Study on the performance evaluation and prediction model of self-compacting concrete in steel shell immersed tube

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Abstract: In order to study the quality control and evaluation methods of self-compacting concrete (SCC) pumping process in Shenzhen-Zhongshan Bridge and similar projects, sample test is performed on self-compacting concrete mixture collected from the pumping field of the E1-E4 steel shell immersed tube; Then a database base on relationship between the variation parameters and the target performance is established. On this basis, the Grey system theory is adopted to analyze the parameter sensitivity of the SCC pumping performance to the different kinds of variables. The results show that variables are related to target performance and some of the variables have a significant influence. Using the powerful data mining capability of support-vector machine and Bayesian statistical inference in the case of uncertain exact mathematical relationship between independent variables and dependent variables, implicit and explicit prediction models of variation of SCC pumping performance are respectively established by pumping distance, number of elbows, pumping time and environmental temperature as the control parameters. Finally, the comparisons between the measured data and calculation result prove that both models have good prediction accuracy and stability.

1 INTRODUCTION

The Shenzhen-Zhongshan Bridge is a world-class megaproject integrating “super-large span bridge-artificial island-undersea immersed tube tunnel-underwater interchange”. The traffic scale adopts two-way 8-lane technical standards. The tunnel section is 6845 m in total length, the pipe section is 5035 m long and consists of 32 pipe sections (E1～E32) and 1 final joint. The immersed pipe adopts a steel shell concrete tube section structure with two holes and one pipe gallery. This kind of structure not only has good load bearing and deformation capacity, waterproof and construction performance, but also has good economic benefits. The cross-sectional size of the standard pipe section is 46 m×10.6 m, of which the E1 pipe section is 123.5 m long, and the remaining pipe sections are standard pipe sections 165 m long. The Shenzhen-Zhongshan Bridge uses high-flow SCC with C50 strength grade, totaling about 670,000 m3, and uses pumping pipelines to transport the concrete into the steel shell to complete the pouring.

SCC has excellent fluidity and homogeneity. Without any vibration or compaction measures, it can be injected into the mold and wrap the steel bar only by its own gravity and achieve the ideal self-compacting effect. The self-compactness of SCC can not only effectively improve pouring efficiency and reduce construction costs, but also ensure construction quality and avoid structural durability problems. In recent years, it has been widely used in fields such as dam and tunnel engineering. Flow filling, anti-segregation and gap passing properties are the key performances of SCC, so they are used as performance evaluation indicators to control the quality of SCC. To ensure construction quality and structural safety, it is necessary to strictly control the working performance of SCC. Therefore, the corresponding index test is a very important link, which mainly includes expansion in slump flow test, H2/H1 in L-box test, V-shaped funnel flow time and other test contents, the measurement of temperature and gas content cannot be ignored either. Specifically, the slump expansion test evaluates the flow filling property of concrete by testing the T500 flow time and expansion in slump flow test; the L-box test evaluates the flow filling property and gap passability of the concrete by measuring the height ratio; the V-shaped funnel flow time is tested to evaluate the segregation resistance and flow filling properties of concrete.

The high fluidity of SCC determines that pumping technology can be adopted in the transportation of the pouring process, but this also puts forward more stringent requirements on concrete pumping technology. If the

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quality of the pumping process is not well controlled, it will directly affect the concrete construction performance and mechanical performance, such as shear thickening, early shrinkage and cracking, and degradation of physical and mechanical properties in the hardened state. The concrete pumping process involves many influencing factors, and it is difficult to avoid the degradation of its construction quality; in addition, the working performance of SCC is highly sensitive to the pumping process, so carrying out test to its pumping performance is required before and after pumping. The Shenzhen-Zhongshan Bridge uses pumped SCC. The amount of concrete is large, the pumping height is high, and the number of elbows is large. The pumping performance of laboratory batch testing will seriously affect the pouring efficiency and reduce the construction quality, so it is not realistic significance. If the SCC pumped on site can be used as the test object, its corresponding performance indicators can be obtained, the correlation between the influencing parameters before and after on-site pumping and the pumping performance can be established, the quality control of SCC can be improved and guide subsequent tube section or the construction process of similar projects, the quality of pumping can be in better control.

Machine learning algorithms have been widely used to solve complex problems in civil engineering due to their excellent calculation accuracy, stability and efficiency. Different from traditional data fitting or regression methods, machine learning algorithms can implicitly simulate the mechanical behavior of materials or structures to find the optimal solution to the target problem. At the same time, the prediction accuracy and algorithm robustness can be guaranteed. Another type of data mining technology that is different from machine learning algorithms is Bayesian statistical inference, which is a type of analysis method developed based on Bayesian theory and has the ability to deal with the uncertainties involved in model parameter estimation, belongs to the posterior distribution. Compared with ordinary least squares regression model, Bayesian estimation usually has smaller variance in value. The proposed explicit probability prediction model can be updated in real time, which can ensure the stability and accuracy of the prediction results and is convenient for practical engineering application.

The single steel shell tube section of the Shenzhen-Zhongshan Bridge has 2500 bins, with many anchor bars and ribs and complex structural forms, which require extremely high filling of SCC; in addition, because the SCC adopts a pumping process, there is a large difference of workability before and after pumping, and it is difficult to establish a reliable mathematical relationship between the changed parameters and the target performance by using conventional data regression and other analysis methods. In view of this, relying on the steel shell immersed tube tunnel project of the Shenzhen-Zhongshan Bridge, using the correlation analysis method of gray system theory, combining the scientific problems of pumping performance indicators with modern data mining technology, the implicit and explicit models between the key parameters and the target performance are established respectively in order to provide references for the prediction and quality control of the SCC pumping performance before and after pumping.

2 Test overview at pumping field

2.1 Concrete raw materials and mix ratio

The steel shell immersed tube section in Shenzhen-Zhongshan Bridge adopted SCC of C50 strength class. The raw materials include Conch brand' P·II42.5R cement, Class I fly ash (F type), S95 mineral powder, river sand, and crushed stone coarse aggregate (two grades of 5-10 mm and 10-20 mm), city water, polycarboxylic acid high range water reducer. The mix ratio of SCC is shown in Table 1.

Table 1 Mix proportion of SCC (kg/m^3)

Cement	FA	GGBS	Sand	10~20mm coarse aggregate	5~10mm coarse aggregate	water	Water reducing agent
1275	192	83	804	482	382	176	5.5

2.2 Pumping workability test method

The air content, slum flow test, T500 test, V-funnel test, and L-box instrument of SCC refer to "Standard for Test Methods of Performance on Ordinary Fresh Concrete " (GB/T 50080-2016) and " Technical Specification for Application of SCC" (JGJ/T 283-2012), " Technical Specification for Application of SCC" (CECS 203-2006), "Guide to Design and Construction of SCC " (CECS 02-2004) for determination. The physical operation of each test index in the SCC field pumping process is shown in Figure 1.

(a) Air content test (b) Slump flow test and T500 test

(c) V-funnel test (d) L-box test

Fig.1 Working performance measurements for SCC

2.3 Test database

All data comes from the sampling test results of SCC pouring of E1-E4 tube sections in Shenzhen-Zhongshan Bridge, considering the influence of pumping distance, the number of elbows in the pumping pipe, the pumping time of the concrete in the pump pipe, and the environmental temperature on the pumping performance. To investigate the changes in the pumping performance of SCC during the pumping process, the temperature of the concrete mixture before and after pumping, T500 flow time, slump expansion in slump flow test, V-funnel flow time, H2/H1of L-box test and air content were tested as evaluation indicators. Then establish the internal relationship between the change in pumping performance of the SCC mixture and the key influencing parameters (pumping distance, number of elbows, pumping time, ambient temperature), and construct the corresponding test database. The relevant statistical information is shown in the Table 2.

It can be seen from Table 2 that the pumping performance of SCC changes significantly before and after pumping, which is manifested as loss of workability (reduction of T500 flow time, expansion degree in slump flow test in slump flow test, and V-funnel flow time) and increase of temperature and air content. This is mainly because the pumping process is often accompanied by the pumping out of free water or slurry water. At the same time, the hydration of cement will consume the free water in the cement slurry, which will lead to insufficient slurry water in the subsequent concrete mixture, and ultimately result in concrete workability loss overtime, concrete temperature and air content increase, and yield stress increase. If the pumping distance or the number of elbows is too large, the concrete mixture after the pump will basically lose its fluidity, and even block the pump; in addition, the concrete in the pump tube is often in a state of high shear stress, and the anti-dispersion ability of the cementitious material particles is greatly weakened, so that the plastic viscosity of the concrete mixture is reduced, which will also reduce its fluidity.

It can be seen that the adoption of on-site quality control methods to detect the pumping process of SCC is indispensable, and it is of great engineering significance to predict the change in concrete pumping performance before and after pumping. By comparing the changes in the pumping performance of the concrete mixture before and after pumping, reasonable control of raw materials, mix ratios, transportation vehicles and construction techniques can be achieved, and the working performance of the SCC before entering the warehouse can be guaranteed to meet the actual construction needs.

Table 2 Statistics of experimental database for pumping performance of SCC

Pumping performance index increment (After the pump-before the pump)	test numbers	Average	Standard deviation	Coefficient of Variation
temperature/℃	199	1.6	0.2	0.2
T500 flow time /s	144	-0.3	0.2	-0.5
Expansion (slump flow test) /mm	195	-41	9.0	-0.2
V-funnel flow time/s	211	-2.2	0.3	-0.1
L-box, H2/H1	125	-0.03	0.01	-0.21
Air content/%	167	0.2	0.1	0.2

3 Grey relational analysis

The characteristic of the grey relational analysis method is to quantitatively evaluate a small group of statistical samples, and to quickly grasp the correlation between specific parameters and target performance by judging the degree of influence between the research objects. In this evaluation, the pumping distance, number of elbows, pumping time and ambient temperature are considered as the change parameters and selected as the sub-sequence $\{x_i(j)\}$ of the gray correlation system, which is defined as the comparison matrix accordingly, $X_i\ (j)$; The change in the pumping performance of SCC (temperature, T500 flow time, expansion degree in slump flow test in slump flow test, V-funnel flow time, H2/H1 in L-box test, air content) is used as the mother sequence of the gray correlation system $\{x_0(j)\}$, correspondingly defined as the reference matrix, $X_0(j)$. The mathematical relationship between the reference matrix and the comparison matrix can be expressed as follows:

$$\begin{pmatrix} \boldsymbol{X}_0 \\ \boldsymbol{X}_1 \\ \dots \\ \boldsymbol{X}_i \\ \dots \\ \boldsymbol{X}_m \end{pmatrix} = \begin{pmatrix} \boldsymbol{X}_0(1), \boldsymbol{X}_0(2), \dots, \boldsymbol{X}_0(n) \\ \boldsymbol{X}_1(1), \boldsymbol{X}_1(2), \dots, \boldsymbol{X}_1(n) \\ \dots \\ \boldsymbol{X}_i(1), \boldsymbol{X}_i(2), \dots, \boldsymbol{X}_i(n) \\ \dots \\ \boldsymbol{X}_m(1), \boldsymbol{X}_m(2), \dots, \boldsymbol{X}_m(n) \end{pmatrix} \tag{1}$$

According to the grey system theory, the correlation coefficient calculation formula is:

$$\xi_i\left[x_0(j), x_i(j)\right] = \left| \frac{\min_{i=1,n} \min_{j=1,m} \Delta_i(j) + \rho \max_{i=1,n} \max_{j=1,m} \Delta_i(j)}{\Delta_i + \rho \max_{i=1,n} \max_{j=1,m} \Delta_i(j)} \right| \tag{2}$$

$$\Delta_i(j) = \left| x_0(j) - x_i(j) \right| \tag{3}$$

$$\begin{aligned} &\min_{i=1,n} \min_{j=1,m} \Delta_i(j) \\ &\quad = \max_i \left(\max_j \left| x_o(j) - x_i(j) \right| \right) \end{aligned} \tag{4}$$

$$\begin{aligned} &\max_{i=1,n} \max_{j=1,m} \Delta_i(j) \\ &\quad = \min_i \left(\min_j \left| x_o(j) - x_i(j) \right| \right) \end{aligned} \tag{5}$$

In the formula: ρ is the resolution coefficient, and its function is to weaken the influence of the distortion of the large second-level maximum difference, so, as to increase the significance of the difference between the correlation coefficients.

The correlation degree γ_i of each comparison

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sequence and reference sequence can be calculated as follows:

$$\gamma_i = \frac{1}{N}\sum_{k=1}^{N}\xi_i(k) \tag{6}$$

Table 3 Calculation results of grey correlation

Influencing factors	temperature	T500 Flow time	Expansion	V-funnel flow time	L type instrument H2/H1	Air content
Pumping distance	0.6	0.6	0.6	0.7	0.8	0.7
Number of elbows	0.7	0.7	0.7	0.7	0.9	0.8
Pumping time	0.9	0.5	0.5	0.8	0.6	0.7
Ambient temperature	0.9	0.6	0.6	0.8	0.9	0.8

It is worth noting that the γ value is used as an evaluation index to evaluate the correlation between the sub-sequence and the parent sequence. Specifically, the closer the γ value is to 1.0, the stronger the sensitivity of the corresponding parameter, and the more significant the correlation between the variables; in addition, the γ value greater than 0.5 indicates that there is parameter correlation. Based on the test database established in Table 2, the correlation degree of each varying parameter to the change of the pumping performance of steel shell immersed tube SCC is shown in Table 3. It can be seen from Table 3 that the pumping distance, the number of elbows, the pumping time and the ambient temperature are all related to the change in the pumping performance of the steel shell immersed tube SCC (temperature, T500 flow time, expansion degree in slump flow test, V-funnel flow time, L-shaped H2/H1, gas content) is related, and the influence of some parameters is very significant.

4 Development of prediction model for pumping performance

4.1 Support-vector machine (SVM) implicit model

Support vector machine (SVM) can identify and represent nonlinear relationships in complex systems and has strong advantages in regression and classification problems. As shown in Figure 2, the SVM model includes an input layer, a support vector layer, a kernel function layer, and an output layer.

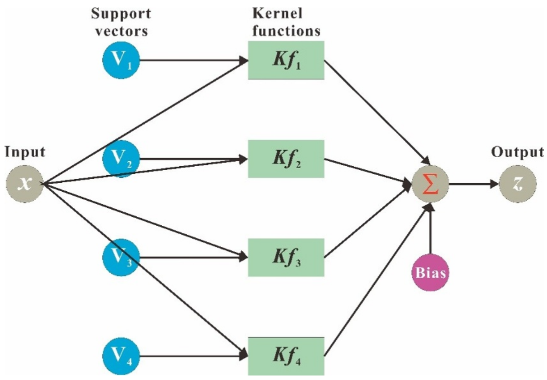

Fig.2 Schematic diagram of SVM model

The SVM model is based on the structural risk minimization theory, which minimizes the error of the training data set (empirical risk) and maximizes the generalization ability of the predictive model. Therefore, the method has strong predictive capabilities and can handle various data set well. In the nonlinear regression model of SVM, low-dimensional space is transformed into high-dimensional space through nonlinear mapping (ie, kernel function), and the linear method in high-dimensional space is finally used to solve the nonlinear regression problem. The SVM model is superior to most other machine learning algorithms in solving problems such as limited samples and nonlinear function fitting.

For a given set of training data $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n), x \in R_n, y \in R_n\}$, the SVM nonlinear regression prediction model can be expressed as:

$$f(x) = \sum_{i=1}^{n} w_i \tau_i(x) + b \tag{7}$$

In the formula: $\tau_i(x)$ represents a set of nonlinear transformations; w_i is the weight; b is the bias term. Introduce the insensitive loss function ε and define it as:

$$|y - f(x)|_\varepsilon = \begin{cases} 0, & |y - f(x)| \le \varepsilon \\ |y - f(x)| - \varepsilon, & \text{others} \end{cases} \tag{8}$$

Introduce relaxation factors ξ_i, $\xi_i^*(i=1,2,\ldots,n)$, Based on the structural risk minimization theory, the convex optimization problem can be constructed as follows:

$$\begin{aligned} &\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \\ &s.t. \quad f(x) - y_i \le \varepsilon + \xi_i^*, \quad i = 1, 2, \ldots, n \\ &\qquad y_i - f(x) \le \xi_i + \varepsilon, \quad i = 1, 2, \ldots, n \\ &\qquad \xi_i, \xi_i^* > 0, \quad i = 1, 2, \ldots, n \end{aligned} \tag{9}$$

In the formula: On the premise of improving the robustness of the model, the first term $\frac{1}{2}\|w\|^2$ can greatly expand the scope of application of the model; second section $C\sum_{i=1}^{n}(\xi_i + \xi_i^*)$ represents the empirical risk to weaken the error in the training process or reduce the inconsistency between the predicted value and the experimental value. The constant C is the penalty parameter, and the larger the value of C is, ξ_i, ξ_i^* the greater the punishment for relaxation factor.

Use Lagrangian multipliers to optimize the model to solve the optimal problem of nonlinear inequality constraints:

$$L(w,b,\xi)=\frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}\left(\xi_i+\xi_i^*\right)-\sum_{i=1}^{n}\left(\chi_i\xi_i+\chi_i^*\xi_i^*\right)-\left[\sum_{i=1}^{n}\alpha_i\left(\varepsilon_i+\xi_i-y_i+f(x)\right)+\sum_{i=1}^{n}\alpha_i^*\left(\varepsilon_i+\xi_i^*+y_i-f(x)\right)\right] \tag{10}$$

Where L (w, b, ξ) is the Lagrangian function; χ_i, χ_i*, α_i, and α_i* are Lagrangian multipliers greater than 0.

Based on Wolf's duality theory, by calculating the partial derivatives of w, b, and ξ in equation (10) and making their value equal to 0, the dual problem of equation (9) can be expressed as:

$$\max L_D=-\frac{1}{2}\sum_{i,j=1}^{n}\left(\alpha_i-a_i^*\right)K\left(x_i,x_j\right)\left(\alpha_j-\alpha_j^*\right)+\sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)y_i-\varepsilon\sum_{i=1}^{n}\left(\alpha_i+\alpha_i^*\right) \tag{11}$$

$$s.t.\ \sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)=0\quad\left(0<\alpha_i,\alpha_i^*<C, i=1,\ 2,\ldots,n\right)$$

Where K (x_i, x_j) is the kernel function used to adjust and perform SVM nonlinear regression analysis, mainly including linear, polynomial, radial basis, and perceptron type.

Solve equation (11), get the optimal α_i and α_i*, then get the optimal SVM nonlinear fitting function:

$$f(x)=\sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)K\left(x,x_i\right)+b \tag{12}$$

The relationship between the pumping performance change of steel shell immersed tube SCC and its changing parameters is uncertain, and SVM has good nonlinear mapping ability and robustness, so consider using equation (12) in the prediction of pumping performance increment is appropriate.

According to the evaluation result of the grey system theory, this paper adopts the four important parameters of pumping distance, number of elbows, pumping time and ambient temperature as the input variables of SVM. At the same time, the database in Table 2 is divided into a training set and a test set at a ratio of 3:1. The training set is used to train the SVM nonlinear regression model, and the test set is used to verify the accuracy of the machine learning prediction results.

4.2 Bayesian Explicit Model

Due to the characteristics of SCC materials, the sensitivity in the pumping process is more significant than that of ordinary concrete. The change of performance of steel shell immersed tube SCC (temperature, T500 flow time, expansion degree in slump flow test, V-funnel flow time, H2/H1 in L-box test, air content) has significant randomness on being affected by different factors. Therefore, the deterministic prediction model is difficult to fully consider the changes in factors such as raw material performance, environmental temperature, construction time, and pumping construction technology under uncertain conditions. Compared with the least squares regression model, the Bayesian probability prediction model can reasonably describe the probability distribution characteristics of each key parameter and the uncertainty caused by these parameters. Bayesian inference updates the prior information and provides the uncertainty information of the prediction by estimating the parameters. Using this method can provide a kind of accurate probabilistic prediction dynamic model for target performance evaluation. Based on the above discussion, a Bayesian probabilistic prediction model for the change in pumping performance of SCC is established that takes into account the influence of pumping distance, number of elbows, pumping time and environmental temperature:

$$\boldsymbol{Y}=\boldsymbol{\theta X}+\boldsymbol{b}+\sigma^2\varepsilon \tag{13}$$

In the formula: $\boldsymbol{Y}$ represents the probabilistic predicted value of the SCC pumping performance change; $\boldsymbol{\theta}$ = [θ_1, θ_2, θ_3, θ_4]^T represents the probability model parameter, which comprehensively reflects the objective uncertainty of influencing factors $\boldsymbol{X}$ = [x_1, x_2, x_3, x_4]^T (pumping distance, number of elbows, pumping time and environmental temperature); $\boldsymbol{b}$ is a constant term, which comprehensively reflects the impact of objective uncertainty and subjective certainty; ε is a random variable; σ^2 is the variance of the error produced by the posterior distribution. It should be noted that, in order to make the probability model suitable for the test results, the variance σ^2 should be independent with the factor $\boldsymbol{X}$ and there is no linear relationship, and ε obeys the standard normal distribution.

It can be obtained from Bayesian inference that the uninformed prior distribution $f(\boldsymbol{\theta}, \sigma)$ of the parameters ($\boldsymbol{\theta}$, σ) should be uniformly distributed within the value range of ($\boldsymbol{\theta}$, σ). The mathematical expression is:

$$f(\boldsymbol{\theta})\propto 1 \tag{14}$$

$$f(\sigma)=\sigma^{-1} \tag{15}$$

The posterior distribution information of the parameter $\boldsymbol{\theta}$ can be expressed as:

$$f(\theta\mid y)=\frac{f(y\mid\theta)f(\theta)}{\int f(\theta)f(y\mid\theta)dy}\propto f(y\mid\theta)f(\theta) \tag{16}$$

In the formula: $f(y|\theta)$ represents the likelihood function; $f(\theta)$ represents the prior distribution.

According to the experimental database established in Table 2, Markov chain-Monte Carlo (MCMC) is used to simulate the sampling of equation (13), and finally the posterior probability distribution of the parameters ($\boldsymbol{\theta}$, σ^2) is determined. Table 4 shows the operating results of the probabilistic model parameters ($\boldsymbol{\theta}$, σ^2) of the change in pumping performance of SCC, and the probabilistic prediction model based on Bayesian-MCMC is obtained:

$$\begin{pmatrix}y_1\\y_2\\y_3\\y_4\\y_5\\y_6\end{pmatrix}=\begin{pmatrix}-0.2379\\1.3806\\-70.8954\\-0.6246\\-0.0022\\0.2617\end{pmatrix}+\left\{\begin{matrix}0.0013&0.0308&-0.0019&0.0555\\0.0003&-0.0077&0.0015&-0.0598\\-0.0425&-0.6746&0.1810&1.3077\\-0.0016&0.0134&-0.0125&-0.0440\\-0.0000&-0.0014&0.0002&-0.0010\\-0.0005&0.0087&0.0002&-0.0023\end{matrix}\right\}\times\begin{pmatrix}x_1\\x_2\\x_3\\x_4\end{pmatrix} \tag{17}$$

Where y_1, y_2, y_3, y_4, y_5 and y_6 are temperature increment, T500 flow time increment, expansion degree in slump flow test increment, V-funnel flow time increment, L-box H2/H1 increment and gas content increment, respectively; x_1, x_2, x_3 and x_4 are pumping distance, number of elbows, pumping time and ambient temperature, respectively.

Fig. 3 is a simulation trajectory diagram of the temperature increment model parameters that iteratively

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forms the Markov chain, where the number of iterations n =10000 times. It can be seen from the figure that in the random simulation process, the samples used to obtain the posterior estimation of the Bayesian model parameters ($\boldsymbol{\theta}$, σ^2) are all from the convergent Markov chain, thereby ensuring that the probabilistic prediction model has good accuracy and reliability Sexuality and robustness.

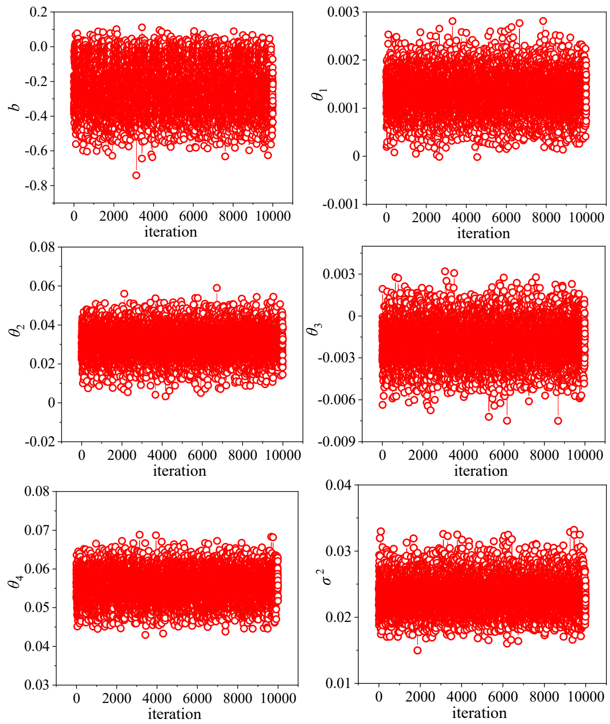

Fig.3 Simulated trajectory map of model parameters

Table 4 Computational results of probabilistic model parameters

Forecast target	Statistical indicators	b	θ_1	θ_2	θ_3	θ_4	σ^2
Temperature increment	Mean	-0.2379	0.0013	0.0308	-0.0019	0.0555	0.0232
	Standard deviation	0.1335	0.0004	0.0071	0.0013	0.0038	0.0023
T500 flow time increment	Mean	1.3806	0.0003	-0.0077	0.0015	-0.0598	0.0188
	Standard deviation	0.1597	0.0004	0.0083	0.0017	0.0044	0.0022
Slump flow test expansion increment	Mean	-70.8954	-0.0425	-0.6746	0.1810	1.3077	52.7327
	Standard deviation	4.5020	0.0200	0.3302	0.0580	0.1438	5.3296
V-funnel flow time increment	Mean	-0.6246	-0.0016	0.0134	-0.0125	-0.0440	0.0619
	Standard deviation	0.1843	0.0006	0.0120	0.0025	0.0060	0.0060
L-box test H2/H1 increment	Mean	-0.0022	-0.0000	-0.0014	0.0002	-0.0010	0.0156
	Standard deviation	0.0589	0.0004	0.0069	0.0013	0.0025	0.0020
Air content increment	Mean	0.2617	-0.0005	0.0087	0.0002	-0.0023	0.0143
	Standard deviation	0.1149	0.0003	0.0068	0.0014	0.0030	0.0016

4.3 Model verification and discussion

In order to test the accuracy of the developed implicit and display model in estimating the change in the pumping performance of steel-shell immersed tube SCC, the calculated value was compared with the measured value and a statistical analysis was performed. Figure 4 shows the comparison of the SVM regression model prediction value, the Bayesian probability model

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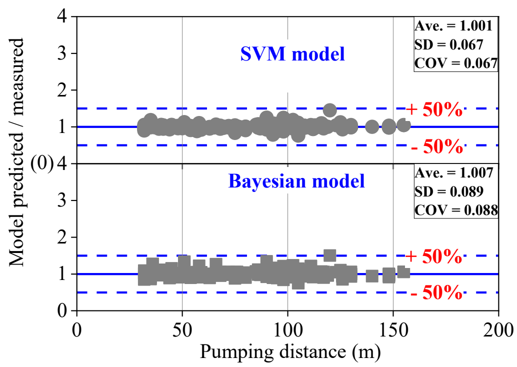
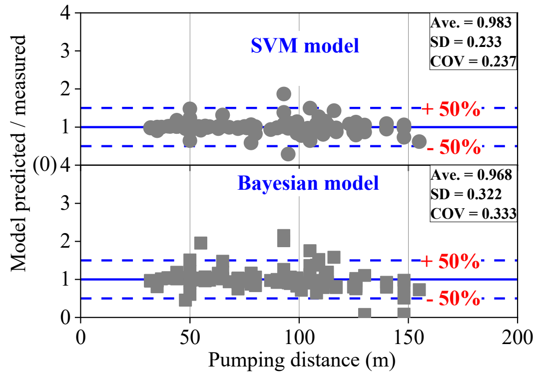
prediction value, and the measured value of the change in the pumping performance of steel shell immersed tube SCC. Taking temperature increment as an example, in the SVM regression model, the average value and the coefficient of variation of the predicted value/measured value are 1.001 and 0.067, respectively; in the Bayesian probability model, the average value and the coefficient of variation of the predicted value/measured value are 1.007 and 0.088, respectively. Obviously, the calculated value of the developed model is very close to the measured value, and the deviation and randomness are small, which fully reflects the rationality and scientificity of machine learning and Bayesian statistical inference in the pumping performance modeling of steel shell immersed pipe SCC, ensures the accuracy and stability of the prediction results.

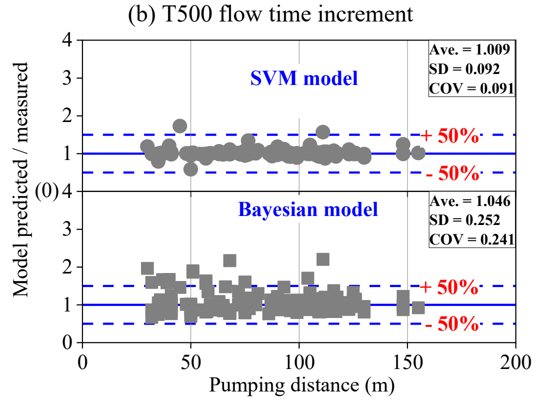
It can be seen from Figure 4 that compared to the Bayesian linear probability model, the SVM nonlinear prediction model based on machine learning has global optimality and better generalization ability and has significant advantages for solving nonlinear computing problems and the prediction result is more accurate. But its limitation is that the mathematical relationship between variables is implicitly expressed, which is not convenient for the rapid design and calculation of the construction site; while the Bayesian linear probability model is an explicit dynamic model, Real-time data feedback can enrich the prior information, and the model can be updated and revised based on Bayesian theory, thereby obtaining a posterior model with higher prediction accuracy. Through the comparison and analysis with the test data, it can be seen that these two types of calculation methods can provide efficient and reliable pumping performance estimation for the quality control of the pumping SCC construction process of the Shenzhen-Zhongshan Bridge and achieve adjustment of construction technology base on key parameter of target pumping performance, provide effective reference for the concrete mixture pumping in subsequent tube section and similar project.



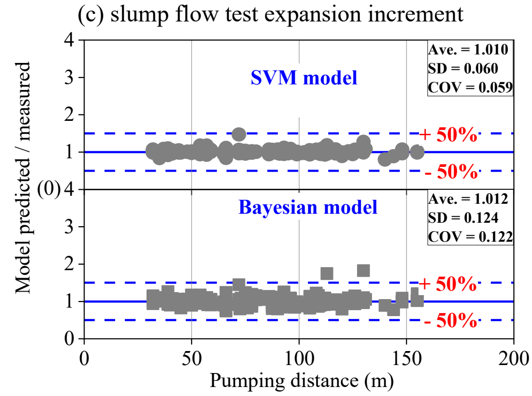
(a) Temperature increment



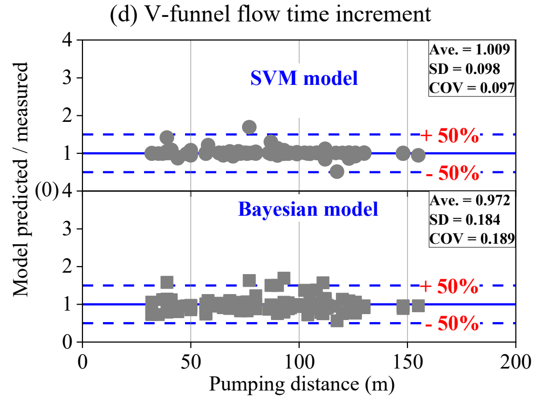
(b) T500 flow time increment



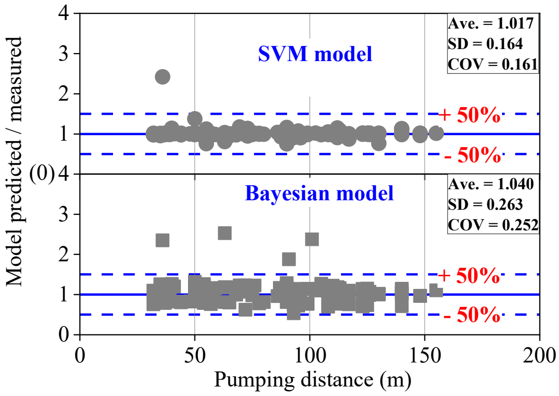
(c) slump flow test expansion increment



(d) V-funnel flow time increment



(e) L-box H2/H1 increment



(f) Air content increment

Fig.4 Comparisons between SVM regression model / Bayesian probability model predictions and measured values

5 Conclusion

The steel shell immersed tube tunnel of the Shenzhen-Zhongshan Bridge uses SCC to fill the immerse tube section. The amount of concrete is large, and the pouring is concentrated. The pumping method can effectively improve the efficiency of on-site pouring and ensure the construction progress. Because the concrete mixture is greatly interfered by external factors during the pumping process, its performance loss is more serious, which directly affects the quality of concrete construction. Therefore, the quality control of the SCC pumping process is an extremely important construction link. Based on the test results of the SCC pouring of the E1-E4 tube section of the Shenzhen-Zhongshan Bridge, and considering the influence of pumping distance, number of elbows, pumping time and ambient temperature on the pumping performance of concrete mixture, two types of high precision evaluation method for predicting the change of the pumping performance of SCC before and after pumping, and the following main conclusions are obtained:

(1) Based on the integration of field measured data information, grey correlation analysis is used to evaluate the sensitivity of various changing parameters. The results show that the pumping distance, the number of elbows, the pumping time and the ambient temperature are all related to the changes in the pumping performance of steel shell immersed tube SCC (temperature, T500 flow time, expansion degree in slump flow test, V-funnel flow time, L-box H2/H1, air content), and the influence of some parameters is very significant.

(2) Using the powerful data mining capabilities of SVM machine learning and Bayesian statistical inference, and under the premise of uncertain mathematical relationship between independent variables and dependent variables, the implicit and explicit prediction models of change of pumping performance of steel shell immersed tube SCC was established respectively, both the model have received good results in terms of prediction accuracy and prediction stability.

(3) In terms of practicality, the Bayesian explicit probability model is more convenient for on-site calculations than the SVM implicit model, and its model comprehensively considers the impact of SCC materials and the subjective and objective uncertainties in the construction process, as a result, the application of this method is flexibility and operability.

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