INTEGRATION OF CUCKOO SEARCH AND FUZZY SUPPORT VECTOR MACHINE FOR INTELLIGENT DIAGNOSIS OF PRODUCTION PROCESS QUALITY

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Abstract. The quality of High-tech products usually influenced by numerous cross-correlation quality characteristics in production process. However, traditional quality control method is difficult to satisfy the requirement of monitoring and diagnosing multiple related quality characteristics. Scholars found that the diagnosis effect of support vector machine method is better than others. But, constructing fuzzy support vector machine for diagnosis by calculating the sample membership degree from the sample point to the class center is vulnerable to the influence of sample noise points because it will lead to low accuracy rate. Therefore, this paper focus on exploring the issue about the abnormal pattern and intelligent diagnosis of interrelated multivariable process quality, by taking the multivariable quality characteristics of capacitor as research object. Using multivariate exponentially weighted moving average (MEWMA) control chart to joint monitor the multiple quality characteristics. Constructing a fuzzy support vector machine (FSVM) based on cloud calculative model and cuckoo search (CS) for intelligent diagnosis on abnormal pattern. The result showed that the diagnostic accuracy rate for sample data is 97.42%. In instance analysis, the average diagnosis accuracy rate is 95.60%. It verifies the CS-FSVM model has a good diagnosis performance.

1. Introduction. New energy has attracted wide attention from all walks of life in recent years. Some scholars described the development trend of new energy vehicles in recent years [43, 38, 47]. In order to realize environmental protection and energy conservation, many counties have issued corresponding policy documents to promote the development of new energy. Among them, the strong support for new energy vehicles is the most prominent. China’s ministry of industry and information technology has issued document to facilitate the promotion and application of new energy vehicles, which has boosted demand for lithium batteries and super capacitors in the upstream of the industry chain. Due to its advantage of long service
cycle, strong environmental adaptability, high charging and discharging efficiency, high energy density, super capacitor has been vigorously promoted and applied in the market. Faced the opportunities and challenges in the market, product quality becomes the key factor for super capacitor suppliers to survive in the market. The final product quality is a comprehensive reflection of numerous production process quality. The statistical process control technology is an effective method for quality control in enterprises, it can effectively judge the abnormal fluctuation of process quality under certain conditions. However, with the improved process complexity and quality standards of products, the quality control in manufacturing process also becomes more difficult. To a certain extent, the control measures of traditional quality statistical process have been unable to guarantee effective monitoring. Super capacitor as a new industry developed in recent years, it has high requirements in technology and product performance parameter, and follows the production mode of multi-variety with small-batch. Besides, the key quality characteristic parameters are correlated with each other and influence each other in the production process. For its quality control, focusing on monitoring the single quality characteristic of products but ignoring the multivariable characteristic of the process quality will lead to false alarm in the control chart, which exists a large misjudgment rate. By this way, it will result in the accumulation of quality problems in the production process and influence the rate of good product. In order to effectively solve this problem and overcome the disadvantage that traditional method only monitor the single quality characteristic, it is necessary to conduct joint monitoring of multiple quality characteristics. Thus, this paper focus on the quality control of multivariable manufacturing process of capacitor based on multivariate statistical process control (MSPC) method which aims to finding out the abnormality during process monitoring.

Joint monitoring of multivariate process quality mainly uses multivariate control chart. Unlike single variable control chart, a multivariate control chart only can judge the process quality is under controlled state or not when implement joint monitoring of multiple quality characteristics. Multivariate control chart can’t point out the specific variables or combined variable which lead to out-of-control when monitoring the abnormality of process quality. In other words, it cannot judge specific abnormal patterns of out-of-control process. So, multivariate control chart just only can be used in monitoring for multivariable process quality control. In order to identify the variables which causes the abnormality of process quality, it needs the help of other methods to do further diagnostic for the abnormal process quality which monitored in control chart.

For other diagnostic methods, as the concept of “Internet plus”, “industry 4.0” and “made in China 2025” are proposed, big data and intelligencialize are penetrated in manufacturing industry. In the research of MSPC, scholars combined neural network technique, support vector machine (SVM) technology to conduct the abnormal diagnosis of multivariable process quality. However, the problem of abnormal diagnosis and control of multivariable process quality has its own complexity. The key and difficulty lie in how to find out and identify abnormality with higher accuracy so as to control the production process and reduce quality loss. This requires continuous improvement of diagnostic methods.

On the basis of existing research, this study introduces cloud calculative model which integrates fuzzification and randomness to calculate degree of membership for each sample point. This is helpful for reducing the influence of the sample
noisy point on the traditional support vector machine (SVM). In addition, utilizing the cuckoo search (CS) to optimize the parameter in model and constructing a CS-FSVM model that combined cloud model and cuckoo search algorithm. Based on the observed problems during the production process of capacitor product in enterprise, it collects the sample data of multivariable process quality with abnormal pattern through production scene data collection and simulation method for research. Besides, building MEWMA control chart for monitoring and introducing cloud model and the cuckoo search algorithm for constructing CS-FSVM model to realize the diagnosis of abnormality. Moreover, applying the model for instance analysis to verify the diagnostic performance.

2. Literature review. The main goal for the research on diagnosis of multivariable process quality is to find out abnormality and identify specific abnormal variables through using intelligent methods. In order to more intuitively analyze relevant researches in the field of multivariable quality control and grasp the research trends, this paper utilizes CiteSpace software to summarize the related literatures in this field. By this way, find out the main research contents and methods in this field. Web of Science database platform is used as the main source for researching the related literature, and the research results of relevant literatures from 1996 to 2018 are shown in Figure 1. Figure 1 visually shows the research trends of multivariable process quality in Web of Science database, which includes the main research directions in this field and the relationship between different research content and method. For statistical process control, scholars have explored the construction and application of multivariable control chart, application of intelligent algorithm in process quality diagnosis, design optimization and application of intelligent classifier such as neural network and support vector machine.

![Figure 1. The relevant literatures of multivariate quality control](image)

For the research on the construction and application of control chart, scholars have made some achievements through continuous exploration and innovation. Hotelling put forward the $T^2$ control chart firstly in the 1940s, so as to determine whether a multivariable process quality under control with the condition of mean...
and covariance of the unknown [18]. But, the $T^2$ control chart for unusually volatile variables effect is obvious while the condition of small offset performance is not sensitive. Based on this, Lowry et al proposed the multivariate exponentially weighted moving average (MEWMA) control chart [30]. In recent years, scholars have proposed different statistical control methods and constructed control charts to monitor the quality of multivariable processes. Bush et al proposed a new nonparametric control chart based on the k-linkage algorithm and demonstrated the effectiveness of the control chart relative to $T^2$ [3]. Tang et al based on the vector difference of adjacent data matrix to construct covariance matrix of $S^2$ as $\sum$ population covariance matrix estimator, established an improved MEWMA chart [26]. Poovich et al proposed a multivariable $T^2$ control chart based on bootstrap, which can effectively monitor the process when the observed data are not normally distributed or unknown [36]. Jiang and Feng proposed a C control graph that monitors the eigenvectors of covariance matrices of multivariable processes, which made up for the defect of the control graph based generalized variance [20]. Zhao and He proposed a joint control chart which can be used to monitor the variation of mean vector and covariance of binary processes simultaneously [52]. Khoo et al proposed a multivariate composite double-sampling $T^2$ chart for monitoring mean vector, and the overall monitoring effect is good [21]. Considering that the traditional $T^2$ control chart is affected by sensitivity and dimension of measured values, Li et al proposed a chart that allows monitoring with the second observation without considering dimensions, which reduces the average running length of detecting early offset in high-dimensional measurement [24]. Tuerhong and Kim proposed a multivariate control chart based on gore distance [41]. Teh pointed out the X chart which can utilize optimization techniques and the best scores and parameters to determine the total running time of variable sampling interval [9]. Park and Jun proposed a new multivariate EWMA control chart for detecting the mean value of the process [35]. Based on the weighted loss function, Liang et al proposed a new single exponential weighted moving average (EWMA) graph, which can detect the changes of mean and variance simultaneously [25]. Nishimura et al pointed out that in multivariable statistical process control, a few variables may change from the control state when the process changes [34]. Based on this, he proposed a multivariate EWMA control graph. Capizzi discussed statistical process monitoring and emphasized the use of control charts based on variable selection for multivariable monitoring is important [5]. Li et al proposed a self-starting control graph for sparse mean drift monitoring which combined the multivariate spatial rank test for forward variable selection and EWMA chart [23]. Chang and Sun proposed a statistical economic design model of adaptive exponential weighted moving average (AEWMA) control chart for the statistical economic design of AEWMA control chart [6]. However, reasonable diagnostic methods should be adopted to accurately judge the variables that generate abnormality for the abnormality found in monitoring. Thus, many researches focus on exploring the diagnostic methods in process quality diagnosis.

Wu applied neural network and support vector machine to classify and diagnose multivariable process quality abnormality [45]. He and Qi grove a model of multivariate process control and diagnosis based on projection transformation for identifying allergen in multivariate statistical process control diagram [17]. Wu and Zhao built the control chart pattern recognition model based on wavelet analysis SVM method, which improved the precision of recognition [44]. Hsu et al integrated the ICA and support vector machine (SVM) in order to develop intelligent fault detector for
multivariate non-gaussian distribution process monitoring [19]. Ranaee et al constructed a new hybrid intelligent system through the three main modules and built the PSO-SVM classification model to realize multivariable process quality diagnosis [37]. Mojtaba proposed a hybrid learning model based on neural network and support vector machine (SVM) for online analysis of multivariable manufacturing process out of control signal [39]. Chong et al integrated support vector machine (SVM) algorithm, guidance method and control chart technology to propose a new multivariable control graph (SYM-POC) to improve multivariable process monitoring [11]. Cheng et al proposed a diagnosis model of process abnormality for two variables covariance matrix based on LS-SVM model identifier [8]. Mojtaba proposed a modular online analysis model composed of two modules to control runaway signals in the process of multivariable by means of support vector machine and neural network method, which can solve the abnormal diagnosis of mean and variance deviation [40]. Ebrahimzadeh et al used MICA algorithm, k-means algorithm, probabilistic neural network, radial basis function neural network and other methods to identify common control chart patterns [14]. Li et al optimized the parameters of support vector machine, identified the subclass of multivariable mode and diagnosed the main changes of abnormal mode based on genetic algorithm [22]. Du et al developed a hybrid method for online recognition of control graph patterns by support vector machine (P-SVM) based on wavelet transform and improved particle swarm optimization algorithm [13]. Zhao et al proposed a support vector machine (SVM) multiple control chart for mean deviation diagnosis model based on particle swarm optimization (PSO) algorithm [51]. Zhu studied the multivariate process anomaly source recognition method based on optimized directed acyclic graph SVM, and studied the identification of multiple abnormal forms in multivariable processes [2]. Masood and Hassan proposed a method which with balance monitoring and accurate diagnosis for bivariate quality control [32]. Cheng and Lee took the diagnosis of runaway signals as a classification task and proposed a multi-variable process variance transfer integrated classification model based on support vector machine (SVM) [7]. Yang proposed an effective learning vector quantization network selective integration MSPC model based on two-stage discrete particle swarm optimization, which was used to monitor and diagnose mean drift in multivariable manufacturing process [49]. Chinas et al combined the scatter diagram, a multivariate pattern recognition method using machine learning algorithm was proposed to monitor the quality characteristics of multivariate products [10]. Masood and Shyen developed a series of methods for pattern recognition (PRS) based on control chart pattern recognition technology [33]. It combined the multivariate exponential weighted moving average (MEWMA) control chart and the artificial neural network (ANN) identifier for monitoring and diagnosis. As the increased research for diagnostic methods, scholars found that multivariate quality control have high requirements on intelligent diagnosis. It encourages scholars to do further research on the abnormal pattern and intelligent diagnosis for multivariate quality control.

Dhini and Surjandari pointed out the importance of multivariate quality control and put forward the future research direction through comprehensive the related literature of MSPC [12]. José et al introduced the main steps of MSPC method based on PCA, mainly focusing on the difference of MSPC method and shortcomings [4]. Martynyuk et al put forward a method of using fractional order model to control the quality of capacitor, and provided the sampling interval and the model
parameters [31]. Support vector machine (SVM) was proposed by He et al based on distance multivariate process control charts, which is known as D-SVM Figure [16]. Wang et al introduced a unilateral control diagram which is based on support vector machines (SVMS) and differential evolution (DE) algorithm, to monitor process of multivariate quality characteristics [42]. For the common diagnostic methods, it can be seen that support vector machine is widely used. In recent years, scholars have improved the traditional support vector machine to increase the diagnostic efficiency. Liu and Han proposed an adaptive fuzzy support vector machine model to diagnose transformer faults by means of neighborhood increment algorithm [27]. Cha et al proposed the FSVM model based on the method of multi-region division and realized the improvement [50]. Shigeo proposed a fuzzy support vector machine (FSVMs) for multi-tag classification, in which, for each multi-tag classification, the region with an associated membership function was defined [1]. Liu et al combined robustness and fuzziness to propose a reconstruction method for a class of support vector machines to improve classification performance [28]. Fan et al proposed fuzzy support vector machine model based on entropy fuzzy membership to classify and identify samples [15]. Yan and Zhang constructed fuzzy support vector machine based on cloud model and conducted classification and diagnosis research on remote sensing images [46]. Han used cloud model to construct fuzzy support vector machine to classify and identify fault signals of wind gearbox bearing [29].

To sum up, scholars have made relevant researches on the quality of multivariable process from the aspects of multivariable control charts and diagnostic methods. Multivariable control charts show different monitoring performance in different application situations. In view of the abnormal found, scholars using intelligent methods which includes the neural networks, bayesian networks, clustering algorithm and support vector machine (SVM) to diagnosis. Compared with those methods, diagnosis effect of support vector machine (SVM) method is better. But, the traditional support vector machine (SVM) is still exists defects. The present study mainly combined with other methods for its improvement and the usual approach is to calculate sample membership degree to construct the fuzzy support vector machine (SVM). The method for calculating the relative membership degree are usually adopted based on distance and tightness, few scholars using the method of cloud model. Particle swarm optimization (PSO), mesh search and genetic algorithm (GA) are mostly adopted for the optimization of model parameters, but these methods often obtain local optimum. Based on this, this paper combines cloud model and cuckoo search algorithm to improve and optimize the traditional support vector machine, so as to realize the multivariable process quality diagnosis with higher accuracy.

3. Theoretical background.

3.1. Support vector machine. Based on the statistical learning theory and the structural risk minimization principle, some scholars first proposed the support vector machine model. Due to its high generalization ability, the model can effectively solve the problems of small samples, nonlinearity and high dimensions. It has been widely used in the field of intelligent diagnosis. Yang and Zhang introduced the theory in detail and pointed out that the basis of support vector machine construction is to find out the optimal classification hyperplane [48]. In this paper, nonlinear classification is mainly used, and the principle is briefly introduced as follows:
This method is usually adopted the way of nonlinear transform the nonlinear problem into a linear problem corresponding to high dimension space. So, it can calculate the linear optimal separating hyperplane in the high dimensional space. This transformation process is mainly realized by kernel function. When calculate the optimal classification hyperplane, the usual method is to find the vector \( w^* \) and the constant \( b^* \) by reasoning. \( w^* \) is the normal vector, which determines the direction of the hyperplane. \( b^* \) is the displacement, which determines the distance between the hyperplane and the origin. Accordingly, the solved objective function becomes:

\[
\max H(a) = \sum_{i=1}^{N} a_i - \frac{1}{2} \sum_{i}^{N} \sum_{j}^{N} a_i a_j y_i y_j k(x_i, x_j) \]

\[
\sum_{i}^{N} y_i a_i = 0, a_i \geq 0, i = 1, 2, \cdots, N \tag{1}
\]

The corresponding discriminant function is:

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{N} a_i^* y_i k(x_i, x) + b^* \right) \tag{2}
\]

In the process of classification and recognition, support vector machine model is trained and tested by sample data.

3.2. Cloud model theory. The cloud model can realize the conversion between quantitative statistical data and qualitative concepts. Han made a correlation analysis of cloud model concepts [29]. In the cloud model, quantitative characteristics of qualitative concepts are expressed through the three digital features of expectation \( E_x \), entropy \( E_n \) and super-entropy \( H_e \), that is \( C(E_x, E_n, H_e) \). The definition of “standard” by different sample data in the production process is expressed in the cloud model below. The standard refers to the product design parameter of 6.8, as shown in Figure 2.

![Cloud Model with Sample Data Standard](image)

**Figure 2.** Cloud model of sample “standard” and its digital characteristics

According to Figure 2, the cloud model of expected value is 6.8 for the sample data, and corresponding to the degree of certainty for concept “standard” is 1, which fully conform to the concept of sample “standard”. Moreover, in Figure 2, closer to the standard value presents the parameters of standard gap is smaller in the actual production process. In addition, the entropy \( E_n \) express the discrete degree of sample data distribution for the concept of “standard”. From the shape of the
cloud droplets super-entropy $He$ reflects the extent of the sample data formatting the concept.

In the implementation process of cloud model, computing the membership degree of $x$ for qualitative concepts is:

$$\mu(x) = \exp\left(-\frac{(x - Ex)^2}{2(En')^2}\right)$$

(3)

$En'$ is the generated Gaussian random number, $En' = NORM(En, He^2)$.

4. Model construction and parameter optimization.

4.1. Constructing fuzzy support vector machine model.

4.1.1. Selecting kernel function. The support vector machine can map the sample of input space to high-dimensional space and realize the optimal classification hyperplane calculation in high-dimensional space, which mainly relies on the kernel function to realize the transformation. Kernel function $k(x_i, x_j)$ maps the high-dimensional samples of input space to high-dimensional space computation through spatial transformation $(\varphi(x_i), \varphi(x_j))$, which reduces the complexity of high-dimensional computation and realizes nonlinear classification problem. At present, kernel function types commonly used include Linear Kernel Function, Polynomial Kernel Function, Radial Basis Kernel Function, and Sigmoid Kernel Function.

Gaussian Kernel Function as a special form of Radial Basis Kernel Function and its expression is $k(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\gamma^2}\right)$. It has strong anti-interference ability to the noise existing in the data, which has been applied by most scholars in recent years. Besides, its high efficiency in the model has been proved, which is suitable for the universal classifier model. The parameters $\gamma$ of Gaussian Kernel Function determine the scope of function. So, it is very important to choose the appropriate parameters according to the actual situation. On the basis of the existing research, the Gaussian Kernel Function is selected as the kernel function to construct the fuzzy support vector machine model in order to achieve more accurate classification because its high efficiency and applicability.

4.1.2. Determining the degree of membership. The main idea of constructing fuzzy support vector machine (FSVM) model is through the membership function in fuzzy set theory, by giving the corresponding degree of membership for each sample point $(x, y)$ and $s \in [\varepsilon, 1]$. For the existing research, the most common way is through calculating the class distance between sample points to the center to calculate degree of membership. This method can improve the classification accuracy in certain extent, but it did not consider the actual distribution and the question of unclear boundary, which will cause to reduce the support vector classification effect when reduce the influence of noise samples. Aiming at this problem, based on the cloud model to realize conversion between qualitative concept and quantitative data, qualitative quantitative mapping between the quantitative data belonging to the degree of certainty for qualitative concept, which can overcome the shortcomings of traditional methods. This article based on cloud model theory to determine degree of membership to construct fuzzy support vector machine model.

Based on cloud model theory, collecting the multivariate quality characteristics of sample data firstly. This paper mainly studied the three qualities. Thus, on the basis of one-dimensional cloud model extended to three dimensional to determine the membership function. Han made a detailed description for the multidimensional
cloud model [29]. Set $R_3$ is a three dimensional normal random function, the corresponding expectation, entropy and super-entropy is extended to three dimensional as $Ex_1, En_1, He_1, Ex_2, En_2, He_2, Ex_3, En_3, He_3$ all are constant coefficient, and the multidimensional normal cloud model are the following:

$$
(x_{1i}, x_{2i}, x_{3i}) = R_3(Ex_1, Ex_2, Ex_3, En_1, En_2, En_3) \tag{4}
$$

$$
(En_1', En_2', En_3') = R_3(En_1, En_2, En_3, He_1, He_2, He_3) \tag{5}
$$

$$
\mu_i = \exp \left\{ -\left[ \frac{(x_{1i} - Ex_1)^2}{2(En_{1i})^2} + \frac{(x_{2i} - Ex_2)^2}{2(En_{2i})^2} + \frac{(x_{3i} - Ex_3)^2}{2(En_{3i})^2} \right] \right\} \tag{6}
$$

In Formula (6), $\mu_i$ is the degree of certainty for multidimensional cloud model, and it is three-dimensional, which can be seen as a composite of three one-dimensional cloud models. In this study, constructing fuzzy support vector machine will rely on this three-dimensional model to calculate degree of membership for the sample.

4.1.3. Fuzzy support vector machine model. In order to improve the recognition accuracy of SVM, this study refer the existing researches and combines cloud model theory and support vector machine theory to construct fuzzy support vector machine (FSVM) model, which is aimed to realize the abnormal diagnosis of multivariable process quality. The essence of constructing a fuzzy support vector machine is to assign corresponding degree of membership value to each sample. In traditional support vector machines, penalty parameters $C$ are used to represent the punishment of right and wrong sample distribution. However, $C$ value remains unchanged and plays the same role on all samples. It is easy for the same sample to be divided into two categories at the same time.

Combining cloud model theory to obtain the training sample set $\{(x_1, y_1, \mu(x_1)), \ldots, (x_i, y_i, \mu(x_i))\}$, $x \in R^n$ by calculating the degree of membership $\mu(x) \in (0, 1]$, which represents that the degree of membership for the training sample belonging to the label $y$. In support vector machine, the classification error is denoted by $\xi$. After introducing the degree of membership $\mu(x_i)$, the error term with weight is denoted by $\mu(x_i)\xi$, which is used to represent the degree to which the first training sample is correctly divided into corresponding categories. Then, the solution of the optimal classification hyperplane can be transformed into the following quadratic programming problem.

$$
\min \frac{1}{2}||w||^2 + \sum_{i=1}^{n} \mu(x_i)\xi \tag{7}
$$

The corresponding constraint condition is: $y_i[w\varphi(x_i)+b] - 1 + \xi_i \geq 0$ for $i = 1, 2, \ldots, n$, According to the KKT conditions, it can transform to the following quadratic programming problems:

$$
\max H(a) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i\alpha_j y_i y_j K(x_i, x_j) \tag{8}
$$

Similarly, multipliers can be derived correspondingly: $\alpha^*_i, w^* = \sum_{i=1}^{n} \alpha^*_i y_i \varphi(x_i)$, $b^* = y_i - \sum_{i=1}^{n} \alpha^*_i y_i K(x_i, x_j)$, the function of classifier can be constructed as:

$$
f(x) = \text{sgn} \left( \sum_{i} \alpha^*_i y_i(x_i, x) + b^* \right) \tag{9}
$$

In fuzzy support vector machine, $\alpha_i = 0$ means that samples $x_i$ are classified correctly; $\alpha_i > 0$ means the sample $x_i$ plays the role of support vector in the
model classification process; $0 < \alpha_i < \mu(x_i)C$ means the support vector $x_i$ is located near the classification hyperplane; $\alpha_i = \mu(x_i)C$ means the support vector is misclassified. The punishment parameter $C$ represents the punishment degree of misclassified samples, and the adjustment of degree of membership indicates the different punishment parameters adopted for different samples, so as to realize targeted punishment of samples. The larger the $C$ value is, the easier to reduce the misclassification rate, but it will lead to the reduction of the classification interval surface and the lower the applicability of the model at the same time. The smaller the $C$ value is, the larger the classification interval surface will be, which will improve the generalization ability of the model, but will lead to the increase of the probability of sample being wrongly divided at the same time. It is very important for the classification accuracy of fuzzy support vector machine to determine the appropriate penalty parameters and construct the optimal classification plane. Thus, adopting the cuckoo search algorithm to optimize the penalty parameters $C$ of the model and the kernel parameters in the kernel function.

4.2. Parameter optimization. This paper realizes parameter optimization of the model through cuckoo search algorithm. Cuckoo search algorithm (CS) was proposed by the inspiration of cuckoo's own parasitic brood strategy. It is a new meta-heuristic algorithm with global optimality and can effectively solve optimization problems. According to the principle of cuckoo search algorithm, this algorithm is utilized to optimize the penalty parameter $C$ and kernel function parameter of fuzzy support vector machine. The specific optimization steps of cuckoo search algorithm is shown in Figure 3:

5. Multivariate process quality diagnosis based on CS-FSVM model.

5.1. Abnormal patterns of multivariable process quality. For multidimensional quality characteristics, multivariate control chart can only through the joint statistics to determine whether a process is abnormal. When abnormality happens, it cannot directly determine which specific variables cause abnormality. The abnormal variables of multiple quality characteristics exist different patterns. In this paper, we consider quality mean-shift in multivariate process result in abnormal situation. The sample data for research is three-dimensional, which includes three related quality characteristics ($P = 3$). For $P$-dimensional quality characteristics, there are $2^P - 1$ abnormal combination patterns. Therefore, there are 7 abnormal combinations for the three quality characteristics studied in this paper, as shown in Table 1:

In table 1, when the quality characteristics is three-dimensional, there is three conditions which includes one abnormal variable, two abnormal variables and three abnormal variables, which is 7 different kind of abnormal patterns. Using fuzzy support vector machine (FSVM) to diagnosis, the original input using sample data, the output mainly aimed at identifying the abnormal combination. As shown in table 1, for seven different abnormal variable combination patterns, it set up seven categories tags as the output of the model.

5.2. Training and testing data collection. When the mean-shift of multivariable process quality occurs, different offsets and abnormal fluctuations model has a variety of unusual combination. For the convenience of study, this paper assumes that the three variables of the offset are the same, with a sample standard deviation
Figure 3. The flow diagram of cuckoo research algorithm

Table 1. The abnormal pattern of $P = 3$

| Number of abnormal variables | Production process status                  | Combination patterns | Output value |
|-----------------------------|--------------------------------------------|----------------------|--------------|
| No abnormity                | No abnormity                               | (0,0,0)              | 0            |
| One                         | Mean-shift of first variable               | (1,0,0)              | 1            |
|                             | Mean-shift of Second variable              | (0,1,0)              | 2            |
|                             | Mean-shift of Third variable               | (0,0,1)              | 3            |
| Two                         | Mean-shift of first and second variable    | (1,1,0)              | 4            |
|                             | Mean-shift of first and third variable     | (1,0,1)              | 5            |
|                             | Mean-shift of second and third variable    | (0,1,1)              | 6            |
| Three                       | Mean-shift of three variables              | (1,1,1)              | 7            |
σ to represent per mean deviation. Corresponding to k times of the standard deviation for the offset, the offset of the mean variables for each variable is expressed as $k_i \sigma_{x_i}$. k value is positive means upward shift while negative value means downward shift. When studying the mean abnormality in multivariate process, usually assumes that the covariance of sample data is stable and unchanged, and the sample mean vector of each observation point obey independent normal distribution. Relevant studies show that, according to the premise hypothesis, the multivariate process statistical model established is expressed as:

$$X(t) = \mu + Y(t) + d(t, t_\eta), \quad t > t_\eta$$ (10)

$X(t)$ represents the observed value of the mean vector of multiple variables at time $t$, $\mu + Y(t)$ represents the eigenvector when the process quality of multiple variables is in a normal state, and $d(t, t_\eta)$ represents the abnormal characteristics of the variable mean, and $d(t, t_\eta) = bk_i \sigma_{x_i}$. $b$ is a random number subject to uniform distribution. Process quality anomalies are simulated by linear superposition. Considering that process data is not easy to obtain, sample data of various abnormal patterns are obtained by simulation, and the rationality of the data is judged by MEWMA control chart. The basic data comes from the belt diameter (D), belt height (L) and seal diameter (E) in the production process of capacitor products. Firstly, 50 groups of process controlled sample data are collected, and the mean value is $\mu = 6.898, 8.018, 19.122$, standard deviation is $\sigma = 0.035, 0.023, 0.053$, covariance matrix is $\sum = \begin{bmatrix} 0.0012 & -0.000062 & 0.00044 \\ -0.000062 & 0.00052 & 0.0002 \\ 0.00044 & 0.0002 & 0.0028 \end{bmatrix}$. According to the statistical model (10), 700 sets of samples including each abnormal mode were obtained by Matlab software simulation, and 100 sets of each abnormal mode were used as training and test data of the model. The corresponding fractal visualization diagram is shown in Figure 4:

![Fractal visualization diagram of sample data and category labels](image)

**Figure 4.** Fractal visualization diagram of sample data and category labels

The 700 groups of samples obtained are monitored through the MEWMA control chart, as shown in Figure 5:

In Figure 5, the first 50 groups are process controlled samples. It can be seen that the sample data obtained from simulation meet the requirements and can be used for model training and testing. In addition, considering that the original sample data of the three quality characteristics are quite different from each other, which has some influence on the final diagnosis effect. In order to improve the accuracy of
abnormality identification for the model, the training and test sample sets obtained above are normalized and preprocessed, and the corresponding calculation Formula is:

\[ y = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \]  

(11)

After normalization, the original data are normalized to a range [0, 1].

5.3. Parameter optimization simulation. Based on the above 700 sets of sample data and the parameter optimization process based on cuckoo search algorithm described in section 3, before model training and testing, firstly optimize the two key parameters \( C \) and \( g \), and obtain the optimal parameter combination through simulation iteration and then construct the optimal classification hyperplane. When the cuckoo search algorithm is used to optimize parameters, the initial number of nests is set to 8, the step size is set to \([-10, 10]\), the threshold value of nest position change is set to \( Pa = 0.25 \), the step size control quantity is set to \( \alpha = [-0.5, 0.5] \), and the total number of iterations is set to 500. The figure of parameter optimization results of the original sample data obtained is shown in Figure 6. After the degree of membership is calculated by cloud model, the figure of parameter optimization results of the sample data with degree of membership is shown in Figure 7.

Parameter optimization results are shown in Figure 6, where the initial values of and are respectively set as \( C \in [0.1, 100] \), \( g \in [0.01, 1000] \). It can be seen that the optimal fitness of the parameter optimization process is stable after 40 iterations. At this time, the optimal parameter combination is \( \text{bestC} = 69.4955 \), \( \text{bestg} = 5.4394 \), and the corresponding accuracy is 85.57%. The simulation results of sample data with degree of membership obtained by computing sample membership by cloud model are shown in Figure 7. It can be seen that the optimal fitness of the parameter optimization process is stable after 20 iterations. At this time, the optimal parameter combination is \( \text{bestC} = 42.6742 \), \( \text{bestg} = 9.5764 \), and the corresponding accuracy is 97.42%. Compared the result in Figure 6 and Figure 7, it indicated that after assigning degree of membership to the original sample, the optimization of parameters can achieve higher accuracy, which is nearly 12%.
Figure 6. Fitness curve of original sample parameter optimization by cuckoo search algorithm

Figure 7. Fitness curve of optimization of sample parameters with degree of membership by cuckoo search algorithm

5.4. Model validation and abnormal quality diagnosis analysis. On the basis of the above research, the abnormal diagnosis of the mean deviation of quality characteristics for $D$, $E$ and $L$ was conducted according to the diagnostic process of the constructed model. Since the sample data of diagnostic quality characteristics are three-dimensional, the input parameters of CS-FSVM abnormal diagnosis model are three-dimensional matrix. That is, the three-dimensional matrix composed of three variables $D$, $E$ and $L$ after data normalization processing, and the output is the corresponding category label and corresponding classification accuracy. The input three-dimensional matrix is 700 sets of sample data with 7 types of abnormal...
combinations. Firstly, 700 sets of sample data are divided into 5 groups through 5 folds cross-validation. Each group contains 140 samples. The classification result of the test data is shown in Figure 8.

![Figure 8](image)

**Figure 8.** Classification results of 7 types of abnormal test for mean deviation of variables $D$, $E$ and $L$

In addition, calculating degree of membership for each sample point through the multidimensional cloud model and the Formula (3). Take the samples of variables $D$ and $E$ as example, the calculated result as shown in Figure 9. In the same way, it can calculate the degree of membership for sample points of three quality characteristics. Then, the degree of membership and the original sample data both are as the input of the model be put into the model, the classification results as shown in Figure 10.

After calculating the membership degree of samples, more accurate classification results can be obtained for the test data of 7 types of anomalies. The key indicator to evaluate the constructed diagnostic model is the classification accuracy. For the original samples without membership calculation, the final diagnostic accuracy is 85.57%. The actual classification and prediction classification results of the test set are shown in Figure 11.

Accordingly, after calculating the degree of membership for the sample, the final diagnostic accuracy of 7 types of abnormal pattern samples is 97.42%. The actual classification and prediction classification results of test sets are shown in Figure 12.

In order to verify that the constructed CS-FSVM model can improve the diagnostic accuracy of multivariable process quality, compared diagnostic effects of CS-SVM model, FSVM based on cloud model and SVM model. The specific diagnostic results of various abnormal patterns are shown in Table 2.
From Table 2, more ideal classification results are achieved for the diagnosis of abnormal patterns after calculating the degree of membership of sample by cloud model and optimizing model parameters by cuckoo search algorithm. The classification accuracy is higher than CS-VSM, FSVM and SVM models, which indicates that the constructed model has good diagnostic performance.
6. **Case study.** The company for case study is a new enterprise which mainly produces capacitors and lithium batteries. It produces different kinds of super capacitor products with high requirements on product quality. At present, the company faced with manufacturing quality problems in the manufacturing process of capacitor products, which has affected the delivery period and quality of products. In addition, it also leads to an increase in operating costs. There are two main reasons for this problem. On the one hand, unnecessary waste and loss exist in the manufacturing process. On the other hand, improper quality control in the
Table 2. Comparison of abnormality diagnostic effect

| Type       | Mean offset | CS-FSVM | CS-SVM | FSVM | SVM  |
|------------|-------------|---------|--------|------|------|
| (1,0,0)    | (3σ, 0,0)   | 96.74%  | 86.44% | 88.28% | 78.86% |
| (0,1,0)    | (0, 3σ,0)   | 98.15%  | 88.5%  | 90.36% | 86.34% |
| (0,0,1)    | (0,0, 3σ)   | 97.24%  | 89.33% | 92.54% | 88.52% |
| (1,1,0)    | (3σ, 3σ,0)  | 96.65%  | 90.65% | 89.25% | 84.3%  |
| (1,0,1)    | (3σ, 0, 3σ) | 98.5%   | 87.5%  | 89.37% | 82.65% |
| (0,1,1)    | (0, 3σ, 3σ)| 97.26%  | 88.26% | 88.42% | 79.64% |
| (1,1,1)    | (3σ, 3σ, 3σ)| 97.71% | 80.71% | 82.77% | 80.22% |
| **Average diagnostic accuracy** |            | 97.42%  | 87.34% | 88.71% | 82.93% |

Manufacturing process leads to bad products. In the process of production practice, it is mainly reflected in the failure of real-time quality control and unreasonable control methods. In the process of quality control, company fails to monitor the quality characteristic parameters that affect each other simultaneously, leading to the accumulation of quality problems in each manufacturing process. The quality problems were not discovered until arrive at the electrical testing stage. However, it is not easy to find the specific process of quality problems in this case.

For further analysis and validation for application effect and feasibility of the constructed CS-FSVM, this paper utilizes the quality for diameters and heights of chip in the winding process of capacitor products as the key quality process for validation data. Those two quality characteristics had a greater influence for capacitor goods. This study chose company’s leading product 2.7 V450F product for research. The chip diameter d processing size is 32.5±0.1mm, the processing technology of the ship height l size is 64±0.1mm. There are three kinds of abnormal patterns combination for two key quality characteristics of the mean-shift. Through field on-site data collection, sample data of each abnormal pattern were obtained as application data. 50 groups of sample data were collected for each abnormal pattern, a total of 150 groups.

MEWMA control chart is adopted to monitor the collected sample data, as shown in Figure 13.

In Figure 13, the first 50 groups are sample data with no mean-shift. It can be seen that all sample data of 51-200 groups exceed the control limit \( UCL = 9 \) and their mean value is offset, which indicates that all collected data are offset.

Similarly, it aimed to utilize constructed model to process abnormality diagnosis for the two quality characteristics. According to the diagnostic process, conducting normalization preprocessing for the sample data firstly. Then, through forward cloud generator and backward cloud generator of cloud model to calculate the degree of membership. Using the sample data with the degree of membership to process cuckoo search algorithm for parameters optimization, the results as shown in Figure 14. According to the optimization process shown in Figure 14, the optimal fitness remains unchanged at 50 iterations, and the optimization result is obtained. At this time, the accuracy rate reached is 95.67%, and the corresponding optimal parameter combination is \( bestC = 23.0816 \), \( bestg = 7.9130 \). Accordingly, the diagnostic model established is used to identify anomalies in the collected sample data, and the final diagnostic accuracy of the samples of 3 types of abnormal patterns is
Figure 13. MEWMA control chart for chip diameter (d) and height (h)

Figure 14. The optimization results for parameters $C$ and $g$

95.60%. The actual classification and prediction classification results of the test set are shown in Figure 15.

The optimized parameters are substituted into the fuzzy support vector machine model to classify and diagnose anomalies, and the final diagnosis results of each anomaly pattern are shown in Table 3.

The final diagnostic accuracy of the two key quality characteristics in the example shown in the table is 95.60%, indicated that the effectiveness and practicability of the model.

7. Conclusion. This paper focus on diagnosis research for the abnormal pattern of multivariate process quality mean-shift. Because multivariate control chart only has monitoring effect but cannot identify specific abnormal variable. Then, constructed
CS-FSVM based on cloud model and the cuckoo search algorithm for further diagnosis to monitored abnormality. The research conclusions are as follows:

1. Considering that the fuzziness of multi-variable sample data will affect the diagnostic effect of model. In order to improve the diagnostic accuracy of process quality, we calculate the degree of membership for the sample by using the cloud model theory, which comprehensively considers the fuzziness and randomness of sample data and converts the qualitative and quantitative concepts to each other. In addition, optimizing the punishment parameter $C$ and kernel function parameter $g$ of model by utilizing cuckoo search algorithm. Finally, constructed the CS-FSVM model by combining cloud model theory and cuckoo search algorithm.

2. According to the diagnostic process of multivariable process quality, we firstly constructs the MEWMA control chart based on the measured data of three quality characteristics of capacitor product that includes band waist diameter $D$, band waist height $L$ and seal diameter $E$. Compared with $T^2$ control chart, it is more suitable for the monitoring of sample mean. We used the sample data of three controlled quality characteristics in the manufacturing process of capacitor products as the basis. First of all, taking the three standard deviations as offset to obtain the mean-shift anomaly pattern of three variables through simulation. We got 7 types of anomalies and each type of abnormal pattern includes 100 groups of sample data. Then, we found that all sample data are out of control by using MEWMA control chart. Utilizing the cuckoo search algorithm to process parameters optimization on the original sample data and the sample data with the degree of membership.

### Table 3. Diagnosis results of application example for model

| Abnormal variable | Combination pattern | Diagnosis accuracy | Average accuracy |
|-------------------|---------------------|--------------------|-----------------|
| (d)               | (1,0)               | 95.42%             |                 |
| (h)               | (0,1)               | 96.08%             |                 |
| (d) & (h)         | (1,1)               | 95.31%             |                 |

**Figure 15.** Comparison between actual classification and prediction classification of sample test set
The results showed that the accuracy for the optimal parameter combination was 85.57%, 97.42% respectively.

(3) Through the training and testing of CS-FSVM model, 7 types of anomalies were diagnosed with an average diagnostic accuracy of 97.42%. Compared with SVM, FSVM and CS-VSM model, the results showed that the constructed model could achieve higher diagnostic accuracy. (4) This paper collected the sample data of the key quality characteristics which includes diameter and height of chip in capacitor production process. Besides, taking the sample data of the mean-shift for three kinds of abnormal combination as an application example data. By conducting the instance analysis with the constructed model, the diagnosis accuracy rate for (1, 0), (0, 1), (1, 1) were 95.42%, 96.08%, 95.31% and the average diagnostic accuracy was 95.60%, which verify the constructed model has a good diagnosis effect in practical application.

The diagnosis of multivariable process quality is a complex research topic. With the improved process complexity and quality standards of products, quality control has new requirements for diagnosis methods. Besides, the method of quality control should solve the practical issues. This study constructed the CS-FSVM model by combining with cloud model and the cuckoo search algorithm. It has contribution for practical applications but also exists limitation.

(1) On the premise of the sample covariance is unchanged, we utilized the constructed model to diagnose the abnormal pattern of mean deviation. However, product manufacturing is a complex process in reality, the abnormal fluctuation of different pattern will occur during the process. Therefore, how to realize effectively real-time diagnosis of more different anomalies still needs to explore.

(2) The monitoring performance of the multivariable control chart has an important impact on the process quality control. Setting the corresponding parameter of control chart should according to specific anomalies. Further research can focus on the parameter such as the sample values and chain length.

(3) In practical applications, the rapid, accurate and real-time monitoring and diagnosis for process quality is particularly important. In the future, continuously optimized the diagnosis methods to achieve online real-time monitoring need to pay attention to.

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