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System reliability prediction by support vector regression with analytic selection and genetic algorithm parameters selection

Wei Zhao [a,*], Tao Tao [a], Enrico Zio [b,c]

[a] Group 203, School of Electronic and Information Engineering, Beihang University, Beijing 100191, China
[b] Chair on Systems Science and the Energetic Challenge, European Foundation for New Energy-Electricité de France, Ecole Centrale Paris and Supelec, Paris, France
[c] Dipartimento di Energia, Politecnico di Milano, Milano, Italy

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ABSTRACT

We address the problem of system reliability prediction, based on an available series of failure time data. We consider support vector regression (SVR) as solution approach, for its known performance on time series forecasting. However, SVR parameters selection is very critical for obtaining satisfactory forecasting. Currently, two different ways are followed to set the values of SVR parameters. One way is that of choosing parameters based on prior knowledge or experts experience on the problem at hand: this is a simple and quick, practical way but often not optimal in complex situations and for non-expert users. Another way is that of searching the values of the parameters via some intelligent methods of optimization of the SVR regression performance: for doing this efficiently, one must avoid problems like divergence, slow convergence, local optima, etc.

In this paper, we propose the combination of an analytic selection (AS) method of prior selection followed by a genetic algorithm (GA) for intelligent optimization. The combination of these two methods allows utilizing the available prior knowledge by AS for guiding the GA optimization process so as to avoid divergence and local optima, and accelerate convergence. To show the effectiveness of the method, some simulation experiments are designed, based on artificial or real reliability datasets. The results show the superiority of our proposed ASGA method to the traditional GA method, in terms of prediction accuracy, convergence speed and robustness.

1. Introduction

Rapid technological development contributes to improving welfare in many ways but also leads to increasing complexity in modern processes, systems and plants. This, together with the usual necessities of business profitability, safety of human life and protection of the environment, requires accurate evaluation of the reliability of systems, components and plants throughout their lives. Therefore, reliability prediction has received an increasing attention in practice and become an active area of research.

The aim of reliability prediction is to estimate the future occurrences of system failures for maintenance planning and replacement policies, etc. [1]. A number of methodologies for this purpose have been proposed, including principle-based methods [2], statistics-based methods [3] and machine learning methods [4]. The first type of methods stands on models based on the physics, chemistry, mechanical and structural principles of the processes of degradation. The second type of statistics-based methods is based on statistical models and is useful when it is difficult to describe the reliability behavior of the system based on poorly known principles. Reliability models are developed by statistically describing the degradation and failure processes based on some assumptions and the values of the models parameters are selected based on failure data. However, the prior assumptions upon which the models are based may not always be applicable in the actual system operation environment, so that the reliability prediction results may not be accurate. The third type of methods, based on machine learning, comprises empirical algorithms that are designed and trained based on failure data. Popular machine learning methods include, for example, artificial neural network (ANN), and support vector machine (SVM). ANNs have already been applied to system reliability estimation, with demonstrated advantages over principle-based models [5–7]. Yet, ANNs may suffer from problems like 'over-fitting', slow convergence and local

* Corresponding author. Tel.: +86 10 82339897.
E-mail address: zhaowei203@buaa.edu.cn (W. Zhao).

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optima [8]. Support vector machine (SVM) is another powerful learning machine paradigm [9]. SVMs are based on statistics learning theory or VC theory (VC-Vapnik, Chervonenkis, from the last names of the original proposers) and embody the idea of minimizing an upper bound of the generalization error by structural risk minimization (SRM), rather than the empirical risk minimization (ERM) adopted by neural networks. Because the ERM principle is only appropriate when there is a large number of training examples that somewhat guarantees good generalization performance, SVMs outperform ANNs particularly when only a small dataset is available for training. SVMs have been applied to many areas spanning from pattern recognition to fault diagnosis [10]. With the introduction of the so called ε-insensitive loss function, it has been extended to support vector regression (SVR) [11] to solve non-linear regression/prediction problems [12,13], including those associated to system reliability prediction [14–18].

When ANN or SVR are used for reliability prediction, reliability prediction problem is often framed as a kind of time series prediction problem, whose goal is to estimate future values based on current and past data samples. Thus, it is necessary to introduce the development of the time series prediction problem, especially methods which are baseline algorithms in our experiments. Besides autoregressive integrated moving average (ARIMA) method [19], Kalman filter [20], ANN and SVR, some approaches related to fuzzy inference have been proposed in recent years. For example, Melin [21] brings up a paradigm that integrates the ANFIS (adaptive network based fuzzy inference system) to an ensemble to predict the value of time series. This EANFIS method is concise, efficient, and effective when forecasting the Mackey–Glass, the Mexican exchange stock, and the Dow Jones time series. Another time series prediction approach is the optimized ensemble neural networks with fuzzy integration (EFNN) proposed by Pulido [22]. This method utilizes the fuzzy inference to integrate the neural network optimized by GA and also shows satisfactory performance in predicting chaotic time series. Though this kind of methods based on fuzzy inference may perform comparably to, or even better than SVR-based methods when addressing the general time series prediction problem, SVR-based algorithms show superiority in case that only small training dataset is available, which common exists in the practice of reliability prediction problems.

However, to obtaining accurate regression/prediction result for SVR, parameters selection is very important. Existing methods of parameter selection for SVR can be divided into two classes. The first kind of methods is based on prior knowledge of the analyst on the problem at hand. For example, Cherkassky proposed an analytical selection (AS) method [23] to choose SVR parameters directly from the training data, based on some existing consensus that the SVR parameters are suitable relative to statistical properties of the training data. This type of methodology is simple and effective for determining the parameters, provided that the prior knowledge is sufficiently informative. Obviously, in complex problem settings (high dimensional spaces, nonlinear functions, few representative data, etc.), these methods are not suitable.

The second type of methods searches for the values of the parameters within an optimization scheme defined on specific performance objectives of the algorithm. In general, there are three types of searching methods that can be used for SVR parameter selection:

(1) First are the exhaustive methods for searching the best values of the parameters in the entire parameter space. A typical exhaustive method is the grid-searching method [24], which divides the parameter space and calculates the SVR generalization performance with the parameters set at the values of each grid point. This process is very time-consuming.
(2) The second class of searching methods comprises the traditional optimization methods including the gradient descent method [25], ellipsoid method [26] and simultaneous perturbation stochastic approximation method [27]. These methods are not easily generalizable and perform well only in specific situations.
(3) The third class comprises intelligent optimization methods which are powerful searching methods that have emerged rapidly in recent years and have attracted significant attention because of their good performances in various problem settings, even highly complicated. For example, simulated annealing (SA) [28], genetic algorithm (GA) [29,30] and particle swarm optimization (PSO) [31,32] have been proposed for optimal values of the SVR parameters applied to system reliability prediction. Of course, these optimization algorithms could also be combined with other methods, such as approaches based on the fuzzy theory, and applied in SVR parameter selection. In 2013, Melin used fuzzy logic to improve the convergence and diversity of the swarm in PSO [33]. Valdez also combined the optimization results of PSO and GA by Fuzzy logic. Because more than one optimization methods are integrated together, these two methods have superior searching ability, but consume much more computational resources. Among these methods, GA is perhaps the most frequently used because of its demonstrated global search efficacy.

Even though different optimization methods have been integrated in some literatures, there is no paper that combines the prior knowledge with the intelligent optimization scheme to choose SVR parameters. However, this combination is very necessary because most of optimization schemes are designed to solve the general problems and prior knowledge is obtained from special applications. If the problem-specific prior knowledge could guide the search process, some problems such as local optima and slow convergence speed, existing in optimization scheme, could be avoided.

The purpose of this paper is to propose a novel SVR-based reliability prediction algorithm which combines two methods belonging to different class, the AS method and the GA method, which actually combines the prior knowledge with the intelligent optimization. In this paper, we consider the reliability prediction as a time series prediction problem, SVR is used to forecast the reliability of a system and a novel hybrid optimization method is presented to optimize parameters of SVR for a special application. The whole algorithm is named ASGA–SVR. The novelty of our algorithm focuses on SVR parameter selection method that combines the prior knowledge as used by AS for guiding the optimization search of GA during SVR parameter estimation. That is, the parameters values selected by the AS method are exploited to adjust the values of chromosomes after each crossover operation of GA evolution process. This new idea takes simultaneously full advantage of prior knowledge on SVR parameter selection and of the search power by intelligent optimization methods. The advantages of our algorithm over other methods exhibit in following aspects:

(1) Compared with SVR using AS to estimate parameters, our ASGA–SVR has more accurate prediction results because of the following optimization by GA.
(2) By guiding with prior knowledge about the SVR parameters, the GA searching procedure avoids falling into local optima or divergences, and actually the prior information accelerates its convergence. Compared with SVR choosing parameters by standard GA, our ASGA–SVR method has more accurate prediction results, higher convergence speed and stronger robustness.
(3) Making comparation between our ASGA–SVR and other SVR methods using different parameter optimization techniques