ORIGINAL PAPER

A quantitative model to evaluate mine geological environment and a new information system for the mining area in Jilin province, mid-northeastern China

Jia-yuan Guo^{1,2} • Wen-xi Lu^{1,2} • Xue Jiang³ • Yu Zhang⁴ • Hai-qing $Zhao⁵$ Tian-sheng Miao^{1,2}

Received: 19 July 2017 /Accepted: 2 October 2017 /Published online: 16 October 2017 \oslash Saudi Society for Geosciences 2017

Abstract The reliability of mine geological environment quality assessment highly depends on a large amount of survey data, a comprehensive evaluation system and an effective evaluation model. Using computer technology to integrate large amount of data can help to ensure the valid management and the effective assessment. Compared with previous studies, this study has improved and enriched the evaluation system and optimized the traditional evaluation method. Moreover, combining geology with computer science, it has developed the evaluation function of mine geological environment and realized the intersection and innovation of the discipline. The specific research content has the following three parts. First, a new design for an evaluation system which can synthetically describe the mine geological environment is presented. Second, a particle swarm optimization (PSO)-support vector machine (SVM) model is established as an alternative to traditional approaches that avoid interference from artificial factors. Third, a new mine geological environmental information system (MGEIS) is presented to efficiently manage data. Then, PSO-SVM evaluation model is embedded in it, and

 \boxtimes Wen-xi Lu luwx999@163.com

- ¹ Key Laboratory of Groundwater Resources and Environment of Ministry of Education, Jilin University, Changchun 130021, China
- ² College of Environment and Resources, Jilin University, Changchun 130021, China
- School of Environmental Studies, China University of Geosciences, Wuhan 430074, China
- ⁴ Songliao River Basin Water Resources Protection Bureau, Songliao Institute of Water Environment Science, Changchun 130021, China
- ⁵ Shenyang Institute of Geology and Mineral Resources, Shenyang 110032, Liaoning, People's Republic of China

the mine geological environment in Jilin province is assessed by using MGEIS. Decisions can be presented based on the evaluation results in this study to better support the recovery of the local mine geological environment.

Keywords Mine geological environmental evaluation . Hierarchical factor evaluation system . PSO-SVM evaluation model . Mine geological environment information system

Introduction

Immoderate, long-term, and disorganized mining activities are the main factors that cause damage to the geological environment such as environmental pollution, geological disasters, and resource destruction (Monjezi et al. [2009](#page-12-0); Zhang et al. [2012;](#page-12-0) Lukichev and Nagovitsin [2013\)](#page-12-0). Unreasonable development and utilization of mineral resources have not only restricted economic development and deteriorated the environment but have also threatened quality of life (Hough et al. [2004;](#page-11-0) Mayes et al. [2009\)](#page-12-0). Environmental impact assessment (EIA) is an effective method in mine geological environment protection and mineral resources development (Mirmohammadi et al. [2009\)](#page-12-0). The main purpose of EIA approaches is indeed to evaluate a proposed action, defining and quantifying its possible environmental impacts, and finding means to mitigate them (Weaver et al. [1996](#page-12-0)). As a result, it is necessary to use a scientific method to evaluate the mine geological environment, and then take effective measures to monitor and manage it. This process forms an important component of sustainable development of the geological environment (Jordan and Project [2009\)](#page-11-0).

Previous research focused on the evaluation methods to evaluate the environmental pollution degree in order to reduce the impact on the environment and human health. A number

of scholars have studied environmental evaluation methods and utilized themselves to quantify mine geological environment, including gray relational analysis (Chang et al. [1997;](#page-11-0) Chang [2001](#page-11-0)), analytic hierarchy process (Saaty [1980;](#page-12-0) Lukichev and Nagovitsin [2013](#page-12-0)), fuzzy comprehensive evaluation (Kuo and Xue [1998\)](#page-12-0), neural networks (Yama and Lineberry [1999](#page-12-0); Yoon et al. [2011](#page-12-0); Khalili et al. [2016\)](#page-12-0), and support vector machines (Sun et al. [2009](#page-12-0)). Regarding improvements to the accuracy of evaluation results, scholars combined two kinds of single evaluation method (Chen [2007\)](#page-11-0). For example, a rough set neural network model (Shi [2008\)](#page-12-0), a multi-level fuzzy comprehensive evaluation model (Zhang et al. [2008\)](#page-12-0), a fuzzy comprehensive evaluation model based on hierarchical analysis (Wei [2010](#page-12-0); Huang et al. [2012\)](#page-11-0), and a fuzzy evaluation model based on gray correlation analysis (Liu et al. [2013\)](#page-12-0) have all been shown to exhibit variable levels of accuracy in the comprehensive evaluation of mine geological environment. However, during the calculation process, these methods have different shortcomings, such as the rough set neural network method cannot guarantee evaluation precision due to limited numbers of samples, while others, such as support vector machine (SVM) model and the comprehensive index method, tend to have difficulty with the determination of parameters and weights because of the influence of artificial factors.

At present, the application of computer information technology which is involved in mining data management and mineral resources utilization in support of government environmental policies is of huge importance, so more and more studies have been carried out in this field (Peck and Gray [1999;](#page-12-0) Knights and Daneshmend [2000](#page-12-0)). The application of computer information technology to the science of environmental protection is known as Environmental Informatics (EI). In this respect, EI is a bridge between computer informatics and environmental science (Pillmann et al. [2006](#page-12-0)). For example, the Czech Republic began to carry out research from 1998 on the combination of multiple space analysis systems and laser radar technology to monitor the environment, developing a system based on an ArcObject component that became responsible for the management and processing of hydrology, soil, and atmospheric testing data as well as threedimensional (3-D) visualization. This system was also able to incorporate the multiple evaluation of risk based on spatial analysis and a raster image algebra system. This research provided a good technical basis to monitor and visualize the regional environment in 3-D as well as a scientific grounding for the Czech government in the future (Bao [2012\)](#page-11-0). Other countries have also attached great importance to environmental geological problems, especially in regard to the processing and development of mineral resources. Examples include the design and construction of mineral resource sustainable development decision support systems (Yang and Dang [2013](#page-12-0)). Spatial system databases are integrated with multiple layers, including mineral geological maps, residential distributions,

vegetated environment, and land use, enabling multiple impact factors to be extracted and comprehensive analyses of mineral resource development zoning in regions within countries to be undertaken. This enables policy-makers to determine regional "fitness level" according to local resources and the environmental situation. In this context, the Geological Environmental Monitoring Institute of China constructed a national mine environment information system using an ACCESS database system (Zhang and Yuan [2006\)](#page-12-0). This system enables a number of management functions including mine data entry, data queries, and data deletion. These systems can enable the goal of managing mine geological environmental information as well as promoting the use of such data.

Based on the previous studies but different from them, this study combines computer technology with mine geological environment assessment. It is not only to achieve the efficient management of data but also to achieve the effective evaluation of the mine geological environment. Thus, we develop a mine geological environmental information system (MGEIS) from basic computer principles in this study that is based on real-life requirements. Compared with previous systems, our new system not only contains basic functions but also has special functions, including "analysis and evaluation" and "map display." We combine particle swarm optimization (PSO) algorithm and SVM to establish PSO-SVM evaluation model which utilizes the PSO to optimize the parameters in SVM to avoid the interference of artificial factors (Chen and Phuong [2017;](#page-11-0) Ma et al. [2017](#page-12-0)). At the same time, we embed the PSO-SVM model and the hierarchical factor evaluation system we established in MGEIS to evaluate the mine geological environment in Jilin province scientifically. The results of evaluation provide a basis for future decision-making with regard to regional environmental restoration.

Study area

Our study area, Jilin province, is located in the northeast of China. It is connected to Liaoning province in the south, to Inner Mongolia autonomous region in the west, to Heilongjiang province in the north, to Russia in the northeast, and to Democratic People's Republic of Korea in the southeast. Jilin province covers an area of $187,400 \text{ km}^2$ and has a population of more than 26 million people. The geographical location of Jilin province is shown in Fig. [1.](#page-2-0)

The general trend in topographic change across this province encompasses lowlands in the northwest and highlands in the southeast. Jilin province can be divided into three geomorphic regions, the eastern Changbai Mountains, the central Songliao Plain, and the western Daxingan Mountains.

Jilin province has abundant mineral resources (Pang and Zhou [2008\)](#page-12-0), including energy and non-metallic minerals, metals, and mineral water. In recent years, the mine geological

Fig. 1 The geographical location of Jilin province

environment of the study area has been damaged to varying degrees due to the impact of human activities. The long-term uncontrolled mining leads to resource depletion. The disorderly mining had greatly damaged the mineral resources and had resulted in a series of mine environmental geological problems. According to the survey, mine environmental geological problems in Jilin province caused by human activities mainly include geological disasters, land resource destruction, and water resource pollution.

Materials and methods

In this study, the following materials and methods are used to evaluate the quality of mine geological environment in Jilin province.

A hierarchical factor evaluation system

The mine geological environment is complex. Not only artificial activities but also the background and natural conditions of mining will induce different kinds of geological environment problems. Based on domestic and foreign research in mine geological environment evaluation system (Weaver et al. [1996](#page-12-0); Huang et al. [2012](#page-11-0); Jiang et al. [2015;](#page-11-0) He et al. [2017\)](#page-11-0), as well as on the basis of actual conditions in Jilin province and the reports on the restoration of mine geological environment, our new mine geological environment evaluation system can be established and referred to as "hierarchical factor evaluation system."

Building on previous work, the evaluation system presented in this paper represents a marked improvement as it is established from the actual situation in the mine geological environment and it includes both natural and man-made factors addressed from multiple levels and angles. Our evaluation system is divided into three levels, used to describe different aspects of the mine geological environment from the large scale to local. Each level contains many factors, which are used to describe specific contents, including an element layer, an index layer, and a factor layer. The evaluation system is more comprehensive and thus enables a more realistic and suitable description of the mine geological environment for the practical needs of government management departments and professional personnel. For example, compared with previous studies, we add three elements in the element layer, the "basic situation of the mine," "sensitive factors of the surrounding mining area," and the "complexity of restoration." Similarly, we add indexes in the index layer, the "ore class," the "lag problem," and the "restoration deposit."

Thus, to evaluate mine geological environment, we consider five elements, encompassing 18 indexes and their magnitudes, as summarized in Table [1](#page-3-0) (Weaver [1996;](#page-12-0) Huang et al. [2012;](#page-11-0) Jiang et al. [2015](#page-11-0); He et al. [2017;](#page-11-0) Jin and Xi 2017). The final mine geological environment damage degree is shown in Table [2](#page-4-0). The corresponding scores of the different indicators in Table [1](#page-3-0) are man-made which can be changed, and the specific score does not affect the evaluation results. The purpose

of setting the score is to distinguish the last three pollution levels during the evaluation.

Mine geological environment evaluation methods

SVM

SVM is able to solve a number of fundamental problems in pattern recognition under given small sample size (Mirmohammadi et al. [2009;](#page-12-0) Gasmi et al. [2016\)](#page-11-0). This approach largely solves the problem of over-learning, as well as issues of non-linearity, disaster dimension, and classification problems (Baly and Hajj [2012;](#page-11-0) Arunkumar and Karthigaikumar [2017](#page-11-0)).

During the process of mine geological environment evaluation, a complex non-linear mapping relationship exists between damage degree and evaluation factors. This non-linear problem can be transformed into a linear problem in the highdimension space through an optimal separation hyperplane generated using a kernel function in transformation space.

To do this, a sample set is first defined as follows: (x_i, y_i) , $i = 1, 2, \dots, n$; $y = \{1, -1\}$ is the category label. Building on this, the hyperplane equation is:

$$
\omega \cdot x_i + b = 0 \tag{1}
$$

Second, a slack variable is incorporated into the constraint condition, $\xi_i \geq 0$, and the largest interval hyperplane is called the generalized optimal separating hyperplane. The constraint condition is:

$$
s.t \quad y_i[(\omega \cdot x_i) + b] \ge 1 - \xi_i \tag{2}
$$

Similarly, the optimization problem is as follows:

$$
\min \frac{1}{2} (\omega \cdot \omega) + C \sum_{i=1}^{n} \xi_i
$$

s.t $y_i[(\omega \cdot x_i) + b] \ge 1 - \xi \quad i = 1, 2, \dots, n$ (3)

In these expressions, ω is the weight vector, b is bias, ξ_i is the slack variable, and C is the penalty factor. Thus, $C > 0$; the larger the C, the greater punishment for misclassification.

Third, we incorporate Lagrange multipliers α , β , as follows:

$$
L(\omega, \xi, b, \alpha, \beta) = \frac{1}{2} (\omega \cdot \omega) + C \sum_{i=1}^{n} \xi_i -
$$

$$
\sum_{i=1}^{n} \alpha_i [y_i(\omega \cdot x_i + b) - 1 + \xi_i] - \sum_{i=1}^{n} \beta_i \xi_i
$$
 (4)

Fourth, the partial derivatives of ω , ξ , and b are taken to determine the duality of the original problem, as follows:

$$
\max_{\alpha,\beta} Q(\alpha) = L(\omega, \xi, b, \alpha, \beta) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}
$$

\n
$$
\times \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j (\psi(x_i) \cdot \psi(x_j))
$$

\n
$$
= \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) s.t \sum_{i=1}^{n} \alpha_i y_i
$$

\n
$$
= 0, \alpha_i \ge 0
$$
 (5)

This leads to the optimal judgment function, as follows:

$$
f(x) = \operatorname{sgn}\left(\sum_{i=1}^{n} \alpha_i^* y_i K(x, x_i) + b\right)
$$
 (6)

where α is a Lagrange multiplier; α^* is the optimal solution of $\alpha, \alpha^* = (\alpha_1^*, \alpha_2^*, \dots, \alpha_n^*)$; K is the kernel function; (x_i, y_i) are the training samples, $i = 1, 2, \dots, n$; and b is the bias.

Defining an appropriate kernel function is necessary to establish a SVM model, as different functions are used in different situations (Wu and Wang [2009](#page-12-0)). Commonly applied kernel functions include linear, polynomial, radial basis function (RBF), and sigmoid kernel function, expressed as follows:

Linear kernel function
$$
K(x_i \cdot x_j) = (x_i \cdot x_j),
$$
 (7)

Polynomial kernel function $K(x_i \cdot x_j)$

$$
= [g(x_i \cdot x_j) + r]^d, g > 0;
$$
\n(8)

RBF kernel function $K(x_i, x_j) = \exp \left[-g||x_i-x_j||^2\right], g > 0;$ (9)

Sigmoid kernel function $K(x_i, x_j)$

$$
= \tanh(g(x_i \cdot x_j) + r), g > 0 \tag{10}
$$

In the process of mine geological environment quality evaluation, the nuclear parameter g and the penalty factor C have a crucial impact on the evaluation results. Therefore, the parameters are important to the evaluation model. In this paper, we select the PSO algorithm to optimize the model parameters and the specific steps are described in "[Establish PSO-SVM](#page-5-0) [model in MGEIS.](#page-5-0)" The remaining parameters are set to default values.

PSO

PSO is a kind of evolutionary algorithm that is derived from a random solution. In order to determine a globally optimal solution, PSO searches from a current to an optimal value using iteration (Armaghani et al. [2017\)](#page-11-0), easily achieving high precision and rapid convergence.

In the first place, we initialize PSO to generate a group of random particles and determine an optimal solution through iteration. Two particles in this system update their speeds and positions according to the following formulae to find optimal values:

$$
v_{id}^k = w_i v_{id}^{k-l} + c_I rand_I (pbest_i - x_{id}^{k-l})
$$

+
$$
c_2 rand_2 (gbest_i - x_{id}^{k-l})
$$
 (11)

$$
x_{id}^k = x_{id}^{k-l} + v_{id}^k (i = 1, 2, ..., m; d = 1, 2, ..., n)
$$
 (12)

In these expressions, m denotes the particle swarm size, n is the particle dimension, v^k is the speed at k iteration step, and x^k is the space position of the particle at k iteration step. c_1 and c_2 are constants. rand₁ and rand₂ are independent random numbers between [0,1].

Establish PSO-SVM model in MGEIS

We establish PSO-SVM model in MGEIS as follows:

Step 1. Data preparation

On the basis of the hierarchical factor evaluation system and classification standard adopted above in this paper, we generate 900 groups of random samples including 600 groups of training samples and 300 groups of verifying samples. In total, there are 200 groups of training samples and 100 groups of verifying samples in each classification standard.

Step 2. Data normalization

We apply the following formula to normalize our data:

$$
\tilde{X}_i = \frac{X_i - \min(X_i)}{\max(X_i) - \min(X_i)}
$$
\n(13)

Step 3. Determination of PSO-SVM model structure

The scores of five evaluation elements are used as input variables in this study, including geological environmental background conditions (X_1) , the basic mine situation (X_2) , sensitive factors in the surrounding mining area (X_3) , the type and degree of mine geological environmental problem (X_4) , and the complexity of restoration (X_5) . In each case, mine geological environmental evaluation levels are used as output variables.

Step 4. Determination of PSO-SVM model parameters

We apply PSO algorithm according to Eqs. (11) and (12) to optimize the penalty factor C and the nuclear parameter g in SVM, as outlined below:

(a) PSO parameters are initialized (i.e., particle dimension n , population size m , number of iterations p) using initial values that randomly denote the solution space position and velocity of the particle, marked as x_i^0 and v_i^0 ,

respectively. SVM parameters (C, g) can be expressed as the current position of the particle, while the next generation parameters (C, g) are updated from velocity which determines the direction and size.

- (b) Calculate fitness value of each particle. Mark it as $s_i(x)$ and compare with $pbest_i$. A particle will adopt the current individual optimal solution if $s_i(x) < pbest_i$.
- (c) Comparisons are made with *pbest*, and *gbest*. A particle will adopt the current group optimal solution if $pbest_i$ < gbest.
- (d) We determine whether, or not, termination conditions are satisfied following calculations for the entire particle group. Given a situation where these conditions are not met, then particles are moved according to Eqs. (11) and (12) to generate a new group and we return to step (b). However, if termination conditions are met, then calculation results are output.

Thus, following these steps to calculate, we generate an optimal penalty factor, $C = 0.01$, and an optimal nuclear parameter, $g = 0.01$.

Step 5. Kernel function selection and establishment of the PSO-SVM model

We write a set of MATLAB programs containing the most optimal penalty and most optimal kernel parameter to train our samples. We then utilize this MATLAB software to establish our mine geological environment evaluation models, applying linear kernel, polynomial kernel, RBF kernel, and sigmoid kernel functions. Test samples are migrated into evaluation models to generate results as well as to enable the analysis of different results in different kernel functions to select the most optimal.

Step 6. Packing the PSO-SVM model and generating a component

We first set up the MATLAB COM Builder external complier using "mex-setup." The compiler used in this study is Microsoft Visual $C++ 2010$. Second, we enter "deploytool" in the command window of MATLAB to start the COM Builder, and follow the sequence "File-New Project" to generate a new project and a new class with the names "Proj3" and "ProjPlot3." Finally, we load the PSO-SVM model code file to create a PSO-SVM component.

Step 7. PSO-SVM evaluation function realization

To complete this step, we establish an interface of "Analysis and Evaluation" module in the Visual Studio 2010 platform. This interface has three parts encompassing a hierarchical factor evaluation system, scoring window, and a results display window. We write C# programming codes to link each part and to invoke the PSO-SVM component for evaluation.

We establish PSO-SVM model in "Analysis and Evaluation" module of MGEIS using the steps outlined above. Following login to the system, a user adds scores in

this window. Operation buttons are clicked to enable PSO-SVM model calculations in the background, and the results of evaluation are subsequently displayed. The "Analysis and Evaluation" module interface is shown in Fig. 2.

Implementation of MGEIS

In order to digitize, visualize, and manage mine geological environmental information and to present these data scientifically to managers, we develop the MGEIS presented in this paper.

Our MGEIS is designed and written using computer technology. Thus, this study makes comprehensive use of the software Visual Studio 2010, SQL Server 2005, MapGIS K9, and MATLAB in development. In addition, according to the actual needs of government departments and professionals, we develop a general geographic information system (GIS) function via secondary development of MapGIS K9 (Matejicek et al. [2006\)](#page-12-0) that applies ADO.NET interface technology to connect

varieties of components with the database efficiently. A number of special user requirements can further be achieved by programming in the C# language.

MGEIS structure and function

Our MGEIS application adopts a client/server mode and includes UIL (user interface layer), BLL (business logic layer), and DAL (data access layer) from top to bottom. Of these, UIL is mainly responsible for displaying information and incorporating external inputs, while BLL plays an essential role in data exchange between UIL and DAL, while the latter accesses the database and XLS documents. The overall architecture of our MGEIS application is shown in Fig. [3.](#page-7-0)

Our MGEIS application contains seven functional modules, including "Data Query," "Data Input," "Data Management," "Analysis and Evaluation," "Map Display," "File Management," and "User Management." The specific functions of each module are presented in Table [3.](#page-7-0)

	BU PSO-SVM Form				$\begin{array}{c c c c c} \hline \multicolumn{3}{c }{\mathbf{C}} & \multicolumn{3}{c }{\mathbf{C}} & \multicolumn{3}{c }{\mathbf{X}} \\\hline \multicolumn{3}{c }{\mathbf{C}} & \multicolumn{3}{c }{\mathbf{C}} & \multicolumn{3}{c }{\mathbf{S}} \\\hline \multicolumn{3}{c }{\mathbf{C}} & \multicolumn{3}{c }{\mathbf{C}} & \multicolumn{3}{c }{\mathbf{C}} & \multicolumn{3}{c }{\mathbf{C}} \\\hline \multicolumn{3}{c }{\mathbf{D}} & \multicolumn{3$					
Evaluation Mine name 2017 Xinglong Coal Evaluation Evaluation Guo Jiavuan Jilin University										
			Geological Environment Background Condition Basic Situation of Mine Sensitive Factor of Mining Ar ^{el}		PSO-SVM Evaluation Result					
	Element Layer	Index Layer	Factor Layer	score	Mine name:Xinglong Coal Evaluation person: Guo Jiayuan Evaluation time: 2017 Evaluation company: Jilin University					
	Geological Environment Background	Landform	\blacktriangle (1) Geomorphic unit type is single (2) Micro landform is simple \equiv (3) The change of terrain is gentle (4) It is conductive to the natural drainage (5) Terrain slope is generally less than 20 degre $\overline{ }$	$\sqrt{2}$ points	Level: 1 level Dangerous Degree: A bit dangerous Level: 2 level Dangerous Degree: Dangerous Level: 3 level Dangerous Degree: Extremely dangerous					
			(1) Geomorphic unit type is more (2) Micro landform is more complicated 티 (3) The change of terrain is medium (4) It is not conductive to the natural drainage (5) Terrain slope is generally less than 20-35 de $\overline{ }$	6 points	Geological Environment Background Condition score:3.36 Basic Situation of Mine score: 5.38 Sensitive Factor of Mining Area Around score:2					
			\blacktriangle (1) Type of landform unit is most (2) Micro landform is most complicated (3) The change of terrain is large (4) It is not conductive to the natural drainage (5) Terrain slope is generally more than 35 degre τ	\Box 10 points	Type and Degree of Mine Geological Environment Problem score:6 Complexity of Restoration score: 5.06 Final score: 5.077					
		Environmental Geology Condition	Simple	2 points	Final Degree: 2 level					
			Moderate	☑ 6 points						
			Complex	\Box 10 points						
		Land Use Status	Waste land, bare land	☑ 2 points						
			Grassland, woodland, industrial and mining land for construction purpose	\Box 6 points						
			Plough	\Box 10 points	calculate ol ear- output					

Fig. 2 "Analysis and Evaluation" module

Fig. 3 Overall architecture diagram

MGEIS workflow

Our MGEIS application has a user-friendly interface and is simple to operate. Initially, all information related to a mine is stored in the software SQL Server 2005 and GDB enterprise manager through a series of data tables that incorporate varies kinds of layers. Secondly, the PSO-SVM model is established and packed as a component via MATLAB (Monjezi et al. [2009](#page-12-0)). The MGEIS application then connects information with GIS and the PSO-SVM model component to realize the evaluation of mine geological environment. Finally, evaluation results are displayed as MGEIS outputs. Operation of MGEIS is simple and the results are clear and intuitive for users. An MGEIS work flowchart is shown in Fig. [4](#page-8-0).

Results and discussion

These results of this study are based on our Jilin province MGEIS project. In this project, mine geological environmental restoration reports of 684 mines are collected and we input the information into our system, alongside a number of evaluation factors. We then use MGEIS to calculate and output the following results.

Fig. 4 MGEIS work flowchart

Accuracy of SVM models using different kernel functions

As shown in Fig. 5, different verification results for the four SVM models are obtained by using different kernel functions. The calculation results presented in Fig. 5 which were compared with the description of mine geological environment damage degree in the reports show that the accuracy of linear, polynomial, RBF, and sigmoid SVM models are 89.33, 94.00, 88.66, and 4.00%, respectively. Data suggest that the polynomial SVM model is slightly more accurate than either linear or RBF models, and far more accurate than the sigmoid model. Results therefore imply that the polynomial SVM model is suitable for mine geological environmental assessment in our study area.

Comparing SVM and PSO-SVM evaluation results

We use both a SVM model and a PSO-SVM model to evaluate the mine geological environmental qualities of 684 mines in this study. Our evaluation results for 30 mines are shown in Table 4. Data show that the two evaluation models achieved the same classification result rate 95.9%. It can be seen from "[Accuracy of SVM models using different kernel functions](#page-8-0)" that the SVM evaluation model is applicable to the evaluation of mine geological environment. Therefore, the PSO-SVM model is suitable for the evaluation of mine geological environment similarly. Previous studies tend to use traditional evaluation models for assessment which affects results because of the influence of artificial factors. This is illustrated by the case of sample, for example, where the SVM result indicates level I and the PSO-SVM result indicates level II. As for M1 mine, although the type and degree of environmental problem is characterized as level I, there are important places in this region where energy minerals need to be mined underground and the landform is complex. However, as the mine has therefore proved difficult to manage and is leading to serious consequences, a level II evaluation result conforms to the actual situation. Similarly, in the case of example M12, the SVM result shows level II while the PSO-SVM result shows level III. Again, as for M12 mine, a method of combined mining is being applied as this site contains abundant metal minerals. The landform is complex, the environmental geological condition is moderate, land resource destruction is serious, and restoration is difficult; thus, a level III evaluation result conforms to the actual situation.

In summary, PSO-SVM is more effective than SVM evaluation model in the process of calculation, which not only

Table 4 Comparison of evaluation results between two models

			Mine number SVM PSO-SVM Mine number SVM PSO-SVM		
M1	I	П	M ₁₆	П	П
M ₂	П	П	M17	Ш	Ш
M ₃	\mathbf{I}	Ш	M18	Ш	Ш
M4	I	T	M19	П	П
M ₅	П	П	M ₂₀	T	П
M ₆	П	П	M21	Ш	Ш
M ₇	Ш	Ш	M22	П	Ш
M ₈	T	П	M ₂₃	Ш	Ш
M ⁹	I	T	M24	П	П
M10	Ш	Ш	M ₂₅	П	П
M11	Ш	Ш	M26	Ш	Ш
M ₁₂	П	Ш	M27	П	Ш
M13	П	П	M28	Ш	Ш
M14	П	П	M29	Ш	Ш
M15	П	П	M30	I	Ι

Fig. 6 The statistical results of mine geological environment evaluation

avoids the interference of artificial factors but also makes the evaluation result more realistic.

Evaluation of PSO-SVM results

The data presented in Fig. 6 shows that 2.64% of our study area can be classified as level I, lightly damaged, while 43.27% can be classified as level II, moderately damaged, and 54.09% can be classified as level III, seriously damaged. Data presented in Fig. 7 shows that the level I area comprises 35.71% metal minerals, 33.04% non-metal minerals, 4.46% energy minerals, and 26.79% vapor minerals. Similarly, the level II area comprises 38.02% metal minerals, 19.39% nonmetal minerals, 40.31% energy minerals, and 2.28% vapor minerals. The level III area comprises 35.92% metal minerals, 17.15% non-metal minerals, 45.96% energy minerals, and 0.97% vapor minerals.

Thus, on the basis of our results, the mine geological environment of our study area has been almost entirely moderately or seriously damaged by mining activities, especially in energy mineral areas such as coal-mining regions.

Figure [8](#page-10-0) illustrates a map of evaluation results produced using the "Map Display" function of our MGEIS; this map is amplified at the bottom of this figure. These data show that PSO-SVM model evaluation results for Jilin province can be classified at three degrees of seriousness, light, moderate, and serious. These results reveal that 54.09% of mine sites are

Fig. 7 The percentage of different ore classes in three evaluation degrees

Fig. 8 A map of evaluation results produced using the "Map Display" function of our MGEIS

seriously damaged, while 43.27% are moderately damaged. Seriously damaged mines are mainly distributed in the Jilin, Liaoyuan, Tonghua, and Baishan regions. The damage degree of mine geological environment is affected by the location, background condition, mining method, and so on. All the underground mining mines in the Jilin province have different degrees of surface subsidence. These mines are mostly distributed in the mountain basin area and around such as Liaoyuan. Surface subsidence often occurs in coal mines. The coal ore body is mostly shallow buried type, the thickness of the loose cover layer is large, the rock strength is low, the thickness ratio is small, the lithological association is complex, and the surface subsidence is easy to occur. The mountainous area in the southeast of Jilin province is seriously damaged, because there are large mined-out area and surface collapse which leads to the occurrence of fissures along the joints of basalt after years of underground mining. In the effect of precipitation, the fracture occurs along the steep slope and causes serious damage. There are landslides mainly distributed in the eastern mountainous area of Jilin province due to open-pit mining. Landslide geological disaster occurs within the mining area of main stem and tributaries every flood season frequently because of the vegetation coverage rate decline caused by mining activity, combined with high and steep mountain terrain, water development, and emissions of waste rock which are piled up in the flood ditch sides basically.

Conclusions

- 1. Compared with previous studies, the establishment of hierarchical factor evaluation system describes the mine geological environment better from multiple levels and angles. The evaluation system contains five elements and 18 indexes including natural and man-made factors. The comprehensive description for the complex mine geological environment lays the foundation for the evaluation work.
- 2. The results of our study suggest that PSO-SVM model is suitable for the mine geological environment evaluation and the results are more accurate and realistic. This study improves the traditional methods and combines PSO method with SVM method to make up for each other. It not only solves mine geological environment problem but also overcomes the parameters in evaluation model which are affected by artificial factors.
- 3. Different from previous information system, we develop MGEIS with the function of mine geological environment evaluation. This study makes the PSO-SVM model and hierarchical factor evaluation system embedded in MGEIS to realize the interface and visualization of mine geological environment evaluation. It provides an easy

approach to realize the complex evaluation process and makes results easy to understand.

4. The MGEIS will perform an important role in the management of mine geological environment and it has already been applied by the Jilin Province Department of Land and Resources. Managers who use MGEIS can reserve, manage, search, retrieve, add, update, analyze, evaluate, input, and output related information. MGEIS meets the actual demands of the government personnel.

Acknowledgments The authors would like to acknowledge the support provided by China Geological Survey Project (No. 121201007000150006), and the study was financially supported by Project funded by China Postdoctoral Science Foundation (No. 2016M602388).

References

- Armaghani DJ, Shoib RSNSBR, Faizi K, Rashid ASA (2017) Developing a hybrid PSO-ANN model for estimating the ultimate bearing capacity of rock-socked piles. Neural Comput Applic 28: 391–405
- Arunkumar R, Karthigaikumar P (2017) Multi-retinal disease classification by reduced deep learning features. Neural Comput Applic 28: 329–334
- Baly R, Hajj H (2012) Wafer classification using support vector machines. IEEE Trans Semicond Manuf 25:373–383
- Bao GD (2012) Research and development of the mine geological environment evaluation system (in Chinese). Northeast Forestry University, Harbin
- Chang BR (2001) Alternative view of grey relational analysis (in Chinese). J Grey Syst 13:31–39
- Chang SH, John HW, Li Z (1997) Optimizing acuraddiecasting process via grey relational analysis. J Grey Syst 9:247–258
- Chen T (2007) Research and application of combined evaluation models (in Chinese). Lanzhou University
- Chen SM, Phuong BDH (2017) Fuzzy time series forecasting based on optimal partitions of intervals and optimal weighting vectors. Knowl-Based Syst 118:204–216
- Gasmi A, Gomez C, Zouari H, Masse A, Ducrot D (2016) PCA and SVM as geo-computational methods for geological mapping in the southern of Tunisia, using ASTER remote sensing data set. Arab J Geosci 9(20):753
- He FH, Gu LJ, Wang T, Zhang ZH (2017) The synthetic geo-ecological environmental evaluation of a coastal coal-mining city using spatiotemporal big data: a case study in Longkou, China. J Clean Prod 142:854–866
- Hough RL, Breward N, Young SD et al (2004) Assessing potential risk of heavy metal exposure from consumption of home-produced vegetables by urban populations. J Environ Health 112:215–221
- Huang SB, Li X, Wang YX (2012) A new model of geo-environmental impact assessment of mining: a multiple-criteria assessment method integrating fuzzy-AHP with fuzzy synthetic ranking. Environ Earth Sci 66:275–284
- Jiang X, Lu WX, Zhao HQ, Yang QC, Chen M (2015) Quantitative evaluation of mining geo-environmental quality in Northeast China: comprehensive index method and support vector machine models. Environ Earth Sci 73:7945–7955
- Jordan G, Project JP (2009) Sustainable mineral resources management: from regional mineral resources exploration to spatial contamination risk assessment of mining. Environ Geol 58:153–169
- Khalili N, Khodashenas SR, Davary K, Baygi MM, Karimaldini F (2016) Prediction of rainfall using artificial neural networks for synoptic station of Mashhad: a case study. Arab J Geosci 9(13):624
- Knights PF, Daneshmend LK (2000) Open systems standards for computing in the mining industry. CIM Bull 93:89–92
- Kuo RJ, Xue KC (1998) A decision support system for sales forecasting through fuzzy neural networks with asymmetric fuzzy weights. Decis Support Syst 24:105–126
- Liu LG, Zhao WL, Chen YW (2013) Comprehensive fuzzy evaluation for transmission network planning scheme based on gray correlation analysis. Therm Power Electr Eng 1:1292–1296
- Lukichev SV, Nagovitsin OV (2013) Information support of mineral mining and exploitation in the Khibiny mountains area. J Min Sci 48:1025–1030
- Ma DL, Tan W, Zhang ZX, Hu J (2017) Parameter identification for continuous point emission source based on Tikhonov regularization method coupled with particle swarm optimization. J Hazard Mater 325:239–250
- Matejicek L, Engst P, Janour Z (2006) A GIS-based approach to spatiotemporal analysis of environmental pollution in urban areas. Ecol Model 199:261–277
- Mayes WM, Johnston D, Potter HAB, Jarvis AP (2009) A national strategy for identification, prioritisation and management of pollution from abandoned non-coal mine sites in England and Wales. I. Methodology development and initial results. Sci Total Environ 407:5435–5447
- Mirmohammadi M, Gholamnejad J, Fattahpour V, Seyedsadri P, Ghorbani Y (2009) Designing of an environmental assessment algorithm for surface mining projects. J Environ Manage 90:2422– 2435
- Monjezi M, Shahrizr K, Dehghani H, Samimi NF (2009) Environmental impact assessment of open pit mining in Iran. Environ Geol 58:205– 216
- Pang JH, Zhou XY (2008) Present situation of mining development and existing problems in environmental geology in Jilin Province. Jilin Geol (in Chinese) 27:45–47
- Peck J, Gray J (1999) Mining in the 21th century using information technology. CIM Bull 92:56–59
- Pillmann W, Geiger W, Voigt K (2006) Survey of environmental informatics in Europe. Environ Model Softw 21:1519–1527
- Saaty TL (1980) The analytic hierarehy process. New york, Me Graw-Hill
- Shi HW (2008) The risk early-warning of hidden danger in coal mine based on rough set-neural network. Proceedings of the 2nd International Conference on Risk Management & Engineering Management. 1:314–317
- Sun A, Lim EP, Liu Y (2009) On strategies for imbalanced text classification using SVM: a comparative study. Decis Support Syst 48:191– 201
- Weaver AB, Greyling T, Van WBW, Kruger FJ (1996) Logistics and team management of a large environmental impact assessment: proposed dune mining at St. Lucia, South Africa. Environ Impact Assess Rev 16(2):103–113
- Wei K (2010) Evaluation of construction project investment risk based on fuzzy analytic hierarchy process method (in Chinese). Int Conf Adv Manag Sci 2:10–14
- Wu KP, Wang SD (2009) Choosing the kernel parameters for support vector machines by the inter-cluster distance in the feature space. Pattern Recogn 42:710–717
- Yama BR, Lineberry GT (1999) Artificial neural network application for a predictive task in mining. Min Eng 51:59–64
- Yoon H, Jun SC, Hyun Y (2011) A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer. J Hydrol 396:128–138
- Zhang JD, Yuan XL (2006) Information system of geo-environmental investigation and its application in mining areas in China (in Chinese). Chin J Geol Hazard Control 17:134–137
- Zhang N, Ye H, Liu YT (2008) Decision support for choosing optimal electromagnetic loop circuit opening scheme based on analytic hierarchy process and multi-level fuzzy comprehensive evaluation. Eng Intell Syst Electr Eng Commun 16:183–191
- Zhang XW, Yang LS, Li YH, Li HR, Wang WY, Ye BX (2012) Impacts of lead/zinc mining and smelting on the environment and human health in China. Environ Monit Assess 184:2261–2273