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Troubleshooting concrete dams using modal responses and the method of least squares

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ABSTRACT

A structure may be damaged during the construction and operation thatwhich, if correct these failures can be prevented from spreading. It is necessary to first identify the location of failures in the structure. In this study, a two-step technique is used to find the location and severity of the failure of concrete dams using the modal responses and least squares method. Firstly, the failure location using an index based on modal strain energy (MSEBI) and secondly, after reducing the number of elements, failure intensity using least squares support vector machine (LS-SVM) is determined. The advantage of this approach is that in the second stage, the number of failure scenarios just as many bad elements that have been diagnosed in the first stage, is created. Secondly, the algorithm input data, difference-frequency normal and defected structures (index MDLAC) for all failure scenarios and the output of the algorithm is severity damaged by the elements of the structure. We will provide a numerical example shows the effectiveness of the proposed method has been checked that the results of this method are the ability to identify the location and severity of damage in concrete dams.
Keywords:*"Concrete dams", "answer modal"," modal strain energy", "Least squares support vector machine", "failure"*

INTRODUCTION:

The purpose of this study, the sensitivity and importance of concrete dams is identifying the location and severity of damage in these structures using modal response. In this study, a two-step procedure is used to find the location and severity of the damage in the dam. Since the dam structure was a large-scale structures can not find severity and location of damage in one step artificial intelligence methods such as support vector machine based least squares (LS-SVM). Hence, in this study, we found the location of faulty elements and secondly, can be found severity damage after reducing the number of elements. So after the modeling structure in ANSYS software Failure location found by using the index based on modal strain energy MSEBI and secondly the number of failure scenarios, only the number of elements is created that have been diagnosed damaged in the first stage. Then LS-SVM is used to determine the severity of damage. For this purpose, the input data to the algorithm is the difference frequency normal and defected structure MDLAC for all failure scenarios and the output of the algorithm is severity damage of structure elements. Then, after describing the modal strain energy index, support vector machine and its improved version are paid to describe the proposed implementation process on a concrete gravity dams.

The damage index based on modal strain energy:

Modal analysis tool for determine the natural frequencies and mode shapes of a structure. Its mathematical form as follows

$$(K - \omega_i^2 M)\varphi_i = 0;\ i = 1, \dots, ndf \quad (1)$$

In this function K and M, respectively are mass and stiffness matrices and$\omega_i$andφ_i respectively are frequency and mode formed structure vector.
is entire structure many degrees of freedom. Since mode formed vector proportional to the deformation of the vibrating structure, so the strain energy stored in each element of structure. Structure strain energy due to them deformed vector is called modal strain energy(MSE)and can be considered a valuable

parameter in trouble shooting it. Modal strain energy in three element of the mode structure can be expressed as follows:

$$mse_i^e = \frac{1}{2}\varphi_i^e K^e \varphi_i^e;\ i = 1, \dots, ndf;\ e = 1, \dots, nte \quad (2)$$

K^e is the stiffness matrix of the structure elements, φ^i is corresponding deformation node vector of element in I mode andante is the total number of elements. Modal strain energy of the mode of structure can be determined by adding the MSE of all elements below:

$$mse_i = \sum_{e=1}^{nte} mse_i^e\ ;\ i=1,\dots,ndf \quad (3)$$

For the purpose it is better to the MSE of elements into the whole MSE of structure being normal as below:

$$nmse_i^e = \frac{mse_i^e}{mse_i} \quad (4)$$

Where n mse_i^e is the normalized MSE of the element of the mode structure.

Form nth mode can be selected effective variables follows:

$$mnmse^e = \frac{\sum_{i=1}^{nm} nmse_i^e}{nm}\ ;\quad e = 1, \dots, nte \quad (5)$$

As a result of this study is to determine the effective parameter $mnmse^e$ for each normal and defective element of the structure in order to$(mnmse^e)^h$ and$(mnmse^e)^d$ shown, an effective index for estimate the presence and severity of defects in the element can be defined. This index is called here modal strain energy index (MSEBI) and it can be determined as follows:

$$MSEBI^e = \max\left[0, \frac{(mnmse^e)^d - (mnmse^e)^h}{(mnmse^e)^h}\right];\quad e = 1, \dots, nte \quad (6)$$

We should note that in real applications structural defects place is not known in advance that we can specify defective structural stiffness matrix, Thus, for the case of normal structural element stiffness matrix is used for parameter estimates $(mnmse^e)^d$.

According to equation (6) for the normal element of zero($MSEBI^e = 0$)and for the defective element index will be greater than zero($MSEBI^e$)> 0)[1].

The support vector machine (SVM)

Support Vector Machine in 1995 has been presented by Vapnik based on statistical learning theory[2]. This method is a supervised learning method for classification and regression and also one-class classification used in recent years. The main idea of support vector machine as the decision is making upper plate so that the margin of separation between the two classes to maximize the positive and negative data. More precisely, support vector machine is a separator that minimizes the risk of separate by maximizing the margin between two classes of data[3]. Suppose a data set of lengthen is given as follows:

$$(x_1, y_1), \dots, (x_n, y_n) \quad (7)$$

Tha t$x_i \in R^n$ and i,the index of the ith data input. For each input there is an output corresponding to a specific class label $y_i \in \{+1, -1\}$. In case the data are not separated linearly,quadratic optimization problem can be formulated as follows:

$$\Phi(w, b, \xi) = \frac{1}{2} w^T w + c \sum_{i=1}^{N} \xi_i \quad (8)$$

$$\text{s.t. } y_i(w^t \varphi(x_i) + b) \geq 1 - \xi_i \quad \text{for } i = 1, 2, \dots, N\ \xi_i \geq 0 \text{ for all } i$$

Where C is a constant parameter, which in this case must be determined before the problem. Parameter C make a compromise between maximizing the margin and the violation of the established classification. Function k that respects the Mercer conditions [4, 5] is the kernel function and its inner product in the feature space and cause Separation those by mapping data to greater spatial dimensions of the space. Given the KKT conditions in the Lagrangian dual form can be obtained as follows:

$$Q(a) = \sum_{i=1}^{N} a_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} a_i a_j y_i y_j K(x_I, x_j) \quad (9)$$

$$\text{s.t. } (1) \sum_{i=1}^{N} a_i y_i = 0\ ;\ (2)\ 0 \leq a_i \leq c \text{ for } i = 1, \dots, N$$

In this regard, a (a_1, ..., a_n)is an on-negative vector of Lagrange multiplier. The data that has an on-zero Lagrange multiplier, called support vector.

The least squares support vector machine (LS-SVM)

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Modification of conventional SVM formulation for working with large data sets was performed by Suykens and constrained convex optimization problem changed as follows[5]:

$$\Phi(w,b,\xi) = \frac{1}{2}w^T w + \frac{c}{2}\sum_{i=1}^{N}\xi_i^2 \quad (10)$$

$$\text{s.t.} \quad y_i(w^T\varphi(x_i)+b) \geq 1-\xi_i \ \text{ for } \ i=1,2,\dots,N \ \xi_i \geq 0 \text{ for all } i$$

Also its Lagrangian function is as follows:

$$L(w,b,\xi_i,\alpha_i) = \frac{1}{2}w^T w - \frac{C}{2}\sum_{i=1}^{N}\xi_i^2 - \sum_{i=1}^{N}\alpha_i[y_i(w^T\varphi(x_i)+b)-1+\xi_i] \quad (11)$$

In which α is the Lagrange multiplier due to same constraints from the KKT conditions can have positive and negative values. Optimal conditions derivative of the Lagrangian function is obtained as follows:

$$w = \sum_{i=1}^{N}\alpha_i y_i \varphi(x_i)\ ; \ \sum_{i=1}^{N}\alpha_i y_i = 0 \ ; \ \alpha_i = C\xi_i \ ; [y_i(w^T\varphi(x_i)+b]-1+\xi_i = 0 \quad (12)$$

The matrix form of the optimal conditions (12) is shown as follows:

$$\begin{bmatrix}\Omega & Y\\ Y^T & 0\end{bmatrix}\begin{bmatrix}\alpha\\ b\end{bmatrix} = \begin{bmatrix}0\\ 1\end{bmatrix} \quad (13)$$

In theform1, Y, Ω, respectively, have below values:

$$\Omega_{ij} = y_i y_j \varphi(x_i)^T\varphi(x_j) + c^{-1}I \ ; \ Y = (y_1,y_2,\dots,y_N)^T \ ; 1 = (1,1,\dots,1)^T \quad (14)$$

As equation (14) is determined, Ω is given a positive value. So the value of α from equation(13) is obtained as follows:

$$\alpha = \Omega^{-1}(1-bY) \quad (15)$$

By replacing(15) in the second equation in matrix form(13), the bias is determined as follows:

$$b = \frac{Y^T\Omega^{-1}1}{Y^T\Omega^{-1}Y} \quad (16)$$

DuetothespecificpositiveΩ^{-1}, Ω is defined as positive and also non-zero values of Y,Y^T Ω^{-1} Y ≠ 0 and the result is b always is calculated. A also by letting(16) in(15) are determined And classified in the dual form as follows:

$$y(x) = \text{sign}[\sum_{i=1}^{N}\alpha_i y_i K(x_i,x_j+b)] \quad (17)$$

Therefore upper plate separator by solving a set of linear equations is obtained in comparison to the problem of quadratic that it reduces the amount of computation, especially in large problems, and this is the distinguishing feature of least squares support vector machine(LS-SVM) against conventional support vector machine(SVM).

Numerical example:

To modeling of concrete gravity dams of ANSYS software was used. .The structure has 20meters high and elasticity modulus is20GPaanddensity of 2402kgper cubic meter.

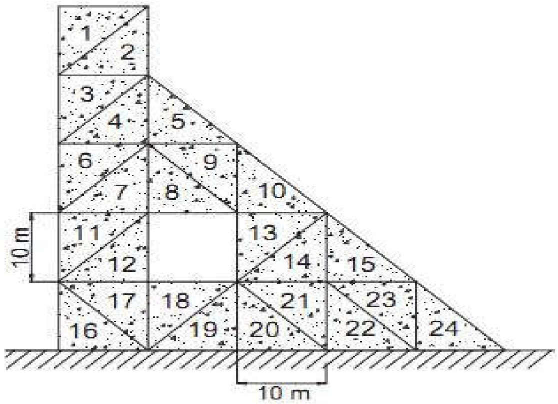

Figure (1) concrete dam

For this purpose, the structure was modeled using a21-element solid quad 42.To model the damage, elements 3, 16 by 15 and 30percent were destroyed and in order elasticity modulus was reduced compared to the normal mode. After modeling the structure 20of the first frequency and mode shapes of the structure associated with the software extracted. Then, using a code based on the frequency difference MDLAC and also difference in strain energy MSEBI the normal and faulty constructions of dam can be found damage location.

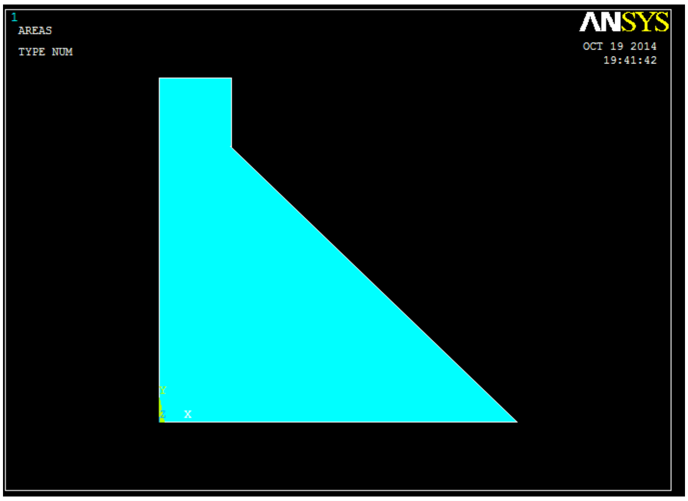

Figure 2gravitydamdesignin ANSYS software

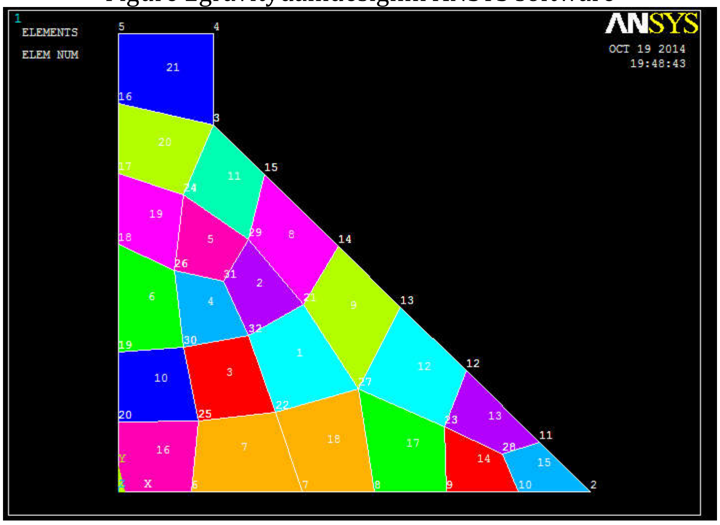

Figure 3concrete gravity dam meshing

Firstly, using modal strain energy can be found defective elements location:

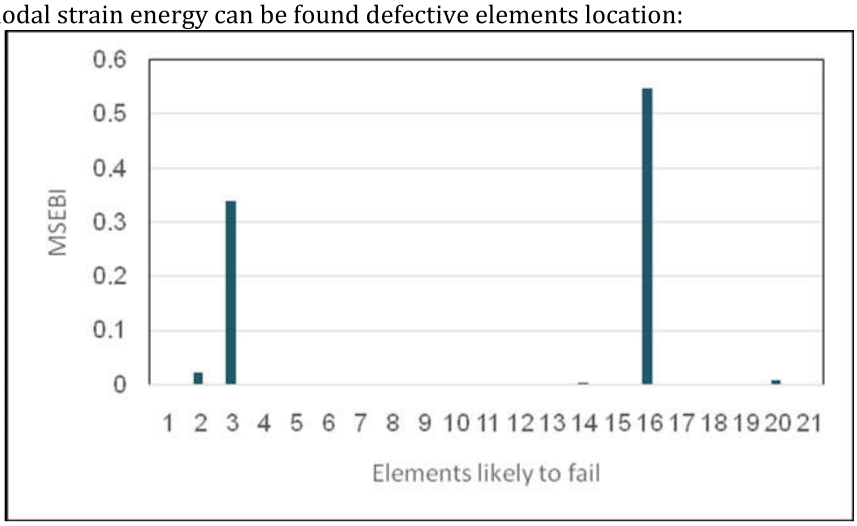

Figure 4graphs of faulty elements location.

As is clear from diagram the defective elements 16 And 3 have been correctly diagnosed defective. However, other elements have very small amounts of MESBI, although they have a very limited amount of strain energy, then only two elements that have MSEBI values higher than0.1 go to second stage.

In the second stage will be created failure scenarios. Meaning that the number of damaged modes for each of the elements is equal to 10 of cases, with step5%.Therefore amount of damaged to be considered from5% to 50%. Therefore the number of failure scenarios is equal to100 according to the following formula. LS-SVM input is frequency difference between the normal state and damaged And the output is damaged intensity for each of elements.

$$\text{Damage Scenario} = 10 \times 10 = 100 \quad (18)$$

After the formation of the data, some of the min a random manner a straining data and part of their are selected as test data. The following diagram shows algorithm out put after learning for the case in this example.

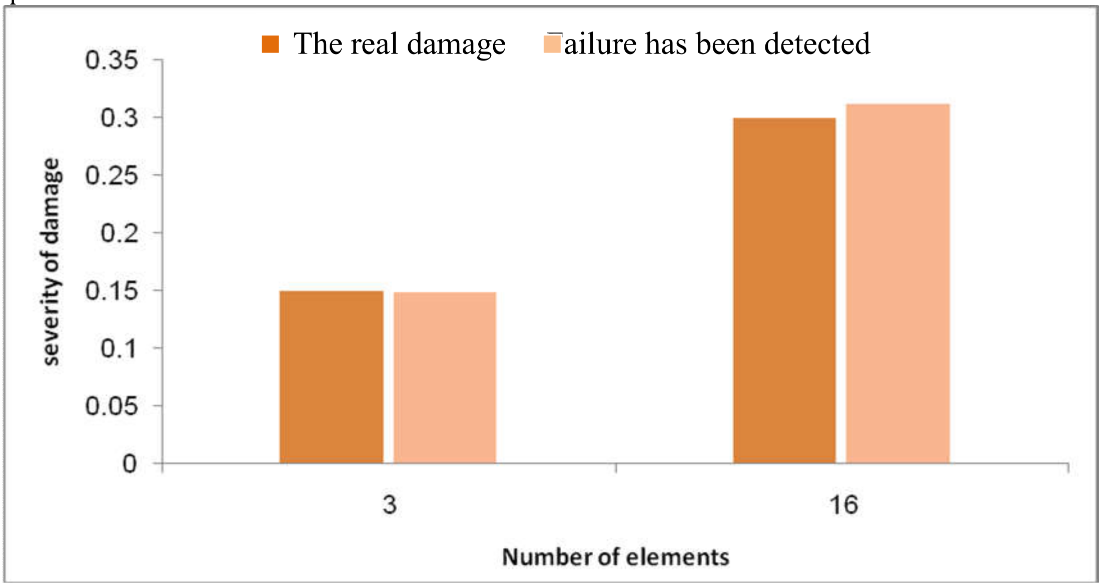

Figure 5 chart of element damage severity

As is clear from the diagram LS-SVM algorithmic detected with very good accuracy damage severity in the faulty element.

CONCLUSIONS

Numerical examples show that cause of damage in the structure, the strain energy of the damaged structure is modified and the strain energy increases. For this purpose of change the natural frequency of the structure was used as an index for trouble shooting and the results show that this method has ability to efficiently identify the location and severity of damage in structures. Further one of the advantages of least squares method is to solve set of linear equations is compared with the solution of quadratic equations that this reduces the amount of computation, especially in large problems, and this is the distinguishing feature of least squares support vector machine (LS-SVM)versus conventional support vector machine(SVM). The proposed method shows well and with good accuracy the location and severity damage to structures with multiple damage.

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