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Product Service System Configuration Based on a PCA-QPSO-SVM Model

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Abstract: To achieve sustainable development and improve market competitiveness, many manufacturers are transforming from traditional product manufacturing to service manufacturing. In this trend, the product service system (PSS) has become the mainstream of supply to satisfy customers with individualized products and service combinations. The diversified customer requirements can be realized by the PSS configuration based on modular design. PSS configuration can be deemed as a multi-classification problem. Customer requirements are input, and specific PSS is output. This paper proposes an improved support vector machine (SVM) model optimized by principal component analysis (PCA) and the quantum particle swarm optimization (QPSO) algorithm, which is defined as a PCA-QPSO-SVM model. The model is used to solve the PSS configuration problem. The PCA method is used to reduce the dimension of the customer requirements, and the QPSO is used to optimize the internal parameters of the SVM to improve the prediction accuracy of the SVM classifier. In the case study, a dataset for central air conditioning PSS configuration is used to construct and test the PCA-QPSO-SVM model, and the optimal PSS configuration can be predicted well for specific customer requirements.

Keywords: product service system (PSS); concept configuration; support vector machine (SVM); principal component analysis (PCA); quantum particle swarm optimization (QPSO)

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1. Introduction

As the product market is nearly saturated, it is getting more challenging for manufacturers to satisfy diversified and individualized consumer requirements. To achieve sustainable growth, many manufacturers have transformed from product-oriented manufacturing to service-oriented manufacturing. This trend of product service system (PSS) to enhance competitiveness and sustainability leads to a massive research effort. The PSS method is based on the simultaneous development of products with tangible features and services surrounding the intangible features, to provide an integrated product that can effectively consider all life cycle stages of the product and related services [1,2].

PSS is described as a hybrid solution that comprises products and services for the purpose of increasing value for customers [3]. On the one hand, customers look forward to being provided with services that aim at enhancing the function and economic performance of the product, such as recycling and maintenance [4]. On the other hand, with ever fierce competition and more diversified customer needs, the low-value-added manufacturing paradigm can no longer meet the requirements of the market and the environment [5]. Therefore, PSS integrates the resources of various parties to meet the needs of customers and reduces the material flow in the consumption process by adding services, which is critical to improve social productivity, living standards, and environmental protection. The emergence of PSS has changed the mode of manufacturing and supply. To create maximum value for customers, PSS has to be individually configured. PSS configuration is to provide a concept by selecting appropriate product modules and service modules among the design modules in advance [6].

The foundation of configuration is to design product modules and service modules by modular design. Modular design is a commonly used approach to realize mass production and individualized design. It combines product elements to form a subsystem with specific functions and uses the subsystem as a versatile module to combine other subsystems to form a system and then produce a product with a certain function. Belkadi et al. [7] proposed a modular design process to support the configuration of production systems that meet the needs of regional markets. Rennpferdt et al. [8] verified the importance of modular product architecture for PSS development. To describe the dependencies between activities, Geng et al. [9] proposed a modular design method based on the fuzzy design structure matrix (FDSM) to obtain the result-oriented PSS. The PSS modular design is a very effective way to improve the response speed and reduce the cost of the industry.

The key in configuration is to combine product modules and service modules to satisfy the customer demands. The existing PSS configuration approaches include genetic algorithm (GA) [10,11], ontology modeling [12,13], convolutional neural network (CNN) [14], multi-objective programming [5,15], and so on. These approaches solve the PSS configuration problem as an optimization model with an objective or a fitness function. The goal of the PSS configuration is to provide a PSS concept that meets certain customer demands. Similar customer demands can be provided with the same PSS configuration. Therefore, the PSS configuration problem is regarded as a classification problem in this paper. The support vector machine (SVM) is an effective tool to solve classification problems. It mainly solves small samples and nonlinear problems. SVM has been successfully applied in the field of classification and regression. Demidova et al. [16] used an SVM based on NSGA-II to predict the effect of medical and technical diagnosis. Pławiak et al. [17] predicted Australian credit scoring based on a deep genetic cascade ensemble of SVM classifiers. Sun et al. [18] proposed a DNN decision-tree-based SVM model for speech emotion classification and recognition.

In this paper, PSS configuration is solved by the SVM method. The PSS configuration problem can be decomposed into three sub-problems: requirement feature extraction, SVM parameter optimization, and PSS configuration classification.

The first task is to reduce the dimension of customer requirements. Among the methods to reduce data dimension, principal component analysis (PCA) shows a strong advantage. PCA utilizes high variance to generate new components that store the most valuable information of elements [19]. Asante-Okyere et al. [20] adopted PCA as a dimension reduction method to improve the performance of the optimized least-squares support vector machine (LSSVM) and the adaptive neuro-fuzzy inference system-subtractive clustering method (ANFIS-SCM). Cao et al. [21] proposed a fault diagnosis method based on PCA and the Gaussian mixed model (GMM), and the PCA was used to reduce the data dimension and increase the feature resolution. Henry et al. [22] proposed an integrated framework based on the use of convolutional neural networks (CNN) and PCA to detect stiction and identify the severity of stiction. The PCA acts as a dimension reduction tool to visualize the extracted features. This paper uses the PCA algorithm to reduce the dimension of customer requirements.

The second task is to optimize SVM parameters. The selection of SVM internal parameters affects the classification performance and fitting effect of the SVM model. The commonly used algorithms are GA, particle swarm optimization (PSO), ant colony algorithm, and so on, while these algorithms have to set many parameters and are easy to fall into the problem of local optimization. Lu et al. [23] proposed a quantum particle swarm optimization (QPSO) algorithm from the perspective of quantum mechanics. The QPSO assumes that the particle swarm optimization system is a particle system that satisfies the basic hypothesis of quantum mechanics. In quantum space, particles do not have a specific trajectory, which allows particles to search for the global optimal solution in the entire feasible solution space. The lack of a defined trajectory means that the speed and position of the particles cannot be determined simultaneously in quantum space. The QPSO algorithm uses the Monte Carlo method to calculate the optimal position of the quantum particle to make sure the global randomness. It has the advantage of a fast convergence rate, and its fitness value is better than that of the traditional PSO [24,25]. This paper takes the advantage of the QPSO algorithm for global random optimization in SVM classification to find the optimal parameters.

The third task is to construct and test a PCA-QPSO-SVM model to predict PSS configuration. The customer requirements and PSS configurations are coded in the model. The PSS configuration is a class label. By comparing the original class label and the predictive class label, the accuracy of the model can be obtained. The PCA-QPSO-SVM model can predict a PSS configuration for specific customer requirements.

The rest of this paper is arranged as follows: In Section 2, the relevant literature is reviewed. The framework of the proposed PSS configuration approach is summarized in Section 3. Section 4 discusses how to use PCA and QPSO to optimize SVM parameters. In Section 5, the PSS configuration model based on PCA-QPSO-SVM is illustrated in detail. Section 6 is a case for an air-conditioner service system to demonstrate the efficacy of the proposed approach. Section 7 is the conclusion of this paper.

2. Literature Review

This section gives a comprehensive literature review consisting of three parts: PSS design, PSS configuration, and PSS configuration optimization.

2.1. PSS Design

PSS is described as a combination of products and services to provide the required utility or function to meet customer needs [26]. To help meet specific customer needs, various PSS development methods have been designed. Durugbo et al. [27] discussed an information flow modeling technique related to the key features of a PSS (such as origin, concepts, and applications). Their proposed model decomposed the iterative process between customers and service providers into different stages to provide total care products. Chiu et al. [28] proposed a process of developing PSS business models to expand current products or services into new market areas. Fargnoli et al. [29] proposed a method based on the collaborative use of PSS quality function deployment, axiomatic design, and service blueprint tools to provide the correlation between customer expectations, PSS components, and PSS modules. Lee et al. [30] utilized a structural services innovation approach to integrating PSS engineering and service engineering in designing intelligent product-service systems. Wang et al. [31] presented a PSS requirements heuristic framework to help engineering designers better improve designs or generate new design concepts.

2.2. PSS Configuration

The system framework for PSS configuration was first proposed by Aurich [32]. Based on the determination of the specific products and service features, technology and service configuration were combined to generate a customized PSS in this framework. The existing PSS configuration approaches include GA, multi-objective programming, ontology modeling, and so on. Sheng et al. [11] proposed a PSS configuration optimization method based on a genetic algorithm. Xuanyuan et al. [10] presented a multi-objective optimization for product configuration and used a multi-objective genetic algorithm to find the Pareto optimal solution set from feasible solutions. Song et al. [5] proposed a multi-objective optimization model for product extension service configuration to solve the problems of too many service solutions and low service delivery efficiency in PSS configuration. Dong et al. [12] proposed an ontology-based service product modeling approach for configuration. Shen et al. [13] presented an ontology-based approach to represent service configuration knowledge and developed a product-extended service configuration system. Based on the combination of quality function deployment and screening life cycle modeling, Haber and Fargnoli [33] proposed a product service system method, which is based on the combination of product service system quality function deployment and screening life cycle modeling tools, which is used to customize solutions for different usage patterns and achieve better environmental performance than independent products.

With the support of artificial intelligence, machine learning algorithms are introduced into the configuration study. To understand customer needs by using quantitative approaches, Yu et al. [34] proposed a knowledge-based artificial neural network (ANN) combined with a decision tree to substantiate customer needs to product specification. Zhou et al. [14] trained the CNN to obtain the complex nonlinear mapping relationship between the customer's demand attributes and the basic types of product-service systems, to determine the PSS configuration. Shen et al. [35] proposed a method that combines cluster neural network and rule algorithm to extract configuration rules between service parameters and functional requirements, customer features, or product features to gain higher effectiveness of configuration solution.

The SVM, as a kind of machine learning algorithm, has shown excellent results in solving small samples and multi-classification problems. Nowadays, a large number of scholars have used SVM for prediction and classification. Ahlawat et al. [36] developed a hybrid model of a powerful CNN and an SVM for the recognition of handwritten digits from the ministry dataset. Viloria et al. [37] used an SVM to predict the diagnosis of diabetes mellitus (DM). Zhou et al. [38] proposed a multi-model latent space-inducing ensemble SVM classifier for early dementia diagnosis with neuroimaging data. Shao et al. [39] studied the energy consumption of hotel buildings by establishing a support vector machine energy consumption prediction model.

2.3. PSS Configuration Optimization

In the process of predicting the PSS configuration by the SVM method, the optimization of the SVM classifier largely determines the optimization of the PSS configuration scheme.

In the PSS configuration problem, the PSS configuration concepts are classified by the customer requirements. There are a number of requirements that affect classification accuracy. Therefore, the quantity of the characteristics should be reduced, which means the dimension reduction in the SVM algorithm. There are many approaches for feature extraction or dimension reduction, such as neural network, PCA, and so on. Zhang et al. [40] used neural networks to extract more sensitive features with a shallow structure, thereby improving the accuracy of small sample classification. Kontonatsios et al. [41] developed a novel feature extraction method based on a neural network. Unlike the previous unsupervised feature extraction methods, this paper extracts document features in a supervised environment. Xiao et al. [42] presented a feature extractor based on Deep Convolutional Neural Networks to extract patterns shared by a family from entropy graphs automatically. Zhang et al. [43] used a PCA based on the AdaBoost algorithm to detect breast cancer. Ratnasari et al. [44] used a threshold-based region of interest (ROI) and PCA to reduce X-ray images, which obtained the best gray-level threshold of 150. Ma et al. [45] leveraged a deep convolutional neural network to extract image features and leveraged a PCA algorithm to achieve dimension reduction. Negi et al. [46] proposed a method that combines PCA and uncorrelated linear discriminant analysis (ULDA) to obtain the best features that control upper limb motion. Therefore, this paper selects PCA for feature extraction of the dataset. The basic idea of PCA is to use fewer mutually independent features to replace a large amount of information of the original features. It is favored by a large number of scholars.

On the other hand, the accuracy of the SVM classifier prediction depends heavily on the selection of the kernel function and penalty factor. Many scholars have used some optimization algorithms to optimize the parameters of SVM, such as the GA, grid search (GS), PSO, and so on.

(1) A genetic algorithm is a computational model that simulates the biological evolution process of natural selection and the genetic mechanism of Darwin's biological evolution theory. It is a method of searching for the optimal solution by simulating the natural evolution process. GA is often combined with SVM to optimize the

parameters of SVM. Huang et al. [47] proposed the GA-SVM model to analyze the quantitative contribution of climate change and human activities to changes in vegetation coverage. The model used genetic algorithms to optimize the loss parameters, kernel function parameters, and loss function epsilon values in the SVM. Based on GA-SVM for rapid and effective screening of human papillomaviruses, Chen et al. [48] proposed a Raman spectroscopy technique that improved the accuracy of the model to optimize the penalty factors and nuclear function parameters in the SVM model. Li et al. [49] used the GA-SVM model to identify and classify flip chips.

(2) Grid search is an exhaustive search method. By looping through the possible values of multiple parameters, it generates the parameter with the best performance, which is the optimal parameter. GS is a common method to optimize the parameters of SVM. Lv et al. [50] used PSO-SVM and GS-SVM to predict the corrosion rate of a steel cross-section. Tan et al. [51] proposed a method combining a successive projections algorithm (SPA) with an SVM based on GS-SVM to classify and identify apple samples with different degrees of bruising. Kong et al. [52] used the GS-SVM model to assess marine eutrophication states of coastal waters.

(3) Particle swarm optimization is an optimization algorithm that simulates the predation behavior of bird swarms. The iteration process forms the optimal position and optimal direction, hence updating the particle swarm. Many scholars apply the PSO algorithm to optimize SVM parameters. García Nieto et al. [53] proposed a hybrid PSO optimized SVM model to predict the successful growth cycle of spirulina. Liu et al. [54] developed the PSO-SVM model to predict the daily PM2.5 level. Bonah et al. [55] combined Vis-NIR hyperspectral imaging with pixel analysis and a new CARS-PSO-SVM model to classify foodborne bacterial pathogens.

In the PSO algorithm, the position and moving speed of the particles co-determine the movement trajectory of the particles. In quantum space, particles do not have a specific trajectory, which allows particles to search for the global optimal solution in the entire feasible solution space. The lack of a defined trajectory means that the speed and position of the particles cannot be determined simultaneously. Ch et al. [56] employed the SVM-QPSO model to forecast the streamflow values of Vijayawada station and Polavaram station of Andhra Pradesh in India. Li et al. [57] presented the use of an LSSVM algorithm based on quantum-behaved particle swarm optimization to establish the nonlinear relationship of slope stability. They verified that QPSO-SVM can provide a high degree of accuracy and reliability. Therefore, this paper applies the QPSO to optimize the SVM parameters to solve the PSS configuration problem.

3. Research Framework

PSS configuration design is based on the modular design concept. Product modules and service modules compose varied PSS configurations. In the design and sales departments, there are many historical data about customers' demands and their purchases schemes. This paper takes full advantage of the historical data to construct and test a PCA-QPSO-SVM model. In this model, PCA is used to reduce the dimension of customer requirements to extract the important features. QPSO is applied to optimize the SVM parameters, and a multi-classification SVM classifies the PSS configurations. The research framework is shown in Figure 1.

(1) Data preparation and preprocessing

Customer requirements and the corresponding PSS configurations are obtained from the design and sales database. The representative historical dataset is extracted.

(2) Reduction of the requirement dimension

The PCA algorithm is used to reduce the dimension of the customer requirements, then the processed dataset is used in the training set and testing set.

(3) Construction of the QPSO-SVM model

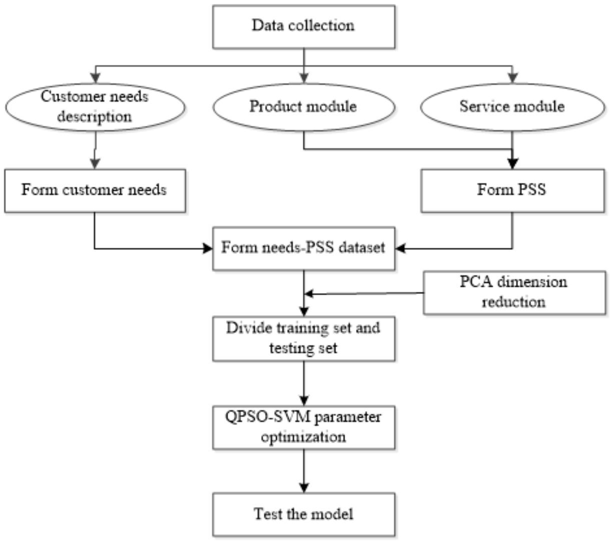

Figure 1. Research framework.

The QPSO algorithm is used to optimize the kernel function σ and the penalty factor C for SVM. Functions that satisfy Mercer's theorem [58] can be used as the kernel function. The kernel function is used to map the samples from the original space to the higher-dimension feature space and make them linearly separable in the feature space. The penalty factor is used to control the balance between margin maximization and deviation minimization [59]. By optimizing relevant parameters, the QPSO-SVM model is constructed and tested to verify the accuracy. In the QPSO-SVM model, the customer requirements are the input, and the PSS configuration meeting the customer requirements is the output.

(4) Prediction of the PSS configuration scheme

According to the PCA-QPSO-SVM model, PSS configuration can be predicted according to the inputting of new customer requirements.

4. Construction of a PCA-QPSO-SVM Model

4.1. Principal Component Analysis

The principal component analysis is a multivariate statistical method for analyzing the correlation between multiple features. The essential idea of PCA is to reveal the internal structure among multiple features through a few principal components. In other words, multiple features in the original data are reduced to a few features, simultaneously the relationships among the original data features are retained as much as possible. PCA has been playing an important role in the fields of artificial intelligence, data mining and image recognition, and so on. The mathematical derivation process of PCA is as follows.

Assuming that the projection of a sample point x_i is $W^T x_i$ on the hyperplane in the new space, then the covariance matrix of the sample points is $\sum_i W^T x_i x_i^T W$ after projection. If the projections of all sample points can be separated as much as possible, then the variance of the sample points would be maximized, so the optimization goal can be written as:

$$\max_{W} tr(W^T X X^T W) \tag{1}$$

$$s.t.\ W^T W = I$$

where, $W = (w_1, w_2, \ldots, w_d)$.

By using the Lagrange multiplier method for Formula (1), we can obtain:

$$X X^T w_i = \lambda_i w_i \tag{2}$$

Then the obtained eigenvalues are sorted: $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_d$. Finally, the eigenvector corresponding to the top d' eigenvalues forms $W^* = (w_1, w_2, \ldots, w_{d'})$.

The steps of the PCA algorithm are as follows:

- Step 1: Set the initial dataset $D = \{x_1, x_2, \ldots, x_m\}$ and the low-dimensional space dimension d'.
- Step 2: Centralize all samples: $x_i \leftarrow x_i - \frac{1}{m}\sum\limits_{i=1}^{m} x_i$.
- Step 3: Calculate the sample covariance matrix XX^T and decompose the eigenvalues of the covariance matrix XX^T.
- Step 4: Take the eigenvector corresponding to the top d' eigenvalues $w_1, w_2, \ldots, w_{d'}$.

4.2. Quantum Particle Swarm Optimization Algorithm

The PSO algorithm was proposed by Kennedy and Eberhart [60]. It is a random search algorithm based on swarm intelligence developed by simulating the foraging behavior of birds. Its basic idea is to find the optimal solution through collaboration and information sharing among individuals in a group. The mathematical description of the PSO algorithm is as follows:

Assuming that the particle swarm size is M, the current optimal position of particle i in the n-dimensional space is expressed as:

$$pbest_i = (p_{i1}, p_{i2}, \cdots, p_{in}) \tag{3}$$

The current optimal position of the entire particle swarm is:

$$gbest = (g_1, g_2, \cdots, g_n) \tag{4}$$

During each iteration, the velocity update formula of each particle is:

$$v_i(t+1) = wv_i(t) + c_1 rand_1(pbest_i(t) - x_i(t)) + c_2 rand_2(\text{g}best(t) - x_i(t)) \tag{5}$$

where, c_1,c_2 are learning factors; w is an inertia factor; $rand_1$, $rand_2$ is a random value in [0, 1]; $v_i(t)$ is the velocity of the i-th particle, $x_i(t)$ is the position of the i-th particle; t is the number of iterations.

The position update formula of each particle is:

$$x_i(t+1) = v_i(t+1) + x_i(t) \tag{6}$$

The PSO algorithm needs to set too many parameters, such as inertia factor w, learning factors c_1, c_2, etc. It is difficult to find the optimal parameters. Moreover, it is easy to fall into the dilemma of a local optimum due to the lack of randomness in the particle position change. To redress these problems, this paper applies the QPSO algorithm with higher performance. The QPSO algorithm cancels the particle's moving direction attribute and increases the randomness of the particle position change. The calculation process of the QPSO algorithm is as follows:

The term *mbest* is introduced in the QPSO algorithm, which represents the average value of *pbest*. It can be expressed as:

$$mbest = \frac{1}{M}\sum_{i=1}^{M} pbest_i \tag{7}$$

The current optimal position of particle i is:

$$p_i = \phi \cdot pbest_i + (1-\phi)gbest \tag{8}$$

where Φ is uniform value in [0, 1].

The position update formula of each particle is:

$$x_i = p_i \pm alpha|mbest - x_i| \ln(\frac{1}{\mu}) \tag{9}$$

where μ is a uniform value in [0, 1] and is the new parameter, which can control the degree of contraction and expansion of the particle position generally. The value of *alpha* is less than 1.

4.3. Support Vector Machine

The SVM was originally proposed by Cortes and Vapnik [61]. It is a supervised learning algorithm that classifies datasets. The essential idea of the SVM is to construct a hyperplane in the sample space as a decision line that divides two different samples. The SVM can solve both binary classification problems and multi-class problems. In this paper, PSS configuration is regarded as a multi-class problem. The derivation process of the SVM algorithm is as follows.

Given a set S containing N training samples, $S = \{(x_i, y_i), i = 1, 2, \ldots, N\}$, the expression of classification hyperplane is:

$$f(x) = w \cdot x + b \tag{10}$$

where w is the normal vector of the hyperplane and b is the translation distance of the hyperplane.

The objective function of partition hyperplane with the "maximum interval" can be expressed as:

$$\min_{w,b} \frac{1}{2}\|w\|^2 \tag{11}$$

$$y_i(w \cdot x_i + b) - 1 \geq 0, i \in \{1, 2, \cdots, N\}$$

To enhance the error tolerance of the SVM classifier, a relaxation variable ξ_i and the penalty factor C are introduced into the objective function. The objective function is expressed as:

$$\min_{w,b} \frac{1}{2}\left|\left|w\right|\right|_2 + C\sum_{i=1}^{n}\xi_i \tag{12}$$

$$s.t. y_i(w \cdot x + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0, i = 1, 2, \cdots, N$$

where ξ_i is a non-negative slack variable, which is used to improve the generalization ability of the model. C is the penalty factor, which is used to control the balance between margin maximization and deviation minimization.

For solving the non-linear classification problem, it is necessary to introduce the kernel function in the SVM. The kernel function is used to map the samples from the original space to the higher-dimension feature space and make them linearly separable in the feature space. In this paper, the Gaussian kernel function is used:

$$k(x_i, x_j) = \exp\left(-\frac{(x_i, x_j)^2}{\sigma^2}\right) \tag{13}$$

The Lagrange multiplier is brought into the objective function. The optimization problem can be expressed as:

$$\max \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j k(x_i, x_j) \tag{14}$$

$$s.t. \sum_{i=1}^{n} \alpha_i y_i = 0$$

$$0 \leq \alpha_i \leq C, i = 1, 2, \cdots, N$$

where α_i is the Lagrangian coefficient.

The final optimized hyperplane is expressed as:

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i k(x_i, x_j) + b, i = 1, 2, \cdots, N \tag{15}$$

4.4. Optimization of the SVM Parameters

The quantity of the feature attributes affects the accuracy of the SVM model. The dimension of the feature attributes should be reduced first by the PCA algorithm. Then, the QPSO algorithm is used to optimize the C and σ of the SVM classifier based on the processes data. Finally, the optimal parameters are brought into the SVM model to realize the PCA-QPSO-SVM modeling. The PCA-QPSO-SVM optimization process is shown in Figure 2. The steps of constructing the PCA-QPSO-SVM model are as follows:

- Step 1: Use a PCA algorithm to reduce the dimension of dataset Q to get a new dataset Q'.
- Step 2: Determine the initial parameters of the QPSO, such as the number of particle swarms, the range of the parameters, the alpha value, and so on.
- Step 3: Set the fitness function in QPSO. In this paper, the fitness function is the average of SVM cross-validation (CV), and its value represents the classification accuracy of the model. The optimal value *pbest* and the global optimal value *gbest* for each particle are updated by iterating the fitness function, where *pbest* is the penalty factor C, *gbest* is the kernel function σ.
- Step 4: Calculate the optimal position *mbest* of the particle swarm and update the new position of each particle.
- Step 5: Determine the end condition. When the optimal search reaches the maximum number of iterations, the optimal search ends; otherwise, go to Step 3.
- Step 6: The optimal parameters (C, σ) are brought into the SVM model to conduct prediction.

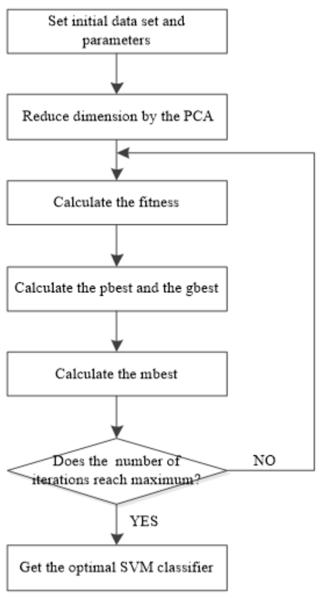

Figure 2. PCA-QPSO-SVM optimization process.

5. PSS Configuration Based on the PCA-QPSO-SVM Model

This paper proposes a PCA-QPSO-SVM model and uses it to solve the PSS configuration problem. The process includes two parts: data collection and construction of the PCA-QPSO-SVM model.

5.1. Data Collecting and Processing

In real life, customers would have different needs for PSS, which generates diversified requirements for PSS configuration. It is vital to collect customer requirements features. Taking central air conditioning as an example, consumers usually use strong stability, high energy saving, and strong reliability to express their requirements. The vague requirements have to be understood and realized by a specific PSS configuration. The proposed PCA-QPSO-SVM model is used to classify customer requirements using PSS configuration as a class label. Individualized PSS configuration can be obtained, which will support the PSS design.

In the PCA-QPSO-SVM model, the input must be a real vector. We assume requirement features of customer C_i are represented by $E_n = \{\mathrm{CN}_i \mid 1 < i < n, \mathrm{CN}_1, \ldots, \mathrm{CN}_i, \ldots, \mathrm{CN}_n\}$, and each feature CN_i has t selectable values. Then numbers can be used to encode the t optional values. For example, $E_1 = \{0, 0, 2, \ldots, 2, 1, -1\}$ represents the requirement features of customer C_1.

A PSS solution is comprised of product modules and service modules. Assuming there are s product modules in the PSS configuration framework, the module features for the product part can be expressed as $P = \{P_i \mid 1 < i < s\}$. There is one or more instances for each module characteristic. For example, there exist t available instances for module P_i, and the set is $\{p_i^j \mid 1 < j < t\}$. Similarly, the module features for the service part can be expressed as $S = \{S_v \mid 1 < v < u\}$. Assume there exist q available instances for module S_v, and the set is $\{\mathrm{s}_u{}^w \mid 1 < w < q\}$. The product instances and service instances make up diversified PSS configuration instances. Assume there exist l PSS configuration instances, and PSS configuration instances can be expressed as $PSS = \{PSS_k \mid 1 < k < l\}$. Product and service modules have different selectable instance values, which can be represented by discrete numbers as tags. For example, a PSS configuration instance is expressed as $\{p_1{}^2, p_2{}^2, \ldots, p_i{}^3, s_1{}^1, s_2{}^2, \ldots, s_u{}^3\}$.

5.2. Construction of the PCA-QPSO-SVM Model for PSS Configuration

- Step 1: Determine the product modules and service modules, then combine the corresponding instances to form different PSS configurations. According to the relevant historical data, the 'requirements-configuration' samples are collected to construct the model.
- Step 2: Reduce the dimension of requirement features by using the PCA algorithm. QPSO is used to perform k-fold cross-validation (CV) to find the best Gaussian kernel function σ and the penalty factor C. For k-fold CV, the entire training set is divided into k subsets with an equal number of samples. One of the subsets is selected as the testing set, and the remaining k-1 subsets are the training set.
- Step 3: Construct the multi-class SVM model by using the best parameter combination (C, σ) to test the testing set. After constructing a reliable classification model, PSS configuration can be predicted by inputting new customer requirements.

6. Case Study

Company A is a central air-conditioning manufacturer. To enhance the company's competitiveness and meet the diversified requirements of customers, company A decides to transform towards a service-oriented enterprise and provides customers with individualized PSS configuration. According to the modular design platform, and the PSS configuration design can be realized by combining different product instances and service instances. To quickly and accurately recommend the schemes to customers among diversified PSS configuration instances, the proposed PCA-QPSO-SVM model is applied in company A.

First, 100 data samples are extracted from the design and sales database. Then, the 100 data samples are divided into a training set and a testing set. The number of samples in the training set is 75 and that in the testing set is 25. Finally, the multi-classification PCA-QPSO-SVM model is used to predict the PSS configuration. The customer's need is used as the input of the PCA-QPSO-SVM model, and the PSS configuration scheme is used as the output of the model.

6.1. Data Coding and Features Analysis

According to customers' using conditions, 11 requirement features were identified by experts, including environmental protection, stability, intelligence, simplicity, convenience, adaptability, reliability, comfort, energy-saving, safety, and heat dissipation. Five-point requirement levels are defined as {L, ML, M, MH, H}, which mean {low, medium-low, medium, medium-high, high}. The corresponding code is $\{-2, -1, 0, 1, 2\}$. The description of requirement features is shown in Table 1. For instance, if a customer requires high energy savings, then the value for CN_9 can be represented by the code '2'. By consulting the experts, the modules and relevant instances of the central air conditioner are shown in Table 2. The modules and relevant instances of the service are shown in Table 3.

Table 1. Descriptions of requirement features.

	Feature	Option	Code
CN_1	Environmental protection	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$
CN_2	Stability	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$
CN_3	Intelligence	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$
CN_4	Simplicity	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$
CN_5	Convenience	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$
CN_6	Adaptability	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$
CN_7	Reliability	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$
CN_8	Comfort	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$
CN_9	Energy saving	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$
CN_{10}	Safety	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$
CN_{11}	Heat dissipation	{L, ML, M, MH, H}	$\{-2, -1, 0, 1, 2\}$

Table 2. Product module description.

Product Module	Instance	Code
Compressor	Permanent magnet synchronous frequency conversion screw type	A_1
	Photovoltaic direct-drive frequency conversion centrifugal	A_2
	DC frequency conversion	A_3
	Permanent magnet synchronous frequency conversion centrifugal	A_4
Condenser	Water-cooled condenser	B_1
	Air-cooled condenser	B_2
	Evaporative condenser	B_3
Evaporator	Horizontal evaporator	C_1
	Vertical tube evaporator	C_2
Throttling parts	Capillary	D_1
	Throttle	D_2
Fan	Axial fan	E_1
	Centrifugal fan	E_2
Reservoir	unidirectional	F_1
	Bidirectional	F_2
	Vertical	F_3
	Horizontal	F_4

Table 2. *Cont.*

Product Module	Instance	Code
Filter drier	Loose filling dry filter Block filter Compact bead dryer filter	G_1 G_2 G_3
Cooling Tower	Dry cooling tower Temperature cooling tower	H_1 H_2

Table 3. Service module description.

Service Module	Instance	Code
Recycling service	Home inspection High price recycling Cash transaction	I_1 I_2 I_3
Maintenance service	Annual maintenance Quarterly maintenance Monthly maintenance	J_1 J_2 J_3
Spare parts service	Original parts supply Non-original parts supply Replacement of faulty spare parts Spare parts upgrade	K_1 K_2 K_3 K_4
Install service	Remote installation and debugging On-site installation and commissioning Fully commissioned installation and commissioning	L_1 L_2 L_3
Control Technology Service	Adaptive location and weather Self-regulation of demand Predictive self-diagnosis	M_1 M_2 M_3
Cleaning service	Duct cleaning Parts cleaning Cooling tower cleaning Condenser cleaning	N_1 N_2 N_3 N_4

The product modules and service modules constitute different PSS configuration schemes. In this case, the PSS configuration scheme $\{A_1, B_2, C_2, D_2, E_1, F_1, F_3, G_1, H_1, I_1, J_2, K_1, L_2, M_2, N_1, N_2\}$ is coded '1′, $\{A_2, B_1, C_2, D_1, E_2, F_2, F_4, G_2, H_2, I_2, J_1, K_3, L_1, M_1, N_3, N_4\}$ is coded '2′, $\{A_3, B_3, C_3, D_2, E_2, F_1, F_3, G_3, H_2, I_1, J_1, K_1, L_3, M_2, N_1, N_2\}$ is coded'3′, $\{A_4, B_2, C_1, D_2, E_1, F_2, F_4, G_1, H_1, I_2, J_3, K_2, L_2, M_3, N_3, N_4\}$ is coded '4′, and $\{A_1, B_1, C_2, D_2, E_2, F_1, F_3, G_3, H_1, I_2, J_3, K_2, L_3, M_2, N_1, N_2\}$ is coded '5′.

The original design data for constructing the PCA-QPSO-SVM model are shown in Table 4. The distribution of each feature is displayed with a frequency diagram and box plots, as shown in Figures 3 and 4.

It can be seen from Figures 3 and 4 that most of the datasets are relatively evenly distributed and have no abnormal feature attributes. Only features CN_8, CN_9, CN_{11} have few outliers, which has little effect on the entire datasets, so the features cannot be eliminated easily. To see the correlation between each feature more intuitively, the establishment of a feature relationship heat map is shown in Figure 5.

In Figure 5, the correlation between features (CN_1, CN_9) and (CN_4, CN_{10}) is higher. Next, by establishing two coordinate systems with CN_1 as the x-axis, CN_9 as the y-axis and CN_4 as the x-axis, and CN_{10} as the y-axis, we can observe whether they are linearly or nonlinearly related in the plane distribution. The result of feature correlation is shown in Figure 6.

Table 4. The original data.

Samples	Inputs											Outputs
	CN_1	CN_2	CN_3	CN_4	CN_5	CN_6	CN_7	CN_8	CN_9	CN_{10}	CN_{11}	
01	0	0	2	1	2	−1	1	1	2	1	−1	1
02	2	2	−1	−1	−1	1	2	1	2	1	−1	3
03	1	1	1	2	0	0	2	1	2	2	0	5
04	1	1	0	2	0	−1	2	0	1	2	−1	2
05	−1	1	2	1	1	2	1	2	0	−1	2	4
......	... ...	... ...	... ...	... ...	... ...	... ...	... ...	... ...	... ...	... ...	......	......
96	0	−1	1	1	2	−1	0	0	2	1	−1	1
97	0	0	2	0	2	−1	2	1	2	0	−1	1
98	0	2	0	2	1	0	2	1	1	2	−2	2
99	1	2	1	2	1	0	2	1	2	2	−1	2
100	1	2	2	1	0	−1	1	1	1	2	1	5

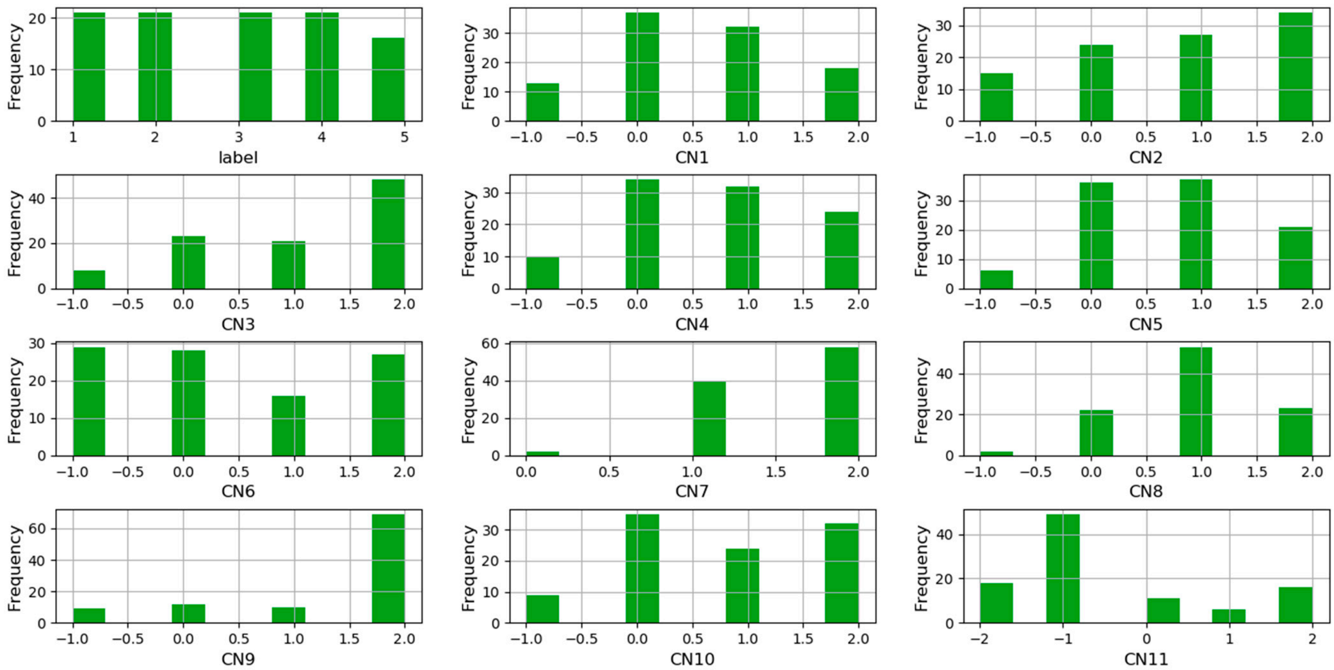

Figure 3. Features frequency diagram.

It can be seen from Figure 6 that the features (CN_1, CN_9) and (CN_4, CN_{10}) do not show a linear correlation, so the features CN_1, CN_9, CN_4, and CN_{10} cannot be eliminated easily.

6.2. PCA-QPSO-SVM Model Construction for PSS Configuration

6.2.1. Dimension Reduction of Requirement Feature

To improve the classification performance of the SVM model, the original feature set is processed to reduce dimension. First, the PCA algorithm is used to reduce the dimension of 11 requirement features in the original 100 sample data. Because the values of the data samples are all in {−2, -1, 0, 1, 2}, there is no need for StandardScaler processing. Second, the principal components are determined by calculating the covariance of each feature. The result of the calculation is shown in Figure 7.

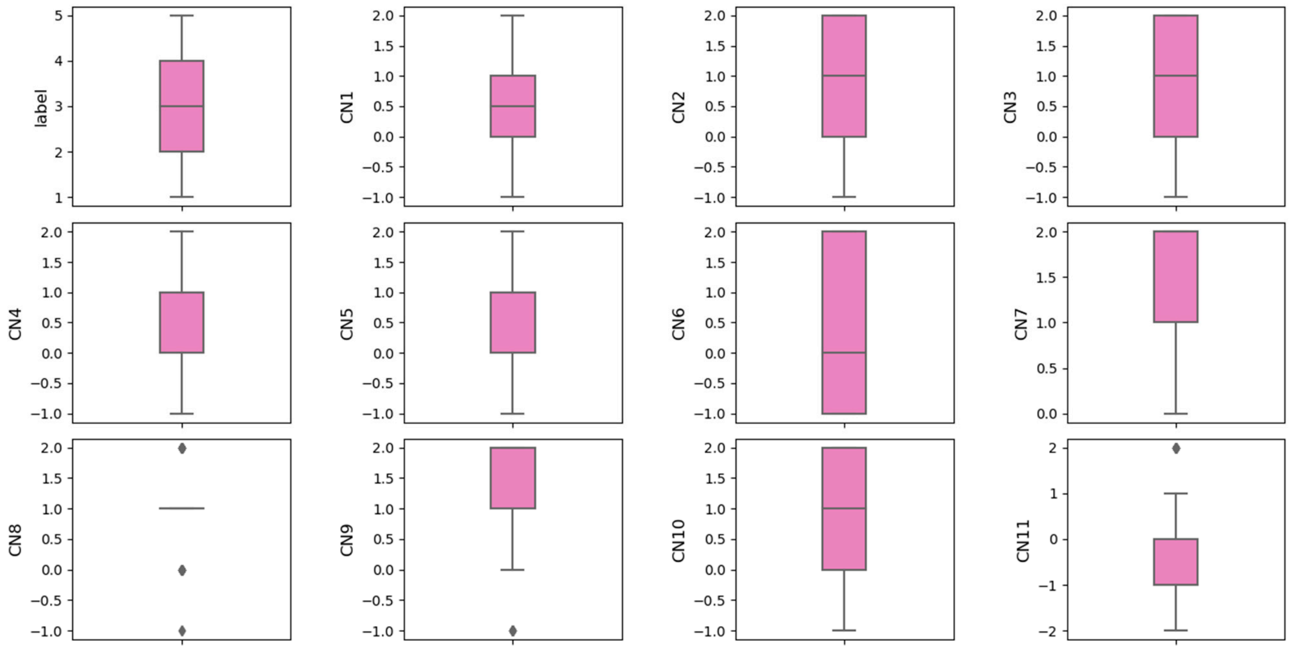

Figure 4. Features box plots.

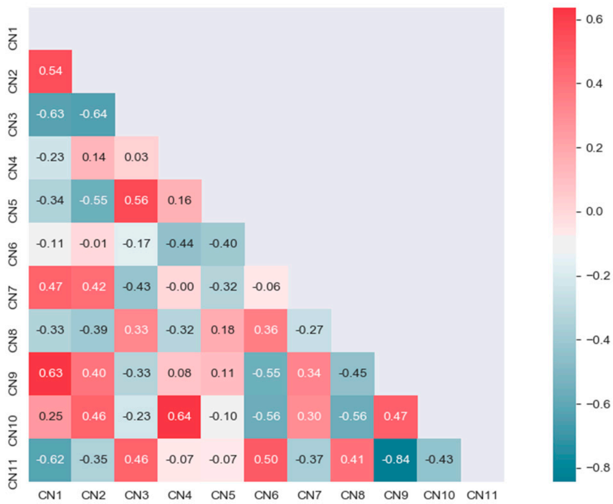

Figure 5. Feature relationship heat map.

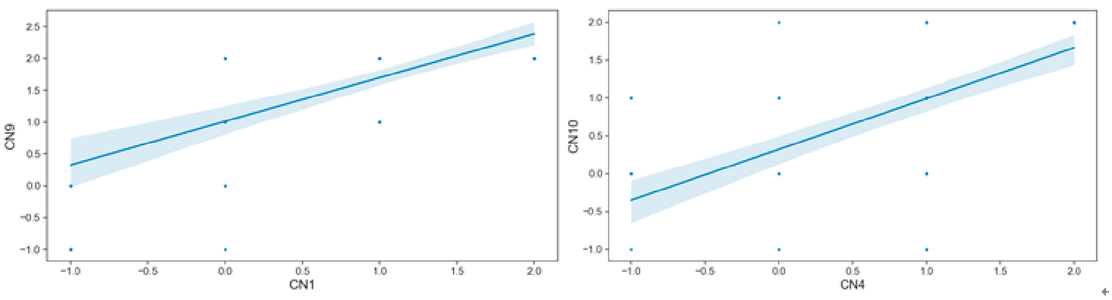

Figure 6. Feature correlation graph.

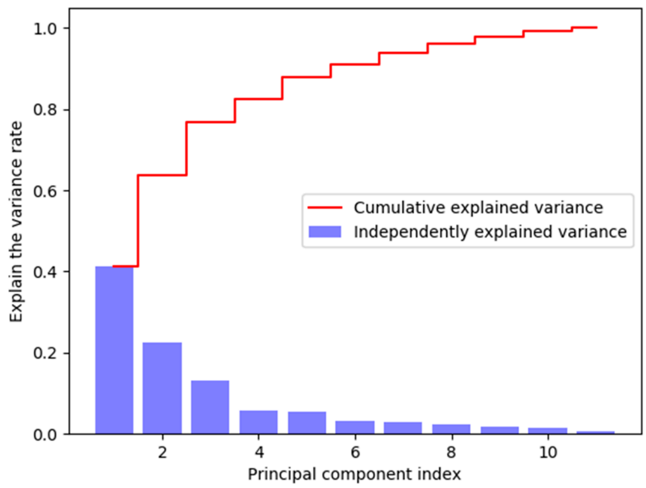

Figure 7. The principal component ratio chart.

In Figure 7, the first and second principal components account for most of the variance, accounting for 63.62%. Therefore, the parameter set of PCA is n_components = 2. The data after PCA dimension reduction is shown in Table 5.

Table 5. PCA dimensionality reduction data.

Samples	Inputs		Outputs
	X_1	X_2	
01	−0.224301033	−2.404274949	1
02	−1.799516865	3.14492011	3
03	−0.986306315	−0.290209173	5
04	−1.898471273	−0.422895036	2
05	3.882774024	0.580798351	4
... ...	... ...	... ...	... ...
96	−0.270004463	−2.44421515	1
97	0.094105412	−1.824376829	1
98	−1.867236441	−0.250669022	2
99	−1.777916303	−0.443148983	2
100	−0.14995178	−0.555739606	5

To demonstrate the distribution of these 100 samples more clearly after PCA dimensionality reduction, this paper visualizes these 100 samples. Take X_1 as the x-axis and X_2 as the y-axis, and the established rectangular coordinate system is shown in Figure 8.

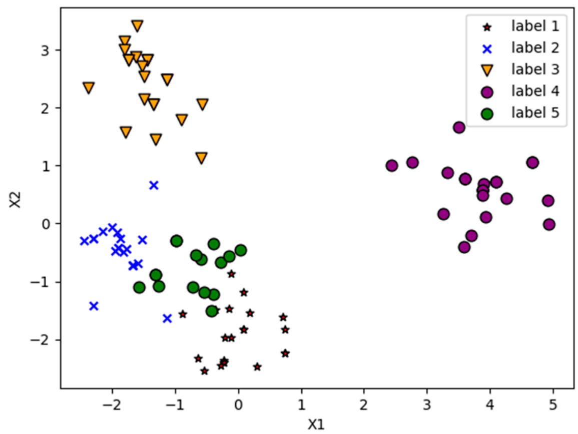

Figure 8. Distribution of PCA dimensionality reduction dataset.

To visualize the data, the original 11-dimensional features are reduced to 2-dimensional features through the PCA algorithm, thereby reducing nine attribute features. To verify the relationship between the 2-dimensional feature and the original 11-dimensional feature, and we can establish a heat map to reflect the relationship intuitively between the original features and PCA principal components, as shown in Figure 9.

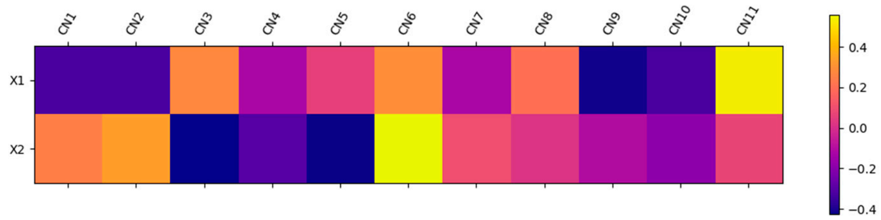

Figure 9. The heat map of the relationship between principal components and eigenvalues.

In Figure 9, the color from dark to light represents a value from −0.4 to 0.5, if the value of a feature is positive, it means that it is positively related to the principal component. If it is negative, then the opposite. It can be seen from Figure 9 that the correlation coefficient of X_1 is extremely low only with CN_1, CN_2, CN_9, CN_{10}, and the correlation coefficients of X_2 are extremely low only with CN_3, CN_4, CN_5, CN_{10}. Then it indicates that the substitution effect of X_1 and X_2 is better.

6.2.2. QPSO-SVM Model Construction and Parameters Setting

First, the 2-dimensional dataset obtained by the PCA algorithm is used as the dataset of the multi-class SVM model. Then, the QPSO algorithm is used for parameter optimization of 2-fold CV to find out the optimal parameter pair (C, σ). In the parameter optimization process, 75 randomly selected samples were used to train the QPSO-SVM model. In the QPSO algorithm, a parameter pair (C, σ) was obtained by each iteration, when the number of iterations reaches the maximum and output the optimal parameter pair (C, σ). The specific parameter settings of the QPSO algorithm are shown in Table 6.

Table 6. QPSO parameter settings.

Parameter	Settings
Number of particles	50
Particle dimension	2
The maximum number of iterations	50
Alpha	0.6
Maximum parameter	15
Minimum parameter	0.01
Fitness function	2-fold CV classification accuracy
Algorithm stop condition	The number of iterations > 50

The optimal parameter pair (C, σ) was calculated by setting the parameter value of the QPSO algorithm, and then it was used as the parameter sets the value of the multi-class SVM model for prediction analysis. The entire process was completed by Pycharm 2019.

6.3. Prediction and Comparative Analysis of PCA-QPSO-SVM Model

To evaluate the performance of the training model, classification accuracy is used as an index. In each iteration of the PCA-QPSO-SVM model, the training accuracy of training samples is shown in Figure 10.

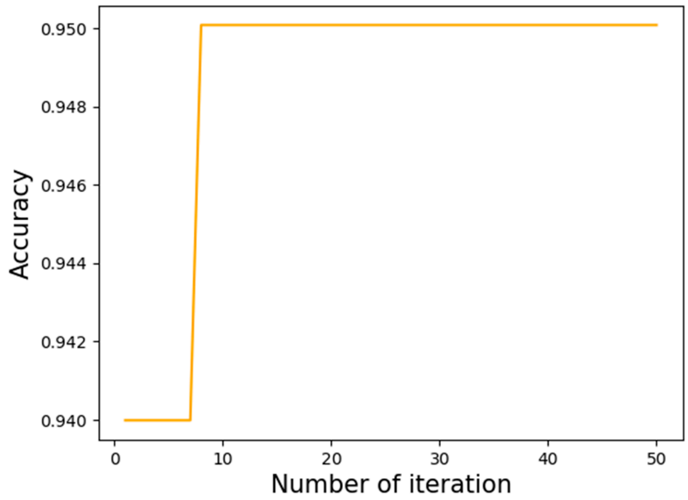

Figure 10. QPSO-SVM parameter optimization.

According to QPSO parameter optimization, when the number of iterations reaches 8, the classification accuracy under 2-fold CV is the highest (95.01%), and the optimal parameter values $C = 3.01$, $\sigma = 2.41$ are obtained at this time. Then the optimal parameters are used in the multi-class SVM model, and 25 samples in the testing set are used to test the classification accuracy of the model. The test results are shown in Figure 11. It turns out that all 25 test samples are predicted correctly, and the accuracy rate is 100%, which verifies that the performance of the QPSO-SVM model is excellent.

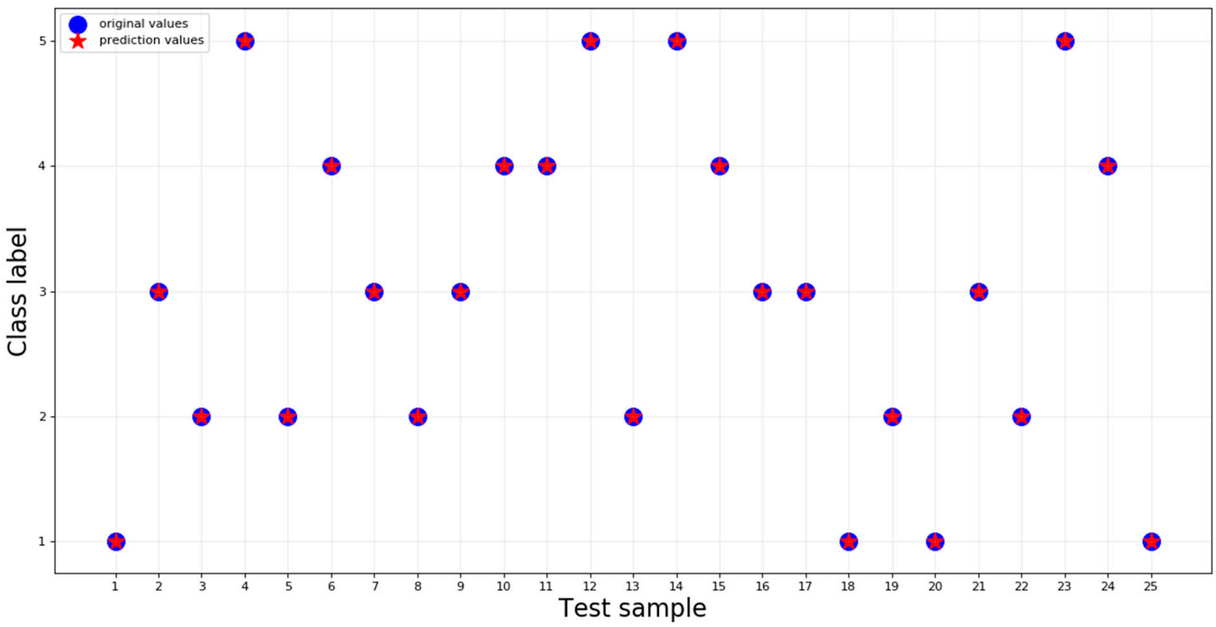

Figure 11. Model performance.

To verify the validity of the PCA-QPSO-SVM model prediction, this paper compares PCA-QPSO-SVM with PCA-PSO-SVM, PSO-SVM, GA-SVM, and GS-SVM. In the experiment, various prediction algorithms are run 20 times, respectively. For each method, the optimal prediction result is selected as the final result. The final results are compared as shown in Table 7. The simulation results show that the prediction accuracy of the PCA-QPSO-SVM model is 100%, which is better than other algorithms. Therefore, the proposed model has a better adaptability and predictive ability. In addition, the mean square error of

PCA-QPSO-SVM is 0, indicating that the PCA-QPSO-SVM model has a good predictive modeling effect.

Table 7. Precision comparison of PCA-PSO-SVM, PSO-SVM, GA-SVM, and GS-SVM.

Model	PCA-QPSO-SVM	PCA-PSO-SVM	PSO-SVM	GA-SVM	GS-SVM
Number of tests	25	25	25	25	25
Number of errors	0	2	9	9	10
Tests accuracy	100%	92%	64%	64%	60%
Mean square error	0	1.0	1.04	1.56	3.32

To verify the reliability of the model to solve actual problems, this article will test the consistency of the PSS configuration provided by a new customer's demand with the actual situation. The first new customer needs to configure central air-conditioning for the hospital. Its requirements are good stability and low noise (that is, the environmental protection is very high). Because the patient is considered, the comfort is also very high. The input is {2, 2, −1, −1, 0, 2, 1, 2, 1, 1, 0}, and the output result is the configuration plan "4", namely {A_4, B_2, C_1, D_2, E_1, F_2, F_4, G_1, H_1, I_2, J_3, K_2, L_2, M_3, N_3, N_4}. In practice, A_1 has low noise and good stability. Because E_1 has the characteristics of low wind pressure and small air volume, it is more comfortable. Configuration plan "4" meets the needs of customers and verifies the reliability of the model.

6.4. Discussion of Results

In the case study, there exist unimportant requirement features, so it is vital to reduce the dimension of customer requirement features. In this paper, we retain 95% information on requirement features. To facilitate the visualization, customer requirements are reduced from 11 features to 2 principal components by the PCA algorithm. Because the PCA algorithm can filter out some small influencing features by reducing the dimension, it will greatly improve the calculation speed and prediction accuracy of SVM. By comparing it with the PSO-SVM model, the PCA-PSO-SVM reaches the optimal result in the 13th iteration, the PSO-SVM model reaches the optimal result in the 21st iteration. In addition, the PCA-PSO-SVM model has the higher prediction accuracy (92%) than the PSO-SVM model (64%). Moreover, the PCA-PSO-SVM model has the lower mean square error (1.0) than the PSO-SVM model (1.04).

The QPSO algorithm is used to optimize the penalty factor C and the kernel function σ of SVM in this paper. The experimental results show that the optimal parameters (C = 3.01, σ = 2.41) and the highest classification accuracy (95.01%) are obtained by the PCA-QPSO-SVM model. By comparing with the PCA-PSO-SVM model, the proposed approach in this paper reaches the optimal result in the ninth iteration, which is faster than the PCA-PSO-SVM model (the 18th iteration). In terms of prediction accuracy, the proposed approach is 100%, which is higher than the PCA-PSO-SVM model (92%). In addition, the proposed approach has the lower mean square error (0) than the PCA-PSO-SVM model (1.0). These verified that the QPSO algorithm has the advantages of fast calculation ability and strong optimization ability in comparison with other optimization approaches.

By comparing with the GA-SVM model, the PSO algorithm can find the optimal parameters faster and lower mean square error. The PSO algorithm reached the optimal in the 21st iteration, which is faster than the GA-SVM model (the 27th iteration). Although the prediction accuracy the PSO-SVM model is similar to the GA-SVM, the mean square error of the PSO-SVM model is 1.04, which is lower than the GA-SVM model (1.56).

Similarly, by comparing with the GS-SVM model, the PSO algorithm can find the optimal parameters faster and with a better prediction accuracy. The PSO algorithm reached the optimal in the 21st iteration, which is faster than the GA-SVM model (the 38th iteration). The prediction accuracy of the PSO-SVM model is 64%, which is higher than the GS-SVM model. In addition, the mean square error of the PSO-SVM model is 1.04, which is lower than the GS-SVM model (3.32).

In general, the experimental results show that it is effective for predicting PSS configuration by the proposed PCA-QPSO-SVM model. The proposed approach has the highest accuracy and best performance by comparing with other approaches, which can provide a more accurate PSS configuration that meets customer requirements. In the product service area, this is beneficial to customers who will receive a better value offering and the manufacturer who can identify the main aspects of its solution more effectively.

The limitation of the dataset is that the sample are relatively small. The optimal parameters and the highest classification accuracy are reached through 50 iterations.

7. Conclusions and Future Research

With the increasingly fierce market competition, more and more manufacturers combine products and services into PSS to provide customers with greater value. Manufacturers must accurately determine which configuration meets customer needs better. The PSS configuration is deemed as a multi-classification problem in this paper. A PCA-QPSO-SVM model is proposed to solve this problem. The validation of the proposed model in air conditioner configuration indicates that it can be used as an effective prediction model for PSS configuration. To sum up, the proposed approach reveals the following features.

The PSS configuration design can be realized by machine learning. The historical design and sales data have great value in supporting individualized PSS design. A multi-classification SVM helps PSS providers to easily predict configuration schemes with higher customer satisfaction.

Compared with the conventional SVM model, the proposed model considers the impact of feature dimension and the selection of key parameters. The PCA algorithm has the advantage of convenience in reducing the dimensions of the dataset. In the process of optimizing SVM parameters, QPSO does not fall into the problem of local optimization and has a better fitness value. The usage of QPSO in optimizing SVM parameters can improve classification accuracy.

Although the proposed optimization method can predict the PSS configuration well, it is restricted by the training data. The predicted model performs effectively when there are adequate and reliable data. Completely new customer requirements are hard to process and generate the appropriate PSS configuration. Therefore, in future research, we can calculate the similarity between new customer requirements and previous customer requirements, and the PSS configuration corresponding to the maximum similarity can be recommended to the new customer.

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