Fuzzy models for predicting the technical state of objects

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***Abstract*—To ensure the reliable operation of an object, it is advisable to perform its technical state predicting and assessment. It is often difficult to obtain the information about the state of an object. The article suggests the using of fuzzy logic models to recognize and predict the technical state of an object under the conditions of limited information availability. To assess the predicting results quality with fuzzy models, such criteria as percentage of true predictions, *AUC* and *F*-measure criteria are used. The proposed models, algorithms and criteria are software implemented in the form of an information and mathematical system, which may be used in production and science activity to increase different technical objects functioning. The real experiment researches were conducted at some technical facilities, aimed at practical evaluation and analysis of the efficiency of the offered models, algorithms, information and mathematical system (e.g. potable water purifying system, hydro unit control system).**

***Keywords*—fuzzy model, predicting, technical object**

I. Introduction

To support the taken decision to control the object, it is reasonable to perform its technical state assessment and reliability predicting.

The article deals with the objects, whose technical state significantly depends on a set of monitored parameters. During monitoring, the values of certain parameters are recorded at definite intervals as discrete signals and the signals are applied to the data collection server and object control stand, which changes or cuts off the load.

For example, in order to assess the hydro unit state, its stator parts, rotor parts and shaft vibration, air gap and other parameters are constantly monitored; in the potable water purifying control system physical-chemical parameters are constantly monitored at definite interval along with its chromaticity, turbidity, etc.

It is assumed, that there are object technical state solid benchmarks, whose value help to assess object serviceable operation and its functioning breakdown. As a rule, this solid benchmarking is represented by the system of time series. It is necessary to construct a model based on these data, by means of which, in case of object parameters new values arrival, one can predict the technical state of the object.

One of the practical approaches to the object technical state prediction is adaptive dynamic regression modeling [1-2], the idea of which is to check the basic premises of regression analysis at each stage of forecast model construction and appropriate adaptive method use (fractal analysis, robust methods, method of maximum likelihood, stepwise regression etc.) in case of their deviation from the reference value, thus enabling to determine the model structure more accurately and to increase the accuracy of approximation and prediction.

Predictive models can be trend functions, periodic functions, autoregressive-moving average model [3], autoregressive model of conditional heteroscedasticity (ARCH) [4] and its modifications, autoregressive model on a cylinder [5], vector autoregression [6], piecewise regression, etc. both individually and in combinations with each other.

Another approach is based on the application of machine learning methods [7-9]: decision tree, neural network, discriminatory analysis, Bayes classificator, support vector machine (SVM), linear logistic regression, etc. However, each of these methods has its own pros and cons; there is no universal model to assess the object state at high accuracy.

At present, technical objects' control systems based on fuzzy logic are widely used and developed [10-26].

The term «fuzzy set» was firstly used by L.A. Zadeh in his work of 1965 [10]. Since that time many works related to fuzzy logic application in technical objects control have been published. The first practical results were obtained in thermal power engineering in 1974, when Professor E.H. Mamdani developed a fuzzy controller for the first sample of steam engine [11]. The first fuzzy logic methods in industry were applied to the cement kilns control system, worked out by a Danish company. In Japan the first fuzzy controller was designed for water purification by M. Sugeno [12].

At present the fuzzy logic methods are used both in industry and homes. In Japan the fuzzy logic based control systems are widely used in fully automatic washing machines and vacuum cleaners production [13]. Also the fuzzy control is used for electro power stations [14]. Besides the industry the control methods based on fuzzy logic started to be applied in finance and business [15-16].

Nowadays the fuzzy logic inference methods are applied in function approximation [17], patterns recognition and classification [18-20], non-linear objects modelling and control [21-23], decision taking under the conditions of uncertainty [18], technical diagnostics for predicting and simulating different objects states [24-26].

At present the fuzzy logic is considered to be a standard method of modelling and design. The practical experience of fuzzy logic based models development testifies to the fact

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that the time period and the costs of their design is much shorter and lower (than of the one with applied traditional mathematical tool), ensuring the required quality criteria [15].

The obvious advantage of fuzzy logic systems is the possibility to use them even in the cases of labour intensivity or impossibility to conduct accurate mathematical calculations.

That is why for technical state prediction and diagnostics the authors of the article present the developed algorithm, based on fuzzy models, enabling to analyze an object operation stability and predict the object technical state in the form of fuzzy statements with truth degree for the obtained result.

II. ALGORITHM OF OBJECT TECHNICAL STATE PREDICTION AND DIAGNOSTICS

The object technical state prediction and diagnostics algorithm, developed by the authors of this article on the basis of fuzzy models, comprises the following stages: fuzzy terms introduction, rule base description, fuzzy models construction, prediction quality assessment, best model selection, object technical state prediction.

A. Fuzzy terms introduction and rule base description

At initial stage of fuzzy models construction the critical areas limits of object monitored parameters are determined experimentally.

Then it is necessary to define the fuzzy terms, describing input and output variables. In this algorithm, we will use two terms for the monitored object parameters (input variables): “excellent”, when the parameter value is not beyond the critical limit, and “bad” – in the opposite case.

The object technical state output variable will be described with two fuzzy statements: “serviceable state” and “unserviceable state”.

Then we construct a rule base, i.e. a linguistic model, which is in fact a set of fuzzy rules. To solve the problem we will use the following rule base: “If at least three parameters of the object are beyond the critical limit and the term “bad” can be applied, the object unserviceable state is predicted”.

Further on in order to describe the fuzzy terms we will select the membership functions [25-26].

For the term “excellent” we will use z-like function:

$$\mu_z = \begin{cases} 1, x \le a \\ 1 - 2\left(\frac{x-a}{b-a}\right)^2, a < x \le \frac{a+b}{2} \\ 2\left(\frac{b-x}{b-a}\right)^2, \frac{a+b}{2} < x < b \\ 0, b \le x \end{cases}, \quad (1)$$

for the term “bad” we will use s-like function:

$$\mu_s = \begin{cases} 0, x \le a \\ 2\left(\frac{x-a}{b-a}\right)^2, a < x \le \frac{a+b}{2} \\ 1 - 2\left(\frac{b-x}{b-a}\right)^2, \frac{a+b}{2} < x < b \\ 1, b \le x \end{cases}. \quad (2)$$

The membership functions parameters a and b characterize the critical limits of the object monitored parameters.

B. Fuzzy models construction

To obtain the forecast of an object technical state we will use three fuzzy models: Mamdani [11], Larsena and Tsukamoto, the construction of which assumes four stages: fuzzification, reasoning, composition and determination of the final result.

At the stage of fuzzification there is a compatibility between input variable numerical value and membership function value of its corresponding odd term:

$$d_i = \mu(c_i),\ i = \overline{1, n}, \quad (3)$$

where n is the number of observations done, c_i is a numeric value of input variable, $\mu(c_i)$ is a membership function value.

The membership function describes numerically the membership degree of the variables’ values to fuzzy sets ratio, and defines the degree of the fuzzy term. If the value of membership function is equal to 0, consequently the unit does not belong to a fuzzy set, if the value is equal to 1, the unit is fully included into a fuzzy set, if the value is between 0 and 1, the unit is fuzzily included into a fuzzy set.

At the reasoning stage, using the found fuzzy values of input variables, through the rule base, output variable fuzzy values are determined.

Output variables fuzzy values truth degree Mamdani and Larsena models are estimated as logical maximum out of all input variables truth degree values:

$$P_i = \max_i\ d_i,\ i = \overline{1, n}, \quad (4)$$

in Tsukamoto model it is a logical minimum:

$$P_i = \min_i\ d_i,\ i = \overline{1, n}. \quad (5)$$

At the composition stage the found output variable fuzzy values unite into a resulting subset: in Mamdani model – with the use of truth degrees’ logical maximum operation:

$$K_i = \max_i\ P_i,\ i = \overline{1, n}, \quad (6)$$

in the Larsena model – with the use of logical multiplication operation, in Tsukamoto model – with weighted average:

$$K_i = \frac{w_i \cdot P_i}{\sum w_i},\ \ i = \overline{1, n}. \quad (7)$$

Then, using the fuzzy set of variable output values we find the final predicted technical state of the object: fuzzy term "serviceable state" or "unserviceable state", following the method of truth degree centroid.

C. Prediction quality assessment and the best model selection

To assess the quality of object technical state prediction, using the fuzzy models, the benchmarks set is divided into two samples: learning sample and test sample. Using the learning sample, the object state prediction algorithm is built, i.e. models and parameters are defined. Then, using the model constructed as per learning sample, object state is predicted. The obtained results are checked as per the test sample.

For that we will use such quality criteria as the percentage of true predictions, criteria *AUC*, *F*-measure.

The percentage of object state true predictions is estimated as per this formula:

$$D = \frac{s}{k} \cdot 100\ \% \ , \tag{8}$$

where s is the number of successful results, k is the number of observations done in a pilot sample.

AUC characterises the area, restricted by *ROC*-curve and the axis of fraction of false predictions of object serviceable states:

$$AUC = \frac{1 + TPR - FPR}{2}, \tag{9}$$

where *FPR* is the fraction of false predictions of object serviceable state, *TPR* is the fraction of true predictions of object serviceable state.

The higher is *AUC* value, the better are the prediction results. If *AUC* is equal to 0,5, then model result is the equivalent of random drawing. If *AUC* < 0,5 the values obtained from the model are replaced by the converse.

If in the learning sample the number of serviceable states significantly exceeds the number of unserviceable states, such characteristics as precision P and range (or completeness) R are applied:

$$P = \frac{TP}{TP + FP},\ R = \frac{TP}{TP + FN}, \tag{10}$$

where *TP* is the number of true predictions of serviceable states, *FP is* the number of false predictions of serviceable states.

Now let us determine *F*-measure:

$$F = \frac{2PR}{P + R}. \tag{11}$$

When F value is close to one, it is assumed that the quality of prediction is better.

For further prediction of the object technical state, based on the described quality criteria, the best model is selected.

Then the selected fuzzy model is used to make a prediction of the object technical state.

III. INFORMATION AND MATHEMATICAL SYSTEM OF OBJECTS STATE PREDICTION

The described object technical state prediction and diagnostics algorithm based on fuzzy models was software-implemented in Visual Studio 2017 Community environment in object-oriented language C#.

The software may be used on PC with operation system Windows 7 and higher.

Information and mathematical system enables to enter the given data from the key pad, and also from different spreadsheets. The program realizes the opportunity to introduce the object monitored parameters critical limits, which are defined by expert means for each object separately.

On reading the data from the file, the program gives the result in the form of three spreadsheets. The first one shows the given data, the second one shows the constructed fuzzy models of Mamdani, Larsena and Tsukamoto, the third one shows the assessment of prediction quality criteria, through which the program reveals the degree of adequacy of models and compares the built models with each other.

After fuzzy models construction and best predictive model selection, there is a chance to make the prediction of the object state, using the selected model. The prediction results are fuzzy statements, characterizing an object technical state, assisted by the truth degree of the obtained object state. These results are displayed on the screen, and saved in a file to be used and analyzed afterwards.

IV. FUZZY MODELS APPLICATION FOR OBJECTS TECHNICAL STATE

To investigate the efficiency of fuzzy models application to predict objects technical state, two objects were used as bench marks: hydro unit, whose technical state is characterized by the values of relative and absolute vibration, and water purifying system, whose state is described by the physical-chemical indexes of the water source.

The process of vibration monitoring was determined by ten indexes: vibrations of the lower X_1 and upper X_3 generator bearing of the upper pool and on the right shore X_2, X_4, hydro unit shaft shaking on the lower pool X_5 and on the right shore X_6, hydro generating set shaft shaking X_7, X_8 and hydro unit cover vibrations X_9, X_{10} as well. The available original sample consisted of 1500 observations, of which there were 966 operable states.

Good condition of the water purifying system (object state at the output) Y was evaluated basing on drinking water quality physical-chemical indexes (input data): temperature X_1, chromaticity X_2, turbidity X_3, pH value X_4, alkalinity X_5, oxidizability X_6, and doses of reactants to be added: coagulant X_7 and flocculant X_8. We have the results of 348 observations for 8 operation indexes. In 47 cases, the system state was found faulty (at least one of the quality indexes of purified drinking water was beyond the allowable limits or values of two indexes approached these limits).

To evaluate the prediction results, the sampling given data were divided into two samples: learning sample (90% observations) and test sample (10% of given). Then the fuzzy models of Mamdani, Larsena and Tsukamoto were constructed and their quality was assessed by means of the criteria mentioned above (Table 1).

TABLE I. MODELS' QUALITY CRITERIA

Model / Criteria	Hydro unit			Water purifying system		
	Mam-dani	***Larse-na***	***Tsuka-moto***	***Mam-dani***	***Larse-na***	***Tsuka-moto***
True prediction percent	0.86	0.62	0.56	0.60	0.63	0.88
F-measure	0.83	0.66	0.62	0.62	0.61	0.85
AUC	0.82	0.61	0.59	0.67	0.64	0.83

This table shows that Mamdani is the best for hydro unit, as the percent of true predictions is higher here than the rest, and *F*-measure and *AUC* for this model are close to one. For the water purifying system Tsukamoto is the best model, judging by all the criteria.

Then on the basis of the selected model the forecast for each object was constructed for its next period of operation. It turned out to be that serviceable state of the object is predicted with 100% probability, i.e. without any mistakes.

V. CONCLUSION

To recognize and predict the technical state of the object under the conditions of limited information availability, fuzzy models algorithm was developed. Based on this algorithm in Microsoft Visual Studio 2017 Community in C# language information and mathematical system was made, which can be used in production and science activities companies and facilities to increase the efficiency of different technical objects operation.

The use of fuzzy control systems is especially effective where the technical object is quite complex and there is not enough a priori information to describe it.

The fuzzy models were investigated to obtain the best prediction. It was revealed that Mamdani model is the best for hydro unit state prediction, and Tsukamoto model is the best for water purifying system. So, there is no one universal fuzzy model, capable to give true predictions for different technical objects' states. Each object has its own optimum fuzzy model, because the fuzzy model prediction result depends on the object monitored parameters critical limits, which are defined by an expert.

The main advantages of the fuzzy models are: the possibility to reject the complicated control systems, where the required accuracy of estimation makes it practical; the description of decision making in natural language, with quality evaluations terms familiar for humans, and association of these evaluations with stringent mathematical methods.

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