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Hybridizing Support Vector Machines into Genetic Algorithm for Key Factor Exploration in Core Competence Evaluation of Aviation Manufacturing Enterprises

Linwei Zhai[a], Jian Qin[b], Lean Yu[c,*]

[a]*School of Economics and Management, Beihang University, Beijing, 100191, China*
[b]*Institute of Industrial Economics, Chinese Academy of Social Sciences, Beijing, 100836, China*
[c]*School of Economics and Management, Beijing University of Chemical Technology, Beijing, 100029, China*

Abstract. In the core competence comprehensive evaluation of aviation manufacturing enterprises, exploring the key factors affecting core competence is crucial to improve the competitiveness of the aviation manufacturing enterprises. In this paper, a novel hybrid approach integrating genetic algorithm (GA) and support vector machines (SVM) is proposed to conduct the key factor exploration tasks in the core competitiveness evaluation of aviation manufacturing enterprises. In the proposed hybrid GA-SVM approach, the GA is used for key factor exploration, while SVM is used to calculate the fitness function of the GA method. Using the survey data from Aviation Industry Corporation of China (AVIC), some experiments analysis is conducted to test the effectiveness of the proposed hybrid approach. Empirical results demonstrate that the proposed hybrid GA-SVM approach can be used as an alternative solution to key factor exploration.

1. Introduction

The aviation manufacturing enterprises are one of the most important manufacturing industries of one country due to its high relevance to national security. How to improve their competitive capability in the markets is a crucial issue in the management of the aviation manufacturing enterprises. In the competitiveness analysis of aviation manufacturing enterprises, it is well known to all that core competence is the generic source of enterprise competitive advantage. Generally, enterprise core competence is the integration of internal resources, knowledge, technology and entrepreneurship, and meantime the coordination of the different capabilities to highlight the advantages of enterprises [1]. In the existing studies, there are a lot of references about enterprise core competence. For example, Barney [2] pointed out the internal and external resources are the key factors for sustainable development of the enterprise's core competence. Hagan [3] and Noe et al. [4] considered the enterprise human resources management is an important factor

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Corresponding author: Lean Yu
Email addresses: zhailinwei@126.com (Linwei Zhai), qinjiancass@126.com (Jian Qin), yulean@amss.ac.cn (Lean Yu)

to improve the enterprise core competence. While Helleloid and Simonin [5] revealed that organizational learning is the core competence of enterprises. Denicolai et al. [6] demonstrated that enterprise resources can provide an important support to the enterprise core competence, especially in the local network and in the field of tourism. They thought enterprise resources is very important to obtain the enterprise core competitiveness. But Petts [7] believed that the use of the enterprise core competence can lead to enterprise sustainable growth.

In the area of aviation manufacturing industry, Shen and Wu [8] analyzed the five key factors affecting the development of Chinese civil aviation, including cost, special resources, management, service and brand awareness, and government intervention. Based on the five key factors, they put forward their views from the strategic point of view on how to improve the competitiveness of Chinese airlines. Liu [9] presented some typical ideas to enhance the Chinese civil aviation enterprises, and put forward relevant suggestions to improve the competitiveness of the civil aviation enterprises in China. Yi and Huo [10] utilized literature review, theoretical deduction and case study to explore the seven key elements affecting civil aviation enterprises based on the industrial key resources. The seven key factors include route optimization and operation capability, aviation management ability, aviation brand marketing capability, aviation learning ability, aviation alliance management capability, aviation and aviation vision attraction and aviation incentive portfolio capability. Zhai and Qin [1] proposed a grey relational analysis method to explore the core competence evaluation indicators in the aviation manufacturing enterprises.

At the same time, Yu and Li [11] proposed a multilevel-fuzzy comprehensive evaluation method to evaluate the airlines' competitiveness and Li et al. [12] analyzed some important factors affecting the aviation manufacturing enterprises and design some competence evaluation indicator system. Using the data from some typical Asian aviation enterprises and suitable evaluation methods, several empirical results can be obtained. Wei et al. [13] adopted a hybrid approach integrating Delphi method with principal component analysis (PCA) to evaluate the core competence of civil aviation enterprises. Fu and Wu [14] constructed an evaluation indicator system including 5 first-category indicators and 17 second-category indicators. Using the data from five civil aviation corporations, the fuzzy-AHP-based aviation core competence evaluation model conducted several experiments and obtained some important results. Li and Li [15] incorporated AHP, linear weighted method and nonlinear weighted method to propose a comprehensive aviation core competence evaluation models and empirical results based on the data from six main aviation corporations demonstrates its superiority of their proposed approach.

As can be seen from the above studies, it is easy to find that the core competitiveness of aviation manufacturing enterprises is the interactive and combinatorial results of internal and external factors. That is, the core competitiveness evaluation of aviation manufacturing enterprise is actually an evaluation of core competence evaluation indicator system. Therefore, constructing a suitable evaluation indicator system is directly related to the accuracy of the evaluation of the enterprises core competiveness. In this sense, construction and selection of evaluation indicator system play a very important role in the core competitiveness evaluation of aviation manufacturing enterprises.

However, in the existing literature about the core competence evaluation of aviation manufacturing enterprises, the most common practice is to directly construct the evaluation indicator system and to conduct a comprehensive evaluation, and few studies analyze and explore some key factors affecting the core competence of aviation manufacturing enterprises. Actually, a comprehensive evaluation result only a total result of an aviation manufacturing enterprise. How to find some key factors to improve the core competiveness is a very crucial issue for the aviation manufacturing enterprises.

In such a background, this paper tried to explore some key factors affecting the core competence to improve the core competiveness of aviation manufacturing enterprises using a hybrid approach integrating genetic algorithm (GA) and support vector machines (SVM). The rest of this paper is organized as follows. Section 2 will present the hybrid approach integrating GA and SVM for key factor exploration of enterprise core competiveness. In Section 3, using the survey data from Aviation Industry Corporation of China (AVIC) and previous literature, the empirical analysis will be conducted by using the proposed hybrid approach and accordingly some key factors affecting core competiveness are explored. The concluding remarks are drawn in Section 4.

2. Methodology Formulation

In this section, a hybrid approach integrating GA and SVM is proposed. First of all, a short introduction of GA is given. Then the SVM for regression is presented briefly. Finally, a hybrid approach integrating GA and SVM is proposed for key factor exploration.

2.1. GA

In this section, some basic knowledge about GA will be given. GA, also known as a meta-heuristic search algorithm, is started from a random initial solution and attempting to find a best solution under some conditions. In GA, a gene is represented by a binary bit, and a chromosome is a set of genes. A population is a set of chromosomes which are produced in different generations. Usually GA learning is carried out by using GA operators — selection, crossover and mutation of a population [18, 19].

The main task of selection operation is to choose the best chromosomes from the population for the next generation and the aim of selection is to give more reproductive chances to population members who have higher fitness. Crossover operation interchanges two chromosomes to create two new chromosomes for the population. The main aim of crossover operation is to give children chances to differ from their parents and to wish that some of the children can be closer to the optimal destination than their parents. There are some forms of crossover: one-point, two-point, multipoint and uniform. When chromosomes are very long, the use of one or two point crossover operation may lead to undesirable results and the learning of parameters values takes more computational time. Mutation operation changes a chromosome into a new chromosome by inverting randomly selected genes of the chromosomes with a mutation rate. Similar to crossover operation, the aim of mutation operation is to give more children chances to increase the opportunity of obtaining optimal solution [19]. More details about these operators of GA can be referred to Goldberg [18].

2.2. SVM

The SVM used in this paper is the support vector regression (SVR) proposed by Vapnik [16]. Based on the structural risk minimization (SRM) principle, SVM seek to minimize an upper bound of the generalization error instead of the empirical error as in the model of neural networks. Additionally, the SVM models can generate the regression function by applying a set of high dimensional linear functions. Usually, the regression function of SVR is formulated as follows:

$$y = w\varphi(x) + b \tag{1}$$

where $\varphi(x)$is called the feature function, which is nonlinearly mapped from the input space x into high-dimensional feature space, the coefficient w and b are estimated by minimizing

$$R(C) = \frac{1}{2}\|w\|^2 + \frac{C}{N}\sum_{i=1}^{N} L_\varepsilon(d_i, y_i) \tag{2}$$

$$L_\varepsilon(d_i, y_i) = \begin{cases} |d-y| - \varepsilon, |d-y| \geq \varepsilon \\ 0, \quad\quad\quad \text{otherwise.} \end{cases} \tag{3}$$

where both C and ε are prescribed parameters. The term $L_\varepsilon(d_i, y_i)$is called the ε-intensive loss function. The d_i is the actual value in the ith period. This function indicates that errors below ε are not penalized. The term $(C/N)\sum_{i=1}^{N} L_\varepsilon(d_i, y_i)$is the empirical error. The term $(1/2)\|w\|^2$measures the flatness of the function. C evaluates the trade-off between the empirical risk and the flatness of the model. Introducing the positive slack variables ξ and ξ^*, which represent the distance from the actual values to the corresponding boundary values of ε-tube. Equation (2) is transformed to the following constrained forms:

$$\begin{cases} Min\ R(w, \xi, \xi^*) = \frac{1}{2}ww^T + C^*\left(\sum_{i=1}^{N}(\xi_i + \xi_i^*)\right) \\ s.t.\ w\varphi(x_i) + b_i - d_i \leq \varepsilon + \xi_i^*, \\ \quad d_i - w\varphi(x_i) - b_i \leq \varepsilon + \xi_i, \\ \quad \xi_i + \xi_i^* \geq 0, i = 1, 2, \cdots N. \end{cases} \tag{4}$$

Finally, introducing Lagrangian multipliers and maximizing the dual function of Equation (4), then the Equation (4) is transformed to the following form:

$$\begin{cases} Max\ R(\alpha_i - \alpha_i^*) = \sum_{i=1}^{N} d_i(\alpha_i - \alpha_i^*) - \varepsilon \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) \\ \qquad\qquad - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) K(x_i, x_j) \\ s.t.\ \sum_{i=1}^{N} (\alpha_i - \alpha_i^*) = 0, \\ \quad 0 \le \alpha_i \le C, \\ \quad 0 \le \alpha_i^* \le C, \\ \quad i = 1, 2, \cdots N. \end{cases} \tag{5}$$

In Equation (5), $\alpha_i$and α_i^* are called Lagrangian multipliers. They satisfy the equalities,

$$\begin{cases} \alpha_i * \alpha_i^* = 0 \\ f(x, \alpha_i, \alpha_i^*) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(x, x_i) + b \end{cases} \tag{6}$$

Here $K(x, x_i)$is called the kernel function. The value of the kernel is equal to the inner product of two vectors x_i and x_j in the feature space $\varphi(x_i)$and $\varphi(x_j)$, such that $K(x, x_i) = \varphi(x_i) * \varphi(x_j)$. Any function that satisfying Mercer's condition (Vapnik, 1995) can be used as the kernel function. The Gaussian kernel function $K(x_i, x_j) = \exp(-\left\|x_i - x_j\right\|^2)/(2\sigma^2)$is specified in this study. The SVR was employed to estimate the nonlinear behavior of the forecasting data set because Gaussian kernel function tends to give good performance under general smoothness assumptions. Consequently, it is especially useful if no additional knowledge of the data is available [17].

From Equations (2) and (4), it is easy to find that the SVR is equivalent to a quadratic programming problem. Thus the process of solving SVR problem is closely related to the feature vector. Too many feature vectors will lengthen training time and lead to slow learning speed. Therefore, selecting some representative pattern as model inputs will be a focal issue. In order to determine appropriate feature vectors, genetic algorithm for feature selection is proposed to improve the SVR performance.

2.3. *A hybrid GA-SVM approach for factor exploration*

In this study, a hybrid approach integrating GA and SVM is used to explore some key factors affecting the core competence of aviation manufacturing enterprise. Usually, GA imitates the natural selection process in biological evolution with selection, mating reproduction and mutation, as shown in Section 2.2. Accordingly the sequence of the different operations of a genetic algorithm is shown in the left part of Fig. 1. The parameters to be optimized are represented by a chromosome whereby each parameter is encoded in a binary string called gene. Thus, a chromosome consists of as many genes as parameters to be optimized. Interested readers can be referred to Holland [20] and Goldberg [18] for more details. In the following, a hybrid GA-SVM appraoch for key factor exploration is discussed.

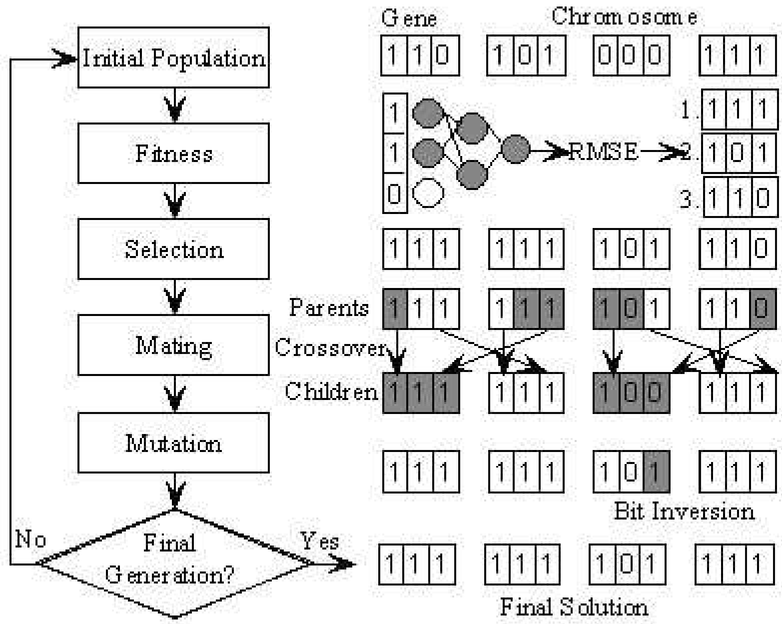

Fig.1 Key factor exploration using the hybrid GA-SVM method

First of all, a population, which consists of a given number of chromosomes, is initially created by randomly assigning "1" and "0" to all genes. In the case of key factor exploration, a gene contains only a single bit string for the presence and absence of a factor. The top right part of Fig. 1 shows a population of four chromosomes for a three-factor selection problem. In this study, the initial population of the GA is randomly generated except of one chromosome, which was set to use all factors. The binary string of the chromosomes has the same size as factors to select from whereby the presence of a factor is coded as "1" and the absence of a factor as "0". Consequently, the binary string of a gene consists of only one single bit. The subsequent work is to evaluate the chromosomes generated by previous operation by a so-called fitness function, while the design of the fitness function is a crucial point in using GA, which determines what a GA should optimize. Here the goal is to find a small subset of factors from many candidate factors. In this study, the SVM is used for modeling the relationship between the input factors and the responses. Thus, the evaluation of the fitness starts with the encoding of the chromosomes into SVM model whereby "1" indicates that a specific factor is used and "0" that a factor is not used by the SVM model. Then the SVM models are trained with a training data set and after that, a testing data set is predicted. Finally, the fitness is calculated by a so-called fitness function$f$. For a prediction problem, for example, the fitness function for the GA-SVM factor selections can use the following form [21].

$$f = 0.2RMSE_{training} + 0.8RMSE_{testing} - \alpha(1 - n_v/n_{tot}) \tag{7}$$

where n_v is the number of factors used by the SVM models, n_{tot} is the total number of factors and $RMSE$ is the root mean square error, which is defined in Equation (8) with N as total number of samples predicted, y_t as the actual value and $\hat{y}_t$ as the predicted value:

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{t=1}^{N} (\hat{y}_t - y_t)^2} \tag{8}$$

From Equation (7), it is not hard to find that the fitness function can be broken up into three parts. The first two parts correspond to the accuracy of the SVM models. Thereby $RMSE_{training}$ is based on the prediction of the training data used to build the SVM models, whereas $RMSE_{testing}$ is based on the prediction of separate testing data which is not used for training the SVM models and is used for testing the performance of the SVM models. It was demonstrated in Kupinski and Giger [23] that using the same data for the factor selection and for the model calibration introduces a bias. Thus, factors are selected based on data poorly representing the true relationship. On the other hand, it was also shown that a factor selection based on a small data set is unlikely to find an optimal subset of factors [23]. In addition, two-eight rule is one of the commonly accepted rules in many cases. Therefore, a ratio of 2:8 between the influence of training and testing data was chosen. Although being partly arbitrary this ratio should give as little influence to the training data as to bias the feature selection yet taking the samples of the larger training set partly into account. The third part of the fitness function rewards small models using only few factors by an amount proportional to the parameter a. The choice of a will influence the number of factors used by the SVM for regression. A high value of results in only few factors selected for each GA whereas a small value of a results in more factors being selected. In sum, the advantage of this fitness function is that it takes into account not only the testing error of test data but also partially the training error and primarily the number of factors used to build the corresponding SVM regression models [21, 22].

After evolving the fitness of the population, the best chromosomes with the best fitness value are selected by means of the roulette wheel. Thereby, the chromosomes are allocated space on a roulette wheel proportional to their fitness and thus the fittest chromosomes are more likely to be selected. In the following mating step, offspring chromosomes are created by a crossover technique. A so-called one-point crossover technique is employed, which randomly selects a crossover point within the chromosome. Then two parent chromosomes are interchanged at this point to produce two new offspring. After that, the chromosomes are mutated with a probability of 0.005 per gene by randomly changing genes from "0" to "1" and vice versa. The mutation prevents the GA from converging too quickly in a small area of the search space. Finally, the final generation will be judged. If yes, then the optimized factor subsets are selected. If no, then the evaluation and reproduction steps are repeated until a certain number of generations, until a defined fitness or until a convergence criterion of the population are reached. In the ideal case, all chromosomes of the last generation have the same genes representing the optimal solution [21, 22]. The optimal solution is the key factors affecting the core competiveness of aviation manufacturing enterprises.

In order to overcome the randomness of the GA in the hybrid approach, the above steps will be conducted 100 times, accordingly the frequency of every selected factors can be calculated. If the higher the frequency of selected factors, the larger the effect of the factor affecting enterprise core competence.

3. Empirical Analysis

In this section, the proposed hybrid GA-SVM approach is used for select the key factors affecting the core competence of aviation manufacturing enterprises. The main purpose of this paper is to find several key factors to improve the core competiveness of aviation manufacturing enterprises. In particular, the data used here is obtained from survey data from the Aviation Industry Corporation of China (AVIC) and the original data can be obtained upon request. For the important factors affecting core competence of aviation manufacturing enterprises, the top 20 high correlational factors shown in Table 1 are selected by grey relational analysis method for further analysis, as the same to Zhai and Qin (2011). By using the hybrid GA-SVM method illustrated in previous section, the detailed steps are shown below.

1. **Data preparation**
   In this paper, 50 experts from AVIC was surveyed through questionnaire. In the questionnaire, there are four different grades for evaluation results: very high, high, ordinary, poor. For the convenience of computation and analysis, different grades will be quantified into different scores in terms of experience. Accordingly, 90 represents very high, 75 represents high, 65 represents ordinary class, and 50 represents the poor. Through such a processing, a total of 50 samples with 20 factors affecting the core competence of aviation manufacturing enterprises can be obtained.
2. **Parameter settings**
   In this paper, the population size of GA is set to be 20, iteration times is 100, the probability of crossover and mutation are 0.6 and 0.5. In SVM, the RBF function is selected as the kernel function of the SVR model and both the penalty parameters and kernel width are set to 5000.

Table 1 The Top 20 high correlational factors affecting the core competence of aviation manufacturing enterprises

<table>
<tr><td>Target</td><td>Criteria</td><td>Indicator/factor</td></tr>
<tr><td rowspan="20">Core competence of aviation manufacturing enterprises</td><td rowspan="2">Technology research and development capability</td><td>Technical level</td></tr>
<tr><td>Quality of personnel</td></tr>
<tr><td rowspan="4">Production capacity</td><td>Equipment level</td></tr>
<tr><td>Production control advantage</td></tr>
<tr><td>Manufacturing costs accounted for sales revenue ratio</td></tr>
<tr><td>Senior technician ratio</td></tr>
<tr><td rowspan="4">Management capability</td><td>Liquidity ratio</td></tr>
<tr><td>Contribution rate of total assets</td></tr>
<tr><td>Labor efficiency</td></tr>
<tr><td>Sustainable growth rate</td></tr>
<tr><td rowspan="3">Strategic management capability</td><td>Rate of return on capital</td></tr>
<tr><td>Enterprise long-term planning level</td></tr>
<tr><td>Enterprise credit</td></tr>
<tr><td rowspan="2">Human resource</td><td>Quality index of corporate executives</td></tr>
<tr><td>Average education level of employees</td></tr>
<tr><td>Enterprise culture</td><td>Adaptability of enterprise culture</td></tr>
<tr><td>Service capability</td><td>Input intensity of customer service</td></tr>
<tr><td rowspan="3">Market controlling capability</td><td>Market share of products</td></tr>
<tr><td>Capability to maintain brand image</td></tr>
<tr><td>Customer loyalty</td></tr>
</table>

3. **Frequency computation**
Based on the proposed hybrid GA-SVM model, the sample data are used for input variables to explore some key factors affecting core competence of aviation manufacturing enterprises. Due to the randomness of the GA in the hybrid approach, the above exploration steps will be conducted 100 times, accordingly the frequency of every selected factors can be calculated. In terms of the statistical results, it is easy to find some key factors affecting the core competiveness of aviation manufacturing enterprises. The frequency of every factor are shown in Table 2.
4. **Key factor identification**
In terms of the calculated frequency of every factors, some key factors affecting the core competence of aviation manufacturing enterprises can be identified.

Table 2 Frequency results of the 20 factors affecting the core competence

Factor	Frequency	Factor	Frequency
Market share of products	33	Sustainable growth rate	24
Capability to maintain brand image	33	Customer loyalty	23
Adaptability of enterprise culture	31	Labor efficiency	23
Rate of return on capital	29	Production control advantage	22
Enterprise credit	27	Technical level	21
Equipment level	26	Quality index of corporate executives	17
Senior technician ratio	26	Liquidity ratio	16
Enterprise long-term planning level	26	Manufacturing costs accounted for sales revenue ratio	11
Contribution rate of total assets	25	Average education level of employee	11
Quality of personnel	24	Input intensity of customer service	6

As can be seen from Table 2, it is not hard to find some key factors affecting the core competence. In this case, the top 10 factors, Market share of products, Capability to maintain brand image, Adaptability of enterprise culture, Rate of return on capital, Enterprise credit, Equipment level, Senior technician ratio, Enterprise long-term planning level, Contribution rate of total assets, Quality of personnel, are considered as the most important key factors affecting the core competence of aviation manufacturing enterprises. Using these key factors, some important targeted measures can be proposed to improve the core competiveness capability of aviation manufacturing enterprises.

4. Concluding Remarks

In this paper, a hybrid approach integrating GA and SVM is proposed to explore key factor affecting core competiveness of aviation manufacturing enterprises. In the proposed hybrid approach, the GA is used for key factor exploration, while SVM is used to calculate the fitness function of the GA method. Through frequency computation, it is easy to find the key factor affecting enterprise core competence. Empirical results showed that the proposed hybrid approach can perform very well and can find some key factors affecting the enterprise core competiveness, revealing the proposed hybrid approach can be used as an effective tool for key factor exploration.

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