

Structural Health Monitoring in Concrete Gravity Dams by Signal Processing Algorithms

SajadEsmailzadeh¹, Hassan Ahmadi²and Seyed Abbas Hosseini³

1- Ph.D. Student, Department of Civil Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

2- Assistant Professor, Department of Civil Engineering, Roodehen Branch, Islamic Azad University, Tehran, Iran

3- Assistant Professor, Department of Civil Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

Email:HassanAhmadi, hgahmadi@riau.ac.ir

Abstract

Destruction in dams often has extreme financial consequences and sometimes results in fatalities. Therefore, structural health monitoring is crucial. In this article, a renowned dam, the Pine Flat, has been chosen for the finite element modeling. The main objective is damage detection based on behavior evaluation of intact and damaged dams when an earthquake is applied, and the practical conditions are considered. To do so, damage is induced in the dam neck through elasticity modulus reduction, and then Northridge earthquake is applied. Following that, the acceleration rates of different nodes of both intact and damaged structures are saved in two vectors. In addition, additive noise is generated as a Gaussian random vector and added to the observations for better modeling of the practical measurements. Using various methods, such as Discrete-time Fourier Transform (DTFT), wavelet and Wiener transforms, the differences of intact and damaged data with noise are investigated. To provide a quantitative and precise analysis of the efficiency of each method, the standard deviation of variations was employed for performance evaluation of different algorithms. The results confirm that wavelet transform outperforms other algorithms. Moreover, it is shown that wavelet transform represents the best robustness regarding noise variance.

Keywords: structural health monitoring, concrete gravity dams, signal processing, discrete-time Fourier transform, Wiener filter.

1. INTRODUCTION

Concrete gravity dams (CGD) are among the most important hydraulic structures for any government. Damage in these dams can cause financial and fatal loss. Any small destruction in CGDs, if not diagnosed on time, may affect the whole structure and would result in the collapse of the dam. Therefore, to diagnose destruction in proper time, it is of prime importance to use structural health monitoring methods, such as signal processing algorithms at the presence of noise. However, to select the most appropriate approach for damage detection, these methods should be investigated.

Many types of research using non-destructive techniques, such as signal processing methods, have been considered, but the structures mostly contain simple structural elements, like frames, beams, and trusses, which have much easier governing equations than dams. The reason why this issue is ignored might be due to complication in modeling, analysis and the interaction among different bodies along with the high degree of freedom of the dams in comparison with other structures [1].

Ambient modal identification based on non-stationary correlation technique was studied by Lin. It was recommended that if the ambient excitation is represented by a product model with a slow time-varying function, the responses of the system could be roughly treated as a stationary random process. The non-stationary cross-correlation functions of the structural response (assessed at arbitrary, fixed time instants) have the same mathematical form as that of the free vibration of a structure. From these non-stationary cross-correlation functions, modal parameters of the original system can thus be recognized [2].

Giacomo Bernagozzi, Luca Landi, and Pier Paolo Diotallevi used and compared some methods for vibration-based damage detection of civil structures, beginning with ambient vibration data. The outcomes of the analyses were grounded on a dynamic identification of the modal parameters, which was carried out in output-only conditions. The reviewed damage-sensitive characteristics were the modal parameters, the modal flexibility matrix, and the damage-induced deflection. Due to unitary inspection loads of the identified structure, potential changes in these parameters could be selected to detect, localize and quantify the damage. Furthermore, the effectiveness of the various detected damage features was evaluated, and the accuracy-related to the identified

modifications was defined through a comparison with those variations presumed in the structural model at first [3].

F. Musafere, A. Sadhu, and K. Liu offered a method using the framework of blind source separation (BSS) to detect the time and severity of the damage. Other time-frequency decompositions, such as Hilbert transform and time-varying auto-regressive modeling were investigated to improve source separation capability of the BSS method [4].

Xuan Kong, Chun-Sheng Cai, and Jiexuan Hu investigated different levels to identify vibration-based damage, which contained anticipation of the remaining useful lifetime of structures and decision-making for suitable actions. They presented a framework that consisted of several major parts, including damage detection via response-based approaches, building logical structural models, selecting damage parameters and constructing objective functions with sensitivity analysis and adopting optimization techniques to solve the problem. For every section, the applied methods were reviewed and the advantages and disadvantages were summarized for further recommendations [5].

Pirboudaghei et al. simulated the Karun 3 dam via numerical modeling and analysis through the finite element method (FEM) and XFEM-based cohesive crack sections successively. The dam was also evaluated under earthquake excitation. The results showed the appropriate ability of the recommended technique, regardless of difficulties of the input effect and modal interference. The physical differences in the structure, cracking initiation time from evaluating time-frequency window of the structure response, the exact location of crack from comparison of the intact and damaged crest and central cantilever vibration modes were made possible by this approach [6].

S.S Kourehli introduced an innovative method for damage detection using extended mode shapes and extreme learning machine (ELM). The approach used the first two extended mode shapes and natural frequencies as the input parameters and damage conditions as output to train the ELM model. Moreover, the noise effect on the measured modal data was examined. This method was applied to three cases, including a four-span continuous beam, plane steel truss, and four-story plane frame. The results showed the exactness and efficacy of the offered approach using incomplete modal data. Also, it was indicated that this method was a suitable procedure for damage detection despite using noisy modal data [7].

A general review of the abovementioned context indicates that detecting structural damage is mainly investigated on the simple structural systems, like multi-story building frames, trusses, etc. In other words, concrete gravity dams mostly neglected in the literature due to their high degree of freedom and complex geometry. Therefore, the current research aims to employ signal processing algorithms for identification of damage within this superstructure. It seems that there are not any similar studies in the field of structural health monitoring of concrete gravity dams with a reduction of modulus elasticity in some elements and application of signal processing algorithms. Accordingly, a well-known concrete gravity dam, i.e. the Pine Flat, is chosen for the finite element modeling of structures in ABAQUS. The damage is done by reduction of elasticity modulus after application of an earthquake. In addition, acceleration is extracted in some nodes. Then, the damage is investigated through signal processing algorithms. The results revealed that wavelet transform was superior to the other algorithms. Moreover, it was seen that wavelet transform had the best robustness with respect to noise variance.

2. PROPOSED FINITE ELEMENT MODEL

In this section, the Pine Flat Dam was chosen for the finite element modeling of structures in ABAQUS. To simulate the mechanical behavior of the dam, a two-dimensional finite element model was developed in ABAQUS software. The program was selected due to its variety in material and geometrical modeling capabilities.

By ignoring the material nonlinearity effects and presuming the linear behavior, the mass concrete mechanical properties, which are roughly the same in both static and dynamic cases, are as follows: the elasticity modulus $E = 33.558$ GPa, the Poisson's rate = 0.255, the density = 2643 kg/m³, the Bulk modulus of water and the density of water.

Furthermore, the following assumptions have been made in modeling of dam-reservoir interaction: a rectangular shape is considered for the reservoir, with a length equal to three times of the height of the dam; the free-board in lake is neglected to easily model the interaction between the dam and the reservoir (the water level is equal to the height of the dam); dam-water interaction is modeled as type tie, where the nodes are constrained together on the interface of the two media [8]; the transmitting boundary condition is appointed to the reservoir's truncated far-end so that the pressure waves are not reflected into the reservoir; and zero hydrodynamic pressure is assigned to the free surface of the reservoir and there is no absorbing boundary condition at the bottom of the

reservoir [9]. In the modeling of the dam-foundation interaction, it is supposed that there is a rigid foundation; there is no sliding along the dam-foundation interface, and the uplift pressure is not modeled in this study.

3. Damage scenario

Most of the damage sustained by earthquakes often takes place at the neck of the dam. In the elements of the dam neck, as shown in the figure below, damage occurs in the form of elasticity modulus reduction by %40 and %80. The elasticity modulus is a quantity that measures the resistance of materials to assessment deformity. In other words, 0% destruction is classified as intact, and any percentage of destruction is categorized as damaged.

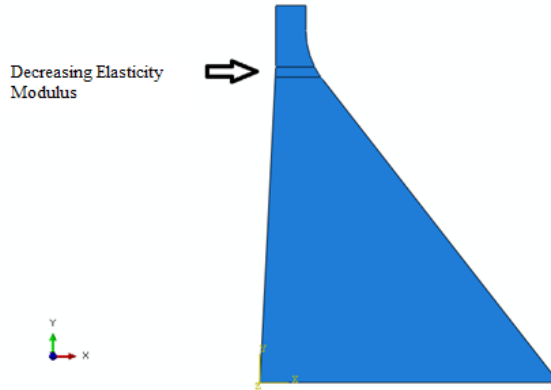


Figure 1. Damage of the elements in the dam neck

Northridge earthquake record is induced at the heel of the dam and the acceleration of the intact and damaged structure is extracted in 26 nodes (Figure 2) in the upstream. It should be noticed that acceleration is an essential dynamic parameter.

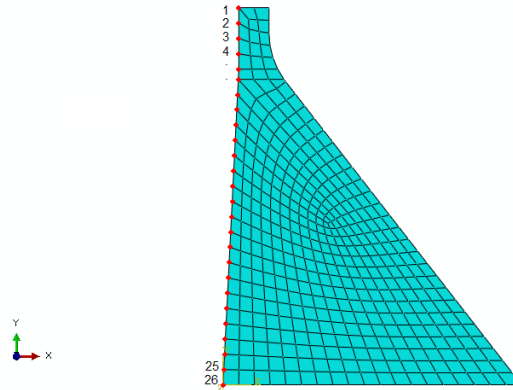


Figure 2. Numbering of the nodes in the upstream of the dam

4. Methodology

In this article, signal processing algorithms have been implemented in MATLAB simulation environment. Moreover, the required data related to 40% and 80% of destruction cases have been produced through ABAQUS.

4.1 Processing at the presence of Additive Gaussian Noise (AGN)

In reality, all measurement instruments have unwanted noise for different reasons. The measured data by these tools, considering the severity of the noise, is to some extent uncertain. In physical systems, various factors, such as measurement error of physical quantities, changes in sensors in different weather conditions, errors in the conversion of quantities, etc., can result in noise. However, the existing noise in the measurement instruments is neglected in most processes and analyses related to the structural behavior in different conditions and simulated environments. In the case wherein the amount of noise (power or variance) is negligible, the analyses will be valid. Otherwise, the results will not be reliable.

In this article, the occurrence of damage was investigated in a concrete gravity dam with application of earthquake under conditions based on which the acceleration data in ABAQUS are contaminated by noise. For this purpose, at first the acceleration measurements for different nodes (26 nodes) are measured after application

of earthquake in two cases of being intact and damaged in the elements between the 5th and 6th nodes. Then, the additive Gaussian noise was added to the measurements. In addition, the destruction was considered as 40% and 80% reduction of the elasticity modulus. The data production had been done in ABAQUS and the implementation of various methods have been performed in MATLAB.

4.2 Investigating the Behaviour of Structure Destruction in the Time Domain, Frequency Domain by Fourier Transform, Wavelet Transform and Wiener Filter at the presence of AGN

For some sample nodes, the difference of acceleration data after the application of earthquake was investigated. Discrete-time Fourier transform for $X[n]$ discrete-time signal is defined as [10]:

$$X(f) = \sum_{k=-\infty}^{\infty} x[n] \exp(-jk2\pi f) \quad (1)$$

Where n and f represent the time and frequency domain variables. The output function of the above equation is in the frequency domain and contains spectral features of $X[n]$ signal in the frequency domain [10].

The V vector space is a set of linear, independent vectors, and each of them can be defined by a linear combination of basic vectors [11]. The dimension of a vector space is the number of basic vectors in a vector space. The definition of a desirable vector in space is as follows:

$$v = \sum_{k=1}^N \alpha_k \psi_k \quad (2)$$

Where, α_k is the coefficient of the linear combination; ψ_k is the vectors of the space basis and N is the space dimension.

The relationship between Wiener filter and $h[n]$ limited impulse response with the length of N is defined as the following. Also, the coefficients are not zero in $0 \leq n \leq N-1$ [11], [16]:

$$\hat{s}[n] = h[n] \otimes z[n] = \sum_{i=0}^{N-1} h[i] z[n-i] \quad (3)$$

In the above equation, the operator shows convolution. $z[n]$ is the variable of the new domain (after transform).

5. Comparison of the Suggested Methods

To compare the suggested methods in this article, the standard deviation of different approaches was considered. The standard deviation curves of various methods present transformation on acceleration changes before and after destruction. Any method which illustrates these changes more vividly is a better choice for this purpose. This quantity is shown in the following figure for 40% and 80% destruction.

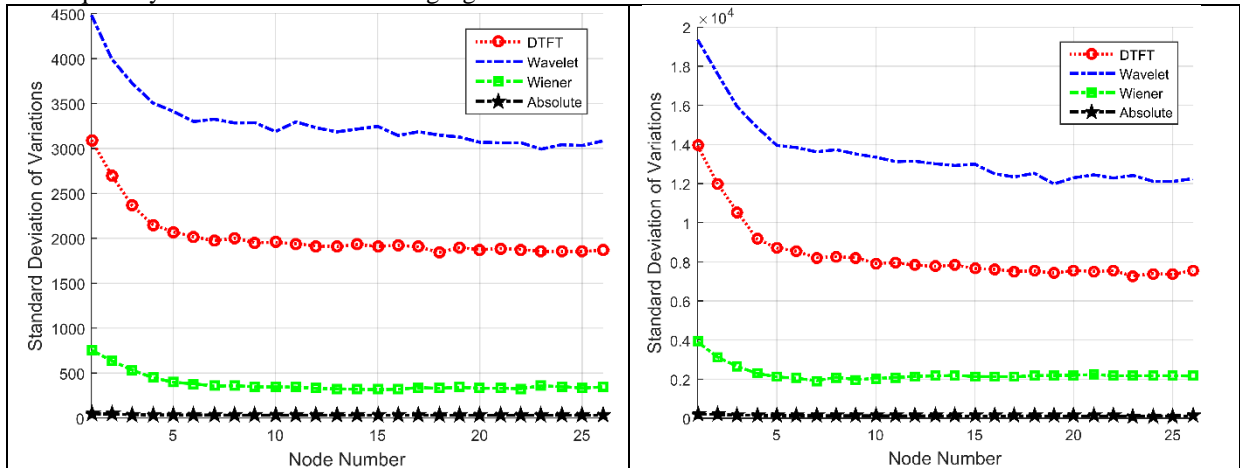


Figure 3. The efficiency of the proposed methods to clarify the existence of damage in the structure for 40% and 80% destruction at the presence of AGN noise with $(0.5)^2$ and $(2)^2$ variances respectively. The left figure 40% destruction. The right figure 80% destruction

Also, the standard deviation of different methods can be shown based on decibel. This parameter is presented in the figure below.

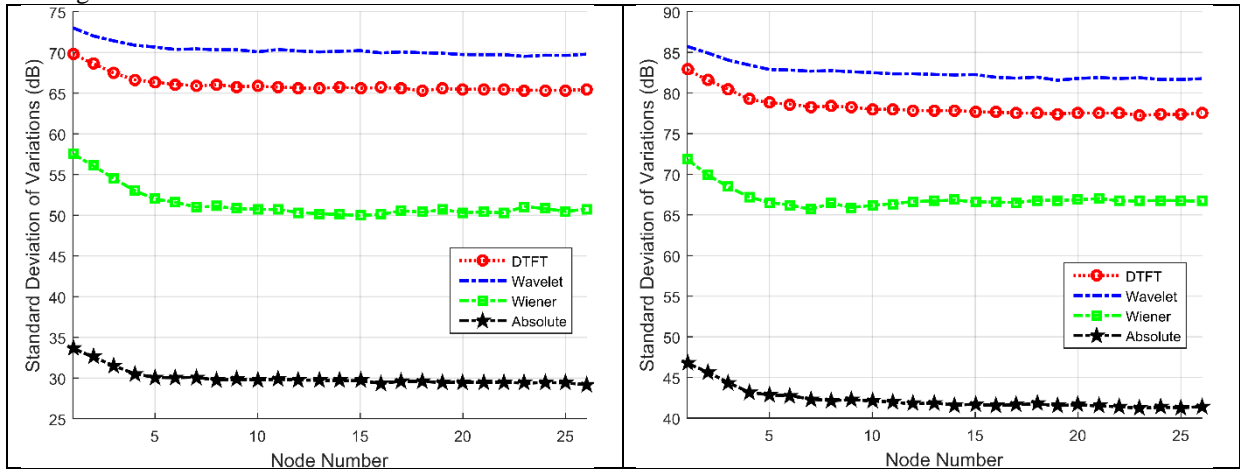


Figure 4. The efficiency of the proposed methods based on decibel (dB) to clarify the existence of damage in the structure for 40% and 80% destruction at the presence of AGN noise with $(0.5)^2$ and $(2)^2$ variances respectively. The left figure 40% destruction. The right figure 80% destruction

From the above figure, it could be understood that wavelet transform had the best function regarding the illustration of destruction in the structure. It should be noted that the above curves were formed based on decibel according to $20 * \log_{10}(\cdot)$. For both destruction cases, the function of the wavelet transform is 4 dB better than DTFT, and that of DTFT is at least 10 dB more suitable than Wiener.

In order to have a better understanding of the algorithms compared, the efficiency of different methods with and without noise is shown below based on decibel for 40% destruction.

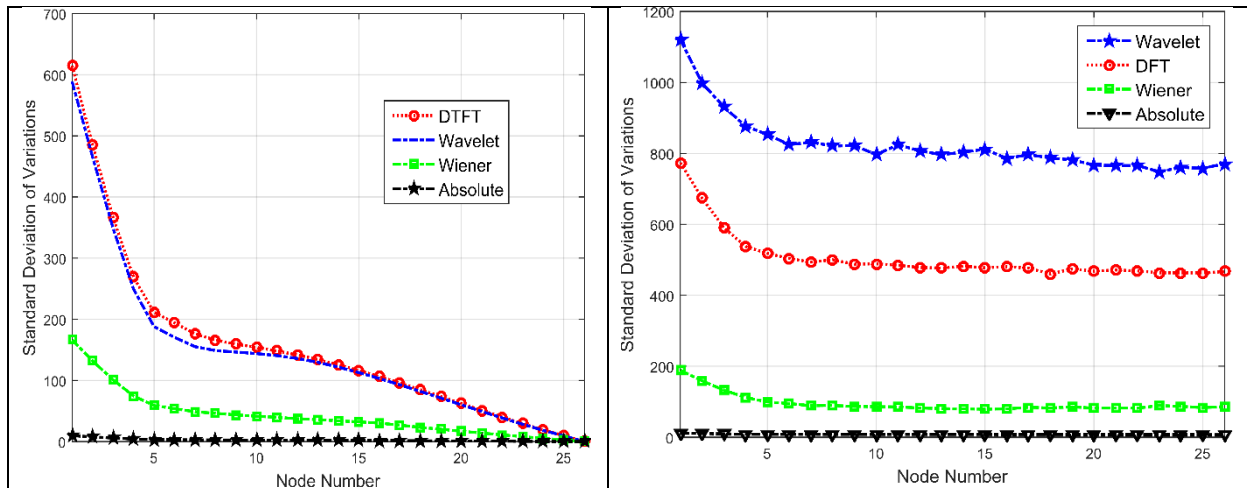


Figure 5. The efficiency of the suggested methods for clarification of the existence of damage in the structure for 40% destruction in both cases of noise-free and adding AGN with $(0.5)^2$ variance. The left figure: noise-free. The right figure: adding noise

The efficiency of different methods with and without noise is shown below based on decibel for 80% destruction.

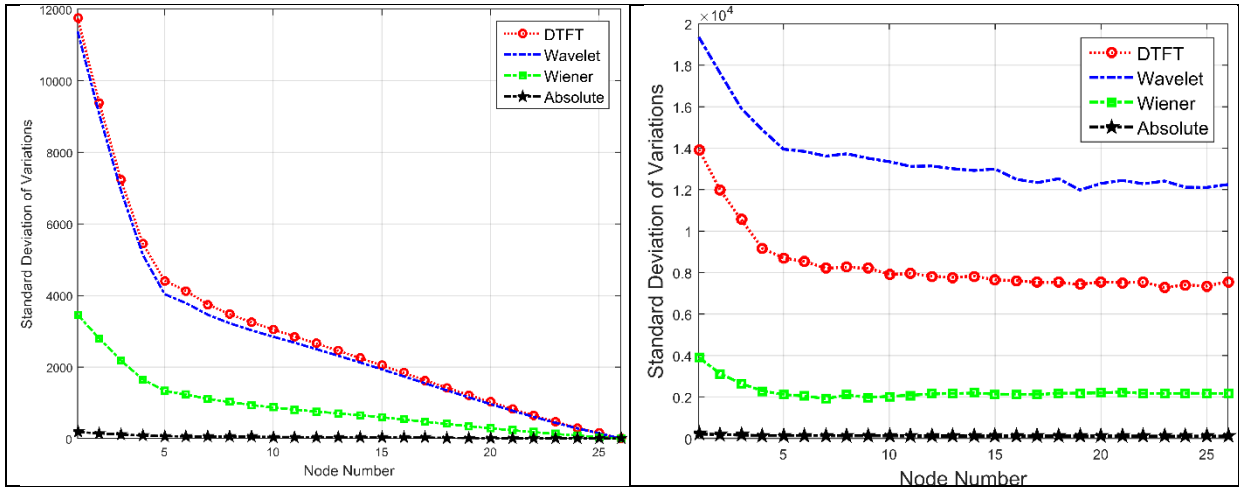


Figure 6. The efficiency of the suggested methods for clarification of the existence of damage in the structure for 80% destruction in both cases of without noise and adding AGN with $(2)^2$ variance. The left figure: noise-free. The right figure: adding noise

The efficiency of different methods with and without noise is shown below based on decibel for 40% destruction.

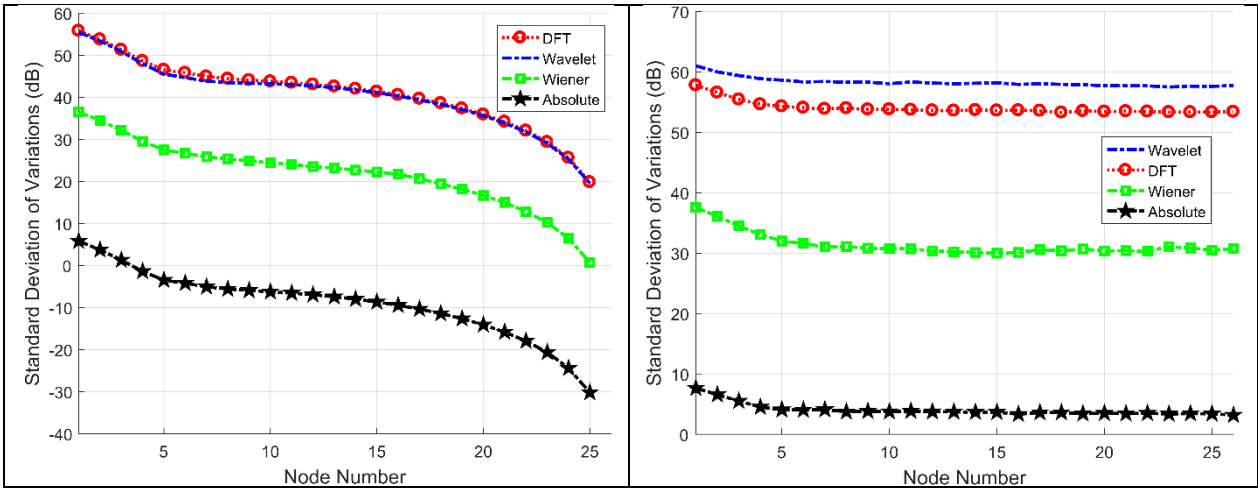


Figure 7. The efficiency of the suggested methods based on decibel (dB) for clarification of the existence of damage in the structure for 40% destruction in both cases of noise-free and adding AGN with $(0.5)^2$ variance. The left figure: noise-free. The right figure: adding noise

The efficiency of different methods with and without noise is shown below based on decibel for 80% destruction.

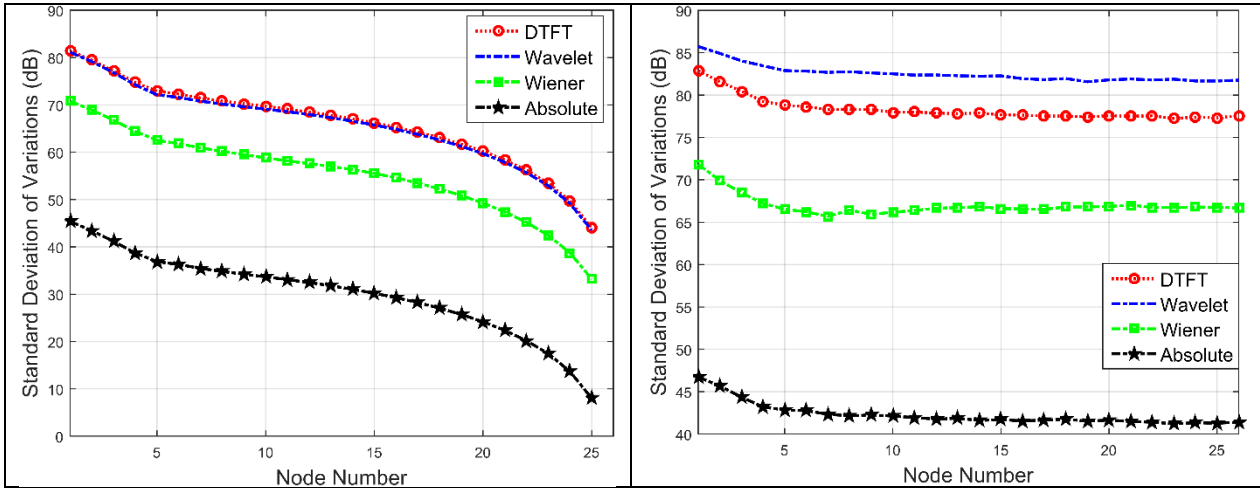


Figure 8. The efficiency of the suggested methods based on decibel (dB) for clarification of the existence of damage in the structure for 80% destruction in both cases of noise-free and adding AGN with $(2)^2$ variance. The left figure: noise-free. The right figure: data with noise

5.2 Robustness threshold of the proposed methods at the presence of AGN noise for Damage Clarification

In the previous sections of the article, to clarify the presence of damage in the structure with noise, the efficiency of different methods was investigated. Furthermore, their efficiency was compared using a numerical quantity. In this part, the threshold of damage clarification is evaluated by the mentioned methods at the presence of noise. The purpose of this section is to evaluate the clarification power of these methods against noise. Therefore, the power (variance) of the added noise to the observations is raised and the efficiency of different clarification methods is observed. The trend of increasing variance noise is continued for each method up to a point where there will be no possibility of damage clarification in the structure. In this case, the noise variance will define the robustness level of each algorithm concerning the variance. Robustness thresholds of various methods against the noise variance are shown in the following table.

Table 1- Maximum noise variance for which damage clarification is possible

Method	Maximum Variance of Additive Noise	
	40% Damage	80% Damage
Absolute Value	3.3	5
DTFT	6.6	9.2
Wavelet Transform	7.8	10.5
Wiener Transform	5.2	7.1

Based on the above table, wavelet transform was the most resistant method against noise regarding damage clarification as it had appropriate damage clarification power against stronger noise.

6. CONCLUSIONS

In this study, the behavior of the intact and damaged dams was examined after inducing the earthquake via signal processing algorithms, while the acceleration measurements were contaminated by additive random noise. The destruction in the Pine Flat Dam was incurred by reducing the elasticity modulus in some elements. After applying of the earthquake, the acceleration data of different nodes were merged by additive random noise and recorded in two different vectors corresponding to the intact and damaged cases. For structural health monitoring in the dam, the differences of the intact and damaged signals were evaluated using various signal processing algorithms. Discrete-time Fourier Transform (DTFT), wavelet and Wiener transforms were used to

assess the dam in both cases. To present a detailed analysis of the effectiveness of these methods, the standard deviation of variations was used to assess various algorithms. According to the simulation results, it could be claimed that wavelet transform represented the best performance. The superiority of wavelet transform was at least twice as much (3 dB) as its closest competitor, i.e. DTFT, and much more concerning others. This rate for DTFT was at least 10dB higher than that of Wiener and 35dB in comparison with the absolute difference. Although the destruction occurred in the elements between the 5th and 6th nodes, acceleration data varied in different nodes and these differences were clarified using signal processing algorithms. Besides, when the noise power increased, the detection threshold of the methods was compared, and it was found that wavelet transform represented the best robustness for a noise variance.

7. REFERENCES

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