SELF-LEARNING FUZZY PREDICTOR OF EXPLOITATION SYSTEM OPERATING TIME

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Abstract

The probability that a system is capable to operate satisfactorily significantly depends on reliability and maintainability of a system. The disadvantage of classic methods of system availability determining is that the probability of realizing by system tasks with expected quality depends on history of operational states and does not take into consideration actual operational conditions that have strong influence on risk-degree of down-time occurring, while *the probability of degradation failure in exploitation system is a function of operating time and actual exploitation conditions. The problem of failures prediction can be solved by applying in diagnostics methods the intelligent computational algorithms. The intelligence computational methods enable to create the diagnosis tools that allow to formulate the prognosis of operating time of a system and predict of failure occurring based on the past and actual information about system's operational state. The paper presents the fuzzy logic approach to forecast the prognoses of the operating time of the exploitation system or its equipments according to the specified exploitation conditions that characterize the system exploitation state at the current time. The fuzzy system was based on the Takagi-Sugeno-Kang type fuzzy implications with singletons specifies in conclusions of rules. The fuzzy inference system input variables are the assumed parameters according to which the current exploitation state of the considered system can be evaluated.*

Keywords: *operating time prediction, fuzzy logic, recursive least squares algorithm, overhead travelling crane*

1. Introduction

The classic approach to evaluate the probability that an exploitation system is capable to operate satisfactorily and successfully perform the formulated tasks is based on operational, achieved or inherent availability that are coefficients estimated based on mean up- and down-time including e.g. operating time, active repair time, idle time and logistic time [1, 3, 5]. However the availability factor is determined based on the historical date only (MTBF – mean time between failures, MTTR – mean time to repair), and can not be used to estimate the current risk of degradation failure which is the function of actual operating time and conditions. The problem can be solved by applying diagnostic methods and computational intelligence for forecasting the prognoses of the operating time under specified exploitation conditions [7, 8].

The fuzzy inference systems (FISs), artificial neural networks (ANNs), genetic algorithms (GAs), as well as combinations of those, are among other methods artificial intelligence tools eagerly used for the purposes of failures detection and prediction. The artificial neural network for example was used for damage detection in composite structures [9]. The ANNs were used for predicting delamination in composite plates [2]. The fuzzy inference system type of Sugeno, which was off-line optimized using ANFIS (*Adaptive Neuro-Fuzzy Inference System*) Matlab program, was applied for forecasting the life of insulating materials for electrical machines windings [4]. The genetic algorithm was applied to develop fuzzy system used to damage detection of composite helicopter rotor blades [6].

This contribution undertakes fuzzy prediction of operating time of the exploitation system under specified conditions. The Sugeno-type self-learning FIS is proposed to estimate operating time $\hat{OT}(T_{f-1} - T_f) \in TBF$ between the last and next (predicted) failure of the system's equipments (Fig. 1).

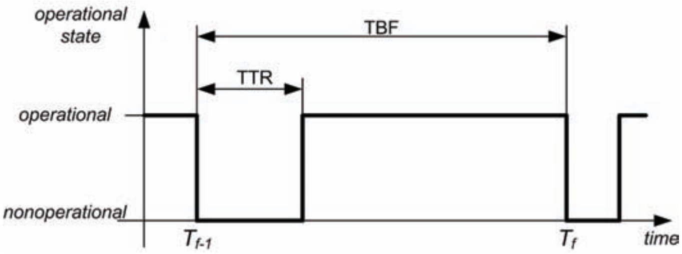

Fig. 1. Operational states of the system, where T_{f-1} and T_f are respectively the times of last and next failures, TBF is the time between failures, and TTR is the time to repair

2. The self-learning fuzzy model of the operating time

The fuzzy predictor of operating time

The fuzzy predictor of operating time is composed of following phases (Fig. 2):

- *fuzzification* – where the **X** crisp input vector of operating conditions consisting of parameters of a system that characterize the system exploitation state at the current time *t*, is fuzzified with using assumed membership functions shapes (MF),
- *fuzzy inference system* – where the outputs of fuzzy rules IF-THEN are calculated according to the membership functions specified for FIS inputs in the antecedent of fuzzy implication and constant value specified in the consequent of fuzzy singleton,
- *base of knowledge* which is composed of fuzzy implications type of:

$$\text{IF } x_1 \text{ is } MF_k(x_1) \text{ and } x_2 \text{ is } MF_k(x_2) \text{ and } x_n \text{ is } MF_k(x_n) \text{ THEN } POT_k(T_{f-1}), \tag{1}$$

where:

$MF_k(x_1), MF_k(x_2), \dots MF_k(x_n)$ - the membership functions specified for input variables,

$POT_k(T_{f-1})$ - the constant value – the predicted operating time (POT) between the last failure occurred at the time T_{f-1} and the next failure at the time T_f,

$k \in \{1, 2, ..., N\}$ - the number of a given fuzzy rule in the FIS base knowledge.

- *defuzzification – where the FIS crisp output variable (POT) is calculated as the weighting* average of all rules outputs (fuzzy singletons):

$$POT(T_f - T_{f-1}) = \left(\sum_{k=1}^{N} POT_k\left(T_{f-1}\right) \cdot w_k(t) \right) \cdot \left(\sum_{k=1}^{N} w_k(t) \right)^{-1}, \tag{2}$$

where weighting coefficient of the *k*-rule w_k is calculated as a product of membership coefficients $\mu_{MF_k}(x_i)$ of all input variables to the membership functions $MF_k(x_i)$ which are specified in the antecedent of fuzzy implication (3).

$$w_k = \mu_{MF_k}(x_1) \cdot \mu_{MF\,k}(x_2) \cdot \ldots \cdot \mu_{MF\,k}(x_n). \tag{3}$$

Consequently the predicted operating time $POT(T_f - t)$ between the actual time *t* and next failure T_f is a difference between FIS output and current operating time $OT(t - T_{f-1})$ of the system:

$$POT(T_f - t) = POT(T_f - T_{f-1}) - OT(t - T_{f-1}). \tag{4}$$

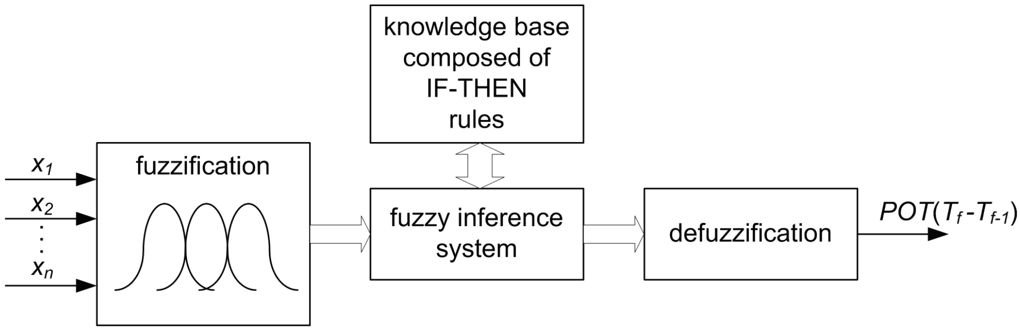

Fig. 2. The general flow-chart of fuzzy predictor of operating time

Some difficulties of fuzzy system designing are connected with selecting the membership functions shapes, specifying the suitable set of rules for considered problem, as well as choosing the defuzzification method, which is used to convert the fuzzy outputs of the rules to crisp output of the system. The problem of defuzzification was solved by using IF-THEN rules type of fuzzy singleton (1), that leads to obtain directly the crisp output from each fuzzy rule of the FIS model calculated as the result of multiplication of crisp value specified in the antecedent and weighting coefficient of a rule (3). The problem of IF-THEN rules number selection is directly connected with number of input variables and fuzzy sets defined for each of the input. Obviously the FIS knowledge base should completely cover the all fuzzy regions of the FIS. In case of conjunction AND (realized by selected T-norm) used in rule's antecedents the mentioned condition is satisfied if base of knowledge consists all combinations of fuzzy sets included in rules antecedents, that leads to obtain the number of rules $N = n_1 \cdot n_2 \cdot \ldots \cdot n_n$, where n_i is the number of fuzzy sets specified for x_i input. Consequently the most significant problem is connected with choosing for FIS inputs the membership functions shapes and their distribution. In principle, the problem can be solved by heuristic methods, for example by conducting the series of off-line experiments for collected training data with different shapes of membership functions [4] that leads to choose the best solution, or to assume, in case of lack of data which can be used for FIS off-line optimization, triangular or Gaussian membership functions with overlap of neighbouring functions set at the 0.5 cross point, that leads to smooth transition of the operating point between fuzzy regions of the FIS. The number of the membership functions, as well as their midpoints can be choose according to heuristic knowledge about considered exploitation system, and can be improved during gathering data from process, or modified by implementing evolutionary algorithm to develop FIS.

The FIS self-learning process with using RLS algorithm

The learning process of FIS was based on the recursive least squares (RLS) algorithm. In each sample time, when the next failure occurs in exploitation system $t = T_f$, the consequents of FIS fuzzy rules $POT_k(T_{f-1})$ are modified based on the operating time between the previous and current failure $OT(T_f - T_{f-1})$ and operating conditions $x \in \mathbf{X}$ or their changes measured in the period of time $\lfloor T_{f-1}, T_f \rfloor$.

The estimator of parameters of the fuzzy model $\hat{\mathbf{\Theta}}(T_{f-1})$ is an *N*-dimensional vector of constant values specified in consequents of *N* fuzzy implications (1):

$$\hat{\mathbf{\Theta}}(T_{f-1}) = \begin{bmatrix} POT_1(T_{f-1}) \\ POT_2(T_{f-1}) \\ \vdots \\ POT_N(T_{f-1}) \end{bmatrix}. \tag{5}$$

The crisp output value of fuzzy predictor (estimated predicted operating time between the last T_{f-1} and next failure T_f) is calculated at the actual time *t* as follows:

$$\hat{OT}(T_f - T_{f-1}) = POT(T_f - T_{f-1}) = \varphi^T(t) \cdot \hat{\mathbf{\Theta}}(T_{f-1}), \tag{6}$$

where:

$$\varphi(t) = \begin{bmatrix} w_1(t) \\ w_2(t) \\ \vdots \\ w_n(t) \end{bmatrix} \cdot \left(\sum_{k=1}^{N} w_k(t) \right)^{-1}. \tag{7}$$

When the next failure occurs at the time $t = T_f$ the one-step prediction error is calculated as a difference between operating time and estimated operating time by fuzzy model:

$$e(T_f) = OT(T_f - T_{f-1}) - \varphi^T(T_f) \cdot \hat{\mathbf{\Theta}}(T_{f-1}). \tag{8}$$

The new auxiliary matrix $\mathbf{P}(T_f)$ and Kalman's vector $\mathbf{K}(T_f)$ are calculated as follows:

$$\mathbf{P}(T_f) = \frac{\mathbf{P}(T_{f-1})}{\beta} - \frac{\mathbf{P}(T_{f-1}) \cdot \varphi(T_f) \cdot \varphi^T(T_f) \cdot \mathbf{P}(T_{f-1})}{\beta \cdot \left(\beta + \varphi^T(T_f) \cdot \mathbf{P}(T_{f-1}) \cdot \varphi(T_f)\right)}, \tag{9}$$

where β is assumed value of the forgetting coefficient that determines the speed of learning process.

$$\mathbf{K}(T_f) = \mathbf{P}(T_f) \cdot \varphi(T_f). \tag{10}$$

The new estimator of parameters of the fuzzy model is calculated based on the one-step prediction error (8) and Kalman's vector (10).

$$\hat{\mathbf{\Theta}}(T_f) = \hat{\mathbf{\Theta}}(T_{f-1}) + e(T_f) \cdot \mathbf{K}(T_f). \tag{11}$$

Only the FIS implications with weighting coefficients greater than zero $w_k(T_f) > 0$, are modified in the learning process. Consequently the value of rule's weighting coefficient, as well as the assumed value of forgetting factor β, determines the range and speed of rule's consequent change.

3. The simulations example

The subject of simulation tests was laboratory model of an overhead travelling crane with hoisting capacity *Q*=150 [kg]. During exploitation process of this laboratory stand were observed frequently occurred failures in power transmission system in which the steps motors were used to drive the crane bridge, trolley and hoisting mechanism. Especially the frequently occurred failures of voltage stabilizer and relays in those subsystems were noticed. The operating time of those elements has depended on the mean acceleration and load of crane‘s motion mechanisms. Consequently the attention was focused to the problem of prediction of the operating time of those elements. The tests of fuzzy predictor were conducted for simulated failures of voltage stabilizer in crane's trolley power transmission system. The fuzzy predictor was used to estimate the operating time of this element based on assumed operating conditions: mean values of load $\overline{m}$ and acceleration of trolley $\overline{a}_t$ measured in the period of time $\lfloor T_{f-1}, t \rfloor$ - between the last occurred failure T_{f-1} and the current time *t*. The input variables were fuzzified with using membership functions presented in the Fig. 2.

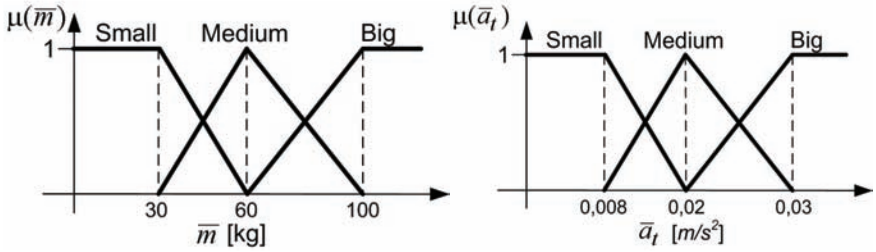

Fig. 2. The membership functions specified for mean load in the range [*0, 100*] [*kg*], *and mean crane acceleration in the range* [*0, 0.045*] [m/s^2]

The FIS knowledge *base was composed of 9 fuzzy rules IF-THEN (fuzzy singletons) type of:*

$$\begin{gathered}\text{IF } \overline{m}(t-T_{f-1}) \text{ is \{Small, Medium, Big\}}\\ \text{and } \overline{a}_t(t-T_{f-1}) \text{ is \{Small, Medium, Big\},}\\ \text{THEN } POT_k(T_{f-1}),\end{gathered} \tag{12}$$

where:

t - current time,

T_{f-1} - the time of the last failure of voltage supplier,

$k = 1,2,...,9$ - where N =9 the number of FIS fuzzy rules.

The simulated history of 9 failures of voltage supplier in trolley movement mechanism was used to learn the FIS with using RLS algorithm. The data used to learn the fuzzy predictor of operating time, as well as the operating time $\hat{OT}(Tf - Tf_{-1})$ estimated by FIS after learning process, obtained for the same values of operating conditions (mean values of load $\overline{m}$ and acceleration of trolley $\overline{a}_t$), are presented in the Tab. 1. The simulations were conducted for mean values of load $\overline{m} = \{30, 60, 100\}[kg]$ and acceleration $\overline{a}_t = \{0.008, 0.02, 0.03\}[m/s^2]$, which equal the midpoints of membership functions *Small*, *Medium* and *Big* (Fig. 2). The good convergence of estimated by FIS operating time $\hat{OT}(T_f - T_{f-1})$ with data used in the learning process $OT(T_f - T_{f-1})$ was achieved by setting high initial values in auxiliary matrix $\mathbf{P}(T_{f-1})$ (9), that determine the high learning speed of FIS rules at the first sample time.

Tab. 1. Failures history simulated for voltage stabilizer in trolley power transmission system

the number of failure	mean value of load $\overline{m}(T_f - T_{f-1})$ [kg]	mean value of trolley acceleration $\overline{a}_t(T_f - T_{f-1})$ $[m/s^2]$	operating time $OT(T_f - T_{f-1})$ [h]	operating time estimated by FIS after learning $\hat{OT}(T_f - T_{f-1})$ [h]
1	30	0.008	22	22
2	30	0.02	17	17
3	30	0.03	13	13
4	60	0.008	21	21
5	60	0.02	18	18
6	60	0.03	12	12
7	100	0.008	19	19
8	100	0.02	15	15
9	100	0.03	10	10

The next failures were simulated for mean values of load $\overline{m} = \{45, 80\}[kg]$ and acceleration $\overline{a}_t = \{0.014, 0.025\}[m/s^2]$ at which the membership functions *Small*, *Medium* and *Big* overlap. After 9 failures presented in the Tab. 1 the operating time estimated by FIS for $\overline{m} = 45[kg]$ and $\overline{a}_t = 0.014[m/s^2]$ was $\hat{OT}(T_f - T_{f-1}) = 19.5[h]$, and for $\overline{m} = 80[kg]$ and $\overline{a}_t = 0.025[m/s^2]$ was $\hat{OT}(T_f - T_{f-1}) = 13.7[h]$. The Tab. 2 and 3 present the results of FIS learning after successive next 6 failures obtained for forgetting factor $\beta = 0.9$ and $\beta = 0.6$ respectively.

Obviously the results obtained during FIS learning with forgetting factor $\beta = 0.6$ (Tab. 3) show better convergence to the expected value of operating time. However, the both simulations results obtained for different forgetting factors illustrate that by adjusting the coefficient β the fuzzy predictor can self-adapt to meet the changes of degradation speed of exploitation system equipments.

Tab. 2. The results of FIS learning by using RLS algorithm with forgetting factor $\beta = 0.9$

the number of failure	$\overline{m}$ [kg]	$\overline{a}_t$ [m/s^2]	$OT(T_f - T_{f-1})$ [h]	$\hat{OT}(T_f - T_{f-1})$ [h]
10	45	0.014	15	17.9
11	80	0.025	7.6	11.9
12	45	0.014	15	16.8
13	80	0.025	7.6	10.6
14	45	0.014	15	16.1
15	80	0.025	7.6	9.6

Tab. 3. The results of FIS learning by using RLS algorithm with forgetting factor $\beta = 0.6$

the number of failure	$\overline{m}$ [kg]	$\overline{a}_t$ [m/s^2]	$OT(T_f - T_{f-1})$ [h]	$\hat{OT}(T_f - T_{f-1})$ [h]
10	45	0.014	15	17
11	80	0.025	7.6	10.9
12	45	0.014	15	15.1
13	80	0.025	7.6	8.7
14	45	0.014	15	14.7
15	80	0.025	7.6	7.7

4. Conclusions

The paper presents a fuzzy logic based contribution to the diagnosis system in which the prognoses of operating time of the exploitation system or its equipments are estimated based on exploitation conditions. The FIS input variables are the assumed parameters according to which the current exploitation state of the considered system can be evaluated. The process of FIS creation requires of knowledge and experience about exploitation system to select a set of FIS input variables, assume the shapes and distribution of membership functions and formulate relations between monitored parameters and predicted operating time in form of fuzzy rules. The crisp values of fuzzy rules specified in consequents of IF-THEN implications are the subject of learning process realized at each time when new failure occurs and delivers the data to train the FIS (operating time and exploitation conditions between the last and new failure). The speed of fuzzy predictor learning depends on the assumed value of forgetting coefficient that can be modified to adjust FIS learning to the speed of degradation of exploitation system equipments. The proposed solution of self-learning fuzzy diagnosis system is based on classic recursive least squares algorithm used to real-time identifies FIS parameters with successful results. However the evolutionary algorithm (e.g. genetic algorithm) can be used as the alternative approach to learn the fuzzy predictor of operating time.

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