

ARTIFICIAL NEURAL NETWORKS IN CONCENTRATION METERS FOR HETEROGENEOUS LIQUID MEDIA

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Abstract – Some practical aspects concerning design of intelligent concentration meters for heterogeneous liquid media are considered. Multi-sensor turbidimeters with artificial neural networks (ANN) are proposed as examples of devices in which high functional reliability and long service life time are provided due to elements of Artificial Intelligence (AI).

Keywords: artificial neural network, concentration meter, heterogeneous liquid media

1. INTRODUCTION

The problem of suspended particles concentration measurement for liquid media (emulsions and suspensions) is very typical for practice of industrial measurement. Generally such measurements are based on absorption and (or) dispersion of energy for any wave process. For example, optical, ultrasonic, microwave and radiation meters of concentration are well known.

Optical devices for measuring turbidity or concentration of particles are called turbidimeters. Turbidity is the optical property of liquid media that causes light to be scattered and absorbed rather than transmitted in the line direction. The cause of the light scattering is the presence of small particles having optical properties different from ones for the liquid medium. So it is possible to measure turbidity by light attenuation or scattered radiation intensity [1].

In all cases there is rather complicated problem of providing invariance of concentration measurement with respect to such influencing factors as dirtying of irradiators' and detectors' windows, dispersity of a medium (mean size of particles) and others.

So-called ratiometric principle is realized in almost all contemporary models of turbidimeters and concentration meters [2]. According to this principle, it is necessary to obtain at least two signals of photoreceiver(s) corresponding to different measuring base (distances between a source and a photoreceiver or angles between their axes) and then to calculate the ratio of these signals. The result will be free of many unstable parameters, such as brightness of source or transparency of windows.

One well-known invention realizing ratiometric principle is called as Four-beam pulsed light method [2,3]. It consists in the following. There are two light sources and two photoreceivers located so that each source is directed to a photoreceiver and its scattered under 90° radiation is directed to another photoreceiver. The sources are pulsed consecutively. Two signals are detected at each of the photoreceivers. Then these four signals are used for calculating the special ratio R , which is free of the mentioned unstable parameters.

It is possible to solve the problem of invariance for concentration meters by means of multi-sensor devices in which the informational redundancy can be obtained by various ways [2]. But determination of concentration with traditional signal processing and calculating algorithms for such devices is rather difficult because of complexity of relationships between signals and influencing physical factors.

2. ARTIFICIAL INTELLIGENCE, INFORMATIONAL REDUNDANCY AND FUNCTIONAL RELIABILITY OF MEASURING DEVICES

Application of AI elements in measuring devices allows complicated measurements to be easily implemented in conditions when traditional approaches behave hardly:

- in multiparameter measurements when relationships are very complicated or underdetermined;
- when signals are noisy or distorted by pulse disturbances;
- in case of environment aggressivity where the high probability of any element failure takes place.

As a result, functional reliability of intelligent measuring devices is incomparably higher than that traditional measuring devices perform.

All intelligent systems, including measuring systems, have to possess informational redundancy to a greater or lesser extent [4]. Thus many of intelligent measuring devices are multi-sensor systems or content a sensor in which a scanning parameter is used.

Informational redundancy, as a prerequisite and a resource for obtaining measurement information reliability, may be used for:

- increase survivability (i.e. keeping working capacity in case of any system's part failure);
- improvement the operational characteristics, such as accuracy (the latter may be achieved by means of statistical treatment, choice of optimal operational range corresponding to a certain sensor, making combined indirect measurements for several quantities some of which are disturbances and others).

Multi-sensor concentration meters for heterogeneous liquid media are the good illustration of using informational redundancy and AI elements, such as ANNs. Informational redundancy may be achieved here not only by additional physical measuring channels, but due to application of such scanning parameters as wavelength of probing radiation, distance or interaxial angle between an irradiator and a detector.

3. TRADITIONAL REGRESSION ANALYSIS AND NEURAL SIGNAL PROCESSING IN CONCENTRATION METERS

To provide concentration measurement invariance under the influencing factors it is necessary to obtain a superabundant set of signals from a multisensor system and then use a special computational tool. Traditionally, the well-known methods of Regression Analysis, such as the Least Squares Method (LSM) are used. By LSM we can determine calibration relationships between measurands (such as voltages) and primitive physical parameters (such as concentration, windows transparency, dispersity). Such several-dimensional relationships can be written as the following equation in vector notation:

$$\mathbf{U}=\mathbf{A}\mathbf{X}, \quad (1)$$

where \mathbf{U} and \mathbf{X} are vectors of measuring and primitive parameters, \mathbf{A} is a linear or non-linear operator. For calculating parameters of \mathbf{X} we must apply the inverse operator \mathbf{A}^{-1} :

$$\mathbf{X}=\mathbf{A}^{-1}\mathbf{U}. \quad (2)$$

But for all that it often happens to confront with the following difficulties:

- it is probably we can find a result having low computational stability due to bad robustness property of \mathbf{A} , so even a small error in elements of \mathbf{U} or \mathbf{A} can lead to an immense error in finding elements of \mathbf{X} ;
- often it is hard to set and define parameters of \mathbf{X} with acceptable accuracy;
- the relationships (1) themselves may be rather complex, their structure and type are often unknown.

From these reasoning we come to conclusion: it is very appropriate to use ANNs for industrial multi-sensor concentration meters' signal processing. They help to simplify considerably the problem of calibration and multidimensional signal processing.

Outputs of detectors (or some generalized parameters calculated from them) from a multi-sensor system may be directed to inputs of an ANN. The ANN single neuron output will represent calculated concentration. Traditional calibration in such concentration meters will be substituted for learning process. In that case for providing measurement invariance under some influencing factors it is not obligatory to know exactly the relationship between measurands and those factors, it is unnecessary to set exactly values of influencing factors during calibration, it is unneeded to carry out any mathematical manipulation like (2) which can be accompanied with the loss of accuracy. It will be enough to study the ANN to ignore fluctuation of influencing factors.

4. REALIZATION OF CONCENTRATION METERS WITH ANNs

4.1. Fiber-optic multisensor turbidimeter specially designed for application with ANNs

The author proposed special construction of online turbidimeter for "oil-in-water" emulsions, which allows to obtain invariant results for measurements of concentration. Obtained results are free of influence of dirtying on light sources' and detectors' windows and dispersity of emulsion. The best technology of signal processing for such turbidimeter is based on the use of ANNs.

The idea is the following.

The Four-beam pulse scheme shortly described above can work not only if the angles between axes of two pairs "light source – opposite detector" are 90° , but if the angles (in further text we'll call these angles as interaxial) have other values. It means that we can obtain the radiometric results as R for various interaxial angles in range $0..360^\circ$ (keep in mind that R is independent of the window transparency). Such information would be rather useful because the intensity of scattered light is the function of the angle between directions of probing and scattered radiation, and the directional diagram for scattered light depends on dispersity of emulsion.

The construction of the proposed turbidimeter is shown in Fig.1. We use 12 fiber-optic sensors, distributed on the surface of a cylindrical measurement cell with angular step 30° . Each sensor consists of a bifurcated fiber bundle, in which the common end is embedded into the wall of the measurement cell and directed to the same end of the opposite bundle, and the two other ends of the bundle are directed correspondingly to the light source and the detector, connected to the special controller.

During the operational round the controller implements the sequential pulse switching on for the 12 light sources and interrogation of all detectors. After that procedure the controller's memory keeps twelve 12-component arrays of detectors signals, from

which we can take the corresponding values for calculating ratios R for 12 different interaxial angles.

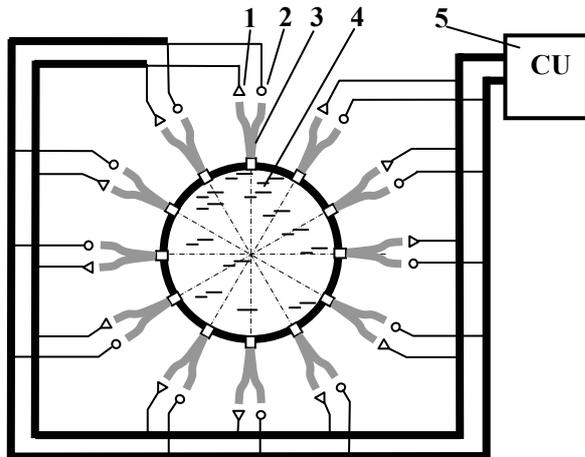


Fig. 1. Multi-sensor fiber-optic turbidimeter: 1 – photodetector; 2 – light source; 3 – bifurcated fiber bundle; 4 – measurement cell; 5 – controller.

So we have 12-component array $\mathbf{R}=(R_1, R_2, \dots, R_{12})$.

The array \mathbf{R} depends as well on concentration of suspended particles C as on dispersity d : $\mathbf{R}=\Phi(C,d)$, where Φ is the vector function (represented by 12 equations).

The traditional way to obtain an invariant result of measuring C includes the following steps:

- to implement a set of calibration experiments for acquisition of values \mathbf{R} for various C and d values combinations;
- to find functional relationships for Φ using methods of Regression Analysis;
- to solve the combined equations of Φ for obtaining C .

There are a lot of difficulties to realize all these procedures. Firstly, the complexity of relationships and the limited accuracy of photometric measurements leads to instability of calculated result C . Secondly, it is very hard problem to measure and to fix at desired values such factor as dispersity during calibration.

So application of ANNs for signal processing in this case appears more preferable. Calibration and further calculations can be substituted for an ANN training.

In our experiments the MultiLayer Perceptron (MLP), shown in Fig.2, was used for the turbidimeter signal processing. 12 inputs corresponds to 12 components of \mathbf{R} . Output neuron is the single; it produces the value of sought quantity C . The number of hidden layers may be 1 or 2. The author applied the single hidden layer with 10 neurons and less. More complicated structure is unreasonable.

The turbidimeter was included into the special calibration workbench with closed hydraulic loop, in which the water could be pumped. Concentration of oil could be changed by means of a special syringe,

and dispersity could be changed by means of the mixing machine.

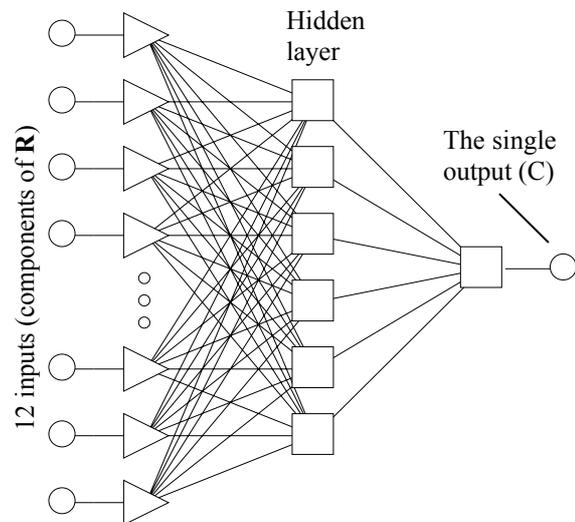


Fig.2. Network structure applied for signal processing of the turbidimeter

It is known that dispersity of emulsions depends on time of mixing. During the mixing process the current values of \mathbf{R} were registered, and it was repeated for different values of oil concentration C . Then, the sample collection, gathered in such a way, was presented during the training session of the ANN. Note that in this case it is unnecessary to know and fix dispersity at certain values: quite enough to know that its quantity changes in full range of its possible values during mixing. Thus the ANN learns to produce the right result ignoring changes of dispersity.

4.2. Wide-range multi-sensor contactless turbidimeter with neural signal processing

Contactless turbidimeters possess the obvious advantage in comparison with contact ones. That is the opportunity of unattended operation over a long period of time. This opportunity takes place due to the absence of dirtying on optical elements (light sources and photoreceivers). Consequently there is the stable transparency of optical channels [3].

An example of multi-sensor contactless turbidimeter is shown in Fig.3. Its photodetectors can be connected to a controller implementing neural signal processing. This construction is based on non-contact measurement in a free-falling liquid stream [5]. The liquid passes through the special vessel-stabilizer, whose overflow arrangement provides a constant supply pressure and the liquid flows through a nozzle at the bottom of the vessel in a free-falling stream. This stream is illuminated from the top. The light beam penetrates the liquid surface in the vessel and passes axially through the free-falling liquid jet. Photodetectors measure the intensity of the 90° scattered light at different levels.

Proposed by the author ring shape of photodetectors allows to exclude the influence of stochastic deflections of the stream, and the set of photodetectors (from 3 to 5 of ones) distributed along the jet and connected to a controller with an ANN provides wide dynamic range of turbidity measurement and high accuracy at all subranges of concentration.

The ratiometric principle is useful here too, and it is expedient to use not signals U_1-U_5 received directly from detectors but their ratios U_2/U_1 , U_3/U_1 , U_4/U_1 , U_5/U_1 , which can be input variables for an ANN.

There are appropriate optimal ratios (from the standpoint of error minimization for concentration determining) for different concentrations of particles in liquid. For example, the ratio U_5/U_1 would be the best for clear liquids, and the ratio U_2/U_1 is more appropriate for heavy turbidized liquids.

So it is available to study the ANN, which has the mentioned inputs and the single output, to determine concentration in extremely wide range. Moreover, such a system is capable of high precision at all subranges, and the converting “inputs-output” itself is permanent and stepless (there is not any evident change-over from subrange to subrange).

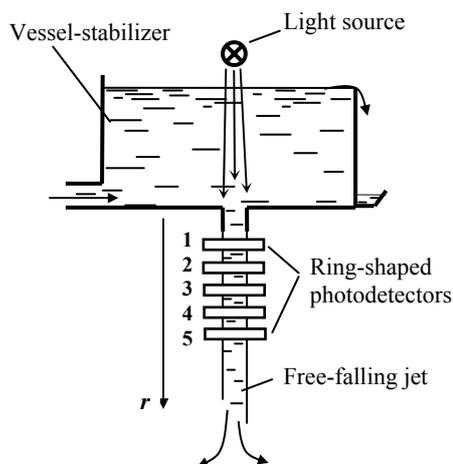


Fig.3. Multi-sensor contactless turbidimeter

5. COMPARATIVE ESTIMATION OF VARIANTS WITH DIFFERENT ANNs

5.1. General features

For every particular project of concentration meter there are proper ANN paradigm, configuration and learning algorithm, which are more efficient than others [6]. In case that it is more preferable to do neural processing directly at a controlled object by means of a cheap controller, Radial Basis Function (RBF) networks can be applied with much success. They are characterized by the fast learning speed, the satisfactory performance and the relatively small

number of neurons. But the number of input variables has not to be large, commonly not more than 4-6. For example, the ANN for the device shown in Fig.3 could be successfully realized on the RBF paradigm basis.

Generalized Regression Neural Networks (GRNN) can be studied almost instantly, but, as a rule, the hidden layer of a GRNN can have rather large number of neurons, which equals to the number of cases (measurements). Generally, such ANNs require more computational resources than RBF networks.

In case of using high-performance controllers or if a remote computer executes a neural processing, the Multilayer Perceptrons (MLP) may be quite acceptable. Moreover, usually it is quite enough to have only one hidden layer in the structure of such ANN. General characteristics of the MLP are its relatively slow learning speed and opportunity for obtaining high network performance. The choice of the MLP is the most reasonable when the number of input variables and amount of sampling are large. Practically, it would be better to choose the MLP if the number of input variables is more than 4.

5.2. Practical experience

The shown in Fig.1 turbidimeter was tested under conditions of optical windows dirty. The turbidimeter was designed for measuring concentration of oil in water inside pipelines. It has a built-in electronic scheme and can be connected with a computer. The special software was applied. Calibration points from 1 to 100 mg/l were set with the special calibration equipment including the closed loop with the circulation pump and the syringe-doser. Windows dirty was emulated by overlap of 0,2-mm brown polyethylene films. Various combinations of sensors' dirtying that decreased the photoreceivers' signals by 30-40 % didn't change results visibly.

The author estimated different numbers of neurons in the hidden layer of the MLP for application in the turbidimeter shown on Fig.1. It was the aim to provide measurement invariance under condition of unstable dispersity. Usually neglect of this factor brings to errors from 20 to 30 % of Full Scale (F.S.). The mixer of the calibration workbench could change the average size of oil globules from 50 to 2 micrometer approximately depending on mixing duration. Values of oil concentration 80, 40, 20, 10, 5 mg/l and 0 (clear water) were set and after each change of concentration the mixing was executed during 30 min when the ratios R_1, R_2, \dots, R_{12} (components of \mathbf{R}) were written into the computer memory one after another at intervals 30 s. We had 360 cases at all. As a result we had a 12-variable set for the ANN inputs and a set of desirable values for the ANN output. Then various ANNs were created and tested with the help of the STATISTICA Neural Networks program package. One half of the sample data set we used as a training set and another half as a verifying set. The best results for various structures (different numbers of neurons in

the hidden layer were tested.) are represented in Table 1 as the averaged errors for the verifying set after 1000 training epochs:

TABLE I. Comparison of ANN structures

Structure	Errors, % F.S.
1 hidden layer, 2 neurons	4,30
1 hidden layer, 4 neurons	3,10
1 hidden layer, 6 neurons	2,62
1 hidden layer, 10 neurons	2,03
2 hidden layers x 6 neurons	2,01

Evidently, the structure with 2 hidden layers proves to be better, but its advantage over 10 neurons single-layer structure is not essential, while its complexity may be more considerable factor. Increasing of neuron number leads to the error decreasing only within the certain limit.

6. CONCLUSIONS

ANNs are very convenient tool for industrial concentration meters' signal processing. The influence of such factors as dispersity of media or windows' transparency could be brought to nothing.

Besides maintaining high functional reliability ANNs can have other purposes such as realization of wide-range concentration measurements on basis of multi-sensor devices.

Many of ideas discussed in this paper concerning optical instruments generally can be easily extended to other types of multi-sensor instruments such as ultrasonic, microwave, radiation or hybrid.

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