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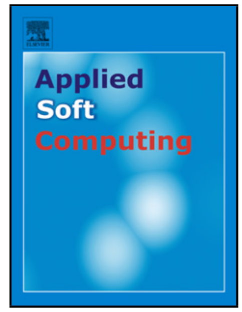

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Artificial Neural Networks for Vibration Based Inverse Parametric Identifications: A Review

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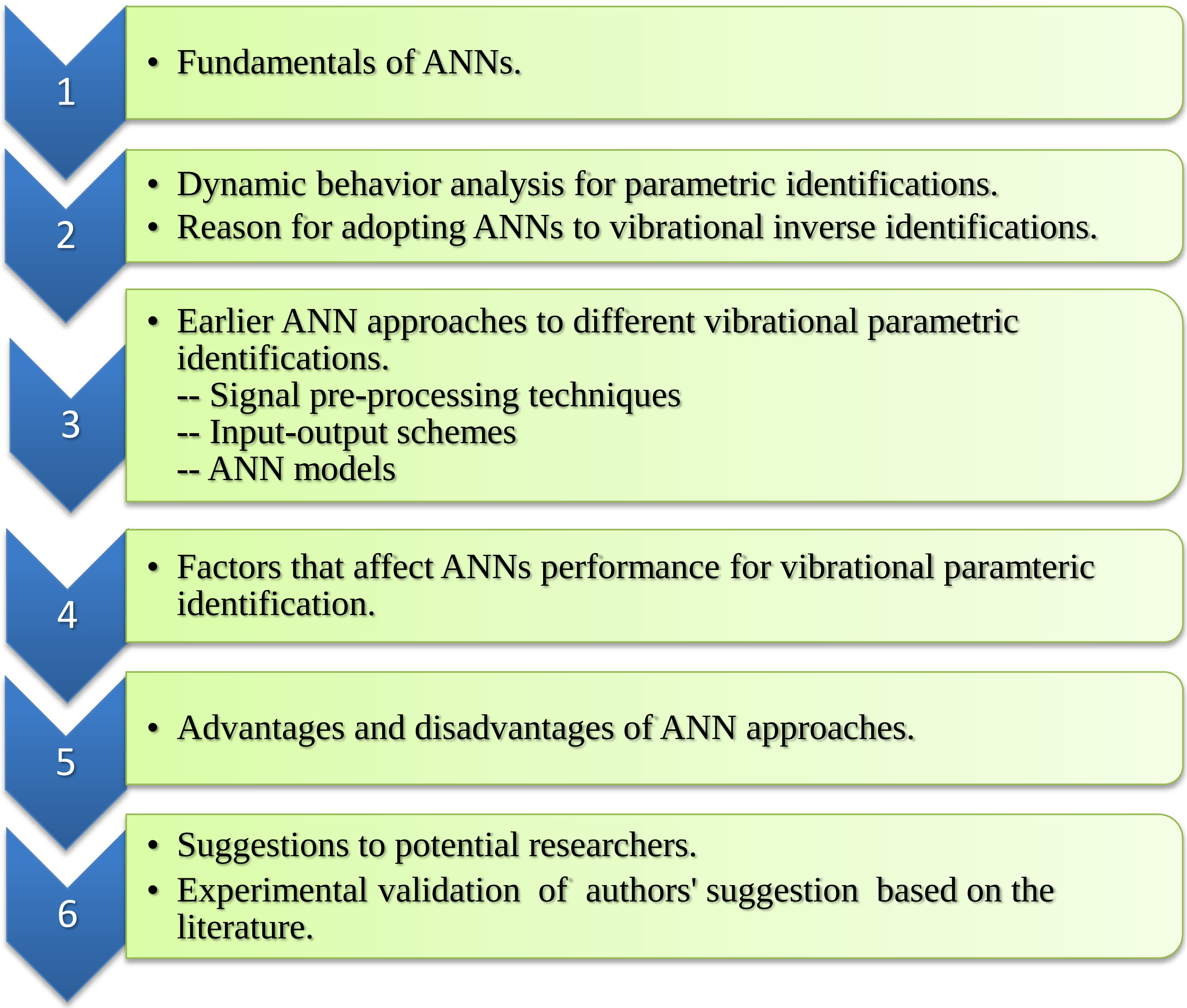
Graphical abstract



Highlights

- ANNs-solved vibration based parametric identification studies are reviewed.
- Factors which affect identification result are discussed.
- Pros and cons of ANN approaches are mentioned.

- Suggestions are given to potential researchers based on the discussion.
- Analysis with experimental results is provided to justify some point of view.

Abstract

Vibration behavior of any solid structure reveals certain dynamic characteristics and property parameters of that structure. Inverse problems dealing with vibration response utilize the response signals to find out input factors and/or certain structural properties. Due to certain drawbacks of traditional solutions to inverse problems, ANNs have gained a major popularity in this field. This paper reviews some earlier researches where ANNs were applied to solve different vibration-based inverse parametric identification problems. The adoption of different ANN algorithms, input-output schemes and required signal processing were denoted in considerable detail. In addition, a number of issues have been reported, including the factors that affect ANNs' prediction, as well as the advantage and disadvantage of ANN approaches with respect to general inverse methods. Based on the critical analysis, suggestions to potential researchers have also been provided for future scopes.

Keywords: Artificial Neural Networks; Inverse Problems; Parametric Identification; Vibration

1. Introduction

A forward problem expresses an output as a multiplication of input and transfer function. So an inverse problem refers to expressing the input as a multiplication of inverted transfer function and the output. Input is the 'cause', e.g. force and heat that makes an 'effect'/output to the reference object, e.g. vibration response and temperature. Transfer function generally refers to the system properties. Inverse identification refers to calculation of either system properties or input(s) to the system from corresponding responses/outputs. Vibration responses acquired from a structure depend directly on the material or dynamic properties of that structure such as modulus of elasticity, natural frequency, stiffness, damping factor, etc. [1-3]. Therefore, inverse identification of certain structural parameters is achievable by analyzing vibration signals which would help in monitoring the physical and dynamic condition of any object. On the other hand, Artificial Neural Networks (ANNs) are computational algorithms which resemble biological neural network of animal nervous systems. They are very effective in predicting any outcome by learning from some preceding data, where the theoretical relation between input/independent variables and output/ dependent variables is quite complicated or there is no known theory at all.

Frank Rosenblatt in 1958, first invented an effective algorithm based on the mechanism of biological neurons [4]. He named it 'Perceptron' and it was basically a computational program of linear mathematical algorithms. Later, during the period of 1959 to 1980, further modifications on perceptron were done, which ultimately resulted in the ANNs. Furthermore, due to the consistent evolution of powerful computing systems, applications of ANNs started to increase equivalently. At present, ANNs are vastly being used in both industries and modern research labs for essential purposes. Some of ANNs' common applications are pattern recognition, chemical compound identification, process control, industrial temperature and force prediction, stock market prediction, making video games intelligence, voice recognition and so on. Apart from these, ANNs have already been represented as a decent method for monitoring and resolving several structural health-related problems; faults in mechanical systems; and heat conduction based inverse problems [5-9]. For recent years, ANNs have been introduced popularly in solving numerous vibration related problems, e.g. vibration caused damage detection, vibration and noise controlling, and some other vibration based parametric identification tasks. This is because vibration characteristics of a structure of given input condition deals with intricate mathematical models to describe the dynamic condition of a system and thus the output result deviates from the theoretical result in presence of noises and minor instrumental faults.

In case of inverse problems, effect of noises or uncertainties gets amplified significantly due to the inversion of matrix, which gives erroneous outputs. Besides, inverse problems possess a major drawback of ill-posedness, which means they provide multiple sets of infeasible solutions instead of specific ones. To deal with this, a number of regularization methods are used additionally such as Singular Value Decomposition method [10], Tikhonov method [11] and Singular Value Rejection method [12]. Nonetheless, the solution is likely to be erroneous, because any slight disturbance at input will cause larger deviation at output due to the inversion of matrix. These are some key reasons why ANNs are chosen in solving such problems, because they are able to predict outputs using any sort of input series such as time-domain, frequency-domain or Frequency Response Function (FRF) data, where output estimation is rather difficult or cannot be done in conventional ways. Moreover, ANN predicted results are rather practical than the theoretically calculated ones, because they consider ambient noises and real life uncertainties. Most significant advantages of using ANNs are that they are self-adaptive, i.e. they can learn from their environment in both supervised and unsupervised ways, and capable of universal estimations. Another key feature of ANNs is that they are capable of massive parallel computations whereas the conventional digital computers (a.k.a. Von Neumann machines) are to capture and execute the instructions sequentially [13]. For these reasons, ANNs have been practiced greatly in solving versatile inverse identification problems using vibration responses in order to obtain acceptable outcomes avoiding ill-posedness and regularization complexities. Conversely, ANN techniques have some notable disadvantages which limit its uses in a wider range. In this paper, some of the earlier ANN approaches and their effectiveness to various vibration-based inverse identification tasks have been analyzed thoroughly including their ANN utilization schemes.

2. Fundamentals of Artificial Neural Networks

Artificial neural networks have already been discussed in several published literatures and books. So in the following section, an introductory overview on ANNs is given.

ANNs follow the working mechanism of biological neurons. Just like biological neurons deal with electrochemical signals, ANNs deal with input and output numerical values. Whereas organic neural networks learn from its environment and control the animal behaviors accordingly, ANNs learn from a set of giving data samples in order to predict the unknown outcomes from future datasets.

Resembling a biological neuron, a single artificial neuron /node, which is the unit or building block of ANNs, comprises 4 core elements: input(s), net function, transfer function and one output (Fig. 1). The input(s) supplied to a node are multiplied by synaptic weights before getting processed by the transfer function. Synaptic or coefficient weights are just random values which define the strength or amplitude of individual input connected to the node. The "learning" part of ANN comes through continuous adjustment of these weight values. The resultant value of the net function passes through the activation function and thereby an ending output value is calculated and delivered by the corresponding node.

The general expression of net function is as Eq. (1),

$$u = b + \sum_{j=1}^{N} w_j x_j \tag{1}$$

where, u = output of the net function; b = bias weight; N = number of inputs; x = input; and w = weight value for corresponding input (w_j: $1 \leq j \leq N$).

In case of activation function, several mathematical formulas are applied depending on different circumstances. Some universally used activation functions have been given in Table 1.

Although a single artificial neuron is able to perform certain information processing, for complex tasks and more powerful computation, especially for linearly non-separable problems, multiple neurons are needed to be connected with one another to make an intricate network. Thus the term "Artificial Neural Networks" is used since they consist of interconnected artificial neurons/nodes with the aim of solving a wide range of problems such as pattern recognition, pattern generation, function approximation, and memory association.

The interconnected neurons of a typical ANN system can be divided into three main layers: input layer, hidden layer(s) and output layer (Fig. 2). Input layer neurons intake the input values from the environment and output layer neurons deliver the ultimate outputs. Hidden layer neurons stay in between the input and output layer. They receive the outputs from other neurons as their inputs (starting from the input neurons) and deliver outputs to their successive layer neurons. Abiding by the basic mechanism, neural networks have been modified into several kinds which follow different architectures and different input-output mapping procedures so that they perform as per necessity in different situations. In Table 2, most commonly used neural networks and their specialism in applications have been given.

Implementation of ANNs for any application (Fig. 3) can be divided into 3 main stages: network parameter selection, training and testing. Selection of some key parameters such as the number of neurons in the input layer and output layer, number of hidden layers, number of neurons in hidden layers, learning rate, activation functions and some others belong to the primary step of modeling a neural network. Upon setting these parameters, the network is fed with sample datasets for training. Each repetition of the network calculations, through which weights are adjusted, i.e. the network learns, is known as epoch. An intermediary step called 'validation' is usually followed for proper adjustment of network parameters using a portion of the testing data. Most frequently used training/learning algorithms for ANNs are Levenberg-Marquardt, Quasi-Newton, Conjugate Gradient, Resilient Backpropagation and Orthogonal Least Squares algorithm [24-26]. The training method is chosen based on the available dataset and category of the application. When ANNs are trained with both inputs and respective outputs, it is called supervised training. When only input data is provided for training, where synaptic weights are arranged according to input pattern, it is then called unsupervised training. After training, the network requires to be tested for performance checking which is done by validating the output values feeding the network a new package of input data. Prediction accuracy of ANNs will be higher if a great number of sample data is available.

3. Applications of ANNs in vibration-based inverse identification

A theoretical model of a physical process is developed by correlating the ‘cause’ and ‘effect’ of that process. As the process relies as well as represents the system properties, the model can be expressed as Fig. 4 and Eq. (2).

$$\{\boldsymbol{Y}\} = [\mathbf{K}]\{\boldsymbol{X}\} \tag{2}$$

where $\{\boldsymbol{Y}\}$ = output vector; $\{\boldsymbol{X}\}$ = input vector; and $[\mathbf{K}]$ = transfer function matrix that represents the system.

Inverse problems deal with such process when $\{\boldsymbol{Y}\}$ is known and $[\mathbf{K}]$ or $\{\boldsymbol{X}\}$ to be determined, where either of them is known as well.

Now, equation of motion of a vibrating system is expressed in Eq. (3).

$$[\mathbf{M}]\{\ddot{\boldsymbol{X}}(t)\} + [\mathbf{C}]\{\dot{\boldsymbol{X}}(t)\} + [\mathbf{K}]\{\boldsymbol{X}(t)\} = \{\boldsymbol{F}(t)\} \tag{3}$$

where $\{\ddot{\boldsymbol{X}}(t)\}$, $\{\dot{\boldsymbol{X}}(t)\}$, $\{\boldsymbol{X}(t)\}$ and $\{\boldsymbol{F}(t)\}$ = time (t) varying acceleration, velocity, displacement and force vectors respectively; $[\mathbf{M}]$= mass matrix; $[\mathbf{C}]> 0$ = damping factor matrix; and $[\mathbf{K}]$ = stiffness matrix.

Eq. (3) shows that a vibrating system responds to external force(s) in forms of displacement, velocity and acceleration where mass, damping factor and stiffness represent the system. Therefore, a vibrating system can be described as a process as shown in Fig. 4 and thus it introduces a diversity of vibration based inverse problems.

General inversion methods require regularization process to avoid the ill-posedness characteristic of inverse problems. Moreover, vibration response usually contains noises due to numerous ambient conditions. Such noises or errors in the input are amplified at output estimation due to the matrix inversion. To avoid these issues, ANNs have become much popular in this field in recent years. In this regard, ANN-solved inverse vibration problems can be classified into two types: 1) Non-parametric and 2) Parametric identification. Non-parametric identifications are basically pattern classification by ANNs. For example, Samanta [27] and Liu [28] detected damage by putting binary values to ANN outputs, where '0' and '1' refer to healthy and damaged condition of the object respectively. Mahfouz [29] identified drill wear by sorting the wear conditions into six classes. In contrast, parametric inverse vibration problem, which is the focusing area of this review, deals with more specific reasoning, where ANNs work as regressors between inputs and outputs. The following part of this paper investigates a number of earlier attempts to identify dimensional or non-dimensional parameters via dynamic response and ANNs.

E. Özkaya and H. Öz [30] determined natural frequencies and stability regions of an axially moving Euler-Bernoulli simple supported beam from flexural stiffness, mean of axial velocity and velocity fluctuation amplitudes using MLBPN. However, the network topology was different for separate identification of natural frequencies and stability regions. M. Çevik et al. [31] identified natural frequencies of a suspension bridge. They used MLBPN and trained it by placing three natural frequencies to the output space and five dimensionless parameters (dependent on cable tension; cables' cross-sectional area, virtual length, and modulus of elasticity; length and cross-section of bridge-span) to the input space. B. Karlik et al. [32] adopted MLBPN to predict the natural frequencies of a beam-mass system due to linear and nonlinear vibration at different boundary conditions. Here, for the linear part investigation, inputs used to train the ANN were two dimensionless quantities α (Eq. 9) and η (Eq. 10), and outputs were the first five natural frequencies. For the nonlinear part, inputs to the ANN were still α and η, but the output was 'nonlinear correction coefficient' in this case.

$$\alpha = \frac{M}{\rho AL} \tag{4}$$

$$\eta = \frac{x_s}{L} \tag{5}$$

where M = concentrated mass; x_s = position of the concentrated mass; ρ = density of the beam; A = cross-sectional area and L = length of the beam.

S. Gholizadeh et al. [33] proposed a combined genetic algorithm and neural network based technique to evaluate the optimal weights of structures for multiple natural frequency constraints. They engaged two neural networks: Radial Basis Function (RBF) network and Wavelet Radial Basis Function (WRBF) network, together with Virtual Sub-Population (VSP) and Genetic Algorithm (GA) in order to evaluate the natural frequencies of structures and thereafter optimize the structural design. Training of both RBF and WRBF network was done by placing the cross sectional areas of the divided structural elements to the input space. The specialty of the WRBF network is that the activation functions of its hidden layers are substituted with a particular kind of wavelet functions, where the position and dilation of the wavelets were fixed all along. The purpose of GA and VSP was to optimize the structural weight-defining objective function. J.B. Ali et al. [34] predicted accurate remaining useful life (RUL) of a rolling element bearing by means of combined Weibull distribution (WD) and Simplified Fuzzy Adaptive Resonance Theory Map (SFAM) neural network. The reason of using WD is to fit measurement and to circumvent fluctuation areas in the time-domain during the neural network training process. So, to train the SFAM network, they used WD-fitted measurements as inputs whereas the outputs were healthy and six ascending degraded conditions, i.e. seven conditions of the bearing. First, the network was trained off-line by run-to-failure history of one full bearing. Then the trained network was employed online to utilize the WD-extracted features so as to predict the degradation level of the bearing (Fig. 5). Afterwards, the output of the network was fed to a smoothing algorithm to estimate the RUL value.

L. Roseiro et al. [35] introduced ANN to recognize forces in the suspension system of a racing car. In this study, applied forces and the respective dynamic behavior of the suspension system were the network inputs and outputs respectively. Two feedforward networks, called Direct Neural Network (DNN) and Inverse Neural Network (INN), were employed for individual purposes: DNN for identifying the local deformation in every single structural member and INN for estimating the horizontal and vertical forces in the suspension triangle using the obtained deformation data. Activation functions of both networks have been given in Table 3.

G. Liu et al. [36] identified the elasticity of anisotropic laminated plates via four-layered MLBPN. First, the experimental dataset was prepared by assuming elastic constants and the estimated respective displacement responses using hybrid numerical method (HNM) solver. Then the ANN was trained with a modified backpropagation algorithm by assigning surface displacement responses to its input space and the elastic constants of anisotropic laminated plates to the output space. In this case, progressive retraining was given to the network until the output deviations were decreased to a desired level. M. Ghajari et al. [37, 38] identified impact locations and magnitudes on a composite panel using MLBPN and sensors' spectral components. The large training data for the network was obtained from nonlinear finite element model of a sensorized composite in order to work with the experimental composite plate. Time domain based feature extraction was followed in order to build the input patterns for impact parameters.

So, from Refs. [30-38], a common pattern is visible in the ANN approaches to inverse vibration-based identifications as shown in Fig. 6.

Therefore, pre-processing of raw signal is a crucial part for ANNs to relate vibration response to the objective parameters as well as to reduce data redundancy. Although ANNs' high accuracy has made them wide popular, ANNs' require a large quantity of sample data to be trained appropriately to be that accurate. This is why the ratio of training and testing data in early mentioned Refs. [30-33] were 6:1, 493:15, 79:31 and 250:150 respectively. Apart from this, ANNs' architectural parameters need to be adjusted as well, which can be done by trial and error or adopting different optimization processes. Once taken care of these weaknesses, ANNs can offer high precision in inverse identification.

Now, similar to other inverse problems, ANN based inverse problems of dynamic structures are of two categories: 1) Input identification and 2) System identification.

3.1 Input Identification

From Eq. (3), it is obvious that externally acted or internal induced force is the only input/cause in any inverse vibration problem. Thereby, function of force, e.g. stress and pressure are also considered as the input parameters since they act on the system. In addition, other factors which control the force, such as input voltage to an MR damper, eccentricity of a rotating machine element, engine power, and rotation speed of a shaft, act as inputs as well since they affect or introduce forces to the system. So, previously mentioned Refs. [35, 37, 38] are input identification approaches as per definition. Table 4 highlights some earlier attempts to find different input factors, by following the process-template of Fig. 5 as well as their strategy to obtain proper ANN-approximation by means of size of sample data and optimization scheme of network parameters.

3.2 System identification

In inverse vibration problems, system is defined as the structure on which force acts and thus induces vibration. Thereby, system identification refers to identification of mass, damping, stiffness, Poisson ratio, Young's modulus and other similar parameters, which define the mechanical or dynamic properties of the system and thus affect the vibration response. In this manner, estimation of crack length, tool wear, tool life, etc. also exists in the domain of system variables. So, early stated Refs. [30-34, 36] refer to the identification of various system parameters. Table 5 scrutinizes (as per Fig. 5) a number of previous studies about ANN and vibration based inverse identification of assorted system parameters.

Exploring Tables 4 and 5, the sample size for training was found larger than that of testing for majority of the cases as expected accuracy is easily obtainable in this manner. Another reason to take a large training sample is that ANNs are greatly erroneous outside the training domain (see Sec. 4.2). Few studies, which did not mention their training and testing data ratio, were mostly numerical simulation based experiments [41, 68]. This is because simulated models offer users a large working domain as well as provide flexibility and variation in data collection. As a result, user can collect as much data as desired to train the ANNs robustly. However, such data collection procedure is highly time costly, even with powerful computation devices due to exceptionally intricate computation procedure. On the other hand, as to network architecture optimization, most of the studies practiced empirical observation, i.e. trial and error since identifying network structure to suit best to a particular problem is still unreported to date. Few studies integrated additional optimization techniques [39, 49] in order to provide more methodical and quicker search method, although they are not proven to have any direct effectiveness on prediction accuracy compared to conventional trial and error method.

Table 6 shows some other studies which are very similar to different studies highlighted in Table 4 and Table 5.

4. Discussion

4.1 Network performance factors

The literature reveals several factors which affect the inverse identification results and intricacy of the experimental procedures, such as input scheme, sample data size and network model.

4.1.1 Input scheme to ANN

Selection of inputs is the most important part of a neural network approach. Vibration response signal from accelerometer or strain gages contains large scale of time varying data; so it is neither reasonable nor effective to use all the response data as input to the network. Therefore, an effective input methodology must be planned with respect to the type of output. This can be done with or without a pre-processing of signal such as Fourier transformation, wavelet transformation, time-integration, Hilbert transformation, FRF construction and PCA compression. Afterwards, features are extracted from either the raw data or the pre-processed data to use them as ANN inputs, because they act as representatives of the respective response. Table 7 shows different features that can be extracted from different signal pre-processing techniques.

Some studies used data compression technique, e.g. PCA to reduce the dimensionality of the raw or FRF data to construct the ANN inputs. Some followed multiple pre-processing techniques at once for extraction of assorted features as in Ref. [51]. A common custom of data pre-processing is normalization/scaling of either raw or early pre-processed data. It is necessary in order to limit the data range, prevent overriding of larger values over smaller ones and to avoid early saturation of hidden neurons [108].

Since different pre-processing extracts different features from the same vibration signal, input should be chosen in the way that desired output depends on it consistently and proportionally. For example, to identify crack length of a damaged structure, Fourier transformed features were used as ANN inputs in Ref. [65] rather using time-domain features, because any deformity in a structure changes its certain physical property which leads a change in its natural frequency. Similarly, different system parameters were identified by taking natural frequency and mode shapes in Refs. [55, 56] since these inputs are constant for a system. On the other hand, to quantify restoring forces in Ref. [39], displacement and velocity based features were selected as the inputs since they are the most proportional factors to restoring force. For the same reason, Ref. [45] also used displacement and velocity features to identify magnitude of an external force. In a number of cases, specified mathematical models were introduced to construct the dependability of the input(s) to the output(s) or vice-versa, e.g. Ref. [63] estimated damage length from the approximation of a designed damage index by ANN, because the input factors they considered proved to barely affect the damage parameters. Addition of few extra inputs (such as cutting speed and cutting depth in Ref. [64]), which affect the structural vibration as well as designed output parameters, may increase the computational time to a negligible extent, but they can improve the result satisfactorily since they add more specificity towards input-output mapping.

Vibration behavior depends on three key conditions which are mechanical properties, dynamic properties and acting forces on the system. Variables, which are force-functions or force-inducers, are also the input-influencer to vibration behavior. It means vibration response does not vary randomly with its 'cause' factors like random variation cases, e.g. weather changes with time, or pixel color of an image changes with position. So, in the field of parametric identification of dynamic systems, ANNs are implemented for function approximation indeed, where theoretical input-output functions are very complex, ill-conditioned and ambient noise is of considerable presence. Therefore, consistent dependency of the input(s) on respective problem's designed output(s) is the primary concern of making a potent ANN input strategy.

4.1.2 Selection of ANN model

MLBPN had been the most frequently used network in the mentioned studies. The reason is that MLBPN works in more straightforward mechanism and can approximate both simple and complex input-output relationships with at least two hidden layers [56, 109, 110]. However, few experiments adopted other networks such as RBFN, GRNN, RNN and FABPN. Analyzing the studies, reasons of using other ANNs over MLBPN (which also depict the limitations of MLBPN) are:

- To achieve quick learning. For example, the convergence speed of FABPN and GRNN in training is higher than that of MLBPN [39, 65].
- To avoid sticking at local minima instead of global minima at the error surface, which is why RBFN and GRNN were used in several studies [45, 48, 65, 67] as these networks use localized non-linearities for approximation.
- To avoid the 'black-box' optimization procedure of hidden layer architecture. For example, RBFN possess only one hidden layer and unlike MLBPN, its accuracy depends proportionally on the number of hidden layer neurons, which make it easier to find optimal network structure.
- To deal with memory-dependent outputs, e.g. Bouc-Wen neural network for hysteric analysis in Ref. [42].
- To predict time-series outputs, e.g. RNN in Ref. [44].

ANNs cannot be chosen in terms of prediction accuracy, because once they are trained well, they perform robustly like the studies mentioned in this literature. So, selection of best ANN model depends on the logistics of the inverse problem, expected computation time limit and availability of sample data. For function approximation, which is the primary job of ANNs in parametric identification problems, most preferred networks are MLBPN, RBFN and GRNN. Hybrid networks such as ANFIS, Fuzzy ANN and WNN are also preferable if the methodological strategy needs to find better reasoning and domain information. Hybrid networks allow users to take benefits from different computational algorithms at once.

4.1.3 Selection of network topology

Hidden layer architecture of MLBPN affects the network performance randomly, i.e. increasing or decreasing its size may or may not improve the prediction accuracy. However, according to Ref. [111], if the network architecture is too complex, overfitting may occur and if the architecture is too simple, desired approximation capability may not be achieved. Due to this confusion, the hidden layer architecture of MLBPN or modified MLBPNs is chosen either arbitrarily, by trial and error, or by adopting an extra optimization algorithm, e.g. GA [112-114] (mostly used algorithm for MLBPNs' topology optimization), Particle Swarm Optimization (PSO) [115] and Optimal Brain Surgeon (OBS) method [49]. Other networks like RBFN and GRNN do not require additional optimization for hidden layer structure since their prediction accuracy is dependent on their hidden units. Nonetheless, in few studies, their parameters (centre, width and hidden layer neurons) were optimized by GA [116, 117] and PSO [118] instead of common least squares function [26, 119].

Occasionally, two simple formulae as Eq. (6) and Eq. (7) are used to determine the number of hidden layer neurons [120, 121] when the MLBPN is of single hidden layer.

$$N = \frac{(n/\lambda) - p}{m + p + 1} \tag{6}$$

$$N = \lambda + \sqrt{m + p} \tag{7}$$

where N = no. hidden layer neurons; n = no. of training data; m = no. of input variables; p = no. of output variables; and $\lambda \geq 1$.

4.1.4 Quantity of training samples

Size of sample data has a direct effect on network performance. It's a notable drawback of ANNs that they require a good number of trial data to be trained properly. For example, in Ref. [69], the average error of IRBF was 1.128% when trained with 1000 samples, but it reduced considerably to 0.101% when trained with extra 500 samples. The basic theme, as stated in Ref. [108], is that training data should cover the problem domain in the way that the trend of input-output variation is learned appropriately by the network. However, if the input-output proportionality and subsets of training data are moderately consistent, fewer sample data would also result in higher accuracy. Therefore, size of training samples can be expressed as the following relation:

$$\text{Training Data Size} \propto \frac{\text{Dimension of the problem space (input-output range)}}{\text{(Consistency of input-output trend)} \times \text{(Consistency between subsets/trials)}}$$

For instance, Refs. [65, 122-124] used 478, 282, 300, and 108 training data respectively due to moderate relationship between input and output, whereas Ref. [44] used 2000 sample data for training over a short time-span since time-series outcomes vary with time almost randomly. Similarly, in Ref. [69], frequency domain method identified a structural damage case with 0.144% ANN prediction error, whereas time domain method identified the exact same case with 0.474% error. It is mainly because frequency domain data is more closely related to system properties and thus to damage occurrences than time domain data.

4.1.5 Noise and uncertainties

Although ANNs have high tolerance to surrounding noise and uncertainties, their predicted result will diverge to a negligible or great extent if any unwanted noise appears during the testing phase which was not present in the training data. In general sense, less noise reduces the demand of large sample data and elevates the network performance. However, there will be always some instrumentation noises occur in response signals practically. So signal denoising should be applied if noise is frequent as in Ref. [75] and sufficient trial data should be provided proportionally as the noise range/spread with respect to the original signal.

4.1.6 Error goal

ANNs carry out their learning until reaching an error goal fixed by the user. It is strongly suggested not to set the error goal at absolute zero; rather it should be slightly higher than zero as Refs. [40, 125, 126] fixed the error goal at 0.001, 0.01 and 0.005 respectively. This is because vibration response usually contains noises to some degrees due to poor sensor calibration, high sensitivity or operational fault of sensors, structure's non-uniformity in material, etc. So, despite having errors in the input data, if the network achieves exceedingly higher precision during training, the network will encounter overfitting problem [127]. An overfitted network provides flawed result at post-training operation (Fig. 7).

4.2 Advantages and Disadvantages

Each of the referred studies in this review gave a higher degree of preciseness where network error was mostly below 10%. As mentioned before, ANN approaches avoided ill-posedness of the inverse problems, made the methodologies simpler, i.e. establishing a general flow of work as illustrated in Fig. 6 and performed successful parallel identifications, while withstanding experimental noises and uncertainties. Despite these advantages, ANNs bring in some issues which limit their use in wider application fields, which is why researchers often practice modified inverse methods instead of ANNs. As stated earlier in this review, the most considerable drawback of ANNs is their requirement of large sample data, because in order to generate such amount of data, plenty of trial observations are needed to be carried out which is inconvenient. The second major drawback is the optimization procedure of hidden layer topology which is time consuming and adds complication to the computation process. Another crucial drawback is the extrapolation inadequacy, i.e. they are weak or rather unable to predict the outputs when given inputs lie beyond the training data space [128]. This is why the input domain should cover the extreme points at both right and left ends (Fig. 8).

4.3 Experimental validation

It has already been explained that ANNs are used for basically function approximation in vibrational parametric identifications. Regarding this, RBFN and GRNN have some significant advantages over MLBPN, although MLBPN was the most used network algorithm. These advantages are: 1) Computation is rapid; 2) Hidden layer architecture is simple; 3) Function approximator rather than pattern classifier; 4) Powerful interpolation capability. So, it is presumed that RBFN and GRNN are more favorable than MLBPN for future inverse parametric identifications. To validate this presumption, an extension work of a previous experiment conducted by the authors has been carried out. The original experiment [130] was a non-ANN approach to identify impact force locations. Same identification was done with the same experimental data by MLBPN, RBFN and GRNN. The implementation plan of ANNs is given in Table 8.

So, number of network inputs = 4; number of outputs = 2; and total number of sample data = number of impact locations × number of trials = 11.

The plate structure and sensors' location are given in Fig. 9. The soft computing procedure was conducted by MATLAB®. The construction of MLBPN, RBFN and GRNN was based on default *'feedforwardnet'*, '*newrb'* and '*newgrnn'* function of MATLAB® respectively. MLBPN used here consisted of one hidden layer and number of hidden neurons was set by Eq. (7). After few trial and errors, MLBPN gave the best result for 6 hidden neurons. Fig.10 shows the predicted results from MLBPN, RBFN and GRNN.

Prediction error was measured by taking the mean of norms between predicted and actual impact locations. Table 9 shows the error and training time of individual network. From Fig. 10 and Table 9, it is observable that RBFN and GRNN are much better in terms of accuracy and training time for our experimentation case.

4.4 Future Research Scopes

Analyzing the literatures, some significant related research issues that require further works in future are as follow.

a) Inclusion of hybrid ANN models such as ANFIS and GA-RBFN would be helpful as they merge additional advantages from other machine learning algorithms. Each ANN type has one or more particular limitations, which it can be minimized by advantageous features of other ANN types or soft computing algorithms. For example, ANFIS includes combined ANN and Fuzzy Inference System (FIS), where membership function parameters of FIS are adjusted by the adaptivity of ANN. Thus, this hybrid model can make quicker and more precise decision-making than conventional ANN alone [131].

b) Application of novel/modified feature extraction or data compression methods to vibration data should be practiced in order to achieve better approximation performance from ANNs for a particular application. Since vibration responses possess heavy-sized data, the input vectors should be constructed from such data in the way that input is smoothly related to the output (as discussed in Sec. 4.1.4). Otherwise, ANNs' approximation would be erroneous. For example, in Ref. [38], accuracy of approximating impact locations decreased by 43% (for same features) due to applying Discrete Wavelet Transform (DWT) to the response signals. Therefore, effective methods of signal processing to extract proper input vectors need further studies.

c) Unsupervised networks, e.g. SOM and ART can be applied for proper quantification of the quality different vibrational features, since these networks are popularly used for enhancing the representation of input classes. As mentioned previously, selection of proper input method is important. For this, unsupervised networks (e.g. SOM) are great tools, because they provide an illustration of order and design of input data by converting their multidimensional space into random grid shape. For example, Ref. [132] used SOM to observe the variation of wavelet coefficients, which were used as input features to identify muscle fatigue.

d) For function approximation problems, extrapolation is a great limitation of ANNs. Although the condition of a system beyond ANN's training space is unknown, if extrapolation is achievable for a system of almost non-varying conditions (e.g. a large rectangular plate of composite material), size of training data could be reduced considerably for much larger work space. Therefore, modification of ANN parameters such as introducing novel network architecture, activation function or convergence theory in order to enable ANNs for robust extrapolation is an important area of future studies.

e) In several past studies [45, 48, 65, 67] including the experimental validation of this study, RBFN and GRNN have been found to be more accurate for approximation tasks. As described in Sec. 4.1.2, the reasons are that these networks overcome some notable limitations of conventionally used MLBPN such as slow convergence and local minimization. Moreover, whereas MLBPN works as a stochastic optimizer, RBFN and GRNN work as a multidimensional curve fitter which is crucial in vibrational parametric identification problems. Therefore, the effectiveness of RBFN and GRNN compared to MLBPN should be further investigated in new or many of the literatures' applications.

5. Conclusion

In this review, some previous studies have been emphasized, where ANNs were applied in various parametric identification tasks utilizing systems' dynamic responses. It is seen that most of the studies were carried out on system parameters identification, e.g. mass, damping, natural frequency, etc., whereas least studies were found on identification of force-inducing inputs, e.g. impact force, pressure, MR damper voltage, etc. In terms of accuracy, each of the studies showed high robustness (around 90% mostly) in predicted results. Besides, a common flow of process has been noticed in every methodology where three most important steps are vibration data reduction, ANN model selection and optimized network parameters selection. Although MLBPN was the mostly implemented ANN model, literature reveals that two analogous and rival networks- RBFN and GRNN possess some major advantages, which provided better accuracy than MLBPN in several past studies. So, an extension of a previous experiment was conducted to verify the hypothesis about the effectiveness of RBFN and GRNN. Experimental verification showed that RBFN and GRNN required considerably less sample data and less training time than MLBPN, which are the most reported disadvantages of ANNs. Since the mentioned networks were compared in one case study, future scopes can be the application of these two networks to some of the previously focused parametric problems and study their effectiveness compared to MLBPN. Considering the overall perspective, although neural networks possess few disadvantages to work with, but if necessary measures are taken such as selection of appropriate network algorithm and signal features, they can forecast very precise results in both linear and nonlinear conditions.

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Vitae

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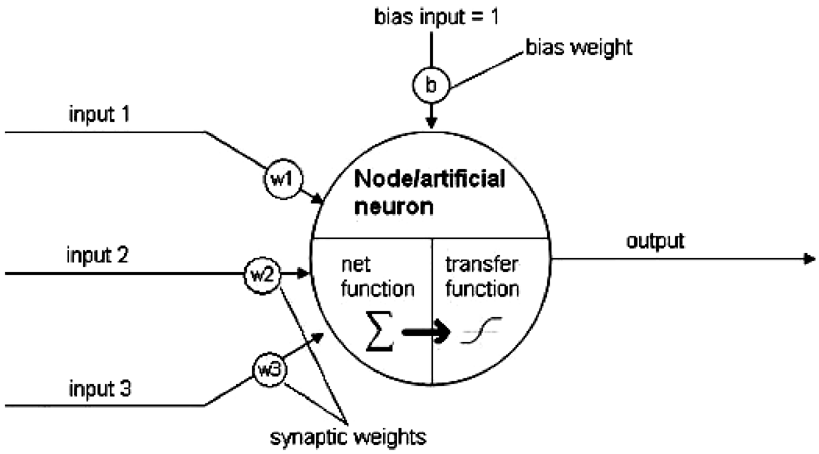


Fig. 1. A single artificial neuron.

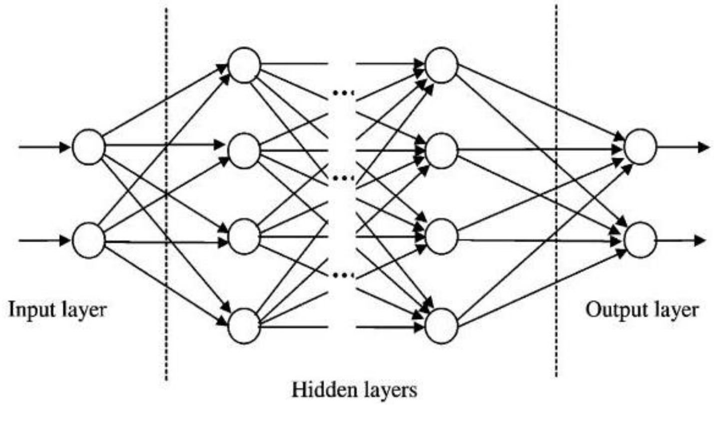

Input layer
Hidden layers
Output layer

Fig. 2.General topology of an ANN [14].

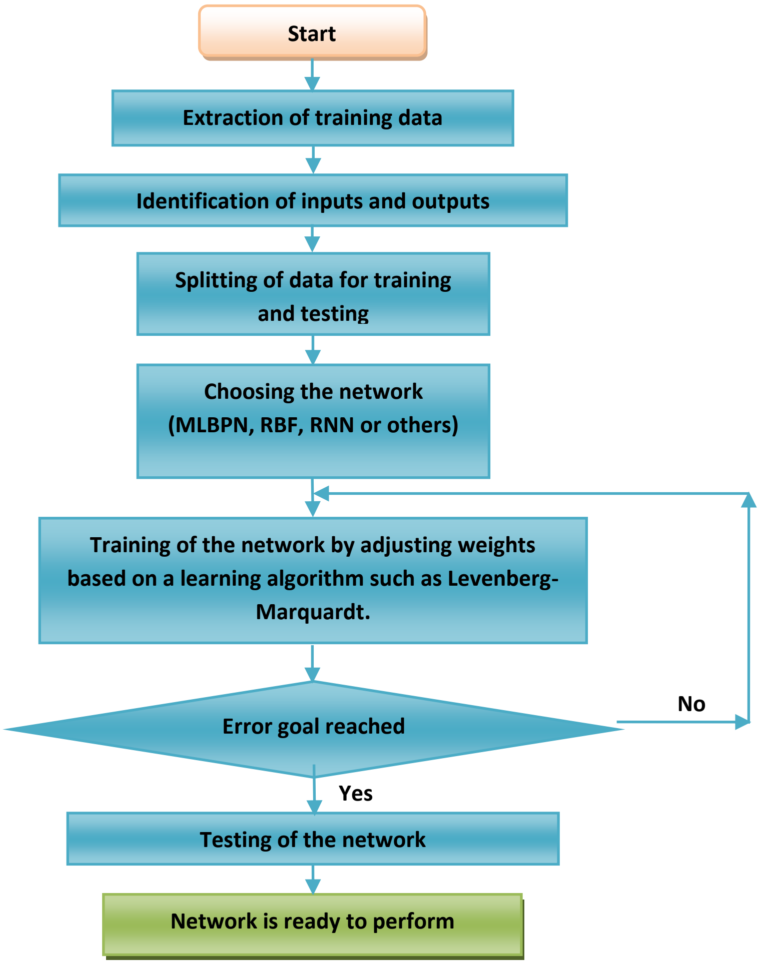

Start
Extraction of training data
Identification of inputs and outputs
Splitting of data for training and testing
Choosing the network (MLBPN, RBF, RNN or others)
Training of the network by adjusting weights based on a learning algorithm such as Levenberg-Marquardt.
Error goal reached
No
Yes
Testing of the network
Network is ready to perform

Fig. 3. ANN implementation steps.

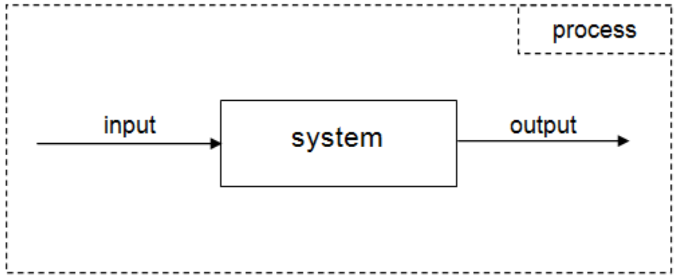


Fig. 4. Model of an input-output process.

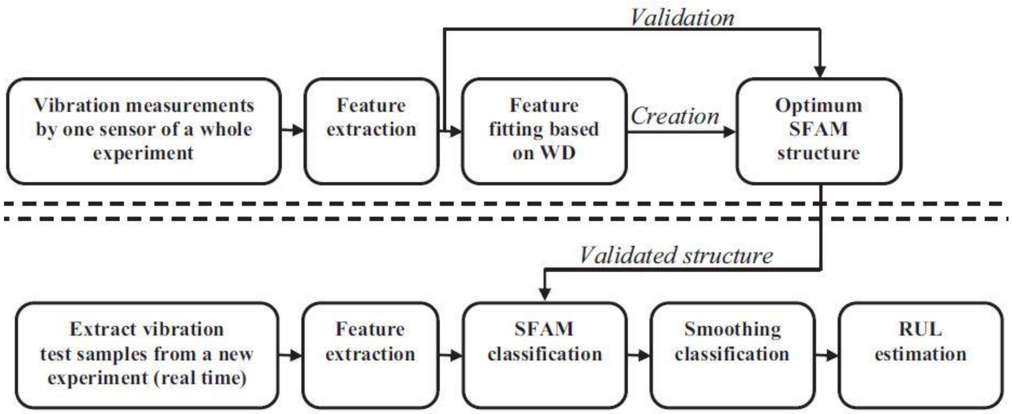


Fig. 5. Accurate bearing RUL estimation by J.B. Ali et al. [34].

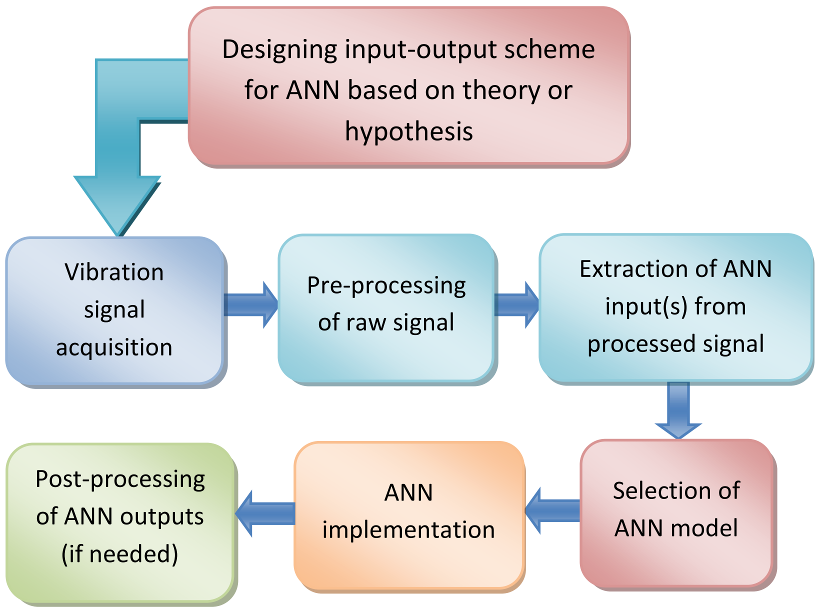
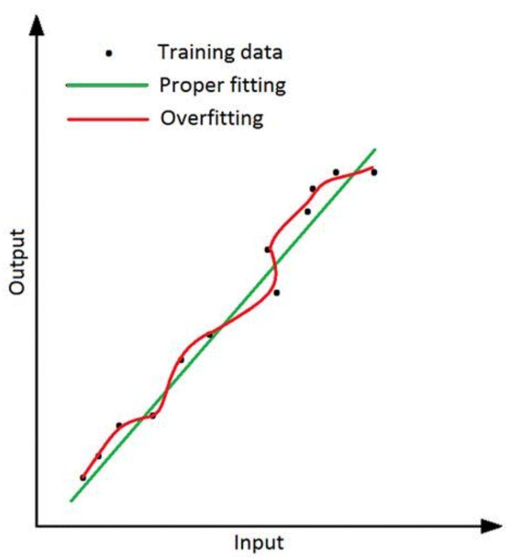


Fig. 6. Schematic diagram of ANN approaches to vibration-based inverse problems.


Training data
Proper fitting
Overfitting
Output
Input

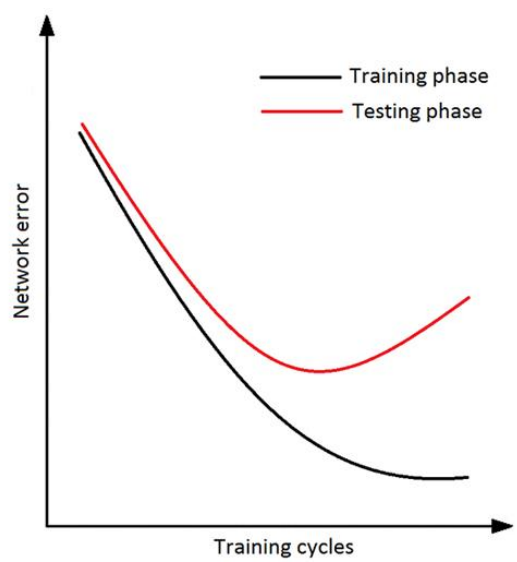

Training phase
Testing phase
Network error
Training cycles

Fig. 7. Visual interpretation of ANNs overfitting.

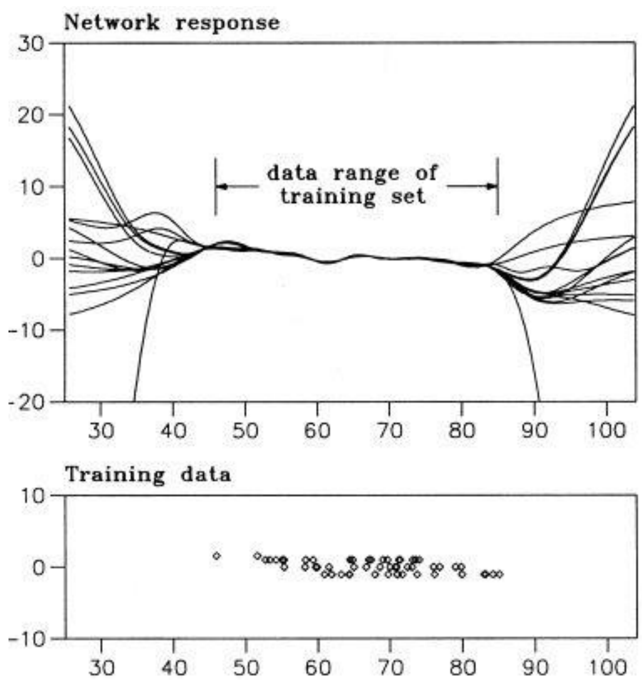


Fig. 8. Extrapolation inadequacy of ANNs [129].

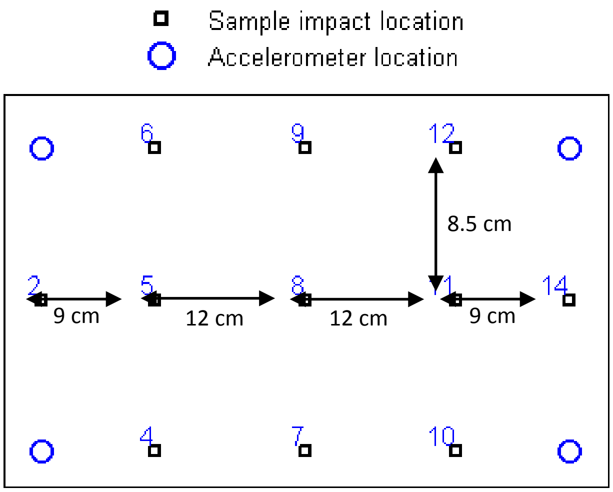


Fig. 9. Accelerometer positions and design of impacts on the test plate.

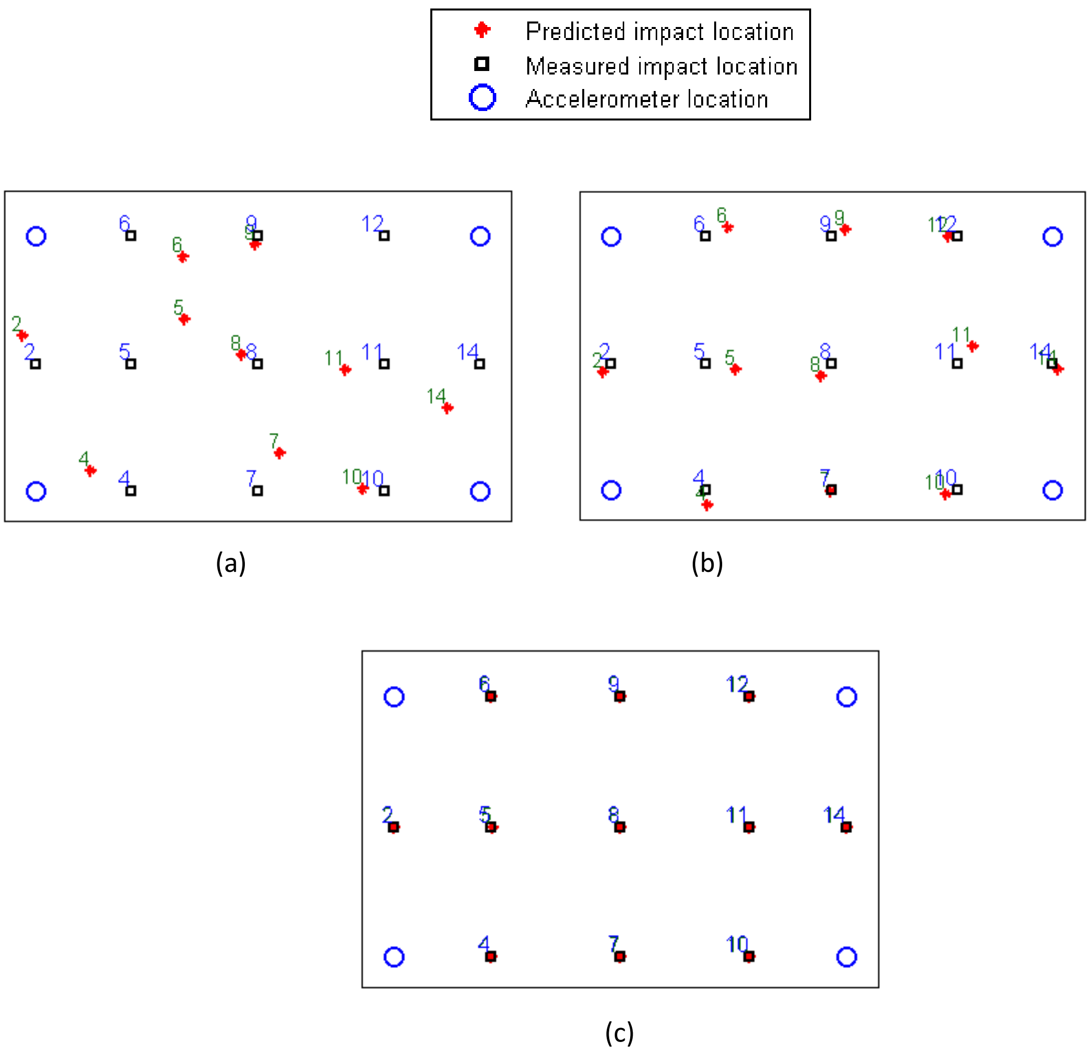


Fig. 10. Impact location detection by (a) MLBPN, (b) RBFN and (c) GRNN.

Table 1. Commonly used activation functions.

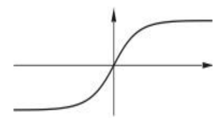
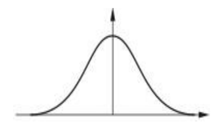
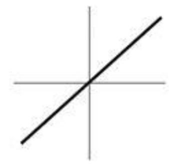
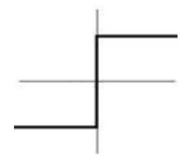
Activation Function	**Formula**	**Graphical Representation**
Sigmoid (or log-sigmoid)	$f(u) = \dfrac{1}{1+e^{-u}}$	
Hyperbolic tangent sigmoid (tanh-sig)	$f(u) = \dfrac{e^{u} - e^{-u}}{e^{u} + e^{-u}}$	
Gaussian	$f(u) = e^{\frac{-\Vert u-c\Vert^2}{2\sigma^2}}$ c = function center; σ = standard deviation	
Linear	$f(u) = u$	
Threshold	$f(u) = \begin{cases} 1 & if\ u > 0 \\ -1 & if\ u < 0 \end{cases}$	

Table 2. Popular ANNs and their specialism.

ANN models	Specialism	Refs.
Multi-layer Backpropagation Network (MLBPN), Probabilistic Neural Network (PNN)	Pattern classification	[15, 16]
Radial Basis Function Network (RBFN), Generalized Regression Neural Network (GRNN)	Function approximation	[17, 18]
Self-Organizing Map (SOM), ART (Adaptive Resonance Theory)	Clustering	[19, 20]
Recurrent Neural Network (RNN), Wavelet Neural Network (WNN)	Time series prediction	[21, 22]
ANFIS (Adaptive Neuro-Fuzzy Inference System)	Controlling	[23]

Table 3. Network details used for force recognition of a racing car's suspension system [35].

Neural network		**Type of identification**	
		Local deformation (DNN)	Force magnitudes (INN)
Activation functions	**Hidden layer**	Hyperbolic tangent	Exponential
	Output layer	Logistic	Hyperbolic tangent

Table 4. ANN applications in vibration-based inverse input identifications.

Author(s)	**Identification objective**	**ANN model**	**Pre-processing of raw signal**	**Training and implementation scheme of ANN**				**Post-processing of ANN outputs**
				Input	**Output**	**Training and testing data ratio**	**Architecture optimization scheme**	
Vibration-inducing force identification								
Y. Liang et al. [39]	Restoring forces	Fuzzy adaptive back-propagation network (FABPN), improved FABPN, MLBPN	Integration and double integration of time-acceleration response to acquire velocity and displacement responses respectively	Measured displacement and velocity factor	Restoring force	200:1	Mutation operation of the genetic algorithm (GA)	--
F.P. Lepore et al., [40]	Excitation forces	MLBPN	Wavelet decomposition with Simulated Annealing optimization	Wavelet parameters (frequency, exponential decay coefficient, phase angle)	Locations, amplitudes, frequencies and phase angles of the excitation forces	60%: 40% (of 464 observations)	Trial and error	--
S. Li and Y. Liu [41]	Load parameters	MLBPN	Integration of time-acceleration response	Time-displacement response	Load parameters (amplitude of load, phase angle)	N/A	Trial and error	--
S.L. Xie et al. [42]	Nonlinear hysteric system	Bouc-Wen model based neural network	--	Displacement and velocity response; five specified constants	Nonlinear hysteric restoring force	6:4	Trial and error	--
Force-involving factors identification								
K.H. Groves and P. Bonello [43]	Squeeze-film damper (SFD) forces	MLBPN	--	Relative displacement and velocity response	x and y axis component of SFD forces	60%: 20% (of total 473,976 data)	Trial and error	--
R. Le Riche et al., [44]	External loads	Autoregressive networks and state-space networks	--	Accelerations at different components	Load magnitudes at the target components (conditioned by pre-predicted mass values)	17,152: 57,848	Trial and error	--
L. Chen et al. [45]	Dynamic thrust	RBFN	--	Acceleration, velocity and displacement response	Thrust force	N/A	Trial and error	--
K. Worden and WJ Staszewski [46]	Impact identification	MLBPN	--	Time-strain features (peak-to-peak and peak arrival time)	Magnitude and location of impacts	80: 47	Trial and error	--

Table 4 (continued)

Force-involving factors identification								
Author(s)	**Identification objective**	**ANN model**	**Pre-processing of raw signal**	**Training and implementation scheme of ANN**				**Post-processing of ANN outputs**
				Input	**Output**	**Training and testing data ratio**	**Architecture optimization scheme**	
J. LeClerc et al., [47]	Impact force locations	MLBPN	Normalization, mean subtraction and enveloping	Extracted low dimensional features from processed signal	x and y coordinates of the impacts	251: 317	Trial and error	--
R. Johnsson [48]	Cylinder pressure reconstruction	RBFN	Fourier transformation of engine structure vibration and crankshaft speed fluctuation	Specified frequency components from frequency domain	Cylinder pressure parameters (current pressure, maximum pressure, location of maximum pressure etc.)	1170: 780	Trial and error	--
PQ Xia [49]	Control voltage for MR damper	MLBPN	--	Displacement, voltage and force	Control voltage	N/A	Optimal Brain Surgeon (OBS) technology	--
M. Nagai et al. [50]	Nonlinear dynamics of a pneumatic suspension	Dynamic neural network	--	Four state variables (found from response from railway irregularity, vehicle body and actuator) at time step K; pressure difference between actuator chamber; and control input to suspension valve	Specified four state variables at time step K+1 which define the nonlinear dynamics of the suspension	N/A	Trial and error	--
B. Lin et al. [51]	Status identification of machining process	Fuzzy ANN	Time and frequency domain based feature extraction at different working condition	Extracted features	Cutting chatter and tool wear	N/A	Trial and error	--
J.M. Fines and A. Agah [52]	Positioning error compensation of machine tool	MLBPN	--	Linear position and direction-of-motion of the machine; a machine location indicator value for one rotation of the leadscrew	Positioning error compensation value	10: 4	Trial and error	--

Table 4 (continued)

Force-involving factors identification								
Author(s)	**Identification objective**	**ANN model**	**Pre-processing of raw signal**	**Training and implementation scheme of ANN**				**Post-processing of ANN outputs**
				Input	**Output**	**Training and testing data ratio**	**Architecture optimization scheme**	
J. Porteiro et al. [53]	Engine power	MLBPN	Integration and Fourier transformation of time-acceleration response to extract several characteristic features	Extracted features	Engine generated power	58: 58	Trial and error	--
B. Akbas et al. [54]	Seismic demand on column splices	MLBPN	--	Designed ground motion and structural parameters	Seismic-induced demands on frame and column splices	192: 48	Trial and error	--

Table 5. ANN applications in vibration-based inverse system identifications.

Author(s)	Identification objective	ANN model	Pre-processing of raw signal	Training and implementation scheme of ANN: Input	Output	Training and testing data ratio	Architecture optimization scheme	Post-processing of ANN outputs
Mass, damping and stiffness identification								
R. Le Riche et al., [44]	System mass	MLBPN	Extraction of candidate features from time-acceleration response and identification of key candidate features which best relate the mass system	Selected features	Mass value	55: 22	Trial and error	--
C.-B. Yun and E.Y. Bahng, [55]	Stiffness matrix	MLBPN	Fourier transformation and Frequency Response Function formation	Natural frequencies and modes of the structure (first four modal data)	Submatrix scaling factors (SSFs)	1650: 150	Trial and error	Submatrix scaling operation of the SSFs to identify the stiffness matrix
Mangal et al. [56]	Percentage of mass value change	MLBPN	--	Natural frequencies	Changes in deck mass	12: 11	Trial and error	--
B. Xu et al. [57]	Stiffness and damping coefficients	MLBPN	Integration and double integration of time-acceleration data	1) Velocity and displacement feature with excitation forces at earlier time step	1) Velocity and displacement feature at the next time step	500: 3	RMS error vector method	--
				2) RMS difference vector of ANN predicted features	2) Stiffness and damping coefficients	288: 2		
Natural frequency and modal parameters identification								
L. Facchini et al., [58]	Eigenvalues and eigenmodes	MLBPN	Extraction of four frequency-dependent indicators which define the spectral tensor behavior at certain frequency	Selected four frequency indices	Probability of the presence of natural frequency	N/A	Trial and error	Identification of eigenvalues and eigenmodes from final probability density function
C. Chen [59]	Flutter derivatives	MLBPN	Determination of horizontal and vertical components of wind velocities in time series for smooth and turbulent flow	Time varied values of wind velocities in horizontal and vertical components	Targeted modal parameters (vertical displacements and torsional angles)	20:20	Trial and error	Matrix operations of predicted modal parameters to obtain the flutter derivatives

Table 5 (continued)

Author(s)	Identification objective	ANN model	Pre-processing of raw signal	Training and implementation scheme of ANN				Post-processing of ANN outputs
				Input	Output	Training and testing data ratio	Architecture optimization scheme	
I. Karimi et al. [60]	Modal properties of a gravity dam system	MLBPN	Fourier transformation to obtain frequency domain	Dimensional parameters and frequency domain based features (when system is in a particular condition)	Specified modal properties of the system (when system is in the defined condition)	14:5	Trial and error	--
L. Wang et al. [61]	Vehicle motion-modes	MLBPN	--	Extracted features from vehicle suspension deflections	Motion-mode energy method calculated mode-ratios	880:4000	Trial and error	--
Damage localization and quantification								
R.B. Walker et al. [62]	Localization of rotor unbalance	MLBPN	Fourier transformation undergoes normalization and averaging	Subsynchronous nonlinear features	Fault location	195: 780	Trial and error	--
A. Budipriyanto et al. [63]	Damage length identification	MLBPN	--	Simulated model's vibration response	Damage index function	N/A	N/A	Damage length estimation using the damage index function
Y. Quan et al. [64]	Tool wear	MLBPN	Feature extraction from acoustic emission (AE) and power signal	Extracted features, cutting speed, cutting depth and feed rate	Tool wear value	N/A	Trial and error	--
M. A. Mahmoud and M.A.A. Kiefa [65]	Crack identification	GRNN	Fourier transformation	Several natural frequencies	Crack size and crack location	478:87	GA	--
P. Ramasamy and S. Sampathkumar [66]	Impact damage tolerance on a composite	MLBPN	--	AE parameters (signal strength, RMS value, counts, counts to peak)	Impact damage tolerance	18:6	Trial and error	--
V. Vallabhaneni and D. Maity [67]	Damage severity	RBFN	Estimation of modal curvatures of healthy and damaged structure	Curvature damage factor	Percentage of damage	450:50	Trial and error	--
Z Zhang et al. [68]	Delamination in composites	MLBPN	Fourier transformation	First seven frequency changes	Delamination parameter (interface, x-location, size)	N/A	Trial and error	--

Table 5 (continued)

Author(s)	Identification objective	ANN model	Pre-processing of raw signal	Training and implementation scheme of ANN				Post-processing of ANN outputs
				Input	Output	Training and testing data ratio	Architecture optimization scheme	
R. Machavaram and K. Shankar [69]	Joint damage severity and location	Improved Radial Basis Function Network (IRBF)	Estimation of normalized damaged signature index (NDSI) from frequency domain features.	Estimated NDSI (frequency domain based method)	Change in rotational stiffness and damage severity	1000:2 (1st stage) 500:2 (2nd stage)	Trial and error	--
				Acceleration response (time domain method)		500:2 (1st stage) 100:2 (2nd stage)		
R.P. Bandara [70]	Damage identification	MLBPN	FRF construction and its dimensionality reduction by Principal Component Analysis (PCA).	Calculated damage indices from reduced FRF data	Damage location and severity	8:18	Trial and error	--
Mechanical properties identification								
Pabisek, E. and Z. Waszczyszyn [71]	Mechanical properties of an elastic isotropic plate	MLBPN	B-scanning and 2D-Fourier transformation	Specified vector of approximate dispersion curve parameters	Young's modulus, Poisson ratio, plate density and thickness	3000: 1772	Trial and error	--
M. A. Kewalramani and R. Gupta [72]	Concrete compressive strength	MLBPN	--	Ultrasonic pulse velocity and weight	Compressive strength	336:303	Trial and error	--
Y.E. Hamzaoui [73]	Useful life of turbine blades	MLBPN (usual and inverse model)	Fourier transformation	Resonance stress, frequency ratio, dynamic stress, Damping, fatigue strength, mean stress	Useful life	2000:500	Nelder Mead optimization method	--
A Chamekh et al. [74]	Material properties	MLBPN	Normalization	Pressure-displacement central point curves	Anisotropic coefficients and hardening curve parameters	24:3	Trial and error	--
Noise identification								
Y.F. Xing et al. [75]	Sound quality of vehicle noise	MLBPN	Denoising, time-frequency feature extraction, defining energy based matrix	Estimated sound feature vector	Loudness and sharpness of vehicle noise	33:33	Trial and error (empirical method)	--
R.S. Magalhaes et al. [76]	Machine-radiated noise	ARX-neural network	--	Vibration signal at noise source (pump) and the spatial coordinate of the source	Sound pressure at the noise source	350:27	Dynamic cross validation	--

Table 6. ANNs + vibration response aided different parametric identifications.

Parameter category	Identification objective	Refs.
Damage	Crack length and location	[77-83]
	Static displacement	[84, 85]
	Tool wear	[86-88]
System properties	Mass	[89]
	Stiffness	[90, 91]
	Natural frequency	[92]
	Residual life of tools	[93]
	Surface roughness	[94]
	Noise level and source	[95]
Acting forces or force-involving factors	Restoring force	[96, 97]
	Excitation force	[98, 99]
	Impact force	[100]
	Damping force	[101]
	Pressure	[102, 103]
Additional input factors (force-inducers)	Wind speed	[104]
	Eccentricity of rotor	[105]
	Control voltage to MR damper/actuator	[106, 107]

Table 7. Popular features from different signal pre-processing techniques.

Signal pre-processing techniques	**Features**
Without pre-processing (raw signal in time-domain)	RMS; kurtosis; standard deviation; variance; maxima; minima; crest factor; mean; and skewness.
Time-integration	Displacement (peak-to-peak); and velocity (peak).
Fourier transformation (frequency domain)	Natural frequencies; frequency ratio; damping; frequency changes; and energy of peak frequencies.
Wavelet transformation	Wavelet coefficients; kurtosis; and skewness.
Hilbert transformation	Peak/centroid of the envelope; and time of peak/centroid.

Table 8. ANN implementation factors.

No. of accelerometers	Extracted feature per acceleration response	Output scheme	Error goal	No. of trials	No. of impact locations
4	1 (peak arrival time)	x-y coordinate of impact	0.6	1	11

Table 9. Performance of MLBPN, RBFN and GRNN.

Network	Mean error	Training time (seconds)
MLBPN	4.89	3.8
RBFN	1.43	2.6
GRNN	0.06	1.3