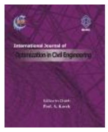
INTERNATIONAL JOURNAL OF OPTIMIZATION IN CIVIL ENGINEERING
Int. J. Optim. Civil Eng., 2013; 3(2):345-358



APPLICATION OF THE HYBRID HARMONY SEARCH WITH SUPPORT VECTOR MACHINE FOR IDENTIFICATION AND CALSSIFICATION OF DAMAGED ZONE AROUND UNDERGROUND SPACES

H. Fattahi[a], M. A. Ebrahimi Farsangi[a], S. Shojaee[*,†,b], K. Nekooei[c] and H. Mansouri[a]
[a]*Department of Mining Engineering, Shahid Bahonar University of Kerman, Iran*
[b]*Department of Civil Engineering, Shahid Bahonar University of Kerman, Iran*
[c]*Department of Electrical Engineering Shahid Bahonar University of Kerman, Iran*

ABSTRACT

An excavation damage zone (EDZ) can be defined as a rock zone where the rock properties and conditions have been changed due to the processes related to an excavation. This zone affects the behavior of rock mass surrounding the construction that reduces the stability and safety factor and increase probability of failure of the structure. This paper presents an approach to build a model for the identification and classification of the EDZ. The Support vector machine (SVM) is a new machine learning method based on statistical learning theory, which can solve the classification problem with small sampling, non-linearity and high dimension. However, the practicability of the SVM is influenced by the difficulty of selecting appropriate SVM parameters. In this study, the proposed hybrid Harmony search (HS) with the SVM was applied for identification and classification of damaged zone, in which HS was used to determine the optimized free parameters of the SVM. For identification and classification of the EDZ, based upon the modulus of the deformation modulus and using the hybrid of HS with the SVM a model for the identification and classification of the EDZ was built. To illustrate the capability of the HS-SVM model defined, field data from a test gallery of the Gotvand dam, Iran were used. The results obtained indicate that the HS-SVM model can be used successfully for identification and classification of damaged zone around underground spaces.

Received: 15 January 2013; Accepted: 5 may 2013

[*] Corresponding author: S. Shojaee, Department of Civil Engineering, Shahid Bahonar University of Kerman, Iran.
[†]E-mail address: saeed.shojaee@uk.ac.ir (S. Shojaee)

KEY WORDS: excavation damaged zone, harmony search, support vector machine, deformation modulus

1. INTRODUCTION

The excavation damage zone (EDZ) is defined as the zone immediately around an excavation boundary where the rock mass has been disturbed due to the excavation and redistribution of stresses [1, 2]. The disturbances can be in the form of creation of new fractures, closure and opening of pre-existing fractures and redistribution of stresses. During these processes, the mechanical, hydraulic and physical properties of the rock mass surrounding the excavation can be considerably affected. The presence of this zone can pose problems related to stability and seepage and consequently impair the performance and functionality of the excavation [3]. Various researches about the assessment and identification of the EDZ with different methods such as displacement measurement, seismic refraction, direct observation, using borehole camera were carried out worldwide [1, 4-13].

Recently, intelligence system approaches such as the support vector machine (SVM) have been used successfully for modeling and classification. SVM is a popular pattern classification method with many diverse applications is an emerging data classification technique proposed by Vapnik [14], and has been widely adopted in various fields of classification problems in recent years [15-18].

Kernel parameter setting in the SVM training procedure, along with the feature selection, significantly influences the classification accuracy. To determine optimized free parameters of the SVM for the identification and classification, the harmony search (HS) is used while discovering a subset of features, without reducing the SVM classification accuracy. Harmony search (HS) is a meta-heuristic search algorithm inspired by the improvisational process of musicians introduced by Geem et al. [19].

In this paper, an HS-SVM for identification and classification of the EDZ was defined. To illustrate the capability of the HS-SVM model presented, field data from a test gallery of the Gotvand dam, Iran were used. According to the authors' knowledge, application of the hybrid HS with SVM for identification and classification of damaged zone around underground spaces is a unique research.

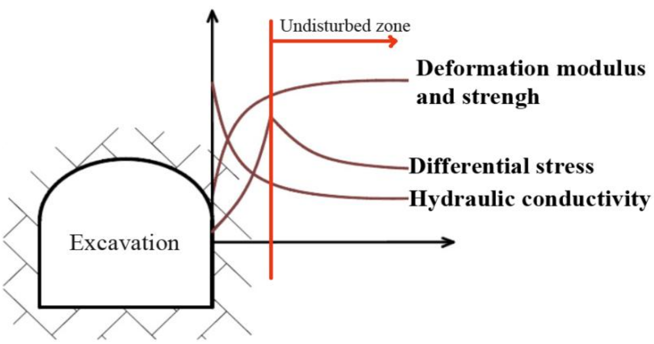


Figure1. Behavior of mass rock surrounding an underground construction

2. EXCAVATION DAMAGE ZONE

EDZ can be defined as a rock zone where the rock properties and conditions have been changed due to the processes related to an excavation. This zone affects the behavior of rock mass surrounding the construction (Figure1), that reduces the stability and safety factor and increase probability of failure of the structure. Different definitions for the damaged or disturbed zone have been used [20, 21]. In this paper, the definitions of Tsang et al. [22] for Excavation disturbed Zone (EdZ), EDZ and Highly Damaged Zone (HDZ) were used. (Figure2).

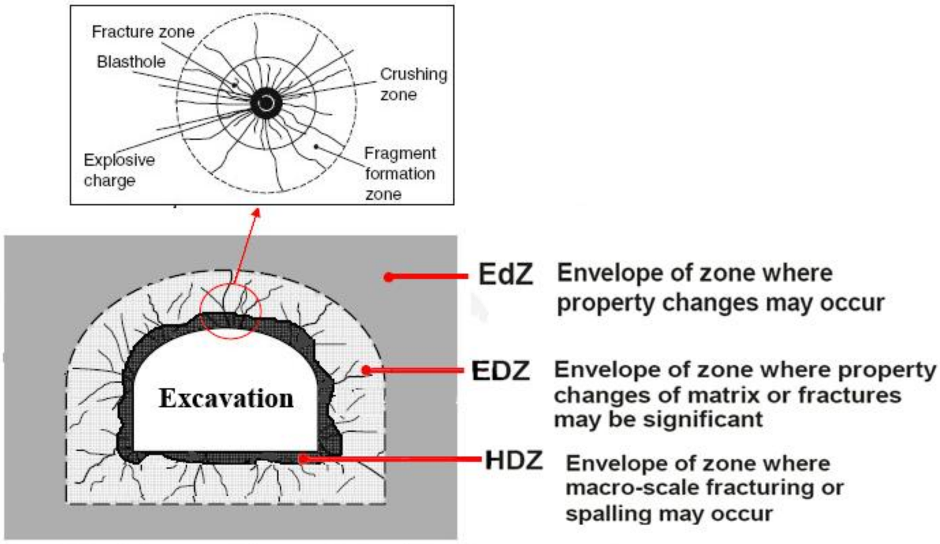


Figure 2. Zones around an underground construction

3. SUPPORT VECTOR MACHINE

The purpose of the SVM classification is to find optimal separating hyperplane by maximizing the margin between the separating hyperplane and the data. Assume that, a set of data $T=\{x_i, y_i\}_{i=1}^{m}$ is given, where, x_i denotes the input vectors, $y_i \in \{+1, -1\}$ stands for two classes, and m is the sample number. It is possible to determine the hyperplane $f(x)$=0 that separates the given data when two classes are linearly separable:

$$f(x) = w.x + b = 0 \tag{1}$$

where, w denotes the weight vector, and b denotes the bias term. w and b are used to define the position of separating hyperplane. The separating hyperplane should be satisfying the constraints:

$$y_i f(x_i) = y_i (w.x_i + b) \geq 1, \qquad i = 1, 2, \ldots, m \tag{2}$$

Positive slack variables ξ_i are introduced to measure the distance between the margin and the vectors x_i that lying on the wrong side of the margin. Then, the optimal hyperplane separating the data can be obtained by the following optimization problem:

$$\begin{aligned} &\underset{w,b,\xi}{Minimize} \quad \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}\xi_i, \quad i=1,\dots,m \\ &Subject\ to: \begin{cases} y_i(w.x_i+b)+\xi_i-1\geq 0 \\ \xi_i \geq 0. \end{cases} \end{aligned} \tag{3}$$

where, C is the error penalty. By the lagrangian multipliers a_i introduced, the above mentioned optimization problem is transformed into the dual quadratic optimization problem, that is:

$$\begin{aligned} &Maximize \quad L(\alpha)=\sum_{i=1}^{m}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{m}\alpha_i\alpha_j y_i y_j (x_i.x_j) \\ &Subject\ to \quad \sum_{i=1}^{m}\alpha_i y_i = 0,\ \alpha_i \geq 0,\ i=1,\dots,m \end{aligned} \tag{4}$$

Thus, the linear decision function is created by solving the dual optimization problem, which is defined as:

$$f(x) = sign\left(\sum_{i,j=1}^{m}\alpha_i y_i (x_i.x_j)+b\right) \tag{5}$$

The SVM can also be used in non-linear classification by using kernel function. By using the non-linear mapping function φ(•) the original data x is mapped into a high-dimensional feature space, where the linear classification is possible. The non-linear decision function is:

$$f(x) = sign\left(\sum_{i,j=1}^{m}\alpha_i y_i K(x_i.x_j)\right)+b \tag{6}$$

where, $K(x_i.x_j)$ is called the kernel function, $K(x_i.x_j)=\varphi(x_i)\varphi(x_j)$. The SVM constructed by radial basis function $\left(K(x_i.x_j)=\exp\left(-\|x_i-x_j\|/2\sigma^2\right)\right)$ has excellent non-linear classification ability.

Several kernel functions help the SVM in obtaining the optimal solution. The most frequently used such kernel functions are the polynomial, sigmoid and radial basis kernel function (RBF) [23, 24]. Among them, the RBF is applied most frequently, because it can classify multi-dimensional data, unlike a linear kernel function. Additionally, the RBF has fewer parameters to set than a polynomial kernel. Consequently, the RBF is an effective option for kernel function. Therefore, in this study an RBF kernel function in the SVM was applied to obtain optimal solution. Two major RBF parameters applied in SVM, C and σ, must be set appropriately. Parameter C represents the cost of the penalty. The choice of a value for C influences on the classification outcome. If C is too large, then the classification accuracy rate is very high in the training phase, but very low in the testing phase. If C is too small, then the classification accuracy rate unsatisfactory, making the model useless. Parameter σ has a much greater influence on classification outcomes than C, because its value affects the partitioning outcome in the feature space. An excessively large value for parameter σ results in over-fitting, while a disproportionately small value leads to under-fitting [25].

4. PARAMETERS OPTIMIZATION OF SVM BASED ON HS

The value of parameters C and σ that lead to the highest classification accuracy rate in this interval can be found by setting appropriate values for the upper and lower bounds (the search interval) and the jumping interval in the search. Meta-heuristic approaches are commonly employed to help in looking for the best feature subset. Although meta-heuristic approaches are slow, they obtain the (near) best feature subset. Jack and Nandi [26] and Shon et al. [27], employed Genetic algorithm (GA) to screen the features of a dataset. The selected subset of features is then fed into the SVM for classification testing. Zhang et al. [28] developed a GA-based approach to discover a beneficial subset of features for the SVM in machine condition monitoring. Samanta et al. [29] proposed a GA approach to modify the RBF width parameter of the SVM with feature selection. Nevertheless, since these approaches only consider the RBF width parameter for the SVM, they may miss the optimal parameter setting. Huang and Wang [30] presented a GA-based feature selection and parameters optimization for the SVM. Moreover, Huang et al. [31] utilized the GA-based feature selection and parameter optimization for credit scoring. Also, various researchers presented a particle swarm optimization (PSO)-based feature selection and parameters optimization for the SVM [32-38].

In this study, the selection of the parameters C and σ has a great influence on the performance of the SVM. The HS was used to determine the optimized C and σ, is based on natural musical performance, a process that searches for a perfect state of harmony. The harmony in music is analogous to the optimization solution vector, and the musician's improvisations are analogous to local and global search schemes in optimization techniques. The HS algorithm does not require initial values for the decision variables and uses a stochastic random search that is based on the harmony memory considering rate and the pitch adjusting rate. The method is very easy to implement, and there are few parameters to adjust.

Here, the harmony is composed of the parameters C and σ. Figure3 presents the process of optimizing the SVM parameters with the HS, which is described below:

(1) Definition: The optimization problem can be defined as:

Minimize f(x) subject to $x_{iL} \le x_i \le x_{iU}$ $(i = 1, 2, ..., N)$ where, x_{iL} and x_{iU} are the lower and upper bounds for decision variables.

The HS algorithm parameters are also specified in this step. They are the harmony memory size (HMS) or the number of solution vectors in harmony memory, harmony memory considering rate (HMCR), distance band width (*bw*), pitch adjusting rate (PAR), and the number of improvisations (K), or stopping criterion. K is the same as the total number of function evaluations.

(2) Initialization. The HS is initialized in the harmony memory (HM). The harmony memory is a memory location where, all the solution vectors (sets of decision variables) are stored. The initial harmony memory is randomly generated in the region $[x_{iL}, x_{iU}]$(i=1, 2,. . ., N). This is done based on the following equation:

$$x_i^j = x_{iL} + rand() \times (x_{iU} - x_{iL}) \quad j = 1, 2, ..., HMS \tag{7}$$

where *rand()* is a random number from a uniform distribution of [0,1].

(3) Improvise a new harmony from the harmony memory. Generating a new harmony x_i^{new} is called improvisation where it is based on 3 rules: memory consideration, pitch adjustment and random selection. First of all, a uniform random number r_1 is generated in the range [0, 1]. If r_1 is less than HMCR, the decision variable x_i^{new} is generated by the memory consideration; otherwise, x_i^{new} is obtained by a random selection. Then, each decision variable x_i^{new} will undergo a pitch adjustment with a probability of PAR if it is produced by the memory consideration. The pitch adjustment rule is given as follows:

$$x_i^{new} = x_i^{new} \pm r \times bw \tag{8}$$

where, r is a uniform random number between 0 and 1.

(4) Training the SVM model and fitness evaluation. The SVM model is trained with the parameters C and σ included in current harmony. The fivefold cross validation, which offers the best compromise between computational cost and reliable parameter estimates, is used to evaluate fitness. In fivefold cross validation, the training data set is randomly divided into 5 mutually exclusive subsets of approximately equal size, in which 4 subsets are used as the training set and the last subset is used as validation. The above-mentioned procedure is repeated 5 times, so that each subset is used once for validation. The fitness function is defined as the 1-$CA_{validation}$ of the fivefold cross validation method on the training data set, which is formulated in the form of Eq. (9). The solution with a bigger $CA_{validation}$ has a smaller fitness value.

$$Fitness = 1 - CA_{validation} = 1 - \frac{1}{5}\sum_{i=1}^{5}\left|\frac{y_c}{y_c + y_f}\right| \times 100\% \tag{9}$$

where, y_c and y_f represent the number of true and false classifications, respectively.

(5) Update harmony memory. After a new harmony vector x^{new} is generated, the harmony memory will be updated. If the fitness of the improvised harmony vector $x^{new} = (x_1^{new}, x_2^{new}, ..., x_N^{new})$ is better than that of the worst harmony, the worst harmony in the HM will be replaced with x^{new} and become a new member of the HM.

(6) Termination. Repeat steps 3-5 until the stopping criterion (maximum number of improvisations K) is met.

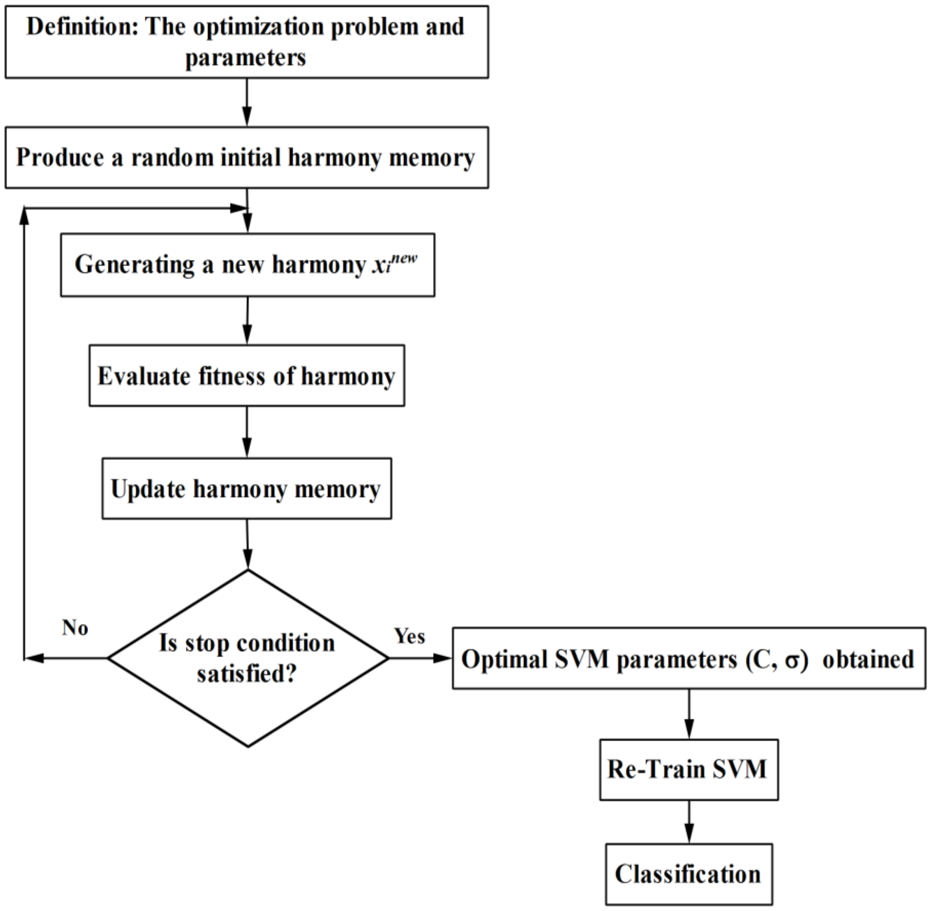


Figure 3. The process of optimizing the SVM parameters with the HS

5. SITE DESCRIPTIONS AND GEOLOGY

The tests carried out at Gotvand dam, which is located on the Karun river in the Khuzestan province, south west of Iran. This dam with 178 m height and 730 m length of embankment, regulates the water of the Karun river, also serves power generation, flood control and irrigation needs [39].

The geology of area is mainly including two formations; Bakhtiary (BK) and Aghajari (AJ). The BK formation is consisted of conglomerate, cherty limestone and inter bedded mudstones and sandstone [40]. The AJ formation contains 2 to 5 m thick layers of gray and greenish gray sandstones, inter bedded claystone, siltstone and brow reddish marlstone [39]. Also, laboratory testing was performed on rock samples from boreholes. A summary of results obtained are shown in Table 1.

Table 1: Summary results of the rock laboratory testing for Gotvand dam [41]

Formation	Rock type	UCS (MPa)	Tensil Strength (MPa)	Dry density (g/cm^3)	Porosity (%)	Young's modulus (GPa)	Wave velocity (m/s)	
							V_p	V_s
AJ	Claystone	16	1.90	2.31	19.5	2.28	1270-2800	820-2330
	Siltstone	16.1	1.95	2.30	16.4	2.6	1800-2800	1520-2280
	Sandstone	41.9	3.20	2.49	2.1	11.2	3960-4480	2560-2780
	Mudstone	25.2	2.51	2.22	18.7	4.95		
BK	Sandstone	15.6	2		12.3	2.1	2180	1530
	Conglomerate	25.8	2.8	2.48	7.5	13.6	2620-5000	1800

6. DETERMINATION OF DEFORMATION MODULUS BY PLATE LOADING TEST

The creation of EDZ due to a blasting impact and stress redistribution after excavation causes significant changes on the mechanical and physical properties and hydraulic conductivity around an underground excavation. The modulus of deformation (E) is an important parameter among other parameters that represents the behavior rock mass after excavation, which can be used for the identification and classification of the EDZ.

The plate loading test (PLT) is the most familiar in situ experiment in rock mass studying. It is generally conducted in special test galleries or underground spaces excavated by conventional drill and blast, having a span of 2 m and a height of 2.5 m [42]. In the PLT, load is directly imposed on the wall of gallery, and the resultant displacement is measured on the loading point in rock [43]. The recoverable displacement is used to evaluate the deformation modulus based on the theory of elasticity. Depending on the loading condition, the PLT can be classified into two types of flexible and rigid [44]. In this paper, the flexible PLT was adopted. An illustration of a PLT site is shown in Figure 4.

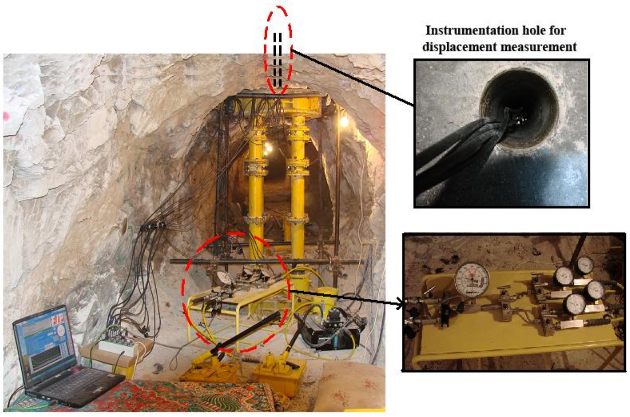


Figure 4. The set-up of PLT

The PLT was carried out in a test gallery, excavated by drill and blast, at Gotvand dam to determine deformation modulus for the identification and classification of the EDZ.

7. IDENTIFICATION AND CLASSIFICATION OF THE EDZ AND HDZ, USING THE HS-SVM MODEL

Popular methods in the SVM multi-class classification are including: ‘one-against-one’ and ‘binary tree’. The ‘binary tree’ SVM classification algorithm needs only k -1 two-class SVM classifiers for a case of k classes, while the ‘one-against-all’ SVM classification algorithm needs k two-class SVM classifiers where each one is trained with all of samples and the ‘one-against-one’ SVM classification algorithm needs $k(k -1)/2$ two-class SVM classifiers where each one is trained on data from two classes [33]. Obviously less two-class classifiers expedite the rate of training and recognition. In this paper, the ‘binary tree’ SVM classification algorithm is adapted for identification and classification of the EDZ and HDZ, using the MATLAB environment (Figure5).

The modulus of deformation for rock mass in the Gotvand dam is 5.8 GPa [45]. As the EdZ is a zone without major changes in flow and transport properties [22] and there are no negative influence on the long-term safety [10], a modulus of deformation of 5 GPa is assumed for this zone. Also, a threshold of less than 2 GPa was chosen to recognize the HDZ, which is a part of the EDZ. As shown in Figure5, the diagnostic model includes two SVM classifiers, which are used to identify the following three states: $E \leq 2$ (HDZ), $E > 5$ (EdZ) and $2 < E \leq 5$ (a part of the EDZ).

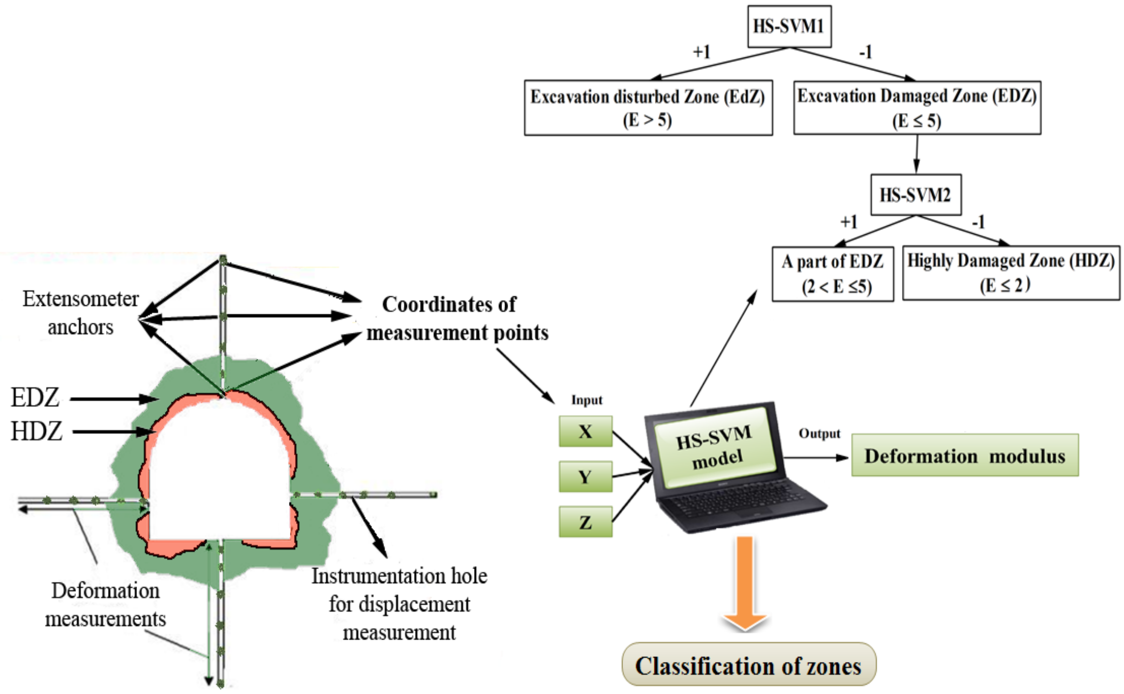


Figure 5. Diagnostic model of the HDZ, EDZ and EdZ based on the HS-SVM classifiers

In all training data sets of the three states, the HS-SVM1 is trained to separate the EdZ from the EDZ. When input of the HS-SVM1 is a sample representing the EdZ, output of the HS-SVM1 is set to +1; otherwise -1. With samples of the EDZ, the HS-SVM2 is trained to separate a part of the EDZ from the HDZ. When input of the HS-SVM2 is a sample representing a part of the EDZ, output of the HS-SVM2 is set to +1; otherwise -1. Thus, diagnostic model of the HDZ, EDZ and EdZ based on the HS-SVM classifiers is obtained, which is shown in Figure5. As it can be seen in Figure5, X, Y and Z coordinates (location of installation extensometers from the portal of test gallery that in these points, displacements and modulus of deformations are obtained) were introduced as input parameters into the HS-SVM model and deformation modulus as output.

The total data (99 data sets obtained from a test gallery in the Gotvand dam, Iran) are divided into two data sets: the training data (80 data sets) and the testing data (19 data sets), in which the training data sets are used to calculate the fitness function and train the SVM, and the testing data sets are used to examine the classification accuracy. A few samples of data sets for training and testing are presented in Tables 2 and 3.

Table 2: A few samples for training the HS-SVM model

No.	Depth of extensometer in instrumentation hole (m)	Input			Output
		X (m)	Y (m)	Z (m)	Deformation modulus (GPa)
1	0.5	6	7.75	3	3.18
2	1	6	8.25	3	6.48
3	0.4	7.65	6	9	7.75
4	1.2	8.45	6	9	14.9
5	0.4	7.65	6	27	4.3
6	0	6	7.25	9	2.11
7	0.9	6	3.85	27	9.42
8	2.3	9.55	6	3	24.95
9	0.4	7.65	6	27	4.32
10	0.5	6	4.25	9	3.33

Table 3: A few samples for testing the HS-SVM model

No.	Depth of extensometer in instrumentation hole (m)	Input			Output
		X (m)	Y (m)	Z (m)	Deformation modulus (GPa)
1	0	6	7.25	3	0.955
2	0.6	4.15	6	3	9.274
3	0.9	6	3.85	3	2.55
4	0.5	6	7.75	27	3.829
5	1.2	3.55	6	27	9.66

Both SVMs adopt RBF as their kernel function. In HS-SVM, the parameters σ, C of SVM model are optimized by HS. The related parameters C and σ for this kernel were varied in the arbitrarily fixed ranges [1, 3000] and [0, 5] so that to cover high and small regularization of the classification model, and fat as well as thin kernels, respectively. In the harmony search, there are several coefficients which their values can be adjusted to produce a better rate of convergence. Table 4 shows the coefficient values in the HS.

Table 4: Coefficient values in the HS.

Maximum number of iterations	100
Harmony memory size (HMS)	30
Number of new harmonies	10
Harmony memory consideration rate (HMCR)	0.95
Pitch adjustment rate (PAR)	0.3
Band width (bw)	bw, max=59.98 bw, min=0.1

The adjusted parameters (σ, C) with maximal classification accuracy are selected as the most appropriate parameters. Then, the optimal parameters are utilized to train the SVM model. The classification accuracies and optimal parameters of SVM classifiers estimated by the HS are given in Table 5.

Table 5: The classification accuracies and optimal parameters of SVM classifiers estimated by HS

	Optimal values of σ parameters	Optimal values of *C* parameters	Optimal classification accuracies of SVM %
HS-SVM1	3.06	1995.89	99.6
HS-SVM2	0.645	2118.93	98.4

The SVM classifiers with the best accuracies were obtained to assess the potential of creating the EDZ and HDZ around a test gallery in the Gotvand dam. For instance, the EDZ and HDZ around 6-section with different distances (Z = 3 m, Z = 5m, Z = 10 m, Z = 12 m, Z = 16 m and Z = 22 m) from the portal of the gallery were obtained, as shown in Figure 6. In these sections, the data generating was carried out, using the MATLAB environment.

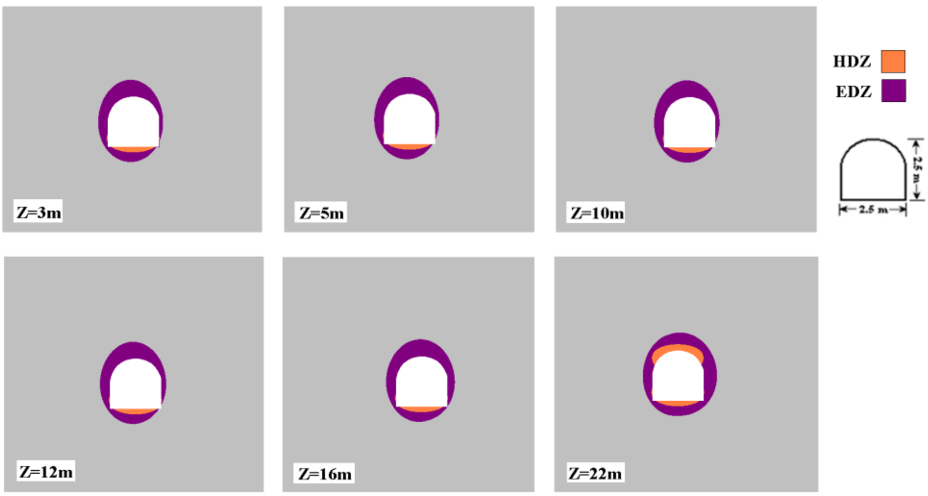


Figure 6. The EDZ and HDZ around different sections of a gallery, Gotvand dam

In Figure 6, the orange region shows the HDZ (E ≤ 2), while the violet region is the EDZ (E ≤ 5). According to the results of the HS-SVM modeling, the EDZ at the test gallery around the Gotvand dam extends approximately 0.5-1 m into the rock mass.

7. CONCLUSION

In rock mechanics engineering, the study of the EDZ and HDZ is very important in terms of the economy, stability and safety; because, these zones affect the behavior of mass rock surrounding the underground spaces, which reduces the stability and safety factor of the underground structure.

In this paper a new approach for the identification and classification of zones (EDZ and HDZ) around underground spaces was proposed and the following remarks were concluded:

- In the HS-SVM model, the HS is used to select suitable parameters for the SVM classifier, which avoids over-fitting or under-fitting of the SVM model occurring because of the improper determining of these parameters.
- Based upon the results of the HS-SVM modeling, the extent of the EDZ at the test gallery around the Gotvand dam is approximately 0.5-1 m into the rock mass.
- The HS-SVM modeling as a good tool can estimate the damage occurred due to blasting around each section of an underground excavation.

REFERENCES

1. Sato T, Kikuchi T, Sugihara K. In-situ experiments on an excavation disturbed zone induced by mechanical excavation in Neogene sedimentary rock at Tono mine, central Japan, *Eng Geol*, 2000; **56**(1–2): 97–108.
2. Sheng Q, Yue ZQ, Lee CF, Tham LG, Zhou H. Estimating the excavation disturbed zone in the permanent shiplock slopes of the Three Gorges Project, China, I*nt J Rock Mech Min Sci*, 2002; **39**(2): 165–84.
3. Saiang D. *Behaviour of blast-induced damage zone around underground excavations in hard rock mass*, Ph.D. Thesis. Lulea˚, Lulea˚University of Technology, Sweden, 2008.
4. Malmgren L, Saiang D, Töyrä J, Bodare A. The excavation disturbed zone (EDZ) at Kiirunavaara mine, Sweden-by seismic measurements, *J Appl Geophys*, 2007; **61**(1): 1–15.
5. Nicollin F, Gibert D, Bossart P, Nussbaum C, Guervilly C. Seismic tomography of the excavation damaged zone of the gallery 04 in the Mont Terri rock laboratory, *Geophys J Int*, 2008; **172**(1): 226–39.
6. Cai M, Kaiser PK, Martin CD. Quantification of rock mass damage in underground excavations from microseismic event monitoring, *Int J Rock Mech Min Sci*, 2001; 38(8): 1135–1145.
7. Suzuki K, Nakata E, Minami M, Hibino E, Tani T, Sakakibara J, et al. Estimation of the zone of excavation disturbance around tunnels, using resistivity and acoustic tomography, *Explor Geophys*, 2004; **35**(1): 62–9.

8. Kwon S, Lee CS, Cho SJ, Jeon SW, Cho WJ. An investigation of the excavation damaged zone at the KAERI underground research tunnel, *Tunn Undergr Sp Tech*, 2009; **24**(1): 1–13.
9. Bossart P, Meier PM, Moeri A, Trick T, Mayor JC. Geological and hydraulic characterisation of the excavation disturbed zone in the Opalinus clay of the Mont Terri Rock Laboratory, *Eng Geol*, 2002; **66**(1–2): 19–38.
10. Blümling P, Bernier F, Lebon P, Derek Martin C. The excavation damaged zone in clay formations time-dependent behaviour and influence on performance assessment, *Phys Chem Earth*, 2007; **32**(8–14): 588–99.
11. Saiang D, Nordlund E. Numerical analyses of the influence of blast-induced damaged rock around shallow tunnels in brittle rock, *Rock Mech Rock Eng*, 2009; **42**(3): 421–48.
12. Saiang D. Stability analysis of the blast-induced damage zone by continuum and coupled continuum–discontinuum methods, *Eng Geol*, 2010; **116**(1): 1–11.
13. Potyondy DO, Cundall PA. A bonded-particle model for rock, *Int J Rock Mech Min Sci*, 2004; **41**(8): 1329–1364.
14. Vapnik V. *The nature of statistical learning theory*, springer, 1999.
15. Cao LJ, Tay FE. Support vector machine with adaptive parameters in financial time series forecasting, *IEEE T Neural Networ*, 2003; **14**(6): 1506–1518.
16. Huang CJ, Lai WK, Luo RL, Yan YL. Application of support vector machines to bandwidth reservation in sectored cellular communications, *Eng Appl Artif Intel*, 2005; **18**(5): 585–94.
17. Ng J, Gong S. Composite support vector machines for detection of faces across views and pose estimation, *Image Vision Comput*, 2002; *20*(5): 359–68.
18. Shin KS, Lee TS, Kim HJ. An application of support vector machines in bankruptcy prediction model, *Expert Syst Appl*, 2005; **28**(1): 127–35.
19. Geem Z, Kim J, Loganathan G. Harmony search optimization: application to pipe network design, *IJMOS*, 2002; **22**(2): 125–33.
20. Bäckblom G, Martin CD. Recent experiments in hard rocks to study the excavation response: Implications for the performance of a nuclear waste geological repository, *Tunn Undergr Sp Tech*, 1999; **14**(3): 377–94.
21. Martino JB, Chandler NA. Excavation-induced damage studies at the underground research laboratory, *Int J Rock Mech Min Sci*, 2004; **41**(8): 1413–26.
22. Tsang CF, Bernier F, Davies C. Geohydromechanical processes in the Excavation Damaged Zone in crystalline rock, rock salt, and indurated and plastic clays-in the context of radioactive waste disposal, *Int J Rock Mech Min Sci*, 2005; **42**(1): 109–25.
23. Liao Y, Fang SC, LW Nuttle H. A neural network model with bounded-weights for pattern classification, *Comput Oper Res*, 2004; **31**(9): 1411–1426.
24. Muller KR, Mika S, Ratsch G, Tsuda K, Scholkopf B. An introduction to kernel-based learning algorithms, *IEEE T Neural Networ*, 2001; **12**(2): 181–201.
25. Pardo M, Sberveglieri G. Classification of electronic nose data with support vector machines, *Sens Actuators B Chem*, 2005; **107**(2): 730–7.
26. Jack L, Nandi A. Fault detection using support vector machines and artificial neural networks, augmented by genetic algorithms, *Mech Syst Signal Pr*, 2002; **16**(2): 373–90.
27. Shon T, Kim Y, Lee C, Moon J. A machine learning framework for network anomaly

detection using svm and ga, *In: Information Assurance Workshop*, 2005, pp. 176–183

28. Zhang L, B Jack L, Nandi AK. Fault detection using genetic programming, *Mech Syst Signal Pr*, 2005; **19**(2): 271–89.
29. Samanta B, Al-Balushi K, Al-Araimi S. Artificial neural networks and support vector machines with genetic algorithm for bearing fault detection, *Eng Appl Artif Intel*, 2003; **16**(7): 657–65.
30. Huang CL, Wang CJ. A GA-based feature selection and parameters optimizationfor support vector machines, *Expert Syst Appl*, 2006; **31**(2): 231–40.
31. Huang CL, Chen MC, Wang CJ. Credit scoring with a data mining approach based on support vector machines, *Expert Syst Appl*, 2007; **33**(4): 847–56.
32. Huang CL, Dun JF. A distributed PSO–SVM hybrid system with feature selection and parameter optimization, *Appl Soft Comput*, 2008; **8**(4): 1381–1391.
33. Fei Sw. Diagnostic study on arrhythmia cordis based on particle swarm optimization-based support vector machine, *Expert Syst Appl*, 2010; **37**(10): 6748–6752.
34. Ranaee V, Ebrahimzadeh A, Ghaderi R. Application of the PSO-SVM model for recognition of control chart patterns, *ISA T*, 2010; **49**(4): 577.
35. Jiang A, Wang S, Tang S. Feedback analysis of tunnel construction using a hybrid arithmetic based on Support Vector Machine and Particle Swarm Optimisation, *Automat Constr*, 2011; **20**(4): 482–89.
36. Gang R, Zhuping Z. Traffic safety forecasting method by particle swarm optimization and support vector machine, *Expert Syst Appl*, 2011; **38**(8): 10420–10424.
37. Chenglin Z, Xuebin S, Songlin S, Ting J. Fault diagnosis of sensor by chaos particle swarm optimization algorithm and support vector machine, *Expert Syst Appl*, 2011; **38**(8): 9908–9912.
38. Lin SW, Ying KC, Chen SC, Lee ZJ. Particle swarm optimization for parameter determination and feature selection of support vector machines, *Expert Syst Appl*, 2008; **35**(4): 1817–1824.
39. Moshanir, CAITEC. *Upper Gotvand hydroelectric power project*. Gotvand1997.
40. Mahab Ghodss, Coyne et Bellier. *Geology of the project area: upper Gotvand dam & HEPP*, Rev A. 2005.
41. Mahab Ghodss, Coyne et Bellier. *Geotechnical characteristics of the dam foundation*. Rev A2004.
42. Palmström A, Singh R. The deformation modulus of rock masses - comparisons between in situ tests and indirect estimates, *Tunn Undergr Sp Tech*, 2001; **16**(2): 115–31.
43. Faramarzi L, Sugawara K. Analyzing of the representative length of rock mass subjected to load by In situ loading tests to evaluation of rock mass deformation modulus, *4th Asian Rock Mechanics Symposium*, Singapore, pp. 273–281
44. Rocha M, Dasilva JN. A new method for the determination of deformability in rock masses, *International Society of Rock Mechanics, Proceedings*, 1970; **1**(1–19).
45. Bashari A, Beiki M, Talebinejad A. Estimation of deformation modulus of rock masses by using fuzzy clustering-based modeling, *Int J Rock Mech Min Sci*, 2011; **48**(8): 1224–1234.