

A new approach for optimal obsolescence forecasting based on the random forest (RF) technique and meta-heuristic particle swarm optimization (PSO)

Yosra Grichi, Thien-My Dao and Yvan Beauregard

Department of Mechanical Engineering

École de technologie supérieure

Montreal, H3C 1K3, Canada

yosra.grichi.1@ens.etsmtl.ca, thien-my.dao@etsmtl.ca,

yvan.beauregard@etsmtl.ca

Abstract

Obsolescence is highly complex problem due to the influence of many factors such as competitive market pressure, technological advancement and short life cycle of technological components. Basically, obsolescence problems are often sudden and not planned, causing delays and extra cost. To overcome this problem, forecasting appears to be one of the most efficient solutions. Indeed, many studies have been conducted to create models that can effectively forecast obsolescence. In addition, applying machine learning techniques have attracted many attentions and have been widely used to predict obsolescence risk and life cycle. Popular algorithms such as random forest, has been reporting satisfactory performance. To improve the accuracy of machine learning algorithms for obsolescence forecasting, this paper proposes a new optimization approach for obsolescence forecasting based on random forest (RF) and Particle Swarm Optimization (PSO). In fact, parameters optimization and features selection of RF have an important effect on it is predictive accuracy and PSO presents one kind of effective method for RF parameters and features choosing. To examine the effectiveness of this approach, this paper presents a comparison between PSO-RF and GA-RF (random forest based on genetic algorithm). Experimental results show that PSO-RF outperformed GA-RF with 96% of accuracy.

Keywords

Obsolescence, forecasting, optimization, machine learning, random forest, particle swarm optimization

1. Introduction

Obsolescence issue occurs in systems that have a longer lifecycle than their components, such as in automotive, avionics, military, etc. The negative effects of obsolescence on the production performances have been studied in the literature and represent a major challenge in long term (Rojo, Roy, & Kelly, 2012; Rojo, Roy, & Shehab, 2010; Peter Sandborn, 2013; P. Sandborn, Prabhakar, & Ahmad, 2011). Rapid technological is one of the factors that increase the rate of obsolescence. The electronic industry has emerged as the fastest growing sector, and has spread widely around the world. As defined by Moore's law, the rapid evolution of electronic components continues to grow, which stipulates that semiconductor density doubles approximately every 18 months (Voller & Porté-Agel, 2002). This evolution creates new electronic components every year with short lifetimes. In the USA, the industry has grown at a rapid rate since the 1990s. New technologies are introduced in the market at increasing rates. Today, the short lifecycle and the lack of forecasting represent a challenge for several companies that need to take into account the risk of obsolescence. Moreover, obsolescence modeling is a complex problem that requires a good knowledge of parts. In the same way, it is necessary to know the lifetime of the components, their technological evolutions and, therefore, know all the factors that influence the obsolescence of components to understand how obsolescence may occur. These factors can include component criticality, technological watching, technological maturity, and the number of sources among others.

Obsolescence forecasting appears to be one of the best solutions in the obsolescence management as it assists manufacturers to identify part obsolescence. Through obsolescence forecasting, companies can ensure support for parts in service. There are two methodologies of obsolescence forecasting: long-term forecasting (1 year or longer), which allows a proactive management and life cycle planning to support a system, and short-term forecasting, which can be observed from the supply chain. Short term forecasting may involve reducing the number of sources, reducing inventories, and increasing the price (Bartels, Ermel, Sandborn, & Pecht, 2012).

To overcome the problems caused by obsolescence, many studies have been conducted to create models that can effectively forecast obsolescence. Statistical methods such as regression, Partial least square regression (PLS), logistical regression and Gaussian method have been previously employed in many works (Gao, Liu, & Wang, 2011; Jungmok & Namhun, 2017; Solomon, Sandborn, & Pecht, 2000). Indeed, machine learning has attracted the attention of many researchers in various disciplines, and has been applied in obsolescence recently (Jennings, Wu, & Terpenney, 2016; D. Wu, Jennings, Terpenney, Gao, & Kumara, 2017; X. Wu et al., 2008; Yun, Ping, & Li, 2010). Random forest algorithm is a kind of machine learning method that has been used in many areas and has shown a high degree of satisfactory classifications accuracies (Grichi, Beauregard, & Dao, 2017). However, the performance of the classification may be reducing due to the irrelevant and redundant features in the dataset. In fact, not all of the features are useful for classification. Indeed the optimization of the model's parameters and choosing the right features can maximize the classification accuracy.

In order to improve the accuracy of obsolescence forecasting, this study attempts to improve the classification accuracy rate of RF to better forecasting the obsolescence risk by developing an approach based on particle swarm optimization (PSO) and random forest (RF). PSO algorithm has applied to some machine learning algorithms such as, SVM, Neural network, etc. However, PSO appears as an optimal approach compared with other optimization techniques like Genetic Algorithms (GAs) and Ant colony, which require a few parameters to adjust. However, the developed PSO-RF approach can optimize the parameter of RF as well as identify the right features extraction to improve the classification accuracy rate of RF. The accuracy of PSO-RF will be compared to GA-RF.

The rest of this paper is organized as follows. Section 2 review pertinent literatures on obsolescence forecasting, PSO optimization and RF, while Section 3 presents the proposed framework PSO-RF. Numerical case study is presented in section 4. Finally, section 5 presents the conclusion and recommendations for future research.

2. Literature review

2.2 Potential obsolescence forecasting strategies : Background

Forecasting obsolescence is reactive in nature and was based on the resolution of the problem once noticed. The most classical approaches include lifetime or last-time buy (Rojo et al., 2010). There are two types of forecasting methods, namely forecasting of the obsolescence risk and forecasting of the obsolescence date (life cycle forecasting). Obsolescence risk forecasting is used to predict the probability that a component still in production (Josias, Terpenney, & McLean, 2004; Rojo et al., 2012). A few researchers focus on the prediction of the risk of obsolescence. In this context, Rojo et al. (2012) conducted a Delphi study to analyze the risk of obsolescence. They developed a risk using some indicators, which are; years to end of life, the number of sources available, and the consumption rate versus availability of the stock. Another approach developed by Josias et al. (2004) aims to create a risk index by measuring the number of sources, life cycle stage (introduction, growth, maturity, decline, end of life), and market risk. (van Jaarsveld & Dekker, 2011) developed a method based on historical demand data to estimate the risk of obsolescence. The risk of obsolescence was estimated based on Markov Chain. Last, (Grichi et al., 2017; Jennings et al., 2016) have used data-driven method by create machine learning algorithms to forecast the obsolescence risk of a large number of parts. Alternatively, for life cycle forecasting, Solomon et al. (2000) were the first to introduce the life cycle forecasting method. In their paper, the researchers conducted a study to predict the life stage of a part from the life cycle curve, which included six stages: introduction, growth, maturity, saturation, decline, and obsolescence. Another method was developed by (P. Sandborn, 2007) using data mining with Gaussian method to predict the zone of obsolescence. This zone is given between $+2.5\sigma$ and $+3.5\sigma$ and gives time intervals for the period for the part will become obsolete. Moreover, other researchers have introduced regression analysis to predict the date of obsolescence (Gao et al., 2011).

2.2 Random forest

Introduced by Breiman (2001), Random forests are an integration of tree predictors where every tree depends on the values of a random vector separately (Breiman, 2001). A similar distribution applies for all the trees in the forest. The tree classifier of a forest has a generalization error which relies on the strong correlation between all trees in the forest. Classification accuracy increases significantly when the group of trees is enlarged. A primary example is bagging, where to raise every tree, an arbitrary selection (without replacement) is done from the set examples. Another example is random split selection where arbitrarily, the split is selected from among the K best splits at every single node. A random forest algorithm consists of rotating many decision trees that are randomly constructed and then generating them. Bootstrap sampling (OOB: Out-Of-Bag sampling) is used in RF to have a better estimate of the distribution of the original data set. Indeed, bootstrapping means randomly selecting a subset of the data for each tree rather than using all the data to build the trees. In statistical terms, if the trees are uncorrelated, this reduces the forecast variance. The main advantage of random forests is their resistance to variances and biases.

The random forest algorithm is used in the regression case to predict a continuous dependence and classification variable in order to predict a categorical dependent variable. For the regression type, a random forest consists of a set of simple prediction trees; each is capable of producing a numerical response when presented with a subset of explanatory variables or predictors. The error in this forecast is called Out Of Bag (OOB).

For the classification type, a categorical variable with N modalities is broken down into a disjunctive array (with $N-1$ variables) according to a 0-1 coding scheme. Thus, a categorical variable with N modalities can be considered as a set of $N-1$ variables, of which only one will assume the value 1 for a given observation. In fact, the ability to make predictions on a random subset of predictive variables is one of the strengths of the Random Forest module, which makes it particularly well suited to processing data sets with extremely high predictive variables. This random feature selection encourages systems diversity, and by the end, it enhances classification performance. The random forest is constructed by sampling arbitrarily the features subset as well as the training subset with regard to every system. The majority vote combines the final prediction. Finally, the random forest attains a favorable and vigorous performance with various applications (Cheng, Chan, & Qiu, 2012; Friedman, Hastie, & Tibshirani, 2001).

2.3 Particle swarm optimization

PSO called swarm intelligence or collective intelligence is developed by Eberhart and Kennedy in 1995 (Kennedy & Eberhart, 1995; Shi, 2001). The overall behavior of the PSO is not programmed in advance but emerges from the sequence of elementary interactions between individuals. In this context, many researchers have applied the PSO in several machine learning for optimization (Lin, Ying, Chen, & Lee, 2008; Xiaodan, 2017).

The Optimization method of PSO can be iterative; each particle consists of changing the velocity toward its fitness value and global version of PSO. For the movement, the particle must decide on its next movement (its new speed) by linearly combining three pieces of information: its current speed V_{ij}^n (velocity), its best performance already found P_{ij}^n and which is known as the personal best position (*pbest*), and the best performance of its neighbors or informants P_{gj}^n known as the global best position (*gbest*) (See equation below). The iteration of the velocity and position of the particles are getting by following equations:

$$V_{ij}^{k+1} = w * V_{ij}^k + c_1 * r_1 (P_{ij}^k - x_{ij}^k) + c_2 * r_2 (P_{gj}^k - x_{ij}^k)$$

$$x_{ij}^{k+1} = x_{ij}^k + V_{ij}^{k+1}$$

Where $P_{ij} = (p_{i1}, p_{i2}, \dots, p_{im})$ and $P_{gj} = (p_{g1}, p_{g2}, \dots, p_{gm})$. k is the number of iteration, x_{ij}^k present the particle position. Positive coefficient r_1 and r_2 are random number, generated uniformly in the range [0 1]. w presents the inertia coefficient of PSO algorithm. This weight is updated according to the following equation (Chen et al., 2011):

$$w = w_{min} + (w_{max} - w_{min}) \frac{(t_{max} - t)}{t_{max}}$$

Where t_{max} presents the maximum number of iterations. Usually, the inertia coefficient is generated in the range [0.4 0.9] (Chen et al., 2011). The coefficients c_1 and c_2 are calculated as follows:

$$c_1 = (c_{1f} - c_{1i}) \frac{t}{t_{max}} + c_{1i}$$

$$c_2 = (c_{2f} - c_{2i}) \frac{t}{t_{max}} + c_{2i}$$

With c_{1f}, c_{1i}, c_{2f} , and c_{2i} are a positive constants.

The position of the particles as well as their initial velocity must be initialized randomly according to a uniform law. The original process for implementing the local version of PSO is as follows:

Step 1: Initialize randomly a population. Step 2: Measure the fitness of each particle in the population (calculate fitness score for each particle using selected features). Step 3: Update the velocity and position of each particle by looking for the best performance for each particle (local optimum). If the current fitness is better than the previous fitness, the previous $pbest$ is replaced with the current $pbest$. Finally, in step 4: continues until the process converges. Stop the algorithm if the termination criterion is satisfied; otherwise, return to step 2.

3 Proposed PSO-RF optimization approach

In this paper, the PSO-RF model is developed and applies for forecasting of obsolescence risk. This main objective of this paper is to apply particle swarm optimization to enhance the classification performance of random forest algorithm by searching for the optimal parameters for RF and discovering the best subset of features as well.

The proposed PSO-RF optimization approach consists of 4 steps as follows:

Step 1: The initialization of the data processing. The dataset is initialized to construct the RF model based on supervised learning (known data), also the data is split into two groups (training and testing) randomly.

Step 2: The initialization of PSO and RF parameters. For the PSO, the number of generations, population size (number of particles) and so one, are initialized. The position and velocity set to x_i^0 and v_i^0 respectively, are determined as well. Each particle has (1) dimension (d) which is the length of features and the number of parameters to be optimized. (2) Position (x): position of the i^{th} particle. The initialization the parameters of RF (number of trees and the number of variables to split on at each node (mtry)) are included into the algorithm as well.

Step 3: PSO is adopted to construct PSO-RF model. In fact, PSO is looking for the optimal solution of particles by evaluation of fitness based on the update particle velocity and its position. However, if the current fitness is better than the previous fitness, the previous $pbest$ is replaced with the current $pbest$ until to find the optimal solution (if current $gbest$ is better than previous $gbest$, then replace $gbest$ score and $gbest$ particle. If the particle is already created and evaluated, then generate a new one. As introduced by Kennedy, the PSO is searching in a discrete space (0 or 1). Each feature in the PSO represents a binary bit (0 or 1), where 1 represents a selected feature while 0 represents a feature that is not selected. The features selected are based on the particle's position.

Step 4: presents the training subset of features selection and parameters optimization is introduced in the RF model; therefore the PSO-RF is obtained. For each terminal node of the tree, these steps are repeated until the specified number of trees is reached and the minimum node size is obtained. Next, the Out of Bag (OOB) error for the model is estimated. For classification, OOB error is estimated as the proportion of times that the categorical variable is not equal to the true class prediction. Finally, the output is represented as an ensemble of trees $\{T_b\}$. To make prediction at a new point x , let $\hat{c}_b(x)$ be the class predicting of the b^{th} random forest tree. The equation is given as follows:

$$\hat{C}_{rf}^b = \text{majority vote}\{\hat{c}_b(x)\}.$$

Finally, the precision of the model is calculated by comparing the current state with the state predicted by the model using a confusion matrix. The fitness function is calculated as follows:

$$f = \text{accuracy (AUC)}$$

The architecture of the proposed method is illustrated in Figure 1.

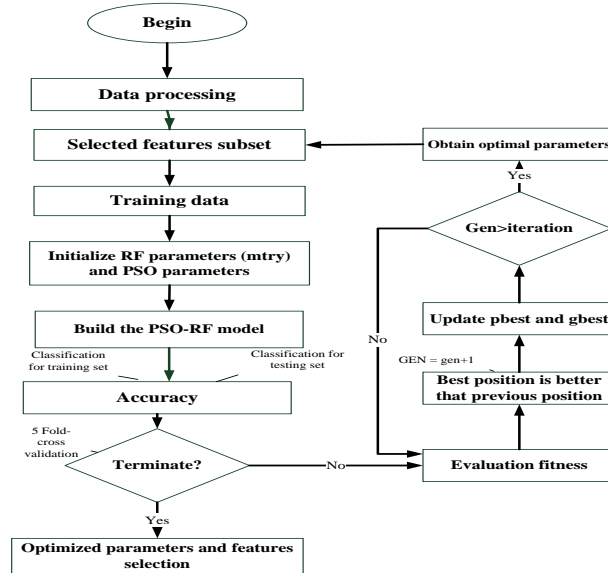


Figure 1. Architecture of the PSO-RF Model

4. Numerical case study

The R programming is adopted to develop the PSO-RF. To measure the performance of PSO-RF approach, a dataset is used, taken from (Jennings et al., 2016). A total of 999 instances provided information about cellphones and thirteen attributes were used as predictive variables. The output present two class (in production/end-of-life). About 70% of the data are randomly selected as the training set for constructing the model while 30% of the data are used as the test set to validate the model accuracy. To obtain a better estimation of classification accuracy, the K-Folds cross-validation method presented by (Salzberg, 1997) was applied and set to 5.

For features selection, we have introduced an assumption for the model: selected features should be greater or equal to 2. The parameters setting for PSO is obtained as follows: number of iteration and number of populations (particles) are set to 10 and 50 respectively. In fact, the iteration tries to generate new particle, however when there is so many particles which were already used, it will try to find other ones. If the solution is already near to the optimal, the result will not be change. Based on the experimental results, PSO is faster to find the solution with small iteration. As suggested by (Ratnaweera, Halgamuge, & Watson, 2004): $c_{1i} \leftarrow 2.5$, $c_{1f} \leftarrow 0.5$, $c_{2i} \leftarrow 0.5$, $c_{2f} \leftarrow 2.5$, $w_{max} \leftarrow 0.9$, $w_{min} \leftarrow 0.4$.

To examine the effectiveness of this approach, the PSO-RF is benchmarked with GA-RF (random forest based on genetic algorithm). The characteristic of GA is as follows: maximum generations, population, crossover and mutation are set to 20, 50, 0.8 and 0.1 respectively.

4.1 Experimental results and discussion

The results in this paper are described in terms of accuracy (AC), error rate, sensitivity (SE), specificity (SP), and Cohen's KAPPA, which are calculated by the following equations (Woods & Bowyer, 1997; Woods, Kegelmeyer, & Bowyer, 1997):

$$AC = \frac{TP + TN}{TP + TN + FP + FN}$$

$$error\ rate = 1 - AC$$

$$SE = \frac{TP}{TP + FN}$$

$$SP = \frac{TN}{TN + FP}$$

$$K = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)}$$

TP, *TN*, *FP* and *FN* are defined as true positive, true negative, false positive and false negative. For KAPPA equation, $\Pr(a)$ presents the probability of success of classification (accuracy) and $\Pr(e)$ presents the probability of success due to chance. In order to validate the accuracy of the proposed PSO-SVM algorithm, the results obtained by PSO-RF is compared with the GA-RF (RF with genetic algorithm) developed by (Grichi, Beauregard, & Dao, 2018). The classification accuracy rates of GA-RF are cited from their original papers that was achieved a good predictive performance. The accuracy of PSO-RF, GA-RF and RF was initially presents by a confusion matrix (See Table 1) for testing set. The comparisons of the algorithms are shown in Table 2 and 3.

Table 1. Confusion matrix of GA-RF, PSO-RF and RF algorithms

		Predict	
		Available	Discontinued
Actual	Available	166	12
	Discontinued	8	113
GA-RF	Available	170	9
	Discontinued	4	116
PSO-RF	Available	163	15
	Discontinued	11	110
RF	Available		
	Discontinued		

Table 2. The accuracy measures comparison across algorithms (testing sample)

Accuracy measure	RF (%)	GA-RF (%)	PSO-RF (%)
Accuracy	91.3	93.3	96
No Information Rate	58.2	58.2	58.2
Kappa	82.1	86.2	91
Sensitivity	88	90.4	97.7
Specificity	93.7	95.4	92.8
Error rate	8.7	6.7	4
Balanced Accuracy ((Sensitivity+ Specificity)/2)	90.8	92.9	95.25

Table 3. The accuracy measures comparison across algorithms (training sample)

Accuracy measure	RF	GA-RF	PSO-RF
Accuracy	94.7	98.6	98.6
No Information Rate	58.3	58.3	0.583
Kappa	89.1	97.1	97
Sensitivity	91.4	98	98.8
Specificity	97.1	99	98.3
Error rate	5.3	1.4	1.4
Balanced Accuracy	94.3	98.5	98.55

The result obtained from the PSO-RF model proves that the prediction through parameters optimization and choosing the best small features can improve significantly the classification accuracy of the RF. The experiments results were compared with RF-PSO and RF. PSO-RF approach yielded a higher classification accuracy rate compared to the other approaches. Thus, PSO-RF yielded more appropriate subset with few iteration.

Figure 2 shows the Receiver Operator Characteristic curve, that presents the false positive rate vs. true positive rate. These curves present as follows: green, blue, orange for PSO-RF, RF and GA-RF respectively.

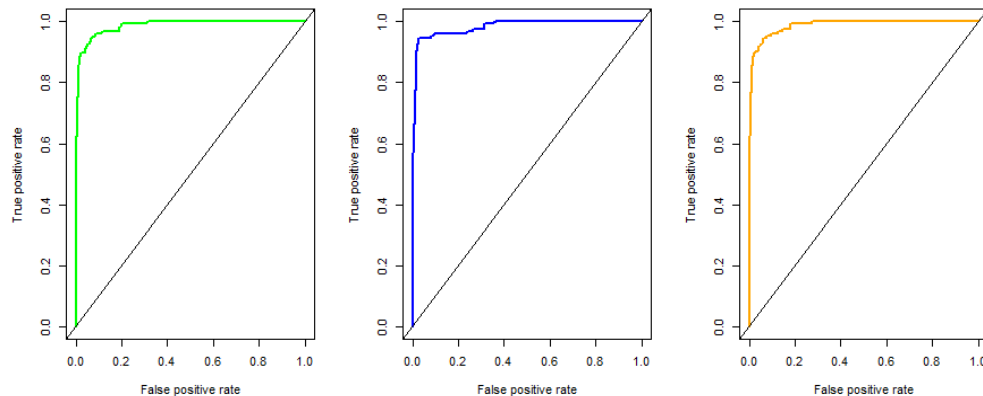


Figure 2. ROC curve

The use of feature selection and parameter optimization were found to improve the classification accuracy rate for random forest to improve the forecasting of obsolescence risk. Experimental results show that PSO-RF has better performance than that of GA-RF.

5. Conclusion

This paper presents an improved approach for obsolescence forecasting risk with a high degree of accuracy based on machine learning and meta-heuristic PSO. PSO search for the optimal parameter value for RF to obtain a subset of beneficial features. The optimal set features were adopted for the training and testing of RF model to improve the classification accuracy of the model. In order to validate this approach, PSO-RF was compared to RF and GA-RF. Experimental results show that PSO-RF outperformed GA-RF with 96% of accuracy.

For future work, larger data with more features can give more accurate results. Other datasets and real-world problems for obsolescence forecasting can be tested using this approach.

Other optimization algorithms can also be used, such as ant colony which is widely used for optimization, and compare it with the existing approach.

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Biographies

Yosra Grichi is currently pursuing the Ph.D. degree at the department of mechanical engineering, École de technologie supérieure (ÉTS), University of Québec (Canada). She received a bachelor's degree (Licence degree) and Master's degree in mechanical engineering from University of Tunisia (ENSIT) in 2012 and 2015 respectively. Her current research interests include predictive modeling, management of manufacturing systems, data mining, machine learning and statistics.

Thien-My Dao is a Professor in the Department of Mechanical Engineering, École de technologie supérieure (ÉTS), University of Québec (Canada). He received a Bachelor's Degree, Master's Degree and PhD in Mechanical Engineering (Design option) from Sherbrooke University in 1969, 1971 and 1974 respectively. After four (4) years in industry sector, he joined the Department of Mechanical Engineering of École de technologie supérieure, University of Québec, in 1976 where he is teaching particularly production and operations management, quality management and design of manufacturing systems. His research interests are in optimization of the design, the reliability and the management of manufacturing systems.

Yvan Beauregard is a professor in the Department of Mechanical Engineering at École de Technologie Supérieure. Mr. Beauregard holds a Bachelor's degree in Industrial Engineering from École Polytechnique de Montréal, a Master's Degree in Administration from McGill University and a PhD in Mechanical Engineering from Concordia University. He has more than thirty years of industrial experience at Pratt & Whitney and IBM Canada. His research interests include among others operations and risk management, as well as product development performance improvement