A GENETIC FUZZY APPROACH TO ESTIMATE OPERATION TIME OF TRANSPORT DEVICE

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Abstract

The classic approach to evaluate the probability that an operational system is capable to operate satisfactorily and successfully perform the formulated tasks is based on availability that is coefficient which is determined based on the history of down-time and up-time occurring, while the risk-degree of down-time occurring strongly depends on the actual operational state of a system. 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, especially genetic fuzzy systems (GFSs) that combine fuzzy approximate reasoning and capability to learn and adaptation.

The paper presents the fuzzy rule-based inference system used to predict the operating time of exploitation system according to the specified operational conditions. The proposed algorithm was used to design the fuzzy model applied to estimate the operating time of a system between the actual time and predicted time of the next failure occurring under the stated operational parameters. The fuzzy system allows to prognoses the time of the predicted failure based on the operational parameters which are used to evaluate the actual operational state of the system. The attention in the paper is focused on the evolutionary computational techniques applied to design the fuzzy inference system.

The paper proposes the genetic algorithm based on the Pittsburgh method and real-valued chromosomes used to optimize the knowledge base and parameters of antecedents and conclusions of the Takagi-Sugeno-Kang (TSK) fuzzy implications. The paper is the contribution to the GFSs, which aim is to find an appropriate balance between accuracy and interpretability, and also contribution to the research field on the diagnosis methods based on soft computing techniques. The evolutionary algorithm was tested for designing the fuzzy operating time predictor of material handling device.

1. Introduction

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 [3, 11] 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. 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 [10]. The combination of soft computing methods like genetic fuzzy systems (GFSs) allows combining fuzzy approximate reasoning and capability to learn and adaptation. The detailed overview of the field of GFSs, methods and approaches proposed for fuzzy inference system (FIS) learning, as well as current research directions are detailed presented in [5, 7]. The paper presents the GFS which was based on the Pittsburgh approach to FIS learning [6], and is the contribution to the current research line [2, 7, 8] directed to multi-objective GFSs, which aim is to find an appropriate balance between accuracy and interpretability (complexity of knowledge base (KB) of FIS). Proposed in the paper genetic fuzzy approach to operating time of a system prediction is also contribution to the research field on the diagnosis methods based on soft computing tools. This field was explored for example in [2], where artificial neural network (ANN) was used for damage detection in composite structures, and in [12] where ANN were used for predicting delamination in composite plates. 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]. In [9] the GFS was applied to damage detection of composite helicopter rotor blades.

2. The fuzzy rule-based inference system to predict operating time

The operating time of a system is the function of operational state which can be evaluated based on the changes of a set of specified operational parameters $\overline{\mathbf{X}}$ between the initial time T_0 at which system has started to operate and the actual time t (1).

$$OT(t - T_0) = f\big(\bar{x}_1(t - T_0), \bar{x}_2(t - T_0), ..., \bar{x}_n(t - T_0)\big). \tag{1}$$

The probability of a failure occurrence depends on the actual and history of operational states changes between previous failures. Therefore the operating time between the last and next failure $OT(T_f - T_{f-1})$ can be estimated based on the changes of assumed operational parameters and operating times between the previous failures. At a given time t, the predicted operating time to the next failure $POT(T_f - t)$ is a difference between predicted operating time between the previous and the next failure $POT(T_f - T_{f-1})$, and operating time between the last failure and the actual time $OT(t - T_{f-1})$:

$$POT(T_f - t) = POT\big(T_f - T_{f-1}\big) - OT\big(t - T_{f-1}\big), \tag{2}$$

where:

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

T_f - the predicted time of the next failure.

The prognosis of operating time till the next failure can be estimated based on the predicted operating time between the last and the next failure $POT(T_f - T_{f-1})$, which in turn can be expressed as a function of changes of operational parameters $\overline{\mathbf{X}}_f\big(t - T_{f-1}\big)$ between the last failure and actual time t, as well as history of those parameters changes and operating times between the previous failures:

$$
\begin{aligned}
POT(T_f - T_{f-1}) = \\
= f\big(\overline{\mathbf{X}}_f(t - T_{f-1}), \overline{\mathbf{X}}_{f-1}(T_{f-1} - T_{f-2}), OT_{f-1}(T_{f-1} - T_{f-2}), ..., \overline{\mathbf{X}}_1(T_1 - T_0), OT_1(T_1 - T_0)\big),
\end{aligned} \tag{3}
$$

where:

T - the time of a given failure occurring.

The predicted operating time (3) can be estimated by fuzzy rule-based system (FRBS) with a set of parameters of membership functions **MF** and knowledge base **KB** designed based on the history of operational parameters changes and operating time between the failures. Therefore the equation (3) can be expressed as follows:

$$POT(T_f - T_{f-1}) = f\left(\overline{\mathbf{X}}_f (t - T_{f-1}), \mathbf{MF}, \mathbf{KB}\right), \qquad (4)$$

The Takagi-Sugeno-Kang fuzzy-type inference system was assumed for operating time estimating. The knowledge base of the TSK-type fuzzy system is composed of N rules, which express the relationship between n input variables (specified operational parameters which are used to estimate the operational state of a system) and operating time predicted for a given operating point specified in antecedent of a fuzzy rule:

$$\text{IF } \overline{x}_1 \text{ is } MF_k(\overline{x}_1) \text{ and } \overline{x}_2 \text{ is } MF_k(\overline{x}_2), \text{and } \overline{x}_n \text{ is } MF_k(\overline{x}_n), \text{ THEN } POT_k(T_f - T_{f-1}), \qquad (5)$$

where:
$\overline{x}_1, \overline{x}_2, ..., \overline{x}_n$ - input variables, the mean values of specified operational parameters,
$MF_k(\overline{x}_1), MF_k(\overline{x}_2), \ldots MF_k(\overline{x}_n)$ - the membership functions specified for input variables,
$POT_k(T_f - T_{f-1})$ - the constant value – the predicted operating time (POT) between the last failure occurred at the time T_{f-1} and the next failure predicted at the time T_f,

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

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

$$POT(T_f - T_{f-1}) = \left(\sum_{k=1}^{N} POT_k\left(T_{f-1}\right) \cdot w_k(t) \right) \cdot \left(\sum_{k=1}^{N} w_k(t) \right)^{-1}, \qquad (6)$$

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:

$$w_k = \mu_{MF_k}(x_1) \cdot \mu_{MF_k}(x_2) \cdot ... \cdot \mu_{MF_k}(x_n), \qquad (7)$$

3. The fuzzy predictor designing based on the genetic algorithm

The proposed fuzzy estimator of system's operating time until the predicted failure can be designed based on the evolutionary computational techniques that enable to tune the parameters of fuzzy system based on the training data, which consist of the history the mean values of operational parameters $\overline{\mathbf{X}}$ and operating times measured in the previous failures. Proposed algorithm was based on the genetic algorithm with individuals encoded by using real-valued vectors, which represent the parameters of membership functions (MFs) specified in the antecedents of fuzzy rules and parameters specified in the conclusions of fuzzy rules (a single value of operating time formulated for a given operating point of a fuzzy system in antecedent of a rule). The aim of the genetic algorithm is to optimize the FIS parameters and number of rules of knowledge base (KB) according to the specified objective function.

The input variables of the FIS were fuzzified with using triangular MFs (Fig. 1) with assumption that the crossover points of neighbouring MFs is at $\mu = 0.5$ the membership coefficient, in order to obtain the smooth transition between the fuzzy sets.

The chromosomes of individuals are composed of vectors (8) with real numbers that represent parameters of triangular MFs (Fig. 1) and a real-valued vector with singletons specified in antecedents of the rules.
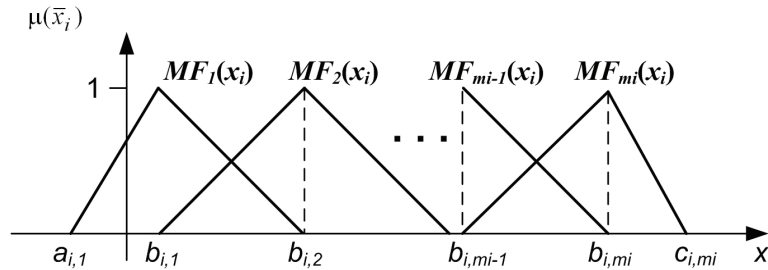

Fig. 1. The fuzzyfication of the FIS input variables with using triangular membership functions

$$
\begin{aligned}
& \left[a_{1,1}, b_{1,1}, b_{1,2}, ..., b_{1,m1-1}, b_{1,m1}, c_{1,m1}\right], \\
& \left[a_{2,1}, b_{2,1}, b_{2,2}, ..., b_{2,m2-1}, b_{2,m2}, c_{1,m2}\right], \\
& \vdots \\
& \left[a_{n,1}, b_{n,1}, b_{n,2}, ..., b_{n,mn-1}, b_{n,mn}, c_{1,mn}\right], \\
& \left[POT_1(T_f - T_{f-1}), POT_2(T_f - T_{f-1}), ..., POT_N(T_f - T_{f-1})\right],
\end{aligned}
\tag{8}
$$

where:

$N = m1 \cdot m2 \cdot ... \cdot mn$ - the number of rules in FIS knowledge base which depends on numbers of MFs specified for input variables,

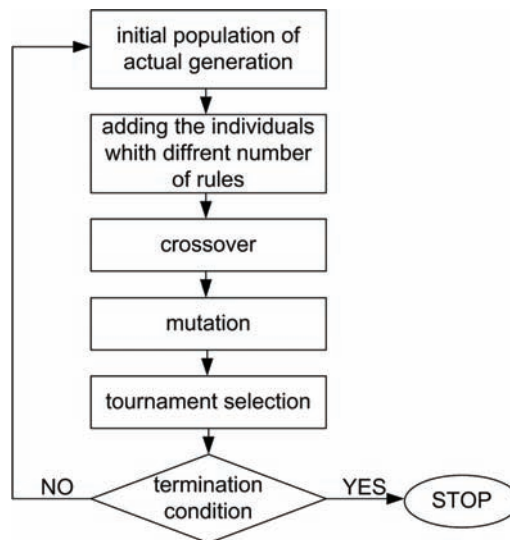mi - the number of MFs used to fuzzify the input variable $\bar{x}_i$.

Fig. 2. The general flowchart of genetic algorithm used to tune the fuzzy predictor of operating time

The genetic algorithm (Fig. 2) in each iteration starts with initial population to which the several new individuals are added. The new FISs are created based on the individuals from initial population which are modified by adding or removing MF in a given input variable. The individual, the number of input variable, as well as a number of MF to remove or the number of

gene of chromosome where the new MF is added are randomly chosen. The process of adding the new MF between the two neighbouring MFs depends on the arithmetical crossover of those two MFs, while addition of the MF before the first or behind the last MF (Fig. 1) specified for a given input is realized by non-uniform mutation:

$$\begin{cases} b'_{i,j} = N(0,1) \cdot b_{i,j} + (1 - N(0,1) \cdot b_{i,j\pm1}), & \text{whith probability } p = \dfrac{1}{mi}, \\ \left[a'_{i,1}, b'_{i,1}\right] = \left[a_{i,1}, b_{i,1}\right] - N(0,1) \cdot \sigma \cdot \left[a_{i,1}, b_{i,1}\right], & \text{whith probability } p = \dfrac{1}{mi}, \\ \left[b'_{i,mi}, c'_{i,mi}\right] = \left[b_{i,mi}, c_{i,mi}\right] + N(0,1) \cdot \sigma \cdot \left[b_{i,mi}, c_{i,mi}\right], & \text{whith probability } p = \dfrac{1}{mi}, \end{cases} \quad (9)$$

where:
$N(0,1)$ - normally distributed random scalar,
σ - the assumed parameter which specifies the strength of the mutation,
$p = 1/mi$ - the probability of choosing the j locus of the vector to add the new gene (MF).

The new population of solutions (FISs) is created through arithmetical crossover and next max-min non-uniform mutation. The crossover process is realized on the randomly chosen two individuals that leads to obtain the two children with number of rules inherited from parents.

$$\begin{aligned} MF(\bar{x}_i)' &= N(0,1) \cdot MF(\bar{x}_i)^{(j)} + (1 - N(0,1) \cdot MF(\bar{x}_i)^{(k)}, \\ MF(\bar{x}_i)'' &= N(0,1) \cdot MF(\bar{x}_i)^{(k)} + (1 - N(0,1) \cdot MF(\bar{x}_i)^{(j)}, \\ POT(\bar{x}_i)' &= N(0,1) \cdot POT(\bar{x}_i)^{(j)} + (1 - N(0,1) \cdot POT(\bar{x}_i)^{(k)}, \\ POT(\bar{x}_i)'' &= N(0,1) \cdot POT(\bar{x}_i)^{(k)} + (1 - N(0,1) \cdot POT(\bar{x}_i)^{(j)}, \end{aligned} \quad (10)$$

where:
$MF(\bar{x}_i)', MF(\bar{x}_i)'', POT(\bar{x}_i)', POT(\bar{x}_i)''$ - the offspring obtained from crossover,
j,k - the numbers of parents in population chosen for recombination.

In case, when chosen parents have the different numbers of MFs specified for the same input variable then the MFs with the closest midpoints are selected to take part in crossover, and the result of this process leads to obtain two children with the numbers of rules inherited from each parent.

The mutation process is realized by using max-min non-uniform method (11) performed on randomly chosen individuals and elements (gene) of the chosen vector of chromosome.

$$\begin{cases} g_{i,j}' = g_{i,j} + N(0,1) \cdot \sigma \cdot (g_{i,j+1} - g_{i,j}), & \text{with probability } p = 0.5, \\ g_{i,j}' = g_{i,j} - N(0,1) \cdot \sigma \cdot (g_{i,j} - g_{i,j-1}), & \text{with probability } p = 0.5, \end{cases} \quad (11)$$

where:
$p_{i,j}, p_{i,j}'$ - the mutated and new value of gene of an individual,
$\sigma = f(Var(\delta_{OT}))$ - the parameter which determines the strength of the mutation, formulated as a function of variance of relative error of the best individual in previous generation.

The self-adaptation of the mutation process is realized by parameter σ which is determined by comparison at each iteration the variance of relative error of the best individual in the current population with the value obtained at first iteration:

$$\sigma(k) = Var(\delta_{OT}(k-1))/Var(\delta_{OT}(1)), \tag{12}$$

The selection is performed by using tournament method based on the fitness of individuals calculated according the objective function formulated as follows:

$$f\left(\frac{N_R}{C_{MF}} \cdot Var(\delta_{OT})\right) \to \text{minimum}, \tag{13}$$

where:

N_R - the number of rules in KB,

$C_{MF} = \sum_{i=1}^{n} \sum_{j=1}^{mi} \mu_{MF_j}(\bar{x}_i)$ - compatibility of the MFs to the learning data.

The iteration process is terminated according the condition formulated as the assumed tolerance of mean value of relative error of the best individual in generation.

4. The simulations results

The simulation tests of the GFS were addressed to the problem of prediction the operating time of the material handling device: an overhead travelling crane. The training data used to design and optimize the fuzzy predictor of operating time was assumed and create based on the data gathered during monitoring laboratory crane with hoisting capacity $Q=150$ [kg]. During exploitation process of this laboratory stand were observed frequently occurred failures depended on the mean values of load $\bar{m}$ and acceleration of the trolley $\bar{a}_t$. The fuzzy predictor of operating time of the crane's trolley was assumed as TSK-type FIS with two inputs variables $\bar{m}$ and $\bar{a}_t$. The population of solution was limited to individuals with from 3 to 6 triangular membership functions specified for a given input that lead to limit the number of rules in generation to 36 rules. The training data was composed of 20 samples.

In each iteration, before recombination, the individuals with different numbers of rules were added to 12 initial individuals. The final population obtained after crossover and mutation was 48. The crossover and mutation probability was assumed respectively $p_c = 87,5\%$ and $p_c = 10\%$. The termination condition was formulated as the mean value of relative error of the best solution in population less the $\delta_{OT} < 2\%$.

The 60% of 20 simulations carried out with using the same training data lead to results with the best FIS with 12 rules obtained within 63 mean value of generations. The example of the membership functions tuned by using the genetic algorithm is presented in the figure 3.

The figure 4 presents the results of simulation during which the fuzzy predictor of operating time consisting of 12 fuzzy rules was designed according the formulated requirements (relative error less then $\delta_{OT} < 2\%$).

The figure shows the number of FISs with a given number of fuzzy rules selected to the initial population (12 individuals) of the next iteration. During the last 20 generations the population is dominated by the individuals with 12 fuzzy rules even though the FISs with others numbers of rules has dominated in previous iterations, and even though the individuals with the 12 rules completely died out during some generations to be next restored. These phenomenon comes from the fact that the individuals with different numbers of rules are added to the initial population before recombination, that allows to recover the genetic material which has been lost during the previous iterations.
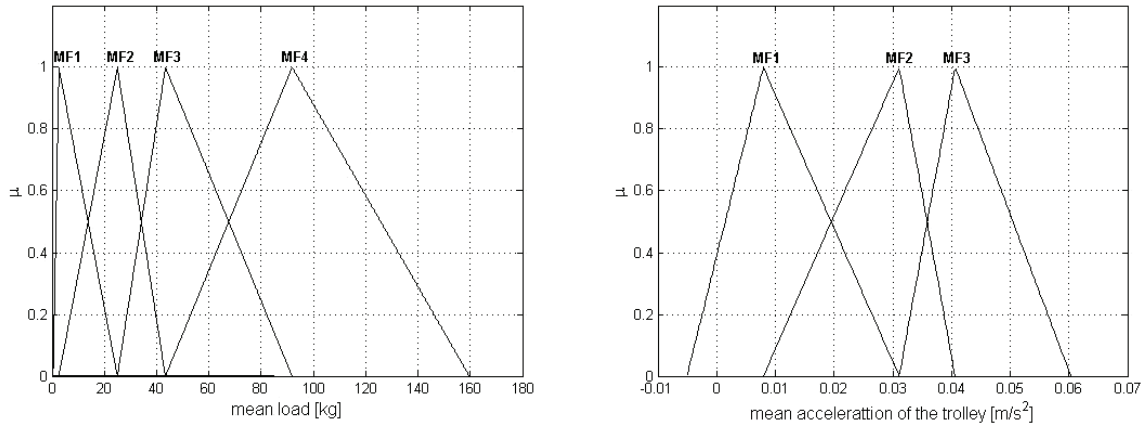
Fig. 3. The MFs tuned by genetic algorithm for inputs variables of fuzzy predictor of operating time of the laboratory overhead travelling crane
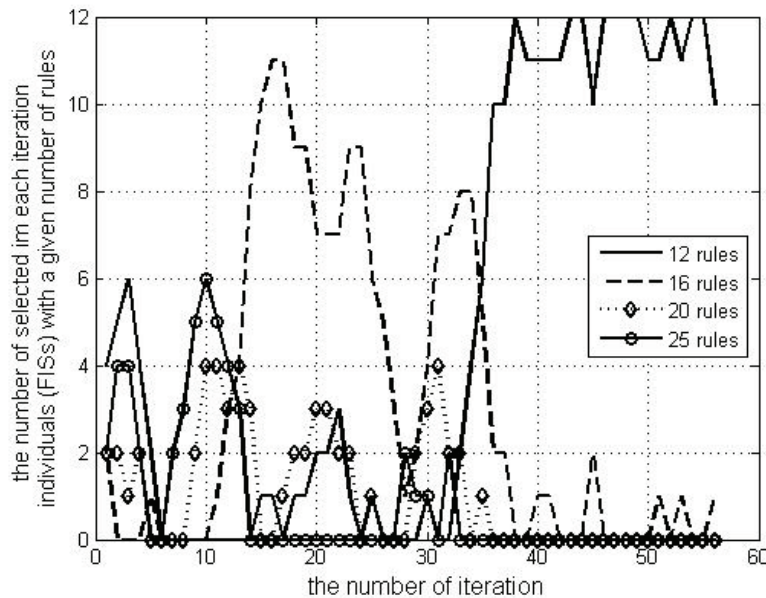

Fig. 4. The number of individuals with a given number of rules in population at each generation

5. Conclusions

The paper is the contribution to the evolutionary computational techniques used to the design the fuzzy rule-based system, as well as contribution to the system diagnosis by used the genetic fuzzy system (GFS). The presented genetic algorithm enables to tune the parameters of the membership functions and conclusions of TSK-type fuzzy implications, as well as optimize the knowledge base of fuzzy inference system. The proposed algorithm based on the Pittsburgh approach allows minimizing the number of rules of FIS even though the initial population consists of the individuals with the significantly more numbers of fuzzy implications.

The proposed algorithm was used to design the fuzzy model applied to estimate the operating time of a system between the actual time and predicted time of the next failure occurring under the stated operational parameters. The fuzzy system allows to prognoses the time of the predicted failure based on the operational parameters which are used to evaluate the actual operational state of the system. The fuzzy operating time predictor is designed based on the history data of previous failures: operating times and operational states changes measured between previous failures. However the genetic algorithm enables to design the FIS in the off-line process according the history of failures occurred in the system. It can be realized to tune the parameters of the FIS and

obtain the initial fuzzy model, which should be modified at each time, when new failure occurs, with using algorithm that can be used in online process. The self-learning fuzzy algorithm can be based on the classic recursive least squares (RLS) algorithm which can adjust the FIS parameters to the speed of degradation of exploitation system.

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