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Compressive Strength-Prediction Model for Coal Gangue Concrete via Genetic Algorithm Theory and Support Vector Machine

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Abstract: The objective of this paper is to construct a prediction model that can forecast the unconfined compressive strength of a coal gangue concrete. An improved support vector machine (SVM) using genetic algorithm (GA) to optimize parameters is proposed in this paper. The SVM is chosen as a method for prediction because it shows many unique advantages in solving small -sample, nonlinear, and high dimensional pattern recognition. The cross-validation model is also established. Through the comparison of its prediction results with those of the cross-validation model, the results show that the mean relative error of the GA-SVM model is smaller than the cross-validation model’s, which proves the feasibility of the method. The GA-SVM model is a very viable-candidate for the prediction of the unconfined compressive strength of a coal gangue concrete.

***Keywords:** support vector machine, coal gangue concrete, compressive strength, genetic algorithm*

1. Introduction

In recent years, increasing attention has been drawn to the development and utilization of coal gangue. The experimental use of coal gangue in highway and railway engineering in China has achieved good results. (J. M. Guo, L. L. Zhu, 2011) made coal gangue concrete with coal gangue instead of some aggregate, fly ash and slag instead of some cement. Coal gangue concrete was studied by the method of orthogonal experiment. Compression strength, its loss of strength after corrosion by sulphate, modulus of elasticity and its loss after freeze-thaw were analyzed. Optimum mix of coal gangue concrete was given by the integrated balance method. And Finally, SEM analysis on coal gangue concrete was researched [1]. (X. Y. Song, J. Y. Han, Z. H. Gao,2011) analyze hydration degree of cement with added-calcium thermal activated coal gangue Through determining $Ca(OH)_2$ content and chemically combined water content, and they conclude that show high contribution of added-calcium coal gangue calcined at 1050°C for pozzolanic properties and high hydration reaction degree in this kind of activated coal gangue cement system, with fewer $Ca(OH)_2$ content, more chemically combined water content and obviously reduced hydration product $Ca(OH)_2$ at each age[2]. (Zhenshuang Wang, Ning Zhao.2015) investigates the feasibility of using coal gangue as coarse and fine aggregates in concrete as well as how the coal gangue aggregate grading affects concrete properties. The conclusion is that it is possible to produce grade 30 coal gangue concrete with coal gangue coarse and fine aggregate [3]. (Ji-xiu Zhang, Heng-hu Sun, Yin-ming Sun, Na Zhang) uses the relative bridging oxygen number (RBO) based on nuclear magnetic resonance (NMR) technique to estimate the degree of $[SiO_4]^{4-}$polymerization of coal gangue[4]. (Zhang Changsen.2006) investigated the pozzolanic activity of coal gangue burned at different burning temperatures, and shows that the compressive strength of cement paste decreases with increasing the content of burned coal gangue. The decrease in strength is small in the range of 20%–30% coal gangue substitution and significant in 30%–60% substitution [5].

It is essential to determine the unconfined compressive strength of coal gangue concrete accurately, especially in practical application. The unconfined compressive strength of coal gangue concrete is affected by many factors, and there is a highly complex nonlinear relationship among factors.1 Therefore, it is important for scholars to determine the unconfined compressive strength of coal gangue concrete and the highly complex nonlinear relationship among these factors.

The prediction methods of genetic algorithm (GA) and support vector machine (SVM) have been widely used in practical problems, but there are some disadvantages in these two methods for prediction. The support vector machine (SVM) theory is a new algorithm based on statistical theory. It can solve nonlinear, high dimensional pattern recognition problems on the basis of limited samples and express nonlinear relationships between input and output, and it also can be used for prediction, so this kind of learning method has received widespread attention. Although the support vector machine can predict the general trend of change in data, the prediction accuracy is not high. So genetic algorithm (GA) was used to optimize parameters is proposed Predicting the unconfined compressive strength of coal gangue concrete based on a support vector machine is a new application. Finally, this project acts as an example for evidence-based analysis, which can demonstrate the feasibility of this method.

Developed by Vapnik(1995), SVM [1-5]is the method that is receiving increasing attention with remarkable results recently. The main difference between ANN and SVM is the principle of risk minimization. ANN implements empirical risk minimization to minimize the error on the training data. However, support vector machine (SVM) implements the principle of structural risk minimization in place of experiential risk minimization, which makes it have excellent generalization ability in the situation of small sample. In addition, SVM can change a non-linear learning problem into a linear learning problem in order to reduce the algorithm complexity by using the kernel function idea present, SVM has been applied successfully to solve non-linear regression estimation problems in financial time series forecasting, bankruptcy prediction, reliability prediction, etc. In this paper, the proposed SVM model is applied to research the forecasting problem of the ratios of key-gas determination of real estate price, among which Mixed kernel function of support vector machine, because the election of the functions plays an important role in the performance of SVM.

This paper is organized as follows: Section 2 introduces the methodology of support vector machine (SVM) genetic algorithm (GA). The foundations of support vector machines are introduced. Four mathematics models of support vector classifications including linearly hard margin SVM, linearly soft margin SVM, non- linearly hard margin SVM and non-linearly soft margin SVM are discussed. The proposed model is presented Section 3. In Section 4, engineering application testifies the performance of the proposed model with the real data sets from several real estate companies in China. Finally, the conclusion is provided in Section 5.

2. Methodology

2.1 Introduction to SVM

SVM, first proposed by Vapnik, can be used for pattern classification and nonlinear regression as an artificial neural network. The basic idea of SVM is to define the optimal linear hyper plane, and to search for the optimal linear hyper plane algorithm that can be reduced to a convex optimization problem. The SVM can solve the problem of two types of classification: linear separable and nonlinear separable. The problem of the linear separable is to set an initial hyper plane partition of the training data, optimized based on the principle of maximum interval, to determine the final decision hyper plane (decision function), so that the training data of a sample can be classified correctly; The problem of the nonlinear separable can map the input vector to a higher dimensional linear feature space by nonlinear kernel functions, The basic concept of SVM regression is to map nonlinearly the original data x into a high-dimensional feature space, and to solve a linear regression problem in this feature space (Keethi, Cristinini N, 2000) as show in Fig.1.

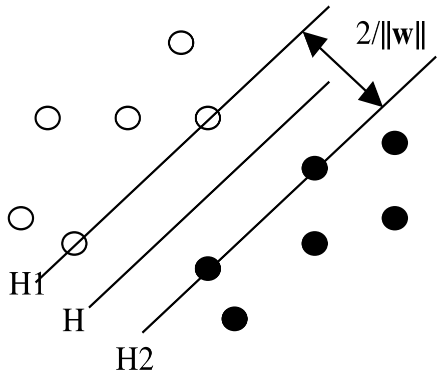

Fig. 1. *The basic concept of SVM regression*

And the nonlinear separable problem can be converted into a linear separable problem.

The steps for the linear regression of the SVM are as follows.

The sample data$\{(x_i, y_i), i = 1,2, \dots n\}$ consist of historical data; the regression function can be expressed by the following linear equation:

$$f(x) = \omega \cdot \phi(x) + b \qquad (1)$$

If we assume that all training data can be fit in linear function without error under the precision ε, we can get the equations as follows:

$$\min \frac{1}{2} \parallel \omega \parallel^2$$
$$st. \begin{cases} \omega \cdot x_i + b - y_i \leq \varepsilon \\ y_i - \omega \cdot x_i - b \leq \varepsilon \end{cases}, i = 1,2, \dots n \qquad (2)$$

Taking into account the condition of the permissible error, introducing the relaxation factorξ_i, ξ_i^*, the formula of the above is transformed into:

$$\min. \frac{1}{2} \parallel \omega \parallel^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*)$$
$$st. \begin{cases} b - y_i + \omega \cdot x_i \leq \varepsilon + \xi_i \\ y_i - \omega \cdot x_i - b \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, i = 1,2, \dots l \end{cases} \qquad (3)$$

Where C expresses the degree of punishment for the sample beyond the error ε. Where ξ_i, ξ_i^*, expresses the upper limit and lower limit of the slack variable, then the Lagrange function is constructed as follows:

$$\mathrm{L}(\omega, \mathrm{b}, \mathrm{a}) = \min. \tfrac{1}{2} \parallel \omega \parallel^2 + C \textstyle\sum_{i=1}^{n} (\xi^* + \xi_i^*) - \sum_{i=1}^{n} \alpha_i [\varepsilon + \xi_i^* + y_i - (\omega \cdot x_i + b)] - \sum_{i=1}^{n} \alpha_i^* [\varepsilon + \xi_i^* + y_i - (\omega \cdot x_i + b)] \qquad (4)$$

The dual problem is as below:

$$\max.[\sum^{n}\sum^{n}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)(x_i\cdot x_j)-\sum^{n}\varepsilon(\alpha_i+\alpha_i^*)+\sum^{n}y_i(\alpha_i-\alpha_i^*)]$$
$$\text{st.}\begin{cases}\sum_{i=1}^{nl}(\alpha_i-\alpha_i^*)=0\\ \alpha_i,\alpha_i^*\in[0,C/l]\end{cases} \quad (5)$$

The regression function is shown as follows:

$$f(x)=\omega\cdot x+=\sum^{n}(\alpha_i-\alpha_i^*)(x_i\cdot x_j)+b \quad (6)$$

Where α and b are found by SVM learning algorithm.

2.2 Introduction to GA theory

That biological organisms survive and species constantly evolve-enables offspring to adapt to harsh environments gradually; the viability of biology in nature is amazing. Inspired by biological genetics, researchers are beginning to study the survival mechanism of organisms, and to apply the results to design and development by simulating their behavior. Genetic Algorithm (GA)[5-8] is a global optimization search tool developed by analyzing the genetic mechanisms of biological natural selection. GA, initially proposed in 1975 by a professor, J, Holland , is a calculation model based on the simulation theory of evolution by natural selection and genetic mechanisms. In a genetic algorithm, a population of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible.[9-11]The evolution usually starts from a population of randomly generated individuals, and is an iterative process, with the population in each iteration called a generation. In each generation, the fitness of every individual in the population is evaluated; the fitness is usually the value of the objective function in the optimization problem being solved. The more fit individuals are stochastically selected from the current population, and each individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

It is an algorithm that can search the global optimal solution by simulating the evolutionary process; not only can the genetic algorithm be easily implemented, but it also has the remarkable characteristic of global search features. Therefore, it is widely used in machine learning, automatic control, combinatorial optimization, image processing and other fields that can solve the complex optimization problem.

3. Prediction model on the compressive strength of coal gangue concrete based on GA - SVM

3.1 Index system

It is a huge problem in systems engineering to study a coal gangue concrete. Many factors have an influence on its unconfined compressive strength, involving all aspects of the construction process. It is very difficult and unnecessary to find all the factors that affect the coal gangue concrete's unconfined compressive strength. An index system is established based on coal gangue, lime, fly ash and cement.

3.2 Steps of GA - SVM

The basic steps to realize the GA - SVM algorithm [12-19] are demonstrated in Figure 2.

(1) Write the codes for the SVM, and confirm the range of the punish parameter and the kernel function parameter;

(2) Initialize the population, and generate the initial group for the genetic algorithm based on the binary encoding that generated randomly generated chromosomes; The chromosome are expressed by the binary string in GA, and an initial population is generated from the function CRTBP;

(3) According to the scope of each variable, chromosome can be decoded by bs2rv function, the transformation between real value and the binary string will be provided. Decoded chromosomes include the penalty parameter and the kernel function parameter;

(4) With the SVM regression, program, we can initialize each population, and find the target values of sample testing which correspond to the output value for prediction. This paper customizes the fit function, which is used to calculate the error value after decoding each chromosome, calculate the error values of the test sample, and then calculate the chromosome of individual fitness value by ranking function;

(5) complete the calculation of initial population for individual adaptive;

(6) Apply the selection operator, crossover operator and mutation operator, get the next generation of new species, and keep the optimal chromosomes from each generation to the next generation. In this paper, the program uses the Select function, Recombination function and Mut function in the GA toolbox to realize the above operations; Once the genetic representation and the fitness function are defined, a GA proceeds to initialize a population of solutions and then to improve it through repetitive application of the mutation, crossover, inversion and selection operators.

(7) If it meets the terminating conditions, stop the iteration; otherwise carry out the recombination to step 4, decode the mutated chromosome and calculate the error of the individual chromosomes and fitness value until it meets the terminating condition.

(8) The known optimal parameter combination from the previous steps can be used to write into the SVM

program, and establish the SVM forecasting model to forecast the data in the test sample.

3.3 Selection of kernel function

The radial basis kernel function was selected, because the more parameters of the kernel function, the more complex a model can be chosen [21-30]. The radial basis kernel function has only one parameter and less constraint for parameter numerical values, and numerical values are limited between 0 and 1.

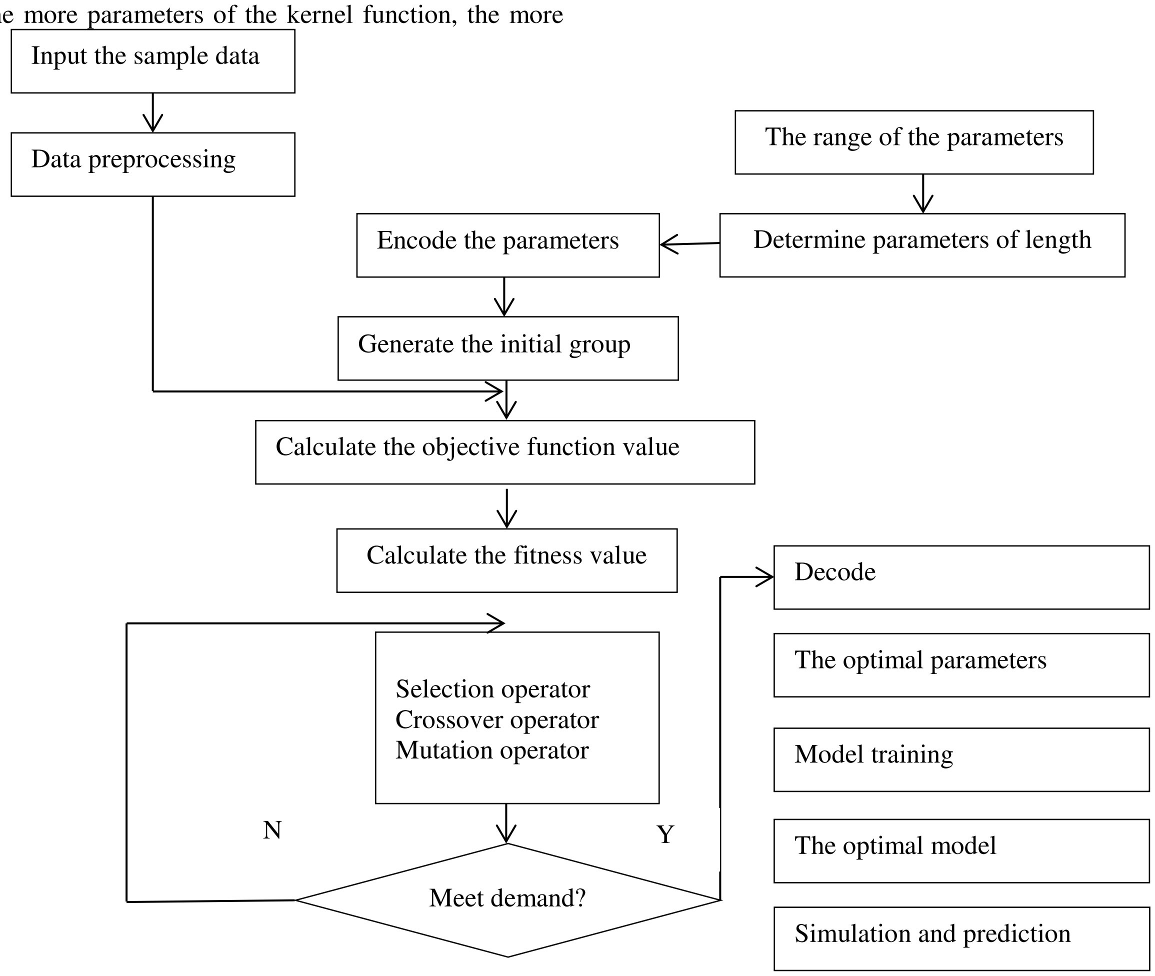

Fig.2. *GA - SVM algorithm steps*

Table 1: *The standardized data*

Coal gangue	Fly ash	Lime	Cement	Strength
0.8159	0.1061	0.0606	0.0174	1.29
0.7626	0.1906	0.0305	0.0162	1.31
0.7129	0.1996	0.0774	0.0099	1.26
0.7974	0.0677	0.1207	0.0140	0.8176
0.7759	0.0775	0.1241	0.0224	1.28
0.7848	0.0899	0.1049	0.0195	1.2502
0.7735	0.1353	0.0773	0.0136	1.2139
0.7616	0.1561	0.0631	0.0190	1.4959
0.7593	0.1214	0.1085	0.0106	0.77
0.8351	0.0584	0.0763	0.0300	1.24
0.7470	0.1979	0.0362	0.0186	1.5299
0.7501	0.1762	0.0492	0.0242	1.6472
0.7725	0.1120	0.0904	0.0249	1.5519
0.7276	0.1600	0.0914	0.0208	1.64
0.7793	0.1480	0.0445	0.0280	1.51

4. Engineering application

4.1 Standardization for original data

This paper selected the unconfined compressive strength of coal gangue concrete as an example for evidence-based analysis. In order to study it, the uniform design of experiment was used. The mixture proportioning had many multilevel factors, resulting in the final ratio of coal gangue, to fly ash, lime and cement. The raw data was collected to carry out the standardized treatment; the standardized data are as shown in Table 1.

4.2 Standardization for original data

The related parameters of GA are: 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 needs 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 σ is between 0.01 and 100. The optimal parameter combination: C = 48.384, σ = 0.95 , ε = 0.001, the fitness graph is as shown in Figure 3.

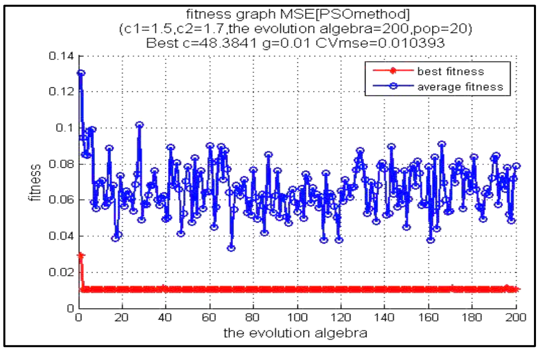

Fig.3.*The fitness curve of genetic algorithm*

4.3 Experimental results and analysis

The index system for prediction is established, the predicted goal is unconfined compressive strength of coal gangue concrete Y; Predictors are coal gangue *X1*, lime *X2*, fly ash *X3* and cement *X4*.The training function of input vector is the first four column data in Table 2 *(X1, X2, X3, X4),* the last column data Y is the training target vector. Taking ten groups of the training sample as machine learning randomly, the remaining five groups are sample data to test the accuracy of prediction model. After the training of model, we can get punishment parameter C , radial basis kernel function parameter σ and the optimal support vector model.

Compare fitting value with the actual value the last five groups based on the optimal model in SVM, the results are as shown in Table 2.

Table 2.*GA-SVM test sample fitted value and the actual value comparison chart*

Sample point	Actual value	Fitting value	Error
11	1.5299	1.513417	-0.016383
12	1.6472	1.655692	+0.008492
13	1.5519	1.549675	-0.001325
14	1.6400	1.706908	+0.066908
15	1.5100	1.402609	-0.107591

As is obvious from Table 2, the difference of five groups of predicted value and actual value is very small after optimizing parameters based on GA, the maximum of absolute error is 0.107591, the accuracy for forecast is 98.1997%, and the mean square error is 0.00154182, prediction effect is very good.

4.4 Comparative analysis between GA-SVM prediction model and SVM prediction model with cross validation

In this paper, two methods of relative error and root mean square error are used to compare actual value and predicted values between two models; the relative error is evaluating the effect of each test sample of the model, and the root mean square error is a model for the prediction error inspection function of the overall effect.

In order to compare with GA-SVM, the sample data are trained and tested in this section by SVM model, randomly selecting ten groups of the training sample for machine learning, the remaining five groups of sample data are used for prediction accuracy of the testing model. Finally, comparing the predictive results of two models, the results are as shown in Table 3.

Table 3.*Two Models results comparison chart*

	Actual Value	Predicted value		Error		Relative Error	
		GA	Cross validation	GA	Cross Validation	GA	Cross Validation
11	1.5299	1.513417	1.512979	-0.016383	-0.016921		
12	1.6472	1.655692	1.654684	+0.008492	+0.007484		
13	1.5519	1.549675	1.549424	-0.001325	-0.002476	98.1997%	98.1484%
14	1.6400	1.706908	1.716275	+0.066908	+0.076475		
15	1.5100	1.402609	1.401586	-0.107591	-0.108414		

As is obvious from Table 3, the results of the prediction error in two models have some fluctuations, but the prediction error in the GA-SVM model is less than the CV-SVM model; the prediction effect is relatively better than the CV-SVM model.

We can see that for the benchmark problems we selected, GA-SVM has the best performance compared with that of obtaining from the other algorithm. Therefore, the neighbor searching method and learning strategy are more effective than that of used by other SVM based algorithms.

5. Conclusions

It is very important to predict the unconfined compressive strength of coal gangue concrete. A new method is proposed to check the accuracy of this model in order to solve the reliability problem in SVM models. SVM implements the principle of structural risk minimization in place of experiential risk minimization, which makes it have excellent generalization ability in the situation of small sample. And it can change a non-linear learning problem into a linear learning problem in order to reduce the algorithm complexity by using the kernel function idea. Non-linear relationships between the unconfined compressive strength prediction and indices of variables which affect the prediction can be built through finite samples with a SVM. However, the choice of SVM parameters has a large effect on the evaluation results. GA is used to confirm the SVM parameters in order to improve prediction accuracy and avoid the shortcomings of artificially provided parameters. It is shown that the GA-SVM with model prediction of the unconfined compressive strength of coal gangue concrete has high accuracy.

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