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УДК 004.8(075.8)

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ПРИМЕНЕНИЕ НЕЧЕТКОЙ НЕЙРОННОЙ СЕТИ ДЛЯ УПРАВЛЕНИЯ ПАРАМЕТРАМИ МАГИСТРАЛЬНОЙ СИСТЕМЫ ГАЗОПРОВОДА

В данной работе рассматривается новый способ для управления параметрами магистральной линии газопровода с применением теории нечетких и нейронных (гибридных) систем управления.

Управления; гибридный; алгоритм.

I.S. Kobersi, V.V. Shadrina, N.E. Minaeva.

APPLICATION OF FUZZY NEURAL NETWORK TO CONTROL PARAMETERS OF TRUNK GAS PIPELINE SYSTEM

In this paper, a new way to control parameters of trunk gas pipeline through the application of fuzzy theory and neural (hybrid) systems

Control; hybrid; algorithm.

At present, one of the most important problems of pipe-line transport is to conserve the normal condition of the linear part of industrial and main pipe lines. The underground pipe lines, working under normal mode, are saved, at least, for several decades. To prolong lifetime of a pipe line it is necessary to check the condition of underground and overground pipe lines systematically and to liquidate appearing defects timely.

As a rule, majority of pipe line defects are results of corrosive and mechanical damages, detection of their location and character is connected with a range of difficulties and costly. It is obviously that uncovering of a pipe line for its direct visual examination is economic unjustified. And it makes possible to examine only external surface of the pipe line.

Thereby, the problem of the technical diagnostics appears, within this problem industrial and ecological safety has to be improved. The given problem is connected with great technical difficulties.

During the diagnostics, it is necessary to define the defects and discrepancies, to reveal their causes and to prognosticate technical condition.

The other important problem of gas transportation is to trace fixed gas leaks or unauthorized pipe line breakings (thefts). Within the given problem it is necessary to define the causes of transporting gas volume reduction versus the pressure and temperature in gas main. The decisions about the future plans have to be made up on the basis of above mentioned facts.

This paper considers the ways to improve the prognostication and to prevent damages and gas leaks by means of fuzzy neuro networks.

The object of the diagnostics is a gas main, intended to transport the treated gas from mining regions into consumption regions. Gas flow in gas main is provided with compressor stations, constructed on gas main at certain distance from each other. The gas mains are classified according to the working pressure and categories. 1^{st} class - a working pressure from 2,5 to 10 MPa inclusive; 2^{nd} class - a working pressure from 1,2 MPa to 2,5 MPa inclusive. Gas pipes with pressure below 1,2MPa are not pertained to main ones.

In the same way gas mains are divided into four categories, depending on purposes, diameters, constructions and montage conditions.

The work estimation of the certain part of the gas main is conducted at a checking point of a compressor station. At the checking point the input gas is observed and valued. Depending on the pressure change in the course of time it is possible to surmise the working condition of the gas main. For example, the pressure decrease in 10 - 15% within 1 - 3 minutes signalizes about damages, consequently the emergency control linear taps have to operate i.e. stop valves have to be closed [2].

The transmitted gas volume dependency against gas temperature and pressure is used as an estimator regardless of the environmental conditions.

In the paper it is also explained the choice of the fuzzy neuron control modules to categorize, regulate and prognosticate the operation of the gas main section between two compressor stations.

To classify we need to determine the types of working. 3 types were defined:

- normal;
- theft;
- damage.

According to the volume change the fuzzy neuron module defines the type of working state and makes the corresponding decisions about further actions. On fig.1. conjectural graphs of pressure dependencies against time at input point of the compressor station are shown.

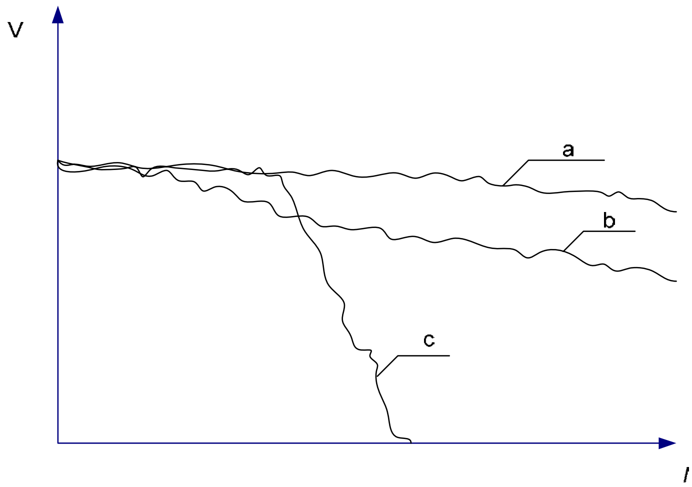

Fig.1. Conjectural graphs of volume dependency against time, a – normal work, b – theft, c – damage

To transport gas first we need to prognosticate the volume of transmitted gas from one control station to another. Decisions to maintain set points have to be based on prognosticated results, which are reference values for control system module.

First, to solve the gas transportation problem, we have to prognosticate the transmitted gas volume from one compressor station to another. On basis of the prognosticate results, which are master values of the control system, the decision of maintenance process' parameters in prescribed limit is made.

To decide the given problems hybrid control system was chosen. By the hybrid control system we understand the fuzzy control modules basesв on neuro networks, their training algorithms and building principles.

The building principle of the hybrid control system consists of a construction, structures, training algorithm and module modification. To construct the standard description of the typical structure of the fuzzy control module is used [1].

The first step of the construction the control system module is considered. During this process the rule base, the output block and the fuzzification block are described. This process is the first network layer and is the fuzzification input.

The rule base is knowledge, which forms base of the correct operation of the fuzzy control module and they are written as a fuzzy rule, which can be presented in the following way:

$$R^{(K)}: IF\left(x_1 \quad is \quad A_1^{(K)} \quad AND\, x_2 \quad is \quad A_2^{(K)} \, ... \quad AND \quad x_n \quad is \quad A_n^{(K)}\right) \\ THEN\left(y \quad is \quad B^{(K)}\right) \tag{1}$$

where $B^{(K)} \subseteq Y_j \subset R \quad u \quad k = 1,....N.$ and $A^{(k)}$ are fuzzy sets

From (1) one can see that each rule consists of IF, named as sending, containing a set of the conditions, and a part THEN, named as consequence, where the conclusion is made. Variables $x = \left(x_1,\ x_2,\ ....x_n\right)^T$ can take linguistical as well as numerical values.

To settle the task of the gas transportation, the correspondence of volume changes of the transmitted gas against its parameters with the determined operating class has to be written into the rule base of the fuzzy neuro module.

Then, these values are introduced as the fuzzy variables with membership function.

The multiplying operation is used as implication functions during the use of this module, so

$$R^{(k)} : A^k \to B^k, \quad k = 1, \ldots, N$$

$$\mu_{A^k \to B^k}(x, y) = \mu_{A^k}(x)\mu_{B^k}(y)$$

where $A^k = A_1^k \times A_2^k \times \ldots \times A_n^k$.

Cartesian product of the fuzzy sets is presented as

$$\mu_{A^k}(x) = \mu_{A_1^k \times \ldots \times A_n^k}(x) = \mu_{A_1^k}(x_1) \ldots \mu_{A_n^k}(x_n)$$

It is necessary to define the generic membership function of the fuzzy set $\overline{B}^k$ in the output block.

The membership function of the fuzzy set $\overline{B}^k$ (the accepted decision) is defined based on fuzzy rules with the usage of the current values (volume, pressure, temperature).

$$\mu_{\overline{B}^k}(y) = \sup_{x \in X} \left[\mu_{A'}(x)^T \times \mu_{A^k \to B^k}(x, y) \right]$$

The certain form of the function $\overline{B}^k(y)$ depends on the given T-norm, the fuzzy set definition and the way of the fuzzy sets Cartesian product introduction.

$$\mu_{\overline{B}^k}(y) = \sup_{x \in X} \left[\mu_{A'}(x)^T \times \mu_{A^k \to B^k}(x, y) \right] = \sup_{x \in X} \left[\mu_{A'}(x)^T \mu_{A^k \to B^k}(x, y) \right] \qquad (2)$$

So the generic membership function of the fuzzy set can be defined by the formula (2).

That brings to final description of the generic membership function of the fuzzy set

$$\mu_{\overline{B}^k}(y) = \sup_{x_1 \ldots n \in X} \left[\mu_{B^k}(y) \prod_{i=1}^{n} \mu_{A'(i)}(x_i) \mu_{A^k(i)}(x_i) \right]. \qquad (3)$$

Every control system with fuzzy logic (the fuzzy output) operates the fuzzy sets. So concrete input values of the fuzzy control module signal $\overline{x} = (\overline{x}_1, \overline{x}_2, \ldots, \overline{x}_n)^T \in X$ are to be fuzzificated, and will be correlated with the set $A' \subseteq X = X_1 \times X_2 \times \ldots \times X_n$ in this case. The fuzzification operation of the solo-set type is often used for control tasks.

$$\boldsymbol{A'}(\boldsymbol{x}) = \begin{cases} 1 \text{ if } & \boldsymbol{x} = \overline{\boldsymbol{x}} \\ 0 \text{ if } & \boldsymbol{x} \neq \overline{\boldsymbol{x}} \end{cases}$$

As it can be seen from (3) that supremum is reached only when $x = \overline{x}$, that is $\mu_A'(x) = 1$. In this case the formula (3) will take the following form:

$$\mu_{\overline{B}^k}(y) = \mu_{B^k}(y)\prod_{i=1}^{n}\mu_{A^k(i)}(x_i). \tag{4}$$

The center average defuzzification method is used as a defuzzification function. According to this one will have

$$\overline{y} = \frac{\sum_{k=1}^{N} \overline{y}^k \mu_{B^k}(\overline{y}^k)}{\sum_{k=1}^{N} \mu_{B^k}(\overline{y}^k)} \tag{5}$$

In (5) $\overline{y}^k$ is the centre of the fuzzy set B^k, so it is the point, where maximum value $\mu_{B^k}(\overline{y}^k)$ is reached. If we input value $\mu_{B^k}(\overline{y}^k)$ in (5), we will get

$$\overline{y} = \frac{\sum_{k=1}^{N} \overline{y}^k \left(\mu_{B^k}(\overline{y}^k) \prod_{i=1}^{n} \mu_{A^k(i)}(\overline{x}_i) \right)}{\sum_{k=1}^{N} \left(\mu_{B^k}(\overline{y}^k) \prod_{i=1}^{n} \mu_{A^k(i)}(\overline{x}_i) \right)} \tag{6}$$

If one takes into account that $\mu_{B^k}(\overline{y}^k)$ will take maximum value in the point $\overline{y}^k$ is equal to one, then formula (7) will take following view

$$\overline{y} = \frac{\sum_{k=1}^{N} \overline{y}^k \left(\prod_{i=1}^{n} \mu_{A^k(i)}(\overline{x}_i) \right)}{\sum_{k=1}^{N} \left(\prod_{i=1}^{n} \mu_{A^k(i)}(\overline{x}_i) \right)} \tag{7}$$

The next stage is to construct the system module structure, herewith it is necessary to choose the membership function form and to split the control system into layers and to set its functional possibilities.

The Gauss function was chosen as the membership function

$$\mu_{A_i^k}(x_1) = \left[\exp\left[-\left(\frac{\overline{x}_i - \overline{x}_i^k}{\sigma_j^k} \right)^2 \right] \right]$$

Put Gauss membership function into (7) and get the total module function. The hybrid system (fig. 2) is built on base of this function

$$\overline{y} = \frac{\sum_{k=1}^{N} \overline{y}^k \left(\prod_{i=1}^{n} \exp\left[-\left(\frac{\overline{x}_i - \overline{x}_i^k}{\sigma_j^k} \right)^2 \right] \right)}{\sum_{k=1}^{N} \left(\prod_{i=1}^{n} \exp\left[-\left(\frac{\overline{x}_i - \overline{x}_i^k}{\sigma_j^k} \right)^2 \right] \right)} \tag{8}$$

where $\overline{x}_i^k$ and σ_j^k are the width and centre of Gauss curve.

The function (8) is described as the most known ways of the fuzzy control system realization. This function consists of sum, multiplying and Gauss function. Then the laminated network (fig. 2) can be created.

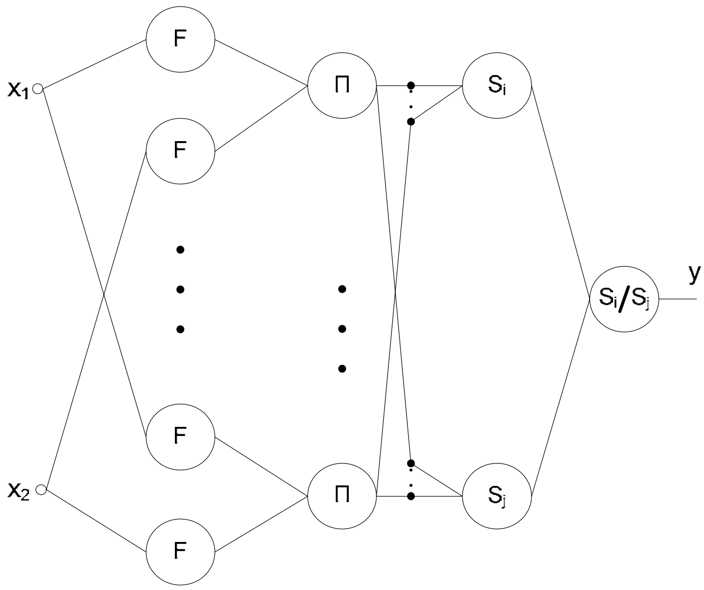

Fig.2. The fuzzy control module, given in (8)

The structure of the fuzzy control module, which is built on the principle of the neuro networks organization, is a laminated control system and consists of four layers.

The first layer, where the signals x_i are input, realizes the membership function. And practically it estimates the correspondence of the membership function of the input signals x_i with the fuzzy sets A^{κ}_i. The function F describes the Gauss function with the parameters $\overline{x}_i^k$ and σ_j^k. They are modified in process of the system training of the fuzzy hybrid module. The function F can differ from the Gauss distribution, but as an example, we have taken it to construct the membership function of fuzzy sets in the fuzzy hybrid control module.

The configuration of this layer junction corresponds to the rule base, and multipliers correspond to the output block (4). The conclusion result is formed at output of the second layer as the membership function, and the amount of this layer elements is defined by the number of the fuzzy rules N.

The multiplier is used as elements of the second layer, since T-norm of the Cartesian product of the sets and implication functions are used in multiplying function (multiplication).

The third and fourth layers are the defuzzification block, parameters of these layers $\overline{y}^k$ are modified in the training process, as well as the parameters for the first layer $\overline{x}_i^k$ and σ_j^k. The accurate value y of the control module is formed on the output of the fourth layer.

All system parameters (weight, separate forming of any layer and etc) have physical interpretation during fuzzy hybrid control unlike the neuro networks. This characteristic is important since knowledge is not distributed over the network and can be localized.

The training process of the control system is an system adapting process as a whole and in particular its parameters tuning.

One of the important stages in the adaptive control system, which can adapt to education, is a training algorithm.

The training method with back-propagation error algorithm is used for the fuzzy hybrid control system.

The structure of the training algorithm for fuzzy hybrid control system is presented for fig. 3.

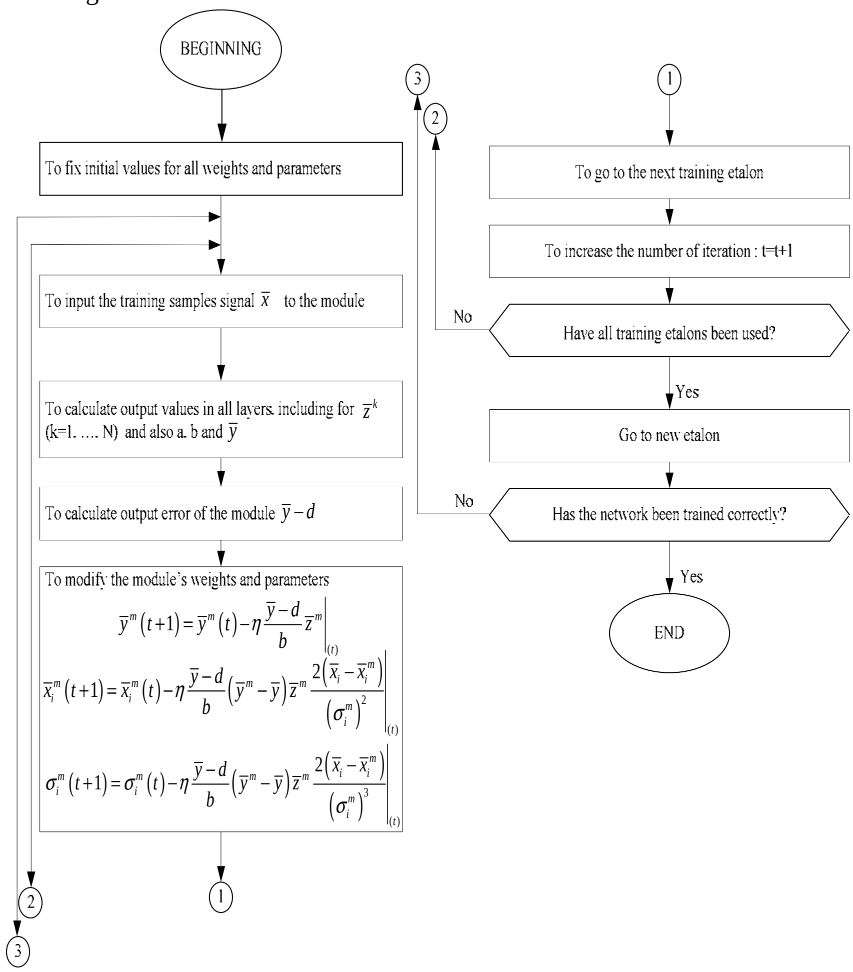

Fig. 3. The training algorithm of the fuzzy control module, demonstrated (8)

The back-propagation error algorithm can be generalized to train any network with direct spreading the signal. Since this algorithm is reliable in neuro networks training, it can be used to train any hybrid systems with direct signal spreading and particular the hybrid fuzzy system module with structure in defuzzification process.

Training sample in the form of the pair ($\bar{x}$, d) is required for the algorithm work

where $\bar{x} = [\bar{x}_1 \dots \bar{x}_n]^T$ is an input vector, d is an etalon signal.

The task is to correct the module parameters of the fuzzy control system, described by formula (8) and to minimize the system error (9)

$$e = \frac{1}{2}\left(\bar{y}(\bar{x}) - d\right)^2 \tag{9}$$

$y\left(\bar{x}\right)$ is changing by $\bar{y}$ to simplify it. When the number of parameter is known, it is necessary to define the error in the training process of the fuzzy neuro control system module $\bar{y}^m$, $\bar{x}_i^m$, σ_i^m for m = 1,…, N.

The module training algorithm consists in reduction of the previous weight value in derived value by error (9), multiplied by the coefficient. The process will continue until the system output error reaches the minimum value priori installed.

The formula for $\bar{y}^m$, which defines the modification way, has the following form(10)

$$\bar{y}^m\left(t+1\right) = \bar{y}^m\left(t\right) - \eta\frac{\partial e\left(t\right)}{\partial \bar{y}^m\left(t\right)} \tag{10}$$

where t = 0,1,2, – an iteration number, $\eta \in \left(0,1\right)$ – a coefficient defining training rate (the correction step).

Similarly for $\bar{x}_i^m$, σ_i^m

$$\bar{x}_i^m\left(t+1\right) = \bar{x}_i^m\left(t\right) - \eta\frac{\partial e\left(t\right)}{\partial \bar{x}_i^m\left(t\right)} \tag{11}$$

$$\sigma_i^m\left(t+1\right) = \sigma_i^m\left(t\right) - \eta\frac{\partial e\left(t\right)}{\partial \sigma_i^m\left(t\right)} \tag{12}$$

Originally, input vector spreads over the network in forward direction, and it is necessary to calculate consecutively the values of $\bar{z}^k\left(k = 1,\ldots,N\right)$, a, b and $\bar{y}$.

$$\bar{y} = \frac{a}{b} = \frac{\sum_{k=1}^{N}\bar{y}^k\bar{z}^k}{\sum_{k=1}^{N}\bar{z}^k} \tag{13}$$

$$\bar{z}^k = \prod_{i=1}^{n}\exp\left[-\left(\frac{x_i - \bar{x}_i^m}{y_i^k}\right)^2\right] \tag{14}$$

On next stage the new values of function weights are calculated by formulas (15-17), which are the results of formulas(10-12) transformations.

$$\bar{y}^m(t+1)=\bar{y}^m(t)-\eta\left.\frac{(\bar{y}-d)\prod_{i=1}^{n}\exp\left[-\left(\frac{\bar{x}_i-\bar{x}_i^m}{\sigma_i^m}\right)^2\right]}{\sum_{k=1}^{N}\prod_{i=1}^{n}\exp\left[-\left(\frac{\bar{x}_i-\bar{x}_i^k}{\sigma_i^k}\right)^2\right]}\right|_{(t)} \quad (15)$$

$$\bar{x}_i^m(t+1)=\bar{x}_i^m(t)-\eta\frac{\bar{y}-d}{b}\left(\bar{y}^m-\bar{y}\right)\bar{z}^m\left.\frac{2\left(\bar{x}_i-\bar{x}_i^m\right)}{\left(\sigma_i^m\right)^2}\right|_{(t)} \quad (16)$$

$$\sigma_i^m(t+1)=\sigma_i^m(t)-\eta\frac{\bar{y}-d}{b}\left(\bar{y}^m-\bar{y}\right)\bar{z}^m\left.\frac{2\left(\bar{x}_i-\bar{x}_i^m\right)}{\left(\sigma_i^m\right)^3}\right|_{(t)} \quad (17)$$

where $\bar{z}^m=\prod_{i=1}^{n}\exp\left[-\left(\frac{\bar{x}_i-\bar{x}_i^m}{\sigma_i^m}\right)^2\right]$.

The programme realization of the given algorithm does not have any greater difficulties.

It is necessary to remember that at each step first, all weight corrections in each layer are calculated, and then weights are corrected [1].

In this article, the parameters of the fuzzy neuro system training algorithm were deduced, but the derivation of the main formula for the system control and prognosticating parameters of the gas main were not considered. It is the subject of the further development.

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