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ORIGINAL ARTICLE

An efficient approach for damage identification based on improved machine learning using PSO-SVM

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Abstract
Structural health monitoring (SHM) and Non-destructive Damage Identification (NDI) using responses of structures under dynamic excitation have an imperative role in the engineering application to make the structures safe. Interpretations of structural responses known as inverse problems are emerging topics with a large body of works in the literature. They have been widely solved with Machine Learning (ML) techniques such as Artificial Neural Network (ANN), Deep Neural Network (DNN), Adaptive Network-based Fuzzy Inference System (ANFIS), and Support Vector Machine (SVM). Nonetheless, these approaches can precisely predict the inverse problems of civil structures (e.g., truss or frame systems) with low damage levels, which have to wait until the structures reach certain damage or deteriorate level. The issue is related to the fact that most of the real structures have very low damage levels during their routine maintenances and usually be neglected due to limitations of the current techniques. This paper proposes a combination of Particle Swarm Optimization and Support Vector Machine (PSO-SVM) for damage identifications. The proposed approach is inspired by the effective searching capability of PSO, which can eliminate the redundant input parameters and robust SVM technique to classify damage locations effectively. In other words, natural frequencies and mode shapes extracted from the numerical examples of truss and frame structures are used as input parameters in which the redundant parameters might lead to reduction of the accuracy in the predicting models. The proposed PSO-SVM shows superior accuracy prediction in both damage locations and damage levels compared to the other ML models. It also substantially outperforms other ML models through validated cases of low damage levels.

Keywords Damage identifications · Truss structure · 3D frame structure · ANN · DNN · ANFIS · SVM-PSO

1 Introduction

SHM or NDI has become popular due to the increasing need to effectively detect various civil structures' damage levels in many countries where numerous services are constantly checked to ensure safety. The inverse problems which employ structural responses under dynamic excitation to back evaluate the structure's properties are the most researching topic due to the recent developments in computer sciences and data acquisition. In other words,

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a reduction of an element's stiffness can lead to different dynamic responses of vibrations, natural frequencies, and mode shapes. Based on these measured dynamic responses, one can predict the damage levels of structures based on a certain computational method. Various computational methods including Model Updating (MU), SVM, ANFIS, ANN, DNN and combination with Optimization Methods such as PSO, Genetic Algorithm (GA), Jaya Algorithm (JA), Teaching–Learning-Based Optimization Algorithm (TLB), Cuckoo Search Algorithm (CS) have been employed for these inverse problems [1–28]. Several computational methods, especially ML models, are widely applied for damage detections of the inverse problems such as ANN, DNN, ANFIS, and SVM. The ANN structure comprises several connected mathematical equations that are similar to the biological neural systems of the human organism. The advantages of ANN are the self-studied or trained abilities that can learn any sophisticated engineering solutions. Mehrjoo et al. [22] employed a shallow neural network (ANN with single hidden layers) and selected the number of neurons by trial and error strategy to identify the damaged joints of bridges structures based on the input parameters frequencies and mode shapes. Recently [29–32], DNN model (an extending number of hidden layers of ANN model) has demonstrated more efficiency than the classical one hidden layer network in many applications such as damage detections, fractures energy predictions, and optimization of structure design. The extending number of hidden layers in DNN can considerably improve performance and make the DNN model more appropriate with complex problems [29–32]. Furthermore, ANFIS with hybrid learning algorithm between ANN and Fuzzy Inference System also perform better than ANN in structural damage identification [33, 34]. Meanwhile, SVM is an algorithm which can classify input data by constructing hyperplanes. Those hyperplanes could separate the solution spaces into several subspaces with maximizing the margins of class boundaries. SVM is also an effective ML model for damage detection [35, 36]. However, none of the above methods are suitable for inverse problems with low damage intensities.

It is noted that the low damage intensity problems can be difficult for ML models to identify as the dynamic responses of the damaged structures are similar to those from the undamaged cases and also similar to each other. In other words, the frequencies and mode shapes generated from damaged structures are not much different and similar to the undamaged case. These issues cause many noises and redundant input parameters, impeding the prediction by current ML models. In this paper, we propose a combination of PSO-SVN to overcome the problem with low damage levels. PSO is a robust and effective algorithm that reflects a flock of birds moving and finding their foods [37]. Therefore, PSO can be used to search input parameters and reduce the noise or redundant input parameters. The SVM, a useful ML model, can be employed to determine damage locations and damage levels.

Figure 1 illustrates the general concept of application different ML models for damage identifications including ANN, DNN, ANFIS and the proposed method of PSO-SVM, The natural frequencies and mode shapes are generated from FEM and involved as an input. Moreover, the damage is simulated based on a reduction in stiffness and used as output. A proposed scheme with reducing element stiffness less than 30% and at each element per times is given to produce input parameters of low damage levels. The accuracy of predicted results of damaged elements and damage levels is verified, and the PSO-SVM shows superiority in comparison with other ML models.

2 General machine learning models

2.1 Support vector machine (SVM)

There was extensive research by applying SVM for the inverse problems such as [35, 36] using SVM for Dam, aluminum beam, and steel pile. Several Kernel functions were introduced to nonlinear map the dataset into a high-dimensional feature space. SVM can effectively improve performance and extend applications in numerous nonlinear classification and regression problems by applying the Kernel function. The basic mathematical structure of SVM is derived from the hyperplane equation or classification model function:

$$f(x) = w \cdot x - b, \tag{1}$$

where x is the input vector, w is weight vector and b is scalar threshold.

Assuming the dataset for SVM is $\{x_i, y_i\}_{i=1}^{i=n}$, where x_i is the input vector, y_i is the target vector and n is the number of pair input and target sample. The core idea of the training process is to determine the couple model parameters of w and b to obtain minimize training error of Eq. (1) in the space domain of dataset $\{x_i, y_i\}_{i=1}^{i=n}$. Furthermore, maximize margin is foraged to obtain the most efficient classification solution. Basically, the ideas are generalized in the following equation.

$$\begin{cases} \underset{w,b,\varepsilon}{\text{Minimize}} \ \frac{1}{2}\|w\|^2 \\ \left| \left(\langle w x_i \rangle + b \right) - y_i \right| \le \varepsilon \end{cases}, \tag{2}$$

where $\varepsilon \ge 0$ is error-insensitive zone, $\|w\|^2 = \langle w.w \rangle$ is the norm of the weight vector.

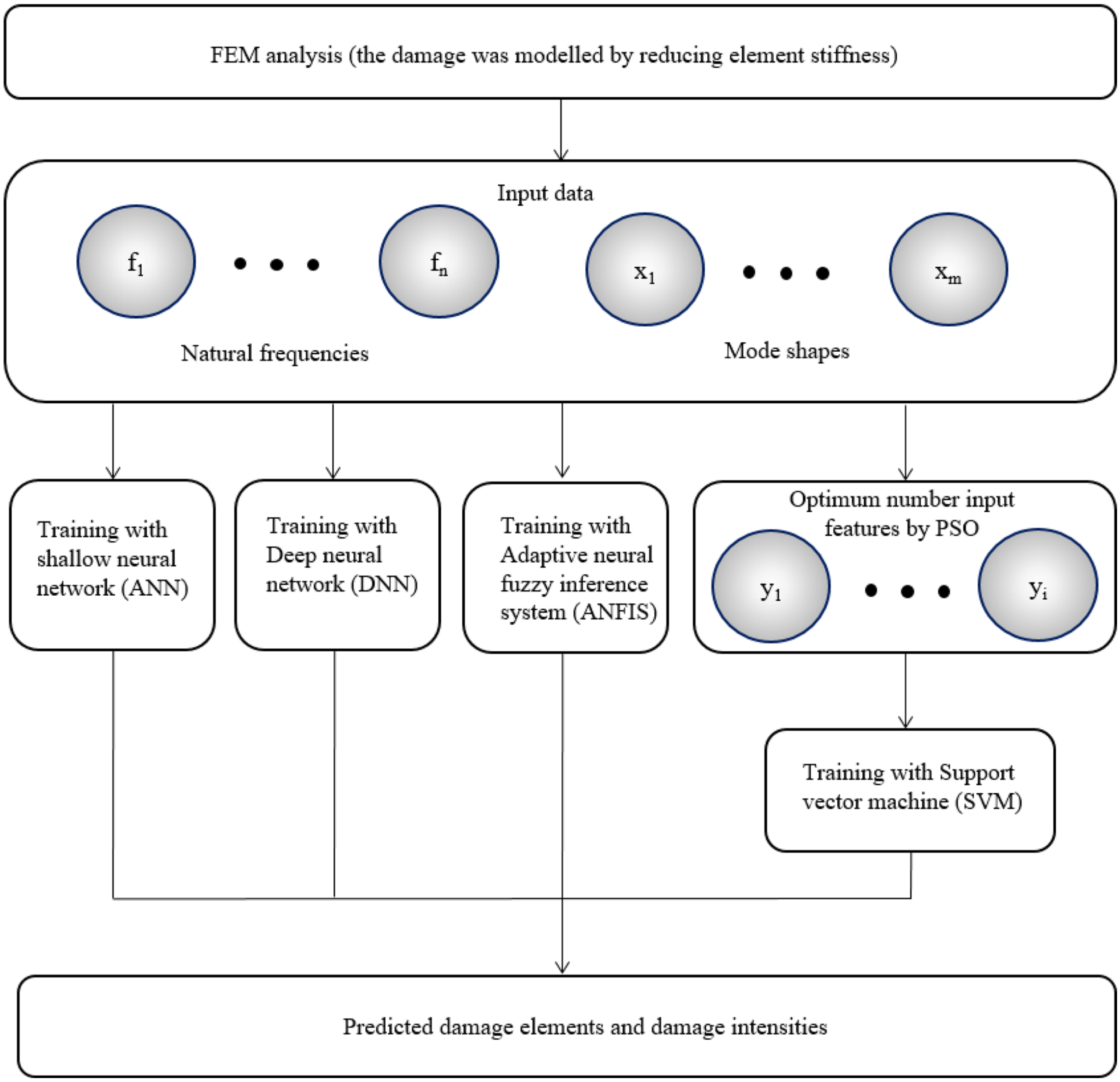

Fig. 1 The flow chart with different approaches for structural damage identification

2.2 Artificial Neural Network (ANN) with shallow network

ML techniques, especially Artificial Neural Network (ANN), are extensively employed for inverse problems. Among them, the ANN with a shallow network is the most popular application. Figure 2 illustrates this network's concept with three basic layers of the input layer, hidden layer, and target output layer. This network is remarkable with only one hidden layer; therefore, that is so-called "shallow network". The shallow network is applied for determining damage based on statistical properties of structural dynamic responses [38]. The network is used in combination with several techniques and algorithms including Particle Swarm Optimization (PSO), IsoGeometric Analysis (IGA) and Cornwell indicator (CI) for damage assessment of composite laminate plate [3]. The shallow network is employed for damage detection of truss bridge joints [22]. The network was also utilized to evaluate damage identification of deck type arch bridges using vibration-based methods [39]. Inspiring from working of the neuron network in the human brain, ANN has several interconnective activated functions from the input layer to the output layer which are presented in Fig. 2.

The activated function is defined as.

$$H_{i,j} = f\left(\sum \left(wx_i + b\right)\right), \tag{3}$$

where $H_{i,j}$ is the output value at layer i and a hidden layer j, $f(x)$ is an active function that can be linear, Sigmoid, and tan-Sigmoid.

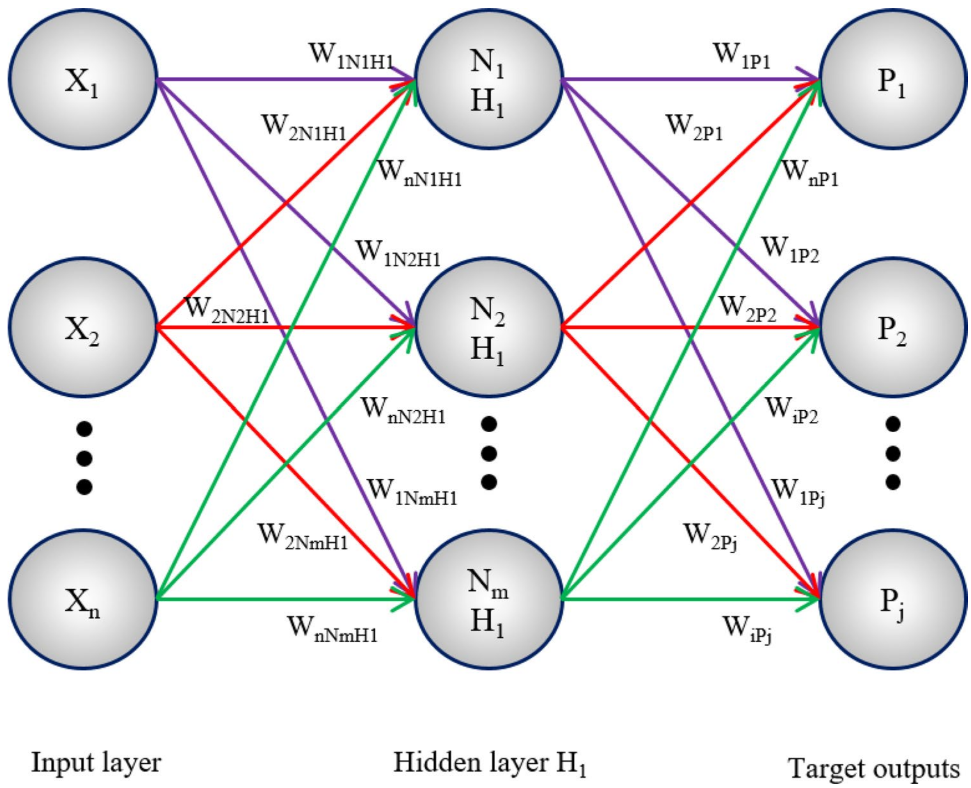

Fig. 2 ANN's topology for a shallow network

Equation (3) is derived from input to the output layer to determine predicted values (p_j). The error between the output target value (y_j) is obtained from the Mean Square Error (MSE).

$$\mathrm{MSE}(w,b) = \frac{\sum_{i=1}^{i=n} \left(y_i - p_i\right)^2}{n}. \tag{4}$$

The error can also be presented with another error indicator of Root Mean Square Error (RMSE) and Correlation coefficient (R^2).

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{i=n} (p_i - y_i)^2}{n}}, \tag{5}$$

$$R = \frac{\sum_{i=1}^{i=n} (p_i - \overline{p}_i)(y_i - \overline{y}_i)}{\sqrt{\sum_{i=1}^{i=n} (p_i - \overline{p}_i)^2}\sqrt{\sum_{i=1}^{i=n} (y_i - \overline{y}_i)^2}}, \tag{6}$$

where p_i is predicted values, $\overline{p}_i$ is mean predicted values, y_i target values, and $\overline{y}_i$ mean target values.

The core idea of ANN training process is improving the performance of the ANN model by minimizing MSE or RMSE, which has two dependent factors of weight (w) and bias (b). From this idea, there are various training algorithms that have been developed during last decades including traditional Backpropagation (BP), Levenberg–Marquardt, BFGS Quasi-Newton, Resilient Backpropagation, Scaled Conjugate Gradient, Conjugate Gradient with Powell/Beale Restarts, Fletcher–Powell Conjugate Gradient, Polak–Ribiére Conjugate Gradient, One Step Secant, and Variable Learning Rate Backpropagation.

2.3 Deep neural network (DNN)

DNN has recently employed and demonstrated excellent performance compared to the classical shallow network [29–32]. Basically, DNN's topology has an extending number of hidden layers (Fig. 3), which can improve learning capacity in many complex problems. Three hidden layers with 100 neurons are applied, each combined with a devised Chebyshev polynomials for activation functions to optimize 2D and 3D truss structures [30]. GA is employed to optimize the DNN's architecture and feature configurations. The optimized DNN models were validated with a case study of computational material design, and also the DNN models show outperform the shallow network and ANFIS [31].

2.4 Adaptive network-based fuzzy Inference System (ANFIS)

ANFIS is a combination of ANN and Fuzzy Inference System (FIS). The combination in ANFIS' model can significantly improve its capacity to capture nonlinear structure progress, adaption and rapid learning capacity [33]. In the engineering field [34], ANFIS is applied for damage

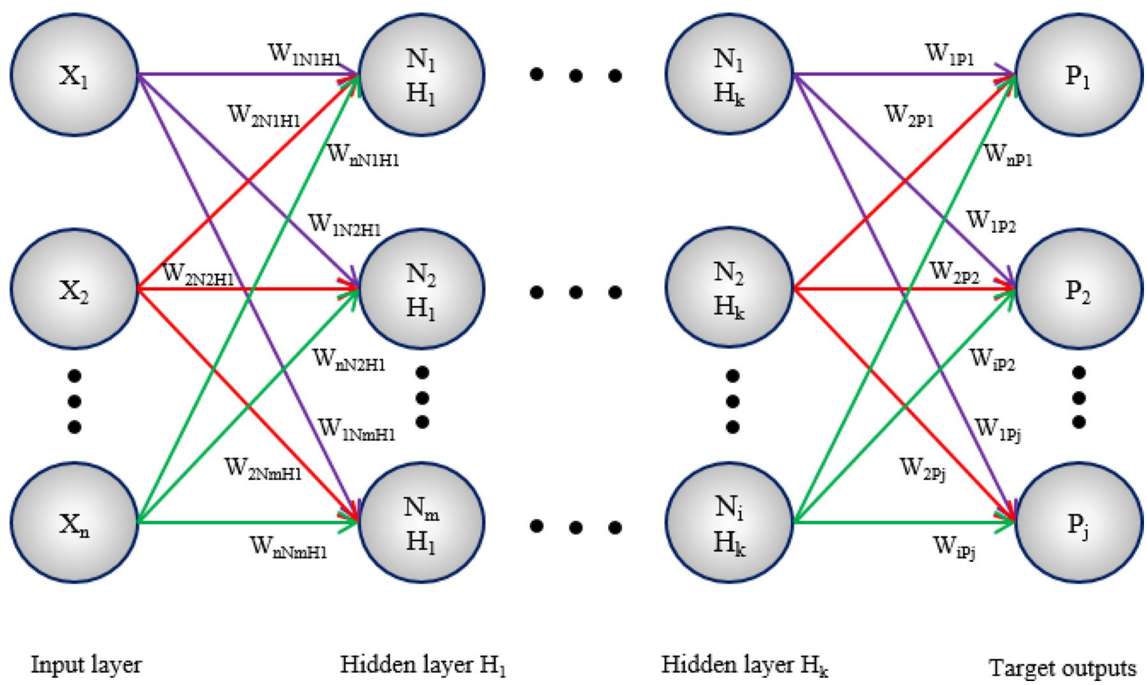

Fig. 3 DNN's topology

assessment of the cantilever beam. However, it is tough to determine which one has better performance between ANN and ANFIS because they strongly depend on different problems with different data types. Although FIS is a reliable tool in solving various problems based on their own rule, training parameters of FIS can obtain by trial and error only. On the other hand, the ANN with back-propagation technique can easily get the optimal training parameters with the minimum MSE. ANFIS is a powerful approach having both ANN and FIS advantages. Generally, the ANFIS' structures include five layers given in Fig. 4.

Layer 1: Several adaptive nodes with membership functions derived with respect to the input vector x_i. The Gaussian function was applied for this study as follows.

$$\mu C_j(x_i) = \exp\left(-\frac{(c_j - x_i)^2}{2\delta_j^2}\right), \tag{7}$$

where c_j and two optional parameters $\delta_j j = 1 \ldots 2$ can be strained by later parts.

Layer 2: including fix nodes which are labeledπ_i. The preliminary weights are calculated in this layer as follows:

$$w_i = \mu C_1(x_1)\mu C_2(x_1) \ldots \mu C_1(x_n)\mu C_2(x_n). \tag{8}$$

Layer 3: including fix nodes labeled N with the average sum weights derived as following

$$\overline{w}_i = \frac{w_i}{\sum_{i=1}^{i=n} w_i}. \tag{9}$$

Layer 4: The adaptive nodes storing the multiplication between the average sum weight and simplify linear function with input parameters

$$\overline{w}_i f(x), \tag{10}$$

where $f(x) = \sum_{i=1}^{i=n} x_i a_i + a_o$ is the linear function concerning the input parameters (x_i), a_i are linear coefficients determined through training progress.

Layer 5: the overall output or the predicted results is the sum of previous output values and defined as

$$p_i = \sum_{i=1}^{i=n} \overline{w}_i f(x). \tag{11}$$

3 The proposed solution of PSO-SVM

PSO is a robust and effective algorithm, which reflects the natural behavior of a flock of birds moving and finding their foods [37]. Each particle or bird has its positions and velocities which continuously gets updated based on their distances to the best location. The general equation for PSO is given by the following formulations.

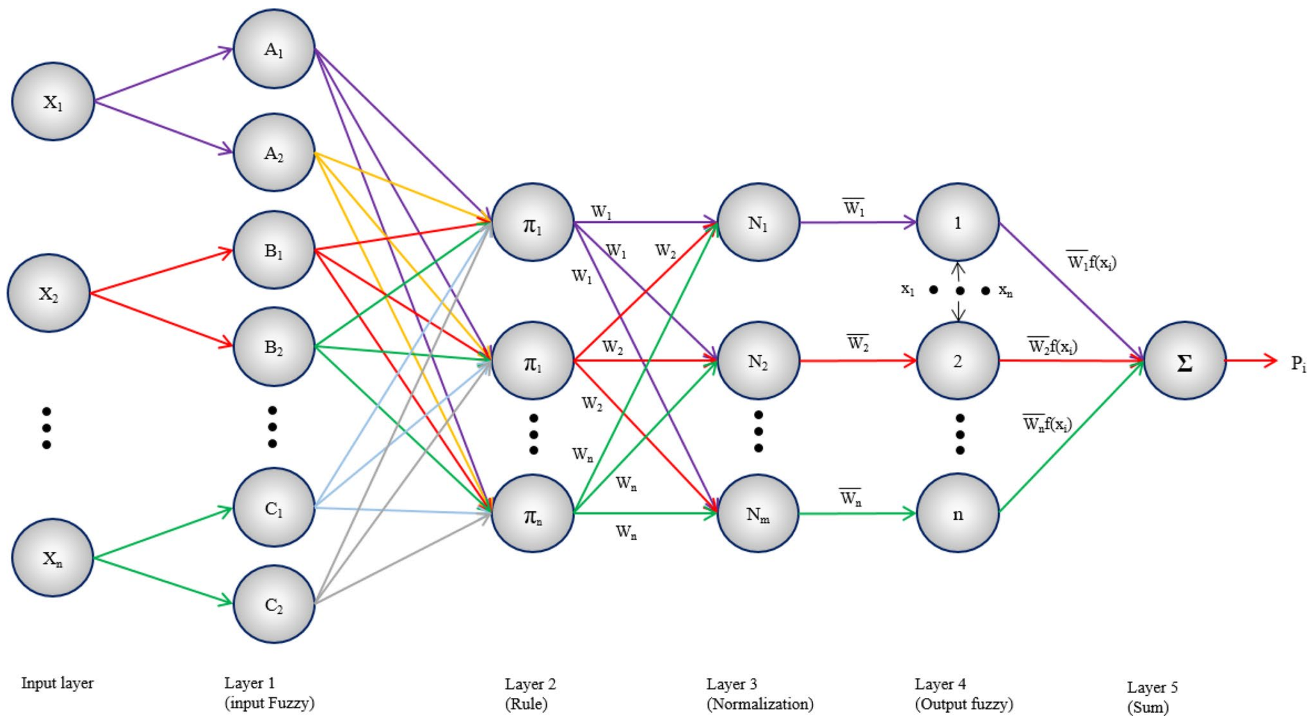

Fig. 4 ANFIS's topology

$$v_{i+1} = \omega v_i + c_1 r_1 \left(p_{\text{best}} - x_i\right) + c_2 r_2 \left(g_{\text{best}} - x_i\right), \tag{12}$$

$$x_{i+1} = x_i + v_{i+1}, \tag{13}$$

where x_i is the position of each particle, v_i is the velocity of each particle, p_{best} is particle best value, g_{best} is the global best value, r_1 and r_2 are random numbers between 0 and 1, whereas c_1 and c_2 are acceleration coefficients.

Figure 5 illustrates the general methodology of the proposed combination of PSO and SVM. The input parameters are firstly generated from FEM analysis with random reduction of element stiffness limited from 30% to create the low damage input database. These parameters are dynamic structure responses, including natural frequencies and mode shapes which still consist of many noise and redundant features. PSO is applied to search for the optimum input dataset with the number of input features increasing until reaching the maximum number of input parameters. In each step, a population is created and each individual is a dataset of random input features. These procedures are continuously carried out until reaching a maximum number of input parameters. SVM is used to evaluate and determine the best dataset that can produce the best performance in the proposed PSO-SVM model. By applying PSO-SVM, the robust searching algorithm can eliminate the noise and redundant features in the input parameters; therefore, it is suitable for the low damage intensity problems.

Table 1 presents the model factors used for analysis with different ML models. Remarkably, ANN is considered with a shallow network of one hidden layer and 50 neurons, while DNN is modeled with four hidden layers [50,50,50,50] neurons. Both methods employ Levenberg–Marquardt training method with early stop technique to avoid overfitting. ANFIS is used with the Sugeno's FIS structure, while PSO-SVM with Radial basic kernel function for SVM and population size used is 50 for PSO.

4 Numerical examples

4.1 Numerical example of a truss structure

A truss bridge structure of 25 elements [24] is employed here as a numerical example to study the ML models and the proposed PSO-SVM model with the geometry illustrating in Fig. 6. The total length of this bridge structure is 12 m including 6 spans each 2 m. Material properties are shown in Table 2, simplifying only one type of section applied for all 25 elements. The cross-section area is 1.8×10^{-3} m^2, Young modulus is 210,000 MPa, and material density is 7800 Kg/m^3. The input database was generated from 1000 cases with randomly damage locations and damage levels. Stiffness reduction was applied with limitation to the

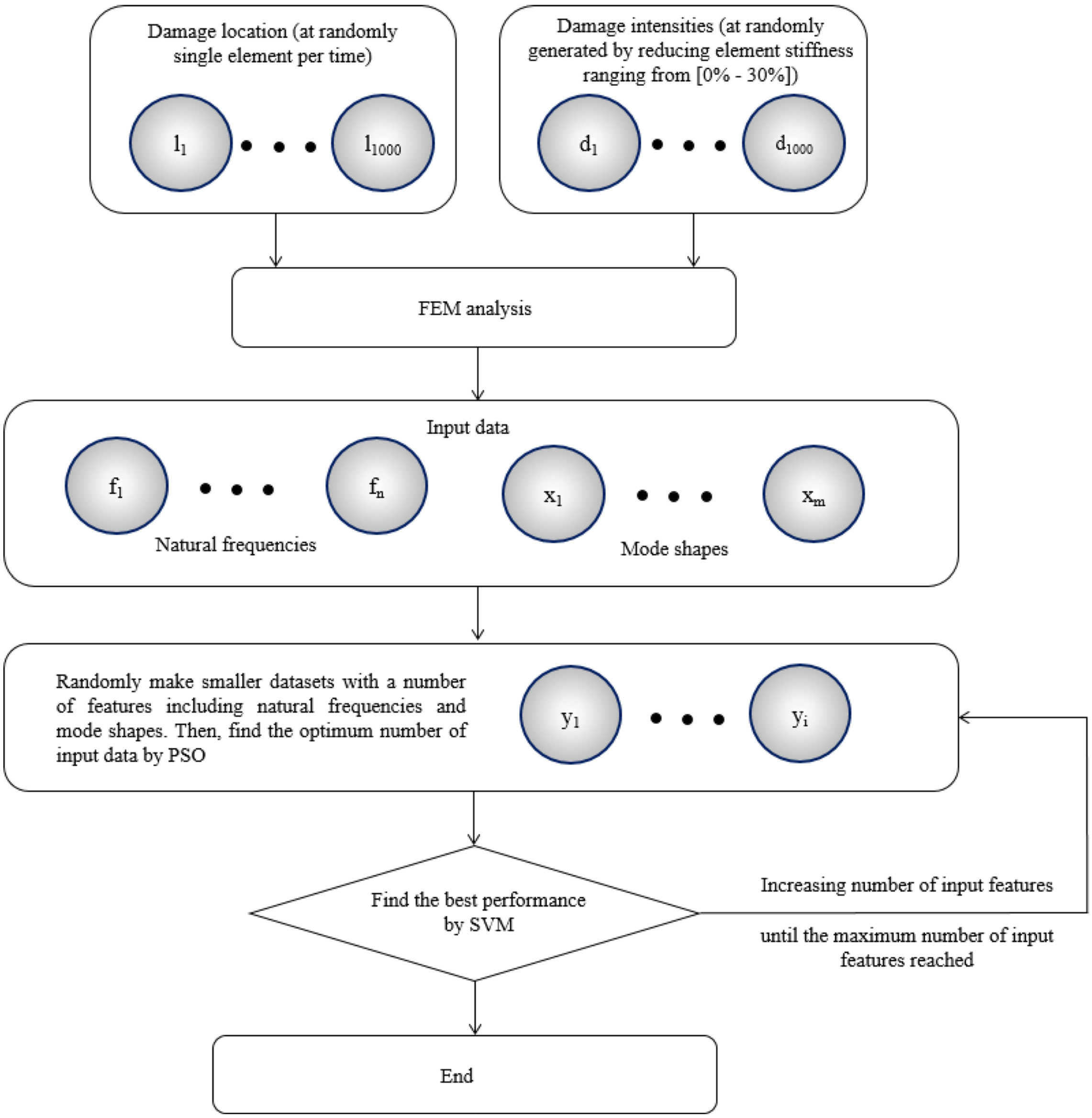

Fig. 5 Concept of the proposed method PSO-SVM

Table 1 General model factors applied

Model	Model factors
ANN	Shallow network one hidden layer with [50] neurons, Levenberg–Marquardt training technique
DNN	Deep network with four hidden layers [50,50,50,50] neurons, Levenberg–Marquardt training technique
ANFIS	Structure of FIS = Sugeno, range of influence = 0.85, squash factor = 1, accept ratio = 0.5, reject ratio = 0.15
PSO-SVM	$C_1 = 1$, $C_2 = 2$, population = 50, maximum Iteration = 200, Radial basic kernel function

maximum reduction ratio is 0.3. Table 3 shows the statistical information relating to damage locations and damage levels where the damage locations range from [0–25] elements and damage levels around [0–0.3]. Maximum damage intensity is 0.2994, while the minimum is 0.0002, and the median is 0.1518. Figure 7 illustrates the distribution of damage

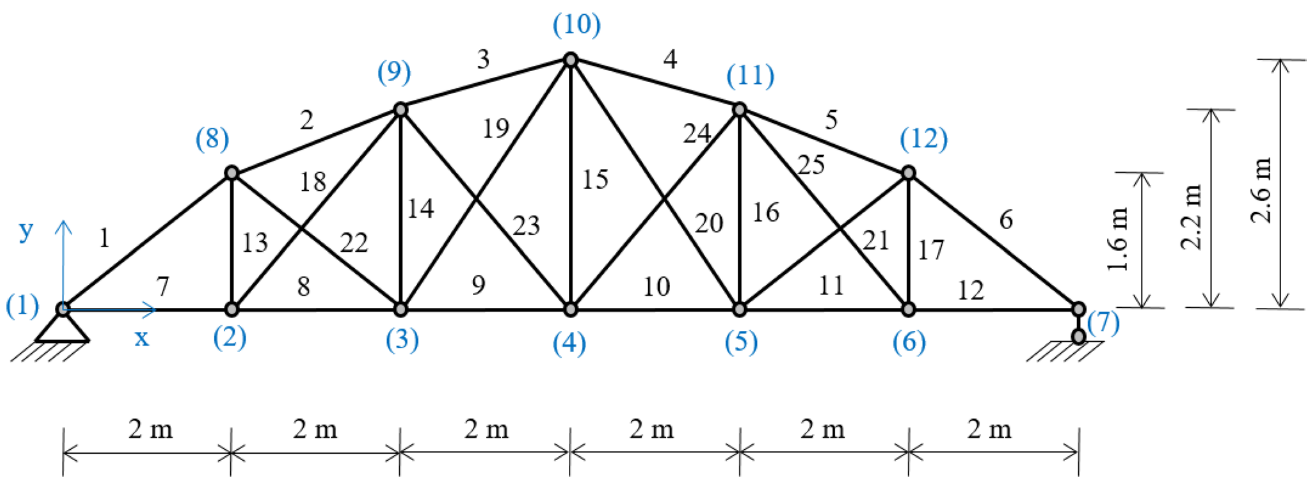

Fig. 6 Geometry of a truss structure after [25]

Table 2 Material properties for truss' structure

Type	Unit	Values
Cross sectional area	m^2	1.8×10^{-3}
Material density	Kg/m^3	7,800
Modulus of elasticity	MPa	210,000
Poisson ratio		0.3

Table 3 Statistical analysis of truss bridge model

Parameters	Damage locations	Damage intensities
Average	12.529	0.1487
Max	25	0.2994
Min	1	0.0002
Range	24	0.2993
Media	12	0.1518

locations and damage levels by the histogram graphs, which can reflect the random distribution.

Figure 8 presents dynamic responses with 9 mode shapes of the undamaged truss bridge structure, while Fig. 9 illustrates the differences in mode shape 1 between the damaged and undamaged truss bridge structure. It can be seen that the damaged element 7 causes changes in the mode shape. Therefore, in the inverse problem, the mode shapes can be used as an indicator of damaged structures [22]. However, the small damage levels can lead to less differences between the damaged and undamaged structures. In turn, it can hardly predict exactly the damage location and damage intensity by current ML models. Regarding the results of dynamic responses, the natural frequencies and mode shapes from the first 9 modes of damaged truss bridge structure are employed as input parameters with 88 features. The total 1000 damaged cases are analyzed to find the dynamic responses with large input database. Moreover, the database are split into 800 cases for training and 200 cases for testing as a common procedure for training ML models to avoid overfitting.

4.2 Numerical example of a frame structure

A 3D steel frame structure was also employed for the structural identification problem with the geometry given in Fig. 10. The two stories frame with 2 m height each and equal spans of 2 m. Total of 16 frame elements includes 8 beams and 8 columns. Boundary conditions are restrained from displacements in 3 directions as shown in Fig. 10. Material properties are remarkable with two typical sections of a beam with 0.075 m^2 and column with 0.025 m^2 (Table 4). Column elements include elements 1, 2, 3, 4, 5, 6, 7, and 8, while the remaining are the beam elements. Young modulus and material density are similar to the previous truss structure with 210,000 MPa and 7800 Kg/m^2, respectively. Table 5 and Fig. 11 present the statistical information and diagrams of 1000 cases with randomly distributing damage locations and damage levels regarding dynamic responses with damaged structures. Similarly, the numerical example for frame structure was also assigned with low damage levels with stiffness reduction limited to 0.3 and randomly distributed among 16 frame elements.

The 8 mode shapes of undamaged frame structure are shown in Fig. 12, while it is compared between the mode shape 1 of the damaged and undamaged frame structure in Fig. 13 (element 1 was reduced stiffness). Unlike truss bridge structure in 2D, the 3D frame structure has various deformation types such as deforming in *x, y, z* directions, and torsions depending on the structure's stiffness. Among dynamic responses, mode shapes are also key factors that

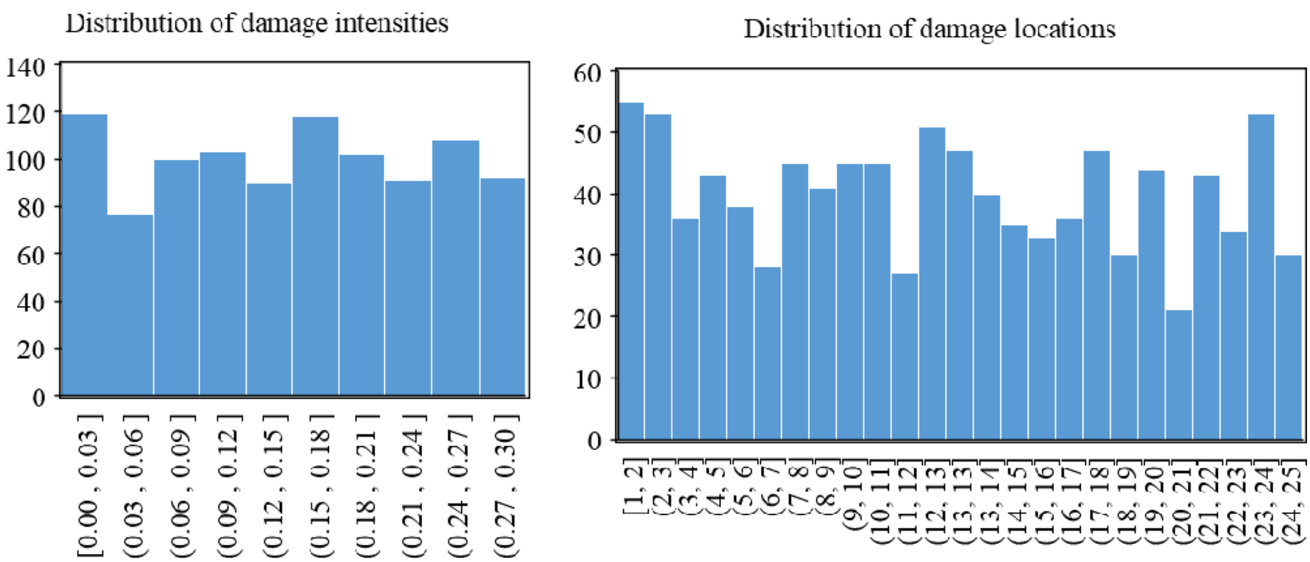

Fig. 7 Statistical diagrams of the truss bridge model

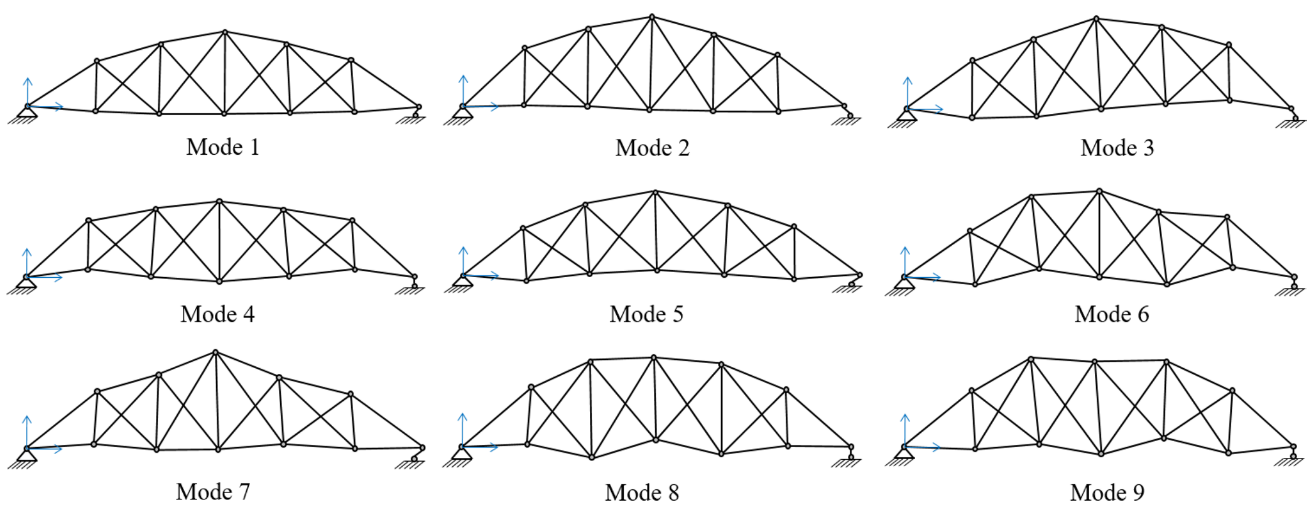

Fig. 8 Mode shapes of truss bridge structure (undamaged structure)

can help determine correctly damaged location. As shown in Fig. 13, the mode shape changes from displacement in the x-direction for the undamaged case to combination of displacement and torsion for the damaged case. However, it can also be difficult for current ML methods for damage identification in case of low damage levels where the mode shapes between the damaged and undamaged cases are not much different. Also, the natural frequencies between them are almost the same. The later sections will discuss the issues associated with the low damage levels and several ML models. Regarding the input parameters, 8 first mode shapes and natural frequencies from 1000 random damaged cases are employed as input database for further analysis by these ML models. Input database was split into 80% for training and 20% for testing to avoid overfitting.

5 Results and discussion

5.1 Truss bridge structure

Training and testing process by ANN with shallow network and DNN are presented in Fig. 14. The optimum number of epochs is 9 for ANN, while there are a larger number of epochs when training by DNN with 24. DNN can clearly show more improvement than ANN with shallow network to overcome the overfitting problem as the shallow neural

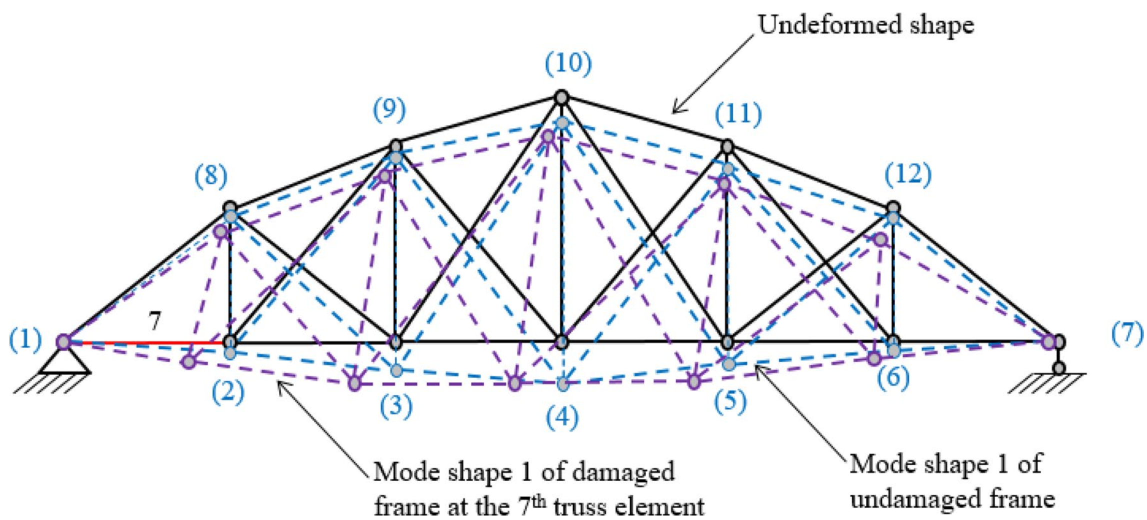

Fig. 9 Compared mode shape 1 of the damaged and undamaged truss bridge structure

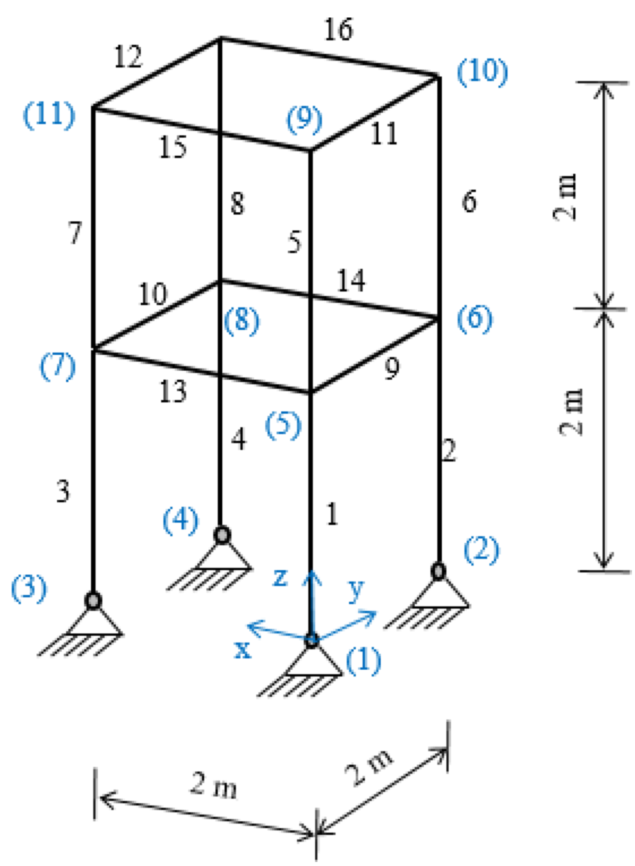

Fig. 10 The 3D frame structure

Table 4 Material properties for frame structure

Type	Element	Unit	Values
Cross sectional area	Beam	m^2	0.0075
	Column	m^2	0.0025
Moment of inertia	Beam	m^4	1.4×10^{-5}
	Column	m^4	5.2×10^{-7}
Material density		Kg/m^3	7800
Modulus of elasticity		Mpa	210,000
Poisson ratio			0.3

Table 5 Statistical analysis of frame model

Parameters	Damage locations	Damage intensities
Average	8.438	0.1476
Max	16	0.2999
Min	1	0.0006
Range	15	0.2993
Media	8	0.1485

network can be easily trapped by overfitting with only a few epochs. Regarding training by the proposed PSO-SVM, several numbers of input features (10, 20, 25, 30, 60, and 88) are plotted with their performances in Fig. 15. The optimum number of features is 25 which is only 28% of total input parameters of 88 features. Moreover, the performance with total input parameters (88 features) also shows less effective than the optimum one with only 25 features. Based on the analysis, it can be concluded that the proposed approach can effectively eliminate the noise or redundant input parameters and considerably help to improve performance by powerfully searching for the optimum input values.

Table 6 shows comparisons between these ML models. It can be seen that DNN models are outperform ANN with shallow network, and PSO-SVM demonstrates superior accuracy among the ML models. First, both DNN and ANFIS (with RMSE are 0.0494, 0.0411, respectively) also

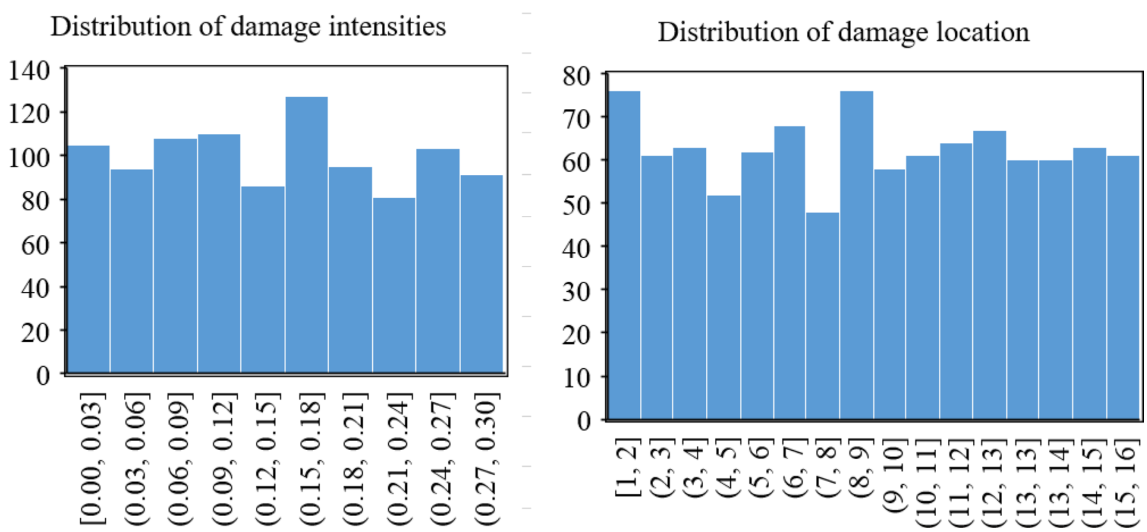

Fig. 11 Statistical diagrams of truss bridge model

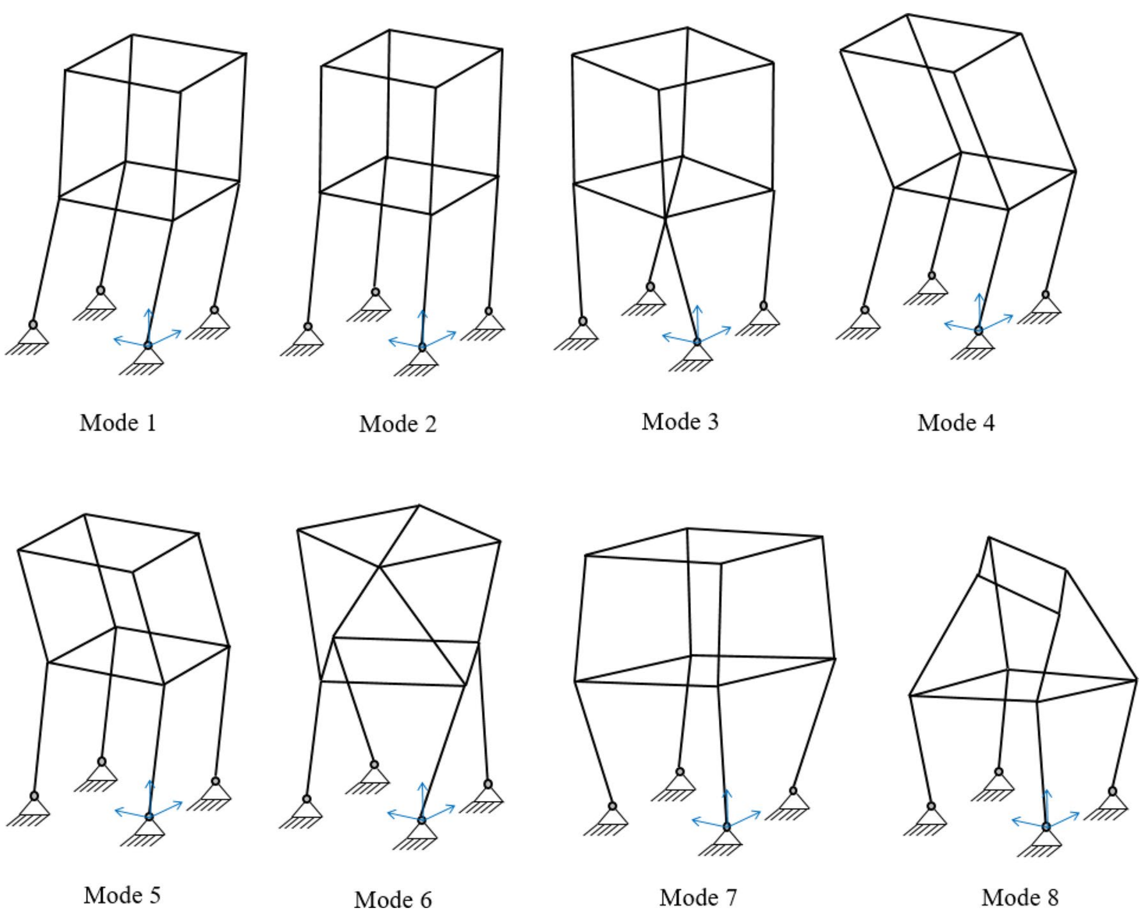

Fig. 12 Mode shapes of frame structure (undamaged structure)

show better training predictions than the classical ANN with shallow network (0.1139). This issue was also good agreement with [31] in their study when comparing the performance between ANN, DNN and ANFIS. Remarkably, the proposed PSO-SVM presents an impressive performance

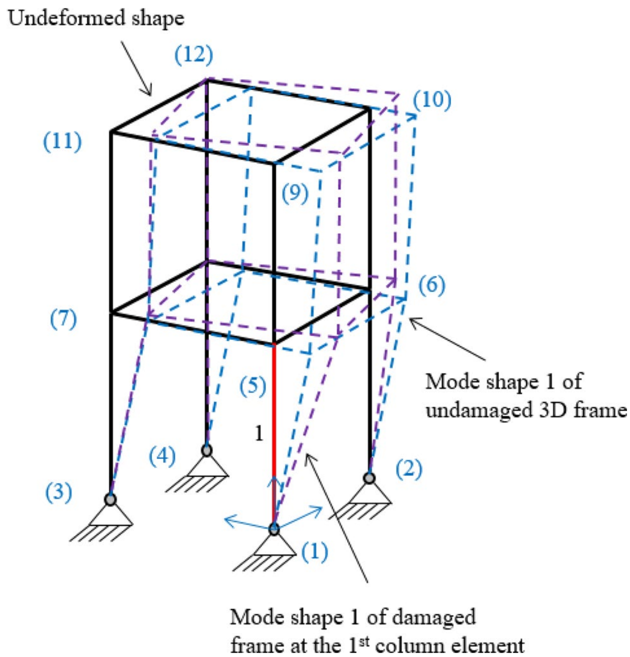

Fig. 13 Compared mode shape 1 of damaged and undamaged frame structure

with the highest accuracy among these ML models for both training and testing procedures.

Regarding validations for the ML models, 10 randomly damaged cases were generated to evaluate the proposed method shown in Table 7. It can be clearly seen that PSO-SVM demonstrate an outstanding prediction when it can correctly predict 8 damaged locations, while they are 3, 5, and 3 for ANN, DNN and ANFIS, respectively. Also, It presents an impressive accuracy in estimating damage levels with RMSE is 0.012 in comparison with 0.04, 0.021 and 0.052 for ANN, DNN and ANFIS, respectively.

5.2 3D frame structure

Similarly, the training and testing for frame structure by ANN with shallow network also yield lower epoch number of 26; while for DNN, it is 90 epochs (Fig. 16). Overfitting can be seen clearly with the testing results in ANN with the values of RMSE gradually increase after reaching 26 epochs. On the other hand, the testing results of DNN still stable after achieving the optimum epoch number of 90. Moreover, RMSE values (both testing and training) by DNN are also lower than ANN with shallow network indicating the DNN has better performance than classical ANN with a shallow network.

Several trainings by the proposed method with the different number of input features are selected to present in Fig. 17. The optimum number of input features is 24, while the total number of features is 76 implying the input parameters are full of redundant or noise features. In other word, the more number of input features are, the less accuracy of the predicting model will be. The PSO-SVM can effectively eliminate these redundant features and enhance the predicting model's performance, especially for the low damaged structures.

Again, the PSO-SVM also demonstrates the outstanding performance among these ML models for frame structure with low damage levels (Table 8). Both statistical values of RMSE and R^2 show that the PSO-SVM model has the highest accuracy. Regarding the remaining ML models of ANN, DNN and ANFIS, both DNN and ANFIS have better accuracy than the classical ANN with the shallow network.

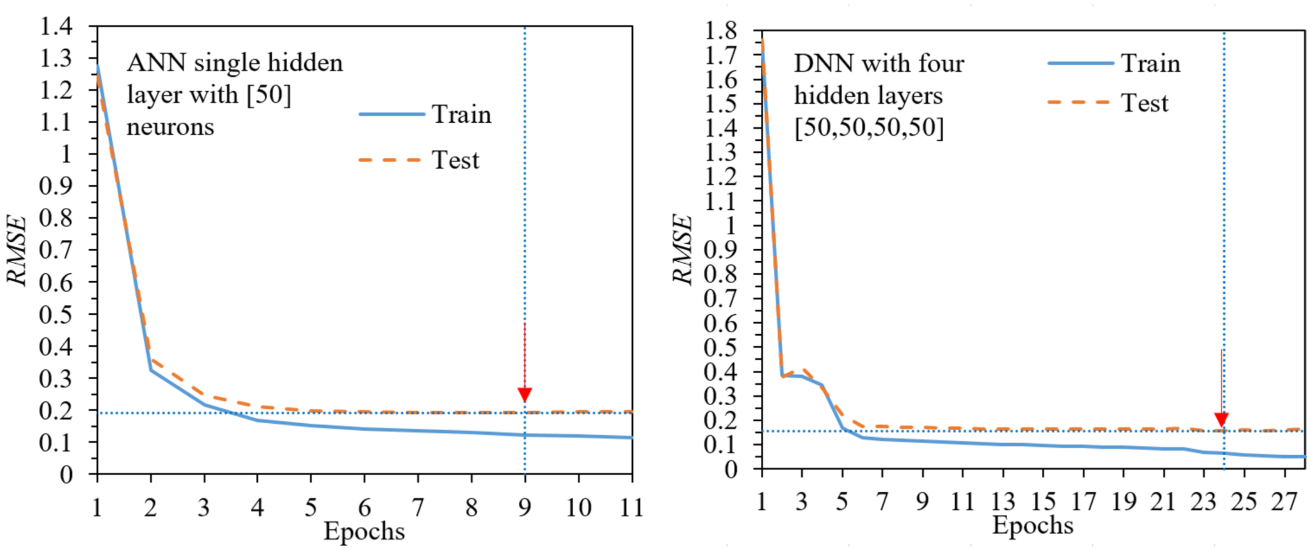

Fig. 14 Training and testing ANN with shallow network and DNN for the truss structure

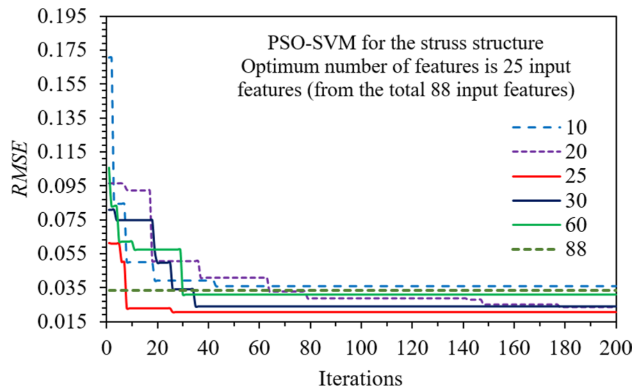

Fig. 15 Training with the PSO-SVM for the truss structure

Even though ANN with the shallow network is very popular in the engineering field, it has lower performance than DNN and ANFIS caused by trapping in a very low number of epochs due to overfitting.

10 randomly damaged cases of the frame structure were generated to validate the current ML models given in Table 9. Impressively, the PSO-SVM can predict exactly 10 locations, while they are 4, 5, and 5 for ANN, DNN and ANFIS, respectively. Furthermore, the PSO-SVM have the lowest RMSE of 0.003, indicating the highest accuracy among other ML models. Based on the comparisons and analyzed results, it can be concluded that the PSO-SVM model has superior accuracy prediction for the inverse problems of the low damaged structures than other ML models such as ANN with a shallow network, DNN, and ANFIS.

6 Conclusions

Damaged structures with low damage levels cause much redundant and noise in the inverse problem's input parameters due to their similar dynamic responses. These issues may impede the identifications by popular ML models such as ANN with a shallow network, DNN and ANFIS. This paper proposed an ML model of PSO-SVM for the inverse problems of truss and frame structures, eliminating the redundant or noise input features and leading to optimum prediction. Two typical structures of the truss bridge and 3D frame structures were employed as numerical examples to verify the proposed PSO-SVM model. Damage levels were limited to 0.3 to create the database with low damage levels. 1000 input database including natural frequencies and mode shapes were used for verification by ML models of ANN with a shallow network, DNN, ANFIS and PSO-SVM. Based on the previous comparison results, several conclusions can be outlined.

Table 6 Comparisons of training and testing by different ML models for the truss structure

Checking model	ANN		DNN		ANFIS		PSO-SVM	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Train	0.1139	0.819	0.0494	0.918	0.0411	0.980	**0.0206**	**0.995**
Test	0.1916	0.773	0.1567	0.833	0.2592	0.525	**0.0461**	**0.957**

Bold values indicate the superior performances of PSO-SVM model

Table 7 Validating with 10 randomly damaged cases for the truss structure

Case	Target		ANN		DNN		ANFIS		PSO-SVM	
	Loc	Inten	Loc	Inten	Loc	Inten	Loc	Inten	Loc	Inten
1	1	0.14	**1**	0.17	2	0.15	2	0.16	**1**	0.14
2	17	0.15	**17**	0.12	18	0.15	**17**	0.12	**17**	0.15
3	9	0.08	16	0.12	**9**	0.11	23	0.11	**9**	0.11
4	22	0.21	**22**	0.19	**22**	0.22	7	0.23	**22**	0.21
5	20	0.26	21	0.28	**20**	0.26	7	0.26	**20**	0.26
6	15	0.02	14	0.10	**15**	0.07	2	0.05	**15**	0.02
7	6	0.08	13	0.15	**6**	0.08	**6**	0.07	**6**	0.08
8	16	0.28	17	0.32	17	0.28	7	0.13	2	0.30
9	25	0.12	16	0.12	23	0.13	2	0.14	17	0.11
10	5	0.09	17	0.10	7	0.06	**5**	0.11	**5**	0.09
Number of accurate locations or RMSE (for damage intensities)			3	0.040	5	0.021	3	0.052	**8**	**0.012**

Bold values indicate the correct predicted locations

Loc. are the damage locations, *Inten.* are the damage intensities

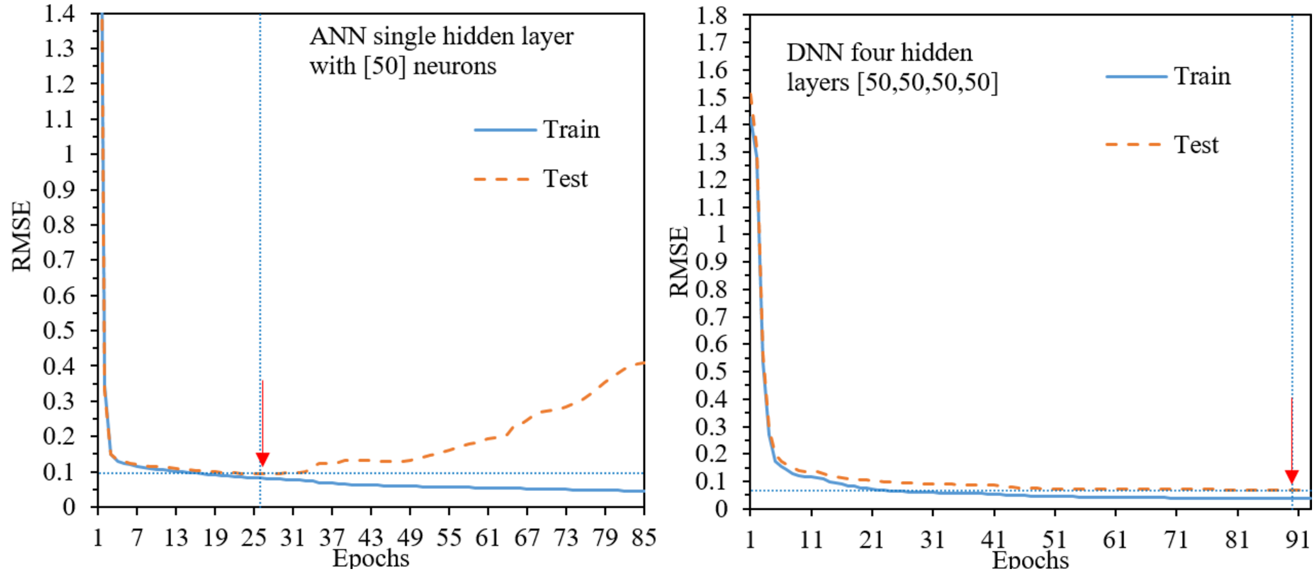

Fig. 16 Training and testing ANN with shallow network and DNN for the frame structure

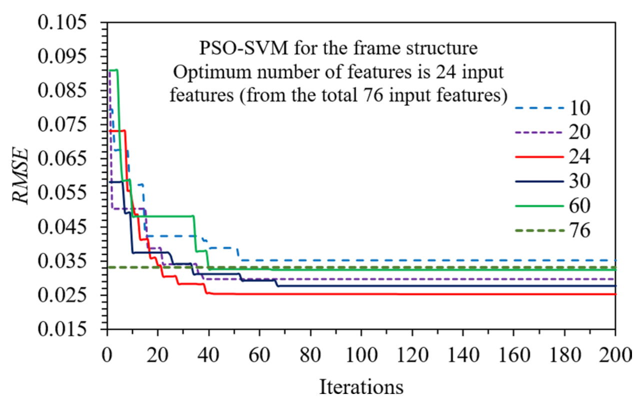

Fig. 17 Training with the PSO-SVM for the frame structure

First, the optimum number of features is 25/88 for truss structure and 24/76 for frame structure. Less than half of the total input database indicating the database by low damaged structures is full of redundant and noise parameters. The proposed PSO-SVM can effectively determine the best input dataset and eliminate the redundant and noise data. Second, the PSO-SVM shows superior performance compared with other ML models such as ANN, DNN and ANFIS. DNN and ANFIS can have better accuracy than the classical ANN with a shallow network. The reason may come from the overfitting of ANN with a shallow network which limited the training capacity and stopped at very few epochs. Finally, PSO-SVM shows an impressive prediction in damage locations and damage levels through the validations with 10 randomly damaged cases (correctly prediction at 8 and 10 locations for truss and frame structures, respectively), while other ML models can only predict correctly maximum 5 damage locations.

Table 8 Comparisons of training and testing by different ML models for the frame structure

Checking model	ANN		DNN		ANFIS		PSO-SVM	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Train	0.0453	0.873	0.0374	0.990	0.0357	0.953	**0.0253**	**0.992**
Test	0.0947	0.587	0.0676	0.922	0.0734	0.892	**0.0621**	**0.955**

Bold values indicate the superior performances of PSO-SVM model

Table 9 Validating with 10 randomly damaged cases for the frame structure

Case	Target		ANN		DNN		ANFIS		PSO-SVM	
	Loc	Inten	Loc	Inten	Loc	Inten	Loc	Inten	Loc	Inten
1	15	0.11	**15**	0.11	**15**	0.11	**15**	0.11	**15**	0.10
2	8	0.22	7	0.22	7	0.22	**8**	0.22	**8**	0.23
3	6	0.24	**6**	0.24	**6**	0.24	7	0.24	**6**	0.24
4	15	0.08	16	0.08	**15**	0.08	**15**	0.08	**15**	0.08
5	13	0.13	**13**	0.13	14	0.13	11	0.13	**13**	0.13
6	1	0.18	3	0.18	3	0.18	**1**	0.18	**1**	0.18
7	11	0.14	**11**	0.14	**11**	0.14	15	0.14	**11**	0.14
8	5	0.23	7	0.23	7	0.23	8	0.23	**5**	0.23
9	10	0.16	9	0.16	**10**	0.16	**10**	0.16	**10**	0.16
10	2	0.21	7	0.23	7	0.19	7	0.23	**2**	0.21
Number of accurate locations or RMSE (for damage intensities)			4	0.008	5	0.005	5	0.006	**10**	**0.003**

Bold values indicate the correct predicted locations

Loc. are the damage locations, *Inten.* are the damage intensities

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