THE SURVEY OF SOFT COMPUTING TECHNIQUES FOR RELIABILITY PREDICTION

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Abstract

The objective of reliability prediction is to estimate a time of upcoming nonoperational state at the current operational state of a system through real-time monitoring operational parameters and/or performances. Hence, the predictive (proactive) maintenance in industrial systems involves operational conditions monitoring and online forecasting the useful life of machines equipment to support the decision-making process in selection of the best maintenance action to be carried out. The advanced warning of the failure possibility can bring the attention of machines operators and maintenance personnel to impending danger, and facilitate planning preventive and corrective operations, as well as inventory managing. This problem has been extensively studied in many scientific works, where the predictive models are based on the data-driven approaches that can be generally divided into statistical techniques (regression, ARMA models, Bayesian probability distribution estimation, etc.), grey system theory, and soft computing methods. The artificial intelligence is frequently addressed to the predictive problem by utilizing the learning capability of artificial neural network (ANN), and possibility of nonlinear mapping using fuzzy rules-based system (FRBS) or recognizing and optimizing data-derived pattern by using evolutionary algorithms. The paper is a survey of intelligent methods for failure prediction, and delivers the review of examples of scientific works presenting the computational intelligence-based approaches to predictive problem.

Keywords: *reliability prediction, artificial intelligence, fuzzy logic, artificial neural network, genetic algorithm*

1. Introduction

Forecasting the useful life of a system and its components fascinates researches in various areas and has the important meaning especially in such fields like structural health monitoring (SHM), reliability of electronic equipments and both hardware and software components of computer systems, as well as process diagnosis and predictive-proactive maintenance in industrial systems. The objective of online reliability prediction is to estimate a time of upcoming nonoperational state at the current operational state of a system through real-time monitoring operational parameters and/or performances. The online reliability prediction provides information to support the diagnostics and decision-making process by advance alarming about failures and estimation of probability that a system is capable to operate satisfactorily in a given period of time. Forecasting the operating time of system equipment leads to reduce the cost of unscheduled maintenance through timely repair actions, planning preventive and corrective operations, resources managing and to enhance availability by increasing maintenance effectiveness and decreasing downtime.

The problem of failure prediction has been extensively studied in many works. Salfner et al. [32] widely surveyed the online failure prediction techniques focusing attention mainly on the predictive applications in software and hardware equipments of computer systems. They proposed taxonomy of surveyed methods by dividing them into four main branches: failure tracking, symptom monitoring, detected error reporting and undetected error auditing. The Authors classify the predictive methods depending on the techniques used to analysis of large data sets to extract knowledge and previously unknown predictive patterns.

The automatic or semi-automatic process of discovering the predictive pattern from data set involves the methods or their hybrid approaches such as statistical techniques (regression, ARMA models, Bayesian probability distribution estimation, etc.), grey system theory, and soft computing methods. The artificial intelligence is frequently addressed to the predictive problem by utilizing the learning capability of artificial neural network (ANN), possibility of nonlinear mapping using fuzzy rules-based system (FRBS) [43] or recognizing and optimizing data-derived pattern by using evolutionary algorithms. The paper provides some selected examples of scientific works and applications utilizing the gray system theory, heuristic techniques, fuzzy logic, ANN, wavelet network, fuzzy wavelet network and genetic algorithm (GA) for failure prediction.

2. The survey of intelligent approaches to failure prediction

In many works a failure prognostics is based on analyzing the circumstances leading to a failure, and correlation between previous occurrences, errors or alarming events and a target event. In [23] the prediction scheme is based on the correlation between the occurrence of a failure, previous failures and non-fatal events. Authors pre-processed and analyzed reliability, availability and serviceability (RAS) data from IBM's BlueGene/L supercomputer in order to categorize the failures into groups and to quantify distribution of failure events in the time and spatial domains. The temporal and spatial compression allowed developing heuristic strategies to detect failures based on the observation of relationships between a failure of a given type and series of consecutive preceding failures or event logs. The temporal and spatial correlation of failure events, depending on their types, was also used for proactive failure management in networked computing systems in [9]. The Authors used RCFA-based (Root Cause Failure Analysis) approach to temporal and spatial clustering of failures utilizing information about distributed system performances associated with the failure events. The performance system variables were used to model the statistical characteristics of failure dynamics and to identify correlations among failure occurrences. The prediction model was offline and online tested with use of time-series algorithms and the artificial neural network. In [31] Authors deliver method of correlation of failures in the time and spatial domains for failure prediction and proactive management without classification of failures on different types. Based on the historical data, RAS events and system activity reports (SARs) collected from distributed computing systems they created predictors with use time-series methods, rule-based classification algorithms and Bayesian network.

The multi modular system for prediction and avoidance of water chemistry faults is presented in [20]. The important part of the system proposed in this work is a knowledge base module supporting the decision-making process. The knowledge bases consisting of rules type of if-then is extracted from multiple pre-processed data. The rules describe dependencies between process performances and the stable and volatile periods. The quality of the knowledge bases is evaluated based on the strength depending on the number of observations.

In some situations, when the small data set causes that the methods for data mining failed, the predictive model can be effectively determined utilizing the grey system theory developed by Deng in 1982 [5]. Grey prediction have been applied for example for power prediction of wind energy conversion unit [8], for forecasting the industry production [1, 41], or in failure prognostics of electronics [10].

The soft computing methods are frequently addressed to the predictive problem by utilizing the ANN, FRBS and GA, and their hybrids to extract the predictive patterns from the database. The ANN was for example employed in [38] and farther in [22] to online monitoring of fatigue damage and failure prognostics in complex mechanical systems based on loading values of system's components. The ANN was applied to fault diagnosis of cable television networks and engineering plants in [19, 27]. The two-stage hierarchical structure of multi-layer ANNs employed to diagnosis of multiply faults in chemical process is provided in [39]. The first stage is used to identify possible failure causes through real-time monitoring process parameters, while the next multi-layers networks discriminate the precise causes based on the outputs of the first stage. The similar approach to detect the faults in industrial process was elaborated and employed to faults diagnose for a model of tank reactor [24]. The primary network identifies dynamic trend during transient period of industrial process based on data pre-processes by moving time window, while a secondary neural network detects and diagnoses the faults. In [14] the linear and nonlinear regression techniques are applied to recognize system failures and to predict the call availability in a telecommunication system. The Authors present results of experiments carried out using the Radial and Universal Basis Functions (RBF and UBF), concluding that the best results were achieved with use UBF. The example of delay-tolerant network employed to formulate the strategy of availability prediction of a node in distributed systems is presented in [25].

The Takagi-Sugeno-Kang-type (TSK) [37] fuzzy inference system was used in [11] for prediction of the residual life of insulating materials for electrical machine windings. The fuzzy predictor was designed in offline learning process for the heuristically specified operational conditions and shapes of membership functions. In [21the fuzzy logic-based control scheme is implemented to control, identify and compensate the aileron and differential elevator failures of F-16 aircraft. The parameters of the direct fuzzy controller are adjusted by the instance controller called 'fuzzy model reference learning controller', which is used to identify system misbehaviour comparing system performances with reference model.

In [6] the fuzzy logic and neural network are combined to design the direct and indirect fault-tolerant control scheme of an aircraft turbine engine. The online learning TSK fuzzy-neural model of a system was used to identify unknown dynamic states caused by faults and to accommodate controller to engine deterioration. Failure prediction approaches based on anomaly recognition by comparison of the system performances with reference model or collected data associated with normal system behaviour are presented also in e.g. [7, 26]. The heuristic strategy to failure prediction in telecommunication network in form of rule-based relationship between error and preceded it occurrences is expressed in [12]. In [42] Authors propose the computational framework for online monitoring the remaining useful life in nuclear power plant based on the data-driven fuzzy approach.

3. The genetic fuzzy approach to failure prediction

The hybridization of the fuzzy logic and GAs leading to genetic fuzzy systems (GFSs) is a frequently utilized approach for classification and data mining. The automatic design of FRBS using GA is a process of exploration of a complex searching space of fuzzy models to find the suitable solution mapping the performance examples. The taxonomy of GFSs, review of wide variety of approaches and classification of methods applied to learn the FRBS is delivered in [13, 16]. The genetic-based fuzzy rule learning methods can be split into two types of approaches called Pittsburgh and Michigan respectively. The Pittsburgh approach [4] is based on the population of fuzzy models, in which each individual represents a set of rules. In the Michigan method, a single rule is encoded in a chromosome of individual, and a set of rules is represented by an entire population [15]. The problem of predictive pattern extracting by data-mining algorithms involves generally data pre-processing before utilizing the techniques used to discover of interesting and previously unknown dependencies and knowledge. The fuzzy logic and GA-based predictive approaches are usually proposed as the separately performed processes of fuzzy clustering partitions, rule-base learning and parameters of rules antecedents and conclusions tuning.

The problem of failure prediction in telecommunication equipment using the rule-based approach and genetic-based machine learning system was studied in [40]. 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 [29] the GFS is applied to solve a problem of online SHM of composite helicopter rotor blades, where the two fuzzy rule-based models are employed for global damage detection based on displacement and force-based measurement deviations between damaged and undamaged conditions, and to identify local damage using strains. The GA is applied to determine optimal representation of fuzzy rules in a Michigan-style. In the proposed genetic fuzzy approach, the number of input variables was fixed in advance.

The genetic fuzzy predictor for estimating the chaotic and non-stationary time series was elaborated in [17]. The Authors propose the two-stage genetic-based design method of fuzzy predictor. In the first step, the GA is used to determine the coarse fuzzy rule base by maximizing the compatibility of fuzzy partitions to training data. In the next stage the membership functions are tuned to minimize the root mean square error (RMSE) defined in a fitness function. This solution is related to the work [36] where Authors, however, propose the Pittsburgh-type GFS to optimize simultaneously the number of fuzzy partitions and parameters of membership functions of fuzzy predictive model used to forecast the time between failure (TBF) of machine equipment.

The approach that is proposed in [36] contributes to the two following problems: the predictive-proactive maintenance in industrial systems involving online monitoring the technical conditions, and predictive pattern recognition based on the classification of data collected from the examples of past failures. Forecasting the useful life of plant equipment enables 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. However, the failure prediction involves collecting the data from previous failures and employing of techniques of data classification to next identify the predictive pattern. The data clustering and pattern recognition are frequently the two independent and separately conducted stages of predictive model design process. This paper describes the fuzzy predictor learning strategy 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 (KB). The each rule of KB represents a certain subspace of the entire solution space, and associated for this subspace nominal value of TBF estimator, where a given subspace is indicated in an antecedent of a rule through combination of fuzzy sets formulated for input domains, while the TBF prognosis is specified in a consequent of a rule. Consequently, the fuzzy predictor interpolates prognosis of TBF based on the weighted average sum of all rules outputs taking into consideration the membership functions distributions for the input domains. 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 KB and membership functions (MFs) according to the fitness function expressed as a ratio of compatibility of fuzzy partitions with data examples to root mean squared relative error. The crossover and mutation operators ensure in the first stage of learning process fast identifying the best promising regions of solution space, and in the next stage those regions are fine explored in order to tune the MFs parameters and rule consequents. The proposed GA-based learning process can be combined with recursive least squares (RLS) method [35] used to online tuning the parameters of fuzzy predictive model at each time, when the new failure delivers the new information about the technical system. The satisfactory results of experiments conducted on the laboratory stand (laboratory scaled overhead travelling crane) encourage to implement the proposed approach as a tool of knowledge base module supporting the decision-making process in material handling systems, and a part of control and diagnostic application type of HMI (Human Machine Interface) [33, 34].

The Pittsburgh-based genetic approach to optimize FRBS for wind speed prediction and power produced electrical power at a wind park is also provided in [3], where, before applying the genetic-based optimization algorithm, the number of input variables and membership functions of fuzzy TSK predictor were assumed based on the Authors experience about the problem under consideration. Hence, the GA with binary coded chromosomes is used only for tuning membership functions and parameters of rule conclusions.

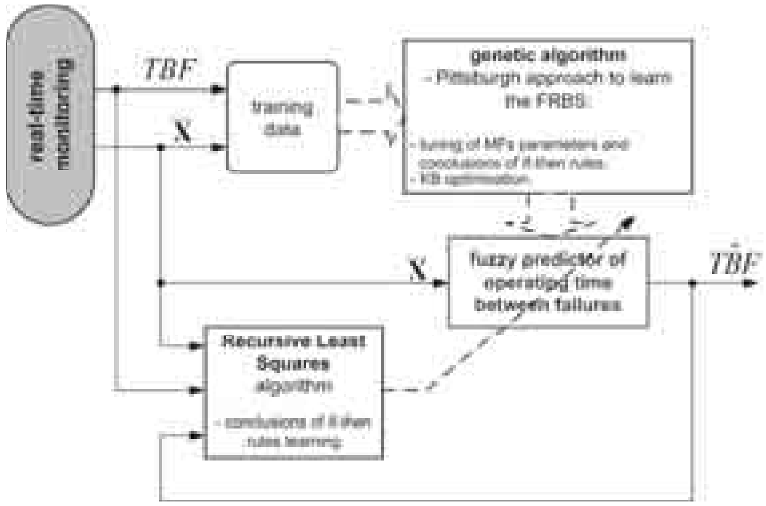

Fig. 1. The combined GA and RLS techniques of TBF predictive model learning based on the historical data: TBF and operating conditions changes between failures $\overline{\mathbf{X}}$*)*

The combination of evolutionary algorithms, fuzzy logic and ANN or wavelet neural network is also frequently implemented in predictive applications. The evolutionary artificial neural network (EANN) was employed for example in the problem of forecasting the streamflow in hydrological system [2]. In [30] Authors propose the genetic approach for optimizing the dilatation and translation coefficients of a wavelet network used for time series prediction. The genetic programming is used in [18] to optimize the coefficients of wavelet-neuro-fuzzy model for forecasting precipitation. The TSK-type fuzzy wavelet network (FWN) is employed in [28] to make prognosis of software aging. The dimensionality of input variables of a predictor was minimized using principal components analysis (PCA), and next the combination of GA and back propagation with additive momentum algorithm were applied to optimize a rule base and wavelet network coefficients. However, the fitness function is defined as an inverse of least-square error, and is not explained how the fuzzy predictor with lesser number of rules is rewarded.

4. Conclusions

The predictive (proactive) maintenance of technical systems involves monitoring the operating conditions and performances of a 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. However, the failure prediction involves collecting data from previous failures and employing of techniques of data classification to next identify the predictive pattern. This goal can be achieved using the soft computing techniques, including artificial neural network, wavelet network, fuzzy logic, fuzzy wavelet network, genetic algorithm, and the hybrids of those methods. Artificial neural network and wavelet network are the powerful tools used in machine learning. 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 to extract from database the predictive patterns and optimize the model parameters. Moreover, the fuzzy logic and genetic algorithm combination (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 paper provides the some examples of solutions and applications in which those methods are addressed to the problem of reliability prediction.

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