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Risk-Oriented Approach to Assessment of Hexamethylenediamine Pollution of Aquatic Ecosystems

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ABSTRACT

HMD is widely used by industry in the manufacture of polyamide materials, as well as a substance in the production of epoxy resins and other substances. At the same time, HMD is a physiologically active, toxic and dangerous substance (hazard class II), which can cause burns, eczema-like dermatitis, diseases of the nervous system and gastrointestinal tract in humans. Wastewater contaminated with HMD, which is discharged into natural reservoirs, causes the death of aquatic organisms and aquatic vegetation, degrades the quality of water, which becomes unusable. HMDA is listed as a hazardous substance by the European Chemicals Agency and the American Conference of Government Hygienists of Industry.

Keywords: hexamethylenediamine, controle system, certain indicators, risk-oriented approach, toxic contaminants.

INTRODUCTION

The global hexamethylenediamine market is projected to reach $ 9.69 billion by 2027, according to a new report by Reports and Data [Water Framework Directive, 2021].

Adiponitrile is produced in the United States, Western Europe and Japan. The gradual increase in capacity in the United States has led to increased production. France is the only producer in Western Europe and will remain so for the foreseeable years. It is projected that changes in capacity in the adiponitrile market will be minimal in the coming years. World consumption of HMDA is presented in the diagram in Figure 1.

The market for mature nylon fibers has the greatest impact on global demand for HMDA. This correlation, however, plays a less dominant role in Japan and a declining role in the United States and Western Europe, as nylon resin begins to account for a larger share of the HMDA market. Demand for nylon continues to be weak, especially in the United States and Western Europe, and aggregate demand is growing below GDP.

Demand for HMDA has slowly recovered after the 2008 downturn, and is expected to reach 14% higher levels by 2027. Demand for HMDA in Northeast Asia over the past five years has been five times higher than in other regions, growing by an average of 10% per year. HMDA consumption and production are projected to grow faster than the average by 3% per year by 2023. HMDA trade will increase to 23% of production in 2023 as exports to Northeast Asia increase.

Due to growing environmental concerns, there is a growing need for bio-based production of hexamethylenediamine. This is expected to create demand for market participants internationally. The production of hexamethylenediamine and the increase in its use in industry is an uncontrolled process. Increased demand for Nylon-66 leads to increased production of HMD. The result is, accordingly, an increase in the burden on the environment and, in particular, on aquatic ecosystems.

The main problem is the lack of a hexamethylenediamine monitoring system in aquatic ecosystems. Thus, in the EU, among toxic substances

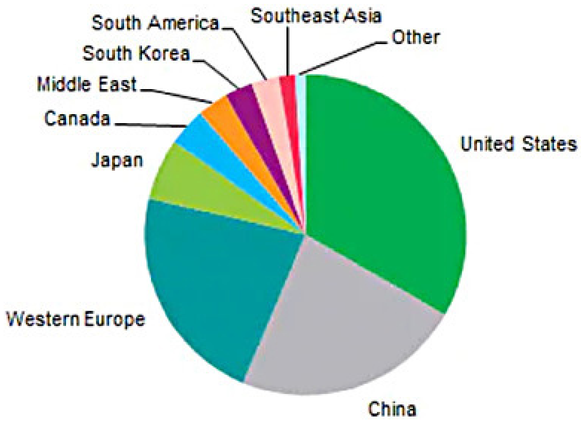

Figure 1. World consumption of hexamethylenediamine

discharged into industrial wastewater, monitoring studies are conducted for Phosphorus, Nitrogen, Oxygen, pH [Gemstat, Water Quality Dashboard, 2020]. HMDA is not in this list.

In addition, ensuring the reliability of data on monitoring of aquatic ecosystems is an urgent problem, because on the basis of these data decisions should be made to forecast the development of enterprises and regions, forecast the necessary measures to protect the environment and population in case of natural or man-made disasters. Existing methods of improving the reliability of monitoring data are based mainly on the use of structural and procedural redundancy. But these methods are usually implemented selectively and unsystematically, which does not ensure compliance of the obtained data with the requirements of environmental standards. At the same time, the state of drainage systems is influenced by more and more factors, most of which are very dangerous for natural reservoirs.

METHOD AND DATA PROCESS

The water quality monitoring system in aquatic ecosystems should include stages of determining the current state of existing pollutants, related factors and their impact on the spectrum and magnitude of pollution, pollution dynamics compared to previous measurements, verification of compliance with the dynamics of pollution trend, and decision making on the reliability of monitoring data and forecasts. To assess the impact of pollution on aquatic ecosystems should begin with the search and analysis of available data. Data mining is one of the most modern approaches to identifying hidden information that may be contained in the routine results of observations and which can not be simply obtained without the use of special methods of analysis [Cronover, 2000]. The fact is that modern complex control and recognition systems, as a rule, operate in conditions of incomplete and unclear information, which negatively affects their effectiveness. To increase the efficiency, accuracy and functional flexibility of such systems use a variety of software and hardware solutions, one of which is "augmented reality" (AR), ie ensuring the sufficiency, completeness, efficiency and reliability of information on which to make certain decisions. by generating additional data that are not directly (directly) present in the obtained observation data. AR can be provided through a variety of intelligent technologies, including analogy, including the Nearest Neighbor (NN) method [Dudnyk and Yevtushenko, 2013], which is used to identify causal relationships when necessary and forecasting further developments. This method is based on estimating the states of the "nearest neighbors", which are, for example, within the confidence interval 2σ, ie the uncertainty interval. Its essence in this case is that the characteristics of the object of study at the point of interest are compared with the data (characteristics) in the nearest (in time or space) to it neighboring points of the object. If there is a consistent change in status at all adjacent (right and left) points within the standard deviation, it can be assumed that there is a certain trend that can be trusted. To assess the above trend, you can use the following heuristics:

$$\textit{IF}\ [\mathrm{MSTAB}]\ \textit{AND}\ [\mathrm{SIGN\Delta ST}_{i\pm j}\mathrm{EQ}],\ \textit{THEN}\ [\mathrm{SPT}] \tag{1}$$

where: MSTAB - situation when the value being determined does not exceed the standard deviation;

$\mathrm{SIGN\Delta ST}_{i \pm j}\mathrm{EQ}$ - result of observation, which indicates that the sign of change of state during the current observation at all points to the right and left of and, ie at points from and to ij and from and to i + j, the same with respect to the state at the same points during the previous observation or in the spatial distribution;

SPT - a certain trend is observed (Figure 2). The increment of the state Δxi in the case of uncoordinated motion of the state indicators at the points x1–x5 has the second index 1 (ie Δxi1), and in the case of the agreed state - index 2 (ie Δxi2).

Another example of the use of the NN is the use of "spectral characteristics" to evaluate

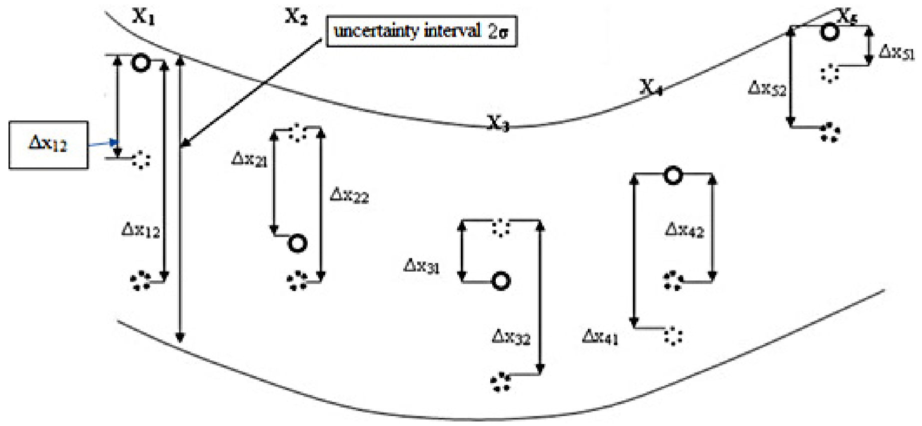

Figure 2. Graphic interpretation of the "Nearest Neighbor Method"

objects. The idea of this approach is as follows (Figure 3). Each object of observation is characterized by a certain number (spectrum S) of parameters (factors), which are characterized by certain indicators (amplitudes of the spectral characteristic A). For example, such indicators (in the case of observing the dynamics of the environment during a man-made accident) may be the emission of the toxic wastewaters with HMDA P, the number of individual types of toxicity emitted N, the maximum toxicity of emission components (HMDA) M, the maximum emission height H, wind force (speed) emission height V, precipitation intensity R, emission duration T, etc. All these indicators are presented in relative (up to the maximum possible value) form in the range [0, 1] at fixed positions of the spectrogram. It is a comparison of several "spectr" - known for all indicators, measures taken to minimize negative consequences, etc. (a) and, for example, unknown (b) and (c), in order to obtain a priori information on possible developments and the choice of preventive measures for normalization of the situation.

The similarity of "spectr" can be a guarantee of adequate comparison not from the point of view of their identity (this can hardly be in reality), but from the point of view of conformity of reflections, for example, when the behavior of each of the "spectr" relative to the left and right (i-1 and i + 1) "spectr" are similar in sign of the increment of the "spectral line". The heuristic can be written as follows:

IF {[signΔA (XY) (a)] = [signΔA (XY) (b)]}
for all corresponding *X, Y (P, N, M, H, V, R, T)*
THEN (spectra are similar), *OTHER*
{look for another standard (A)} (2)

Finally, there is another option for using the NN (Figure 4), when estimating the affiliation of an unknown object to the standard is done by finding

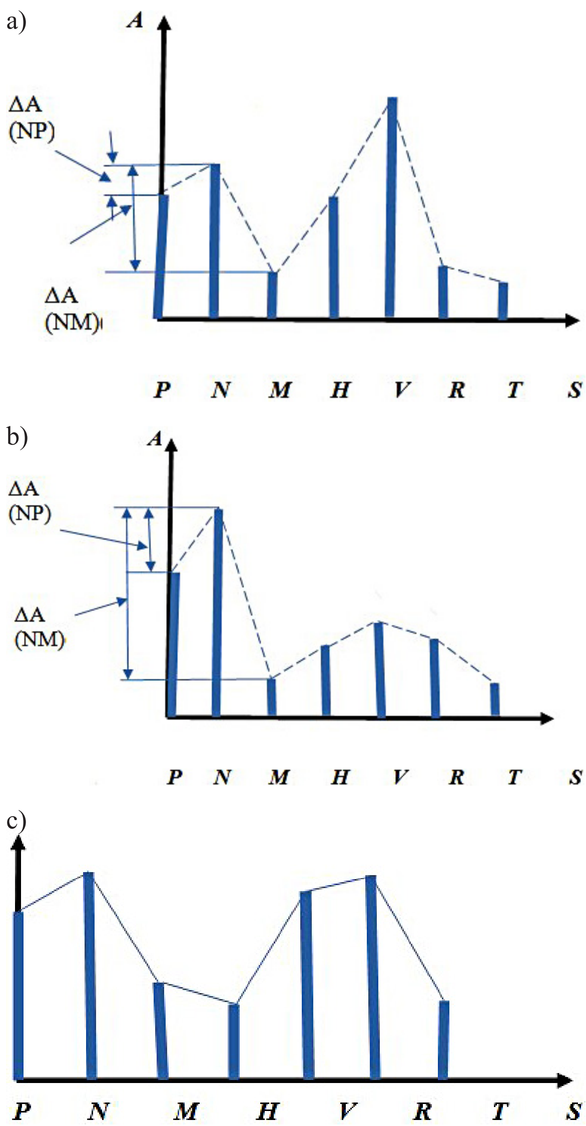

Figure 3. Graphical interpretation of the "spectral method"

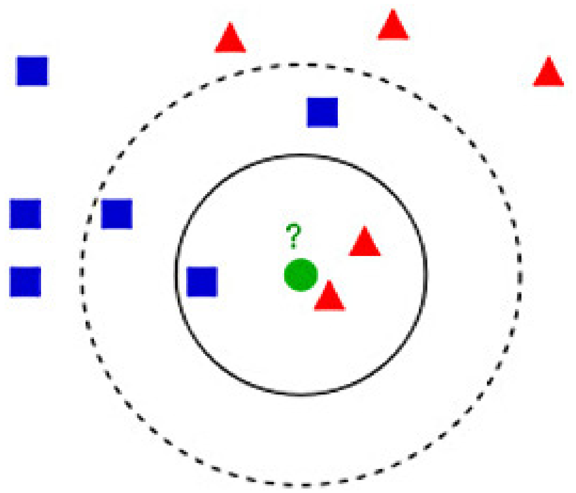

Figure 4. Example of k-NN classification

most analogies by expanding the confidence interval (increasing the number of k reference objects being compared). This is the so-called k-NN classification [Dudnyk and Yevtushenko, 2013].

The sample under test (circle in the center), can be assigned to the first class (samples in the form of squares), or to the second (triangles). If k = 3 (circle with a solid line), sample belongs to the second class, because there are two triangles and only one square in a circle. If k = 5 (circle with a dotted line), the sample is to the first class (three squares against two triangles inside outer dotted circle).

There is another way to use the NN, which can be called the method of model pluralism [Tsyganok and Roik, 2018]. The fact is that modern automated process control systems operate in a vague and incomplete information, which is accompanied by the presence of various risks in terms of adequacy of the selected objective function, the chosen algorithm and methods of evaluating results. In addition, in many cases there is an operation of indirect data, technological processes are often characterized by significant transport delays and inertia, process models are usually approximate, and the objects themselves are distributed in space, which creates a number of problems in terms of management processes and in terms of quality management. In such cases, the use of accelerated models of object M is often resorted to, which allows to predict the future response of the system to perturbations F (perturbations) and input signals F (input) and to take prudent management actions to ensure the required level of control quality. But such an approach is fruitful only if the model of the object adequately reflects the behavior of the real technological object within acceptable limits of change. But any empirical model adequately reproduces the behavior of a technological object only in a fairly narrow range of changes in input parameters and perturbations, within certain limits of the real state of the system and its connections. Beyond these limits, the model may be inadequate and, instead of improving the quality of regulation, may have the opposite effect. Therefore, it is proposed to use a set of models, each of which under certain conditions (within appropriate limits) can adequately reproduce the real situation, although it is not possible to objectively choose one or another model in advance. The idea of the approach is as follows (Figure 4). All models are initiated simultaneously and generate output signals that correspond, for example, to a response to a single input pulse. The same pulse is applied to the input of the real system and at its output a corresponding reaction is generated in the form of y_f (t). Output signals from all models and from the real system are fed to a unit that calculates Euclidean measures (distances) between the signal at the output of the real system and the signals at the output of each of the k models.

$$d_j\left[f^{(f)}, f^{(j)}\right] = d^{(k)} =$$

$$= \{[(n-1)^{-1}] \sum_{i=1}^{I} \{[x(fi) - x(ki)]^2\}^{1/2}\} \tag{3}$$

where: k - number of selected models;

n - number of points at which the values of the output signals of the models and the real object (quantization points) were measured,

x (fi) and *x (ki)* - values of the functions x (f) and x, respectively) at the i-th points *(*i $= \overline{I, L}$*),* where *I* - number of quantization points.

The choice of the optimal M_{opt} model meets the condition:

$$M_{opt} = M\,(min\,\{d^{I}E, d^{II}E, d^{III}E\}) \tag{4}$$

The paradigm of automation is the presence of feedback, which allows to respond to the deviation of the controlled parameter from the desired value, and take measures to return it to the specified limits. All other ideas (using external influences to predict system behavior, or ensuring control invariance, finding optimal modes, etc.) are helpful. At the same time, the processes in water treatment systems have their own characteristics: insufficient and unclear information at the input and output of systems, irregularity or significant delay in obtaining input and output data, the impact on processes of many factors that can not always be identified. All this creates certain problems that interfere with process management, reduce the quality and efficiency of automation [Lytvynenko and Dychko, 2021]. In order to avoid these problems, it is proposed to focus on the following areas:

- representation of variables and parameters in linguistic form and in the form of membership functions;
- use of heuristics instead of "exact" control algorithms;
- using a risk-oriented approach when choosing methods and tools.
- use of "hybrid" control methods.

RESULTS

At most water treatment processes the initial data and parameters are sometimes difficult to present in the form of accurate information (this applies primarily to data, for example, on the content of ingredients in water (including hexamethylenediamine) sent to the water treatment system, pH, BOD etc.), so it is necessary to evaluate such data in the form of linguistic variables, characterizing the content of certain components, for example, in the form of such terms as "absent" or A (0,0), "little" or M (0,25), "Average" or C (0.5), "many" or B (1.0), etc.

The procedure for using membership functions is exhaustively illustrated in Figure 5.

Instead of an "exact" control algorithm, you can write a heuristic that determines the necessary control actions under certain conditions, for example, as follows:

IF (necessary conditions) *YES /*
OR (necessary conditions)
YES / OR (necessary conditions), (5)
THEN (necessary measures)
OTHERWISE (alternative measures)

The risk-oriented approach in the choice of management methods and tools involves minimizing the risks of inadequate management in conditions of uncertainty and unpredictable sets of source data and parameters. This approach is based on an a priori statistically weighted definition of the limits within which processes can be managed for each of the values of acceptable risks. This can be implemented as follows.

In some cases, the assessment of risks to management decisions is ambiguous in estimates, due to the fact that estimates based on different approaches and using different models (ie in the presence of several risks of different nature) can differ significantly from each other and the result evaluation may become unacceptable due to significant ambiguity and blurring of the input data. Therefore, such an assessment is best done using the method of step-by-step comparison of pairs of estimates [Pankratova and Manyak, 2018], when it comes to identifying such estimates that correspond to the minimum consistency index I.

$$I = \sum_{i \neq j} f(|x_i - x_j|) \tag{6}$$

where: x_i and x_j are the estimates of the i-th and j-th evaluation steps in relative units. In this case, the optimal estimate will be:

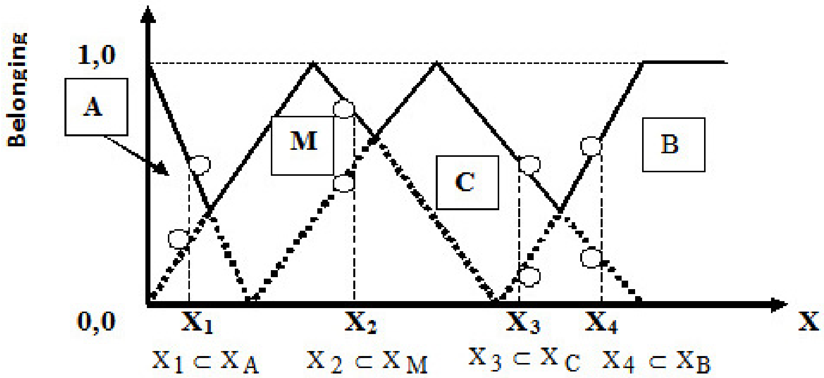

Figure 5. The procedure for determining whether a particular value belongs to the corresponding linguistic variables

$$I_{opt} = \underbrace{\min}_{i,j}\{\sum_{i \neq j} f(|x_i - x_j| \tag{7}$$

that is, acceptable solutions will be those that differ little from each other.

It should also be borne in mind that the system, the behavior of which is made by certain decisions, is always influenced by certain factors, which can be divided into those that facilitate or, conversely, create obstacles to achieving the goal, as well as factors which provide certain additional opportunities for the successful solution of the problem, or, conversely, pose a threat to its successful solution. Therefore, it is worth using SWOT-analysis, which just allows you to effectively solve the problem of finding the optimal solution [Dychko and Yeremeev, 2014]. Indeed, if we consider the system in terms of factors that facilitate the solution of the problem, or create additional opportunities for its successful solution, we can obtain a certain formalism such as

$$K_{sc} = \max\{\underbrace{\max}_{j}\{\mu_s K_s\}, \underbrace{\max}_{k}\{\mu_o K_o)\} \tag{8}$$

where: K_{SC} is the coefficient of success of the problem under consideration, max is the operator of multivalued logic of "addition" (or "OR"),
μ is the correction factor that takes into account the presence of risks and their mutual influence on each other,
K_S and K_O are the coefficients of influence of factors, which facilitate the solution of the problem and the influence of factors that provide certain additional opportunities for successful solution of the problem. Here

$$\mu_p = 1 + \{\frac{r-1}{2r}\}\sum_{i=1}^{r} k_i \tag{9}$$

where: r is the number of identified risks;
μ_p is the value of the correction factor for p = [s, o];
k_i is the effect of risk on each other.

The same formalism can be made for factors that worsen the conditions for achieving the goal, or carry hidden threats to the successful solution of the problem (or unsuccessful):

$$K_{usc} = \max\{\underbrace{\max}_{m}\{\mu_w K_w\}, \underbrace{\max}_{n}\{\mu_t K_t)\} \tag{10}$$

The overall decision-making efficiency (DME) can be considered as the difference between the above coefficients:

$$K_{dme} = K_{sc} - K_{usc} \tag{11}$$

and

$$K_{dme} >> 0 \tag{12}$$

Finally, it is worth mentioning the methods of "hybrid" process control [Dychko and others, 2020], which involves the use of several alternative models of behavior of the controlled object, and each of the models fundamentally accurately reflects the object, but with different sets of internal factors (parameters). it is impossible to identify in advance and therefore use an adequate model. Moreover, the simultaneous use of all relevant models operating on an accelerated time scale, allows you to choose the model (optimal), which most closely corresponds to the behavior of the real object at the initial stage of modeling, determined by estimating the Euclidean metric, which indicates or other difference in the distributions of real values and simulation data. Figure 6 shows a block diagram of a module that implements the above control method. Here F (input) and F (perturbation) are the input signal and the test perturbation signal, respectively, uf is the actual signal at the output of the real system, and y1, y2 and y3 are the signals at the outputs of the respective models, tfr and tpij are the durations of the real transients. object and i-th models. The Euclidean metric d_E (the distance between the distribution of actually measured values of amplitudes y_i and the distribution of values y_{ij}, which correspond to the i-th model) is from the expression

$$d_E = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(y_i - y_{ij})^2} \tag{13}$$

The choice of the optimal M_{opt} model meets the condition:

$$M_{opt} = M\,(min\,\{d^I E, d^{II} E, d^{III} E\}) \tag{14}$$

The management of the company's treatment facilities takes place in conditions of limited (incomplete) and unclear information, which affects the efficiency of treatment processes both in terms of treatment quality and in terms of reagent and energy costs. The fact is that the indicators of wastewater (SE) that come to treatment plants are not determined, as a rule, online and, in addition, certain average data are often used in management practice. At the same time, regulatory influences aimed at achieving effective management may become inadequate to the current situation and there is a risk of losing control over the cleaning process. The problem of JI HMD sewage treatment plants (STP) can be represented in the form of the following scheme (Figure 7).

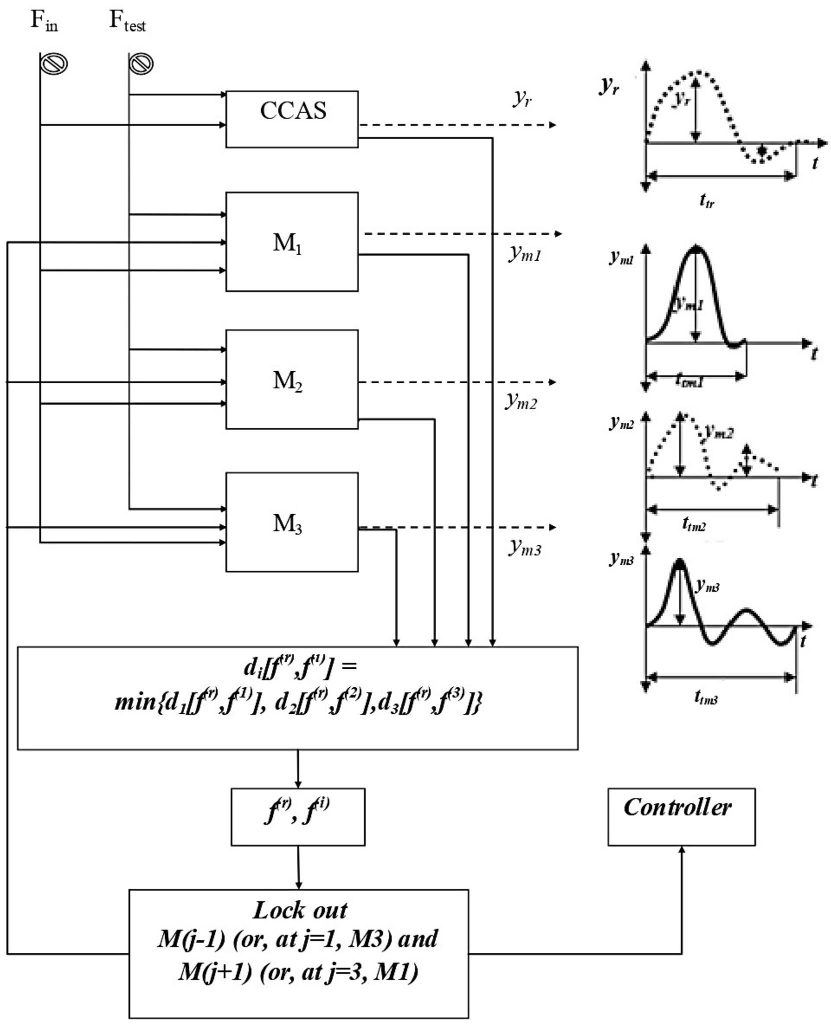

Figure 6. Block diagram of a module that implements hybrid control

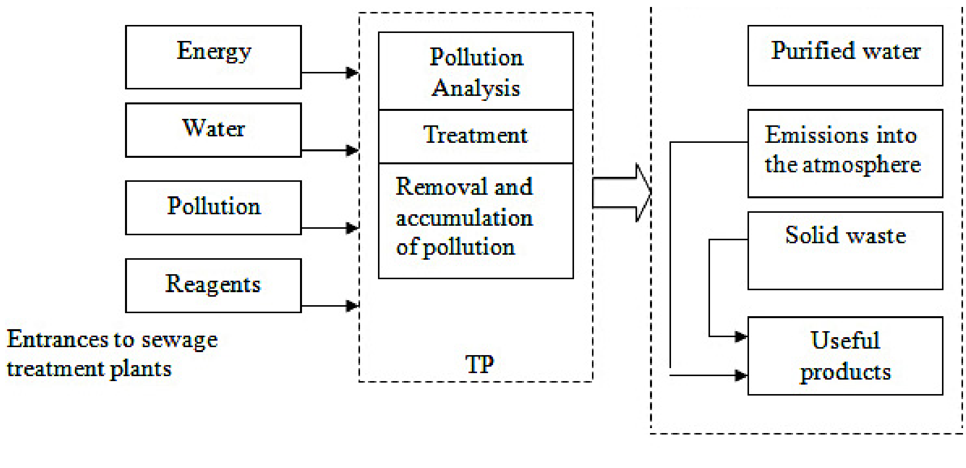

Figure 7. Inputs, handling procedures and STP outputs

There are risks of inadequate management during STP management due to downpours, hazardous microorganisms, accidental chemical discharges, and personnel errors. In addition, there are risks of inability to clean a particular contaminant, as well as the priority of cleaning (PC) of certain pollutants, and the software is adjusted by the confidence factor (CF) of the cleaning efficiency of this particular pollutant

$$\mathrm{OS} = \mathrm{PC} * \mathrm{CF} \tag{15}$$

where: *OS* is the optimal software.

For example, the treatment of wastewater from hexamethylenediamine is the maximum (PC_{HMD} = 6), but the efficiency of its removal from wastewater is only 70% and therefore OS_{HMD} = 6 * 0.7 = 4.2.

Heuristics are also often required to be guided by confidence factors (CF). If there is a heuristic type

$$\text{IF (condition) AND (condition), THAT (consequence)} \tag{16}$$

and the CF of the first condition CF_1 = 0.6, and the second – CF_2= 0.8, and confidence in the consequence of CF_3 = 0.9, the total confidence factor CFΣ can be represented as

$$\mathrm{CF\Sigma} = (\min[\mathrm{CF1}, \mathrm{CF2}] * \mathrm{CF3}) = 0.6*0.9 = 0.54 \tag{17}$$

The risk-oriented approach in the choice of management methods and tools involves minimizing the risks of inadequate management in conditions of uncertainty and unpredictable sets of source data and parameters. This approach is based on a priori statistically weighted determination of the limits within which processes can be managed for each of the values of acceptable risks. If you specify through N - the number of cases of reduced quality of cleaning for verified reasons; N_i - the number of cases of reduced quality of cleaning, the objective cause of which is di; N_{ij} - the number of cases of reduced quality of treatment, for which the theoretical diagnosis (according to the fuzzy model) is dj, and the real reason for their occurrence is di, it is possible to formulate statistical estimates of the quality of water treatment process [Pankevich and Shtovba, 2005]:

- $\dot{p}_{\mathrm{ii}} = \frac{N_{ii}}{N_i}$ assessment of the probability of decision-making di under the conditions of objective necessity of decision-making di;
- $\dot{p}_{ij} = \frac{N_{ij}}{N_i}$ assessment of the probability of decision-making dj under the conditions of objective necessity of decision-making di;
- $\dot{p} = \frac{1}{N}\sum_{i=1}^{m} N_{ii}$ assessment of the probability of error-free diagnosis for all possible reasons for reducing the quality of treated effluents.

To design the intelligent part of the water quality management system you need to know:

- a list of possible reasons for reducing the efficiency of the process;
- fuzzy output tree;
- base of fuzzy rules *IF* {…}, *THEN* {…};
- training sample.

Chemical fiber production plants are a constant source of pollution of aquatic ecosystems in the form of individual spots, including spots of toxic contaminants of vehicles (TCV), such as hexamethylenediamine. The latter are characterized by rather low levels, which differ slightly from the background, which complicates the problem of studying the dynamics of TCV. The task of identifying the dynamics of TCV can be reduced to the analysis of observations and comparing their results with each other by estimating the metric, ie a negative function that characterizes the degree of proximity of an ordered pair of points (curves, surfaces) in the metric space. Euclidean metrics can be used as a criterion for the degree of discrepancy in the identification of TCV.

To implement the proposed approach, it is necessary, first of all, to form a set of standards - alternative models, each of which simulates the migration of vehicles outside a particular region in relation to one of the possible situations that may occur in the region or its surroundings (tectonic shifts, flooding of the region, downpours, tornadoes, etc.). In addition, as a reference, you can use information about the actual distribution of TCV in the area within the region, obtained by processing data from representative samples in the period preceding the start of the study. This information will characterize the "acceptable" level. Finally, the distribution of TCV at any time after the start of the study can be used as a reference, including the distribution of TCV after the actual "incident" that took place, ie the incident involving the release of CV (as a result of inefficient cleaning). wastewater or emergency) into the environment with the subsequent migration of TCV in the controlled region.

The whole procedure is generally implemented in the following sequence:

- a set of SM = {smk} alternative models is formed, which is known that for each case it is possible to choose the optimal model $sm_{opt} \in SM$;
- simultaneously or sequentially extrapolated (using k models) data characterizing the state of the object or process being controlled, at those points $i \in I$, where then (after the end of the extrapolation interval) the actual state of the object can be determined (measured). object (process); the obtained distributions are smoothed using the same smoothing algorithm and reference sets are formed

$$x_{smk} = \{x_{smki}\}, k \in K \quad (18)$$

- the real state of the object (process) is measured at the points $i \in I$; the obtained distribution is smoothed using the algorithm used earlier in the formation of xsmk, and a fuzzy set x (r) = {x (ri)} is formed;
- for the relation on x (r) and x (smk) the same order of ordering S [x (i)] is used, which proceeds from the same for both sets procedure of construction of smoothed (flat or spatial) curves on point values of x (smki) and x (ri);
- the relation on S [x (r)] in S [x (smk)] is taken to be a fuzzy set k of ordered pairs of flat or spatial curves of extrapolated (using k models) and actual distributions of states (parameters) that cause interest, which is characterized membership function

$$d^{(k)} = d\,[x(ri);\, x(smki)], k \in K \quad (19)$$

or the inverse of its value - the metric

$$d^{(k)} = \{[(n-1)^{-1}]\sum_{i=1}^{I}\{[x(ri) - x(smki)]^2\}^{1/2} \quad (20)$$

- the metric corresponding to the optimal smopt model is determined, for example by means of procedure

$$d^{(k)}_{opt} = \min\{d^{(1)}, \ldots, d^{(k)}\} \quad (21)$$

- the obtained metric $d^{(k)}_{opt}$ is correlated with the upper (maximum allowable) limit (measure) of non-compliance of the standard dmax, for example by means of inequality

$$d^{(k)}_{opt} \le d_{max} \quad (22)$$

in the case of non-fulfillment of inequality (1), the membership of individual elements of the fuzzy set k is determined to some ordered ensemble of points, which is characterized by the values

$$\sup|x(ri) - x(smki)| \le pd^{(k)}_{opt}) \quad (23)$$

where: p > 1 is a coefficient proportional to the value of the confidence interval;

- construction on the basis of the analysis of the results of comparisons (18) and (19) of the heuristic, which unambiguously characterizes the state of the environment.

A separate issue when considering the problems of migration of TCV is the digitization and display of the boundaries of the contour of TCV and their storage to further determine the trends of migration of pollutants. It is proposed to use a modified fractalization algorithm based on the classical algorithm for constructing a fractal curve according to observations [Pankevich and Shtovba, 2005], which involves the creation of a dichotomous fractal structure. His idea is to use the "floating" height of the approximate isosceles triangle, and the latter is not based on the middle third of the segment, but on the entire segment L_{m-1}: is the middle of the original segment of straight length L_{m-1}, which connects the boundary points of "chaos", and at this point a perpendicular is raised, the height of which h_{mj} is equal to the sample mean deviation ξ of the actual distribution $F^{(F)}(f_i)$ from the "model" $F^{(R)}(f_i)$ (which in this case is the segment L_0), and the sign (ie orientation inside or outside the approximation area) corresponds to the sign of this deviation. If | ξ | ⊲ | ξ_max |, where ξ_{max} is the maximum allowable deviation value, which is determined by the value of the allowable approximation error, the fractalization process stops. In the opposite case, an isosceles triangle is constructed on the basis of L_m taking into account the height h_{mj}, the sides of which represent a new model of distribution of the variable we are interested in, and now a sample mean deviation (and its sign) is determined at each of the obtained approximation sections. Each time the next segment of the approximating straight line is replaced by a broken line, which is the side of the triangle, the basis of which is the segment of the approximating straight line L_m obtained in the previous step of fractalization. After each fractalization step, a sample standard deviation $d[F^{(R)}, F^{(F)}]$ is calculated, which is compared with | ξ_max |. Based on the obtained results of the comparison, a decision is made to continue the process of building a fractal structure, or its completion. The result of fractalization (a model that approximates the "chaotic" process on the approximation section) can be written as the value of the fractal $L_m = L_0(2^{m-1})^{-1}$, where m - is the number of steps performed during the construction of the fractal structure, as well as a set of 2^{m-1} values of fractal coordinates.

CONCLUSION

The above algorithms are simple, easy to implement and allow to obtain a fairly good degree of approximation of non-smooth functions in a small number of steps.

The obtained results provided unambiguous identification of the facts of TCV migration, which allows us to consider the above method of identification as a fairly universal tool for detecting the dynamics of any type of pollution, close in level to the permissible level in nature.

The proposed approach was tested during the assessment of the dynamics of migration of NCV (hexamethylenediamine contamination) low (close to acceptable levels) pollution of the aquatic environment at the border of the sanitary protection zone of PJSC "Chernihiv Khimvolokno".

The development of automated control systems for biological wastewater treatment processes, taking into account the above areas, will significantly improve the quality of management and safety of processes and operation of technical means. An effective method for wastewater treatment of chemical plants is the use of biological methods. Based on the conducted experimental work, the most destructive microorganisms capable of immobilization on carriers were selected, as well as a complex biotechnology of water environment rehabilitation containing HMD and other xenobiotics was proposed. The essence of the proposed latest biotechnology is to involve in the process of wastewater treatment a wide range of aquatic organisms, from bacteria-destroyers of the most dangerous, toxic synthetic chemicals (xenobiotics) - and ending with highly organized filters, predators, higher aquatic plants and even fish.

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