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FUZZY ESTIMATION PROCEDURE OF THE CONCENTRATION OF THE COMPONENTS OF A SULFURIC ACID PICKLING SOLUTION

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The task of many technological processes (TP) is to maintain the optimal level of concentration of the individual components of the working solutions. The lack of operational and objective information about the change in the composition leads to a decrease in productivity, overspending of solutions, and often to an emergency stop of the equipment. Similar problems arise in the following processes: heating of circulating water in district heating and formation of deposits on heat exchange plates, sedimentation of ferrous sulfate monohydrate in the bath and on heat exchange plates of continuous pickling lines in metallurgy. Sulfuric acid is one of the most important industrial acids with a production volume of more than 190 million tons per year with an annual growth of about 1.8% [1]. One common process in metallurgy is steel pickling and descaling. Moreover, the number of enterprises using sulfuric acid exceeds the number of enterprises using other acids [2]. Sulfuric acid pickling wastes include sludge, acidic water, ferrous sulfates, metal salts and spent acid. Pickling sludge is the most hazardous waste according to the EPA [3]. In continuous pickling lines for carbon steel, solutions have to be regenerated in large volumes or discharged into process water for neutralization, followed by water treatment and preparation of a new fresh solution. All these activities increase the operational, resource and energy costs of the process, as well as pollute agricultural areas: they acidify and saline the soil. The process of continuous sulfuric acid pickling of carbon steel is carried out on a pickling line consisting of several pickling baths. The process medium is a pickling solution, which is dilute sulfuric acid. The pickling solution removes oxides and other impurities, but also partially dissolves the steel surface. Therefore, it is necessary to control such process parameters as holding time, temperature and composition of the pickling solution in the baths. At present, the heating of the pickling solution in special plate heat exchangers with the regulation of its temperature is a progressive trend in sulfuric acid pickling [4–6].

Controlling the composition of pickling solution components in pickling baths is a complex task, directly related to the final quality of the pickled steel strip and the efficiency of the pickling line. Fuzzy systems (FSs) originated from the fuzzy set theory proposed by Zadeh in 1965 [7], which are based on fuzzy rules. As soft computing techniques, FSs have achieved great success in dealing with numerous problems of uncertainty, such as the prediction of the irrigation water infiltration rate [8], the seismic vulnerability assessment of buildings [9–11], the automatic classification of crop disease images [12], etc. FSs are more interpretable and intuitive methods that can match any set of input–output data by each fuzzy rule [13].

Numerous mathematical models of salt crystallization in solutions often do not allow one to determine the course of the process with sufficient accuracy, although they take into account additional factors of deposit accumulation with an increase in the number of deposit crystallization centers [14]. The main drawback of these models is the absence in each case of sufficient information about the values of the concentrations of the individual components of the solution. The existing methods and equipment for monitoring the composition of solutions require additional laboratory analysis with mandatory operational personal participation or are not universal enough in terms of the composition of solutions. Currently, methods of direct chemical titration and non-destructive testing (NDT) or non-contact methods are used to measure the maximum permissible concentration (PC) of salts in a pickling solution. The electrical NDT method, with high sensitivity and relative simplicity of instrumental implementation, is one of the most informative. Opportunities for operational control of the concentration of electrolytes in solutions (which are a solution of ferrous sulfate in sulfuric acid) opens up a direct measurement of electrical conductivity. But existing analyzers are designed to measure pickling with hydrochloric acid, which is a fairly stable ternary salt system. The analyzers allow to measure the total pH in the temperature range of the solution T=5÷80 ºC, but do not allow to determine the concentration of the solution components separately in an aggressive sulphate environment.

In the case of sulfuric acid pickling, one of the main problems is the presence of *FeSO_4* salts in the pickling solution in three forms: *FeSO_4•7H_2O*, *FeSO_4•4H_2O*, *FeSO_4•H_2O*. Ferrous sulfate salts are formed as a result of the reaction of carbon steel mill scale and its iron part with sulfuric acid. The use of exact analytical relationships to predict this process is not always correct. Ferrous sulfate heptahydrate *FeSO_4•7H_2O* and iron sulfate monohydrate *FeSO_4•H_2O* have the main influence on the process of sulfuric acid pickling. As the acid content in the pickling solution decreases, the content of iron sulfates increases accordingly. With the addition of sulfuric acid, the pickling process continues, but the content of iron sulfates increases. Under certain conditions of temperature and concentration, the pickling solution will contain only the allowable amount of dissolved salts, otherwise the excess will begin to crystallize. At the metallurgical enterprises of Ukraine, a solution of sulfuric acid with a concentration of up to 20÷24 % and a solution temperature range of T=85÷98 ºC is traditionally used as a pickling solution. In this range of parameters, the total presence of *FeSO_4* salts in the pickling solution is set by the technological regulation at the level of 15 %, and the presence of *FeSO_4•H_2O* is regulated by the limit of 4 %, which will lead to the maximum pickling rate. During sulfuric acid pickling, conditions may arise when ferrous sulfate crystals will change from one type to another. The phase transition [15] of ferrous sulfate heptahydrate (transparent green large crystals, soluble in hot water) to ferrous sulfate monohydrate (very fine white cement-like precipitate, insoluble) begins when the temperature of the solution reaches T = 80 ºC and leads to precipitation of the monohydrate on heat exchange surfaces heat exchangers or heating elements of pickling baths, bath walls, etc., which makes the pickling process difficult or abends enough.

Among modern non-contact systems for determining the composition, ultrasonic seemed to be ideal. But in the case of sulfuric acid pickling, this method has a drawback. Ultrasonication can cause crystallization of salts in the pickling solution to be about a hundred times more intense than under normal conditions, and can lead to unpredictable formation of *FeSO_4* n-hydrates, which significantly reduces the quality of the pickling solution.

Effective control of continuous technological processes is possible only on the basis of the creation of more accurate models and methods, which must be insensitive to significant noise and measurement errors. Such requirements are met by intelligent methods for monitoring and identifying dynamic systems that are operated with significant uncertainty about the characteristics of the object and the environment, based on the combination of the principles of artificial neural networks and fuzzy control theory. Various aspects of the intellectual identification of objects and their parameters were studied. However, there are three challenges at least in developing optimal FSs through the analysis of the research status:

– optimizing FSs to achieve higher accuracy and faster convergence is now worthy of in depth study;

– the number of fuzzy rules increases exponentially with the dimensionality of the input, which leads to the computation not being able to be completed within a reasonable time. Hence, it is difficult for FSs to deal with high-dimensional problems;

– as the number of fuzzy rules increases, the interpretability of FSs will be affected. Therefore, how to solve the high-dimensional problem on the basis of ensuring better interpretability is one of the current bottlenecks. In recent years, great efforts have been made to improve FSs [16].

The adaptive neuro-fuzzy inference system (ANFIS) formed by the gradient descent (GD) algorithm plus least squares estimation (LSE) has been widely applied in national energy demand forecasting [17], geographic temperature forecasting [18], and so on. The SC-ANFIS is proposed in this paper, which applies subtractive clustering (SC) to construct a Sugeno fuzzy inference system in the ANFIS. The SC-ANFIS can effectively avoid the combinatorial explosion of fuzzy rules when the dimensionality of the input is very high. In addition, the fuzzy rules generated by SC are more consistent with the data than those obtained without clustering. The input space can be divided appropriately, and the number of membership functions (MFs) and the parameters for each input domain can be reasonably determined [19]. Two methods to construct fuzzy inference systems are known and used well:

– fuzzy *c*-means clustering;

– grid partitioning [20].

Relevant studies have demonstrated that the performance of the Gaussian MF is better than others in many nonlinear complex problems [21, 22]. In view of the foregoing, the present paper is devoted to development of an inexpensive intelligent method for identifying the composition of technological liquid solutions based on fuzzy *c*-means clustering (FCM). The system is considered as one of the ways to control the concentration of *FeSO_4* in the pickling solution and the consumption of sulfuric acid for the process of continuous pickling of carbon steel. The development of methods for monitoring the PC of iron sulfate salts is relevant for conducting the pickling process with maximum efficiency.

There are no reliable and fully automated methods in the task of selective color segmentation yet. To solve them in a natural way, fuzzy soft approximations can be used [23]. Ferrous sulfate salts which affect the quality of the pickling solution are presented as three compounds [24] (see Table 1).

Table 1 – Color classifier of FeSO_4 *n*-hydrates

k	Chemical formula	Formation temperature, °C	Color cluster	LR-interval estimation of RGB - code of color		
				R L-R	*G L-R*	*B L-R*
1	*FeSO_4 • 7H_2O*	21<	clearly green	81÷145	147÷183	81÷111
2	*FeSO_4 • 4H_2O*	>= 21	green	0÷2	128÷125	64÷82
3	*FeSO_4 • 1H_2O*	>= 80	white	245÷255	245÷255	245÷255

For definite values of bath temperature and pickling liquor flow rate through heat exchangers the concentration change *dc* of *FeSO_4* influences on pickling line processing efficiency. These changes estimated with fuzzy intervals are significant disturbance factors of uncertainty for the process. This dynamic process may be characterized with monotonic function $C_{FeSO\_4}(t)$ non-decreasing on interval $(0;\ t_0)$ and limited with the value $sup(c(t)) = c$. If summary PC of *FeSO_4 •nH_2O* in liquor reaches $C_{FeSO\_4}(t_0) = c$, the system becomes ineffective or stops abnormally. The control action for such state is the solution refreshment. The part of liquor is regenerated in unit and fresh regenerated pickling solution is supplied to bath till reaching scheduled $C_{FeSO\_4}(t_0 + \Delta t_r) = c_0$. The proposed approach saves the solution in process up to 25%, reducing the harmful emission and working solution consumption.

The process still is effective in case PC of *H_2SO_4* belongs to interval $C_{H\_2SO\_4} = (a`;\ a)$ and becomes ineffective or stops in case PC reaches value $C_{H\_2SO\_4} = b$. Segments X1, X2, X3 in Fig. 1 represent an integrated assessment of savings flow solution. Control actions are generated on the base of monitored *c(t)* values (partial or complete refreshment or full update of pickling bath solution, heat exchanger cleaning with turning on the back-up one). The modeled object is represented as a black box, characterized by a lack of information about what physical phenomena is happening inside itself [25].

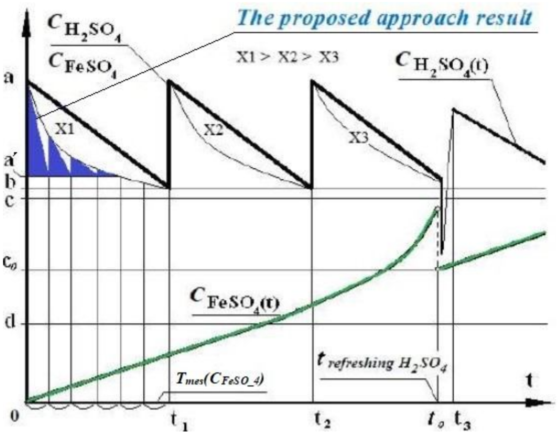

Figure 1 – Pickling solution refreshment

The development of the production model is the formation of the rule set *R* with a minimum number *k* that describe a mapping of its inputs (the vector X_n) to the output *Y*, which will provide the most accurate approximation of the real system in the sense of average absolute error [26]. Each of *k* rules specify some fuzzy point in the display space defined Cartesian product $X_1 \times X_2 \times \ldots X_n \times Y$ in the next form:

$$\begin{aligned} &R_1:\ IF\ (x_1 \approx a_1)\ AND\ (x_2 \approx a_2)\ \ldots\ AND\ (x_n \approx a_n)\ THEN\ (y_1 \approx b_1),\\ &\bullet\bullet\bullet\bullet\bullet\\ &R_k:\ IF\ (x_1 \approx z_1)\ AND\ (x_2 \approx z_2)\ \ldots\ AND\ (x_n \approx z_n)\ THEN\ (y_k \approx b_k). \end{aligned} \quad (1)$$

A fuzzy graph in the display space is formed from a set of fuzzy points. The mechanism of interpolation between points depends on the used tools of fuzzy logic. The approach of active salts concentration *c(t)* measurements in the pickling bath based on fuzzy estimation of this value with using the classifier is proposed. In general, the problem of classification is to determine the size and location of the MFs of the individual classes in the feature space $X_1 \times X_2 \times \ldots X_n$. The structure of each classifier string is presented below:

$$<CL, X, ST, R\,(Y, x)>, \qquad (2)$$

where CL – class label < color of the salts in the test solution volume >, X – < valid interval characteristic values in the Red-Green-Blue (RGB) color coordinate space >, ST – < area of the salts in the test solution volume >, $R(Y, x)$ – is a set (defined on the set X) of fuzzy interval estimations of Y – <values of parameters measured in series of N measurements of salt concentration >. The process of knowledge extracting about the object [27] is to obtain statistics of the measurement inputs – (X, ST and R) and output *(c)*.

The proposed intelligent identification method is implemented in the production site of control of solution parameters in the following composition of technical means:

– developed software;

– light source of constant calibrated spectrum, which depends on the optical properties of the components of the solution placed under the cuvette;

– dispensers;

– a cuvette for a solution that is automatically washed before each measurement with a given period of $T_{mes} \leq 45$ min;

– digital photo-recorder-analyzer FESTO SBOC-Q for 6 million pixels (with a matrix of 1280 x 1024 pixels, shooting speed 150 frames/s) with a data channel (USB, RS-485, HDMI), which forms graphic image files of the pickling solution in the cuvette in graphic format.

After the time interval equal to $0.1 \cdot T_{mes}(C_{FeSO\_4})$ (Fig.1), the dosed volume of the solution, circulating through the technological circuit "bath-heat exchanger-bath", is taken and placed in a cuvette. The solution dose is analyzed using an optical microscope and a digital camera that generates 2D graphic files in .JPG and .PNG format. These files are processed by the computer vision methods image identification system, developed in Open Source Computer Vision Library [28]. After recording the obtained measurements in the database to build a classifier, the same dose of the solution is analyzed by the dry residue method to obtain reference salt concentration values. The method of optical segmented color identification used in the system [29] was partly applied to instantaneously measure mineral concentrations in flotation froths and other stages of beneficiation processes [30]. The system of ferrous sulfates *n*-hydrates image identification according to color and occupied area has to analyze automatically the images and classify each pixel of the image according four objects ($FeSO\_4 \cdot 7H\_2O$, $FeSO\_4 \cdot 4H\_2O$, $FeSO\_4 \cdot H\_2O$ and pickling solution background color). It calculates the volumetric parts of analyzed objects (%), their weight parts (%), and their surface area per unit of volume (cm2 /cm3).

The system is able to analyze up to 256 images step by step, keep them in memory as a table and present these data as graphical plots for dispersion. Each from m measurements, that is equivalent to fixed state of pickling line, is a quantitative estimation V_k of the k-th hydrate presence: the surface occupied by appropriate color is calculated according to pixels with color code number $V_k(RGB)$ taking into account:

$$V_k = S_k \cdot V_k(RGB), \qquad (3)$$

where $V_k(RGB)$ describes the membership of a pixel in the k-th color cluster according to the RGB code LR-interval (see Table 1) and takes the values 0 or 1 in the case of clear visibility of the color class; S_k – the number of pixels allocated to the k-th color cluster, defined by images analysis results. In general, during the setting of classifier the boundaries of the classes definition region can change in the space X_n. This leads to a situation where two classes are almost identical and cannot be distinguished. The classical evaluation of an object x_j belonging to a specific i-cluster is the smallest Euclidean distance between estimated object and centers of classes ci selection:

$$dij = \| xj - ci \| = [\, \sum (cl,i - x\, l,j)2 \,]^{1/2}\,, \tag{4}$$

where l=1,…n; ci – is the coordinate of the cluster center relative to the axis OXl in space Xn ;

xj – is the coordinate of the classified object relative to the OXl axis.

The prototype of Graphic User Interface (GUI) of FCM identification method of the process liquid solutions composition in Integrated Development Environment "Processing 3.0" based on C++ programming language under operation system Windows 10 using Open Source Computer Vision Library was developed. The presentation of GUI is illustrated in Fig. 2.

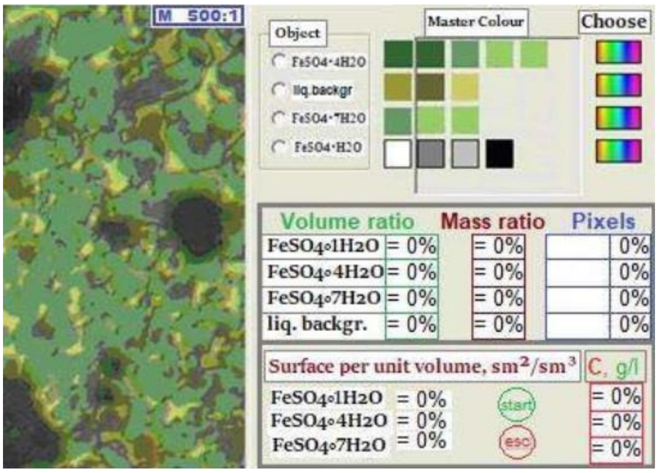

Figure 2 – The presentation of application GUI

On the basis of statistics estimates of distances it is possible to construct radial membership functions $V_k(RGB)$ [15], but it is not effectively in case of large dimension X_n. The proposed method uses a fuzzy classification with two-dimensional projections of multidimensional clusters [11]. Classes are clearly separated from each other and holding the classification is not difficult in our case. Simultaneously the test titration to measure $C_{FeSO4}(t_i)$ and measurement of $V_k(t_i)$ are carried out at the t_i moment. Also l series of N_l reference measurements of concentration of the k-th salt $c_k(t_i)$ is made by gravimetric analysis of the dry residue with satisfactory accuracy δ_t.

On the base of statistical data on the state of salts in solution, obtained by the method of fuzzy classification, the membership functions $\mu(V_k(t))$ are formed. The membership function $\mu(x)$ establishes the accordance between actually measured values of $V_k(t)$ and value of $C_k(t)$, establishing next relations:

$$V_k \rightarrow C_k. \quad (5)$$

The algorithm of the FCM-method is well known, has positively proven itself in solving tasks of this type, and is not given in this paper in detail. The formation and configuration of the classifier is made under the following assumptions: the k-th salt is clearly related to the class on the basis of color, are known its footprint with a relative accuracy of 1 pixel to 10^6 pixels (feature digital camera FESTO SBOC-Q) and mass, the specific volumeresistance of mist in the test samples of dimensions. Given that the measurement accuracy of the inputparameter of 0.005%, is not difficult to split samples of measurements between clusters. Function $C_{FeSO\_4}(t) = f(V_k(t))$ is considered to be one-dimensional, monotone and non-decreasing. Measurements are taken at equal time intervals. The configuring of classifier is based on a common clustering k-means method for one-dimensional case [26].

The number of clusters in each of the l series, consisting of N measurements, is determined empirically – according to the frequency of manifestations and by the modal number of input and output values in a series of measurements. Each element of the sample of measurements is included in the closest cluster. The inclusion of elements into clusters can be done on the basis of (4). The median (center) of the i-th cluster in the input coordinate of v is determined by the cumulative [28], taking into account all of the included elements according to the formula:

$$m_{Vi}(t) = 1/N_i \cdot \sum v_j(t),\ i=1,\ldots,l;\ j=1,\ldots N_i. \quad (6)$$

Three experimental series of a total elements number of 48 measurements $(v_j,\ c_j)$ for $FeSO\_4 \bullet H\_2O$ at intervals of input values e_i – size of the interval in which the cluster lies, the medians of the input and output values were get. A series of n measurements forms a single cluster. As maximal close to v_i the i-th cluster is defined according to formula (4):

$$MIN(d_{ij}) = \|\ m_{Vj} - v_i\ \|,\ \ j=1,\ldots l. \quad (7)$$

Representation of c_i* in a neighborhood of a point $v_i = v_i \pm \Delta$ can be calculated by using Gaussian MFs according to the formula:

$$c_i^* = \sum c_j \cdot exp\ [-(v_i - v_j)^2/2\Delta^2]\ /\ \sum exp\ [-(v_i - v_j)^2/2\Delta^2], \quad (8)$$

where $(v_j,\ c_j)$ – are the points of the real n measurements; $j=1,\ldots,n$; Δ – configurable value of the variation of the cluster membership function, which typically assigns a value:

$$\Delta = 1/3 \cdot MIN\ \|\ m_{Vj} - v_i\ \|,\ \Delta v_j \in (m_{Vj} - 0.5e_i;\ m_{Vj} + 0.5e_i), \quad (9)$$

where e_i – is the size of the interval in which the cluster lies. The calculation of the distance of the displacement of the clusters centers relatively to their positions in the previous cycle clustering $(t-1)$ (by accident for the first time) is carried out in accordance with following expression:

$$dm_i(t) = \|\ m_i(t) - m_i(t-1)\|. \quad (10)$$

If the minimum offset dm_i does not satisfy the specified condition:

$$MIN\ (dm_i(t)) \le \Delta_m\ ,\quad i=1,\ldots,k. \quad (11)$$

we will return to the allocation of elements to clusters. Otherwise, the adjustment of cluster centers m_i ends and moves to the next step. The condition (11) is not fulfilled and another iteration is carried out until the offset of values of the cluster centers will satisfy the accuracy requirements. Given the uneven distribution of cluster centers in the input space, as well as possible increasing the dimension of the model, it is appropriate to use Gaussian MFs [22] of formula (9):

$$\mu_{Vi}(x)= exp\ [-(m_i- x)^2/2\Delta^2],\quad i=1,\dots,k. \qquad (12)$$

In the absence of measurements in a neighborhood of the coordinate system origin the dummy cluster, completely excluding any element, is declared (m_{V0} =0.00). The value of δ_i is chosen to be equal one-third the distance $|m_i - m_{i+1}|$ in the input space V in accordance to (9).

The exception (12) for the *1*-st cluster is transformed in the asymmetric Gaussian function:

$$\mu_{V1}(v)= exp\ [-(m_1- v)^2/2(w\Delta_1{'}+ (1-w\,\Delta_1{''}))^2], \qquad (13)$$

where $m_1 = m_{V1}$ =25.33; w – auxiliary Boolean variable of the next form:

$$w= \{1,0\},\ w=1\ \forall v:\ 0\leq v\leq m_1. \qquad (14)$$

As a result of the clusters projection in the input space V m_{V1} = 25.33, m_{V2} = 178, m_{V3} = 255.33 are obtained. Output single-point MFs are defined in points m_{C1} = 46.67, m_{C2} = 210.67, m_{C3} = 313. The value $c(v)$ at the output of the fuzzy model is calculated by the formula (8). The membership functions of input and output parameters are presented in Fig.3.

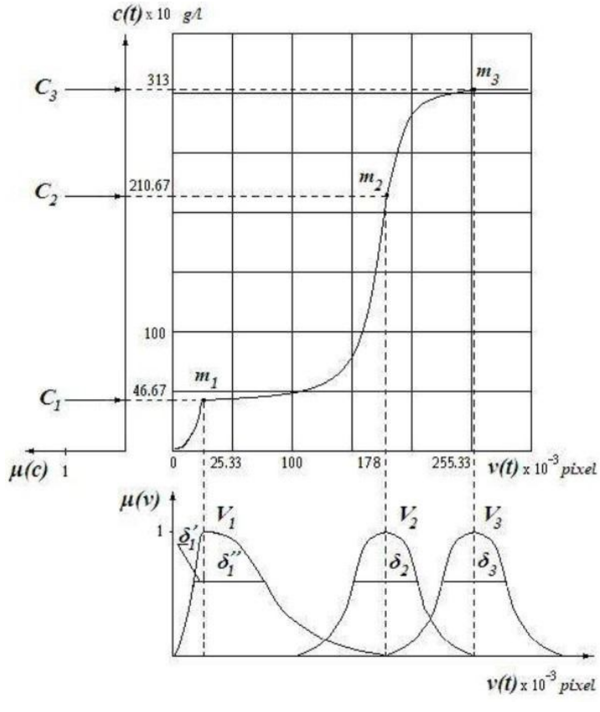

Figure 3 – Resulting fuzzy dependence of c(v) the resulting clustering and membership functions

After definition of such dependencies for all kinds of salts from Table 1 and the dependence of the form $c(V)$, we have the possibility to carry out the operational control of salts' PC, and indirectly to determine the dynamic changes in the concentration of pickling solution C_S with the recalculation of the mass of the *SO_4* groups in *FeSO_4 n*-hydrates. Within the cluster, the integrated function (8) is implemented using Gaussian MFs by the FCM – method, v_i and v_{i-1} are accepted as the centers of neighboring classes. The current value of $v(t) = x$, obtained during the execution of TP, belong to the i-th class by the criterion of the minimum Euclidean distance from the estimated object to the center of the i-th cluster – v_i.

Simultaneous accounting of the number of pixels of certain colors using computer vision tools corresponding to different types of salts in a solution makes it possible to fuzzy estimate the concentrations of several components of the solution at the same time. The proposed approach is based on measuring changes in the physical properties of solutions caused by the change in the concentration of the individual components. The obtained dependencies can form the basis of software converter for fuzzy estimation of the concentration of salts in solution.

It should be noted, that the greatest influence on the process has a change in the concentration of *FeSO_4 •H_2O*. Approbation of the proposed procedure showed the following result [31]: acid consumption for the pickling process was reduced from 1230 to 976 kg/h approximately while maintaining the same capacity of the pickling line.

The model for this type of monohydrate must take into account the errors associated with the presence of measurement noise. The following is proposed for this purpose. The range of initial values of the monohydrate *FeSO_4 •H_2O* concentration C is divided into segments having the same width, due to the required accuracy of measurements δ_{C1}. The formation of the neurofuzzy model is carried out based on the results of experimental serial measurements in M reference points of the model – cluster centers (V_n , C_n) with uniform sampling step and segments of values $((n-1)\delta_{C1}, n\delta_{C1})$, n= 1,2,… M, where M is estimated as:

$$M = [C_n / \delta C_1]. \tag{15}$$

Fuzzy sets C_n, formed at the output of the model in the process of data accumulation are replaced by singletons (cluster medians), which coincide with the modal values $C_1 = \delta_{C1}$, $C_2 = 2\delta_{C1},\ldots,$ $C_n = n\delta_{C1}$, to the maximum allowable value according to the process requirements:

$$C_n = sup(c(t)) = c_0 . \tag{16}$$

After adaptation, the presented procedure can also be used for evaluation of the rolled steel surface treatment quality by the number of areas of different colors defects at the exit of the pickling line. Also, it is planned to be applied the proposed procedure to build a coolant supply flow controller to control the temperature of the solution: class medians are built at reference points with known parameters of the flow valves.

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МЕТОД НЕЧІТКОЇ ОЦІНКИ КОНЦЕНТРАЦІЇ КОМПОНЕНТІВ ТРАВИЛЬНОГО РОЗЧИНУ СІРЧАНОЇ КИСЛОТИ

Стаття присвячена питанню визначення рівня концентрації окремих компонентів робочих розчинів. Актуальність теми полягає в тому, що деякі домішки в розчинах (наприклад, при травленні сталі) неможливо вимірювати в автоматичному режимі, що знижує ефективність технологічного процесу і збільшує навантаження на ділянку регенерації розчину. Також домішки є шкідливими відходами для навколишнього середовища та людини.

Розробка методу оперативного контролю складу компонентів травильного розчину травильних ваннах є основним завданням роботи. Дано докладне обґрунтування вибору математичного апарату методу. Процес нечіткої ідентифікації складу компонентів здійснюється за кількістю пікселів з певними цифровими колірними RGB-кодами з цифрових зображень контрольних доз розчину. Описано набір технічних засобів забезпечення методу для практичної реалізації в технологічному процесі. Представлений прототип графічного інтерфейсу користувача (GUI) запропонованого методу ідентифікації складу технологічних рідких розчинів, розроблений в інтегрованому середовищі Processing 3.0 з використанням додатків відкритої бібліотеки Open Source Computer Vision Library.

Запропоновано методику вилучення експериментальних даних для наповнення бази нечіткого класифікатора опорними точками моделі. Суть її полягає в одночасних вимірах концентрації компонент травильного розчину класичними методами титрування і сухих залишків і пропонованим методом з кроком, що дорівнює регламентованої точності. Наведено результати апробації запропонованого методу.

Представлена методика отримання нечіткого класифікатора може бути використана для розробки IT-інструментів оперативного контролю складу різних рідких розчинів з непрозорими кольоровими компонентами і колірної ідентифікації дефектів різних плоских поверхонь за умови їх колірної помітності і визначення меж RGB-інтервалів оцінок кольору окремих компонент (дефектів).

Ключові слова: класифікатор, метод нечітких середніх, комп’ютерний зір, функція належності, компонент травильного розчину, концентрація.

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МЕТОД НЕЧЕТКОЙ ОЦЕНКИ КОНЦЕНТРАЦИИ КОМПОНЕНТОВ СЕРНОКИСЛОТНОГО ТРАВИЛЬНОГО РАСТВОРА

Статья посвящена вопросу определения уровня концентрации отдельных Статья посвящена вопросу определения уровня концентрации отдельных компонентов рабочих растворов. Актуальность темы заключается в том, что некоторые примеси в растворах (например, при травлении стали) не представляется возможным измерять в автоматическом режиме, что снижает эффективность технологического процесса и увеличивает нагрузку на участок регенерации раствора. Также примеси являются вредными отходами для окружающей среды и человека.

Разработка метода оперативного контроля состава компонентов травильного раствора в травильных ваннах является основной задачей работы. Дано подробное обоснование выбора математического аппарата метода. Процесс нечеткой идентификации состава компонентов осуществляется по количеству пикселей с определенными цифровыми цветовыми RGB-кодами из цифровых изображений контрольных доз раствора. Описан набор технических средств обеспечения метода для практической реализации в технологическом процессе. Представлен прототип графического пользовательского интерфейса (GUI) предлагаемого метода идентификации состава технологических жидких растворов, разработанный в интегрированной среде Processing 3.0 с использованием приложений открытой библиоткеки Open Source Computer Vision Library.

Предложена методика извлечения экспериментальных данных для наполнения базы нечеткого классификатора опорными точками модели. Суть ее состоит в одновременных измерениях концентрации компонент травильного раствора классическими методами титрования и сухих остатков и предлагаемым методом с шагом, равным регламентированной точности. Приведены результаты апробации предлагаемого метода.

Представленная методика получения нечеткого классификатора может быть использована для разработки ИТ-инструментов оперативного контроля состава различных жидких растворов с непрозрачными цветными компонентами и цветовой идентификации дефектов различных плоских поверхностей при условии их цветовой различимости и определения границ RGB –интервалов оценок цвета отдельных компонент (дефектов).

Ключевые слова: классификатор, метод нечетких средних, компьютерное зрение, функция принадлежности, компонент травильного раствора, концентрация.

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FUZZY ESTIMATION PROCEDURE OF OF THE CONCENTRATION OF THE COMPONENTS OF A SULFURIC ACID PICKLING SOLUTION

The article is devoted to the issue of determining the level of concentration of individual components of working solutions. The relevance of the topic lies in the fact that some impurities in solutions (for example, when pickling steel) cannot be measured automatically, which reduces the efficiency of the process and increases the load on the solution regeneration section. Also, impurities are hazardous waste for the environment and humans.

The development of a method for the operational control of the composition of the pickling solution components in pickling baths is the main task of the work. A detailed substantiation of the choice of the mathematical apparatus of the method is given. The process of fuzzy identification of the composition of the components is carried out by the number of pixels with certain digital color RGB codes from digital images of the control doses of the solution. A set of technical means for providing the method for practical implementation in the technological process is described. A prototype of a graphical user interface (GUI) for the proposed method for identifying the composition of technological liquid solutions, developed in the Processing 3.0 integrated environment using applications from the Open Source Computer Vision Library, is presented.

A technique for extracting experimental data for filling the base of a fuzzy classifier with model reference points is proposed. Its essence lies in simultaneous measurements of the concentration of the components of the pickling solution by classical methods of titration and dry residues and the proposed method with a step equal to the regulated accuracy. The results of approbation of the proposed method are presented.

The presented technique for obtaining a fuzzy classifier can be used to develop IT tools for the operational control of the composition of various liquid solutions with opaque colored components and color identification of defects in various flat surfaces, provided that they are color distinguishable and determine the boundaries of RGB - intervals for assessing the color of individual component (defects).

Keywords: classifier, fuzzy c-means method, computer vision, membership function, pickling solution's component, concentration