Spectral Method and Machine Learning approach to Wind Turbine damage detection

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Abstract. Wind energy is one of the cleanest energy source currently used in the world, an energy source that interferes least with the environment. It is important to locate Wind Farms (WF) in such a way as not to limit the living space and not to reduce the comfort of people in the area. Due to the intensity of the wind and minimal human impact, offshore farms seem to be the required solution. Another aspect important from the point of operational reliability, is ensuring continuous working conditions due to the design and material solutions. Wind Turbine (WT) structures are exposed to the dynamic action of wind and waves from the sea, as well as to the corrosive environment, causing accelerated damage to WT. The action ensuring safe use of structural elements of WT is monitoring the technical condition of the structure based on the analysis of frequency response functions (FRF). At the design, as well the operational stage, it is important to predict the failure of the element. The paper presents the simulation results of the monitoring and prediction of damage of IEA 15-Megawatt offshore wind turbine using the analysis of changes in resonant frequencies in the FRF and the Machine Learning technique.

Keywords: Wind Turbine, Spectral Method, Machine Learning, Frequency Response Functions

1 Introduction

For several years, we have been observing a dynamic increase in the number of installations of devices producing energy from wind: onshore and offshore wind energy sector.
In 2020, 6% of the world's electricity production was provided by wind power. 15 % of electricity was produced in Europe with use of the wind [1].

Table 1. Wind capacity by region, unit GW, NAM – North America, LAM – Latin America, EUR – Europe, CHN – China, based on [32]

	2020			2030			2050		
Region	Onshore	Fixed offhore	Floating offshore	Onshore	Fixed offhore	Floating offshore	Onshore	Fixed offhore	Floating offshore
NAM	136	0.04	0	271	29	2	691	150	31
LAM	33	0	0	98	29	0	334	120	7
EUR	183	25	0.06	289	118	8	505	379	60
CHN	280	10	0	801	120	2	2072	582	99
World	708	35	0.07	1733	385	14	4841	1703	300

The European Commission expects that offshore wind energy will be of increasing importance in the future, as offshore wind is part of its Green Deal, as general policy accordingly that energy, transport and taxation policies fit for reducing net greenhouse gas emissions by at least 55% by 2030, comparing to 1990 [2].
Onshore water areas such as lakes, fjords and sheltered coastal areas as well as deeper-water areas are considered as offshore wind power. Compared to the onshore, offshore wind farms are characterized by higher turbine efficiency, related to greater stability and strength of the wind blowing in the sea areas. On the sea, offshore turbines are much larger and more effective. There are higher wind speeds offshore than on land. Taking the capacity installed, the offshore farms generate more electricity. The offshore farms have less impact on people and

the landscape. Fixed-foundation wind turbines in relatively shallow water are used in most cases of offshore wind farms. Nowadays the floating wind turbines for deeper water are developed.
In 2022 total worldwide offshore wind power capacity is 64.3 GW [3], where China has 49% of the capacity, the United Kingdom 22%) and Germany 13%. One of the world's largest offshore wind farm is 1.2 GW Hornsea Project One in the United Kingdom [4]. Vindeby Offshore Wind Farm was the first offshore wind farm in the world being installed in Denmark in 1991[5]. In 2017, the Vindeby Offshore Wind Farm was taken down. The components were recycled into new use, particularly metals and concrete [6]. By 2050, the expectation is that the installed offshore wind power capacity will reach 1550 GW on a worldwide scale [1].
Due to the importance of the above arguments regarding clean energy sources, there is a real need for further development of the electricity wind power sector, which is environment friendly. Further research into the recycling and reuse of materials from decommissioned wind turbines is essential. It is also important to extend the operation of wind farms, which operate reliably and supply electricity for many years. Numerical models that allow for forecasting the work of structures, monitoring and classification of technical condition are part of this research direction. Adewuyi et al. [7] presents the vibration-based damage identification methods using displacement and distributed strain measurements. The authors state that long-gage distributed strain measurements are efficient for the reliable civil structural health monitoring. In [8] the modal shape identification of large structure by operational modal analysis technique is presented. The article [9] provides a summary of modal testing and structural model validation of wind turbine blades. The theory and practice of the modal testing, theoretical basis, measurement techniques, models are studied in the [10]. Based on the vibration features, the damage identification methods are classified into four major categories [11]. A.K.Pandey and M.Biswas [12] presents the flexibility difference method for locating damage in structures. They emphasize that damage diagnosis can be divided into three sub-problems: damage detection, i.e. determining the presence of damage, damage location, i.e. determining the location of damage, damage quantification, i.e. determining the amount of damage. Interesting methods of damage detection are presented in [13-15]. There has been a lot of works on the analysis of the frequency response functions (FRFs) as a source of information on the state of the structure based on SEM. The methodology is described in [16-22]. Machine Learning (ML) is the tool which support the structural health monitoring (SHM) in the scope of qualification of elements as damage or non-damage. In particular ML is useful in the prediction of the structural state of analyzed systems. In the last period the ML is observed as the useful tools which is used in many industrial sectors as the algorithms of ML can be applied in wide scope of engineering [23].

2 Spectral Element Model and Support Vector Machine technique

The dynamic analysis of the one-sided fixed composite-cement beam was carried out by SEM. The influence of the height of the crack on the resonance frequency was investigated. For each frequency the damage index (DI) was calculated with the refence to mean value of the natural frequency. The Support Vector Machine (SVM) algorithm was used to train the system to qualify the beam as damage or health. 80% of data was used for training and 20% for testing.

2.1 Spectral Element Model

Considering a simplified model, the governing differential equation for the un-damped Euler-Bernoulli for free vibration can be written as [22]:

$$EI\frac{\partial^4 v(x,t)}{\partial x^4} + \rho A\frac{\partial^2 v(x,t)}{\partial t^2} = 0 \tag{1}$$

where ρA is mass per unit length, EI the uniform bending rigidity and $v(x,t)$ is the beam displacement as a function of the position x and time t. By considering a constant coefficient, a displacement solution can be assumed in the form:

$$v(x,t) = v_0 e^{-i(kx-\omega t)} \tag{2}$$

where v_0 is a amplitude, ω is the frequency and k is the wave number.

The dynamic stiffness matrix for the spectral beam element under axial tension can be determined as:

$$\boldsymbol{S}(\omega) = \boldsymbol{K}(\omega) - \omega^2 \boldsymbol{M}(\omega) \tag{3}$$

By solving the integral, the dynamic stiffness matrix is:

$$\boldsymbol{S}(\omega) = \frac{\mathrm{EI}}{\Delta}\begin{bmatrix} s_{11} & s_{12} & s_{13} & s_{14} \\ s_{21} & s_{22} & s_{23} & s_{24} \\ s_{31} & s_{32} & s_{33} & s_{34} \\ s_{41} & s_{42} & s_{42} & s_{44} \end{bmatrix} \tag{4}$$

where $\Delta = cos(k\,L)cosh(k\,L) - 1$ and the components of element matrix (Eq.4) are given as:

$$\begin{aligned} &s_{11} = -k^3(cos(kL)sinh\,(kL) + sin(kL)cosh(kL)), && s_{12} = -k^2 sin\,(kL)sinh\,(kL), \\ &s_{13} = k^3\,(sin\,(kL) + sinh\,(kL)), && s_{14} = k^2\,(cos(kL) - cosh(kL)), \\ &s_{22} = k(cos(kL)sinh(kL) - sin(kL)\,cosh(kL)), && s_{23} = k^2(cosh(kL) - cos(kL)), \\ &s_{24} = k(sin\,(kL) - sinh(kL), && s_{33} = -k^3(cos(kL)sinh(kL) + sin(kL)cosh(kL)), \\ &s_{34} = k^2\,sin(kL)\,sinh(kL), && s_{44} = k\big(cos(kL)sinh(kL) - sin(kL)cosh(kL)\big). \end{aligned} \tag{5}$$

The spectral model of wind turbine a spectral beam element with a lumped mass representing the tower and the rotor-nacelle, respectively [24]. For the model considering a continuous tower only a spectral element is assumed, and for the tapered case, the tower is meshed into beam spectral elements, where each beam element has a reduction in the cross-section area from element one up to the top. The equation of motion that represents the wind turbine is:

$$EI\frac{\partial^4 v(x,t)}{\partial x^4} + \rho A\frac{\partial^2 v(x,t)}{\partial t^2} + m_{nac}\frac{\partial^2 v(x=L,t)}{\partial t^2} = 0 \tag{1}$$

The above equation with the spectral representation has the form:

$$EI\frac{d^4\hat{v}}{\partial x^4} + \omega^2(\rho A + \widetilde{m}_{nac})\hat{v} = 0 \tag{1}$$

where $\widetilde{m}_{nac} = m_{nac}\,EI\beta^3$.

WT spectral matrix for beam spectral element and a lumped mass has the following form

$$\boldsymbol{S}(\omega) = \frac{\mathrm{EI}}{\Delta}\begin{bmatrix} s_{11} & s_{12} & s_{13} & s_{14} \\ s_{21} & s_{22} & s_{23} & s_{24} \\ s_{31} & s_{32} & s_{33} + s_{m_{nac}} & s_{34} \\ s_{41} & s_{42} & s_{43} & s_{44} + s_{m_{nac}} \end{bmatrix} \tag{4}$$

$s_{m_{nac}} = -\omega^2 \widetilde{m}_{nac}$.

2.2 Machine Learning and Support Vector Machine Technique

Machine Learning (ML) is part of Artificial Intelligence (AI) [23]. ML is the learning through experience and based on the measured data. Part of ML is Deep Learning (DL), i.e. algorithms that allow to filter the data. In ML we can distinguish: super-vised, unsupervised and reinforcement learning. Supervised Learning includes classification and regression. The classification includes: Support Vector Machines (SVM), Naïve Bayes Classifier (NBC), Decision Trees (DT), Random Forest (RF) and K – Nearest Neighbors (K-NN). In the SVM algorithm, the line that separates the data must be in the optimal place. The distances between the line and the nearest set points should be as small as possible. These distances are the Support Vectors. SVM idea is presented in Fig.1 where s_1 and s_2 mean the analyzed plane.

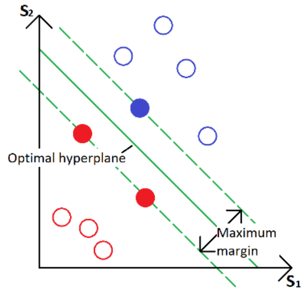


Figure 1. SVM for two dimensional training set

The advantages of SVM are finding the optimal distances (margins) between groups of points, it is a computationally efficient method - the complexity increases only linearly with the number of dimensions, it solves both linear and non-linear problems.

3 Numerical analysis and results

The turbine chosen for the study is IEA 15MW offshore wind turbine (OWT) which corresponds to IEC Class 1B. The turbine has a horizontal axis with an upwind orientation. The turbine is equipped with a rotor with three blades. The geometry of IEA 15MW OWT is presented in Fig.2 [25].

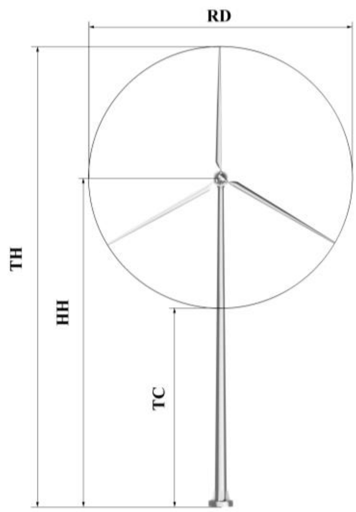


Figure 2. Geometry of IEA 15 MW OWT, from the sea level: hub height HH = 150 m, rotor diameter RD = 240 m, tip clearance TC = 30 m, tip height TH = 270 m

The mass of the rotor-nacelle assembly has 1446 tons, a tower height of 150 m, an average tower diameter of 10 m, a tower wall thickness of 0.05 m, Young's modulus of 210 GPa, and a density of 7850 kg/m3. The OWT model is considered as continuous diameter beam with a lumped mass. It assumed a fixed base neglecting the soilstructure interaction. In the SEM model 2 elements were assume. A dynamic analysis was made with application of two dimensional spectral element model. The model was excited by a unitary force, and the translational and rotational responses were estimated at the top of the tower. In the numerical analysis the influence of wind turbine tower wall thickness was researched. Change of wall thickness simulates the real condition of corrosion reducing the wall thickness of wind turbine tower. The optimal geometry parameters of tower is marked as health state and presented in Tab.2.

Table 2. Parameters of health OWT

Segment / Item	1	2	3	4	5	6	7	8	9	10	11
Diameter	10,00	9,99	9,89	9,50	9,07	8,7337	8,48	8,25	8,08	7,51	6,71
Wall thickness	0,0492	0,0458	0,0430	0,0413	0,0394	0,0368	0,0335	0,0298	0,0262	0,0306	0,0306

The wall thickness reduction is marked as damage state, as case 1 to 5, and is presented in Tab.3.

Table 3. Parameters of damaged OWT

Segment / Damage	1	2	3	4	5	6	7	8	9	10	11	12	13
damage 1	0,0328	0,0305	0,0287	0,0275	0,0263	0,0245	0,0223	0,0199	0,0175	0,0204	0,0204	0,0328	0,0305
damage 2	0,0246	0,0229	0,0215	0,0206	0,0197	0,0184	0,0167	0,0149	0,0131	0,0153	0,0153	0,0246	0,0229
damage 3	0,0197	0,0183	0,0172	0,0165	0,0158	0,0147	0,0134	0,0119	0,0105	0,0123	0,0123	0,0197	0,0183
damage 4	0,0164	0,0153	0,0143	0,0138	0,0131	0,0123	0,0112	0,0099	0,0087	0,0102	0,0102	0,0164	0,0153
damage 5	0,0141	0,0131	0,0123	0,0118	0,0113	0,0105	0,0096	0,0085	0,0075	0,0088	0,0088	0,0141	0,0131

Totally 6 resonance curves for the health and damage wind turbine tower were investigated. The resonance frequencies are presented in Tab. 4.

Table 4. Resonance frequencies of health and damaged OWT

frequency, [Hz]	1	2	3	4	5	6	7
health	0,1955	1,9550	5,7674	11,6813	19,5015	29,1789	40,2248
damage 1	0,2440	2,3950	6,4520	12,2680	19,9900	29,1790	39,9320
damage 2	0,1955	2,3460	6,4027	12,0723	19,4526	28,1036	38,9541
damage 3	0,1955	2,3460	6,3539	11,9257	18,9150	27,3216	38,3675
damage 4	0,1466	2,3460	6,3050	11,7791	18,4262	26,7840	38,0254
damage 5	0,1466	2,3460	6,3050	11,5836	17,9863	26,3441	37,7322

Figure 4 presents the inertance response curves obtained for wind turbine tower for health and damage states defined in Tab. 3 and 4.

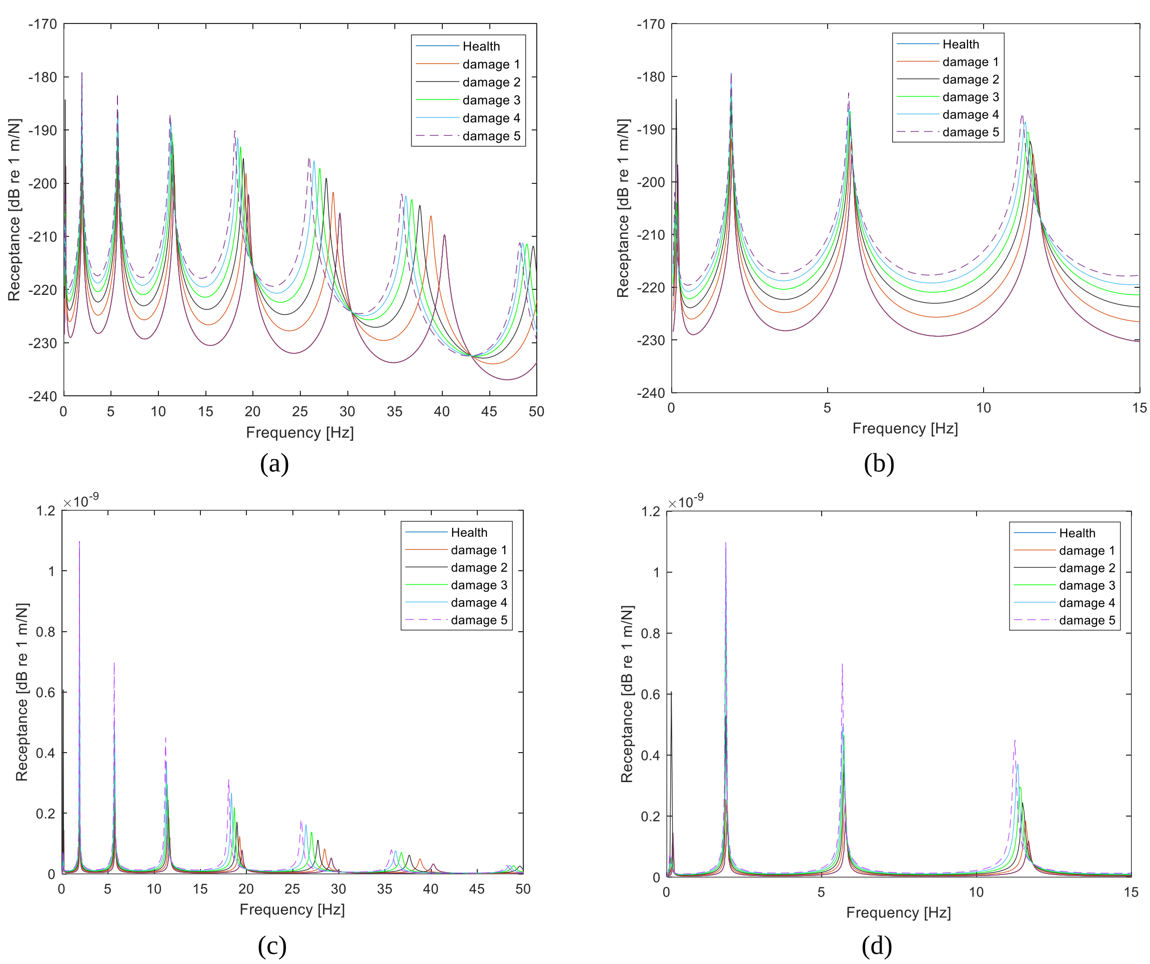
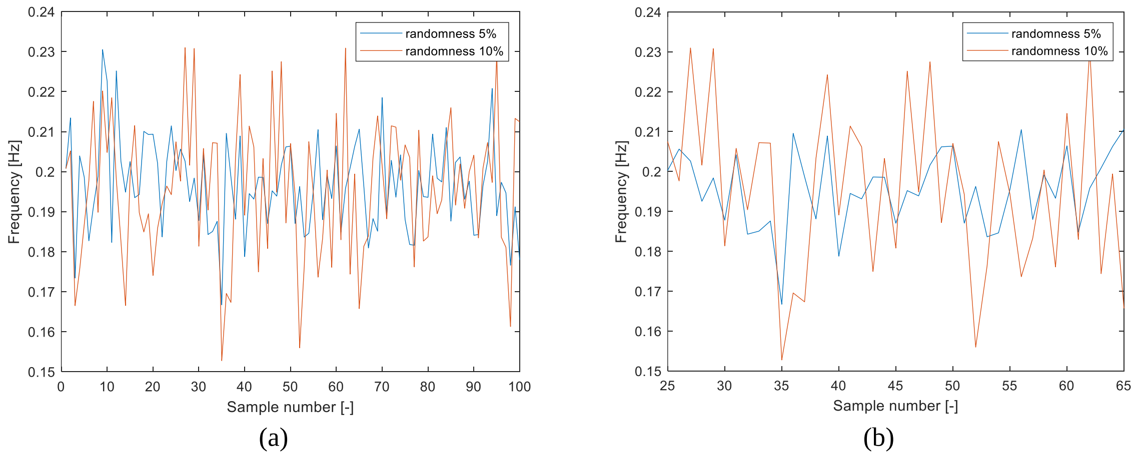
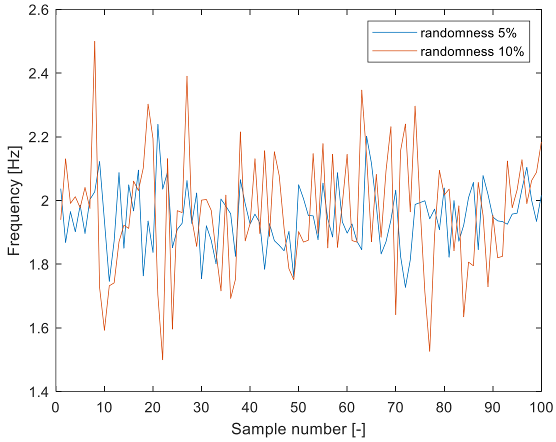


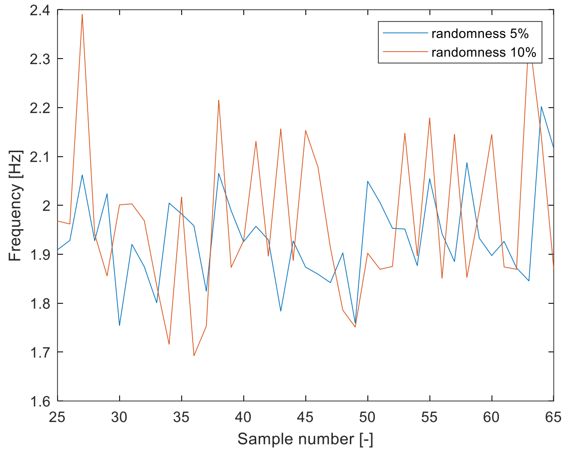
Figure 4. Inertance response for offshore wind turbine tower, (a) full range of analysed frequency, log scale, (b) zoom for frequency range <0,15> Hz, log scale, (c) full range of analysed frequency, nonlog scale, (d) zoom for frequency range <0,15> Hz, nonlog scale

For the average resonant frequencies, a distribution of 100 frequencies were determined for the first four resonance frequency as a random number from the normal distribution with randomness of 5 % and 10 %. The distribution curves are presented in Fig. 5

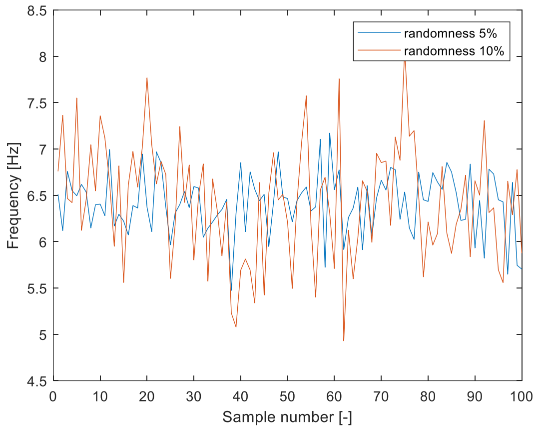




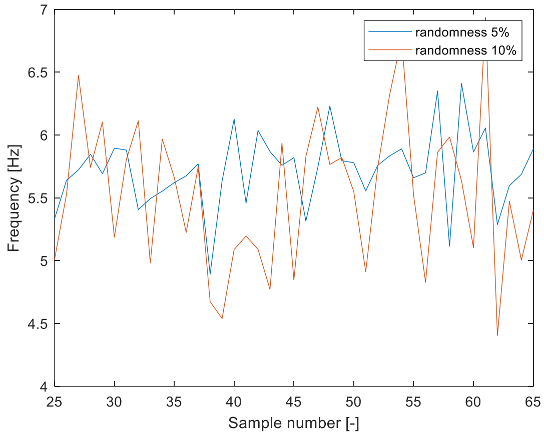
(c)



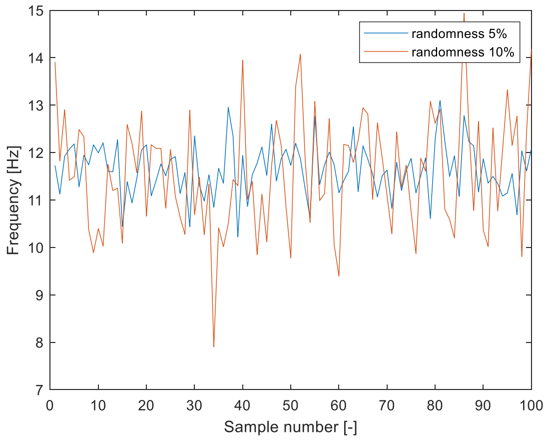
(d)



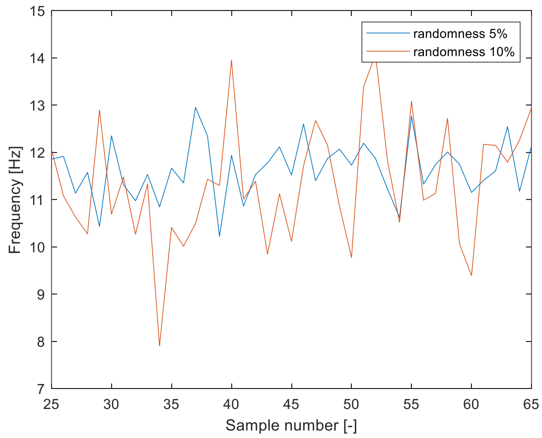
(e)



(f)



(g)



(h)

Figure 5. Samples generated with 5%, 10% randomness of frequencies for first four resonance frequencies, for ML training; (a), (c), (e), (g) full range samples; (b), (d), (f), (h) zoom of analysed samples

For each frequency the damage index (DI) was calculated with the reference to mean value of the natural frequency. The tower was qualified based on DI as damage beam if DI ≤ 0.99, otherwise the beam was qualified as health. Then, the Support Vector Machine (SVM) algorithm was used to train the system to qualify the beam as damage or health. 80% of data was used for training and 20% for testing.

Samples generated with 5% randomness of frequencies [0.1955; 1.9550; 5.7674; 11.6813] Hz for ML training are presented in Fig. 6.

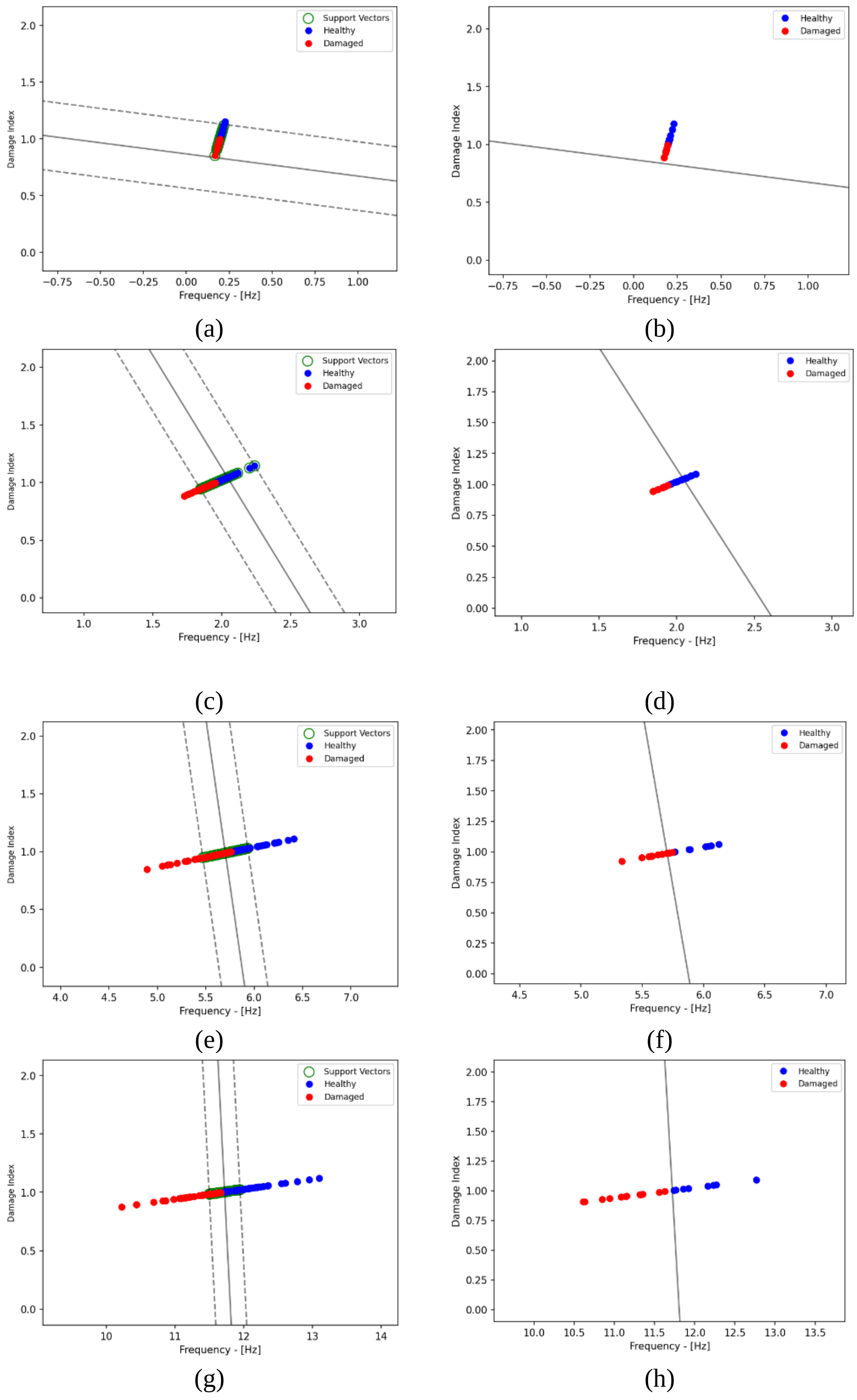


Figure 6. ML for 5 % randomness samples; (a), (c), (e), (g) training; (b), (d), (f), (h) testing

For damage and health state the accuracy of training algorithm, 5 % randomness (Fig.6.), 100 samples, frequencies [0.1955;1.9550;5.7674;11.6813] Hz, is [65, 65, 80, 100] % respectively, for 10 % randomness is [95, 100, 100, 100] %.

4 Conclusions

The subject of the analysis was the use of SEM and ML in damage prediction for offshore wind turbine tower IEA 15MW. The FRF analysis showed how damage affect the shift of resonance frequency. The obtained results confirm the effectiveness of SEM and FRF in damage detection.
The ML technique was used to classify the tower element. Structural elements were described by a number of parameters. Based on the data obtained from the simulation, the elements were classified depending on the resonance frequency depending on the level of the damage. The learning process was carried out using the SVM algorithm for randomly generated data with a distribution of 5% and 10%. The obtained classification results confirm the efficiency of the learning process.

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Authorship statement. The authors hereby confirm that they are the sole liable persons responsible for the authorship of this work, and that all material that has been herein included as part of the present paper is the property of the authors.

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