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S. S. Sandhu, R. Kanapady, K.K. Tamma, C. Kamath, and V. Kumar

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Damage Prediction and Estimation in Structural Mechanics Based on Data Mining *

S. S. Sandhu, R. Kanapady and K. K. Tamma
sandhu@me.umn.edu, ramdev@me.umn.edu and ktamma@tc.umn.edu
Dept. of Mechanical Engineering, University of Minnesota, 111 Church St. S.E, Minneapolis MN 55455

C. Kamath
kamath2@llnl.gov
Center for Applied Scientific Computing, Lawrence Livermore National Laboratory, Livermore, CA 94551

V. Kumar
kumar@cs.umn.edu
Dept. of Computer Science and Engineering, University of Minnesota, 200 Union Street S.E, Minneapolis MN 55455

ABSTRACT

Damage in a material includes localized softening or cracks in a structural component due to high operational loads, or the presence of flaws in a structure due to various manufacturing processes. Methods that identify the presence, the location and the severity of damage in the structure are useful for non-destructive evaluation procedures that are typically employed in agile manufacturing and rapid prototyping systems. The current state-of-the art techniques for these inverse problems are computationally intensive or ill conditioned when insufficient data exists. Early work by a number of researchers has shown that data mining techniques can provide a potential solution to this problem. In this paper, we investigate the use of data mining techniques for predicting failure in a variety of 2D and 3D structures using artificial neural networks (ANNs) and decision trees. This work shows that if the correct features are chosen to build the model, and the model is trained on an adequate amount of data, the model can then correctly classify the failure event as well as predict location and severity of the damage in these structure.

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1. INTRODUCTION

Damage in a material includes localized softening or cracks in a structural component due to high operational loads, or the presence of flaws in a structure due to various manufacturing processes. Methods that identify the presence, location and the severity of damage in the structure are useful for non-destructive evaluation procedures that are typically employed in agile manufacturing and rapid prototyping systems. In addition, these techniques will be critical to reliable prediction of damage to bridges, skyscrapers and structures deployed in space.

Damage detection involves three stages of characterization. First, whether the damage has taken place in the structure (recognition); second, where the damage has taken place in the structure (location); and finally, the severity of the damage in the structure (quantification). Structural damage results in changes in structural responses such as static displacements and dynamic properties such as natural frequency, and the mode shapes of the structure. Although rigorous damage models exist, in this work we focus on the structural damage that is assumed to be associated with structural stiffness as a reduction in Young's modulus (E) [1].

A practical damage assessment methodology must be capable of predicting structural stiffness as a function of changes in structural response and dynamic properties [2]. Standard analytical techniques employ mathematical models to approximate the relationships between specific damage conditions and changes in the structural response or dynamic properties. Such relationships can be computed by solving a class of so called inverse problems [3, 4]. The current state-of-the art techniques for these inverse problems are computationally intensive or ill conditioned when insufficient data exists.

Early work by a number of researchers [1, 2, 5, 6, 7] has shown that data mining techniques can provide a potential solution to this problem. These efforts have focussed on employing ANNs to predict damage using static displacements and dynamic properties. However, these studies only considered small scale plane structures in two dimension. Furthermore technical details related to selection of features, training and testing data sets etc, were not investigated in detail. In this paper, we investigate the use of data mining techniques for predicting failure in a variety of two dimensional (2D) and three dimensional (3D) structures using artificial neural networks (ANNs) and decision trees. ANNs approach is attractive in that it can learn complex, highly nonlinear relationships, and can be used to solve inverse problem. On the other hand decision tree models are easy to understand and have the potential to discover useful rules. This work shows that if the correct features are chosen to build the model, and the model is trained on an adequate amount of data, these model can correctly predict the location and severity of the damage in these structure.

This paper is organized as follows. In Section 2, the problem statement and generation of the data to build data mining models is discussed. In Section 3, the data mining models using static displacements are built and evaluated. In section 4, dynamic properties of structures are used to build and evaluate data mining models. Section 5, presents conclusion and suggestion for future work on this topic are discussed.

2. PRELIMINARIES

2.1 Problem statement and description of data mining models used

The goal is to construct data mining models that can predict the Young's modulus (E) of the elements in the structure as a function of static displacements and dynamic properties.

We use ANNs developed by Rumelhart and McCelland [8] and, decision tree algorithms based on the work of Ross Quinlan (1993) to build predictive models for Young's modulus. Finding a suitable architecture of ANN for the problem is non trivial. All the ANN models built in this study have two hidden layers each employing roughly 20 nodes each. In this study, decision tree models are build using the algorithm provided in Clementine software[1], and ANN models are build using Matlab's ANN toolbox[2].

2.2 Generating the data

To build the right data mining model it is important that useful features are considered. The selected features should possess the property of correctly identifying damage states and should capture the physics of the problem at hand. The data is generated by using a finite element analysis code. The data layout is shown in Table 1 where $\mathbf{f} = \{f_1, \dots, f_n\}$ is the feature set and $\mathbf{E} = \{E_1, \dots, E_n\}$ represents the target variables where each record in the table pertains to a failure state. Each failure state is simulated by failing either one (single element failure) or more elements (multiple element failure) in the structure, in steps (e.g. failing each element by reducing **E** from the base value of E to E' in steps of ϵE where ϵ is a small fraction). Such simulations

[1]©1999 SPSS Inc., Version 5.0.1.

[2]©1984-2000 The MathWorks, Inc. Version 6.0.0.88 Release 12.

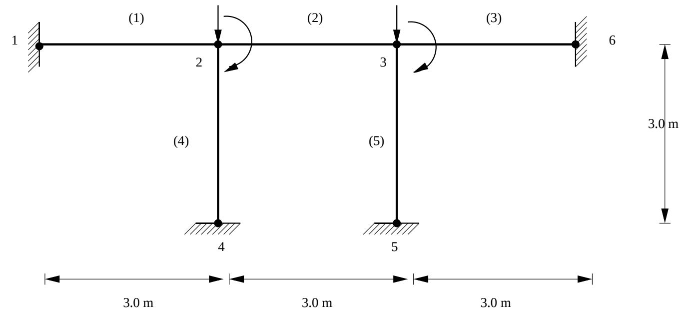


Figure 1: Plane frame structure discretized using beam elements.

give the structural response such as the static displacements (at the nodes) and dynamic properties such as the natural frequencies of the structure. This data can then be used directly to train and test the data mining algorithms. New features can be derived from these raw features. In some cases, they lead to a better predictive model.

	Features				Target variable			
S.No	f_1	f_2	...	f_n	E_1	E_2	...	E_n
1	72.833	151.67	...	213.45	0.5E	E	...	E
2	73.45	152.56	...	213.65	0.6E	E	...	E
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
500	74.01	153.01	...	214.21	E	E	...	E

Table 1: A typical input to the data mining model.

3. BUILDING DATA MINING MODELS USING STATIC DISPLACEMENTS OF STRUCTURE AS FEATURES

In this section, data mining models are developed by considering the static displacements at the nodes of the structure as features. Various examples with increasing complexity are considered to study the performance of data mining techniques.

2-D Structure – plane frame: The first structure used to build the data mining model is shown in the Fig. 1. It is a plane frame studied in [5] with the loads as shown. The nodes 1, 4, 5 and 6 are fixed and the nodes 2 and 3 are subjected to loads. During the generation of the data the loads are kept constant. Absolute static displacements namely $|u_2|$, $|v_2|$, $|\theta_{y2}|$, $|u_3|$, $|v_3|$, $|\theta_{y3}|$ (instead of raw data of displacements at nodes) of the nodes 2 and 3 were selected as the features. It was seen that selecting the absolute value of the nodal displacement leads to a better model, because changes in stiffness influence the magnitude of the displacements and not their sign.

The testing and training data set of 500 damaged states is generated by failing each element at a time. The value of E is varied from 0.01E to 0.99E in steps of 0.01E. The ANN is built by training it on a random sample of 60% of this data. The results for ANN are shown in Table 2. For this simple problem the models built by ANN are accurate, as the features considered are enough to accurately predict the target variable. A plot of the predicted value of E versus actual value of E for some typical element is shown in Fig. 2. Figure 2 shows an almost linear correlation between the predicted and actual E. From this, it is evident that the neural network can effectively predict the value of Young's modulus, and consequently the damage for this simple structure.

	E_1	E_2	E_3	E_4	E_5
e_r (%E)	0.032	0.04	0.082	0.076	0.026
σ (%E)	0.20	0.22	0.39	0.50	0.18
r	0.9999	0.9999	0.9998	0.9998	0.9999

Table 2: Result of testing ANN with absolute value of displacement as features for plane frame shown in Fig. 1,where e_r = mean relative error, σ = standard deviation, r = linear correlation.

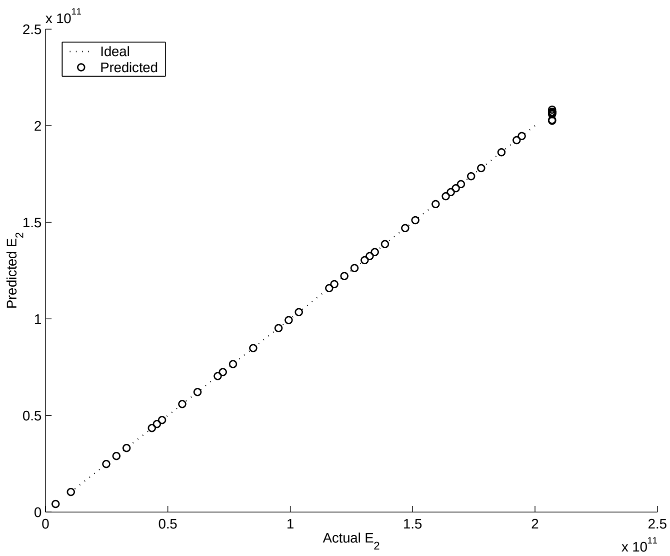


Figure 2: Comparison between ideal and actual E for typical element 2 for plane frame shown in Fig. 1.

To employ the decision tree algorithm the target variable E needs to be discretized. Hence in this case the value E was restricted to : i) 0 - severely damaged, ii) 1 - moderately damaged, and iii) 2 - undamaged. The data for training and testing the decision tree model is generated in exactly the same manner as that for the ANN. The decision tree is trained on 60% of the data generated and tested on the entire data. The result obtained on testing the decision tree is shown in the form of coincidence matrix (which shows the number of damage states that have been classified correctly and incorrectly) in Table 3. Since the coincidence matrix is predominantly diagonal, the model build by using decision tree is highly accurate.

3-D Structure – electric transmission tower: The second structure we consider is a 3-D electric transmission tower. This structure shown in Fig. 3, consists of beam elements oriented in 3-D space. The transmission tower consists of 10 nodes out of which the representative transmission

		Predicted E's					
		E_2			E_5		
		0	1	2	0	1	2
Actual E's	0	72	0	0	72	0	0
	1	0	19	0	0	16	3
	2	0	0	409	0	0	409

Table 3: Coincidence matrix with absolute value of displacement as features for plane frame shown in Fig. 1.

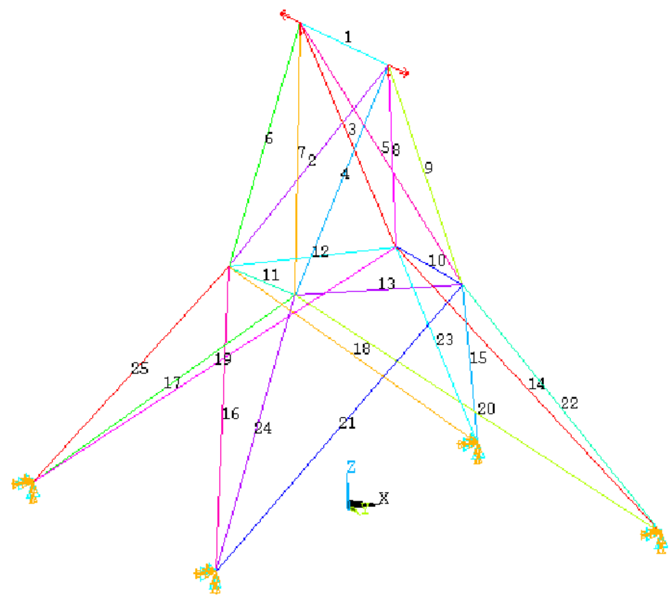


Figure 3: Three dimensional electric transmission tower discretized using beam elements.

cable loading is applied at nodes 3 and 4. The nodes 7, 8, 9 and 10 are fixed to the ground. In this case, unlike the case of the plane frame, each node and element has displacements in all three direction (u, v, w), together with bending about two axes (θ_y, θ_z) and torsion about the axis of the beam (ϕ_x). These are commonly referred to as the degrees of freedom at any point in the structure. Due to the complexity of the structure, the problem is non trivial. To develop an adequate data mining model, a significantly large number of damage states are required. The study is conducted with two different sets of features. In one set of features, the absolute value of the displacements at the nodes is used. Hence there exist 36 features for each damage state. Another set of features are defined as follows. For any element e defined by nodes i and j, the element displacement measures are defined as

$$d_e = \sqrt{(u_i - u_j)^2 + (v_i - v_j)^2 + (w_i - w_j)^2} \quad (1)$$

$$\theta_{e1} = |\theta_{yi} - \theta_{yj}| \quad (2)$$

$$\theta_{e2} = |\theta_{zi} - \theta_{zj}| \quad (3)$$

$$\phi_e = |\phi_{xi} - \phi_{xj}| \quad (4)$$

where d_e is a measure of the element translation, θ_{e1} and θ_{e2} are measure of element bending and ϕ_e is a measure of element torsional displacement. Hence, there are a total of 100 features in this case.

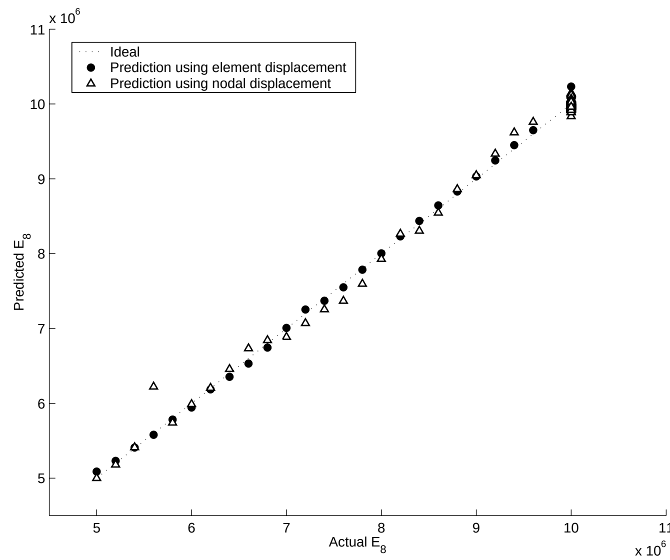


Figure 4: Comparison between ideal and actual E for typical element 8 for electric transmission tower shown in Fig. 3.

The testing and training data are generated with each element of the structure being damaged by reducing the value of E to 0.5E in steps of 0.02E leading to 600 damage states. Both ANNs and decision trees are trained using 70% of the total generated damage states. Figure 4 shows the comparison between the test results of the model using displacement of the nodes and the model using element displacement measure as features. It is evident from the figure that the model using the element displacement measure features (Eqs. 1 – 4) is more accurate.

	Predicted E's						
		E_1			E_4		
		0	1	2	0	1	2
Actual E's	0	13	0	0	0	0	13
	1	0	9	1	0	0	10
	2	7	0	570	0	0	577

Table 4: Some typical coincidence matrices with absolute displacement of nodes as features for transmission tower shown in Fig. 3.

	Predicted E's						
		E_1			E_4		
		0	1	2	0	1	2
Actual E's	0	13	0	0	13	0	0
	1	0	10	0	1	9	0
	2	0	0	577	0	0	577

Table 5: Some typical coincidence matrices with elemental displacement measures as features for transmission tower shown in Fig. 3.

Tables 4 and 5 show the results for decision trees with absolute nodal displacement and element displacement measure features respectively. Again, it can be clearly seen that the element displacement measure prove to be better features for decision tree models. Unlike neural networks, the models developed by decision tree can be readily understood and interesting rules can be found. For example, a rule generated in this case is given by

if $\theta_{12} \leq 0.185$ then
    if $\theta_{10} \leq 0.09$ then
        if $\theta_7 \leq 0.545$ then $E_3 = 2$
        else $E_3 = 1$
    else $E_3 = 2$
else if $\phi_3 \leq 0.083$ $E_3 = 2$
else $E_3 = 0$

This rule says that the failure of element 3 depends on the displacement of elements 7, 10 and 12 which are connected to element 3 (Ref. Fig. 3). Such interesting rules not commonly known in the traditional analysis community can be discovered which can be potentially useful to a structural designer.

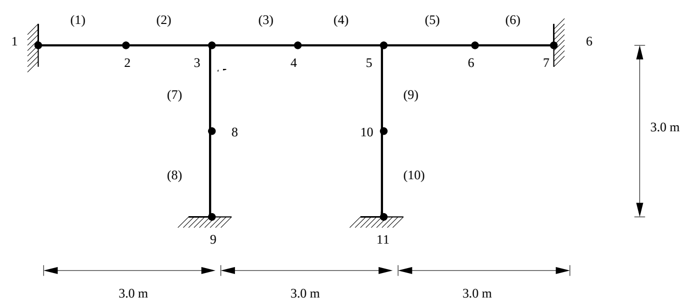


Figure 5: Plane frame discretized using beam elements.

Static displacements with varying loads: In the cases considered previously the data mining models were built using constant loading. But many structures are subject to variable loading (when the loads the structure is subjected to are continuously changing) and so an effective model should be able to correctly predict damage in this case. Although the static displacement features are not load independent, in this section their performance is studied when they are used to build a model for predicting failure under variable loading conditions. The plane frame structure in Fig. 5 is used to build the model. The feature set consists of features which correspond to the location and magnitude of the loads in additional to the static displacements of nodes 2 and 3. Three different loading conditions are considered. First, node 2 and 6 are loaded. Next, node 3 and 5 are loaded. Finally, node 8 and 10 are loaded.

The training data is generated by failing each element in the structure by reducing its Young's modulus from 1.0E to 0.5E in steps of 0.1E. The loads in each of the three loading conditions considered are varied from 500N to 2500N in steps of 500N. The testing data is generated by failing each element in the structure by reducing its value of E from 0.95E to 0.45E in steps of 0.1E. The loads in each of the three loading conditions considered are varied from 250N to 2250N. This leads to 2250 failure states, each for testing and training the ANN. The test results are shown

	E_1	E_5	E_7	E_9
e_r (%E)	1.35	1.22	1.12	0.95
σ (%E)	2.06	2.24	1.90	1.76
r	0.98	0.98	0.98	0.99

Table 6: Result of testing ANN when a variation in loading is considered for plane frame shown in Fig. 5.

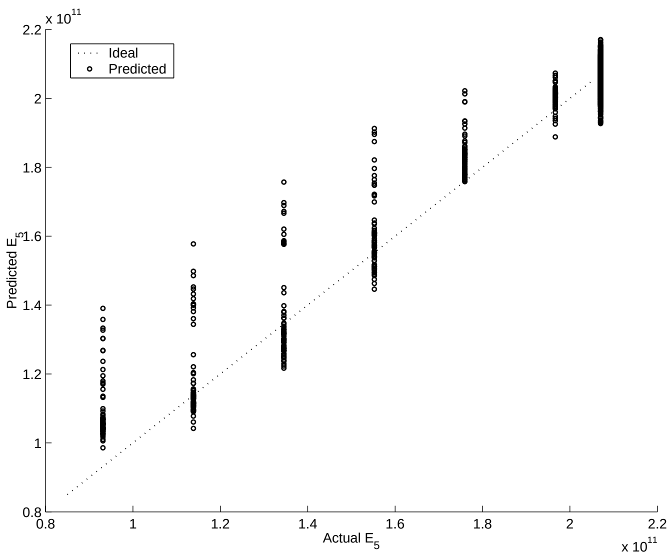


Figure 6: Comparison between ideal and actual E for typical element 5, when variation in the load is considered for plane frame shown in Fig. 5.

in Table 6. The plots of the predicted and actual E for a typical element 5, is shown in Fig. 6. From the results it can be seen that predicting capability of the model using static displacement reduces when the loads are varying, because two different loads corresponding to different failure states can produce the same response. Further investigations are necessary to rectify this situation.

Failure of multiple elements: In the previous examples, the model is trained and tested to predict damage with only one element failure in the structure. This seems relevant because failure in the structure generally starts from one element and then spreads to other elements. Here the case when multiple elements of the structure have failed is discussed. For predicting damage in multiple elements of the structure, the plane frame structure used previously in Fig. 1 is employed. The set of features are again the displacement coordinates of nodes 2 and 3.

The data used for training is generated by reducing the Young's modulus of each of the elements simultaneously from E to 0.5E in steps of 0.1E. This results in $6^5 - 1 = 7775$ failure states and one undamaged state. After the data is generated both the ANN and the decision tree are used to build models for predicting the damage in the structure. For ANN 5% (395 failure states) of this generated data is randomly sampled for training. Testing data of 1000 failure states is generated by failing each element and choosing its E randomly. The results for the ANN are shown in Table 7.

	E_1	E_2	E_3	E_4	E_5
e_r (%E)	0.032	0.046	0.057	0.050	0.028
σ (%E)	0.040	0.063	0.074	0.064	0.037
r	0.9999	0.9999	0.9999	0.9999	0.9999

Table 7: Result of testing ANN when multiple elements are failed for plane frame shown in Fig. 1.

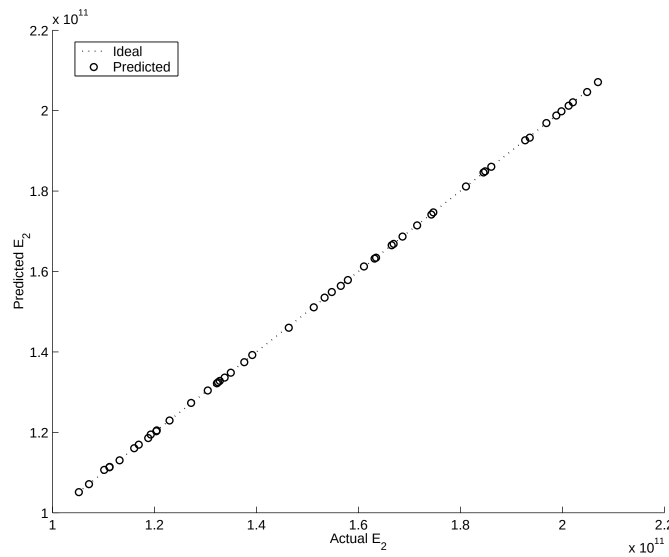


Figure 7: Comparison between ideal and actual E for typical element 2, when multiple elements of structure fail for plane frame shown in Fig. 1.

The plots of the predicted E versus actual E for a typical element 2, is shown in Fig. 7. It is evident that the correlation between them is almost linear. Hence, static displacements, prove to be effective features in building an ANN model to predict failure in multiple elements. In the case of decision tree the coincidence matrix shown in Table 8, is predominantly diagonal.

		Predicted E's					
		E_2			E_4		
		0	1	2	0	1	2
Actual E's	0	3771	116	0	3588	298	1
	1	97	2365	130	282	2016	294
	2	0	145	1151	2	416	878

Table 8: Some typical coincidence matrices for the case when multiple elements of the structure are failed for plane frame shown in Fig. 1.

4. BUILDING DATA MINING MODELS USING DYNAMIC PROPERTIES OF STRUCTURE AS FEATURES

Dynamic properties of the structure as features provides an alternative approach for predicting damage. Its advantages over using static displacements are:-

1. While different loads produce different static displacements, the dynamic properties of the structure are essentially load independent. For example, dynamic properties of the structure include natural frequencies and mode shapes.

2. In the case of static displacements, different components of the displacement at each node are used as features, which result in a large number of features for larger finite element discretizations. On the other hand if dynamic properties like natural frequency are used, then features in the form of only the lowest 'n' natural frequencies can be used resulting in a reduction of the number of features.

The natural frequency and the mode shape of the structure are obtained by solving the eigenvalue problem:

$$[-{\omega_i}^2\mathbf{M} + \mathbf{K}]\Phi_i = 0 \qquad (5)$$

where $\mathbf{M}$ and $\mathbf{K}$ are mass matrix and stiffness matrix, of the structure respectively, and ω_i is the natural frequency corresponding to the mode shape Φ_i. Damping in the structure has been neglected in this study. Structural damage results in changes in dynamic properties. The prediction of damage in the structure can be achieved if the model is taught to recognize the changes in the frequencies and the mode shapes with the failure of specific members in the structure. To train the ANN, the elements of the structure are failed one at a time by reducing their modulus of elasticity. For this failure state the natural frequencies and mode shapes are obtained by solving the eigenvalue problem in Eq. 5.

Natural frequency: 2-D Structure – three span bridge:

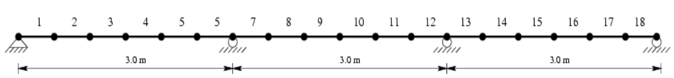


Figure 8: Three span bridge structure modeled using beam elements.

The structure used for this study is a three-span, equal length continuous beam, with constant properties that was studied in [5]. This structure is shown in Fig. 8. The beam is divided into 18 beam elements, with 6 equal length elements in each span. This structure is unsymmetric as regards to the boundary conditions. It is fixed at one end and simply supported at the other. The training data is generated by reducing the value of E from 1.0E to 0.5E in steps of 0.05E. The testing data is generated by reducing the value of E from 0.975E to 0.525E in steps of 0.05E. This results in the training and testing data of 181 and 180 records respectively.

The lowest 'n' natural frequencies of the structure $(\omega_1, \omega_2 \ldots \omega_n)$ are employed as features to predict damage. The study is conducted with a varying number of first 'n' natural frequencies. For the bridge structure studied here, the first 4 natural frequencies are adequate to build a fairly accurate predictive model. However, considering additional natural frequencies improved the accuracy of the model upto first nine natural frequencies. Further increase in the number of natural frequencies leads to a saturation and a slight deterioration in the model's performance. Table 9 and Fig. 9 shows the results for the model with lowest 9 natural frequencies.

	E_1	E_4	E_{10}	E_{14}	E_{17}
e_r (%E)	0.06	0.09	0.09	0.08	0.09
σ (%E)	0.106	0.13	0.17	0.12	0.15
r	0.999	0.999	0.999	0.999	0.999

Table 9: Result of testing ANN when natural frequencies are used as features for three span bridge shown in Fig. 8.

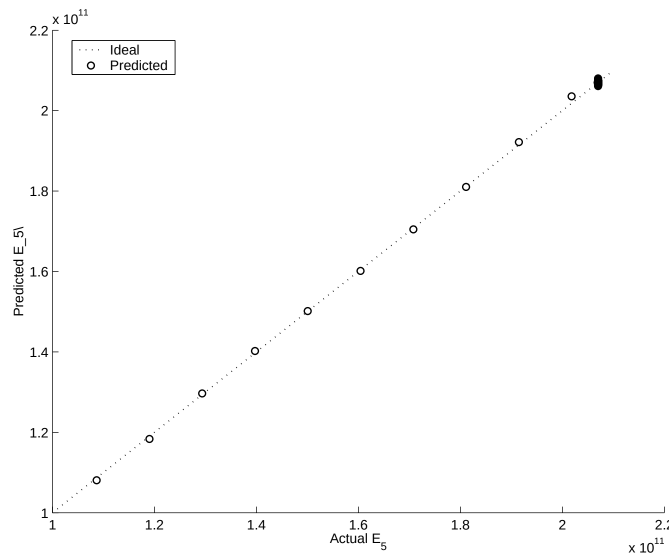
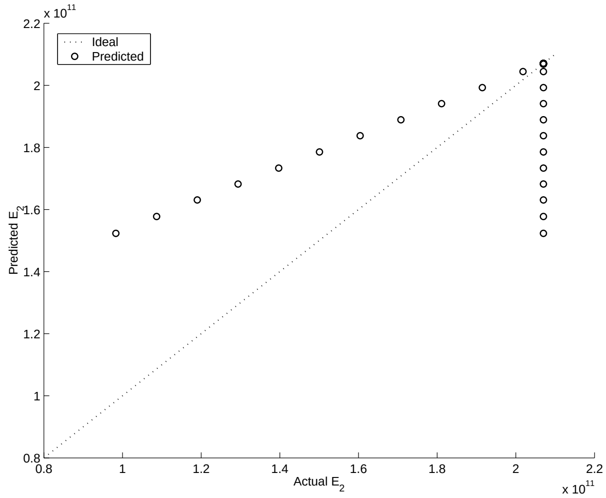
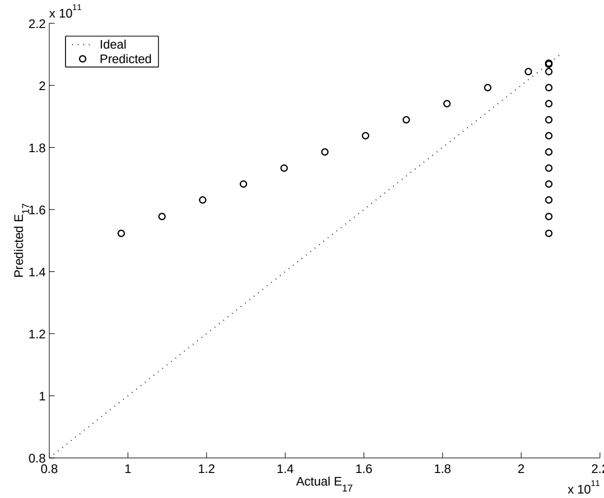


Figure 9: Comparison between predicted ideal and actual E when natural frequencies are used as feature for unsymmetric structure shown in Fig. 8.

Next, the structure in Fig. 8 is modified so that it is simply supported at both ends, to study the suitability of using natural frequency as features in case of structures exhibiting symmetry. The testing and training data is generated in the same manner as in the unsymmetric case. In Fig. 10, the results of testing the ANN for two symmetrically equivalent elements, element 2 and 17 is shown. In Fig. 10, the cases in which element 2 has not failed but has been predicted to have failed, corresponds to failure states when element 17 has failed and vice-versa. The same is the case for the other symmetrically equivalent elements. This is due to the fact that natural frequency is a global feature and, the change in the natural frequencies is the same, when either one of the symmetric elements is failed . The ANN has no reason



(a) Element 2



(b) Element 17

Figure 10: Comparison between predicted ideal and actual E when natural frequencies are used as feature for symmetric structure.

to favor the prediction of the failure of one element over the other. In order to keep the mean squared error, which is the performance criteria used to train the ANN to a minimum, the model predicts that both the elements have failed. The predicted value of the Young's modulus in this case is higher than the actual value of the failure, in order to keep the mean squared error a minimum. Thus, when a structure exhibits symmetry, using natural frequencies alone as the features is not sufficient and other dynamic features need to be considered or the structure may have to be modeled differently using symmetry considerations.

3-D Structure – electric transmission tower: Natural frequencies are used as features to predict damage in the structure shown in Fig. 3. The symmetry of the structure is disturbed by changing the cross-sectional area of the symmetric elements. The training data is generated by reducing the value of E from 1.0E to 0.5E in steps of 0.05E, generating a total of 251 records. The testing data set of 500 records, is generated by failing each element by an arbitrary amount. The first 12 natural frequencies were considered while building the model. The results of testing the ANN are shown in Table 10 and Fig. 11. The results show that the model is accurate in predicting the location and severity of the damage. Natural frequencies prove to be good features for predicting single element failure in an unsymmetric structure.

	E_1	E_4	E_{10}	E_{14}	E_{19}	E_{25}
e_r (%E)	0.13	0.17	0.11	0.15	0.15	0.20
σ (%E)	0.16	0.26	0.15	0.20	0.19	0.28
r	0.999	0.998	0.999	0.999	0.999	0.998

Table 10: Result of testing ANN when natural frequencies are used as features for transmission tower shown in Fig. 3.

5. CONCLUDING REMARKS

This paper presented data mining models to predict the failure in the structure as a function of static displacements and dynamic properties. Damage was simulated by reduction in the values of Young's modulus of the elements in the structure. The prediction of the data mining technique greatly depends on the features chosen. A more meaningful attribute produces better results. Hence the data from the finite element analysis of the structure should be suitably preprocessed so that the raw data is converted into features that have a closer relationship with the target function. While using static displacements, new features such as absolute nodal displacements and elemental displacement measures were used to generate models for predicting failure. These features proved to be better than nodal displacements.

Performance results of developed ANN models are significantly better when compared to other relevant results published in the literature for 2D structures [5, 1, 6, 7]. Furthermore effective ANN models are developed to predict damages in 3D structures with excellent performance results. Although ANNs are effective in detecting damage in the structure, the developed model can not be interpreted easily. Decision trees have the added benefit of generating rules that can be manually interpreted as illustrated in the case of transmission tower. Such rules may not be commonly known in the traditional analysis community and can be potentially useful to a structural designer.

The development of predictive model that can correctly predict the location and severity of damage in large complex structures can be a considerable challenge. For the case with variable loading and static displacements as features, the

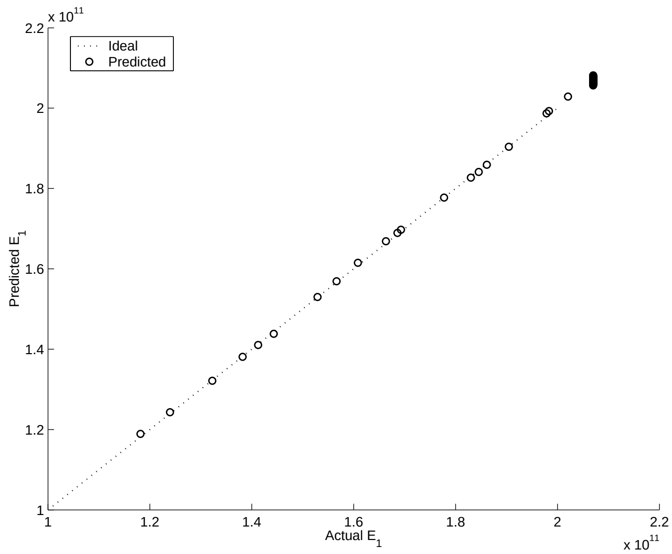


Figure 11: Comparison between predicted ideal and actual E for element 1 when natural frequencies are used as feature for electric transmission tower shown in Fig. 3.

models developed are not sufficiently accurate. Further work needs to be done to preprocess static displacements and extract features which will result in more accurate data mining models. Natural frequencies prove to be good features when load independent models are to be built. However, for complex structures, the values of natural frequencies are close to each other. This can cause the close natural frequencies to be mistaken for one another. To prevent this, MAC numbers (modal assurance criteria) can be used to distinguish such close frequencies, where MAC numbers are scalars that can distinguish two mode shapes from one another. Increased complexity of the structure would also cause the number of target variables (E), to increase. To handle this situation sub-structuring may need to be investigated.

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University of California
Lawrence Livermore National Laboratory
Technical Information Department
Livermore, CA 94551