Neuro-Fuzzy Model in Supply Chain Management for Objects State Assessing

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***Abstract*— This article considers the task of objects state assessing in conditions of uncertainty by considering the supply chain strategy. To solve it, the need to use fuzzy-production knowledge bases and fuzzy inference algorithms as part of fuzzy decision support systems is being updated. As a tool for constructing a knowledge base, a neural-fuzzy model is proposed. The proposed type of fuzzy-production rules and the logic inference algorithm on rules for objects state assessing are described. A structure of a fuzzy neural network, consisting of six layers, each of which implements the corresponding stage of the logic inference algorithm, is proposed. As a result of training a fuzzy neural network, a system of fuzzy-production rules is formed, which make up the knowledge base of the decision support system for objects state assessing. On the basis of the proposed neuro-fuzzy model, a software package has been implemented for automating the processes of forming fuzzy-production rules. The main components of the software package are the knowledge base generation module and the fuzzy inference module. As an approbation of the neuro-fuzzy model, the formation of fuzzy rules for assessing the state of water lines at the cluster pumping stations in reservoir pressure maintenance systems has been carried out. The testing results confirmed the high efficiency of the neural-fuzzy model and the possibility of its practical use for the formation of fuzzy-production rules in various subject areas of human activity.**

***Keywords*—** *neuro-fuzzy model, supply chain strategy, fuzzy-production rule, knowledge base, object state assessment, decision support.*

1. Introduction

Currently, in various subject areas of human activity, the task of of objects state assessing often has to be solved under conditions of uncertainty, which is characterized by incompleteness (lack of a part) of initial data, physical uncertainty (presence of noise and outliers), and linguistic uncertainty (subjective expert assessments). To reduce and handle physical uncertainty, the methods of eliminating data outliers [1, 2] and noise filtering [3, 4] are traditionally used. For processing the linguistic uncertainty and taking into account the incompleteness of the source data, respectively, fuzzy logic methods [5-7] and fuzzy logic inference algorithms [8-12] are used. Therefore, to make the objects state assessing under uncertainty, it is important to use fuzzy expert systems [10, 11, 13-26]. These artificial intelligence systems are widely used in many subject areas [27-29] and often play the role of intelligent decision support systems [14, 23-25].

The main problem for the effective implementation of an intelligent decision support system is the formation of adequate knowledge bases in the conditions of uncertainty. In most existing decision support systems, the experts have to be involved in solving particular problems related, for example, to specifying the parameters of the membership functions, determining their form, optimal number of fuzzy gradations for the input linguistic variables. The subjective nature of expert assessments can lead to an incomplete adequacy of the fuzzy knowledge base and, as a result, affect the accuracy of the estimates obtained about the object state and the final decisions made by the person. In order to get away from subjectivity, it is necessary to form fuzzy knowledge bases based on the intellectual analysis of the available data completely automatically (without an expert's participation). This actualizes the need for the development and practical use of effective tools for data analysis and the formation of knowledge bases of intelligent decision support systems [15-18, 30-32]. As such a tool, a specially developed neural-fuzzy model for automating the formation of fuzzy rules for objects state assessing is proposed [19].

2. Methods

To describe the object being modelled under uncertainty, the following basic requirements for the type of fuzzy-production rules shall be considered in supply chain strategy:

1) ability to handle clear and fuzzy values of input variables;

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2) to take into account the features of the input conditions in terms of their weight in the antecedent rules, as well as take into account the reliability of each of the fuzzy rules.

The following kind of fuzzy rules satisfies these requirements [19]:

IF $x_1 = \overleftrightarrow{A}_1 (w_1)$ AND $x_2 = \overleftrightarrow{A}_2 (w_2)$ AND … $x_n = \overleftrightarrow{A}_n (w_n)$ THEN $y = B$ [CF], (1)

where x_i – input variable rules, $w_i \in [0,1]$ – weights of conditional parts of the rule $"x_i = \overleftrightarrow{A}_i"$, $\overleftrightarrow{A}_i = \{A_i, \widetilde{A}_i\}$, A_i – clear input values, $\widetilde{A}_i = \{x_i, \mu_{\widetilde{A}_i}(x_i)\}$ – unclear input values, $\mu_{\widetilde{A}_i}(x_i)$ – membership functions, y – output variable, B – clear output value, $CF \in [0,1]$ – rule validity.

For the object state assessing, an algorithm of logical inference on rules of the form (1) has been developed. Let us consider the terms and notation used in this algorithm.

1. $R \in [0,1]$ – the degree of antecedent triggering in the rule:

$$R = \min_{i: x_i^* - known} (\mu_{\widetilde{A}_i}(x_i^*)), \tag{2}$$

where $x_i^*, i = \overline{1,n}$ – clear values of n input rule variables, $\mu_{\widetilde{A}_i}(x_i^*)$ – the degrees of belonging of input values x_i^* to $\overleftrightarrow{A}_i$.

2. $T \in [0,1]$ – the weight of antecedent in the rule:

$$T = \frac{\sum_{kn=1}^{n_{kn}} w_{kn}}{\sum_{i=1}^{n} w_i}, \tag{3}$$

where $w_i, i = \overline{1,n}$ – the weights of all restrictions $\overleftrightarrow{A}_i$ on variables in the rule, $w_{kn}, kn = \overline{1,n_{kn}}$ – the weights of restrictions $\overleftrightarrow{A}_i$ with known values;

3. $C \in [0,1]$ – assessment of the accuracy of proposed solution:

$$C = R * T * CF, \tag{4}$$

where $CF \in [0,1]$ – rule vailidity.

Formulas (2) - (4) are used in the inference algorithm on fuzzy rules of the form (1) for the object state assessing. Let us consider the steps of this algorithm.

1. Input of x_i^* values for all input variables x_i in the rules.

2. For each rule, the degree of antecedent response is calculated by the formula (2).

3. Grouping of all the rules in which the degree of antecedent triggering is non-zero into a conflict set.

4. For all the rules from the conflict set, the calculation of the antecedent value by the formula (3), as well as a comprehensive assessment of the reliability of formed decision by the formula (4).

5. Conflict resolution - the choice of rules with the maximum assessment of reliability.

6. Getting the value B^* of the output variable y_j of the selected rule as the desired object state.

Operation of the inference algorithm on fuzzy rules is schematically presented in Figure 1.

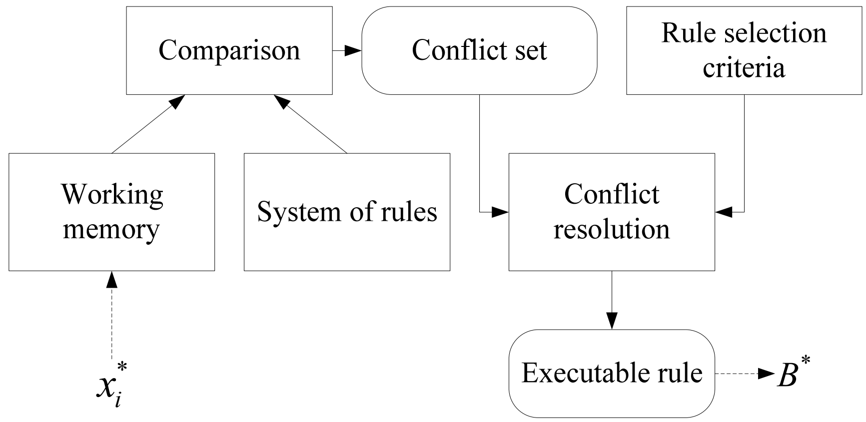

Figure 1. Operation scheme of the logical inference algorithm for the object state assessing

The logical inference algorithm on fuzzy rules of the form (1) is one-pass and allows selecting at the output a single rule, the sequential value of which corresponds to the object state.

For the formation of fuzzy-production rules of the form (1), a neuro-fuzzy model was developed based on the training of a fuzzy neural network. Its structure is uniquely defined by the following parameters [19]:

1) the number of input variables in the fuzzy-production rules;

2) the number of membership functions for input variables;

3) the number of values of the output variable in the rules;

4) an algorithm for fuzzy inference on rules of the form (1).

Figure 2 presents an example of the structure of a fuzzy neural network [19].

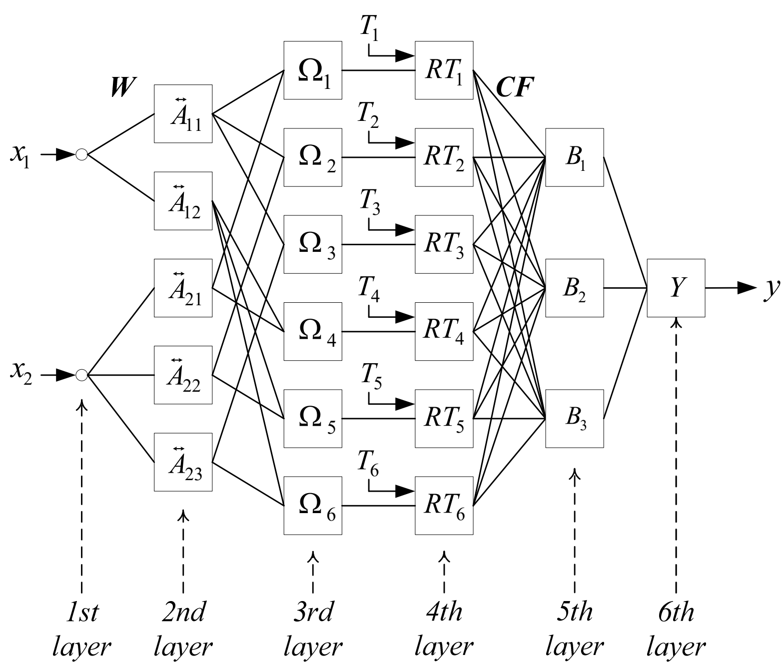

Figure 2. Example of the structure of a fuzzy neural network

The figure shows that the model of a fuzzy neural network has 6 layers. The first layer contains the input neurons. Their number corresponds to the number of input variables in the fuzzy-production rules. The neurons of the second network layer omodel the input conditions of fuzzy antecedents in the rules. Their outputs are the corresponding values of the membership functions. Neurons of the next layer of a fuzzy neural network model the antecedents of fuzzy rules. At the output of these neurons, the degrees of antecedent triggering are calculated. The fourth layer calculates the product of estimates of the rules *R* and the weights of their antecedents *T*. The fifth layer contains the values of the output neuron of the network. The last layer of a fuzzy neural network consists of a single neuron that corresponds to the output variable in the fuzzy rules and forms the output value - a particular object state.

The described model of a fuzzy neural network is implemented in a software package for the formation of fuzzy-production rules for the objects state assessing. The program complex was developed with the aim of constructing a neuro-fuzzy model and automating the stages of the formation of fuzzy rules. Let us consider its structure and features of its components.

The implemented software package includes two basic modules: a knowledge base generation module, designed to automate the processes of generating fuzzy rules, and a fuzzy inference module, used for the objects state assessing based on the fuzzy rules that have been generated. Let us consider the structure of the software package presented in Figure 3.

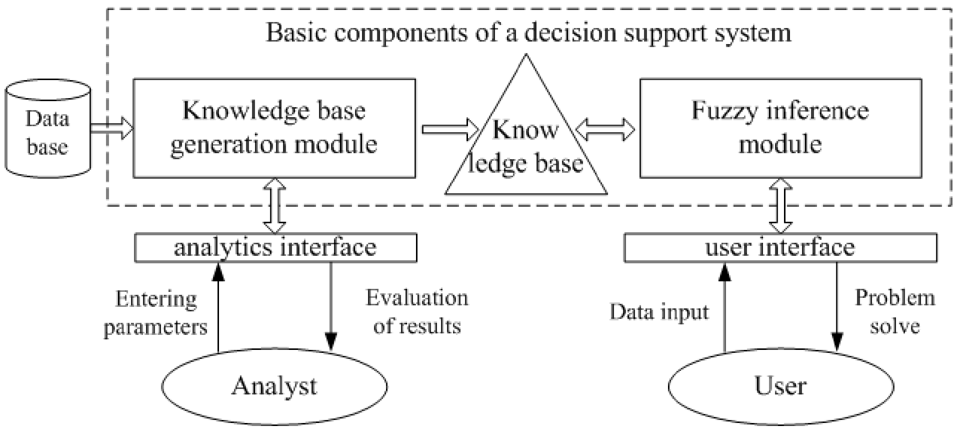

Figure 3. Structure of the developed software package

The knowledge base generation module, as the main component of the software package, is responsible for the following steps in the operation of the intelligent SPPPR:

- formation and preparation of data sample for analysis;

- building a model of a fuzzy neural network;

- assessment of the adequacy of formed knowledge base.

The analyst launches the knowledge base generation module, loads the data for analysis, trains the fuzzy neural network, tests the constructed neuro-fuzzy model, evaluates the results obtained. In addition, the analyst performs the visualization of the generated fuzzy-production rules, evaluates the obtained membership functions for the input linguistic variables.

The fuzzy inference module is an intermediate link between the decision maker and the knowledge base of an intelligent system. Based on the logic inference algorithm implemented in it, this module accepts object data as input, compares the data with antecedents of fuzzy rules and generates an output in the form of object state assessment. This is how the software works.

3. Results and Discussion

As an approbation of the neuro-fuzzy model and evaluation of the effectiveness of its practical use, the formation of fuzzy rules for assessing the state of water lines at the cluster pumping stations in reservoir pressure maintenance systems has been carried out [20-22]. Expertly, leakage of fluid from water lines is established on the basis of data on its costs for discharge of the pumping station and on each of the water lines. Water lines can be placed on blocks of combs and on remote blocks of combs. In this case, the cluster pumping station consists of pumping units pumping fluid into the oil reservoir through the distributed conduit systems.

Figure 4 shows the structure of water lines at a cluster pumping station.

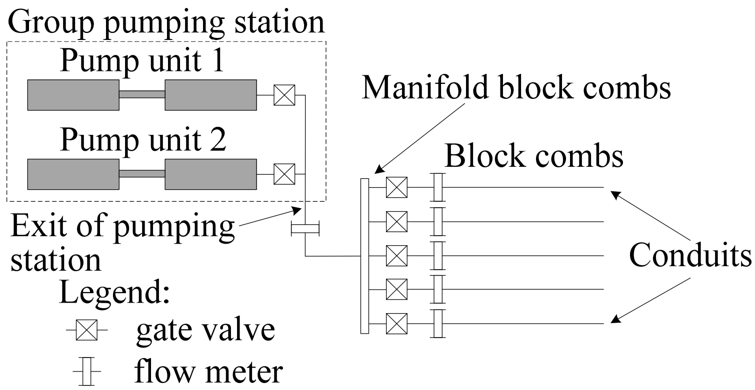

Figure 4. Example of the structure of water lines at a cluster pumping station

The figure shows an example of the layout of ten conduits at a cluster pumping station with two pumping units. The conduits are located on the blocks of combs. At the same time, it is installed a flow meter to account for fluid flow at the entrance of each conduit. The readings of this device are automatically taken every 0.5 hours and stored in the appropriate database. Analysis of the accumulated data using a fuzzy neural network allowed forming a base of fuzzy rules for evaluating one of two possible states of a particular conduit: "norm" or "accident". “norm” corresponds to the normal state of the water lines (without leakage), and “accident” corresponds to the emergency state (leakage at the water line).

For the formation of fuzzy rules for assessing emergency situations in conduits, a developed fuzzy neural network was used, which processed statistical information on the conduits of one of the reservoir pressure maintenance shops collected over 2 years. The values of the following input variables were used as the initial data for building a neuro-fuzzy model and forming fuzzy rules for assessing the state of conduits.

a) fluid flow through each conduit in 0.5 hours (m^3):

- Q_0 - flow through the conduit at the moment;

- Q_1 – flow through the conduit for the previous 0.5 hours;

- Q_2 – flow through the conduit for the previous hour;

b) pressure in the manifold of the block of combs and remote blocks of combs (MPa):

- P_0 – current reservoir pressure;

- P_1 – reservoir pressure in the previous 0.5 hours.

The preparation of data for training a fuzzy neural network required the calculation of the values of relative deviations of fluid flow in each conduit using the formula:

$$\varepsilon = \frac{Q_0 - Q}{Q} * 100\%,$$

where $Q \in \{Q_1, Q_2\}$.

In addition, the absolute pressure changes in the reservoir are calculated:

$$\Delta P = P_1 - P_0.$$

Training data samples for the formation of fuzzy rules for assessing the state of water lines included the values of the following variables:

- ε_1 – deviation of fluid flow through the conduit for 0.5 hours;

- ε_2 – deviation of fluid flow through the conduit for 1 hour;

- ΔP – pressure change in the reservoir.

The target was the variable *D* (the state of conduit), which takes one of two possible values: "norm" or "accident". The values of these variables were represented by the groups of input and output variables for each conduit of the cluster pumping station. The total number of cluster pumping stations was 28, and the number of water lines - 303.

Each input variable has three fuzzy gradations corresponding to the categories “small”, “medium”, and “large”. Figure 5 shows an example of the constructed membership functions.

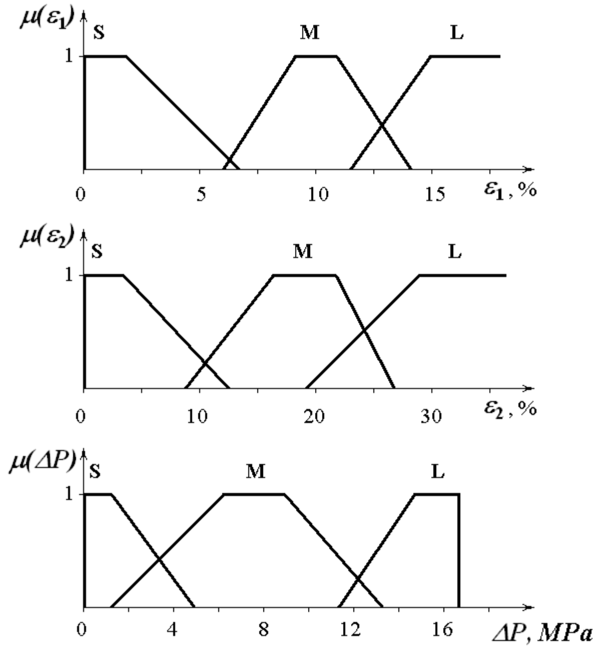

Figure 5. Example of constructed membership function

It can be seen from the figure that the deviation of fluid flow is not less than 15% for 0.5 hours and not less than 30% for an hour that is significant for assessing the state of water lines. The emergency state of the conduit also corresponds to the change in pressure in the reservoir from 15 to 17 MPa.

It should be noted that in the general case, the specific values of the parameters of similar membership functions differ for different conduits. It depends on the design pressure in the collector of the block of combs and at discharge of the cluster pumping station, installed half-hour volumes of fluid injection, number of wells in the conduit, height of the conduit relative to the pumping station, as well as the injected agent into the well (wastewater, fresh, sulfur).

As a result of training of the neuro-fuzzy models, 28 systems of fuzzy-production rules were formed on the obtained data. The average number of rules in each system was 12. The total number of rules for determining the status of water pipelines was 342.

4. Summary

The developed neuro-fuzzy model was successfully tested in the intelligent decision support system for assessing the state of water lines. During operation, the system showed a 100% level of detection of fluid leaks in the conduits of the cluster pumping stations. Its use made it possible to halve the average response time for technical personnel to leakage from water mains (from 24 to 12 hours). As a result of the introduction of the developed system into operation, the efficiency of detecting emergencies at the conduits has increased.

5. Conclusions

Thus, the testing results have shown the high efficiency of the neural-fuzzy model and the possibility of practical use of the software for the formation of fuzzy rules in various subject areas. The formed fuzzy rules are a model for the objects state assessing together with a fuzzy inference algorithm. This model is relevant to use in practical problems characterized by heterogeneity, incompleteness, and the fuzzy nature of initial data describing the object assessed.

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