Research on Equipment Life Cycle Cost Prediction Based on GA-LSSVM

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Abstract. Penalty parameter $\gamma$ and kernel parameter $\sigma^2$ are two important parameters of LSSVM. In this paper, the GA-LSSVM prediction model is constructed, which the genetic algorithm was used to optimize the parameters. Comparing with LSSVM model, the GA-LSSVM model improves the disadvantage that the parameters can only obtained by experience. Also in order to check model prediction accuracy, the posterior difference method (PDM) was used. The calculation results show that the GA-LSSVM model has higher prediction accuracy than other models, and it is a feasible and reliable method for equipment life cycle cost prediction, also the model can be extended to other prediction fields.

1. Introduction

Life cycle cost (LCC) of equipment was first proposed by the U.S. Department of defense in the 1960s, it is defined as the sum of all costs paid for the demonstration, development, production, service, maintenance, support, and retirement of equipment within the life cycle, its main purpose is to reveal the law of the occurrence and development of LCC, so as to take effective methods to control it [1, 2, 4].

The control of LCC is one of the important contents of equipment integrated logistics support (ILS). The purpose of ILS is to minimize the LCC on the basis of ensuring the equipment integrity, so as to maximize the cost-effectiveness ratio of the equipment cost [3, 4]. As in [5], Li Hongtao studied the equipment selection of wind turbine system using the LCC model.

The methods of LCC predication are analogy estimation method, parameter estimation method and engineering evaluation method [1, 2, 4]. Parameter estimation method is be commonly used, which is not only suitable for the cost evaluation in the later stage of demonstration and early stage of development, but also can be used to verify the conclusions of other estimation methods [4].

In this paper, the least square support vector machine model based on genetic algorithm is constructed to predict the life cycle cost of equipment, so as to explore the feasibility of this method in the prediction of the life cycle cost of equipment.

2. Least square support vector machine

Support vector machine [5, 6] (SVM) is an algorithm with good adaptability to non-linear and small sample problems. It uses a non-linear mapping to map the non-linear data to a high-dimensional feature space, and then realizes the linear regression in the high-dimensional space, thus reducing the non-linear problem to a high-dimensional linear problem. The least squares support vector machine
(LSSVM) is an improvement of SVM, which uses the square sum error loss function to replace the insensitive loss function in SVM, and uses the equality constraint to obtain the linear equations, the basic principle is as follows:

Given the following training sample set \( D = \{ (x_i, y_i), i = 1,2,3,\cdots,N \} \), where \( x_i \) is the input sample, \( y_i \) is the output sample. For nonlinear regression, LSSVM uses the following model to model the sample data:

\[
y(x) = \omega^T \phi(x) + b + e_i
\]

In the equation (1), \( \omega \) represents the weight vector; \( \phi(x) \) is a non-linear function, which is used to make the input space complete the mapping of high-dimensional feature space; \( b \) is a deviation amount; \( e_i \) represents the fitting error, which is the \( i \) error amount of the actual training output and the estimated output of the group data, and \( \omega \) and \( b \) can be solved by the following optimization problems:

\[
\min J(w, \varepsilon) = \frac{1}{2} \omega^T \omega + \gamma \sum_{i=1}^{N} e_i^2
\]

Equation (2) satisfies the equality constraint:

\[
y_i = \omega^T \phi(x_i) + b + e_i, i = 1,2,3,\cdots,N
\]

In the formula (3), \( \omega^T \phi(x) \) is adjust the weight and punish the heavy weight, \( b + e_i \) is the error of training data. Define Lagrangian function \( L \) for equation (2):

\[
L(w, b, e, \alpha) = J(w, e) - \sum_{i=1}^{N} \alpha_i [\omega^T \phi(x_i) + b + e_i - y_i] = \frac{1}{2} \omega^T \omega + \gamma \sum_{i=1}^{N} e_i^2 - \sum_{i=1}^{N} \alpha_i [\omega^T \phi(x_i) + b + e_i - y_i]
\]

In the equation (4), \( \alpha_i \) is Lagrange multiplier; \( \gamma \) is penalty parameter to balance the complexity of LSSVM model. According to the KKT (Karush Kuhn Tucker) optimization condition, the partial derivatives of equation (4) for \( w, b, e_i, \alpha_i \) and make them equal to 0, and the optimization condition is obtained:

\[
\begin{align*}
\frac{\partial L}{\partial w} &= 0 \rightarrow w = \sum_{i=1}^{N} \alpha_i \phi(x_i) \\
\frac{\partial L}{\partial b} &= 0 \rightarrow \sum_{i=1}^{N} \alpha_i = 0 \\
\frac{\partial L}{\partial e_i} &= 0 \rightarrow \alpha_i = \lambda e_i \\
\frac{\partial L}{\partial \alpha_i} &= 0 \rightarrow \omega^T \phi(x_i) + b + e_i - y_i = 0
\end{align*}
\]

Eliminate \( \omega \) and \( \alpha_i \), the LSSVM regression model can obtained:

\[
y(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b
\]

Where, \( K(x, x_i) \) is the kernel function; \( x \) represents the input vector of the training sample, \( x_i \) is the kernel function center point, \( \alpha \) and \( b \) are the solution of equation (5). In general, radial basis function (RBF) is selected as the kernel function, which is:

\[
K(x, x_i) = \exp(-\frac{||x - x_i||^2}{2\sigma^2})
\]

Where: \( \sigma^2 \) is the core parameter.

The value of penalty parameters \( \gamma \) and kernel parameters \( \sigma^2 \) have great influence on the accuracy of LSSVM prediction model. Generally, the value is obtained by experience. The generalization ability of the model increases with the value of \( \gamma \) decrease, but the training error of the sample
increases; the smaller the value of $\sigma^2$, the higher the complexity of the model, and the larger value of $\sigma^2$ may lead to under-learning, so it is necessary to take a reasonable value for $\gamma$ and $\sigma^2$ in LSSVM prediction model.

3. GA-LSSVM model
Genetic algorithm [7] (GA) is a random search optimization method designed according to the genetic mechanism of nature. It is characterized by group search strategy and information exchange between individuals, and the search does not depend on gradient information. It is especially suitable for dealing with complex and nonlinear problems which are difficult to be solved by traditional methods, and widely used in pattern recognition, image processing, machine learning, etc.

In order to obtain the reasonable value of $\gamma$ and $\sigma^2$, and improve the accuracy of the LSSVM prediction model, the GA-LSSVM model is built, which takes $\gamma$ and $\sigma^2$ as the unknown parameters, takes the mean variance $\varepsilon$ between the actual output of the model training samples and the predicted output as the fitness function, and uses genetic algorithm to optimize the value of $\gamma$ and $\sigma^2$. The fitness function is:

$$f = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$$

4. Posterior Difference Method
In the process of prediction, the PDM [8] is used to check the prediction accuracy of model. The principle of PDM is calculated as follows:

Original sequence mean value:

$$\bar{x} = \frac{1}{N} \sum_{i=1}^{N} x(i)$$

Absolute error mean value:

$$\bar{e} = \frac{1}{N} \sum_{i=1}^{N} |e(i)|$$, which $e(i) = x(i) - \hat{x}(i)$

Original sequence variance:

$$S_1 = \frac{1}{N} \sum_{i=1}^{N} (x(i) - \bar{x})^2$$

Absolute error variance:

$$S_2 = \frac{1}{N} \sum_{i=1}^{N} (e(i) - \bar{e})^2$$

Thus, the posterior difference ratio $C = S_2 / S_1$ and small error frequency $P$ are defined to evaluate the model, which:

$$P = P\{|e(i) - \bar{e}| \leq 0.6745S_1\}$$

Generally, the smaller $C$ and the larger $P$ were indicates that the prediction model has a better fitness with the original sequence, and the model accuracy is higher [7], the relationship between $C$, $P$ and the prediction accuracy of the model is shown in Table 1.
### Table 1. Value of $C$, $P$ and model prediction accuracy level

| $C$   | $P$   | Level description                                      |
|-------|-------|--------------------------------------------------------|
| $C<0.35$ | $P>0.95$ | The model prediction accuracy is high.                |
| $C<0.50$ | $P>0.80$ | The model prediction accuracy is acceptable.          |
| $C<0.45$ | $P>0.70$ | The prediction accuracy of the model barely meets the requirements. |
| $C\geq0.45$ | $P\leq0.70$ | The model prediction accuracy cannot meet the requirements. |

### 5. Example

In the paper, the GA-LSSVM prediction method is calculated by an example. In order to facilitate the comparison of the results, this paper uses the case data in reference [9] to calculate and compare with the prediction results of other models. The maintenance cost series $X = \{1.15, 1.95, 2.35, 2.70, 3.08, 3.50, 3.89, 4.69, 6.5, 8.19\}$ of a certain type of equipment from 1999 to 2001 is shown in Table 2.

#### Table 2. Calculation results of each prediction model

| Year | 1992 | 1993 | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | Value of $C$ | Value of $P$ |
|------|------|------|------|------|------|------|------|------|------|------|-------------|-------------|
| Cost (million) | 1.15 | 1.95 | 2.35 | 2.70 | 3.08 | 3.50 | 3.89 | 4.69 | 6.50 | 8.19 | 0.1609 | 1 |
| Grey separating model[9] | 1.1815 | 1.8311 | 1.9322 | 2.3374 | 2.8282 | 3.4228 | 4.1434 | 5.0169 | 6.0759 | 7.3600 | 0.1609 | 1 |
| Unbiased Grey Model | 1.150 | 1.6935 | 2.0489 | 2.4790 | 2.9993 | 3.6288 | 4.3904 | 5.3119 | 6.4269 | 7.7758 | 0.1580 | 1 |
| Unbiased Grey Markov Model | 1.150 | 1.8055 | 2.1177 | 2.5590 | 3.0713 | 3.6856 | 4.4382 | 5.3578 | 6.4727 | 7.8226 | 0.1539 | 1 |
| GA-LSSVM | - | - | - | - | - | 3.3237 | 3.5022 | 4.6724 | 6.5989 | 8.2490 | 0.0116 | 1 |

In GA-LSSVM model, in order to train the model, the data of the first five years is used to predict the data of the sixth year as the sample data, then the sample data of input $X$ and output $Y$ are:

$$X = \begin{bmatrix} 1.15, 1.95, 2.35, 2.70, 3.08 \end{bmatrix}, \begin{bmatrix} 1.50, 1.69, 2.47, 2.99, 3.63 \end{bmatrix}, \begin{bmatrix} 2.56, 3.07, 3.65, 4.44, 5.36 \end{bmatrix}, \begin{bmatrix} 3.32, 3.50, 4.67, 6.59, 8.25 \end{bmatrix}$$

In the genetic algorithm, the initial group is 20, the number of iterations is 200, the probability of crossover is 0.9, the probability of replication is 0.05, and Gauss mutation is used, the value range of $\gamma$ is $\gamma > 0$. Through calculation, the optimization value of $\gamma$ and $\sigma^2$ are 30.536 and 2.685. So the LSSVM prediction model is obtained and the prediction results comparison with other prediction models are shown in Table 2.

Because the GA-LSSVM model uses the data of the first five years to predict the sixth year data, the cost value of the first five years is true value and have not be predicted. Through calculation, the value of $C$ in the four models are 0.1609, 0.1580, 0.1539 and 0.0116 respectively, and the value of $P$ are all 1. According to Table 1, the prediction model accuracy is: GA-LSSVM > Grey Markov model > unbiased grey model > grey separation model.

### 6. Conclusion
In this paper, the GA-LSSVM prediction model is constructed by using genetic algorithm to optimize the parameters $\gamma$ and $\sigma^2$ in the least squares support vector model, in order to check model accuracy, the posterior difference method (PDM) was used. Also the life cycle cost of an equipment is predicted by using the model. The results show that:

- Compared with other prediction models, GA-LSSVM model has higher accuracy;
- GA-LSSVM model improves the disadvantage that the parameters value of $\gamma$ and $\sigma^2$ in LSSVM model can only obtained by experience, and the model can choose the optimal value according to the needs of various forecast situations;
- It can be seen from the prediction results that GA-LSSVM model can be well applied to equipment life cycle cost prediction, is a feasible and reliable prediction method, and can be further extended to other prediction fields.

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