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THE GENETIC FUZZY BASED PROACTIVE MAINTENANCE OF A TECHNICAL OBJECT

Jarosław Smoczek, Janusz Szpytko

AGH University of Science and Technology
Faculty of Mechanical Engineering and Robotics
Mickiewicza Av. 30, 30-059 Krakow, Poland
tel.: +48 12 6173104, +48 12 6173103, fax: +48 12 6173133
e-mail: smoczek@agh.edu.pl, szpytko@agh.edu.pl

Abstract

The proactive maintenance is an effective approach to enhance the system availability through real time monitoring the current state of a system. The key part of this method is forecasting the nonoperational states for advanced warning of the failure possibility that can bring the attention of machines operators and maintenance personnel to impending danger facilitate planning preventive and corrective operations, and resources managing as well. The paper presents the HMI/SCADA-type application used to support decision-making process. The proposed approach to proactive maintenance is based on forecasting the remaining useful life of device equipment and delivering the user-defined maintenance strategy developed during system operation. The HMI/SCADA application is used to collect data in form of failures history, changes of operational conditions and performances of a monitored process between failures, as well as heuristic knowledge about process created by experienced user. The data history is used to design the predictive fuzzy models of time between failures of system equipment. The fuzzy predictive models are designed using the genetic algorithm applied to optimize the fuzzy partitions covering the training data examples, as well as to identify fuzzy predictive patterns represented by a set of rules in the knowledge base. The evolutionary learning strategy, which has been proposed in this paper, provides the effective reproduction techniques for searching the solution space with respect to optimization of knowledge base and membership functions according to the fitness function expressed as a ratio of compatibility of fuzzy partitions with data examples to root mean squares error. The proposed application was created and tested on the laboratory stand for monitoring the availability of the overhead travelling crane.

Keywords: *proactive maintenance, failure prediction, fuzzy logic, genetic algorithm*

1. Introduction

The paper addresses the predictive approach to maintenance of technical object to the problem of monitoring the availability of material handling system (MHS) and supporting the decision-making process of operators and maintenance personnel. The proactive maintenance involves real-time monitoring the operating conditions and performances of a technical system for advanced warning of the failure possibility that can bring the attention of machines operators and maintenance personnel to impending danger, and facilitate planning preventive and corrective operations, and resources managing as well. The papers presents the concept and example of application tested on the laboratory scaled overhead travelling crane of supervisory system equipped in tools for monitoring the technical conditions and performances of MHS, collect historical data and heuristic maintenance strategies of users/personnel/operators, soft computing based design the predictive models of equipment failures, monitor the availability of a technical object, forecast the time between failures (TBF), and support the maintenance decision making process. The system has been realized on the laboratory stand in form of application type of HMI/ SCADA (Human Machine Interface/ Supervisory Control and Data Acquisition) created using the Wonderware System Platform/ InTouch HMI/SCADA software. The core of this system is the algorithm used to design the predictive models of TBF of technical object equipment. The predictive models of TBF are designed using soft computing methods, fuzzy logic and genetic algorithm (GA). The GA is applied to simultaneously classify the data history to the fuzzy partitions and optimize the rule base (RB) size of fuzzy rule-based system (FRBS). The parameters of fuzzy predictors are next on-line tuned using the recursive least squares (RLS) algorithm.

In many works, the problem of failure prediction is solved using soft computing methods including artificial neural network, wavelet network, fuzzy logic, fuzzy wavelet network, genetic algorithm, and the hybrids of those methods. Combination of neural network and fuzzy set theory gives possibility of approximating the nonlinear functional mapping. However, the essential problem consists in designing the efficient structure of neural network. This problem can be solved using the genetic algorithm, which allows extracting from database the predictive patterns and optimizing the model parameters. Moreover, combination of the fuzzy logic and genetic algorithm (genetic fuzzy system) is a useful approach to automatic classification and data mining, and to design of fuzzy rule-base model through exploration of a complex searching space to find the suitable solution mapping the performance examples by supervised or unsupervised learning. The genetic fuzzy system (GFS) is for example implemented in [11] to the problem of failure prediction in telecommunication equipment. The Author employed the GA to identify as well as minimize a set of predictive temporal and sequential patterns within training data. The predictive strategy is based on if-then rules expressing the relationships between sequences of occurrences leading to a specific event. In [6] the GFS is applied to solve a problem of online structural health monitoring (SHM) of composite helicopter rotor blades. The two-stage genetic-based design method of fuzzy predictor is proposed in [3] for estimating the chaotic and non-stationary time series. In the first step the GA is used to determine the coarse RB by maximizing the compatibility of fuzzy partitions to training data. In the next stage the membership functions (MFs) are tuned to minimize the root mean square error (RMSE). The Pittsburgh-based genetic approach to optimize FRBS for wind speed prediction and power produced electrical power at a wind park is proposed in [2], where the GA with binary coded chromosomes is used for fixed number of input variables and MFs to tune the MFs and parameters of rule conclusions. The evolutionary artificial neural network (EANN) is employed in the problem of forecasting the stream flow in hydrological system in [1]. The genetic approach for optimizing the dilatation and translation coefficients of a wavelet network used for time series prediction is proposed in [7]. In [4] the genetic programming is employed to optimize the coefficients of wavelet-neuro-fuzzy model for forecasting precipitation. The TSK fuzzy wavelet network (FWN) is used in [5] to make prognosis of software aging. The dimensionality of input variables of a predictor is minimized using principal components analysis (PCA), and next the combination of GA and back propagation with additive momentum algorithm is applied to optimize the RB and wavelet network coefficients.

The paper is organized as follows. The section 2 provides the conception of failure prediction using the TSK-type FRBS. The fuzzy predictive model designing process based on the GA is described in the section 3. The section 4 depicts the proactive maintenance application created and tested on the laboratory stand and addressed to the MHSs. The section 5 provides the summary and concludes the paper.

2. The conception of TTF forecasting

The conception of TBF prediction of technical object equipment is based on evaluation of the current operational state through monitoring the mean values of selected technical condition $\mathbf{X} = [\bar{x}_1, \bar{x}_2, ..., \bar{x}_n]$ since the last failure. Assuming that the failure process is depended on variation of operational state of a system, the estimator of operating time between failures $T\hat{B}F$ is a function of temporal variations of monitored variables - the mean values of impact factors measured within operating time period between the last failure t_f and the current instant t_c. This relationship can be expressed in a form of *N* fuzzy rules, type of:

$$R_k : \text{IF } \bar{x}_1 \text{ is } MF_{j_1}(\bar{x}_1) \text{ and } \bar{x}_2 \text{ is } MF_{j_2}(\bar{x}_2) \text{ and ... } \bar{x}_n \text{ is } MF_{j_n}(\bar{x}_n) \text{ THEN } y_k = T\hat{B}F_k, \quad (1)$$

where:

$k = 1, 2, ..., N$ – the number of a rule in a RB,

$\bar{x}_1, \bar{x}_2, ..., \bar{x}_n$ – the input variables, which domains are covered by fuzzy membership functions $MF_{j_1}(\bar{x}_1)$, $MF_{j_2}(\bar{x}_2)$, ... $MF_{j_n}(\bar{x}_n)$,

y_k – the rule output,

$T\hat{B}F_k$ – the nominal value of TBF prognosis for a given fuzzy region.

Hence, the fuzzy predictive model maps the non-stationary of the failure process in the form of fuzzy regions of operating points represented by dependencies between varying operating states and the estimated values of TBF. The crisp output value of a fuzzy predictor is weighted average of all rules outputs:

$$T\hat{B}F = \sum_{k=1}^{N} w_k \cdot T\hat{B}F_k \cdot \left(\sum_{k=1}^{N} w_k \right)^{-1}, \quad (2)$$

where w_k is the weight of a rule calculated as a product of fuzzy grades of input arguments to the membership functions (MFs) (Fig. 1):

$$w_k = \mu_{MF_{j1}}(\bar{x}_1) \cdot \mu_{MF_{j2}}(\bar{x}_2) \cdot ... \cdot \mu_{MF_{jn}}(\bar{x}_n), \quad (3)$$

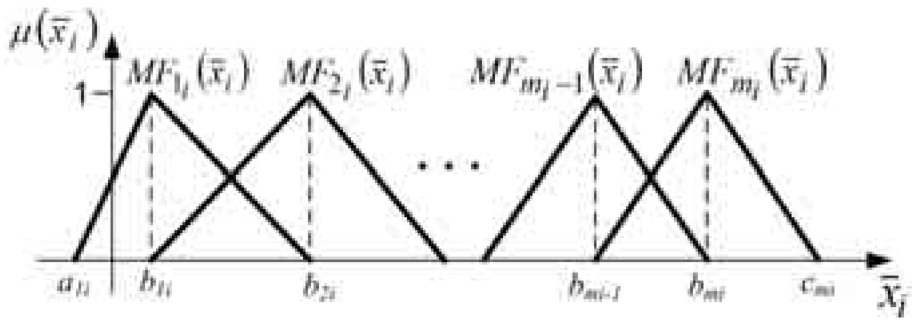

Fig. 1. The distribution of triangular MFs within the interval of input variable $\bar{x}_i$

The designing process of a fuzzy predictive model is performed in the two-stage learning process consisting in the off-line GA-based designing and on-line tuning by RLS algorithm the FRBS. The off-line design of fuzzy predictive model is based on the history of registered failures (the TBF and changes of operating conditions during the uptime), while the RLS method is used in the next stage to on-line tune the parameters of FRBS based on the time between current and previous failure and the temporal variation of operational state between the last two failures. Hence, the conception of supervisory application leads to obtain and upgrade during system operation a set of predictive models of TBF, which are used to produce prognoses of time to failure (TTF) of the system equipment as the difference between estimated TBF and the current operating time Δt since the last failure (Fig. 2).

3. The GA-based designing the TBF predictive model

The fuzzy predictive model is designed in learning process based on the historical data containing the mean values of operating parameters $\mathbf{x} = [\bar{x}_1, \bar{x}_2, ..., \bar{x}_n]$ measured between successive failures and TBF. The searching process of predictive patterns represented by fuzzy rules (1) consists in exploration the solutions space in which the single individual (solution) is represented

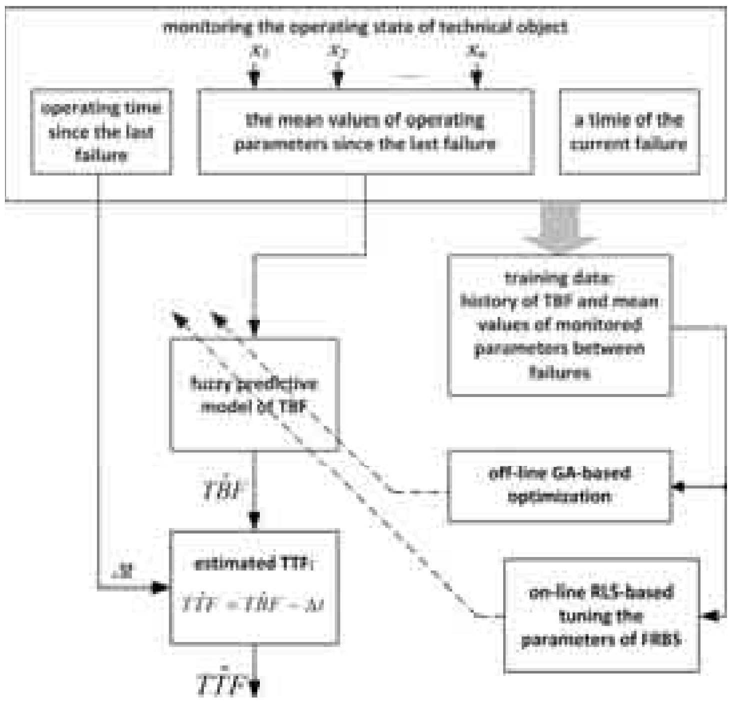

Fig. 2. The general flowchart of the designing process of TBF predictive model and forecasting the TTF

by chromosome created by vectors containing the parameters of the MFs specified for *n* input arguments and estimated values of TBF specified in *N* rules' conclusions:

$$\bar{x}_i : \left\lfloor a_{1_i}, b_{1_i}, b_{2_i}, \ldots b_{j_i}, \ldots, b_{m_i-1}, b_{m_i}, c_{m_i} \right\rfloor, \tag{4}$$

$$\left\lfloor T\hat{B}F_1, T\hat{B}F_2, \ldots, T\hat{B}F_k, \ldots T\hat{B}F_N \right\rfloor. \tag{5}$$

The GA-based learning process is the three-stage reproduction strategy consisting of two different types of mutation operations and arithmetical crossover which ensure exploration of searching space of fuzzy models differing in size of rule base (RB). The first stage consists in adding to a set of parents μ a small group of individuals μ' differing from current population in the number of rules that prevents of premature convergence. The operation is based on the mutation performed by adding or removing the selected MF of randomly chosen parent, and adding the new individual to the current group of parents. The number of MFs of considered individual is decreased or increased based on, respectively, $p_D^{(i)}$ and $p_I^{(i)}$ probabilities, which are calculated based on $\overline{m}_i$ average, $m_{\min}$ minimum, and $m_{\max}$ maximum number of MFs for a given input $\bar{x}_i$:

$$p_D^{(i)} = \frac{\overline{m}_i - m_{\min}}{m_{\max} - m_{\min}}, p_I^{(i)} = 1 - p_D^{(i)}. \tag{6}$$

This operation leads to obtain a new set of parents ($\mu + \mu'$), which are next used to produce the offspring by recombination, which is based on the arithmetical crossover, and next max-min non-uniform mutation used to change the selected gene of randomly chosen. The selection process is based on the tournament method, where the new parents of next population are obtained from competitions of individuals in small groups based on the accuracy and efficiency of fuzzy predictive models quantified by fitness function. The accuracy of prognosis is evaluated based on the root mean squares relative error (RMSrE) (7), while the efficiency of a fuzzy model is measured by the number of rules or partitions and their coverage of training data examples. The efficiency of fuzzy predictor is expressed by the factor C_{MF} determined based on compatibility of training data examples with the fuzzy partitions divided by the number of fuzzy rules (8).

$$RMSrE = \sqrt{\frac{1}{F}\sum_{f=1}^{F}\left(\frac{TBF_f - T\hat{B}F}{TBF_f}\right)^2}\ , \tag{7}$$

$$C_{MF} = \frac{\sum_{f=1}^{F}\sum_{i=1}^{n}\sum_{j=1}^{m_i}\mu_{MF_{j_i}}(\bar{x}_i)}{\prod_{i=1}^{n} m_i}\ , \tag{8}$$

where F is the number of failures in database.

Hence, the fitness function is formulated as a ratio of compatibility of data examples with fuzzy partitions to RMSrE:

$$Fitness = \frac{C_{MF}}{RMSrE}\ . \tag{9}$$

The GA-based algorithm to design the TBF predictive model is detailed described in [10], while the method of learning the FRBS using RLS method is provided in [8, 9].

4. The proactive approach to maintenance of MHS

The example of supervisory system supporting proactive maintenance of automated material handling system was created and tested on the laboratory stand equipped with the laboratory model of an overhead travelling crane with hoisting capacity Q = 150kg. The control-measurement system was built based on the PLC, incremental encoders used to measure the positions and speeds of crane motion mechanisms, and the strain-gauges used to identify the crane load.

The higher level of control system was created using the Wonderware System Platform/ InTouch HMI/ SCADA software, and equipped with tools used to real-time monitoring and analysing historical data, creating user-defined heuristic maintenance strategies, defining hierarchical structure of visualized process, specifying alarms and their conditions, monitoring the failures history, as well as designing fuzzy predictive models using GA based on data history and on-line tuning the parameters of fuzzy predictors using the RLS algorithm. The objective of the supervisory system is to deliver information about upcoming failures (prognoses of TTFs, localisation of the upcoming failure, user-defined maintenance strategy), as well as monitoring the transportation device availability (Fig. 3).

The objective of proposed approach to proactive (predictive) maintenance is to support decision-making process by forecasting the upcoming failure and delivering the maintenance heuristic strategy based on the knowledge base created by experienced user/operator, and a predictive model of TBF, both evolved during system operating and monitoring the operational states between failures. The conception of maintenance-aided decision-making tool is based on the supervisory application used for real-time monitoring the operating conditions and performances of a system. The operational parameters measured between failures are collected in database. The application simultaneously delivers the tools for experienced user/operator of a system to create the heuristic database including the hierarchical structure of a system decomposed for subsystems, their elements and components. The integration of those databases enables to create the knowledge base consisting of historical data about occurrences in a system, including the downtime and uptime (TTR - time to repair, TBF) of system equipments, and heuristic maintenance strategy (history of reactive and proactive actions, potential consequences and reasons of occurred events).

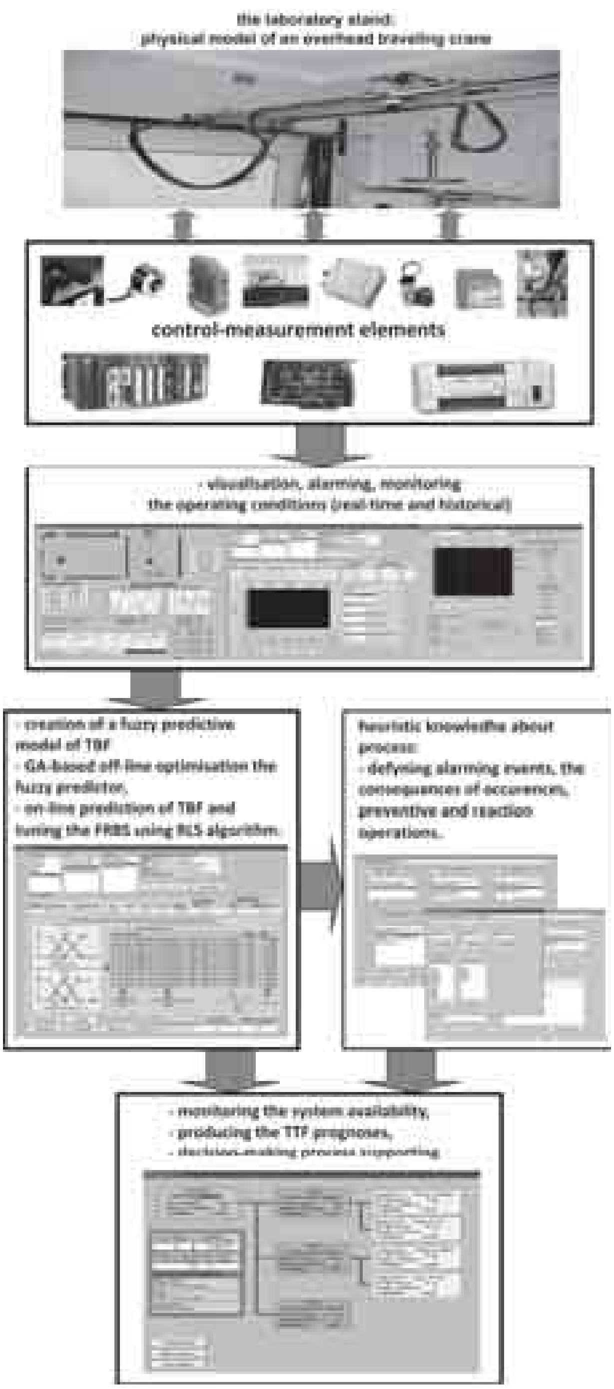

Fig. 3. The HMI/ SCADA supervisory system

The application delivers tools for runtime creating and updating distributed alarming system. The user can analyze the real-time and historical data (input/output variables of a system) for defining the alarms and their conditions validated next during system operation.

The system was inspired by observed on laboratory stand problem of frequently occurred failures of power supply elements (voltage stabilizers and relays) of DC motors used in crane motion mechanisms. The analysis of this problem carried out based on the monitored operational parameters and performances of the object leads to the straightforward conclusion that the failure frequency depends on the operational conditions such as the crane load and accelerations of the crane movement mechanisms. The mean values between failures of those operational parameters $\overline{m}$ and $\overline{a}$ (the crane load and acceleration respectively) were assumed as the input variables of the fuzzy predictive model.

5. Conclusions

The paper presents the approach to the proactive maintenance of technical system, and describes the example of HMI/SCADA-type application implemented on the laboratory stand: laboratory scaled overhead travelling crane. The proposed approach is based on the real-time monitoring the technical object operating conditions to collect the data in form of failures history, changes of operational conditions and performances of a monitored process between failures, as well as heuristic knowledge about process delivered and evolved by users. The data history is used to design the predictive models of TBF. The learning process is based on the GA, used to simultaneously optimize the fuzzy partitions covering the training data examples as well as to identify fuzzy predictive patterns represented by a set of rules in the knowledge base of FRBS. The example of application implemented on the laboratory stand delivers tools, which allow to runtime change the maintenance strategy, modify the alarming conditions, change and create fuzzy predictors for the same alarming event using different operating conditions, and after validation removing those models, which show the worst quality of prognoses.

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