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Research article

A novel method for the natural frequency estimation of the jet engine turbine blades based on its dimensions

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ABSTRACT

This study provides a novel methodology for the natural frequency estimation of the jet engine turbine blade by using the dimension check. This paper presents a summarization of the ongoing research devoted to the method for the turbine blade natural frequency estimation. The main target of the research presented in the paper is to develop a novel method that can calculate the natural frequency of a particular turbine blade by using the dimensions of investigated turbine blade from a dimension check. This goal is achieved by the combination and interaction of several methods as for instance computed aided design (CAD) finite element modelling (FEM), artificial neural network (ANN) and others. As it is mentioned in the following chapters of the article a unique novel method is developed that can predict natural frequency according to the dimensions. The results confirmed the correctness of the new methodology, which can predict natural frequency by the dimensions of a turbine blade immediately with a relatively high level of accuracy (maximal errors are under 1.5%). Every jet engine manufacturer (GE aviation, Rolls Royce, Prat and Whitney, etc.) has to test jet engine parts for the natural frequencies in order to avoid the resonance at early stage of the manufacturing process in order to mount the blades into the engine. The experimental tests of every single turbine blade are time-consuming, a novel method can predict natural frequency according to the dimensions by using data from dimension check in 0.0051 s. The presented method is under patent pending.

1. Introduction

Today, jet engines are most often used as a power unit for aircraft and are ensuring movement on the ground but mainly after take-off in the air. The thrust has to be changed spontaneously according to the demands of the aircraft operation regimes, which means a jet engine is exposed to the unfavourable conditions. Due to the operation conditions and high loads, the stress and life of the jet engine parts are strictly limited. A large number of various methods and research have already been carried out in order to predict different stress and life parameters of the particular jet engine parts. There are conventional methods available for stress and life of jet engine parts predictions in terms of numerical and experimental methods. However, the current trend is to create new and faster methods, that can predict different mechanical parameters of the engineering parts. The aviation industry is no exception, there are several publications that deal with new methods for determining stress and life characteristics. New methods are using the cooperation of artificial intelligence and classic engineering methods for creating novel predictive techniques. The proposed article is devoted mainly to the aviation industry, therefore following already existing techniques that are dedicated to the jet engine parts. The most limiting part of

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the jet engine is the turbine section, thus the trend is to create novel methods for design, stress and life prediction, for instance, the creep reliability of turbine blade tip clearance using novel neural network regression is presented in Ref. [1]. The neural network regression with distributed collaborative strategy is applied to multi-failure probabilistic design for turbine bladed disks [2], the stator vane settings of multi-stage compressors is numerically optimized by neural network and genetic algorithms, this study is described in Ref. [3]. The fatigue life assessment for turbine blades using novel methods is also mentioned in Ref. [4], but also the variety of physical issues of jet engine engineering related to the flow analyses are solved by novel methods. CFD problems such as active boundary layer control, numerical investigation of flow control effects of dynamic hump for turbine cascade, the effect of tip gap variation on transonic turbine blade tip leakage flow and many others are solved using artificial neural networks (ANN) described in articles [5–7]. The fact that ANN's are used for various mechanical parameters has been obviously proved, also the FEM and CFD modelling are useful tools when it comes to jet engine engineering. The proper combination of mentioned methods could lead to the creation of a new method for natural frequency prediction.

The stress and life of the turbine section are significantly affected by high loads and the natural frequencies of the particular parts are highly important. Jet engine producers test the mechanical properties and the natural frequencies during engine manufacturing. Once the turbine blade is manufactured it is experimentally tested for the natural frequency, whether it reaches the standards for safe operation. There are conventional methods for natural frequency estimation, for example, the modal analyses performed by FEM, experimental analyses, and others. However, mentioned analyses have significant requirements on time [8], one of the approaches is acoustic natural frequency identification. The acoustic method has some advantages, one of which is the price of the essential equipment. There are several studies that are describing this method [9]. The mentioned method requires a significant amount of time for a large number of samples [10]. Another approach is modal analysis with mechanical excitation and strain gauge [11], difference from the previous method is only in the sensor where mentioned strain gauge instead of acoustic sensor is used [12,13]. In the article, Natural Vibration Frequency Definition of Turbine Blades, the principle of modal analysis is nicely described [14]. There are also other experimental methods for natural frequency estimation, an example is Estimation of Turbine Blade Natural Frequencies from Casing Pressure and Vibration Measurements where the authors described experimental frequency identification by using the casing pressure [15]. There can be found a large number of different methods for natural frequency estimation that are meant for various purposes [16–18]. There are many methods that are used for natural frequency estimation, however, each of them requires a huge amount of time in terms of the testing set up, etc. During the development of a new engine and turbine blades the required time for FEM modelling and experimental testing is acceptable, however after development, during production, the situation is more complicated [19,20]. As jet engines are improving their performance characteristics with higher temperatures, forces, and needs for testing (frequencies) more failure can occur. Therefore big engine manufacturers such as Rolls Royce, GE Aviation, etc. have included in their manufacturing process an experimental test for the turbine blade natural frequency estimation [21,22]. When the experimental test is performed for the single disassembled blade for the manufacturing process, as already mentioned each blade has to be attached into the clamp, excited by a hammer and the frequency is measured using a sensor, the final step of the process is the result evaluation. The mentioned process requires a few minutes and an operator. FEM analysis is not applicable because each blade would have to be measured, specially modelled using modal analysis which would require at least a few hours to carry out the pre-processing, solving, and post-processing parts. For the thousands of blades, FEM modelling would mean ages of the time. As it was mentioned nowadays there is no method, that would estimate natural frequency in a short amount of time during serial production at the manufacturing process. The goal of the proposed article is to develop a new method for natural frequency estimation. The target should be reached by using special modern tools such as artificial neural networks and FEM modelling and its combination in order to create a novel method for natural frequency assessment. FEM modelling is used in order to create inputs for ANN in the training process. The goal is to describe the relationship between the turbine blade dimensions, which are described by FEM model nodes, and natural frequencies calculated by FEM. There are many mathematical techniques to describe this relationship, nevertheless, according to the inputs character, the ANN is the most effective and suited method. In order to solve the correlation between the turbine blade dimensions and natural frequencies regression ANN is developed as a feed-forward back propagation type. The ANN uses deviations of coordinates from nodes of FEM models, which are equivalent to dimensions from dimension check and natural frequencies, thus ANN describes a relation between dimensions (coordinates) and natural frequencies during the development. In the application stage ANN predicts natural frequencies based on dimensions from the dimension check. A completely new approach based on the blade dimension is used for the creation of a novel method which is described in the following chapters. ANN and FEM modelling have been until now used for a wide range of engineering problems in aviation such as for blade tip clearance control [23] and also in relation to frequency ANN was used for mass detection [24]. Another combination of CFD and ANN is described in Ref. [25] in terms of temperature field perdition, the publication presents also other problems that are solved by combining various numerical methods, but until nowadays such a combination has never been used for natural frequency estimation.

The presented method is intended for the manufacturing process of gas turbine blades. During the production process, the blades are subjected to dimensional control and subsequently to an experimental test of their natural frequencies. The trained ANN uses the dimensions from the dimensional control to determine the natural frequencies. Thanks to the ANN, which calculates the natural frequencies using the dimensions of the blade, no more natural frequency tests are needed. One ANN completely replaces experimental tests of the natural frequencies. The feed forward ANN is used for this surrogate model since it is the most commonly used type for the regression and classification problems in engineering [26,27]. In Ref. [28] similar approach is chosen with FEM modelling in ANSYS and a surrogate model represented by ANN in Matlab software, where the authors chose two hidden layers. There are many other applications with similar ANN architecture for mechanical properties prediction [29–32].

2. Methodology and partial results

As it was already mentioned, the method is based on a completely novel method in terms of dimensional prediction of a natural frequency. There is not a notice in the scientific papers about such a method.

2.1. An object of the experiment

The iSTC-21v (showed in Fig. 1) [33] jet engine is an object to which the method is applied to. It is a single shaft jet engine with one impeller, and combined combustion chamber. The methodology is applied, tested and investigated on the single part of the engine, which is a turbine blade.

The particular part the method is applied to is shown in Fig. 2, it is a turbine blade, that is not cooled. The turbine blade of iSTC-21v is a part of a single turbine, which consists of one turbine disc with 27 turbine blades attached by fir tree base and safety locks.

2.2. A novel method for the frequency estimation – methodology

Companies that are producing jet engines as Rolls Royce, GE Aviation, Pratt & Whitney, etc. have to test natural frequency of jet engine parts in order to avoid resonance and destruction of the whole engine. The natural frequency test is one part of the manufacturing process as well as for example machining, dimension check, etc. Companies are mainly testing the natural frequency of the turbine blades during the engine production, it means that every single blade has to be tested by the conventional methods, however these methods are time consuming and also expensive. Firstly, Campbell diagram for a particular part has to be created and the range of resonance frequencies have to be estimated. For example, for the first mode frequency range can be from 7100 Hz to 7500 Hz variously on the different factors. One of the main factors is turbine blade dimensions therefore the new method is based on the object dimensions. The whole method consists of the two parts. The first one is devoted to the training part or called as training life and the second part of the methodology is just simple called "life" and it is presented in Fig. 3, the particularised description is in the following chapters.

According to Fig. 3 there are several principles used that are a crucial part of the method. In the first phase CAD modelling, FEM modelling, and ANN are used. Eventually, the method should predict the natural frequency in accordance with the object, in this case, turbine blade dimensions nevertheless the various dimensions (within the tolerance limit ± 0.05 mm) have a main impact on the turbine blade's natural frequency. As it was already mentioned every single blade has to pass a dimension check during the manufacturing process so there is evident information about the dimensions (which is used for the second part – life phase). The turbine blade 3D CAD model is created based on a real geometry (First part of Fig. 3.) subsequently by using the 3D model, the specific novel FEM model with variable geometry (morphing blade) of blade is created, morphing process is described in the theoretical framework. The FEM mesh of turbine blade can be seen in Fig. 4. The mesh nodes are offset within the tolerance ±0.05 mm. Morphing technology in programmed script allows to offset FEM nodes of blade in x_i, y_i coordinates. It means by offset combinations of 48 turbine blade geometries are morphed by all FEM nodes at the blade within the tolerance and the modal analysis for each blade geometry is performed in ANSYS software. The first three modes are calculated by FEM for every blade geometry, so total of 144 natural frequencies correspond to 48 morphed blades. Data obtained from analyses are used for the training ANN (still first part of the methodology). In the second part during the method life the ANN input will be instead of FEM nodes dimensions used dimensions from dimension check from the manufacturing process, the training principle and life principle is described in the following chapter also partial results are mentioned.

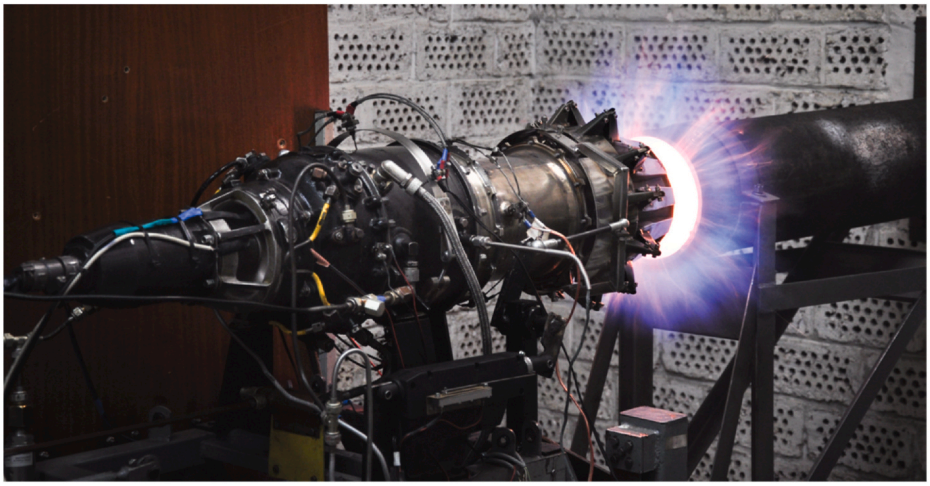

Fig. 1. iSTC-21v experimental jet engine in the laboratory [33].

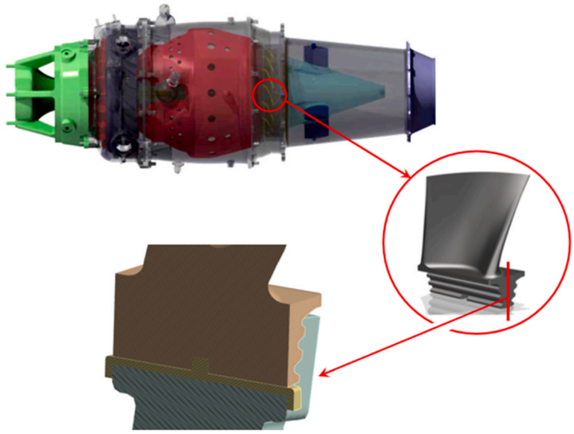

Fig. 2. Object of the interest – turbine blade of iSTC-21v jet engine.

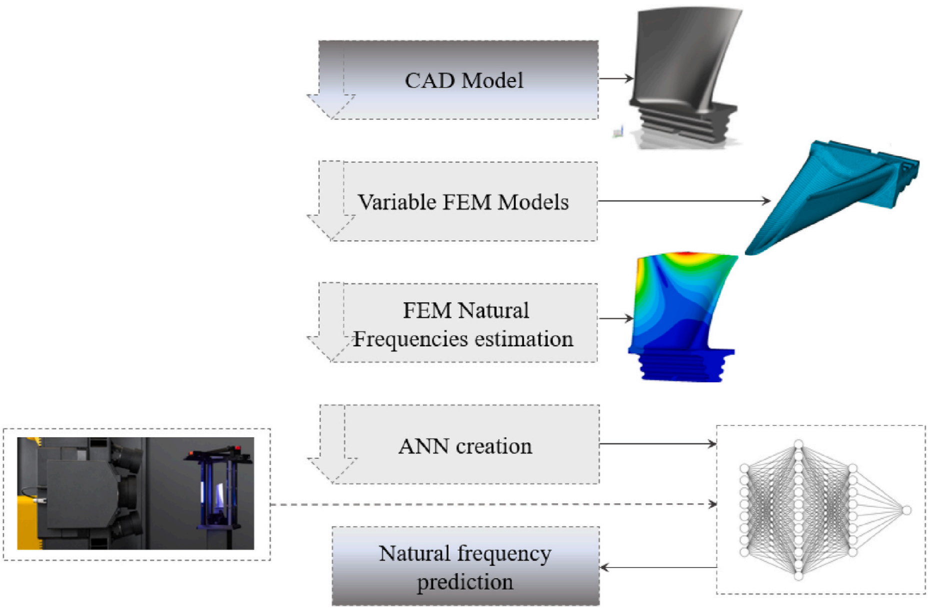

Fig. 3. The principle of the novel method.

2.3. A novel method for the natural frequency estimation – theoretical framework

According to the 3D model of the turbine blade the FEM model is created in the study. The FEM model has nominal shape with nominal dimensions. In order to create FEM models with dimension deviations that represent real turbine blades with dimensions deviations the morphing technique has been used.

The morphing technique is already known method for change geometry without remeshing the model. Initial blade has nodes that are moved using morphing method into offset position (Fig. 4.) defined by its coordinates. Radial Basis Functions (RBF) interpolate distance basis, scalar information known only at discrete points [34]. The interpolation function is composed of the basis φ and by the polynomial term h with degree that depends on the kind of the chosen basis. N is total number of nodes and thus the interpolation function is as follows:

$$s(x) = \sum_{i=1}^{N} \gamma_i \varphi(\|x - x_{s_i}\|) + h(x) \tag{1}$$

where x is a generic position, x_{s_i} is the vector of source points positions, φ is the selected interpolating radial function, γ_i is a vector of unknown coefficients and h stands for a correction polynomial [34]. An interpolation exists of coefficients and wights of the polynomial can be found such that the given value at source points can be retrieved exactly. At source points the polynomial contribution

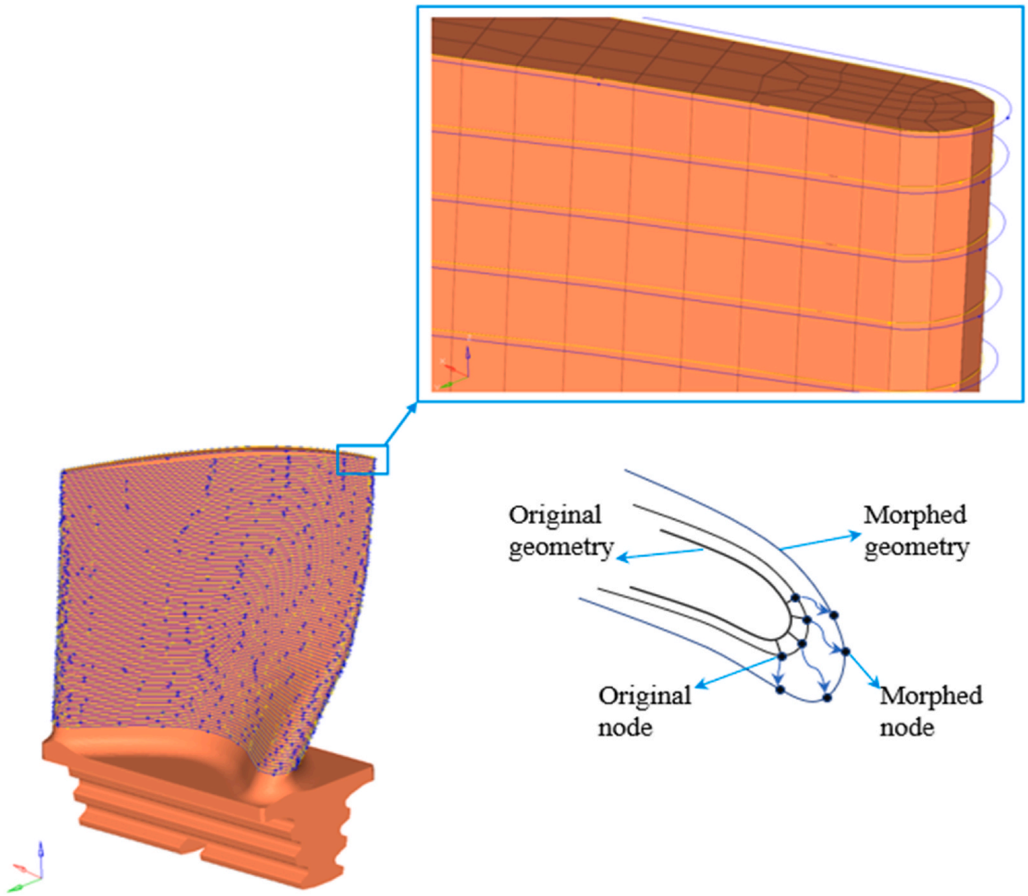

Fig. 4. The principle of the morphing technique for obtaining various geometries.

should be zero. It is:

$$s(x_{s_i}) = g_i, 1 \le i \le N \quad \text{and} \quad \sum_{i=1}^{N} \gamma_i p(x_{s_i}) = 0 \tag{2}$$

For all the polynomials p of degree less or equal to polynomial h. A single interpolant exists if the basis is conditionally positive definite. If the degree is $m \le 2$ a linear polynomial can be used:

$$h(x) = \beta_0 + \beta_1 x + \beta_2 y + \beta_3 z \tag{3}$$

The linear problem can be also written in matrix form:

$$\begin{bmatrix} M & P \\ P^T & 0 \end{bmatrix} \begin{Bmatrix} \gamma \\ \beta \end{Bmatrix} = \begin{Bmatrix} g \\ 0 \end{Bmatrix} \tag{4}$$

where g are the known values of the interpolating function at the source points (nodes) and β are the coefficients of the polynomial h. M is the interpolation matrix defined by calculating all the radial interactions between the source points. The new nodal positions, if interpolating the displacements, can be retrieved for each node as:

$$x_{node\ new} = x_{node} \begin{bmatrix} s_x(x_{node}) \\ s_y(x_{node}) \\ s_z(x_{node}) \end{bmatrix} \tag{5}$$

Being the problem solved pointwise, the approach is meshless and able to manage every kind of element (tetrahedral, hexahedral, polyhedral and others), both for surface and volume mesh smoothing ensuring the preservation of their topology [34,35]. The quality of mesh is ensured by morphing always original nodes in terms of moving all nodes inward or outward. In order to summarize the morphing application, Fig. 4 is taken into an account, where the offset lines are shown in detail. The nodes are morphed into the blue lines, which are offset within the tolerance.

Using morphing method (Fig. 4) 48 geometries represented by FEM models are created and in ANSYS the natural frequencies using modal analyses are calculated. These numbers (differences in coordinates for each geometry and natural frequencies) are used for ANN training process.

The ANN is feed-forward back propagation type, and an activation function used for each layer is symmetrical sigmoid (6).

$$S(x) = 2s(x) - 1 = \frac{1 - e^{-x}}{1 + e^{-x}} \tag{6}$$

As the training algorithm, scaled conjugate gradient (SCG) for the supervised learning is used. The SCG updates weight and bias values according to the scaled conjugate gradient method [35,36]. The SCG can train any ANN if its weight, net-input, and transfer functions have derivative functions. In order to calculate derivatives of the performance with respect to the weight and bias variables, backpropagation was used [37–39].

2.4. The methodology application – steps and partial results

In order to obtain inputs for the ANN the FEM analyses are performed in ANSYS software. The variable model has been created by the morphing modelling, subsequently FEM modal analysis is used in order to calculate natural frequencies for various geometries (48 blade geometries). Three of the 48 geometries are shown in the following pictures to present the results from FEM analyses that are used as an input for ANN. For each of 48 geometries the natural frequencies of the first three modes are calculated (Fig. 5) so eventually 144 frequencies are used as ANN input. For instance, in Fig. 5 one geometry is presented, in Fig. 5a the FEM model is shown with 368 961 elements. In Fig. 5a the offset of first four element rows can be seen. The first mode in Fig. 5b has the natural frequency 7328 Hz, the second mode in Fig. 5c has frequency 13 007 Hz, and the third mode in Fig. 5d has frequency value 18 684 Hz. The solution time for one geometry is 495.85 s.

Another first three modes calculated for second geometry with 8 offset mesh rows is shown in Fig. 6. The first natural frequency has a value 7401.21 Hz, and the mode shape can be seen in Fig. 6b. The second mode shape is in Fig. 6c and has a natural frequency 13133.9 Hz and eventually the third shape is shown in Fig. 6d with natural frequency 18760 Hz.

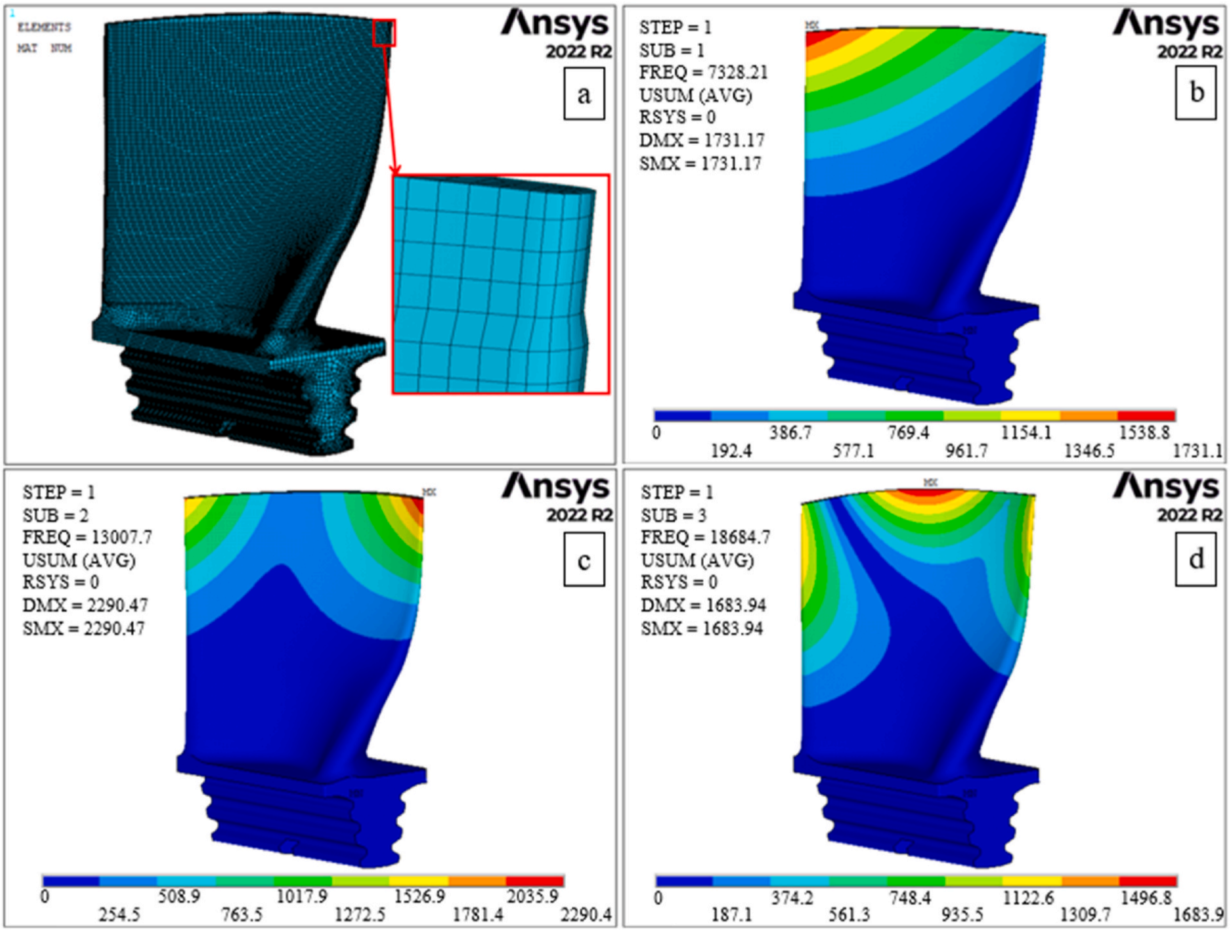

Fig. 5. Data calculated in ANSYS APDL a, iSTC-21v turbine blade mesh b, first calculated mode c, second calculated mode d, third calculated mode.

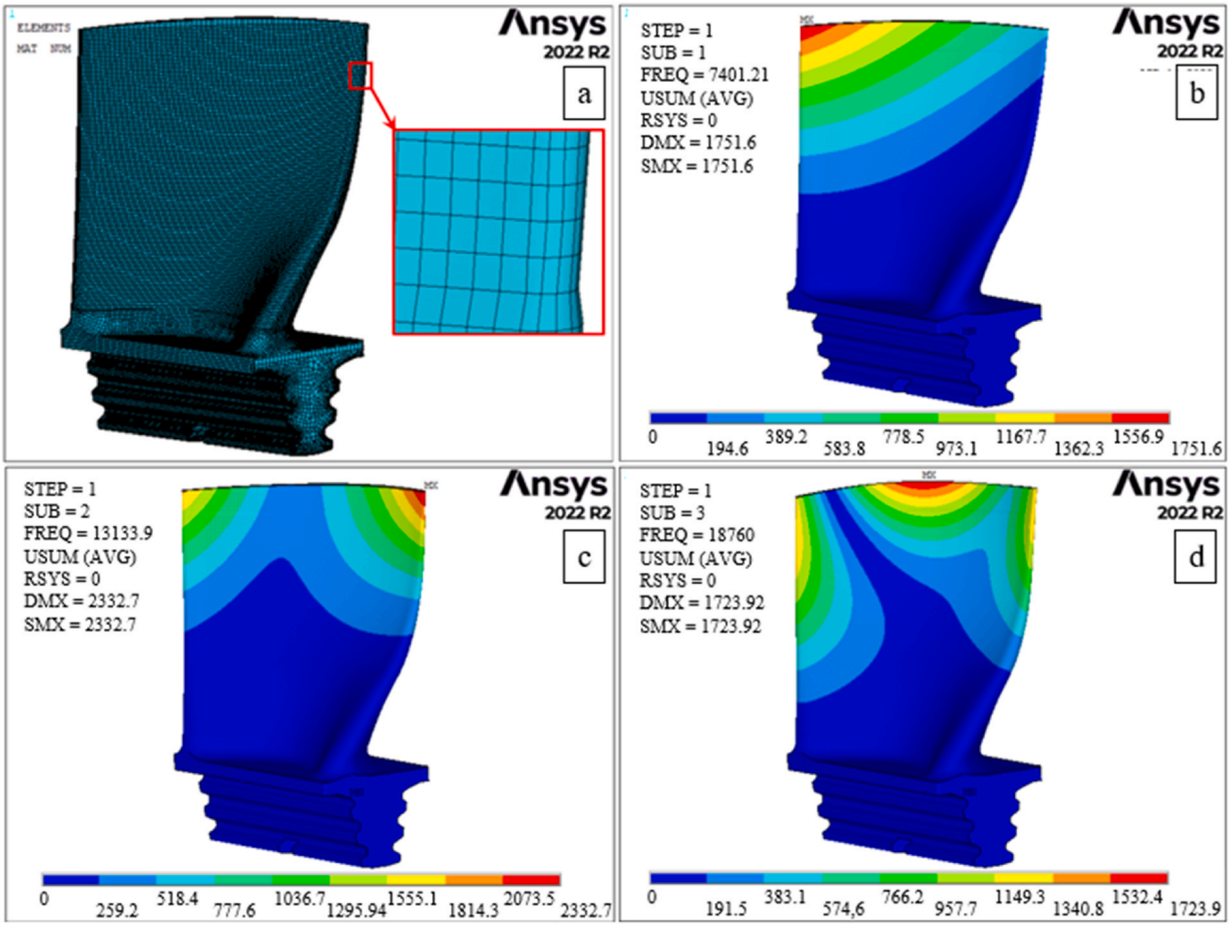

Fig. 6. Data calculated in ANSYS APDL a, iSTC-21v turbine blade mesh b, first calculated mode c, second calculated mode d, third calculated mode.

The third geometry of the turbine blade has 12 offset mesh rows and is shown in Fig. 7a, first mode shape with natural frequency 7488.5 Hz is in Fig. 7b. Fig. 7c represents second mode shape of the turbine blade iSTC-21v with the natural frequency of 13255.8 Hz. The third natural frequency has a value 18739.7 Hz and mode shape is shown in Fig. 7d.

The assumed frequencies for all 48 morphed geometries in ANSYS APDL are postprocessed in Matlab software and plotted in Fig. 8, where dispersion depending on frequencies can be seen. Fig. 8 is also pointing out on the fact that the natural frequency is dependent on the investigated object dimensions, this is proved using combination of CAD and FEM modelling subsequently according to the methodology an ANN is used in order to predict blade natural frequency based on the dimensions.

The natural frequencies for all three modes and for the 48 geometries are summarized in Fig. 8, where the range for each mode can be seen by red lines. For each blade the frequency range is calculated, the frequency that would exceed the range would lead the blade to the resonance (according to Campbell diagram). The calculated frequencies and x_i, y_i node coordinates differences are used as an input for ANN, thus the novel method.

In Table 1 the data used as the inputs for the ANN are summarized, it is the numerical representation of Fig. 8. The inputs can be divided into two groups, first group consists of the data from FEM model, thus they are the coordinates x_n and y_n of the turbine blade geometries g_n. The coordinates are gained in this phase from FEM model, and they are simply the coordinates of the turbine blade mesh nodes. The difference in coordinates have different values, but all are within the manufacturing tolerance limit ± 0.05 mm. The morphing of the x_n and y_n together for each blade is approximately ± 0.05 mm in the normal direction. The coordinates from the nodes can be replaced by the coordinates from the measuring check during the production of the blade. The results from the measuring check are the same numbers as the node coordinates so the results when the method will be applied in the practical use will be with the same accuracy as in the presented research.

The second part of the inputs comprise the natural frequencies of the turbine blade stated as NF_1, NF_2, NF_3 (Table 1). The natural frequencies are calculated for the 48 geometries (g_n). The variation or the dependency of the dimensions and natural frequencies can be observed from Table 1. The relationship between the frequencies and dimensions of the turbine blade is mathematically described by ANN, so the numbers from Table 1 are used as a training data for ANN (Fig. 9). The geometries g_n are morphed as in Figs. 5a, 6a and 7a, so the g_1 has morphed first four rows of mesh, g_2 eight rows, g_3 has twelve etc., and g_{48} has all rows morphed, the plus means the

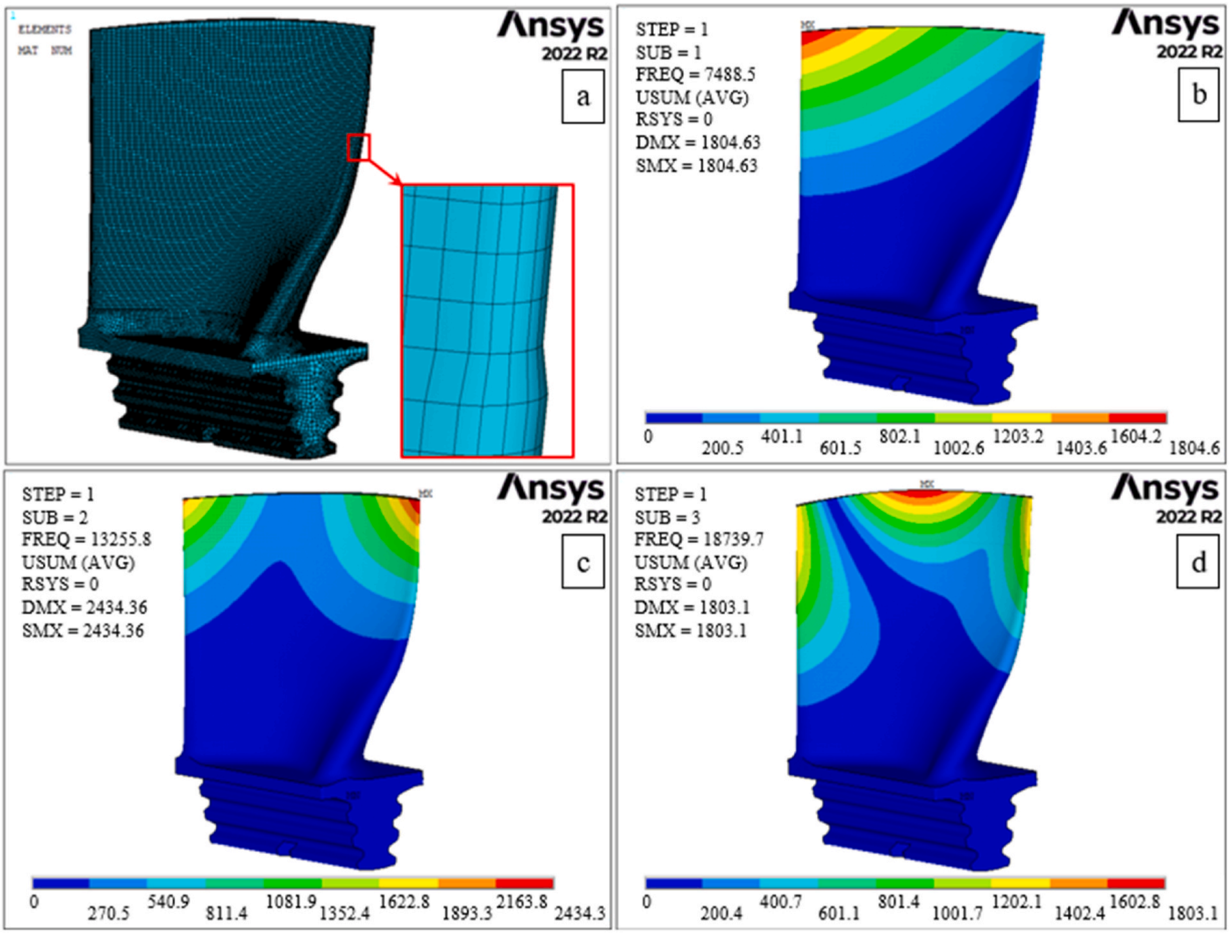

Fig. 7. Data calculated in ANSYS APDL a, iSTC-21v turbine blade mesh b, first calculated mode c, second calculated mode d, third calculated mode.

morphing is performed outside. The minus indicates morphing the mesh rows inwards.

The first step during the training process of ANN is preparing the data, which are in input layer presented by x_i, y_i dimensions (Fig. 9) in [mm] using 78 FEM nodes positions (they also represent measuring points during the manufacturing measuring check). Output Layer consists during the training process of input data which are natural frequencies accordingly to the blade geometry. The principal chart is presented in Fig. 9. It is essential to emphasize that in Fig. 9 is only one iteration of ANN or in better words input of one training geometry from the 48 geometries.

The 48 morphed geometries represent basically 48 datasets, so in Fig. 9 on the FEM model of the turbine blade white dots represents nodes which are defined by difference between standard blade and real offset node. These deviations are measured for x and y co-ordinates in 78 positions (nodes) on the blade surface. It is also represented in Fig. 4 as the position of the original node and morphed node. It means inputs for ANN in input layer consists of 156 x_i, y_i deviations for one blade geometry, once there are 48 geometries, 7488 deviations are used for the training process in input layer, which are normalized by the mapminmax function in Matlab. This processing function is mapping row minimum and maximum values to [−1 1] interval. The output layer for the training process consists of 3 modes of natural frequency for each geometry, thus 144 natural frequencies in the output layer normalized also by mapminmax processing function (Fig. 10).

The ANN shown in Fig. 10 is designed in Matlab software and consists of input layer in which are 156 nodes defined by 78 x_i, y_i coordinate differences from normal state (Table 1), in the output layer is one frequency of the blade. There are four hidden layers, number one consists of 468 neurons, second layer has 374 neurons, third hidden layer has 280 neurons and last one forth has 187 neurons. The processing functions used in each hidden layer are symmetrical sigmoids (as described in the theoretical framework).

3. Results

The following chapters are presenting unique novel results of research in the field of natural frequency estimation. The figures present the results of the innovative method that can predict the natural frequency of the turbine blade according to the dimensions of the blade measured or extracted from the nodes of FEM model.

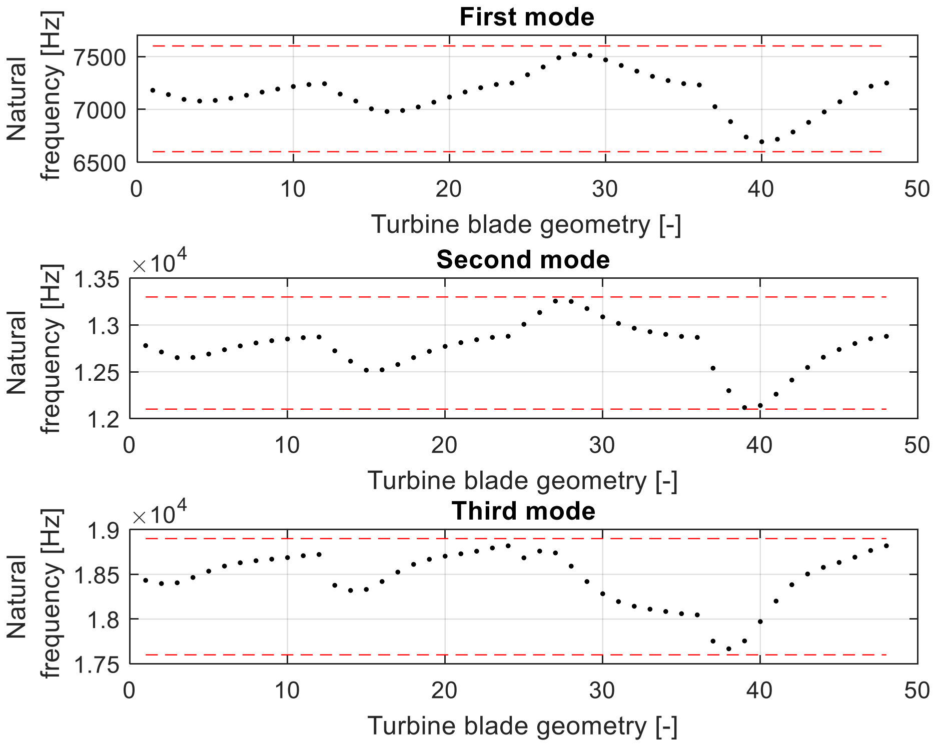

Fig. 8. Calculated frequencies in Ansys APDL plotted in the Matlab software.

Table 1
The coordinates of morphed geometries with frequencies as an example of the inputs for the ANN.

	g_1	g_2	g_{n+1}	…	g_{48}
x_1	−0.039	−0.039	−0.039	…	0.048
y_1	−0.031	−0.031	−0.031	…	0.021
x_{n+1}	−0.040	−0.040	−0.040	…	0.049
y_{n+1}	−0.032	−0.032	−0.032	…	0.016
…	…	…	…	…	…
x_{78}	0	0	0	…	0.049
y_{78}	0	0	0	…	0.017
NF_1	7328.2	7401.2	7488.5	…	7249.7
NF_2	13007.7	13255.7	13133.9	…	12879.9
NF_3	18684.7	18739.7	18760	…	18819.9

Results are divided into the two parts, first figures for each of the three-frequency represent the real natural frequency for specific blade with unique geometry estimated by FEM method and novel method that is using ANN. Results shown for first mode are in Fig. 11, there can be clearly seen the dependency of natural frequency on dimensions of investigated object, in our case turbine blade. In x axis the number of blade geometry is stated. It means there are 48 iSTC-21v turbine blades with slightly different geometries, however within the tolerance limits. In Fig. 11 the natural frequencies estimated by FEM methods are shown with red dotted line and full red dots. Black line with black circles is devoted to the natural frequencies calculated using a novel method (ANN), there can be seen quite accurate match between estimated frequencies by FEM and ANN – presented method. The elapsed time for one blade, three natural frequencies is 0.0051 s.

The high level of accuracy is confirmed also by the following Fig. 12, where the errors are calculated and visualized. There are absolute errors in percentage and also in Hz, in order to better present accuracy. According to Fig. 12 there is highest absolute error peak for blade 44, the values in Hz are under 100 Hz. This can be hight but based on the fact that natural frequencies are around the 7000 Hz maximum error is below the 1.5%.

Errors are calculated according following formulas for quantitative comparison. The mean absolute error (MAE) is calculated based on the predicted frequencies using the equation:

$$MAE = \frac{1}{n} \sum_{n}^{1} \left| \frac{y_i - \widehat{y}_i}{y_i} \right| \tag{7}$$

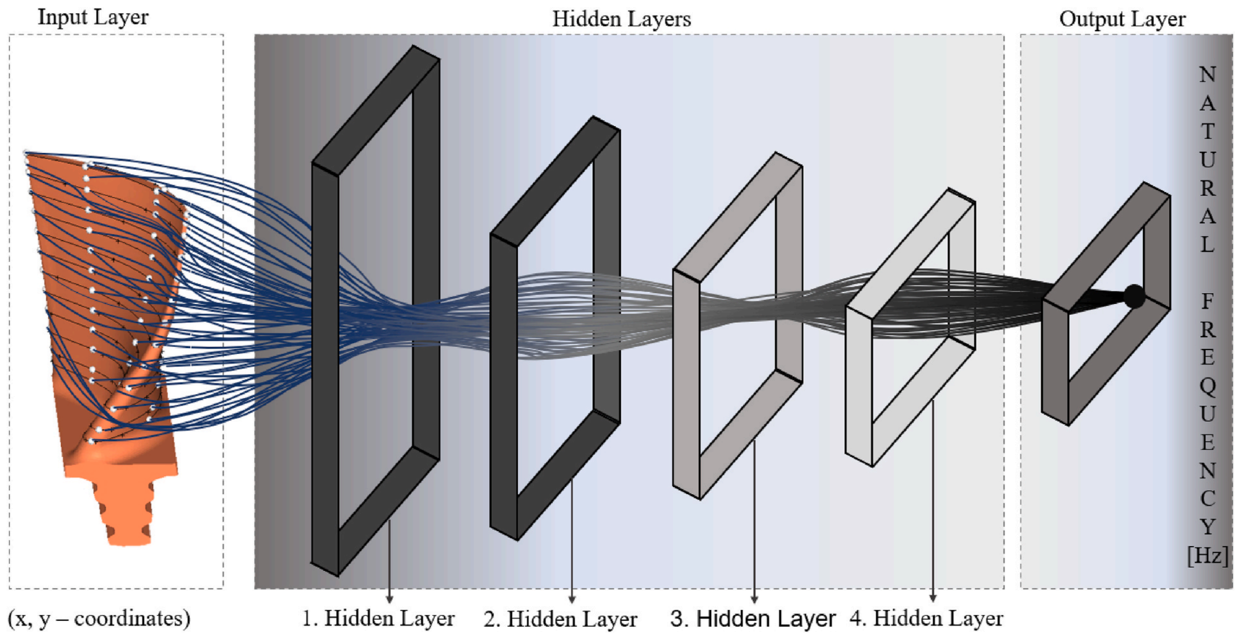

Fig. 9. Graphical architecture of ANN for frequency prediction.

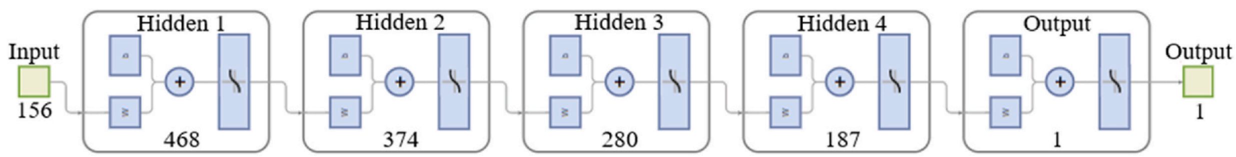

Fig. 10. ANN architecture for prediction the natural frequency of investigated turbine blade.

The mean absolute percentage error (MAPE) is calculated accordingly to the formula:

$$MAPE = \frac{100}{n} \sum_{n}^{1} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{8}$$

The errors calculated errors in Matlab software have MAE value 15.04 Hz, MAPE mean value is 0.21% and the maximal difference between the calculated frequency by the FEM and novel method using ANN is 83.92 Hz which is only 1.2 %.

A regression analysis between the ANN outputs and the targets is carried out. Fig. 13 demonstrates the correlation of predicted natural frequencies by ANN and calculated by the FEM method. The R is also called the regression coefficient, the R equal to 1 responds to perfect linear match. For the first mode is the R value 0.99241, which represents highly accurate match.

Analogically natural frequencies for 48 blades for the second mode were also estimated using FEM and novel method. FEM results for the second mode are presented in Fig. 14 by the red dotted line and black line belongs to the estimated frequencies by novel method. Again, accurate match can be seen at first contact and secondly apart from qualitative indicator, results are quantitative reviewed.

The MAE and MAPE errors have calculated values for the second mode as follows, MAE has for second mode the value 25.82 Hz. The number 0.202% stands for the second mode MAPE and the maximal difference between FEM and a novel method is 133.9 Hz, which is 1.076%. The calculated errors are plotted in Fig. 15, there can be also clearly seen high level of accuracy. For the second mode also the regression plot in Matlab software is created. The correlation between predicted natural frequencies by the ANN and FEM is shown in Fig. 16. The R correlation coefficient is 0.98804, which is also high accurate value.

The third mode of resonance is the last investigated in the presented work, in practice the first two, maximum the first three modes of natural frequency and resonance are usually investigated. The methodology for determining the natural frequencies for the third mode is identical to the previous two, the difference is again only the data on the system response, which represent the natural frequencies for the third mode in the case under investigation. From the graph in Fig. 17, it is possible to observe again a relatively accurate determination of the natural frequencies based on the natural frequencies for the third resonance mode.

The maximum difference in determining the third natural frequency is for geometry 45, while the largest error is 127.02 Hz. The percentage maximum difference for the 45th geometry is 0.6857 Hz. The width of the frequency range for the third mode is 1152 Hz, the natural frequencies range from 17 666.7 Hz to 18 119.4 Hz. Considering the width of the frequency range, it is possible to state a

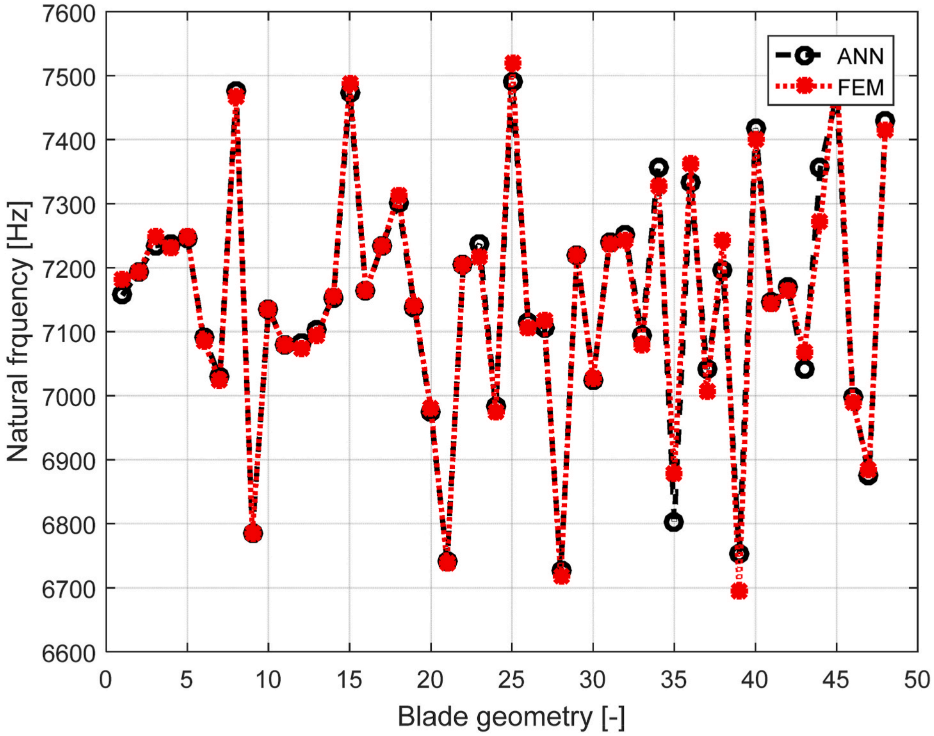

Fig. 11. Calculated iSTC-21v jet engine turbine blade natural frequencies using FEM method and novel method for the first mode.

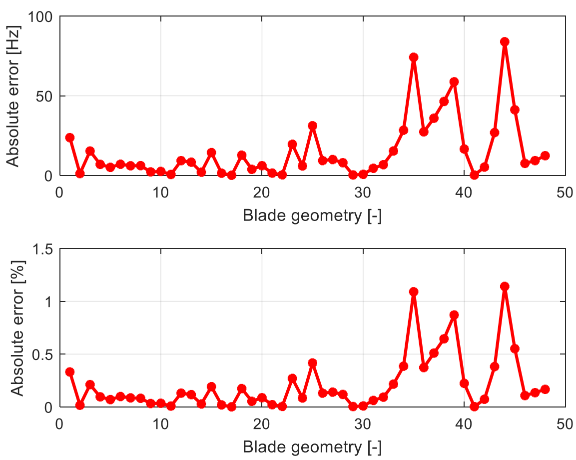

Fig. 12. Estimated errors for the first modes in Hz and percentage.

relatively high accuracy of determining the natural frequencies for the third mode.

An overview of concrete errors of the neural network model for the third form of oscillation is presented in the following part of research, the mean value of the absolute error reaches a value of 27.34 Hz, the mean percentage value of the absolute error is 0.145 Hz. The development of the absolute error of the calculated natural frequencies of individual blade geometries is shown in Fig. 18. From Fig. 18 the high accuracy of predicting natural frequencies using an artificial neural network is evident, as the absolute percentage error does not exceed the value of 0.8% for any of the calculated frequencies.

The corelation coefficient 0.99095 is devoted to the R value for the third mode, which also stands for high accuracy. This R value shows the correlation between the predicted values and the targets, the regression plot is in Fig. 19.

4. Discussion

We have created a new method for the natural frequency prediction of the turbine blade for the jet engine manufacturing process.

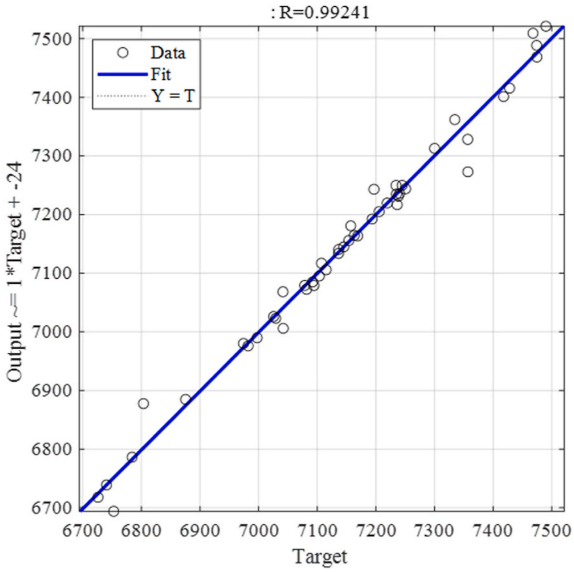

Fig. 13. The regression plot for the first mode.

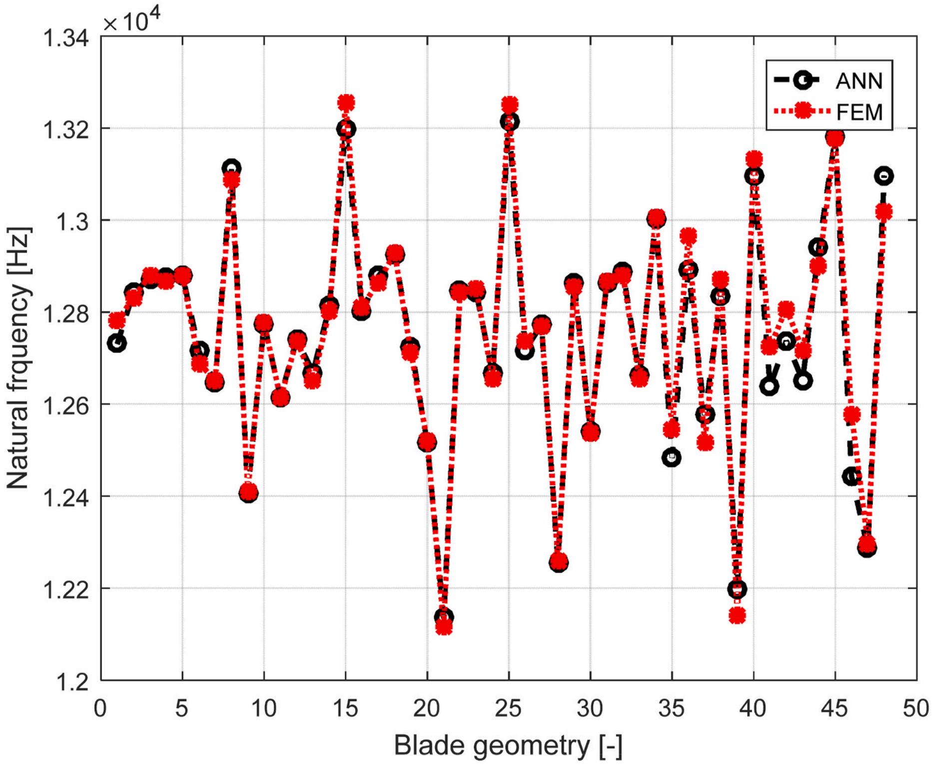

Fig. 14. Calculated natural frequencies using FEM method and novel method for the second mode of iSTC-21v jet engine.

The results confirmed the hypothesis that it is possible to create a novel method for the natural frequency prediction using the dimensions of the investigated object with acceptable error. The ANN surrogates FEM modelling and its results (Figs. 5–7) when at the first stage of the method are used for the training process as shown in Fig. 3 and at the second stage the ANN predicts the natural frequency immediately using the dimensions from the dimension check. The results support the hypothesis and set goal, where in Figs. 11, 14 and 17 the comparison of the calculated results by FEM and by the ANN surrogate model is shown. These figures prove at the first sight high accuracy, which is also supported by the calculated errors between the FEM analyses and ANN method. We also

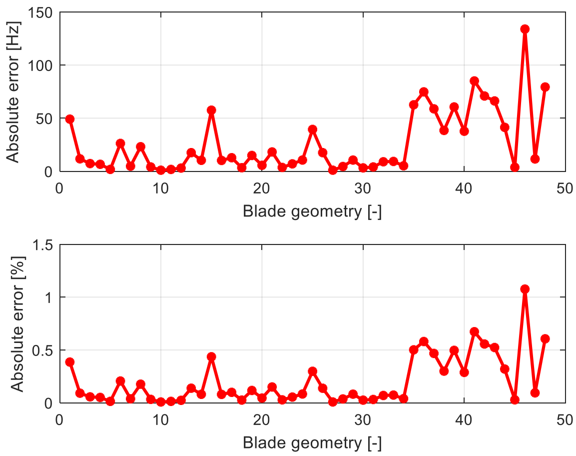

Fig. 15. Estimated errors for the second modes in Hz and percentage.

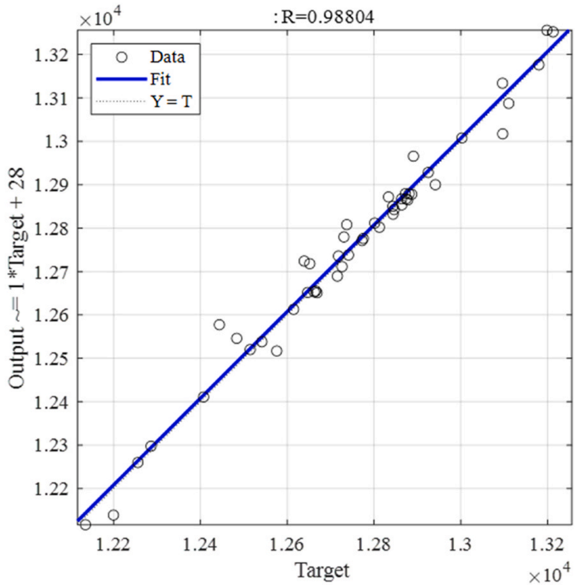

Fig. 16. The regression plot for the second mode.

observed from the regression plots created in Matlab software in that the R value is higher than 0,98 for each natural frequency what indicates high results accuracy. Some higher errors are observed during the investigation as in Fig. 15, where absolute error is above 100 Hz, however apart from this the method can predict natural frequencies relatively accurately. All figures in the results section of the paper proved that the method is suitable as a part of manufacturing process, where the frequencies can be predicted from the available data from the measuring check with sufficient accuracy.

There are many research studies and experimental methods for the natural frequency estimation, for example using two sensors the natural frequency of turbine during the engine operation is estimated in Ref. [40]. The uncertainty reduction used Pan et al. in Ref. [40] to find multimode blade vibration frequencies for the engine, they also performed the experiment of the single disassembled blade, where the special equipment is essential (test ring, etc.). There are many studies for the frequency estimation during the jet engine operation, which predict the frequency quickly and also for the running engine [41–43], however as for disassembled blade during the very early stage of the engine production there are only time-consuming methods that require special equipment [44–46].

The results of our study presented method for the manufacturing process, where the manufactured brand-new blade is still disassembled and measured in measuring machine (part of the manufacturing process). Simply, using these dimensions from the dimension check the natural frequency is estimated by ANN created according to the steps presented in this manuscript (Fig. 20). In our research there is no need of other experimental test for the natural frequency estimation, it is possible to calculate from the measured dimensions, so from the data that are already available from the manufacturing process (dimension check).

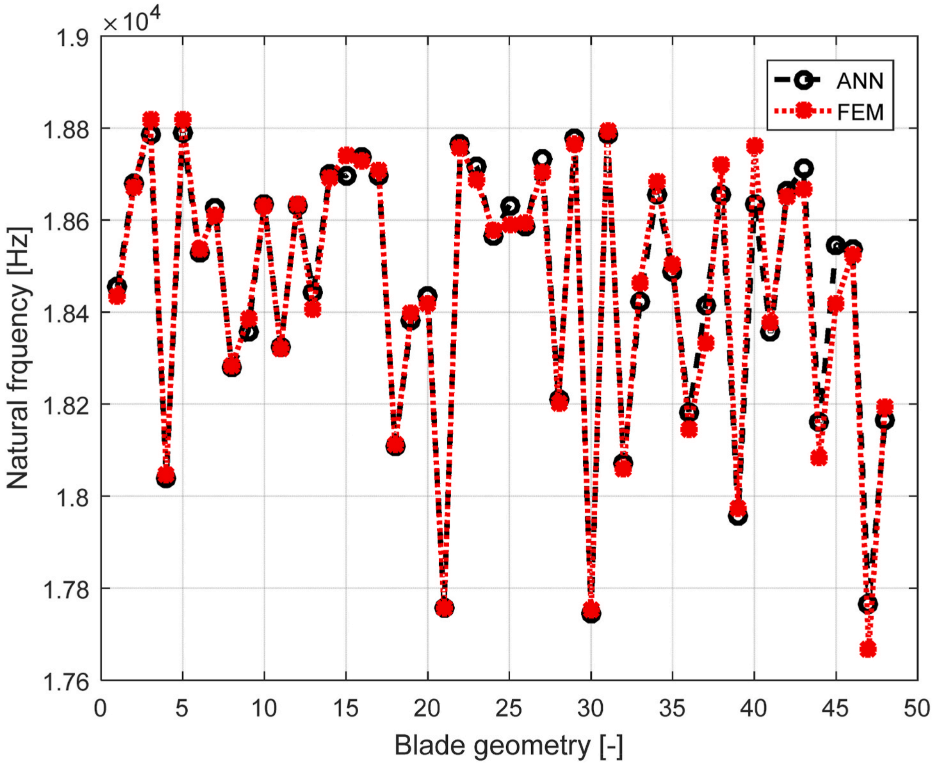

Fig. 17. Calculated natural frequencies using FEM method and novel method for the third mode of iSTC-21v jet engine turbine blade.

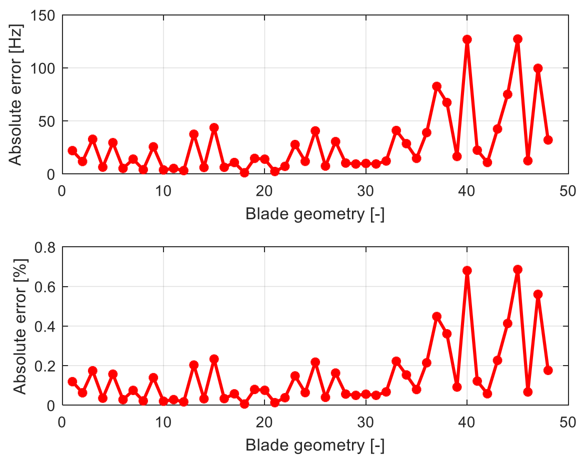

Fig. 18. Estimated errors for the third modes in Hz and percentage.

5. Conclusion

In order to summarize the proposed method, it is essential to emphasize two phases, in the first one ANN is prediction frequencies based on the dimensions from FEM models (x_i, y_i coordinates of finite element nodes), in second phase ANN is taking x_i, y_i dimensions from dimension check (part of manufacturing process) and predicting natural frequency of the turbine blade. Once the method is predicting according to the dimensions from dimensions elapsed time for one blade is 0.0051 s instead of several minutes' experimental tests or several hours of FEM modelling.

As the results already proved it is possible to pronounce several highlights as follows:

1. It is possible to calculate natural frequency based on dimensions from dimension check for all requested modes.
2. The level of accuracy is high enough as the results proved. Maximal error is less than 1.5 % thus 83.92 Hz.

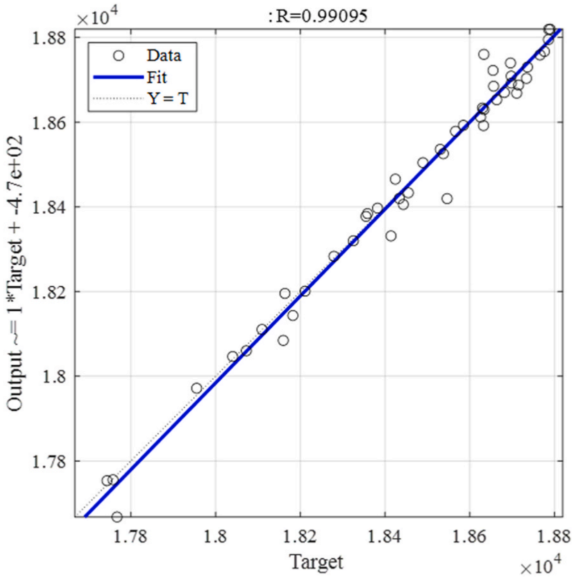

Fig. 19. The regression plot for the third mode.

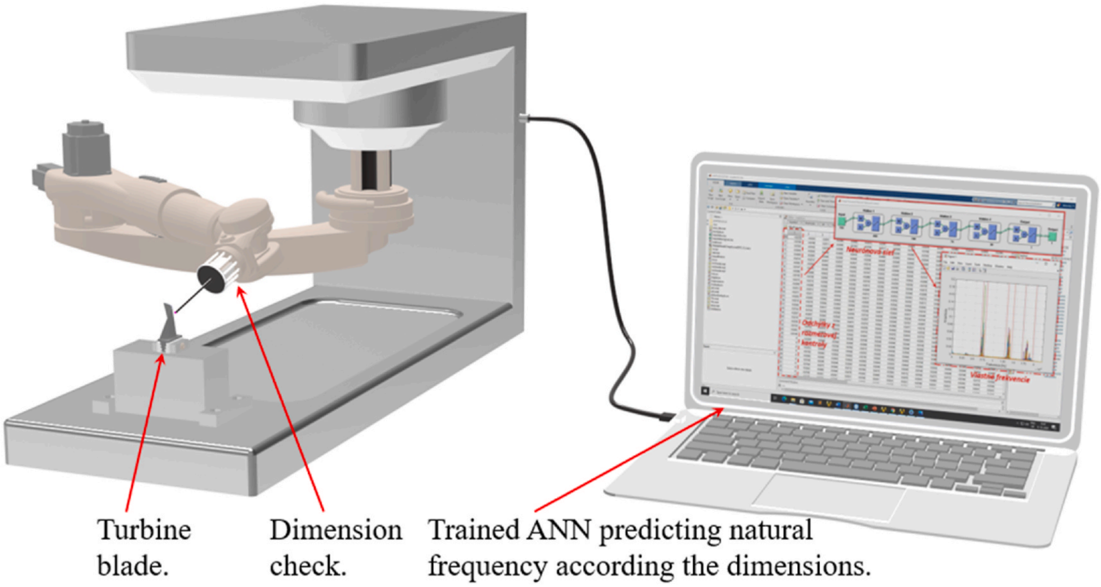

Fig. 20. The dimension check and the application of the novel method for the natural frequency prediction.

3. 78 nodes or measured points while dimension check is enough to estimate natural frequency of the investigated object by a novel proposed method.
4. Elapsed time for natural frequency estimation of one blade is significantly decreased by using novel method. One blade is calculated in 0.0051 s by novel method, FEM solution takes 495.85 s plus several hours of creating new geometry and mesh.
5. There can be other applications of the proposed novel methodology not only in aviation industry but also in other fields of mechanical engineering, where the natural frequencies have important role.

As it was already mentioned the high level of an accuracy is reached, however it can be even enhanced by taking into the account more nodes or measured points and the errors would decrease.

The last fact that needs to be pointed out is that the proposed article is only one part of the ongoing research in the field and the main goal is to present novel method applied on the turbine blade frequency estimation. The novel method is under patent pending, and the paper is also the following on from previous articles, which are supporting the results. The one that is worth mentioning is

Turbine Blade Natural Frequency Estimation Using Various Methods and their Comparisons, which describes the approach in terms of estimation natural turbine blade frequencies of iST-21v jet engine [10]. The article also describes the experimental and numerical results of estimation natural frequency and the turbine blade dimension impact.

Data availability statement

The authors do not have permission to share data.

CRediT authorship contribution statement

Miroslav Spodniak: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Michal Hovanec:** Conceptualization, Formal analysis, Funding acquisition, Project administration, Supervision. **Peter Korba:** Conceptualization, Formal analysis, Funding acquisition, Project administration, Supervision.

Declaration of competing interest

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

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