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# Integration of Support Vector Machine with Particle Swarm Optimization in Quality Modeling of CFG Composite Foundation

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**Abstract:** The purpose of this paper is to develop models to predict the quality (bearing capacity of foundation and pile completeness) of the Cement Fly-ash Gravel (CFG) composite foundation. To ensure the models are useful to both designer and construction of composite foundation, the study employs a broad range of bearing capacity of foundation and pile completeness variables through investigating the load transfer mechanism and reinforcement mechanism of mattress layer mechanism, the pile, layer, replacement ratio, construction machinery and other aspects of CFG pile composite foundation systematic and comprehensively. In addition, the research develops a model integrating of support vector machine with particle swarm optimization (PSO-SVM) for predicting the bearing capacity and pile completeness of the Cement Fly-ash Gravel foundation. This paper contributes to the scarce literature on design and construction of CFG pile composite foundation. The models developed in this paper are useful to give those design and construction of CFG pile composite foundation an early warning. And through specific examples of analysis, the model practical application effect was test. It was concluded that using the established model for CFG pile composite foundation quality verification, is of feasibility and validity.

***Keywords:** Cement Fly-ash Gravel (CFG); composite foundation; support vector machine(SVM); pile integrity; particle swarm optimization (PSO); prediction*

## 1. Introduction

Construction is very important to the China economy due to the industry's contribution to the gross domestic product (GDP) and jobs in closely related industries such as cement and steel industry, realtors, landscapers, furniture salesmen, and drapery makers. In recent years, with the growing of infrastructure construction in China, more and more problems of inferior foundation have troubled practitioner in the construction of civil engineering, water conservancy, transportation and railway engineering. When the natural foundation cannot meet the requirements of building construction, we must take action to deal with the original base. The technology to deal with foundation has become an important subject for the general engineering, technical personnel and scientific research workers (Xu Zhijun, Shuguang Wang, 2004)[1]. Cement Fly-ash Gravel (CFG) pile composite foundation is widely used among the form of ground treatment. It is widely used in dealing with poor foundation, and also can be used in the waste generated industrial production, although it does not need to configure the reinforcing steel. With dealing with the CFG pile composite foundation, it not only can improve the bearing capacity of natural foundation, but also save construction cost, thus it plays a very important role in the foundation treatment. Recently, the design formula in the bearing capacity of composite foundation used is based on half experiment experience and half theory formula, which experience coefficient values have a large impact on the calculation results of the bearing capacity, and there is error difference between the calculation results and the data of static load experiment. This method tends to be conservative in the practical engineering design.

Support vector machine can solve nonlinear, high dimensional pattern recognition problems on the basis of limited samples and express nonlinear relationships between the input and output, but its accuracy has a relationship with the values of training parameter, and the parameters is important for forecasting accuracy. Particle swarm optimization (PSO) algorithm is a new kind of evolutionary computation technology, it finds the optimal solution through collaboration and information sharing between individuals in the group, convergence rate is fast and is easy to implement. The combination of particle swarm optimization (PSO) algorithm and support vector machine (SVM), using the global search ability of particle swarm to optimize the model parameters, we can avoid the blindness of man-made choice parameters, also will improve the training speed and precision of prediction models. In this paper, it is effectively to predict the quality of CFG pile composite foundation combining particle contemplating the algorithm and support vector machine (SVM), in order to find a new way to determine the quality of CFG pile composite foundation.

## 2. Background of CFG pile composite foundation Approaches

In theoretical research, Rong WenGuang,(2011)[2] Luo Dongyuan etc.(2007)[3] expounds the basic definition of CFG pile composite foundation, analyzed the bearing capacity of CFG pile composite foundation, calculation of deformation and the method of settlement calculation of composite foundation, put forward the value demands of single pile vertical bearing capacity characteristic value and a method for determining the thickness of mattress layer, and suggestions on Some misuses of design for CFG pile composite foundation. Minghua Zhao, et al.(2010)[4]analyzed the load transfer mechanism of CFG pile composite foundation, in view of pile, soil and cushion layer interaction characteristic the CFG pile composite foundation of, established the basic differential equation of CFG pile composite foundation settlement calculation, and then put forward a new settlement calculation method considering coactions of pile-soil – cushion. Aijun Zhou, et al.(2010)[5] by means of field static load experiment, analyzes the influence of variation of thickness and material of mattress layer to the stress ratio between pile and soil, and put forward some valuable Suggestions of optimization of mattress layer of CFG pile composite foundation design. The CFG pile effect principle, design idea, the bearing capacity of composite foundation and pile body completeness inspection technology were summarize and discuss for the design and construction of CFG pile composite foundation and some valuable Suggestions and made a great contribution to the promotion were put forward (Yao Yong, et al. 2010)[6]. In research of experiment, LouGuo et al.(2002)[7] produced the design idea of CFG pile composite foundation based on studying of mechanism of CFG pile composite foundation and pile through analyzing the interaction between the pile and soil. Field test was introduced to analyze the influence of load, pile length, mattress layer thickness and modulus of soil in the treated area on pile soil stress ratio, and proposed the experience formula of the stress ratio of pile-soil according to the test data by linear regression to (Qiao Jingsheng et al.2004).[8]

Duan Xiaopei et al.(2010)[9] developed a model experiment that such as in-depth study of mattress layer under the different thickness of mattress layer mechanism, summarizes the pile and soil under loading force changing with the thickness of mattress layer, it is concluded that the reasonable thickness of mattress layer design requirements. Test was mattress layer thickness is reasonable can make up for the defect of pile end bearing layer properties is poor, effectively control the settlement of composite foundation, provides the reference basis for the design and construction. In numerical simulation research, finite element analysis software ANSYS was used to study the characteristics of CFG short pile compound foundation, and induces the pile length, pile soil modulus, thickness of mattress layer, replacement ratio and a series of factors. And compared with other foundation treatment technology, it is concluded that use of CFG short pile compound foundation bearing layer after processing to a larger bearing capacity, settlement after the construction of the building to be smaller. End of CFG short pile compound foundation, summarizes the advantages, so as to provide experience for future design and construction reference.( Cui Yanwei 2011)[10]Zhang Jianwei, and Dai Zihang (2005)[11] used the finite element numerical simulation method solve the settlement deformation of soil under the upper load of pile, mattress layer obtained by research of the change of the material and thickness of pile soil stress ratio and the settlement deformation of piles and soil between the influence of the rule. The study results provide the beneficial reference to determine the mattress layer thickness and material of the CFG pile composite foundation design.

Several studies have been devoted to combining artificial intelligence of the bearing capacity of CFG pile composite foundation, by studying the influence factors of CFG pile composite foundation bearing capacity, and analyzes the complicated nonlinear factors, with the aid of the BP neural network advantage in dealing with nonlinear problems, the bearing capacity of the established based on BP neural network prediction model, and the bearing capacity are the effective prediction (Hongwei Qi 2005)[12]. In the study by Jiang Wei et al.(2010)[13], an Ann model based on genetic was presented to predict CFG pile composite foundation bearing capacity using Matlab toolbox, which overcome the deficiency of the traditional BP neural network, and get a more accurate prediction results. CFG pile composite foundation bearing capacity prediction model was proposed based on Gaussian process by Guoshao Su et al.(2011)[14] and the model was applied in engineering practice. The results show that process model of Gaussian include unique properties that distinguish it from the other models such as high prediction accuracy, applicability, has the characteristics of algorithm parameters from specialization and easy to implement, and a better prospect of engineering application.

## 3. Research Methodology

### 3.1. Support Vector Machine (SVM)

SVM (Support Vector Machine, SVM) was proposed by Vapnik in 1995(Vapnik v. N.1995)[15], and it is important between theoretical research and engineering application, and successfully applied to many problems of practical engineering(Nello Cristinaini, John Shawe-Yaylor.2004)[16]. The SVM regression function is:

$$f(x) = w \cdot x + b \quad (1\text{-}1)$$

According to the concept of the optimal hypersurface, when constraints are difficult to realize, introducing the slack variables $\xi_i, \xi_i^*$, punish coefficient $C$, then the SVM modeling problem translates into a minimization problem as shown below:

$$\min_{w,b,\xi} J = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*) \quad (1\text{-}2)$$

$$s.t. \begin{cases} y_i - w \cdot x_i - b \le \varepsilon + \xi_i \\ w \cdot x_i + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i \ge 0 \\ \xi_i^* \ge 0 \end{cases} \quad i = 1, 2, \cdots l \quad (1\text{-}3)$$

The type based on the dual principle:

$$\max_{\alpha,\alpha*} \left\{ L_D = -\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j, \alpha_j^*) x_i \cdot x_j - \varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{l} y_i(\alpha_i - \alpha_i^*) \right\} \quad (1\text{-}4)$$

$$s.t. \begin{cases} \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \\ 0 \le \alpha_i \le C \\ 0 \le \alpha_j \le C \end{cases} \quad (1\text{-}5)$$

Nonlinear regression problems need to introduce kernel function, the kernel function training data can set the nonlinear function map $\phi(x)$ to a higher dimensional linear feature space, the kernel function need $K$ which meets $K(x_i, y_i) = \phi(x_i) \cdot \phi(y_i)$. If the kernel function satisfies the conditions, the dimensions of the high dimensional space of disaster problem can be avoided. It can translate into a quadratic programming problem by the dual principle of nonlinear function regression, calculation method is as follows:

$$\max_{\alpha,\alpha*} \left\{ L_D = -\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)(\alpha_j, \alpha_j^*) K(x_i \cdot x_j) - \varepsilon\sum_{i=1}^{l}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{l} y_i(\alpha_i - \alpha_i^*) \right\} \quad (1\text{-}6)$$

$$s.t. \begin{cases} \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0 \\ 0 \le \alpha_i \le C \\ 0 \le \alpha_j \le C \end{cases} \quad (1\text{-}7)$$

We can get the Lagrange multiplier $\alpha_i$ and $\alpha_i^*$ through the above calculation, a few $\alpha_i$ and $\alpha_i^*$ is not zero, the support vector is zero the sample which is corresponding Lagrange multiplier, it usually appears on the location of the dramatic change in the function. The nonlinear regression function can be founded by Lagrange multiplier which has been calculated:

$$f(x) = \sum_{x_i \in SV}(\alpha_i - \alpha_i^*) K(x_i, x) + b \quad (1\text{-}8)$$

The regression estimate function parameter b is as below:

$$b = \frac{1}{N_{NSV}} \left\{ \sum_{0<\alpha_j<C} [y_i - \sum_{x_j \in SV}^{l}(\alpha_i - \alpha_i^*) K(x_j, x_i) - \varepsilon] + \sum_{0<\alpha_j<C} [y_i - \sum_{x_j \in SV}^{l}(\alpha_i - \alpha_i^*) K(x_j, x_i) + \varepsilon \right\} \quad (1\text{-}9)$$

If the Kernel function which has been chose is appropriate, regression model will has high prediction accuracy, now the kernel function involves polynomial kernel function, the radial basis function and so on.

### 3.2. Particle Swarm Algorithm

Particle swarm algorithm is simple and easy to implement, and the basic operation is not complex, low memory computer can also satisfy the processing of data. It can complete the optimization of the input values to a function without the gradient information. Particle swarm algorithm can solve a lot of problems of the global optimization, and it is widely used in theoretical research and practical application. More valuable is that the data exist in the form of a database can be solved better through the parallelism and distributed characteristics of particle swarm algorithm. We can optimize the parameters of support vector machine (SVM) which is difficult to determine based on particle swarm, and then establish the PSO - SVM prediction model for practical application.

In this paper, on the basis of the load transfer mechanism of CFG pile composite foundation, strengthening mechanism and the mechanism of the mattress layer, from several aspects such as the soil characteristics of the soil layer, CFG pile from strength of pile, construction technology, the displacement rate, time and space factors, analyzing all aspects of the factors that affected the bearing capacity of CFG pile composite foundation and integrity of pile, and finally the forecasting index system is established.

The implementation steps of PSO - SVM quality prediction model of CFG pile composite foundation is as follows:

(1) Collect various data about the quality of CFG pile composite foundation, the data are divided into the training sample and test sample; Initialize the various parameters, such as the size of particle swarm, the initial position, velocity as well as the punishment function and kernel function parameters of the SVM.
(2) According to the initialization of the training sample data values of each particle, the samples will be learned and trained and establish their corresponding prediction model.
(3) The error can be obtained for each particle through the training samples training to get the value of particle fitness function.
(4) Calculate the fitness function value of all individual particles, and compare with the particle at the moment with their best fitness

value, if the current value is less than the best fitness value, adjust the best fitness value is equal to the moment fitness value, this position will be the particle's best position.

(5) Update the optimal location of fitness value between a single particle and all particles.

(6) Adjust the velocity and position of particles based on the evolution equation of PSO, and then obtain the new parameters of support vector machine.

(7) Determine the iterations of all particles, when the optimal position of the fitness value can meet the requirements, stop the calculation, save the best overall position of the position. If it does not meet, the calculation will be returned to the second step of the optimization process.

(8) Select the optimal parameters and estimate the test sample.

Using the PSO - SVM model that has been established to effectively predict the quality of CFG pile composite foundation, its modeling flowchart is as shown in fig 1.

**4. Data Analysis and Model Implementation**

The relevant data of CFG pile composite foundation what we need are come from several engineering in Handan region, which play the part of the training samples and test samples in PSO-SVM model, the specific data are shown in table1 and table2. The technology of construction are long spiral drilling and pipe pump pressure mixture pile, the pile what have been chose do the CFG pile composite foundation static load test and low strain test in the stipulated time.

In the forecasting models of characteristic values of bearing capacity of CFG pile composite foundation and the integrity of pile, the first 20 groups of data come from table 1 and table 2 act as the training sample which will have to do the learning practice, in order to establish a nonlinear law between input and output, the last five groups of data act as the test sample, in order to check out the effect of PSO - SVM model prediction. Finally compare the prediction results with the cross validation of the SVM model.

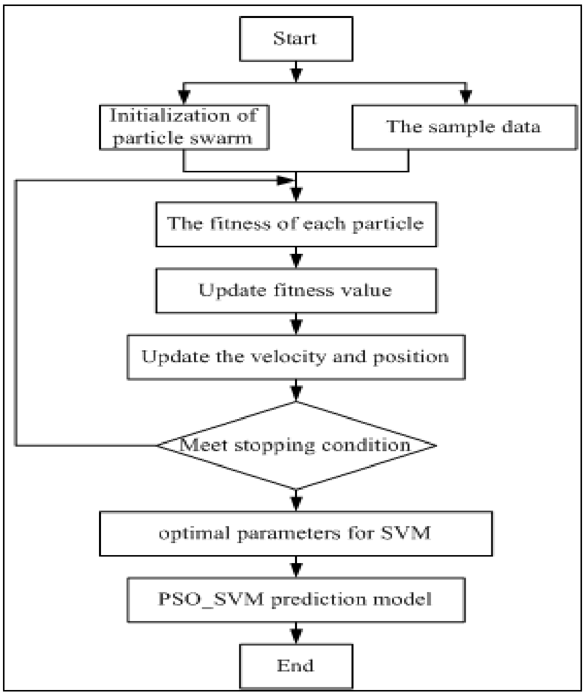


***Figure 1*** *Methodology*

***Table 1:*** *Original data of CFG pile composite foundation bearing capacity*

| Pile No. | Pile length (m) | Pile diameter (mm) | Pile Strength | Replacement ratio | Mattress layer thickness (mm) | Side friction Resistance(kPa) | Pile tip Resistance(kPa) | Bearing capacity (kPa) |
|---|---|---|---|---|---|---|---|---|
| 1-112 | 23 | 420 | 25 | 0.0819 | 150 | 40 | 1000 | 440 |
| 2-40 | 23 | 420 | 25 | 0.0672 | 150 | 42 | 1100 | 396 |
| 3-33 | 23 | 420 | 25 | 0.0693 | 150 | 38 | 960 | 360 |
| 4-154 | 23 | 400 | 25 | 0.0719 | 150 | 44 | 1120 | 440 |
| 5-74 | 23 | 420 | 25 | 0.0712 | 150 | 45 | 1180 | 440 |
| 89 | 14 | 400 | 25 | 0.0632 | 150 | 30 | 860 | 230 |
| 1418 | 14 | 400 | 25 | 0.0632 | 150 | 32 | 860 | 230 |
| 2-138 | 23 | 420 | 25 | 0.0672 | 150 | 45 | 1080 | 396 |
| 3-36 | 23 | 420 | 25 | 0.0693 | 150 | 40 | 960 | 360 |
| 1517 | 14 | 400 | 25 | 0.0632 | 150 | 32 | 860 | 230 |
| 5-123 | 23 | 420 | 25 | 0.0712 | 150 | 46 | 1180 | 440 |
| 272 | 14 | 400 | 25 | 0.0632 | 150 | 32 | 860 | 230 |
| 394 | 14 | 400 | 25 | 0.0632 | 150 | 34 | 860 | 230 |
| 1-247 | 23 | 420 | 25 | 0.0819 | 150 | 42 | 1000 | 440 |
| 2-224 | 23 | 420 | 25 | 0.0672 | 150 | 42 | 1100 | 396 |
| 3-280 | 23 | 420 | 25 | 0.0693 | 150 | 38 | 960 | 360 |
| 5-274 | 23 | 420 | 25 | 0.0712 | 150 | 45 | 1180 | 440 |
| 487 | 14 | 400 | 25 | 0.0632 | 150 | 32 | 860 | 230 |
| 1-341 | 23 | 420 | 25 | 0.0819 | 150 | 40 | 1000 | 440 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2-294 | 23 | 420 | 25 | 0.0672 | 150 | 44 | 1100 | 396 |
| 2-386 | 23 | 420 | 25 | 0.0672 | 150 | 47 | 1100 | 396 |
| 3-282 | 23 | 420 | 25 | 0.0693 | 150 | 39 | 960 | 360 |
| 4-231 | 23 | 400 | 25 | 0.0719 | 150 | 44 | 1120 | 440 |
| 5-394 | 23 | 420 | 25 | 0.0712 | 150 | 43 | 1180 | 440 |
| 656 | 14 | 400 | 25 | 0.0632 | 150 | 32 | 860 | 230 |

***Table 2:*** *Original data (Continued from Table 1)*

| Pile No. | Natural void ratio | Liquid index | Replacement ratio | Concrete slump (mm) | Pile drawing speed (m/min) | Pile type |
|---|---|---|---|---|---|---|
| 1-112 | 0.647 | 0.48 | 0.0819 | 160 | 2.8 | 2 |
| 2-40 | 0.624 | 0.36 | 0.0672 | 180 | 2.6 | 1 |
| 3-33 | 0.658 | 0.52 | 0.0693 | 160 | 2.6 | 1 |
| 4-154 | 0.636 | 0.38 | 0.0719 | 180 | 2.4 | 1 |
| 5-74 | 0.726 | 0.58 | 0.0712 | 180 | 2.7 | 2 |
| 89 | 0.714 | 0.53 | 0.0632 | 160 | 2 | 1 |
| 1418 | 0.714 | 0.53 | 0.0632 | 160 | 2 | 1 |
| 2-138 | 0.624 | 0.36 | 0.0672 | 180 | 2.8 | 2 |
| 3-36 | 0.658 | 0.52 | 0.0693 | 160 | 2.6 | 1 |
| 1517 | 0.714 | 0.53 | 0.0632 | 160 | 2 | 1 |
| 5-123 | 0.726 | 0.58 | 0.0712 | 180 | 2.7 | 2 |
| 272 | 0.714 | 0.53 | 0.0632 | 160 | 2 | 1 |
| 394 | 0.714 | 0.53 | 0.0632 | 160 | 2 | 2 |
| 1-247 | 0.647 | 0.48 | 0.0819 | 160 | 2.8 | 2 |
| 2-224 | 0.624 | 0.36 | 0.0672 | 180 | 2.6 | 1 |
| 3-280 | 0.658 | 0.52 | 0.0693 | 160 | 2.6 | 1 |
| 5-274 | 0.726 | 0.58 | 0.0712 | 180 | 2.5 | 1 |
| 487 | 0.714 | 0.53 | 0.0632 | 160 | 2 | 2 |
| 1-341 | 0.647 | 0.48 | 0.0819 | 160 | 2.6 | 1 |
| 2-294 | 0.624 | 0.36 | 0.0672 | 180 | 2.8 | 2 |
| 2-386 | 0.624 | 0.36 | 0.0672 | 180 | 2.6 | 1 |
| 3-282 | 0.658 | 0.52 | 0.0693 | 160 | 2.6 | 1 |
| 4-231 | 0.636 | 0.38 | 0.0719 | 180 | 2.6 | 2 |
| 5-394 | 0.726 | 0.58 | 0.0712 | 180 | 2.5 | 1 |
| 656 | 0.714 | 0.53 | 0.0632 | 160 | 2 | 1 |

Because of the difference of the dimension of the predictors and each index value, the original data need to be the normalization of processing in the forecast of the characteristic values of bearing capacity of CFG pile composite foundation and the integrity of pile in PSO - SVM model, the sample data will scale to the range of 0 and 1, in order to avoid the influence of different data units from sample data.

## 5. Results and Discussion

The PSO - SVM procedure is progressed in Matlab toolbox and particle swarm optimization toolbox. The precision of the prediction model in support vector machine (SVM) has close relation with the selection of parameters, considering the lack of support vector machine (SVM), the paper introduces the parameters of particle swarm to optimize the support vector machine (SVM), the optimal parameters what we need to model include the punishment $C$, insensitive loss function $\varepsilon$ and kernel function $\sigma$. The related parameters of GA are as below: the maximum of the evolution algebra T is 200, the population pop size is 20, the learning factor c1 is 1.5 and c2 is 1.7. The coding length of each variable which need optimize is 20, the number of variables NUM is 2, the generation of GAP is 0.9, crossover probability is 0.75 and mutation probability is 0.02. The selection for SVM is support vector regression machine, the kernel function is radial basis kernel function, the scope of penalty parameter $C$ is between 0.1 and 100 and the scope of the radial basis kernel function parameter $\sigma$ is between 0.01 and 100. The optimal parameter combination: $C$ = 48.34, $\sigma$ = 7.07 , $\varepsilon$ = 0.001, we can get the fitness curve, the comparing between the raw data and predicted data.

The PSO - SVM model and SVM model with cross validation are used in this paper, compare the relative error, root mean square error and classification accuracy for two prediction results, the results are shown in table 3 and table 4.

***Table 3:*** *Prediction results of PSO-SVM model*

| Project No. | Prediction model of bearing capacity | | | Prediction model of integrity of pile | |
|---|---|---|---|---|---|
| | Actual value | Predictive value | Relative error | Actual type | Prediction type |
| 1 | 396 | 394.2575 | 0.0044 | 1 | 1 |
| 2 | 230 | 231.9005 | 0.0083 | 1 | 1 |
| 3 | 440 | 439.5674 | 0.0010 | 2 | 2 |
| 4 | 360 | 360.3716 | 0.0010 | 1 | 1 |
| 5 | 230 | 230.4217 | 0.0018 | 1 | 1 |
| 6 | MSE = 2.8176 | | | Accuracy = 93.3333%(14/15) | |

***Table 4:*** *Prediction results of Cross-validation SVM model*

| Project No. | Prediction model of bearing capacity | | | Prediction model of integrity of pile | |
|---|---|---|---|---|---|
| | Actual value | Predictive value | Relative error | Actual type | Prediction type |
| 1 | 396 | 394.8424 | 0.0030 | 1 | 1 |
| 2 | 230 | 237.1817 | 0.0312 | 1 | 1 |
| 3 | 440 | 437.8862 | 0.0048 | 2 | 2 |
| 4 | 360 | 360.7285 | 0.0020 | 1 | 1 |
| 5 | 230 | 232.0865 | 0.0091 | 1 | 1 |
| 6 | MSE =4.6429 | | | Accuracy = 86.6667% (13/15) | |

As shown in Table 3 and Table 4, it is accurate to predict the characteristic value of the CFG pile composite foundation bearing capacity with two models of PSO - SVM and SVM, the fluctuation for the results of the error is slight, in general, the error of the PSO - SVM model prediction is less than the SVM model prediction, can have good effect on prediction. The accuracy rate was 93.33% (14/15) in the model of the classification of integrity of pile in PSO-SVM, The accuracy rate was 86.67% (13/15) in the Cross-validation SVM model, so the accuracy in PSO - SVM classification model is higher than the Cross-validation SVM model. The results showed that the PSO - SVM model has more advantages over the prediction of quality of CFG pile composite foundation under the condition of small sample.

## 6. Conclusions

This study proposes a novel approach of a quality forecast of CFG pile composite foundation while considering uncertainties and interdependencies among criteria and subcriteria that affecting the quality of CFG pile composite foundation. The developed model can be used for prequalification and conceptual design stage, which is uncertain and complex of nonlinear. In this paper, the main research results and conclusions are as follows:

(1) The index system of CFG pile composite foundation bearing capacity and integrity of pile are based on the peripheral soil properties, the characteristics of the pile, replacement ratio and construction technology, providing the reasonable input parameters for the PSO-SVM prediction model.

(2) Aiming at the shortcomings of the support vector machine (SVM), the particle swarm optimization algorithm is introduced into the support vector machine forecasting model, in order to establish the PSO-SVM quality prediction model of CFG pile composite foundation, the paper programs the prediction of the bearing capacity and integrity of pile based on the PSO-SVM in simulation platform of Matlab.

(3) In order to test the superiority of PSO-SVM prediction model, the results were shown by the example analysis that the prediction model was better than the traditional SVM prediction model. The feasibility and effectiveness of the PSO-SVM prediction model was also verified in the quality of CFG pile composite foundation.

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