Predicting the High-rise building construction project safety risk based on QPSO-SVM model

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Abstract

In this paper, we aim to solve the problem of high-rise building construction project safety risk forecasting. The main innovation of this paper lies in that we convert the project safety risk forecasting problem to a classification problem, and design a novel QPSO-SVM model to implement the classification process. Before predicting the project safety risk, we present an index system, which contains six first-layer indexes, such as "Falling accident", "Objects striking accident", "Collapse accident", "Mechanical injury", "Fire disaster in construction", and "Electric shock injury". Particularly, 29 indexes are included in the second-layer of this index system, and these 29 indexes can effective represent almost all influencing factors in high-rise building construction project safety risk prediction. Next, we describe how to select optimal parameters of SVM classifier using the quantum behaved particle swarm optimization policy. Finally, experimental results demonstrate that, compared with other schemes, the proposed hybrid QPSO-SVM can forecast the high-rise building construction project safety risk with higher accuracy.

Keywords: high-rise building, safety risk predicting, QPSO, SVM, particle

1 Introduction

With the fast development of the global economy and modern construction technology, the height of high-rise buildings has been promoted greatly in recent years. Profiting from the fast development of economy and the rapid urbanization, China has focused on constructing high-rise buildings[1, 2]. Currently, although high-rise building construct has mature technology, the risk of high-rise building construct safety is still need to study carefully. With the fast development of real estate industry and modern urbanization process, the construction industry is developed greatly as well. Meanwhile, this trend also urges construction excessive competition, reduces engineering cost, and then increases the risk of construction safety [3]. Particularly, accidents in high-rise buildings construction happened frequently, and the situation of construction safety in high-rise buildings is required to be enhanced. Thus, it is critical to solve the problem of constructing high-rise buildings safely.

As mentioning of high-rise building construction safety is of great importance in modern building design. Construction industry is belonged to one of China's basic industries, however, this industry is also a safety accident-prone industry [4]. As the mainstream of modem architecture buildings, a lot of accidents happen in high-rise building construction every year [5, 6]. Construction accident may directly cause casualties, engineering ontology damage and other property loss, and it has been attracted more and more attentions of the building research and design. Hence, effective high-rise building construction safety risk management is an important problem for the construction enterprise, and it can also lower the construction safety risk and reduce the number of safety accidents [7, 8].

Considering the above analysis, in this paper, we aim to prevent accidents in high-rise building construction project by forecasting the safety risk. The main idea of this paper lies in that we convert the risk prediction problem to a classification problem by a hybrid QPSO-SVM model.

The rest of this paper is organized as follows. The next section gives an overview of the related works about SVM with PSO model. Section 3 explains how to construct the index system for the high-rise building construction project safety risk prediction problem. Afterwards, in section 4, the high-rise building construction project safety risk forecasting algorithm based on the hybrid QPSO-SVM model is proposed. In section 5, a series of experiments are implemented to make performance evaluation. Finally, we conclude the whole paper in section 6.

2 Related works

In this paper, we will survey on the application of using particle swarm optimization to optimize parameters of SVM classifier, and the quality of parameter selection may greatly influence classification results.

Sudheer et al. studied on the accuracy of the hybrid SVM-QPSO model in the field of monthly stream flows forecasting. Moreover, this algorithm is utilized in predicting the streamflow values of Vijayawada station and Polavaram station of Andhra Pradesh in India. The support vector machine with different input structures is built and the best structure is obtained via normalized mean square error and correlation coefficient [9].

Yilmaz et al. exploited least squares support vector machine with a binary decision tree for classification of cardiotocogram to compute the fatal state. Particularly, the parameters of LS-SVM are optimized by PSO model. Robustness of the proposed approach is tested by executing 10-fold cross-validation [10].

Wu et al. presented a hybrid mutation scheme which integrates Gaussian mutation operator and Cauchy mutation operator for particle swarm optimization. The combinatorial mutation with the fitness function value and the iterative variable is used to compute inertia weight. Experimental results demonstrate that after computing parameters of SVM by PSO, hybrid mutation strategy based on Gaussian mutation and Cauchy mutation is effective as well [11].

Wu et al. illustrated a new PSO model based on the hybrid mutation policy. As random number obtained from Cauchy distribution has better convergence characteristic than the methods from Gaussian distribution in the process of mutation strategy. Afterwards, Cauchy mutation is exploited to modify the decision-making variable of Gaussian PSO model. Furthermore, the adaptive mutation obtained by the fitness function value and the iterative variable is exploited to calculate the inertia weight of particle swarm optimization [12]. Afterwards, in paper [13], Wu et al. presented a novel PSO model which utilized chaotic mappings for parameter adaptation of the Wavelet v-support vector machine.

Li et al. provided a modified particle swarm optimization algorithm to train the fuzzy support vector machine in the process of pattern multi-classification. In this paper, different from the existing works, the mean values of other particles are utilized as well [14].

Wang et al. integrated least squares support vector machine with particle swarm optimization is to forecast time series. The least squares support vector machine can solve the problem of multilayer perceptron and the particle swarm optimization algorithm can modify the LS-SVM parameters automatically. Experimental results testify that the proposed method can escape from the blindness of manual selection of LS-SVM parameters, and then the forecast accuracy can be promoted obviously [15].

Lee et al. enhanced the performance of Support Vector Machine classifier in the classification of incipient faults of power transformers. Particularly, PSO model is used to promote the accuracy of classification. The proposed method has the ability to prune misleading input features and then optimize the kernel parameters as well [16].

3 Index system for high-rise building construction project safety risk prediction

To accurately forecast the risk of high-rise building construction project safety, an effective index system should be constructed in advance. As is shown in Figure 1, the proposed index system is made up of six first-layer indexes, such as “A1: Falling accident”, “A2: Objects striking accident”, “A3: Collapse accident”, “A4: Mechanical injury”, “A5: Fire disaster in construction”, and “A6: Electric shock injury”. Furthermore, 29 indexes are included in the second-layer, and these 29 indexes can cover most influencing factors of the problem of high-rise building construction project safety risk prediction.

4 Forecasting the high-rise building construction project safety risk by the hybrid QPSO-SVM model

Based on the above index system, in this section, we will describe how to forecast the high-rise building construction project safety risk using a hybrid QPSO-SVM model in detail. The main ideas of SVM can be represented as follows.

$$\begin{cases} w^T x_i + b \ge 1,\ y = 1 \\ w^T x_i + b \le -1,\ y = -1 \end{cases} \tag{1}$$

Although SVM is an effective classifier, the quality of parameter selection of SVM greatly affects its performance. Hence, in this paper, we aim to propose an effective parameter selection method utilizing the quantum behaved particle swarm optimization (QPSO) policy. Based on QPSO proposed abilities and conditions, it would be more practical to analyzing the convergence of particle swarm optimization and quantum system using its features. Particularly, In the QPSO model, the state of quantum is represented as a function $\varphi(x,t)$, and the Monte Carlo algorithm is used. Position of each particle in QPSO can be calculated by Equation (2).

$$x_{ij}^{t+1} = p_{ij}^t + \chi \cdot L_{ij}^t \cdot \ln\left(\frac{1}{u_{ij}^t}\right), \tag{2}$$

$$L_{ij}^t = 2 \cdot \lambda \cdot \left| mbest_j^t - X_{ij}^t \right|, \tag{3}$$

where the value of the symbol χ is set to 0.5 or -0.5, and p_{ij}^t denotes to the local attractor:

$$P_{ij}^t = \varphi_{ij}^t \cdot P_{ij}^t + (1 - \varphi_{ij}^t) \cdot P_{gj}^t, \tag{4}$$

where φ_{ij}^t means a random number in the range $(0,1)$, and P_{gj}^t represents to the global best position. Furthermore, L_{ij}^t is computed by Equation (5).

$$L_{ij}^t = 2 \cdot \lambda \cdot \left| p_{ij}^t - X_{ij}^t \right|, \tag{5}$$

where parameter λ is utilized to modify the convergence speed. Thus, the position is improved as follows.

$$X_{ij}^{t+1} = p_{ij}^t + \lambda \cdot \left| p_{ij}^t - X_{ij}^t \right| \cdot \ln\left(\frac{1}{u_{ij}^t}\right). \tag{6}$$

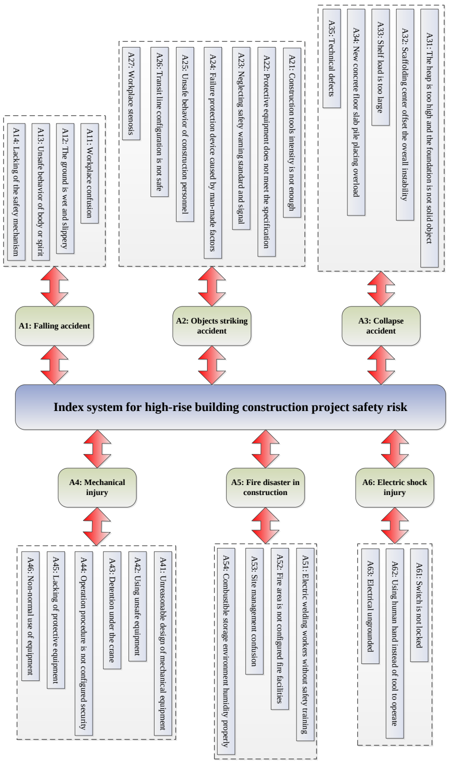

FIGURE 1 Structure of the index system for high-rise building construction project safety risk

QPSO algorithm is not same to the PSO, the reason lies in that the approach of iterative update for QPSO is different, and it can guarantee the particles which exist in the whole search space in every iteration process. Our proposed parameter selection algorithm using QPSO is described as follows.

Algorithm 1: Parameters selection for SVM using quantum behaved particle swarm optimization.

Step 1: Initializing particles by random positions $X(0)=\{X_1(0), X_2(0),\cdots, X_M(0)\}$

Step 2: Initializing $pbest\ P$, $gbest\ P_g$, the contraction-expansion coefficient α and let k be equal to 0.

Step 3: While $k < k_{\max}$

Step 4: Computing the mean best position $C(k)$

Step 5: Computing $p_i(k)$

Step 6: Updating the positions of all the particles.

Step 7: Evaluating all the particles $J[Xi(k)],\ i\in\{1,2,\cdots,M\}$

Step 8: Re-computing $pbest\ P$ and $gbest\ P_g$.

Step 9: Re-computing the parameter α.

Step 10: $k=k+1$

Step 11: End while

Step 12: Let $gbest\ P_g$ as the final parameters for support vector machine.

Next, the high-rise building construction projects risk prediction problem can be converted into a classifier problem, and the proposed hybrid QPSO-SVM method is used to tackle this problem.

5 Experiment

We collect the experiment data from 100 high-rise building construction projects, and then use these data as the training dataset. To let the experimental data be easily used, we normalize them, and some samples are illustrated in Table.1. as follows.

TABLE 1 Samples in the testing dataset

S1	A11	A12	A13	A14	A21	A22	A23	A24	A25	A26	A27	A31	A32	A33	A34
	0.58	0.49	0.44	0.70	0.76	0.59	0.61	0.76	0.42	0.68	0.68	0.47	0.43	0.73	0.70
	A35	A41	A42	A43	A44	A45	A46	A51	A52	A53	A54	A61	A62	A63	
	0.70	0.74	0.67	0.71	0.67	0.48	0.64	0.69	0.74	0.64	0.42	0.42	0.66	0.66	
S2	A11	A12	A13	A14	A21	A22	A23	A24	A25	A26	A27	A31	A32	A33	A34
	0.79	0.53	0.45	0.61	0.47	0.76	0.78	0.71	0.61	0.72	0.44	0.48	0.51	0.50	0.56
	A35	A41	A42	A43	A44	A45	A46	A51	A52	A53	A54	A61	A62	A63	
	0.68	0.48	0.65	0.51	0.72	0.69	0.44	0.40	0.45	0.74	0.71	0.61	0.75	0.51	
S2	A11	A12	A13	A14	A21	A22	A23	A24	A25	A26	A27	A31	A32	A33	A34
	0.71	0.72	0.42	0.43	0.69	0.57	0.41	0.44	0.75	0.55	0.52	0.74	0.48	0.54	0.72
	A35	A41	A42	A43	A44	A45	A46	A51	A52	A53	A54	A61	A62	A63	
	0.75	0.64	0.44	0.68	0.67	0.48	0.43	0.44	0.68	0.69	0.72	0.65	0.55	0.64	

where in Table 1, S1, S2, and S3 denote sample 1, sample 2 and sample 3 respectively. Particularly, we define five safety risk level, that is, “lowest risk”, “lower risk”, “normal risk”, “higher risk” and “highest risk”. Moreover, the value of the risk forecasting score of the above five risk levels are set as $[0,0.3]$, $(0.3,0.5]$, $(0.5,0.7]$, $(0.7,0.9]$ and $(0.9,1]$ respectively. The data normalization method is given as follows.

$$N=\frac{O-O_{\min}}{O_{\max}-O_{\min}}, \tag{7}$$

where O, $O_{\min}$, $O_{\max}$ and N denote the original data, minimum value in the original data, maximum value in the original data, and the data after normalizing respectively.

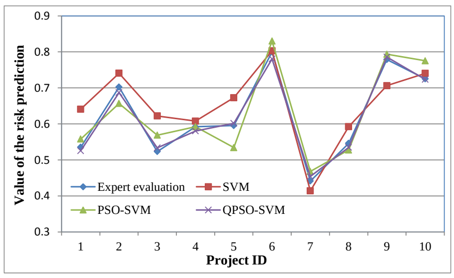

FIGURE 2 Value of the risk prediction for different methods

Afterwards, we collect another 100 high-rise building construction projects to construct the testing dataset. To evaluate the performance of risk predicting, we compared our proposed QPSO-SVM model with PSO-SVM[16] and SVM classifier respectively, and the expert evaluation are utilized as the base line. Risk prediction results of ten projects in the testing dataset are shown in Figure 2.

Combining experimental results of all the 100 testing dataset, the overall performance of each method is given as follows.

TABLE 2 Error rate of risk prediction for different methods

Method	SVM	PSO-SVM	QPSO-SVM
Error rate of risk prediction	8.61%	5.12%	1.75%

Based on the above experimental results, the conclusions can be seen that the proposed hybrid QPSO-SVM model can obviously promote the risk prediction accuracy than SVM and PSO-SVM. The reasons mainly lie in that, using the quantum behaved particle swarm optimization policy, parameters selection process is more effectively, and then high-rise building construction projects can be classified more accurately according to the risk predicting results.

6 Conclusions

This paper proposes a novel high-rise building construction project safety risk forecasting approach. We construct a two layer index system, in which the first-layer includes: "Falling accident", "Objects striking accident", "Collapse accident", "Mechanical injury", "Fire disaster in construction", and "Electric shock injury". Next, 29 indexes are designed in the second-layer of this index system, and these 29 indexes can cover nearly all influencing factors in high-rise building construction project safety risk prediction. Afterwards, we explain how to choose optimal parameters of SVM classifier via the quantum behaved particle swarm optimization policy. In the end, a series of experiments are conducted to testify the effectiveness of the proposed algorithm.

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