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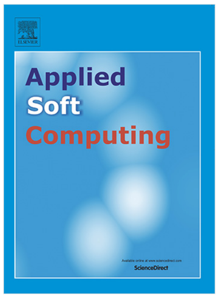

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A two-step method for damage identification in moment frame connections using support vector machine and differential evolution algorithm

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Abstract

The main aim of this study is to introduce a two-step method for damage identification in moment frame connections using a support vector machine (SVM) and differential evolution algorithm (DEA). In the first step, the possibility location of damage in connections is determined through SVM leading to reducing the dimension of the search space. Then, the accurate location and precise amount of damage in connections are determined in the second step via DEA with a high speed. In order to simulate damage in connections, a moment frame is modeled through semi-rigid beam to column connections and the analytical model is used to randomly generate structures with damaged connections as data. Then, SVM is trained and tested using this data, to facilitate natural frequencies are considered as input data and the characteristic of damage in beam to column connections are considered as output data of the network. Now, the possible location of the damage in connections can be determined using the SVM trained. The accurate location and severity of damage are determined by DEA based on the prediction of SVM in the first step. In order to assess the efficiency of the proposed method, two numerical examples are considered with different damage cases and considering noise. A comparative study is also made to judge the performance of the method with that of a work available in the literature. The outcome shows the high efficiency of the proposed method to identify the location and severity of the damage in moment frame connections.

Keywords: Damage identification, moment frame, connection, support vector machine, optimization

1. Introduction

Occurrence of damage in structural systems such as buildings, bridges, oil platforms and so on is inevitable in their lifetime. There are many examples of damage in structures that have been led to an overall failure. In order to prevent from spreading the local damage to overall one, it is important to identify and repair damage by inspecting the current status of structures. Damage identification methods are categorized into destructive and non-destructive methods. The destructive methods are not a suitable method for most structures because of their cost and inefficiency, hence, researchers turned to non-destructive methods. One of the most important non-destructive identification methods is based on observing the change in structural responses such as dynamic and static responses. The changes in structures due to damage are shown better by dynamic responses, made the dynamic based methods more popular.

The damage identification in structures should be in some way that the location and severity of damage in structures are accurately determined. Over the last few years, various methods have been proposed to identify damage in structural members, however, damage identification in connections has been less studied. This issue in earthquake-zone areas that a localized damage in connections may be led to an overall failure of structure, increases the importance of damage identification in connections.

In 2001, a research was carried out by Yun et al. for estimating the joint damage of a steel structure from modal data using a neural network technique. The beam-to-column connection in a steel frame structure was modeled by a zero-length rotational spring at the end of the beam element. The severity of joint damage is defined as the reduction of the connection fixity factor. The concept of sub-structural identification was used to assess the localized damage in a large structure. It was found that damage in a joint can be reasonably estimated even for the case where the measured modal vectors were limited to a localized sub-structure and data were severely contaminated with noise [1]. A method for estimating the damage intensities of joints for truss bridge structures using a back-propagation based neural network was presented by Mehrjoo et al. in 2008. In the study, the natural frequencies and mode shapes were used as input parameters to the neural network for damage identification, particularly for the case with incomplete measurements of the mode shapes. A simple truss and a real truss bridge were considered as numerical examples to demonstrate the efficiency of the proposed method. The results showed that, the location and severity of damage in joints of truss bridges can be found with a good precision and the proposed method is attractive for on-line or real-time damage diagnosis of structures in the framework of structural health monitoring [2]. In 2010, local damage identification in beam-column connections using a dense sensor network was carried out by Labuz et al. A prototype beam-column connection was constructed and instrumented by a dense sensor network. Damage was introduced to the system by replacing a portion of the beam element with a smaller section, and thus reduced its stiffness. The results showed that densely clustered sensor network was successfully implemented for local damage identification of both a simulated model as well as an experimental prototype of a steel beam-column connection. Linear regression was used to estimate the influence coefficients from vibration-induced acceleration responses of the structure. By statistically comparing influence coefficients, damage was accurately diagnosed to a 95% confidence bound made the propose method be efficient [3]. In 2013, a two-stage improved radial basis function (IRBF) neural network technique to predict the joint damage of a fifty-member frame structure with semi-rigid connections in both frequency and time domain was proposed by Machavaram and Shankar. The conventional RBF network was used in the first stage of IRBF network and in the second stage reduced search space moving technique was employed for accurate prediction with less than 3% error. The prediction results of the proposed IRBF method were compared with those of conventional RBF method and the CPN–BPN hybrid method in terms of accuracy and computational effort with and without addition of noise to the input patterns in both domains. The results showed that there is a significant improvement in the prediction performance of the novel IRBF method compared to the conventional RBF method and the CPN–BPN hybrid method [4]. In 2014, a method based on a particle swarm optimization (PSO) was introduced by Nanda et al. to identify damage in beam to column connections of framed structures. The joint damage was measured as the ratio of reduction in joint fixity factor at connections. The results indicated that the method has an appropriate accuracy in identifying damage in connections [5]. In 2015, a research was carried out by Ghiasi et al. where 7 artificial intelligence (AI) methods including back-propagation neural networks, least squares support vector machines (LS-SVMs), adaptive neural-fuzzy inference system, radial basis function neural network, large margin nearest neighbor, extreme learning machine (ELM), were used to identify the location and severity of damage in structures. By considering the dynamic behavior of a structure as input variables, seven AI methods are constructed, trained and tested to detect the location and severity of damage in structures. The variation of running time, mean square error, number of training and testing data, and other indices for measuring the accuracy in the prediction were considered to inspect advantages as well as the shortcomings of each algorithm. The results indicated that the ELM and LS-SVM methods demonstrate a better performance in predicting the location and severity of damage than other methods [6]. In 2015, a research was carried out by Satpal et al. which used support vector machine (SVM) to identify damage in aluminum beams. In the work, SVM was explored to find damage locations in aluminum beams using simulation data and experimental data. Displacement values corresponding to the first mode shape of the beam were used to predict the damage locations. Damages are introduced in the form of rectangular notches along the width of the beam at different locations [7]. In 2016, a study was carried out by Ghiasi et al. which used the least square support vector machines (LS-SVM) based on a new combinational kernel function named as thin plate spline littlewood-paley wavelet (TPSLPW). During the structural damage identification process, a harmony search algorithm was used to optimize the LS-SVM and TPSLPW parameters. The research indicated the high accuracy of LS-SVM with TPSLPW in detecting damage compared to some methods based on other kernel functions in the same conditions [8]. In 2017, a method using incomplete modal data by Bayesian approach and model reduction technique was proposed by Yin et al. for detecting damage in structural connections. The research presented a practical method for structural bolted-connection damage identification using noisy incomplete modal parameters identified from a limited number of sensors. The efficiency of the proposed methodology was demonstrated by numerical simulations and experimental verifications. In addition, the results showed that the bolt loosening has a substantial influence on the connection stiffness of the bolted joint for the frame-type structure, so more attention needs to be paid in the design and service stages [9].

Most researches reviewed above employed an artificial intelligence method for damage identification. The main drawback of an artificial intelligence based model is that when damage variables increase or data are contaminated by the measurement noise, their efficiency for accurately identifying damage may be decreased. As a result, their solutions need to be improved by another technique such as an optimization method. During the last years, numerous optimization algorithms have been introduced for different applications. Some recently proposed optimization algorithms can be described as below.

In 2017, an improved modified grey wolf optimizer (GWO) algorithm was proposed by Heidari and Pahlavani to solve either global or real-world optimization problems. In order to boost the efficiency of GWO, Lévy flight (LF) and greedy selection strategies were integrated with the modified hunting phases. Experimental results and statistical tests demonstrated that the performance of the modified Lévy-embedded GWO (LGWO) is significantly better than GWO and many optimization algorithms [10]. A new hybrid stochastic training algorithm using the grasshopper optimization algorithm (GOA) for multilayer perceptrons (MLPs) neural networks was proposed by Heidari et al. The proposed GOAMLP model was then applied to five important datasets: breast cancer, parkinson, diabetes, coronary heart disease, and orthopedic patients and the results were confirmed in comparison with eight recent algorithms. It was proved that the proposed GOAMLP is significantly valuable in improving the classification rate of MLPs. In 2018, a wrapper-feature selection algorithm was proposed based on the binary dragonfly algorithm (BDA) by Mafarja et al. The performance of the dragonfly algorithm was improved using different transfer functions (TFs) to convert the step vector from continuous to a binary space. Eight different TFs that belong to two groups (S-shaped and V-shaped) were employed to investigate their effectiveness on the basic BDA. Results showed that the time-varying S-shaped BDA approach outperforms compared approaches[12]. In 2018, A grasshopper optimization algorithm (GOA) was employed as a search strategy to design a wrapper-based feature selection method by Mafarja et al. An efficient optimizer based on the simultaneous use of the GOA, selection operators, and evolutionary population dynamics (EPD) was proposed in the form of four different strategies to mitigate the immature convergence and stagnation drawbacks of the conventional GOA. The proposed approaches were utilized to tackle 22 benchmark datasets. The comparative results shown the effectiveness of the proposed algorithm for solving different feature selection tasks [13]. In 2019, an intelligent detection system based on genetic algorithm (GA) and random weight network (RWN) was proposed by Faris et al. to deal with email spam identification tasks. An automatic detection ability was also embedded in the proposed system to detect the most relevant features during the identification process. The experimental results confirmed that the proposed system can achieve significant results in terms of accuracy, precision, and recall. Furthermore, the proposed detection system can automatically identify the most relevant features of the spam emails [14]. In 2019, an enhanced whale optimization algorithm (WOA) was proposed with a modified global searching operator by Heidari et al. to mitigate the immature convergence of the WOA and tackle different optimization challenges. The results were compared with different well-known techniques on multi-dimensional classic problems. The experiment tests revealed the superiority of the proposed algorithm compared to standard WOA and several well-established algorithms [15].

The main purpose of this study is to introduce a two-step method for identifying damage in moment frame connections using support vector machine (SVM) and differential evolution algorithm (DEA). In the first step, to determine the possible damage location in connections and reduce damage variables, SVM is used and in the second step, an optimization method named DEA is employed to determine the accurate location and the severity of damage. Numerical results indicate the efficiency of the proposed method. The speed and accuracy of finding damage can be increased by the two-step method when comparing with methods based only on an optimization approach. Moreover, the proposed method is more accurate than an artificial intelligence method.

2. Damage simulation in moment frame connections

Among the variety of connections, beam-to-column connections in steel structures are generally considered as rigid or pinned and designed. There are various methods for modeling the behavior of connections divided into two main groups: mathematical models and mechanical models that in this paper a mechanical model is used. The mechanical models are known as springy models, based on the simulation of the joint or connection using a zero-length torsional spring at the end of the beam connected to the column. Therefore, in this study, the beam-to-column connections are modeled with zero-length torsional springs with an ended fixity factor (p_j) related to the bending stiffness of member ($\frac{EI}{L}$) and torsional spring stiffness (k). Fig.1 shows the connection of a semi-rigid beam-to-column [16, 17].

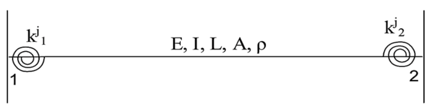


Fig. 1. Semi-rigid beam-to-column connection

The torsional spring stiffness is defined in accordance with the bending stiffness of the member by Eq. (1):

$$k_j = \gamma_j \frac{EI}{L} \tag{1}$$

where k_j is the rotational spring stiffness of the connection; E, I and L are the modulus of elasticity, the inertia moment and the length of the beam element, respectively. Also, γ_j is a constant and the index j (1 or 2) represents the two ends of the beam.

The fixity factor of connection p_j can be expressed by Eq. (2) as:

$$p_j = \frac{1}{1 + \frac{3EI}{Lk_j}} \quad , \; j = 1, 2 \tag{2}$$

The value of p_j is between 0 and 1, which the value of 0 is for a pinned connection and the value of 1 is for a quite rigid connection. Therefore, a semi-rigid joint has a fixity factor between 0 and 1, aiding to simulate the damage in the connection of moment frames. This means that if, in a structure with rigid connections, the value of fixity factor for a connection is less than 1, then the connection will not be rigid and it has been damaged.

2.1. Introducing the finite element relations

The structures studied in this research are 2D moment frames. Therefore, the mass and stiffness matrices of 2D frame element with semi-rigid connections are introduced to use in modal analysis based on finite element method. If the ended fixity factor of the connections for the beginning and the end parts of an element are shown by p_f and p_e respectively, the mass matrix for an element of the frame by considering the semi-rigid connection in the local coordinate system can be given by Eq. (3) as [16,17]:

$$\overline{M} = \frac{\overline{m}L}{420D^2}\begin{bmatrix} 140D^2 & 0 & 0 & 70D^2 & 0 & 0 \\ 0 & 4f_1(p_e,p_f) & 2Lf_2(p_e,p_f) & 0 & 2f_3(p_e,p_f) & -Lf_4(p_e,p_f) \\ 0 & 2Lf_2(p_e,p_f) & 4L^2f_5(p_e,p_f) & 0 & Lf_4(p_f,p_e) & -L^2f_6(p_e,p_f) \\ 70D^2 & 0 & 0 & 140D^2 & 0 & 0 \\ 0 & 2f_3(p_e,p_f) & Lf_4(p_f,p_e) & 0 & 4f_1(p_f,p_e) & -2Lf_2(p_f,p_e) \\ 0 & -Lf_4(p_e,p_f) & -L^2f_6(p_e,p_f) & 0 & -2Lf_2(p_f,p_e) & 4L^2f_5(p_f,p_e) \end{bmatrix} \tag{3}$$

where $\overline{m} = \rho A$ is the mass per unit length. Also, D and functions f_1 to f_6 are defined by Eq.(4) as:

$$\begin{aligned} &D = 4 - p_e p_f \\ &f_1(p_e,p_f) = 560 + 224p_e + 32{p_e}^2 - 196p_f - 328p_e p_f - 55{p_e}^2 + 32{p_f}^2 + 50p_e{p_f}^2 + 32{p_e}^2{p_f}^2 \\ &f_2(p_e,p_f) = 224p_e + 64{p_e}^2 - 160p_e p_f - 86{p_e}^2 p_f + 32p_e{p_f}^2 + 25{p_e}^2{p_f}^2 \\ &f_3(p_e,p_f) = 560 - 28p_e - 64{p_e}^2 - 28p_f - 148p_e p_f + 5{p_e}^2 p_f - 64{p_f}^2 + 5p_e{p_f}^2 + 41{p_e}^2{p_f}^2 \\ &f_4(p_e,p_f) = 392p_f - 100p_e p_f - 64{p_e}^2 p_f - 128{p_f}^2 - 38p_e{p_f}^2 + 55{p_e}^2{p_f}^2 \\ &f_5(p_e,p_f) = 32{p_e}^2 - 31{p_e}^2 p_f + 8{p_e}^2{p_f}^2 \\ &f_6(p_e,p_f) = 124p_e p_f - 64{p_e}^2 p_f - 64p_e{p_f}^2 + 31{p_e}^2{p_f}^2 \end{aligned} \tag{4}$$

The stiffness matrix for the element considering the semi-rigid connection in the local coordinate system can be given by Eq. (5) as [16,17]:

$$\overline{K} = \frac{EI}{L}\begin{bmatrix} \frac{A}{I} & 0 & 0 & -\frac{A}{I} & 0 & 0 \\ 0 & \frac{4(b_{11}+b_{12}+b_{22})}{L^2} & \frac{2(2b_{11}+b_{12})}{L} & 0 & \frac{-4(b_{11}+b_{12}+b_{22})}{L^2} & \frac{2(2b_{12}+b_{22})}{L} \\ 0 & \frac{2(2b_{11}+b_{12})}{L_i} & 4b_{11} & 0 & \frac{-2(2b_{11}+b_{12})}{L} & 2b_{12} \\ -\frac{A}{I} & 0 & 0 & \frac{A}{I} & 0 & 0 \\ 0 & \frac{-4(b_{11}+b_{12}+b_{22})}{L^2} & \frac{-2(2b_{11}+b_{12})}{L} & 0 & \frac{4(b_{11}+b_{12}+b_{22})}{L^2} & \frac{-2(2b_{12}+b_{22})}{L} \\ 0 & \frac{2(2b_{12}+b_{22})}{L} & 2b_{12} & 0 & \frac{-2(2b_{12}+b_{22})}{L} & 4b_{22} \end{bmatrix} \tag{5}$$

where

$$b_{11} = \frac{3p_e}{4-p_e p_f}\ ,\ b_{12} = \frac{3p_e p_f}{4-p_e p_f}\ ,\quad b_{22} = \frac{3p_f}{4-p_e p_f} \tag{6}$$

The matrices of Eqs. (3) and (5) are in the local coordinate system and it is needed to transform them in a general coordinate system. Therefore, the global stiffness matrix K_e

and the global mass matrix M_e are determined by Eqs. (7) and (8):

$$K_e = T^{\mathrm{T}}\,\overline{K}\,T \tag{7}$$

$$M_e = T^{\mathrm{T}}\,\overline{M}\,T \tag{8}$$

where T is a transformation matrix.

2.2. Modal analysis

According to the modal analysis, the specifications and motion modes of a structure are determined which the output of this analysis will include vibrational frequencies and mode shapes. The vibrational modes obtained from the modal analysis are useful for correct understanding the behavior of the structure. Determining the vibrational specifications including the natural frequencies and modes of a structure requires the solving of an eigenproblem. From the dynamical knowledge of structures, the free vibration of an undamped system can be expressed as a mathematical form [18, 13]:

$$u_n = q_n(t)\emptyset_n \tag{9}$$

where $\emptyset_n$ is the nth mode shape function and shows the deformation of that mode and it is not time-dependent, $q_n(t)$ is a time-coordinate or briefly it is expressed the nth mode-coordinate that it is time-dependent. Time variations of deformation or mode-coordinate are defined by a simple harmonic function as the following [18, 19]:

$$q_n(t) = A_n \cos w_n\, t + B_n \sin w_n\, t \tag{10}$$

where A_n and B_n are constants which can be determined from initial conditions.

By combination of two relations above, the following relation can be obtained where ω_n and $\emptyset_n$ are unknown:

$$u_n = \emptyset_n(A_n \cos w_n\, t + B_n \sin w_n\, t) \tag{11}$$

Moreover, in structures that are considered as damped systems, the equation governing on free vibration system is determined from the following equation:

$$M\ddot{u} + C\dot{u} + Ku = 0 \tag{12}$$

where M, K are the matrix of mass and stiffness of the structure, respectively and C is the damping matrix.

If the damping C is ignored, the merge of Eqs. (11) and (12) will result in the following relation:

$$[-\omega_n^2 M\emptyset_n + K\emptyset_n]q_n(t) = 0 \tag{13}$$

When the expression in parentheses is equal to zero, it is led to the following algebraic equation:

$$K\emptyset_n = \omega_n^2 M\emptyset_n \rightarrow K\emptyset_n = \lambda M\emptyset_n \tag{14}$$

The relation is a matrix eigenproblem which $\lambda = \omega_n^2$ and $\emptyset_n$ are called an eigenvalue and eigenvector, respectively. By obtaining the value of ω_n, the frequency of structure is obtained accordance to the following relation:

$$f_n = \frac{\omega_n}{2\pi} \tag{15}$$

3. Support vector machine algorithm

The original SVM algorithm [20] was introduced by Vladimir Vapnik and Alexey Chervonenkis in 1963. The algorithm is one of the supervised learning models generally used for two important issues: classification and regression. In classification issue, SVM is used and in the regression issue employed in this article, a special case of SVM called support vector regression (SVR) is used [20]. In many applications for analyzing a system, at the first step the behavior of the system is modeled based on information from the system, and then the model is used to predict the future behavior of the system. As a matter of fact, this process is the same as process performed in the inverse engineering. The algorithm is one of the relatively new methods that have shown a good performance over recent years than older methods such as neural networks [6, 21 and 22].

3.1. Formulation of support vector regression

The SVR, which is a special case of SVM, is designed to perform the prediction operation. In the SVM case, where the classification was binary, the inputs were actually in the M-dimensional space, but the outputs were actually two values, and in general, there were no more than two cases. But in the SVR, it is supposed that the outputs are to be more than two values or infinite quantities, therefore, outputs are real and their purpose is to estimate. In fact, the purpose is to do a nonlinear regression, however, it is needed to convert the linear regression to a nonlinear regression using Kernel Trick. The SVR is briefly presented here with the observance of abbreviations in mathematical relations. The linear regression case where the dependency of a scalar variable *d* on an independent variable *x* is represented as follows [23]:

$$d = w^{\mathrm{T}}x + b \tag{16}$$

where the parameter vector *w* and the bias *b* are unknowns. The problem is to estimate *w* and *b* given *N* training samples $\mathcal{T} = \{(x_i \, , d_i)\}_{i=1}^{N}$ where the elements x_i are assumed to be statistically independent and identically distributed. The problem formulated is aimed to minimize, on the variables *w* and *b*, the structural risk functional below [23]:

$$R = \frac{1}{2}\,\|w\|_2^2 + C\sum_{i=1}^{N}|d_i - y_i|_{\varepsilon} \tag{17}$$

The parameter *C* is intended to implement the hard margin in the MATLAB software. It should be noted that in normal mode only the soft margin state can be implemented because the value of *C* can be increased to infinity (∞) and that's why it causes to MATLAB solvers get mistake and cannot provide output. Therefore, in general, the hard margin state cannot be implemented. To solve this problem, in the state of the soft margin, parameter *C* can be set to a large number until its behavior approaches to the hard margin. In fact, the factor of *C* must be set and there is no particular rule so that it could be a weakness of the SVM. In fact, setting these parameters is a trial and error process unless consign the parameter into an optimization algorithm. It should be mentioned that the variable y_i is the estimator output produced in response to the input x_i, that is $f(x_i) \equiv w^{\mathrm{T}}x + b = y_i$; the function $|.|_\varepsilon$ describes the ε-insensitive loss function defined as [23]:

$$L_\varepsilon\big(d\,, f(x)\big) \equiv |d - f(x)|_\varepsilon = \begin{cases} |d - f(x)| - \varepsilon & |d - f(x)| > \varepsilon \\ 0 & \text{otherwhise} \end{cases} \tag{18}$$

The functional given in Eq.(17) can be expressed as a standard optimization problem as follows [21]:

$$\min_{w,\,b} \ \tfrac{1}{2}\|w\|_2^2 + C\textstyle\sum_{i=1}^{N}|d_i - y_i|_\varepsilon \tag{19}$$

$$\mathrm{s \cdot t \cdot} \quad \begin{cases} d_i - y_i \le \varepsilon - \xi_i \\ y_i - d_i \le \varepsilon - \xi_i^* \end{cases} \quad \xi_i, \xi_i^* \ge 0$$

$$\text{for} \quad i = 1,2, \dots, N$$

where the summation in the cost function accounts for the ε -insensitive training error, which forms a tube where the solution is allowed to be defined without penalization for the linear and non-linear regression cases. The constant $C > 0$ describes the tradeoff between the training error and the penalizing term $\|w\|_2^2$. The term $\|w\|_2^2$ is penalized to enforce a sparse solution on *w*. The variables ξ_i and ξ_i^* are two sets of nonnegative slack variables that describe the ε -insensitive loss function. The objective function in the primal form can be rewritten in terms of the slack variables ξ_i and ξ_i^* , by observing the restrictions of the primal and the definition of the ε-insensitive function, and thus defining $\xi = d_i - y_i - \varepsilon$ and $\xi^* = y_i - d_i - \varepsilon$. Then, another common version of the primal problem can be obtained as follows [23]:

$$\min_{w,b,\xi,\xi^*} \frac{1}{2}\|w\|_2^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \tag{20}$$

$$\text{s}\cdot\text{t}\cdot \begin{cases} d_i - w^T x - b \le \varepsilon - \xi_i \\ w^T x + b - d_i \le \varepsilon - \xi_i^* \end{cases} \xi, \xi^* \ge 0$$

for $\quad i = 1.2.\cdots.N$

Then, the dual problem is defined using the Lagrange multiplier method, where the Lagrangian function can be defined as [23]:

$$L(w,b,\xi,\xi^*,\alpha,\alpha^*,\gamma,\gamma^*) = \frac{1}{2}\|w\|_2^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) - \sum_{i=1}^{N}(\gamma_i\xi_i + \gamma_i^*\xi_i^*) -$$

$$\sum_{i=1}^{N}\alpha_i(w^T x_i + b - d_i + \varepsilon + \xi_i) - \sum_{i=1}^{N}\alpha_i^*(d_i - w^T x_i - b + \varepsilon + \xi_i^*) \tag{21}$$

where $\gamma_i, \gamma_i^*, \alpha_i$ and α_i^* indicate the Lagrange multipliers associated with the objective function and constraints, respectively.

The associated stationary points are defined by the following partial derivatives [21]:

$$\frac{\partial L(w.b.\xi.\xi^*.\alpha.\alpha^*.\gamma.\gamma^*)}{\partial w} = w - \sum_{i=1}^{N}(\alpha_i^* - \alpha_i)x_i = 0 \tag{22}$$

$$\frac{\partial L(w.b.\xi.\xi^*.\alpha.\alpha^*.\gamma.\gamma^*)}{\partial b} = \sum_{i=1}^{N}(\alpha_i^* - \alpha_i) = 0 \tag{23}$$

$$\frac{\partial L(w.b.\xi.\xi^*.\alpha.\alpha^*.\gamma.\gamma^*)}{\partial \xi} = C1 - \alpha - \gamma = 0 \tag{24}$$

$$\frac{\partial L(w.b.\xi.\xi^*.\alpha.\alpha^*.\gamma.\gamma^*)}{\partial \xi^*} = C1 - \alpha^* - \gamma^* = 0 \tag{25}$$

Then, the dual problem using the method of Lagrange multipliers can be stated as follows [23]:

$$\max_{w,b,\xi,\xi^*,\alpha,\alpha^*,\gamma,\gamma^*} L(w,b,\xi,\xi^*,\alpha,\alpha^*,\gamma,\gamma^*) \tag{26}$$

$$\text{s}\cdot\text{t}\cdot\begin{cases}\frac{\partial L(w.b.\xi.\xi^*.\alpha.\alpha^*.\gamma.\gamma^*)}{\partial w}=0\\ \frac{\partial L(w.b.\xi.\xi^*.\alpha.\alpha^*.\gamma.\gamma^*)}{\partial b}=0\\ \frac{\partial L(w.b.\xi.\xi^*.\alpha.\alpha^*.\gamma.\gamma^*)}{\partial \xi}=0\\ \frac{\partial L(w.b.\xi.\xi^*.\alpha.\alpha^*.\gamma.\gamma^*)}{\partial \xi^*}=0\end{cases} \qquad \xi,\xi^*,\alpha,\alpha^*,\gamma,\gamma^*\geq 0$$

And the following problem is the expanded version of problem of Eq.(26) above [21]:

$$\max_{w,b,\xi,\xi^*,\alpha,\alpha^*,\gamma,\gamma^*} \frac{1}{2}\|w\|_2^2+C\sum_{i=1}^{N}(\xi_i+\xi_i^*)-\sum_{i=1}^{N}(\gamma_i\xi_i+\gamma_i^*\xi_i^*)-\sum_{i=1}^{N}\alpha_i(w^Tx_i+b-d_i+\varepsilon+\xi_i)-\sum_{i=1}^{N}\alpha_i^*(d_i-w^Tx_i-b+\varepsilon+\xi_i^*) \tag{27}$$

$$\text{s}\cdot\text{t}\cdot\begin{cases}w-\sum_{i=1}^{N}(\alpha_i^*-\alpha_i)x_i=0\\ \sum_{i=1}^{N}(\alpha_i^*-\alpha_i)=0\\ C1-\alpha-\gamma=0\\ C1-\alpha^*-\gamma^*=0\end{cases} \qquad \xi,\xi^*,\alpha,\alpha^*,\gamma,\gamma^*\geq 0$$

for $\quad i=1,2,\cdots.N$

However, it is possible to remove three constraints by noticing from Eq. (22) that one can solve for *w* as follows [23]:

$$w=\sum_{i=1}^{N}(\alpha_i^*-\alpha_i)x_i \tag{28}$$

Also, one can solve for both γ and γ^* from Eqs. (24) and (25) as [23] :

$$\gamma=C1-\alpha \tag{29}$$

$$\gamma^*=C1-\alpha^* \tag{30}$$

which yields the boundary condition $\alpha\geq 0$, $C1\geq\alpha^*$.

If Eqs. (28) to (30) are substituted into the objective function, and perform some analytic operations; the well-known reduced dual problem can be arrived as [23]:

$$\max_{\alpha,\alpha^*} -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)x_i^Tx_j-\varepsilon\sum_{i=1}^{N}(\alpha_i+\alpha_i^*)+\sum_{i=1}^{N}d_i(\alpha_i-\alpha_i^*) \tag{31}$$

$$\text{s}\cdot\text{t}\cdot \quad \sum_{i=1}^{N}(\alpha_i-\alpha_i^*)=0 \qquad \alpha_i\geq 0\ ,\ C\geq{\alpha_i}^*$$

for $\quad i=1,2,\cdots.N$

Eqs. (20) and (31) solve the linear regression problems, and for the non-linear regression case, a kernel function formulation is needed to just introduce. For the primal case, the sole modification is on the restrictions which are redefined as follows [23]:

$$w^{\mathrm{T}}k(x_i,0)+b-d_i \leq \epsilon-\xi_i \tag{32}$$

$$d_i-w^{\mathrm{T}}k(x_i,0)-b \leq \epsilon-\xi_i^* \tag{33}$$

for $i=1,2.,\cdots.N$

For the dual problem, the objective function is redefined as [15]:

$$\max_{\alpha.\alpha^*} \; -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i-\alpha_i^*)\left(\alpha_j-\alpha_j^*\right)k(x_i,x_j)-\varepsilon\sum_{i=1}^{N}(\alpha_i+\alpha_i^*)+\sum_{i=1}^{N}d_i(\alpha_i-\alpha_i^*) \tag{34}$$

4. Damage identification using an optimization method

The purpose of the damage identification using an optimization method is to accurately determine the location and severity of damage. Due to various reasons such as increasing damage variables and the noise effect, the SVM algorithm may achieve some false locations of the damage in addition to exact location. Therefore, an optimization process is used here as the second stage, to modify possible errors. The general form of the optimization problem related to identifying the damage can be expressed as follows:

$$\begin{aligned} &\text{Find:} && X^{\mathrm{T}}=\{x_1,x_2..,x_n\} \\ &\text{Minimize:} && W\left(X\right) \\ & && X^{l}\leq X\leq X^{u} \end{aligned} \tag{35}$$

where X is the vector of the damage variables, including the location and severity of unknown damages, X^l and X^u are the lower and upper bounds of damage vector and W is the objective function that should be minimized.

4.1. Damage variables

In this study, the damage variables are defined via a parameter x_i as follows:

$$x_i = 1 - \frac{p_{id}}{p_{ih}} \quad , \ i = 1, \dots, n \tag{36}$$

where p_{id} is the fixity factor of a damaged connection and p_{ih} is the fixity factor of the healthy (rigid) connection.

4.2. Objective function

The objective function is one of the most important parts of an optimization problem. The efficiency of an optimization based damage identification problem can be affected by selecting an appropriate objective function. In this research, the objective function is considered as follows [24]:

$$ECBI(X) = \frac{1}{2}(MDLAC(X) + obj\ (X)) \tag{37}$$

where multiple damage location assurance criterions (MDLAC) can be expressed as follows [25]:

$$MDLAC(X) = \frac{|\Delta F^T . \delta F(X)|^2}{(\Delta F^T . \Delta F)(\delta F^T(X) . \delta F(X))} \tag{38}$$

where ΔF indicates the change of the natural frequency vector of damaged structure, F_d with respect to the natural frequency vector of the healthy structure, F_h as follows:

$$\Delta \mathrm{F} = \frac{F_h - F_d}{F_h} \tag{39}$$

Similarly, the change of the natural frequency vector of an analytical model, $F(X)$ with respect to the natural frequency vector of the healthy structure can be defined as:

$$\delta F(X) = \frac{F_h - F(X)}{F_h} \tag{40}$$

In Eq. (37), the function *obj* (X), is defined as follows [24]:

$$obj(X) = \frac{1}{n_f}\sum_{i=1}^{n_f}\frac{\min\,(f_{xi}, f_{di})}{\max\,(f_{xi}, f_{di})} \tag{41}$$

where f_{xi} and f_{di} are the ith component of vectors F (X) and F_d, respectively.

4.3. Optimization algorithm

In this study, for accurately finding the site and severity of damage, differential evolution algorithm (DEA) is used. The DEA was proposed by Storn and Price in 1995. The behavior of the algorithm is a random behavior and the optimization process begins with a series of initial solutions and the result is obtained after several successive iterations. In order to start the algorithm, only 3 control parameters are required, which include: *NP* is the population size, *MF* is the mutation factor and *CR* is the crossover ratio which indicates the probability of mutation in each iteration. The general process of DEA is shown in Fig. 2 [26-29].

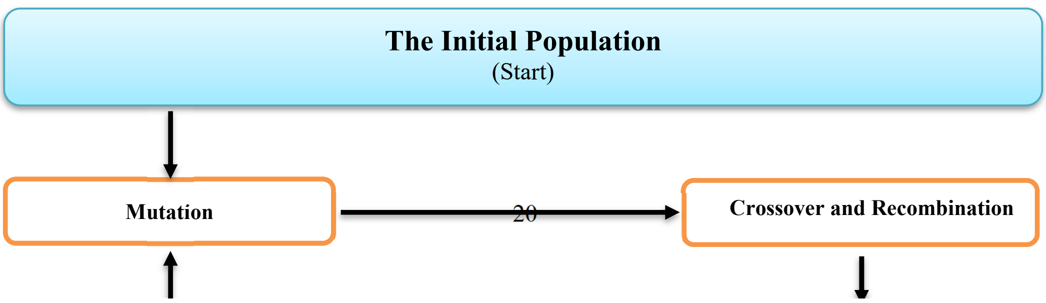


Fig. 2. The general process of differential evolution algorithm

5. Steps to the research

To do research, at the first an analytical model is provided to simulate the moment frames with semi-rigid connections and then using the model, some structures having damage are randomly generated and natural frequencies of damaged structures are extracted. Then, using a part of the data, SVM is trained, with the difference that the role of input and output data is changed, that is, the natural frequencies are considered as input data and the damage properties are considered as output data. In the following, using the remaining data, the accuracy of the trained SVM is checked. Now, using the trained SVM, the possible location and inaccurate severity of damage in connections can be obtained. Therefore, the first step of the study is to determine the probability location of damage in connections and reduce the size of the search space based on SVM algorithm. In the second step of this study, an optimization algorithm named DEA is used to determine the accurate location and precise amount of damage in connections. The steps of the proposed method are shown in Fig. 3.

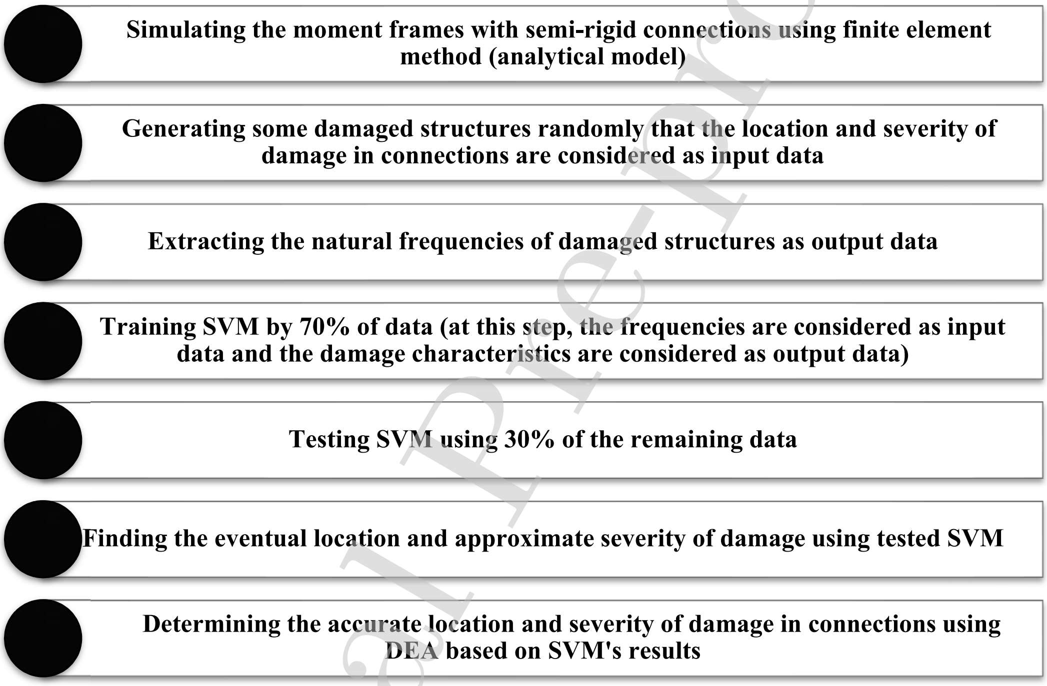


Fig. 3. The research steps for damage identification using SVM and DEA

5. Numerical examples

In order to demonstrate the efficiency of the proposed method for identifying damage in moment frame connections, two planar-steel frame structures with 18 elements and 49 elements are investigated. For the mentioned frames, the modulus of elasticity is $2 \times 10^6 \frac{\mathrm{kg}}{\mathrm{cm}^2}$ and the mass density is $7850 \frac{\mathrm{kg}}{\mathrm{m}^3}$. The height of the columns in the ground floor is 4.5 m and for other floors is considered 3.5 m. The length of the beams in all floors is 7 m. In these structures, single and double damage cases are considered and numerical results are presented as diagrams. Also, the efficiency of the method by considering the noise 1% on the frequencies is assessed. The relation considered for applying the noise is defined as follows:

$$f_{r_d} = f_{r0}\,(1 + \left(2\text{rand}\left(n_f, 1\right) - 1\right) noise) \tag{42}$$

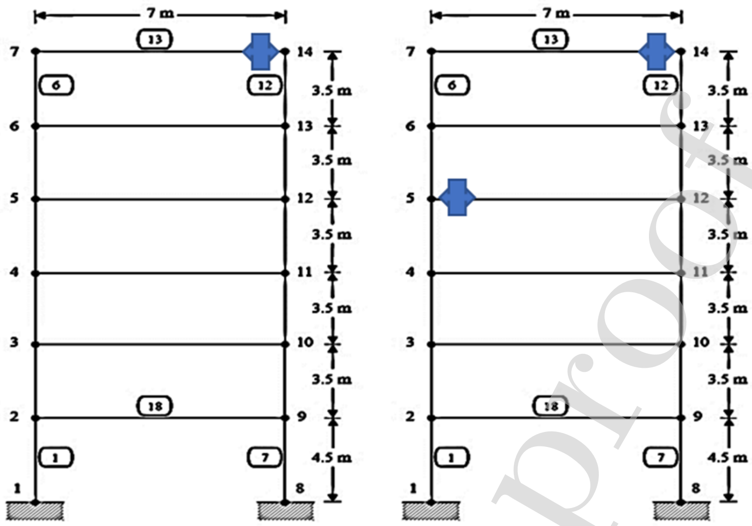
where f_{r_d} is the vector of noisy frequencies of damaged structure, f_{r0} is the vector of initial frequencies of damaged structure, rand is a function to uniformly generate the random number, n_f is the number of frequencies considered and $noise$ is the level of noise.

Based on the section 3, the SVR algorithm has two main parameters including ε and *C*. It should be noted that there is no particular way to set them up and a trial and error approach may be employed. In this study, for a more accurate function of the algorithm, the value of ε is considered to be 0.15 and the value of the parameter *C* considered as a penalty coefficient is set to 1000.

For the optimization by differential evolution algorithm, *NP*, *MF* and *CR* are set to 20, 0.40 and 0.20, respectively. Also, the maximum number of iterations is set to 1000.

5.1. 18-element planar frame

The 18-element frame having 14 nodes and 12 beam-column connections is investigated for single and double damage cases as shown in Fig. 4. In the single damage case, damage with severity of 0.32 is induced in the right joint of element 13 without considering noise and with considering 1% noise. Also, in the case of double damage, the right joint of element 13 and the left joint of element 15 are damaged with the severity of 0.32 without considering noise and with considering the noise level of 1%.



(a) (b)

Fig. 4. 18-element moment frame, (a) single damage case, (b) double damage case

For the single damage case, 500 damaged structures are randomly generated and the first 5 natural frequencies of damaged structures are determined. For training the SVM, 70% of data, i.e., 350 data are considered and 30% of remaining data, i.e. 150 data are considered for the testing the SVM. After testing the SVM using 30% of test data, the accuracy of the algorithm is checked again using some data outside of the test data as the final test of the algorithm. The performance of SVM in testing mode for single damage case without considering noise and with considering noise are shown in Figs. 5 and 6, respectively. The results obtained show that the SVM is properly trained.

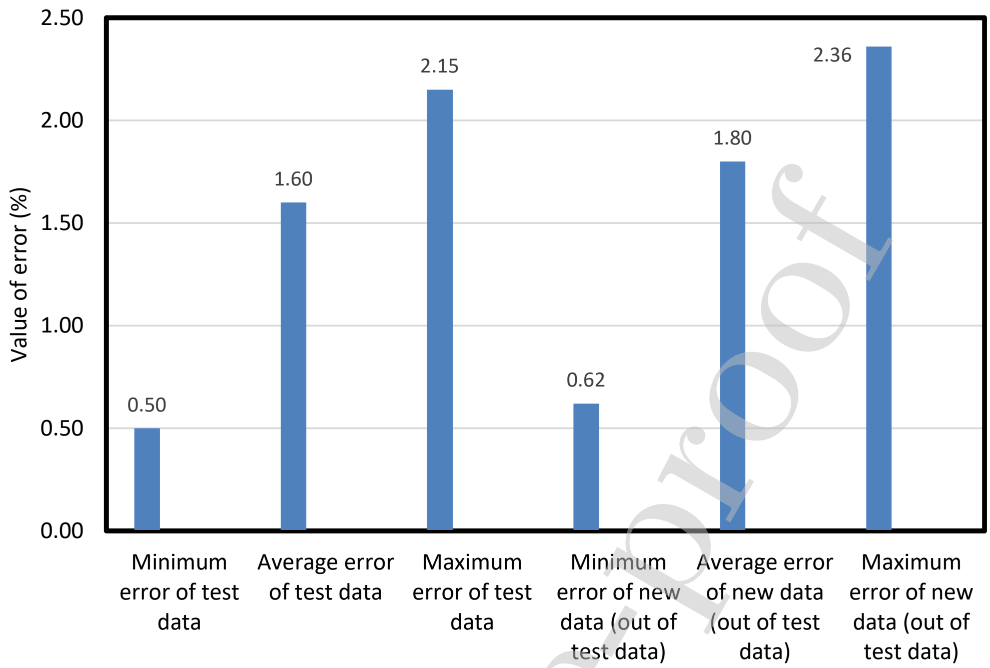


Fig. 5. Testing error of 18-element frame for single damage case without considering noise

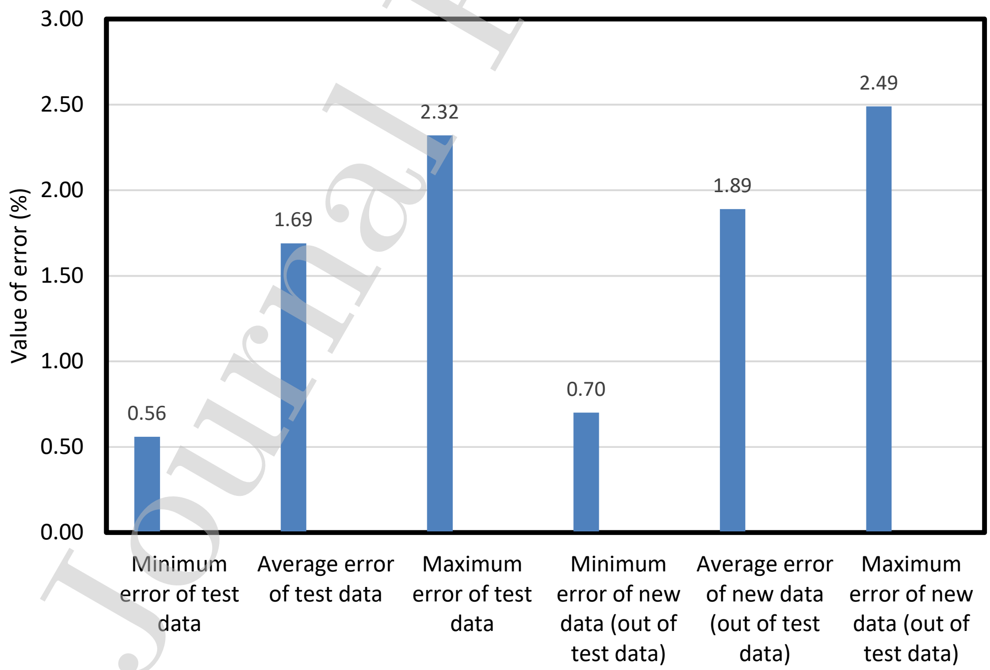


Fig. 6. Testing error of 18-element frame for single damage case with considering noise

Now as the first step, the possible location of damage can be obtained by the SVM and in the second step, the results obtained by the SVM are considered as input data for DEA. In this situation, if the location and severity of the damage are determined incorrectly by the SVM, the optimization process can improve the SVM's identification. Damage identification result for single damage case using SVM is shown in Fig. 7 and the final identification result obtained using DEA is shown in Fig. 8. It should be noted that the letters of L and R in the diagrams represent the left and right end connections of beams, respectively. Also, the induced and identified words in diagrams represent the actual damage considered and the damage detected by the algorithm, respectively.

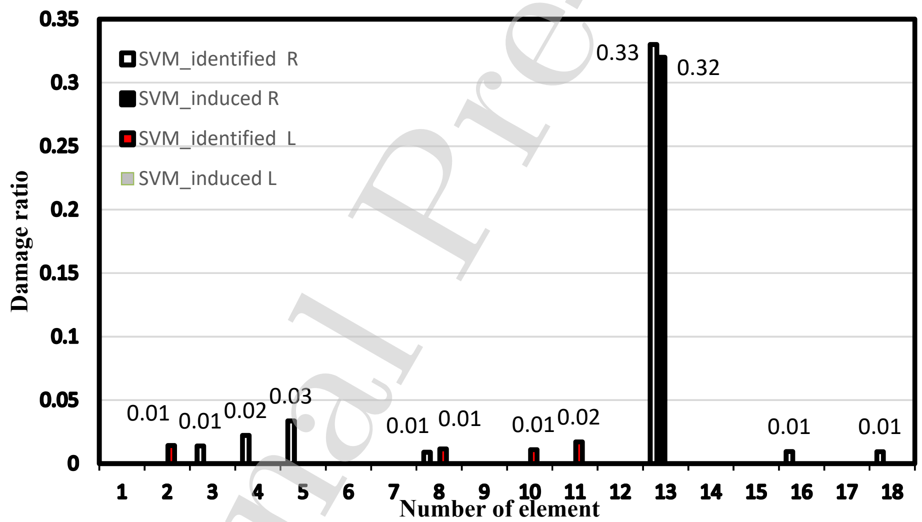


Fig. 7. Damage identification result of 18-element frame for the single damage case using SVM without considering noise

As can be observed in Fig. 7, the SVM algorithm can correctly predict the location of damaged connection of 18-element frame for the single damage case and noticeably reduce the damage variables. It should be noted that when the noise is not considered, connections with the damage ratio more than 0.05 will be selected as potentially damaged connections

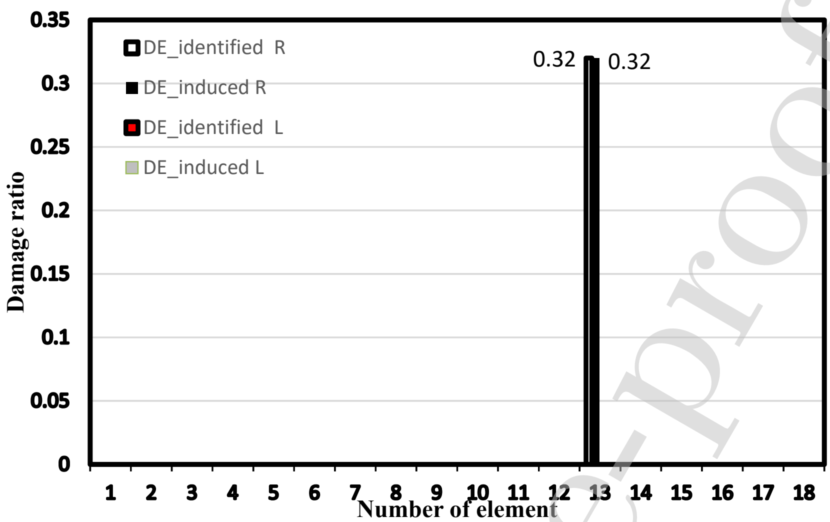


Fig. 8. Final damage identification result of 18-element frame for the single damage case using DEA without considering noise

It should to be mentioned that, based on the result obtained by the SVM algorithm in the first phase, DEA can meet to the accurate solution as shown in Fig. 8. The damage identification results obtained by SVM and DEA for considering 1% noise are also shown in Figs. 9 and 10, respectively.

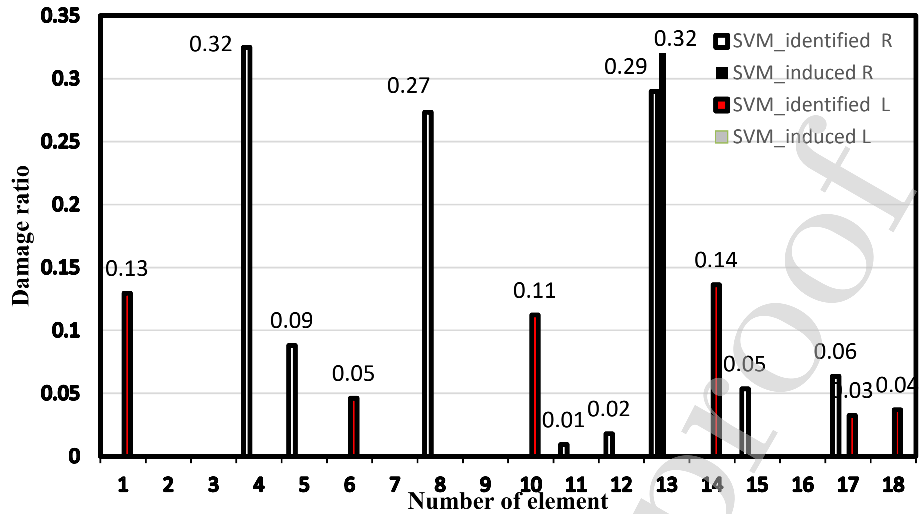


Fig. 9. Damage identification result of 18-element frame for the single damage case using SVM with considering 1% noise

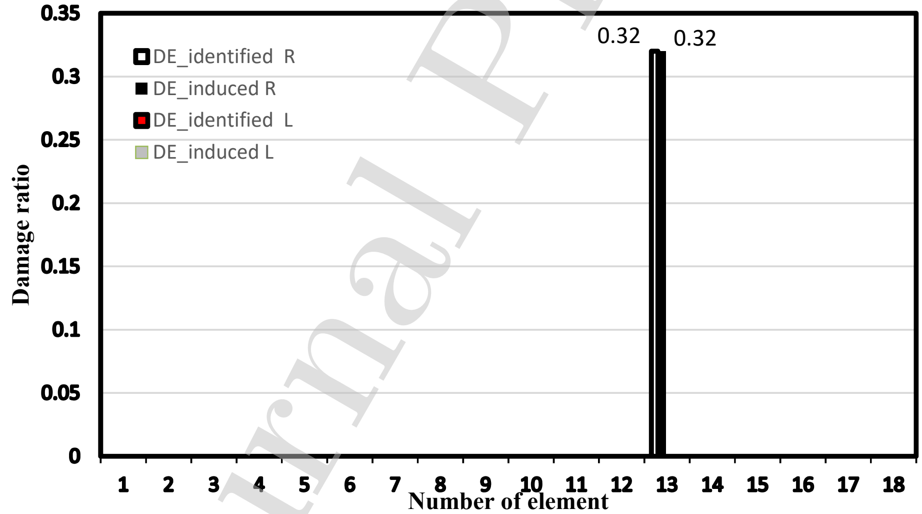


Fig. 10. Final damage identification result of 18-element frame for the single damage case using DEA with considering 1% noise

As can be seen in Fig. 9, when considering the noise, more connections of the structure are predicted by the SVM algorithm as possibly damaged joints, however, it can also be reduced the damage variables considerably. It should be mentioned that when the noise is considered, connections with the damage ratio more than 0.1 will be selected as possibly damaged connections. Moreover, the final identification result shown in Fig. 10 represents that the solution obtained by SVM is modified by DEA to reach the accurate damage induced.

For the double damage case, 1000 structures having damaged joints are randomly generated and the first 5 natural frequencies of structures are considered. For training the algorithm, 70% of data, i.e., 700 data are considered and 30% of the remaining data, i.e., 300 data are selected for testing the algorithm. After testing the SVM using 30% of data, the accuracy of the algorithm is checked again using some data outside of the test data as the final test. The performance of SVM in testing mode for double damage case without considering noise and with considering noise are shown in Figs. 11 and 12, respectively. The results obtained show the efficiency of SVM.

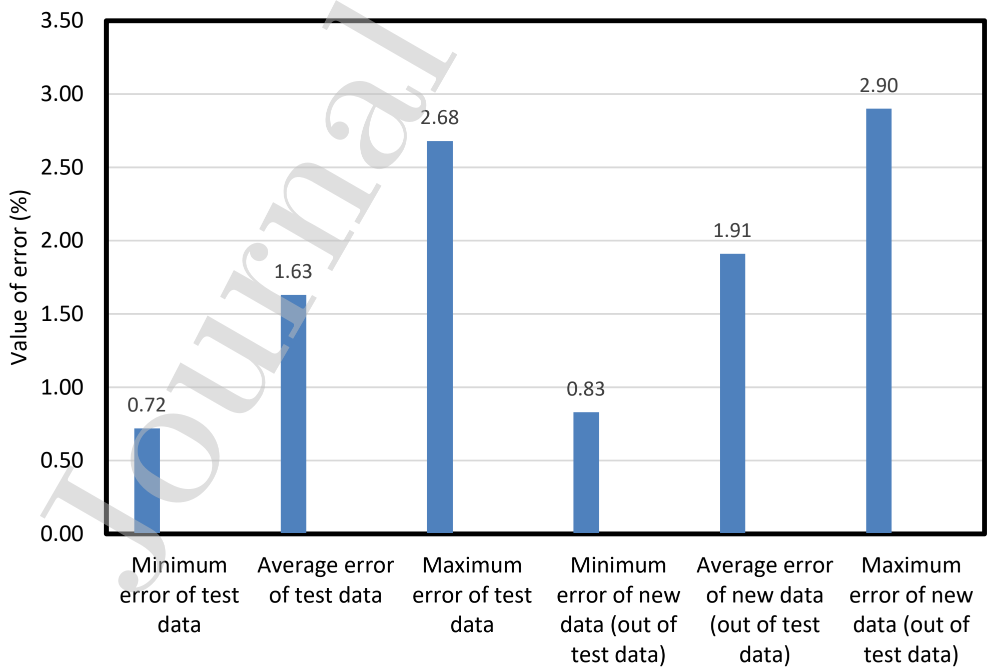


Fig. 11. Testing error of 18-element frame for double damage case without considering noise

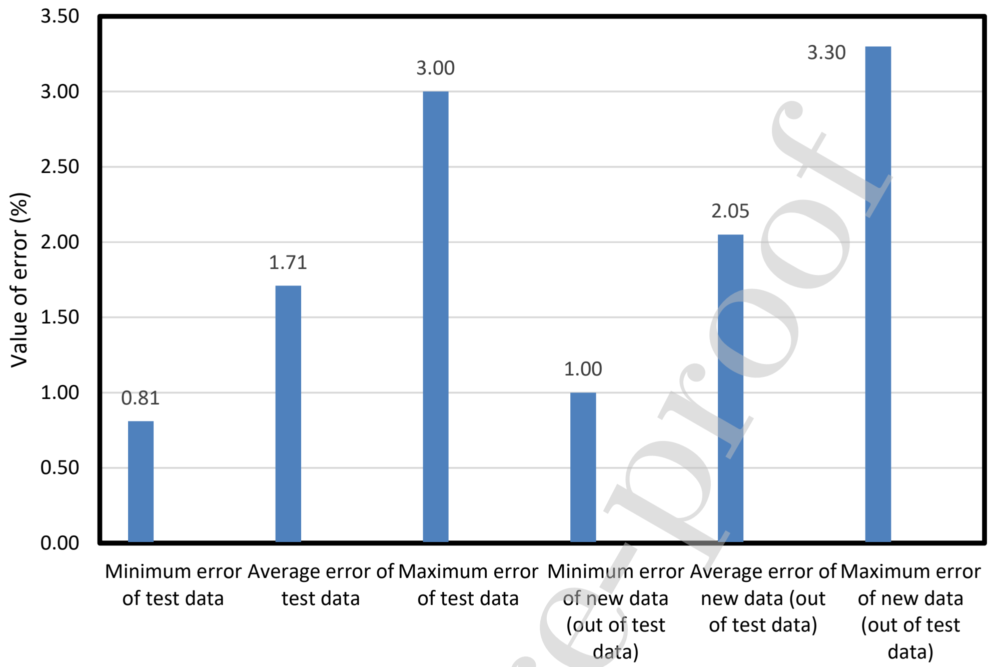


Fig. 12. Testing error of 18-element frame for double damage case with considering noise

The SVM trained and tested can now be used to identify the damage and reduce the search space for the optimization. In the second step, the result obtained by SVM is considered as input data to DEA. In this situation, if the location and severity of the damage are determined wrongly by SVM, the optimization process can be improved the SVM's result. The outcome of the first step, namely, damage identification using the SVM and the outcome of the second step, namely, the damage identification using DEA are shown in Figs. 13 and 14, respectively, when noise is not considered.

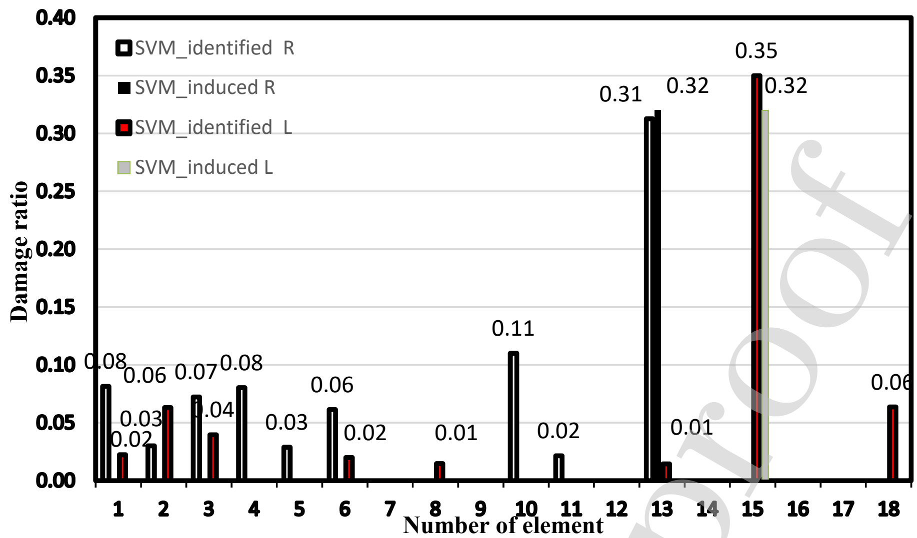


Fig. 13. Damage identification result of 18-element frame for the double damage case using SVM without considering noise

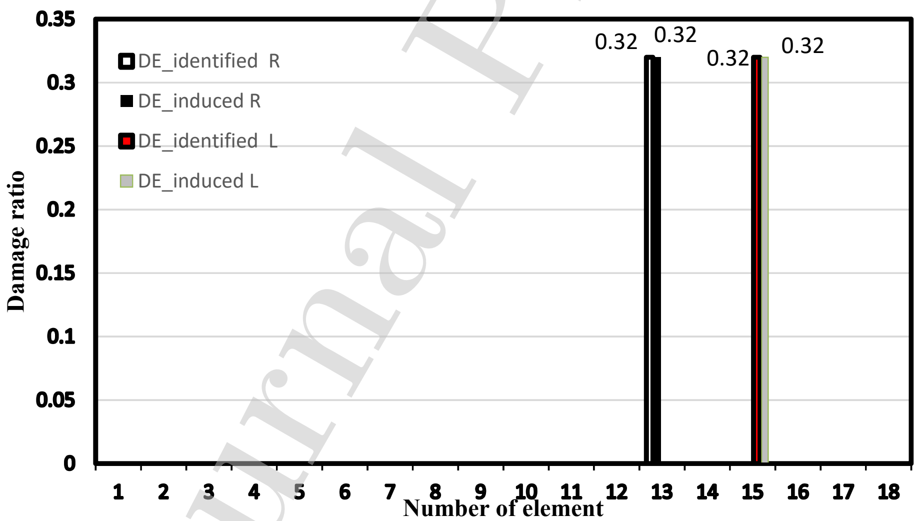


Fig. 14. Final damage identification result of 18-element frame the double damage case using DEA without considering noise

As can be observed in the figures, for the double damage case of 18-element frame, the SVM can predict the location of damaged connections and noticeably reduce the damage variables leading to the accurate solution using DEA. The damage identification results obtained by SVM and DEA for considering 1% noise are also shown in Figs. 15 and 16, respectively.

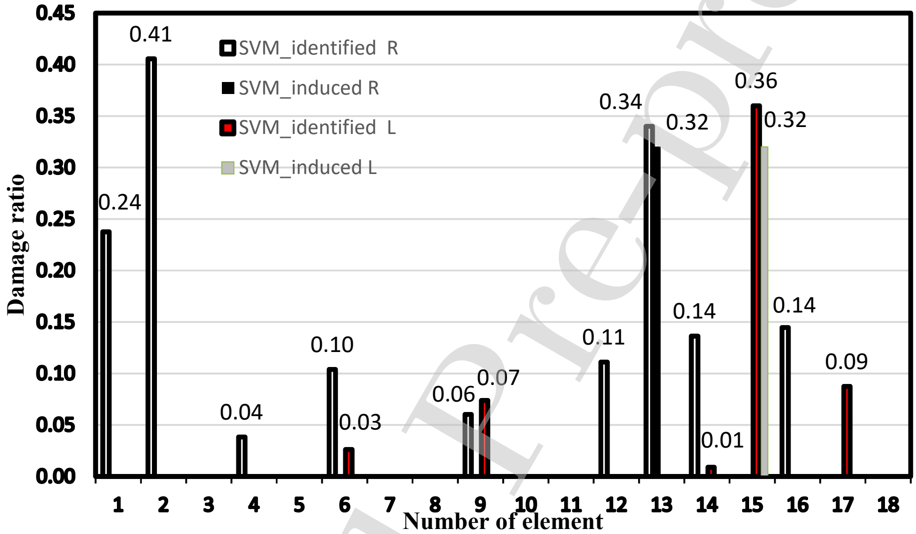


Fig. 15. Damage identification result of 18-element frame for the double damage case using SVM with considering 1% noise

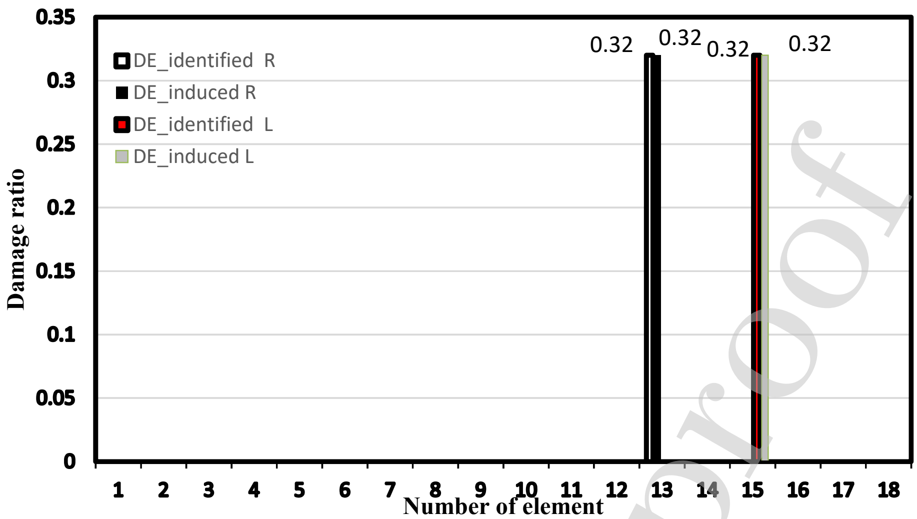


Fig. 16. Final damage identification result of 18-element frame for the double damage case using DEA with considering 1% noise

It can be observed that for the double damage case of 18-element frame when the noise is considered, based on the result obtained by the SVM in the first stage, the final damage identification result achieved by DEA in the second stage, is led to the proper solution indicating the high performance of the proposed method.

5.2. 49-element planar frame

In order to show the capability of the proposed method for identifying damage in connections of larger structures, 49-element frame with 32 nodes and 21 beam-column connections is investigated for single and double damage cases as shown in Fig. 17. In the case of single damage, the right joint of element 29 is damaged with the severity of 0.32 without considering noise and with considering 1% noise. In double damage case, the right joint of element 29 and the left joint of element 47 are damaged with the magnitude of 0.32 without considering noise and with considering noise 1%.

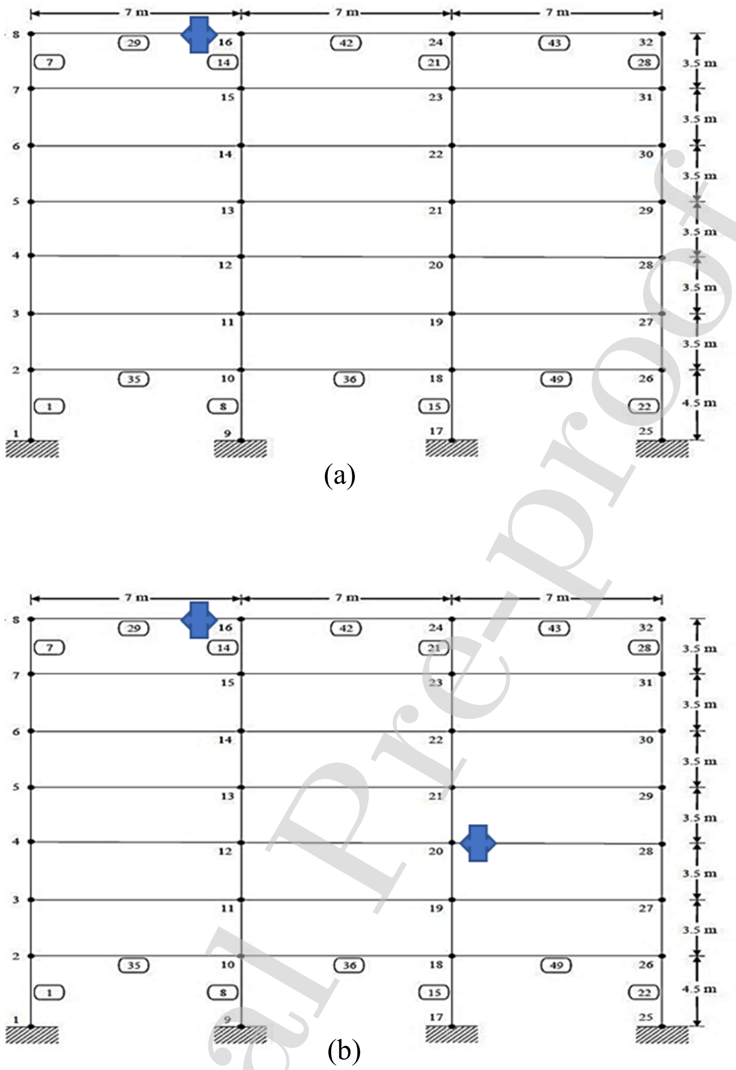


Fig. 17. 49-element moment frame, (a) single damage case, (b) double damage case

For the single damage case, 750 data are generated, which 70% of data, i.e. 525 data are selected for training the algorithm and 30% of the remaining data, i.e. 225 data are considered for testing. After testing the algorithm using 30% of generated data, the accuracy of the algorithm is checked again using some data outside of the test data as the final test. The performance of SVM in testing mode for single damage scenario without considering noise and with considering noise are shown in Figs. 18 and 19, respectively. The results obtained demonstrate the competence of SVM in testing mode.

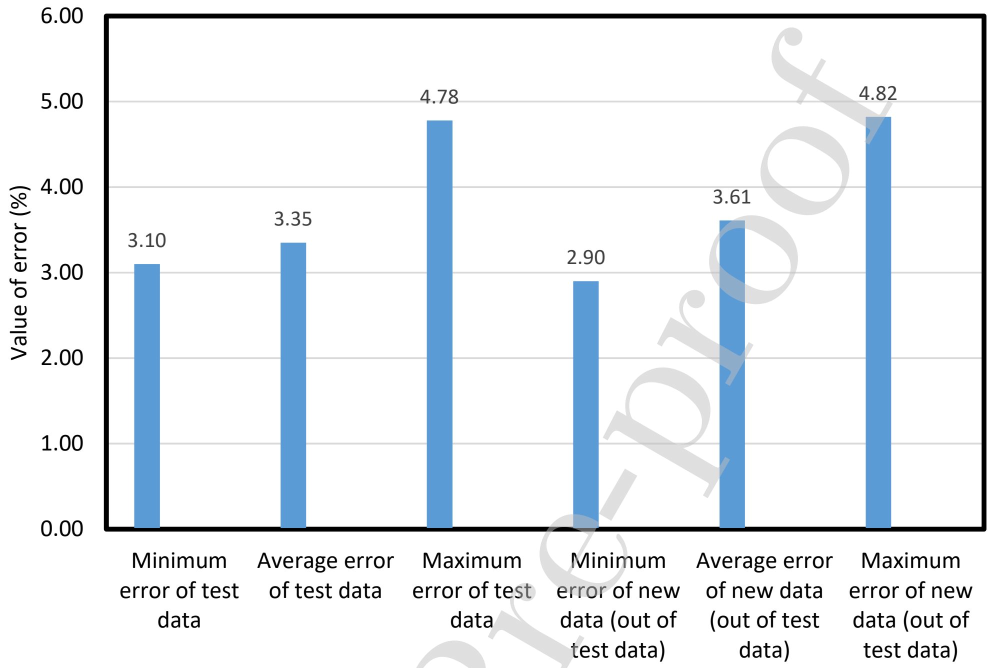


Fig. 18. Testing error of 49-element frame for single damage case without considering noise

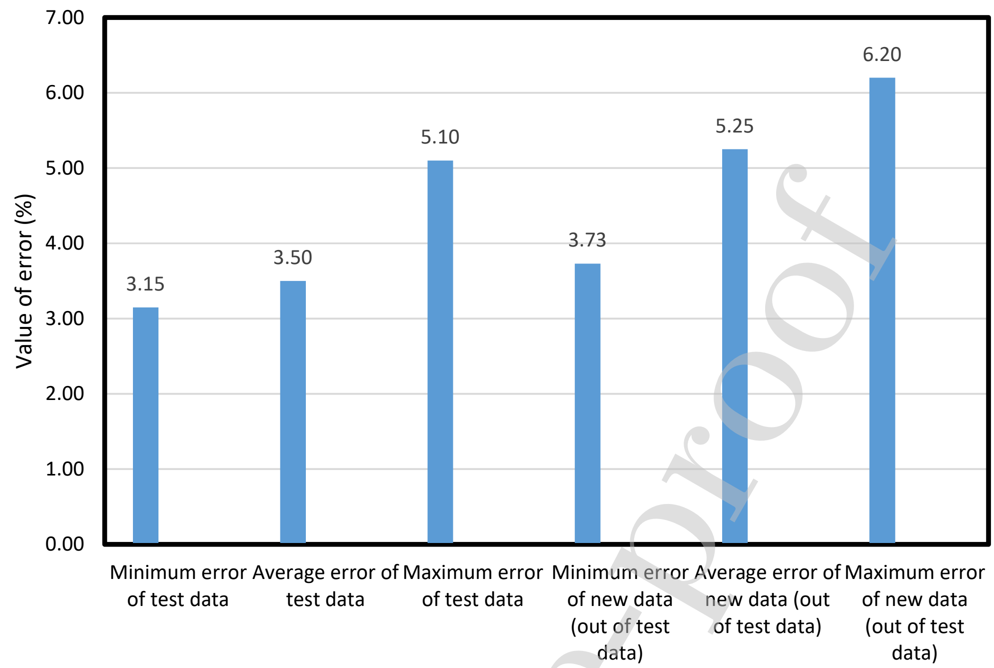


Fig. 19. Testing error of 49-element frame for single damage case with considering noise

The SVM trained and tested can now be used to identify the damage and reduce the damage variables. In the second step, the final results obtained by the SVM are considered as input to the DEA. In this situation, if the location and severity of damage are determined wrongly by SVM, the optimization algorithm will be able to improve the SVM's result. The result of the first step, namely, the identification of the damage using the SVM and the result of the second step using DEA, are shown in the Figs. 20 and 21, respectively.

Considering 750 data for the single damage case of 49-element frame and also according to the results shown in Figs 18 and 20, it can be concluded that the SVM algorithm works efficiently for reducing damage variables and can identify the damaged connection. Here, joints with damage ratio bigger than 0.05 is nominated as possibly damaged connections

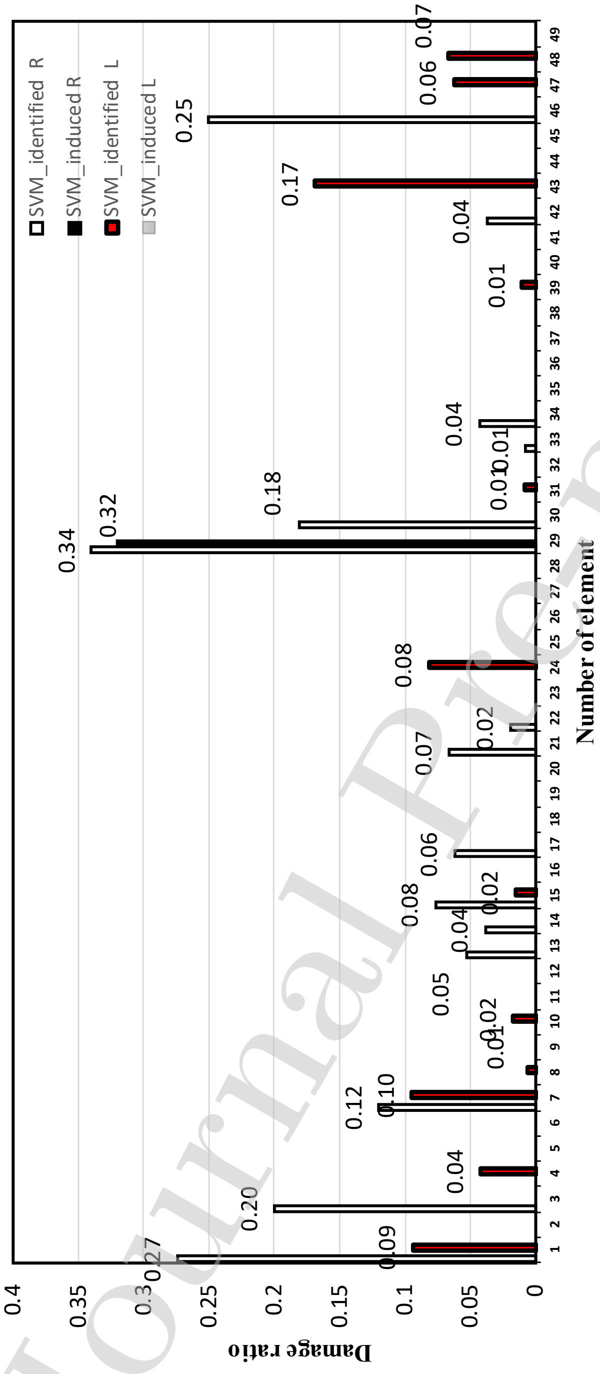


Fig. 20. Damage identification result of 49-element frame for the single damage case using SVM without considering noise

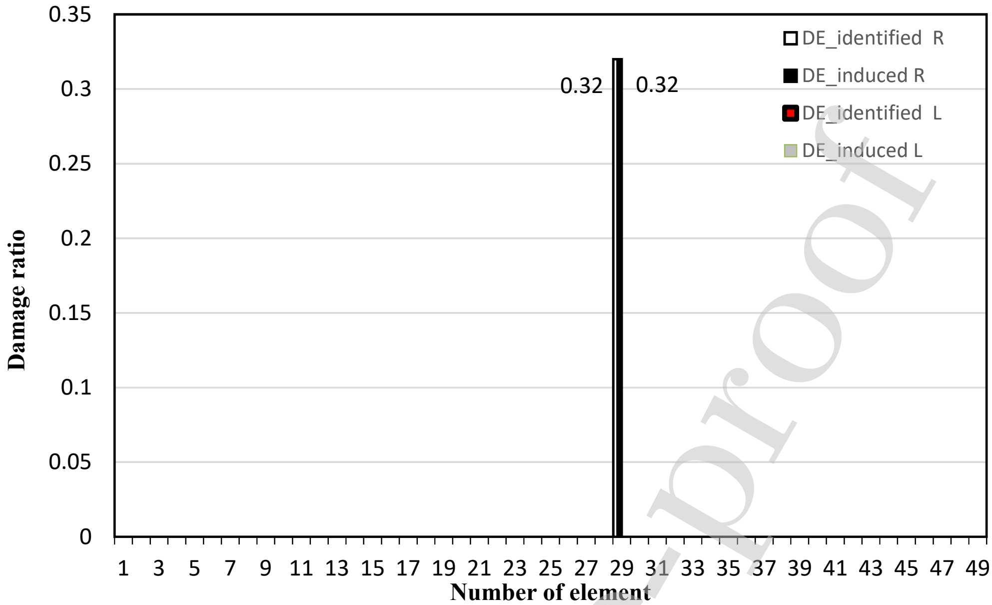


Fig. 21. Final damage identification result of 49-element frame for the single damage case using DEA without considering noise

It is imperative to be mentioned that, the final damage identification result shown in Fig. 21 indicates that the DEA is very effective in obtaining the actual damage. The damage identification results obtained by SVM and DEA for considering 1% noise are also shown in Figs. 22 and 23, respectively.

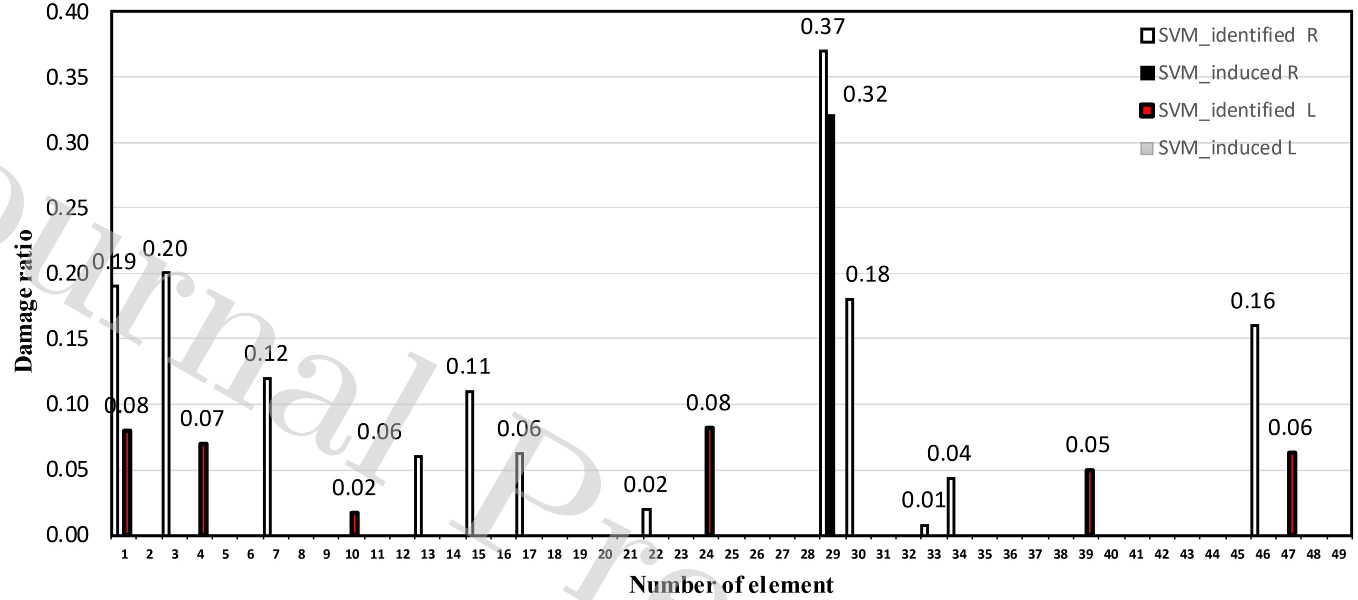


Fig. 22. Damage identification result of 49-element frame for the single damage case using SVM with considering 1% noise

As can be observed in Fig. 22, SVM can find the damaged connection and reduce damage variables considerably, when the noise is considered.

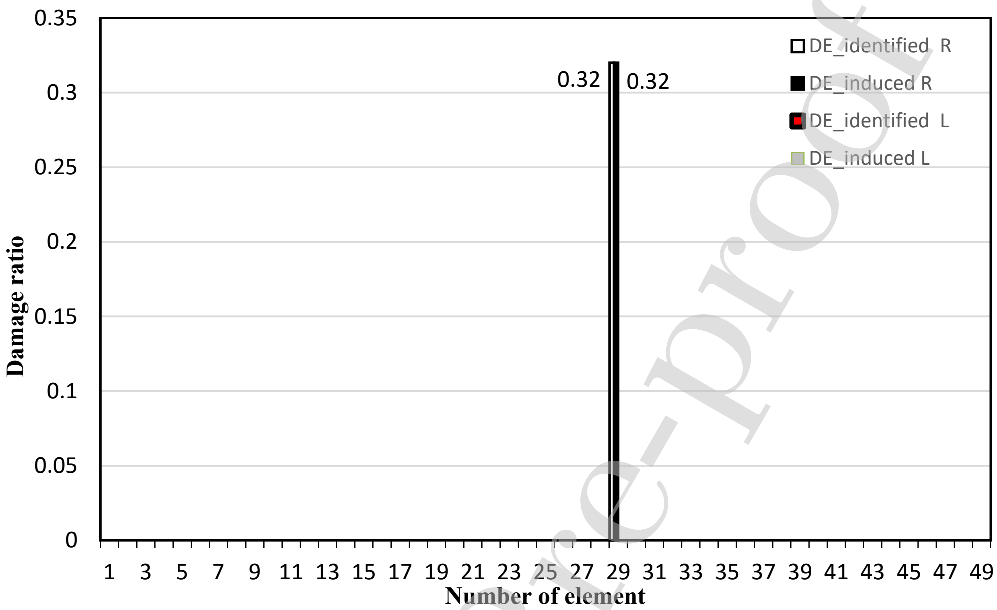


Fig. 23. Final damage identification result of 49-element frame for the single damage case using DEA with considering 1% noise

Based on the final identification result shown in Fig. 23, it is obvious that DEA is effective in converging to the actual solution.

For the double damage case, 1500 data are randomly generated, which 70% of data, i.e. 1050 data is considered for the training phase and 30% of the remaining data, i.e. 450 data are considered for the testing phase. After testing the algorithm using 30% of the test data, the accuracy of the algorithm is controlled again using new data outside of the test data as the main test of the algorithm. The performance of SVR in testing mode for double damage scenario without considering noise and with considering noise are shown in Figs. 24 and 25, respectively. The results obtained prove the proficiency of SVM in the testing mode.

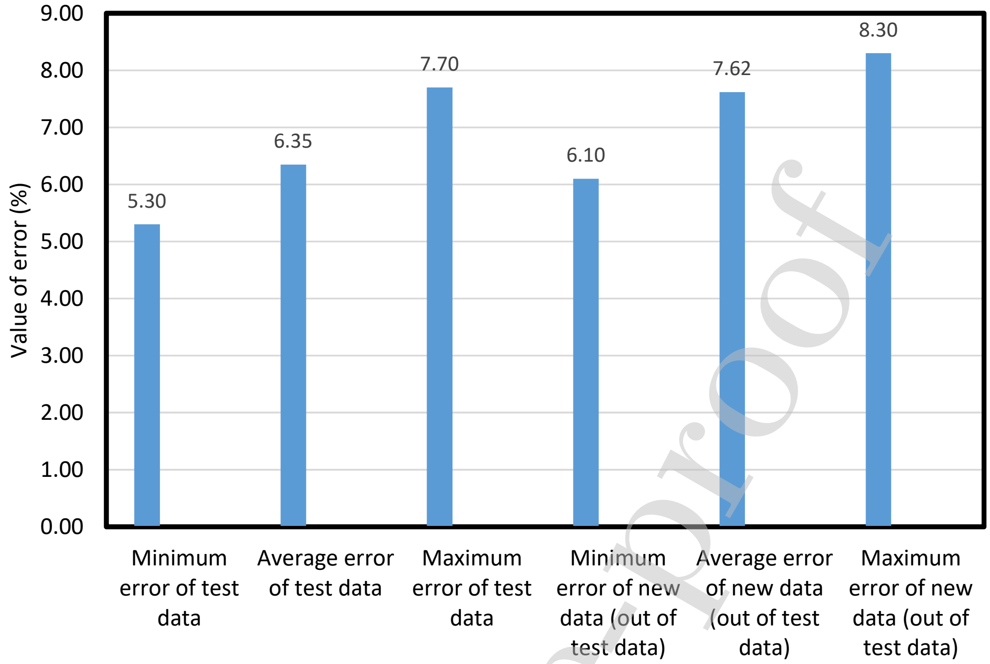


Fig. 24. Testing error of 49-element frame for double damage case without considering noise

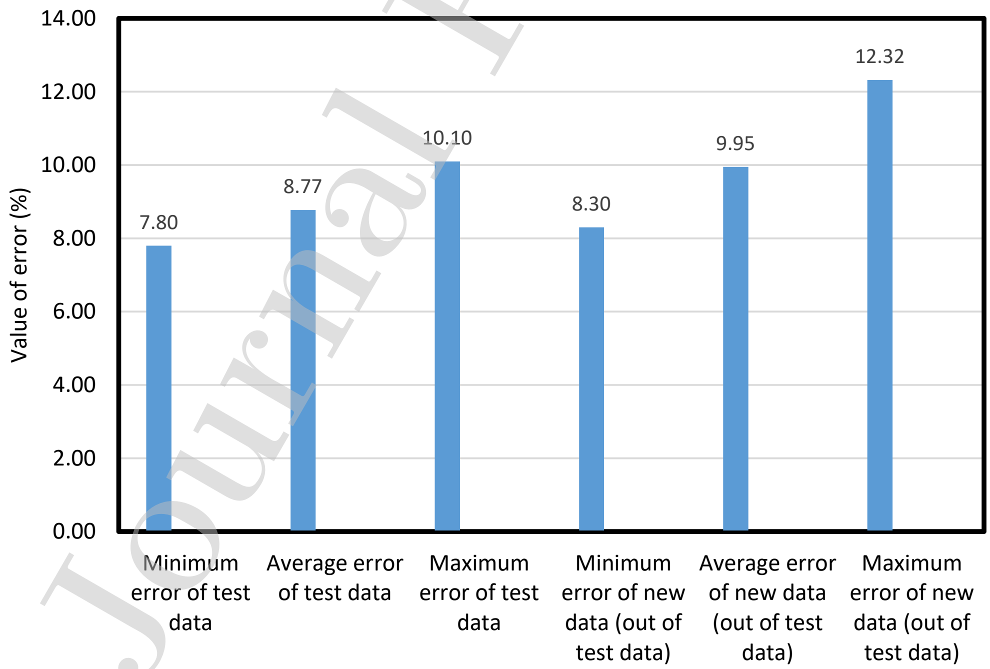


Fig. 25. Testing error of 49-element frame for double damage case with considering noise

The result of the first step, namely, the damage identification using the SVM algorithm and the result of the second step using DEA without considering noise are shown in Figs. 26 and 27, respectively.

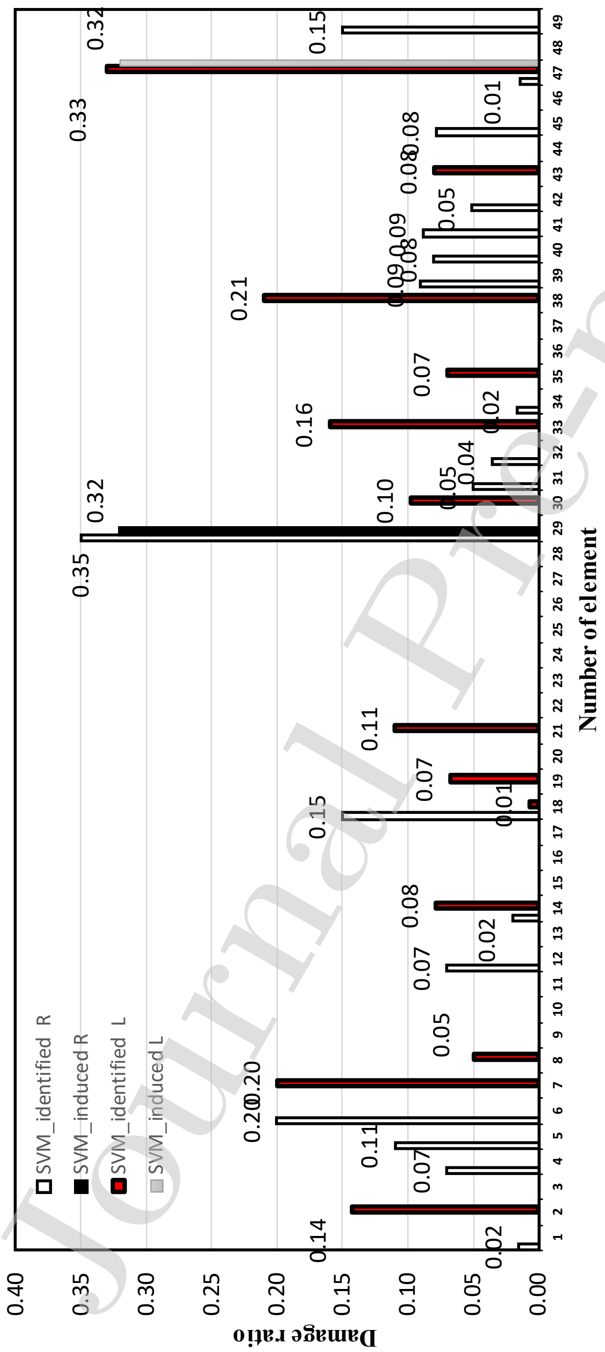


Fig. 26. Damage identification result of 49-element frame for the double damage case using SVM without considering noise

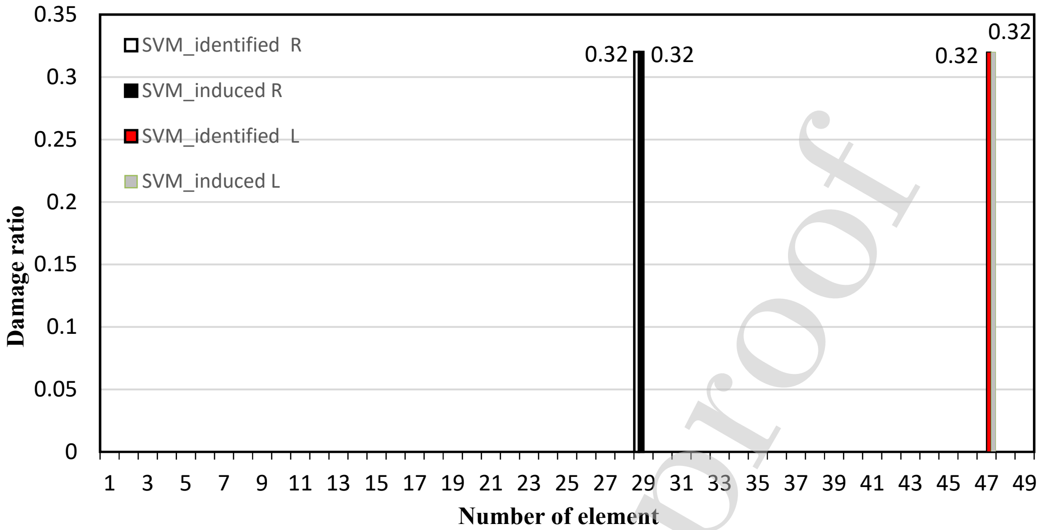


Fig. 27. Final damage identification result of 49-element frame for the double damage case using DEA without considering noise

The damage identification results shown in Figs. 26 and 27 reveal that the combination of SVM and DEA can obtain the actual solution for double damage scenario of the structure without considering the noise. The damage identification results obtained by SVM and DEA for considering 1% noise are also shown in Figs. 28 and 29, respectively. It is also demonstrated that the two-step method based on SVM and DEA is very effective for accurately locating and quantifying two damaged connections of the frame when noise is considered.

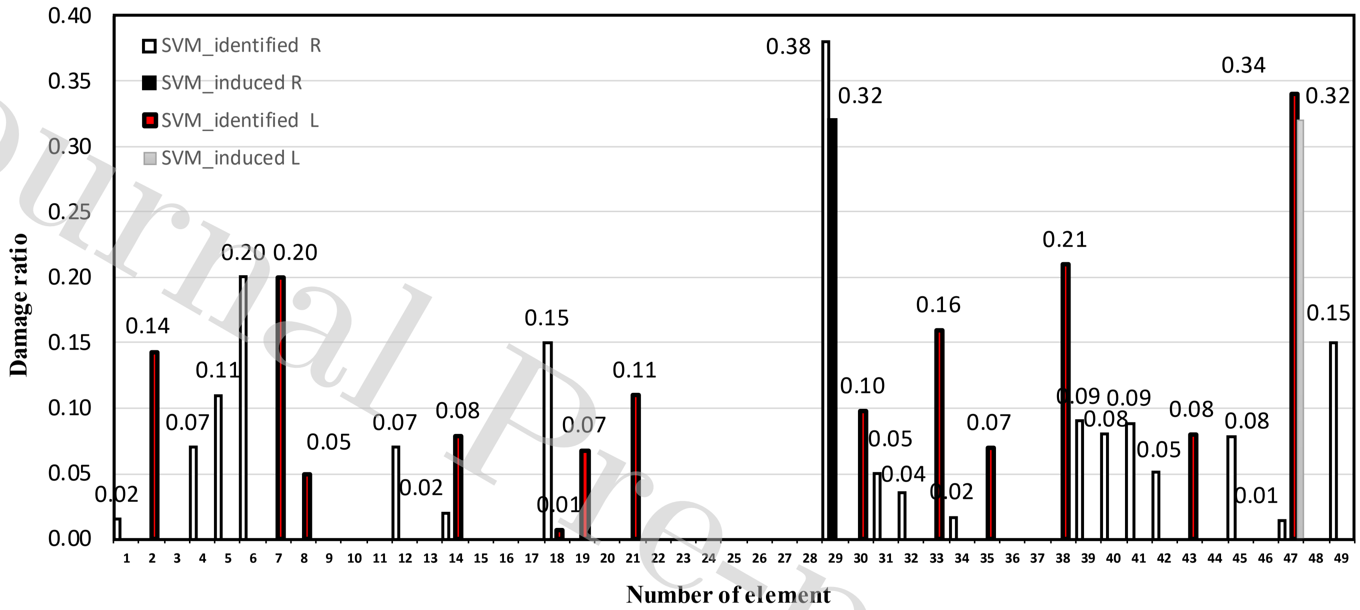


Fig. 28. Damage identification result of 49-element frame for the double damage case using SVM with considering 1% noise

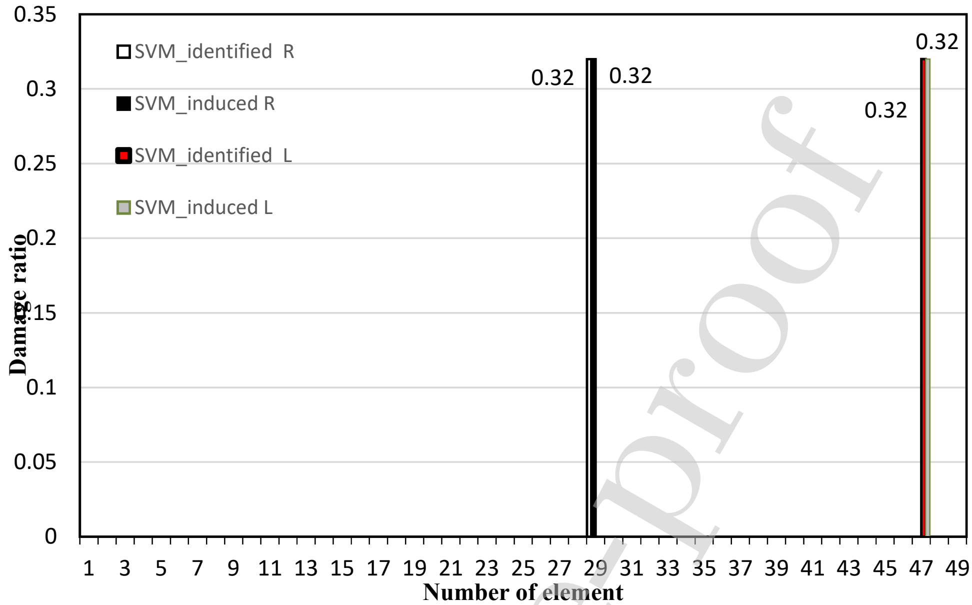


Fig. 29. Final damage identification result of 49-element frame for the double damage case using DEA with considering 1% noise

As a general outcome from the results, increasing damage variables (structural joints) and considering the effect of noise can reduce the efficiency of the first step method, which can be easily distinguished by comparing the SVM graphs. As a further explanation, when the structure has more joints and the number of damaged joints are increased, as well as the noise is considered, it can be seen that the false identification by SVM will be increased, which should be aided by increasing the number of data to the SVM algorithm until the more reliable results has been provided and the best performance of SVM to be presented. However, for various conditions, the initial solution can be properly enhanced by DEA.

6. Comparative study

In order to compare the performance of the proposed method with that of an existing method [5] based on optimization using PSO, 30-element frame having 30 nodes is considered as shown in Fig. 30. The cross section of the frame elements are 30 mm width and 6 mm depth. The frame is modeled using aluminum material with Young's Modulus=70 GPa and material density = 2700 kg/m^3. Single and double damage cases are induced in connections of the frame as reported in the literature. In the single damage case, damage with severity of 0.50 is induced in joint 6 without considering noise and with considering 0.50% and 1% noises. Furthermore, in the cases of double damage, joint 6 and joint 17 are damaged with the severity of 0.35 without considering noise and with considering the noise level of 0.50% and 1% and also joint 11 and joint 22 are damaged with the severity of 0.50 without considering noise and with considering the noise level of 0.50% and 1%. The damage identification results obtained by the present work and PSO based damage identification method is listed in Table 1. It should be noted that, only the damage severities of damaged connections induced are listed in the table.

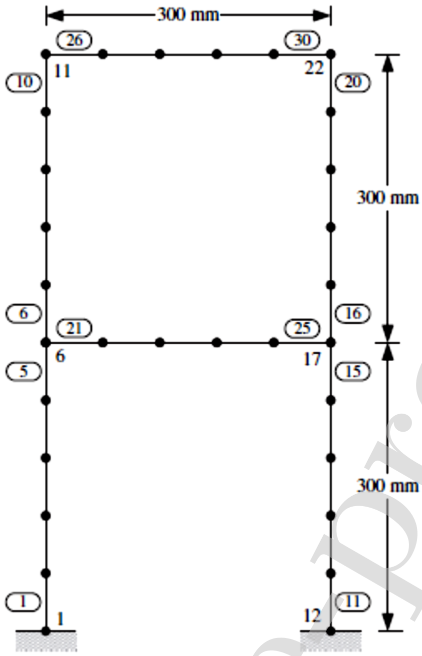


Fig. 30. Specifications of 30-element frame for single and double damage cases

Table 1. Damage identification results obtained by the present work and PSO based method

Damage case ID	Induced location and severity of damage											
	6			11			17			22		
C1:Single damage case	0.50			0.00			0.00			0.00		
C2:Double damage case	0.35			0.00			0.35			0.00		
C3:Double damage case	0.00			0.50			0.00			0.50		
Damage case ID	Identified location and severity of damage											
	Level of Noise											
	No Noise	0.50	1.00	No Noise	0.50	1.00	No Noise	0.50	1.00	No Noise	0.50	1.00
C1-PSO	0.500	0.529	0.541	-	-	-	-	-	-	-	-	-
C1-SVM-Phase 1	0.500	0.510	0.523	-	-	-	-	-	-	-	-	-
C1-DEA-Phase 2	0.500	0.500	0.500	-	-	-	-	-	-	-	-	-
C2-PSO	0.350	0.368	0.382	-	-	-	0.350	0.393	0.405	-	-	-
C2-SVM-Phase 1	0.350	0.350	0.364	-	-	-	0.350	0.370	0.383	-	-	-
C2-DEA-Phase 2	0.350	0.350	0.350	-	-	-	0.350	0.350	0.350	-	-	-
C3-PSO	-	-	-	0.500	0.502	0.498	-	-	-	0.500	0.501	0.499
C3-SVM-Phase 1	-	-	-	0.500	0.500	0.510	-	-	-	0.500	0.490	0.510
C3-DEA-Phase 2	-	-	-	0.500	0.500	0.500	-	-	-	0.500	0.500	0.500

Result comparison of two methods indicates that the results obtained are close to each other, but with further investigation, the results of the present study show a better performance than those of the optimization by PSO. According to the results presented in Table 1, both methods regardless of the effect of noise, can obtain the location and the severity of damage correctly. However, when noise is considered, the accuracy of the two-stage identification method proposed here is higher.

7. Conclusion and future directions

In this study, a two-step method for identifying damage in connections of moment frames has been proposed. In the first step, the possibility location of damage in connections has been obtained through SVM leading to reducing the size of damage variables. Then, the accurate location and precise amount of damage in connections has been determined in the second step via DEA. In order to simulate damage in connections, moment frames have been modeled with semi-rigid beam to column connections and the analytical model is used to generate structures with random damage in connections as data. Then, SVM is trained and tested using data, so that natural frequencies are considered as input data and the location of the damage in beam to column connections are considered as output data of the network. The damage identification of 18-element frame and 49-element frame for single and double damage cases has been investigated. Based on the numerical results, the trained SVM showed a high accuracy in testing mode for predicting the damaged connection in term of estimating error with and without considering noise. So, it can be used to locate possible damage in connections. The results demonstrated that by employing the SVM trained, damage variables can be reduced to a small number of ones. The results obtained in the second step showed the high accuracy of DEA for accurately determining location and severity of damage. The results indicate the high efficiency of the proposed method to identify the location and severity of the damage in the structures for different damage cases including single damage as well as double damage scenarios in the state of without and with considering the noise.

The identification of structural damage is one of the challenging issues and there are a lot of opportunities for many future research and work. Hence, there are some suggestions as future directions for researchers who are demanding work on this topic. For example, in order to enhance the performance of SVM, instead of using a trial and error approach, an optimization method can be used to properly determine the SVR parameters. Conducting laboratory tests for assessing the proposed method are recommended. Generalization of the SVM method for damage identification of real-world structures, such as 3D frames, bridges, dams and so on may be considered as another suggestion. Also, use of other algorithms such as least squares support vector machine to identify structural damage may be considered as future work.

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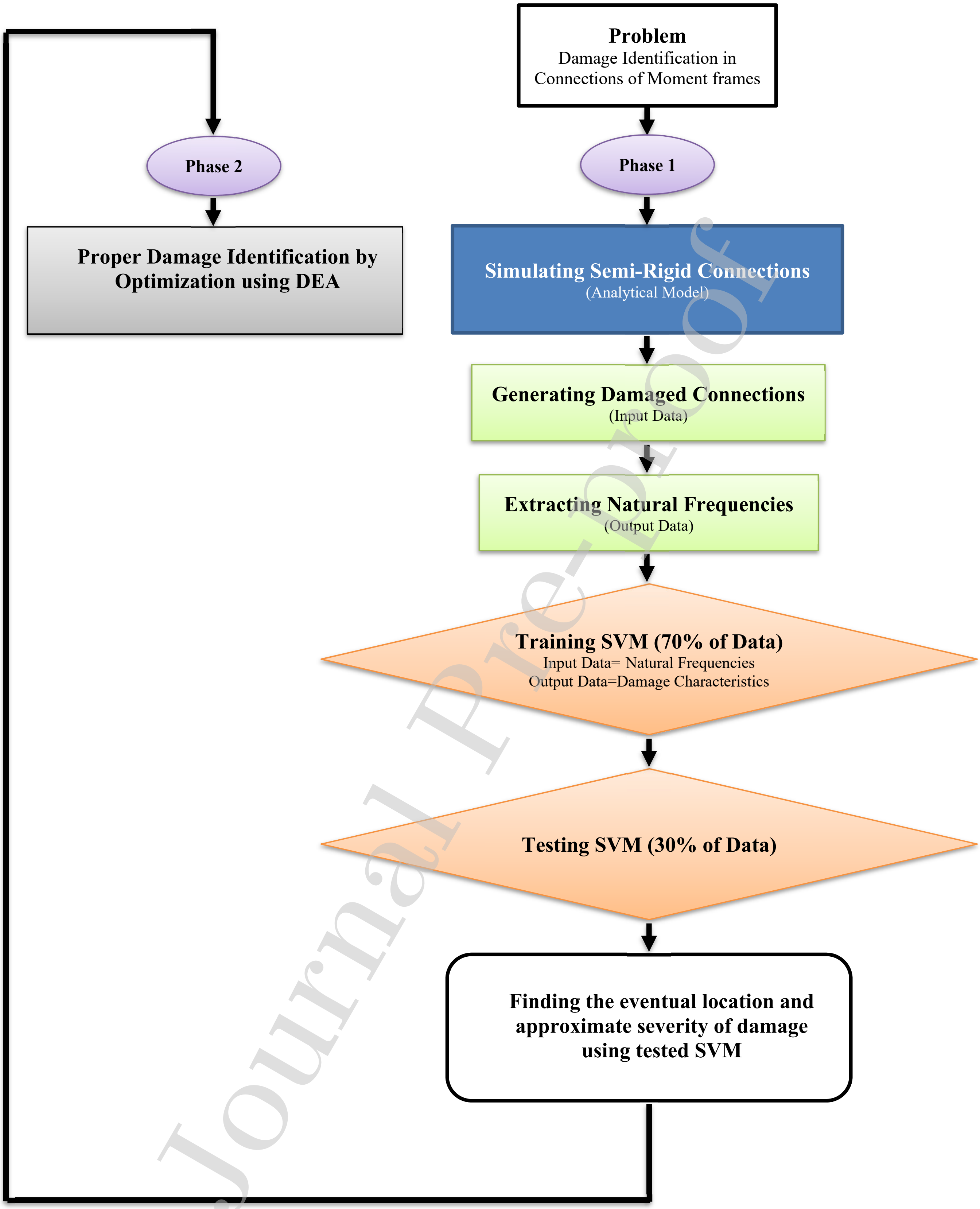

Problem
Damage Identification in Connections of Moment frames
Phase 1
Phase 2
Proper Damage Identification by Optimization using DEA
Simulating Semi-Rigid Connections
(Analytical Model)
Generating Damaged Connections
(Input Data)
Extracting Natural Frequencies
(Output Data)
Training SVM (70% of Data)
Input Data= Natural Frequencies
Output Data=Damage Characteristics
Testing SVM (30% of Data)
Finding the eventual location and approximate severity of damage using tested SVM

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

A two-step method is proposed to identify damage in moment frame connections. Damage is approximately located using a support vector machine (SVM). The accurate location and severity of damage is obtained via DEA based optimization. The combination of SVM and DEA is an efficient tool for identifying the damage.