzy index for the term T1 = "small":

$$I^{E}_{T_1} = \sqrt{\frac{2\Delta}{(x_{\Gamma}+\Delta)\cdot 3}} = \sqrt{\frac{2\delta}{(1+\delta)\cdot 3}},\ where\ \frac{\Delta}{x_{\Gamma}} = \delta \qquad (3)$$

Thus, the relationship between the fuzzy index of the MF term "small" and the measurement uncertainty the limit value of the term is obtained and what's more the shape of MF is set taking into account the measurement uncertainty. With increasing Δ and decreasing a_1 fuzzy index increases and when $a_1 = 0$, shape of the MF becomes triangular.

Researches have shown that the use of nonlinear forms of MF has little effect on the value of the fuzzy index, but this violates the rule of unit division, which is true for linear MF. And this, in turn, affects the decisions that are made with fuzzy classification. To illustrate the results obtained, we present the MF of two classes of equivalence $\mu_{T_1}(x)$ ("small") and $\mu_{T_2}(x)$ ("medium") using a trapezoidal and power form (concave $\mu'_{T_1}(x)$ and convex $\mu''_{T_1}(x)$) (Fig. 1).

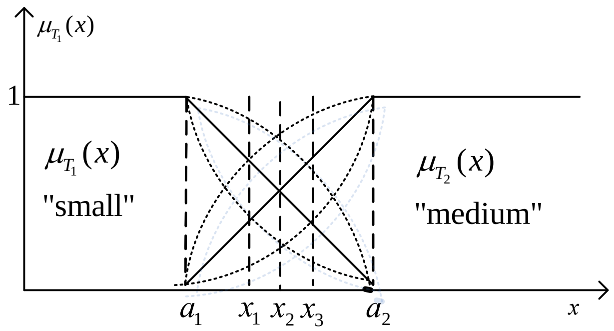

Fig. 1 - Illustration of the classification for different forms of MF

Affiliation functions $\mu'_{T_1}(x)$ i $\mu''_{T_1}(x)$ for $U = R^{+}U\{0\}$ are:

$$\mu''_{T_1}(x) = \begin{cases} 1, & if\ \ 0 \le x \le a_1; \\ 1-(\frac{x-a_1}{a_2-a_1})^{2}, & if\ \ a_1 \le x \le a_2; \\ 0, & if\ \ a_2 < x. \end{cases}$$

$$\mu'_{T_1}(x) = \begin{cases} 1, & if\ \ 0 \le x \le a_1; \\ 1-(\frac{x-a_1}{a_2-a_1})^{\frac{1}{2}}, & if\ \ a_1 \le x \le a_2; \\ 0, & if\ \ a_2 < x. \end{cases}$$

If the property of the object x is classified according to the measurement results x_1, x_2, x_3, the results of fuzzy classification are obtained by the cross section of the ordinates corresponding to the values x_1, x_2, x_3 from the MF of two classes of equivalence (Table 1).

Table 1

The results of classification by degree of affiliation classes "small" and "medium"

Form od MF	Measurement results		
	$x_1 = a_1 + 0,25 \cdot (a_2 - a_1)$	$x_2 = a_1 + 0,5 \cdot (a_2 - a_1)$	$x_3 = a_1 + 0,75 \cdot (a_2 - a_1)$
Trapezoidal	$T_1 \mid 0,75;\ T_2 \mid 0,25$	$T_1 \mid 0,5;\ T_2 \mid 0,5$	$T_1 \mid 0,25;\ T_2 \mid 0,75$
Concave	$T_1 \mid 0,5;\ T_2 \mid 0,06$	$T_1 \mid 0,3;\ T_2 \mid 0,25$	$T_1 \mid 0,13;\ T_2 \mid 0,56$
	$T_1 \mid 0,89;\ T_2 \mid 0,11$	$T_1 \mid 0,55;\ T_2 \mid 0,45$	$T_1 \mid 0,19;\ T_2 \mid 0,81$
Convex	$T_1 \mid 0,94;\ T_2 \mid 0,5$	$T_1 \mid 0,75;\ T_2 \mid 0,7$	$T_1 \mid 0,44;\ T_2 \mid 0,87$
	$T_1 \mid 0,65;\ T_2 \mid 0,35$	$T_1 \mid 0,52;\ T_2 \mid 0,48$	$T_1 \mid 0,34;\ T_2 \mid 0,66$

Based on the results of calculations (Table 1), the following conclusions can be drawn:

- only for trapezoidal MF the results of classification correspond to the condition of division of the unit. Therefore, the second line of classification results for concave and convex MF is obtained with the transformation to fulfill the condition of unit division;
- for all forms of MF the result of assignment to the equivalence class at the maximum degree of MFfiliation is the same;
- nonlinear MFs allow classification on the line of separation of two classes of equivalence;
- if in the area of separation of two classes of equivalence to apply two forms of MF - convex and concave, then the priority when assigning to the equivalence class will be in the class with convex MF (in this case could be predicted the priority assignment to higher or lower equivalence class).

4.2. Use a consistency measure for estimation the scattering of classified data

In order to analyze samples of classified data, it is important to assess their scattering relative to the central tendency, because decision-making on a sample with less scattering is more informative than when the scattering is large. In [7] is proposed the use of information criteria, which is a consistency measure between the ordinal data (Cns - consensus measure) and the degree of discrepancy (Dnt - dissention measure), related by the relationship:

$Cns(x) = 1 - Dnt(x)$.

Based on the previous rank arithmetic [7] the ratio is:

$$Cns(x) = 1 + \sum_{i=1}^{n} p_i \log_2 (1 - \frac{|x_i - \mu_i|}{d_x}), \qquad (4)$$

where x_i – rank of equivalence class, p_i - probability or frequency combined with x_i, d_x - area of definition that is equal to $x_{\max} - x_{\min}$, μ_x - an average value equal to $\mu_x = \sum_{i=1}^{n} p_i x_i$.

Opponents of artificially entering the distance using the ranks [8], [9] believe that this contradicts the established restriction of operations with ordinary data. This is true. But when we have a previously constructed classification scale, where the distance between equivalence classes is determined, formula (4) can be modified to use a measure of consistency between the sampled classified data. The disadvantage of formula (4) is also the definition of the central tendency as the arithmetic mean of the ranks. Therefore, it is proposed to determine the central tendency by operators med and OWA, namely the odd number of sample members can be used the median of the sample med, which is the central member of the ranked sample, and regardless of the number of sample members - the operator OWA, that can act as an arithmetic mean emulator [10,11] for verbal sampling

If an equivalence class corresponding $T_ц$ to the sample center is determined, then a value $x(T_ц)$ corresponding to the center (i.e the middle) of the equivalence class can be obtained using a classification scale $T_ц$. Accordingly, the following ratio may be proposed to determine the degree of consistency:

$$Cns(x) = 1 + \sum_{i=1}^{n} p_i \log_2 (1 - \frac{|x(T_i) - x(T_ц)|}{x_{\max} - x_{\min}}), \quad (5)$$

where $x(T_i)$ for $i = 1,..n$ – the middle of the equivalence class T_i in the area of definition of the classification scale.

This method of estimating the degree of consistency allows it to be used with an uneven arrangement of equivalence classes.

But with a uniform distribution of equivalence classes can be used and the probabilistic estimate of the variance proposed in [9]:

$$D = \frac{\sum_{k=1}^{n} F_k (1 - F_k)}{(n-1)/4} \quad (6)$$

where F_k - cumulative relative frequency for the k-th equivalence class.

Therewith F_n is always equal to one. The degree of variance for the ordinal scale reaches a maximum of 1 when the data distribution is polarized to two extreme levels, and zero when one equivalence class contains all the data. Thus, the extreme values the range of the variance measure D and the degree of data discrepancy Dnt coincide. But as the analysis showed at other points in the range, the value D always exceeded the value Dnt. That is, when comparing the scattering of sample data, one of the above measures should be chosen.

The following are examples of practical application of the results of theoretical research

5. Practical application of research results

5.1. Determination of the linguistic variable term set oin the classification of soils by the content of mobile phosphorus for optimize the rate of fertilizer application

The grouping of soils by the content of mobile phosphorus by the Machigin method is given below (Table 2). The first task of constructing a classification scale is to determine the number of terms set based on the measuring accuracy the content of mobile phosphorus.

Table 2

Classification of soils

Linguistic characteristics	**The content of mobile phosphorus in the samples soil by the Machigin method mg / kg**
Low	less than 15
Average	16-30
Increased	31-45
High	46-60
Very high	more than 60

For this measuring method the value of the relative interval of the analysis results for the two-way confidence probability P = 0.95 is in percent:

30 - at a content P_2O_5 of up to 15 mg / kg; 20 - more than 15 mg / kg.

Then, in accordance with [5], the number of distinguishing gradations with a uniform probability distribution of the values of the measured quantity and the entropy uncertainty interval found for the normal distributive law of the measurement error is

$$N = \frac{x_2 - x_1}{d} = \frac{x_2 - x_1}{4{,}133 \cdot \sigma} \approx 5$$

where x_2, x_1 – upper and lower limits of the measurement interval, d – entropy uncertainty interval, σ – standard deviation of the measurement error.

That is, 5 terms of the set correspond to the intervals of grouping of soils and the condition of distinguishing terms. It should be noted that in the brochures there are recommendations for grouping soils with more gradations, which according to the current uncertainty of phosphorus measurements are indistinguishable. The term set of the linguistic variable "the level of mobile phosphorus in soil samples", built taking into account the above recommendations, is presented in the figure.

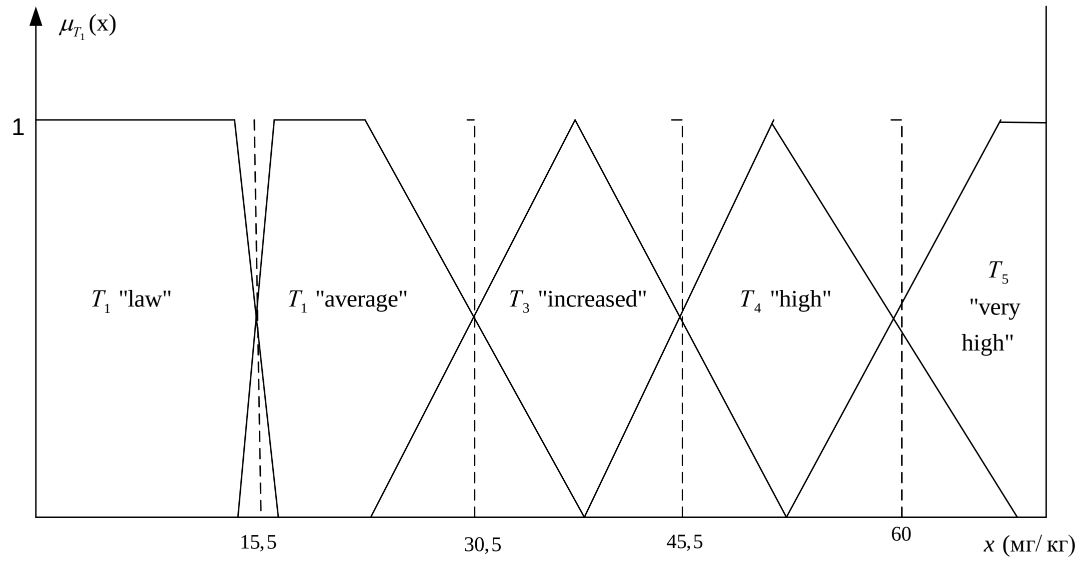

Fig. 2 - Term set of the linguistic variable "the level of mobile phosphorus in soil samples", constructed taking into account the measurement uncertainty

The results of fuzzy classification are used to decide on the application of fertilizers according to the rules:

R1: If the content of mobile phosphorus is "low", the application rate of ammophos is "high (90 kg / ha)"

R2: If the content of mobile phosphorus is "average", then the rate of application of ammophos is "average (71 kg / ha)"

R3: If the content of mobile phosphorus is "increased", the rate of application of ammophos "below average (57 kg / ha)"

R4: If the content of mobile phosphorus is "high", the application rate of ammophos is "low (33 kg / ha)"

R5: If the content of mobile phosphorus is "very high", then ammophos do not need to be applied.

To classify the phosphorus content, the fuzzy classifier determines the ordinate cross section, which corresponds to the measurement result with the term set of the linguistic variable. If the cross section corresponds to a value $\mu_{T_i}(x)$ equal to one, the corresponding rule from the set R1-R5 is used. If the section includes two terms of the set, for example $T_1 | 0,6; T_2 | 0,4$, then the rate of fertilizer application is calculated according to two rules with weights, namely

$$H = 90\,кг/га \cdot 0,6 + 71\,кг/га \cdot 0,4 = 82,4\,кг/га$$

But such a situation with the calculation of the fertilization required rate occurs when the rules base works with agreed data. Therefore, the first step in processing classified data should be to check their consistency.

For demonstration in table 3 is shown two samples of the results of measuring the content of mobile phosphorus:

Table 3

The results of measuring the mobile phosphorus content

Sample 1	16	14	15	16	17	16	17
Sample 1 after classification	T_2	T_1	T_1	T_2	T_2	T_2	T_2
Sample 2	15	20	31	47	18	25	50
Sample 2 after classification	T_1	T_2	T_3	T_4	T_2	T_2	T_4

The median of the ranked sample corresponds to the equivalence class T_2, respectively, the value $x(T_2) = 23$ *мг / кг*. Integral characteristic of assigning data to the corresponding equivalence classes for the rule base:

$T_1 | 0,29$; $T_2 | 0,71$.

The degree of consistency of the data obtained by formula (8):

$$Cns(x) = 1 + 0,29 \cdot \log_2(1 - \frac{|7,5-23|}{75}) + 0,71 \cdot \log_2(1 - \frac{|23-23|}{75}) = 0,9,\ Dnt = 0,1.$$

Since the equivalence classes are evenly distributed in the measurement range (Table 2), we can use formula (6) and the integral characteristic of the sample according to which the scatter is estimated $D = 0,205$. According to the results of calculations, we can assume that the data sample is quite consistent.

For sample 2 are obtained: $med = T_2$, $x(T_2) = 23$ *мг / кг*, the integral characteristic of the assignment of data to the corresponding equivalence classes: $T_1 | 0,14$; $T_2 | 0,43$; $T_3 | 0,14$; $T_4 | 0,29$; degree of consistency $Cns(x) = 0,693$, degree of disagreement $Dnt = 0,307$, scattering measure $D = 0,541$.

According to the classification results, these sample is inconsistent and require additional analysis of it obtaining method.

5.2 Application of the classification scale when measuring the garbage level that filling of the underground bin

One of the urgent problems of large cities is the collection and rational recycling of garbage. To collect garbage in the city center, in the excursion areas it is proposed to use underground ballot boxes [11]. Successful operation of such bins, which are a large garbage container, is possible under a number of conditions: autonomous power supply, the ability to measure the level of garbage, the ability to call garbage collection equipment with information about the average filling of the bin group, etc.

The distance from the top point of the ballot box to the level of the garbage dump is subject to direct measurement. The maximum height of the ballot box is $2400\ mm$. By constructing the classification scale, the number of terms was determined and their membership functions were formed taking into account the total of measurement uncertainty of the distance, the components of which were the rangefinder error, the components of the impact on the measurement of density and heterogeneity of garbage, garbage color (grey, white), form of mound (presens of "hump") and other influential quantities. The total measurement error is $\pm 14\%$. In accordance with this, 5 terms of the set of states of filling the ballot box are set: T_1 - the ballot box is almost empty ($0 \div 300\ mm$); T_2 - the ballot box is less than half full ($300 \div 900\ mm$); T_3 - the ballot box is half full ($900 \div 1500\ mm$); T_4 - the ballot box is more than half full ($1500 \div 2100\ mm$); T_5 - the ballot box is practically filled ($2100 \div 2400\ mm$).

The classification scale and matrix are presented in fig. 3 and table 4, where in the diagonal of the matrix are the probabilities of correct assignment to a certain class of equivalence, calculated on the obtained scale. The values of the probability of correct assignment to a certain equivalence class indicate that the number of equivalence classes cannot be increased with high measurement uncertainty.

Table 4

A classification scale matrix with probabilities of correct assignment to certain equivalence classes

The state of filling the ballot box	T_1	T_2	T_3	T_4	T_5
The level of filling the ballot box					
$0 \div 300$ *mm*	$P_{11} = 0,75$	$P_{12} = 0,25$	$P_{13} = 0$	$P_{14} = 0$	$P_{15} = 0$
$300 \div 900$ *mm*	$P_{21} = 0,12$	$P_{22} = 0,79$	$P_{23} = 0,09$	$P_{24} = 0$	$P_{25} = 0$
$900 \div 1500$ *mm*	$P_{31} = 0$	$P_{32} = 0,09$	$P_{33} = 0,86$	$P_{34} = 0,05$	$P_{35} = 0$
$1500 \div 2100$ *mm*	$P_{41} = 0$	$P_{42} = 0$	$P_{43} = 0,05$	$P_{44} = 0,93$	$P_{45} = 0,02$
$2100 \div 2400$ *mm*	$P_{51} = 0$	$P_{52} = 0$	$P_{53} = 0$	$P_{54} = 0,03$	$P_{55} = 0,97$

When performing one-time measurements, we can recommend the algorithm of fuzzy classifier for the cross sections of all terms of the classification scale (Fig. 3).

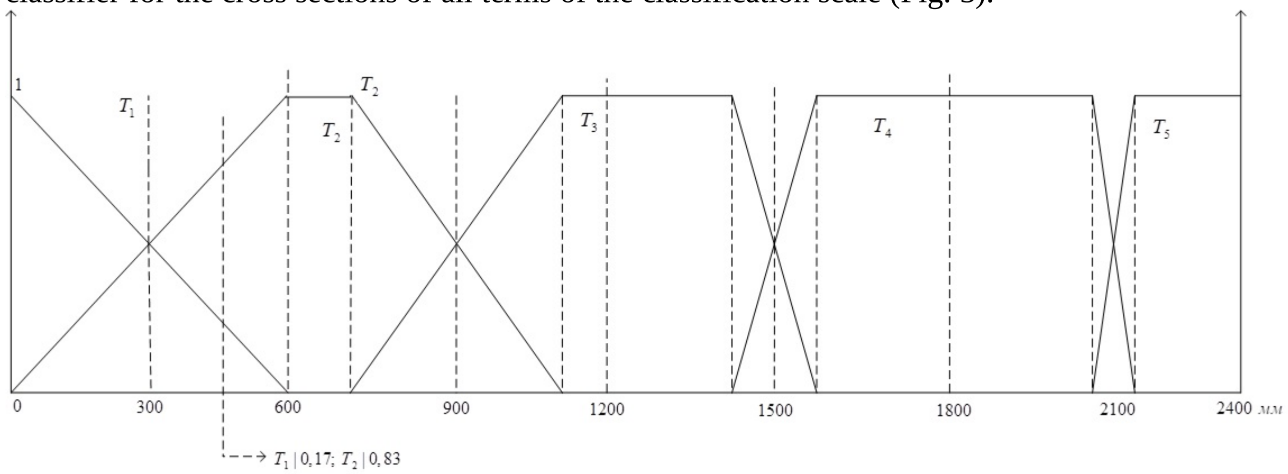

Fig. 3 – Filling state classification scale for underground bin

In Fig.3 is shown an example of the classification result: $T_1 \,|\, 0{,}17;\ T_2 \,|\, 0{,}83$. The formation of this result takes into account the measurement uncertainty, which leads to the scattering of the classification result by equivalence classes.

5. Conclusions

In order to cooperate the measuring channel of intelligent system with the fuzzy base of rules, it is necessary that measurement results were used in fuzzy calculation. With this purpose of classification procedure is used, that includes classified data obtaining and its elaborating in accordance to algorithm of fuzzy classifier.

Authors analyzed the procedure for establishing a fuzzy classification scale, taking into account the measurement uncertainty both by determining the number of linguistic variable terms, and by choosing the form of individual terms membership function.

The method of applying the classification scale in determining the consistency or scattering of classified data is offered, this method are used in the future to obtain a conclusion based on the rules.

Examples of practical application of methods for obtaining classified data in intelligent measuring systems are considered, these examples are relating to the establishment of a classification scale taking into account the measurement uncertainty, to the interaction of the classification scale with the fuzzy classifier algorithm and to the methods of using classified data.

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