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Parameter learning for the belief rule base system in the residual life probability prediction of metalized film capacitor

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A B S T R A C T

The Inertial Confinement Fusion (ICF) laser device consists of thousands of Metalized Film Capacitors (MFC). The Belief Rule Base (BRB) system has shown privileges in reflecting complex system dynamics. However, the BRB system requires the referenced values of each attribute to be limited. The traditional BRB learning and training approaches are no longer applicable since the referenced values of the attributes in the BRB system are pre-determined. A parameter learning approach is proposed with three strategies and each strategy is designed for one specific scenario. Strategy I (for Scenario I) is designed when only the training dataset is selectable. Strategy II (for Scenario II) is designed when new referenced values are predictable yet there is only one scale in the conclusion part. Strategy III (for Scenario III) is designed when new referenced values are predictable and there are multiple scales in the conclusion part. The Differential Evolution (DE) algorithm is used as the optimization engine to identify the key referenced values. A case is studied to validate the efficiency of the proposed parameter learning approach with multiple referenced values. The comparative results show that the parameter learning approach performs best in Scenario III.

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1. Introduction

The Inertial Confinement Fusion (ICF) laser device uses the high power laser for the thermonuclear fusion in the laboratory condition [1]. ICF, such as the National Ignition Facility (NIF) in the United States and the ShenGuang in China [2], consists of thousands of Metalized Film Capacitors (MFC). MFC is crucial to reliability analysis and maintenance policy-making for the energy systems as well as for the high power laser devices themselves. Therefore it is necessary to evaluate the reliability of MFC, which in essence is to predict MFC's residual life or its residual life probability [3].

The traditional MFC reliability analysis estimates the parameters based on the assumption that the failure data follows the Weibull distribution [4]. However, since MFC is highly-reliable and has long-life expectancy, it is hard to gather enough failure data within a short period. Therefore, the traditional reliability analysis has lost its privileges in dealing with most practical cases. More attention is given to the degradation data based methodology. Zhao and Liu [5] proposed a Poisson-based degradation process for MFC reliability analysis. Peng et al. [6] considered the degradation process of MFC as a Wiener process based on which the average residual life of MFC was predicted.

Wang et al. [2,3,7] proposed a residual life prediction approach in which the degradation data on single MFC performance and the prior distribution degradation information were integrated. The approach included model construction, the Expectation–Maximization (EM) [8], and the Bayes approach. However, it was not applicable when there were both degradation data and life related information, which is a common practical situation.

Although there are multiple factors that share influence on the residual life, the most common form of the residual life probability function is a time series. In the residual life probability function, the independent variable (input) is the time and the dependent variable (output) is the residual life probability. During the formation of the residual life probability function, there could be multiple sets of data in which contains the time as the input and the residual life probability as the output.

The Belief Rule Base (BRB) system [9,10] which is a collection of rules in the same belief structure [11–13] is applied to model the process of predicting the residual life probability of MFC. The BRB system is a powerful tool in representing system dynamics and integrating different types of information under uncertainty

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[13]. The application fields of the BRB system include the Multiple Attribute Decision Analysis (MADA) problem [14], group decision making [15], risk analysis [16], customer perception risk analysis [17], trade-off analysis [18], system readiness assessment [19], military capability evaluation [20], etc. To apply the BRB system in the residual life probability prediction of MFC, there is only one antecedent attribute, the time, which is required to be of limited number of the referenced values.

Although the background of this study is focused on the residual life probability prediction of MFC, the parameter learning approach is discussed in a more generic fashion so as not to lose its versatility.

There are two kinds of BRB systems classified by their originations: the BRB system derived from the experts and the BRB system derived from practical systems.

For the BRB system derived from the experts, the referenced values of each attribute are fixed while the attributes are changeable. Chang et al. [21] used multiple dimensionality reduction techniques for the structure learning approach to downsize the BRB system. In Chang's structure learning study [21], the attributes of the BRB system are selectable while the referenced values are fixed. As in this study, the situation is reversed: the referenced values of the attributes in the BRB system are selectable while attributes are fixed. Therefore the structure learning approach is not applicable.

For the BRB system derived from practical systems, the situation is reversed since the attributes are fixed while the referenced values are selectable. There have been extensive studies regarding on the training and learning of the BRB system derived from practical systems. The first generic BRB learning framework was proposed by Yang et al. [22] with an optimization model. Xu et al. [23] proposed another BRB training approach and applied it in the pipeline leak detection. Zhou et al. [24,25] argued that these approaches were offline and proposed an online updating approach which however still required the attributes must be discretized first. In Refs. [26,27], the two attributes in the pipeline leak detection case, the "*FlowDiff*" and "*PressureDiff*" were discretized into seven and eight parts of equal size before the learning process. In Ref. [28], Chen also discretized the only attribute "*x*" into six/four parts with seven/five referenced values and then adapted the learning process. In conclusion, these training and learning approaches demanded that the referenced values of the attributes must be pre-determined. This leads to the main work of this study: the parameter learning of the BRB system, which in essence is to identify the key referenced values of each attribute.

There are fundamentally differences between structure learning and parameter learning for the BRB systems. To summarized, the targeted object and the techniques to be applied are different.

The structure learning approach for BRB system is targeted at expert systems whose information are mainly derived from experts' knowledge and experiences, mostly through brainstorming and/or questionnaires. The attributes of this kind information are selectable whereas the referenced values of these attributes are fixed. It is like the questions and the choices on a questionnaire, where the questions are selectable yet the number of the choices is fixed.

Comparatively, the parameter learning approach faces a completely different challenge. Since the targeted systems are based on actual systems with mostly continuous attributes, the key problem is to identify the most representative referenced values of each attribute so that an appropriate BRB system can be constructed. In this case, the attributes are fixed (decided by experts or simply the readings of a practical system) whereas the referenced values must be discretized from the continuous attributes, which is just the work of this study.

As for the techniques used in the two kinds of studies, they are completely different as well. For the structure learning approach, certain dimensionality reduction techniques (which are originally used in feature extraction and image processing) are applied to identify the key attributes. For the parameter learning approach, the Differential Evolutionary (DE) algorithm is applied to identify the key referenced values out of the continuous attribute(s) with a set of readings from metalized film capacitor (also acquires certain mathematical calculation) as the training dataset.

The challenge of the parameter learning for the BRB system lies in that the correlation between the input and the output is unknown (if it is known, there would be no meaning to conduct the parameter learning). This challenge must be addressed in multiple scenarios regarding on whether just the initial dataset is available or new referenced values could be predicted.

In the BRB parameter learning approach, an optimization model is constructed with the referenced values of the attributes (of the BRB system) as extra parameters to be estimated. With this in mind, an optimization engine is required. Traditionally, certain mathematical process is applied which however requires the initial solution identified and the inference result may be trapped in local optimality if the initial solution is poorly selected.

To meet this challenge, the Differential Evolutionary (DE) algorithm is an applicable candidate. The DE algorithm, as one of the most advanced Evolutionary Algorithms (EAs), was first proposed by Store et al. [29]. Das and Suganthan [30] summarized that DE was much simpler (with less parameters) and straightforward compared with other EAs since DE outperformed several other algorithms in a series of performance contests (ICEOs) [31,32]. Moreover, DE does not require the initial solution and has been proved to be of global optimization capabilities [30–32]. Certain progress on DE has been made in both practical fields such as parameter identification on a building thermal model [33] and large scale evolutionary optimization [34], and theoretical fields regarding on the adaptive mutation and parameter control [35], competitive population evaluation [36], etc. There have been several improved DE variants with real parameter optimizers. However it is believed that the Classical DE (CDE) [29] is sufficient for this study. MAE is used to as the efficiency measure of the proposed parameter learning approach.

Note that it is not the intension of this study to identify DE as the most appropriate technique and/or algorithm for the parameter learning approach. Instead, it is believed that each technique and/or algorithm has its own advantages and therefore it has its own fittest application fields. For the DE algorithm, it is proved to be sufficient by the case study results in this study.

The remainder of this study is organized as follows. The background and the problem are introduced in Section 2. The parameter learning approach is proposed in Section 3 using three strategies. Section 3 also introduces the basics of DE. In Section 4, a case is studied in corresponding three scenarios. This study is concluded in Section 5.

2. Background and problem demonstration

2.1. Background

A generic process to predict the residual life probability of MFC is described as following [2,3,7]:

(1) Establish the assumptions for following analysis, and the most basic of which is that the degradation process of MFC is a Weiner process.
(2) Use the Wiener process to model the residual life prediction of MFC. In order to improve the accuracy of the residual life prediction, certain parameters are estimated.

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