Apply Pruning Algorithm for Optimizing Feed Forward Neural Networks for Crack Identifications in Francis Turbine Runner

Raza Abdulla Saeed, Loay Edwar George

Abstract— In this study the Feed Forward Artificial Neural Networks (FFANN) for crack identification and estimates the turbine operating conditions in Francis turbine type was investigated. The sets of vibration data were used as vibrational signatures for studied mechanical structure, and they fed to FFANN as input vector for identification purpose. Different arrangements of FFANN were taken into consideration to find out the best topology which can produce identification results with acceptable accuracy levels. In order to examine the performance of the FFANN and obtain the satisfactory arrangements, different numbers of input data sets are tested. The test results showed that the use of very large number of input data will cause a large increase in training time beside to it may lead to unstable FFANN with over-fitting. To avoid these deteriorated results, different data reduction techniques have been proposed for reducing dimensionality of the input data to achieve an acceptable data reduction level.

The conducted results indicated that the FFANN models have been successfully employed for crack identification and estimates the turbine operating conditions using vibration data sets. Moreover the results revealed that the pruning mechanism which is based on the data reduction mechanism can led to satisfactory results.

Index Terms— Crack Identifications, Feed Forward Artificial Neural Networks, Francis Turbines Runner, Pruning Algorithm

I. INTRODUCTION

Damages initiate a breakdown period on the hydropower station; therefore the structures are required to work safely during service life. Damage detection is very important to provide early detection of damage and allow maintenance planning to take place before the catastrophic failure occurs [8]. Recently, there are growing interests for non-destructive techniques allowing the early detection of damages; these techniques are based on vibration analysis.

Significant efforts have been spend for developing different diagnosis approaches for damage identification in structures based on vibration characteristics [3], [13]. Measured amplitude of *FRFs* are often used for damage identification with satisfactory accuracy [2]. For instance, [7] used measured amplitude of *FRFs* data for damage detection in truss structure and a plate structure. A detailed literature review of the various methods for damage detection in different structures was reported by [15]. All these studies indicate that there is a connection between the change in the vibration characteristics of the structure and damage in structure. Therefore, vibration-based methods have been intended for the identification of crack and estimate the structural conditions. Those methods based on comparison of the vibration data with a standard level since the characteristic of vibrations are different when the turbine is not operating satisfactorily.

Crack identification in Francis turbine runners is considered to be a very difficult problem [1]. Therefore, Artificial Intelligent (*AI*) techniques are used for automation crack identification and estimate the turbine operating conditions (Power output- *P*, Net Head - *H*, and Discharge - *Q*). Different *AI* techniques are applied for damage detection, such as fuzzy logic, artificial neural network (*ANN*) and genetic algorithms (*GA*) [9]. The *ANN* approach based on vibration characteristics have been used for damage identification in different structures, such as: different kinds of vessels [5], beam structure [11], rectangular plate [9], truss structure [18], railway wheel [19] and composite frames [20]. Several authors used *ANNs* technique based on vibration characteristics for fault detection and diagnosis in various machines, such as: fan turbo-jet [8] and power station [10], axial-flow fan [12] and residual gas compressor [16].

During a routine inspection of Unit 2 in Derbendikhan power station, in February 2002, it was found that multiple fatigue cracks were developed in turbine runners. Derbendikhan hydropower station is one of the major suppliers of electrical power generation in the north of Iraq-Kurdistan region which consists of 3 Units. Each Unit has the following parameters [14]: the rated head is 80 m, power output at rated head is 83 *MW*, discharge at rated head is 113 m^3/s, and rotational speed 187.5 *rpm*.

The aim of this study is developing and examining a Feed Forward Artificial Neural Network (*FFANN*) with back propagation (*BP*) algorithm for crack identification in the runner and for making expectations about the turbine operation conditions using its vibrational data; which can be provided from implementation some mechanical-numerical analysis methods. Additionally the main objective of this work is the investigating the possibility reducing the number of input data sets to *FFANN* using the pruning mechanism which is based on the data reduction techniques.

II. SIMULATION

This section discusses the three-dimensional simulations of the flow through the whole turbine, and the structural model of the turbine runner. Afterwards, integrating fluid-structure simulation to analyse the vibrations of the turbine runner is explained.

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A. *Flow Simulations*

The flow simulation of the Francis turbine is quite complicated and can be calculated only by using numerical methods. Therefore, *CFD* simulation of all flow channels of the Francis turbine has been performed. According to the provided specifications from Derbendikhan hydropower station a three-dimensional geometrical model has been created, as shown in Fig 1, the computation of the Spiral Casing, Stay Vane, Guide Vane, Runner and Draft tube was handled. As shown in the figure, the entire fluid passageway between the inlet from the Spiral Case side and the outlet at the draft tube side for the turbine is considered. The geometry of the fluid domain has been created used AutoCAD software and then inserted into ANSYS software.

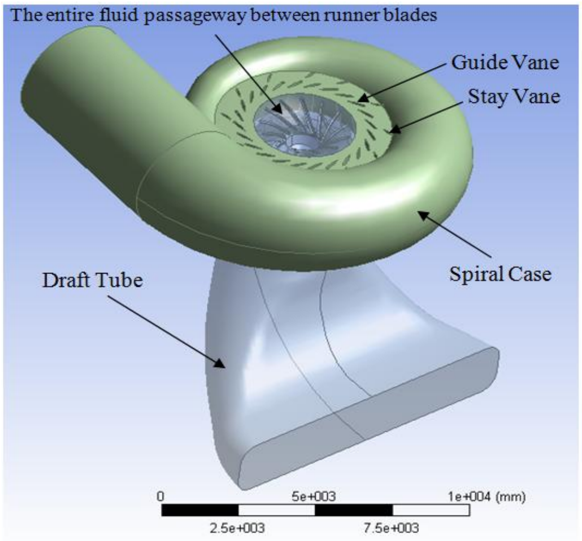

Fig 1: The geometrical model used in the simulation

B. *Structural Modelling*

In order to investigate the influence of cracks and load conditions on the dynamic behaviour of the runner, a *3D FEM* simulation of the whole turbine runner has been designed according to the dimensions of the turbine runner at Derbendikhan power station. A complete *3D* model of the turbine runner is shown in Fig 2.

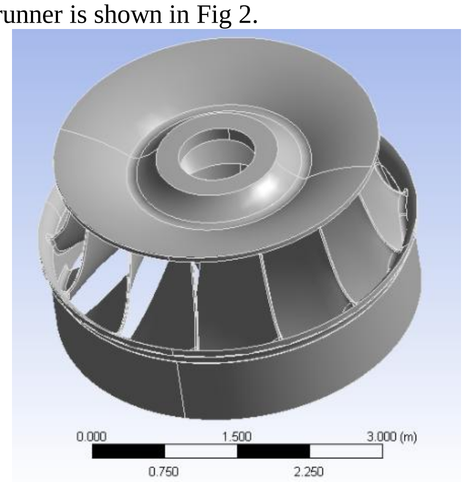

Fig 2: Model of the runner

C. *Fluid–Structure Coupled Analysis*

The vibrations of the Francis turbine runner are examined by coupling fluid-structure models in order to compute the amplitude of *FRFs* for the intact and damaged runner under different load conditions. Fig 3 shows the details of the connection between flow domains for *CFD* simulation and Francis turbine runner model. The analysis of vibration modes has been performed by ANSYS software.

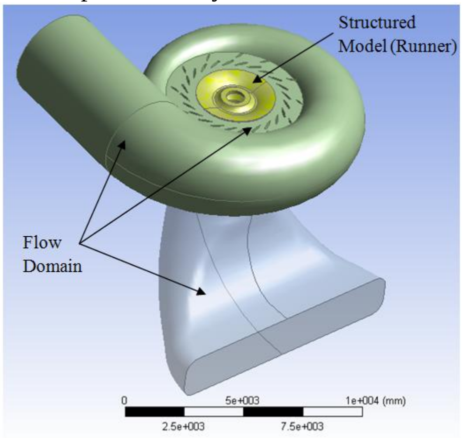

Fig 3: The flow domain and structure model

Since the computational domain has a very complicated geometry, the analysis of the fluid flow model and turbine runner models at each operational condition requires large computer memory and computational time. Therefore, in order to analyze the vibrational behaviour, the simulations of the flow through the turbine runner and the structural model of the Francis turbine runner used in the computations. Three different data sets of the amplitude of *FRFs* along *x* (Horizontal), *y* (Vertical) and *z* (Axial) directions have been obtained as a result of the modelling.

D. *Boundary Conditions*

Inlet boundary condition at given performance point of the hydraulic turbine runner are derived from the operation condition. Outlet boundary condition is defined to an opening case with an average relative pressure equal to the atmospheric pressure. The simulations were carried out for different real operation conditions of Francis turbine in Derbendikhan power station to address different load conditions.

The runner is rigidly connected to the shaft of the runner through the crown (zero displacements are assumed at the top edge of the crown). It is assumed that a single crack is located in one of the blades of the runner. The positions of the cracks in all calculations presented further are always in the trailing edge of the runner blade towards the crown, while the crack length varies. The spectrum computed for 10 cases of the damaged runner (crack lengths varying from 10mm to 100mm) and 1 case of the undamaged runner (without crack) for 24 different operation conditions for each case makes in total 264 cases. The size of the amplitude of *FRFs* data sets obtained from numerical analysis is represented by 500 spectral lines in each measurement, where each line is represented by a portion of the frequency spectrum (1 *Hz*).

The numerical analysis provide amplitude of *FRFs* along *x*, *y* and *z*-directions under different operating loads and different sizes of damage in the structure. Subsequently, the data sets are formulated and fed into Artificial Neural Networks (*ANNs*) in order to identify the crack length in the runner and estimate the turbine operational state.

III. ARTIFICIAL NEURAL NETWORKS

The amplitude of *FRFs* data sets contains information regarding the turbine operation load and damage conditions. Therefore, the *ANNs* have been produced using MATLAB code to establish the relationship between the turbine conditions and dynamic characteristics of the runner. The amplitude of *FRFs* data sets along *x*, *y* and *z*-directions have been used for training *ANN* to identify the crack in the runner and estimate turbine operating parameters. Each data sets of amplitude of *FRFs* along *x*, *y* and *z*-directions was used separately for training an appropriate single *ANN* to identify the turbine conditions, and they aggregated together and used for training multiple *ANN* scheme to improve the crack identification.

The implementation of an *ANN* model includes the training and testing procedure. In the training process, Feed Forward Artificial Neural Networks (*FFANN*) were trained using the obtained amplitude of *FRFs* data sets along *x*, *y* and *z*-directions. For training purpose the back propagation (*BP*) training algorithm was adapted. A sufficient number of combinations of input and output pairs is introduced for training; then the network become a “trained network” capable of identifying the crack size and estimates the turbine operating conditions. After that, the trained *FFANN* model was tested on the data that has not been used in the training process.

Large numbers of input data (high number of neurons in the input layer of the *FFANN* model) make the system unstable. Therefore, in order to reduce dimensionality in the input layer, different data reduction techniques have been proposed. A data reduction technique is used to achieve an acceptable data reduction level and obtain suitable number of spectral lines data, which retaining all features of the original data sets. This approach allows to significantly reducing the amount of amplitude of *FRFs* data sets.

A. Pruning Neural Network

The pruning process is a continuous process of reducing the number of input nodes of the neural network. The pruning goal is to reduce the number of involved nodes in the *NN* that have no significant effect on classification. In this study, selection of all spectral lines of *FRFs* data sets are excessive for training *ANN* directly, it may lead to unstable model and over-fitting the training data. To avoid large models, a subset of the amplitude of *FRFs* data sets can be used by considering fewer measurement points (input nodes), and its extra (un-necessary) nodes should be pruned. Pruning process begins by training a fully-connected neural network, and then pruning process is implementing by eliminating a number of input nodes. The pruning process is used for reducing the size of the network significantly without causing significantly degradation in classification accuracy because pruning eliminates the less effect and redundant inputs.

In this study, in order to apply pruning process for selecting the nodes to be deleted and to investigate the required number of neurons in the input layer of the *ANN*, two different techniques have been proposed.

1) The First Proposed Technique

In the first proposed technique, to determine the required number of frequencies/neurons in the input layer the training, testing and validation data sets are loaded. In the first step, the number of frequencies/neurons in the input layer is reduced sequentially (1 input frequency/neuron at each attempt). For the first attempt, 1st frequency/neuron is eliminated from the input data sets then *ANN* is trained and tested with the new data sets. In the second attempt, 1st frequency/neuron is returned back to the input data sets and the 2nd frequency/neuron is eliminated from the input data sets then *ANN* is trained and tested. In the third attempt, 2nd frequency/neuron is retained back to input data sets and the 3rd frequency/neuron is eliminated from the input data sets and then *ANN* is trained and tested. This process is continuing until the last frequency/neuron is reduced. In the next step, the summation of correlation coefficients between predicted and existence data for each attempt have been determined. In the final step, the maximum correlation coefficients are identified which are corresponding to one of the attempts, and then the frequency/neuron that is eliminated in this attempt is removed from the input data sets permanently. The explained procedure is continuing until reaching the satisfactory reduction number of frequencies /neurons in the input layer of the *ANN*.

2) The Second Proposed Technique

In the second proposed technique, to determine the required number of frequencies/neurons in the input layer the training, testing and validation data sets are loaded. The applied method for selecting the nodes to be deleted is based on the values of best weights matrix between input and first hidden layer. In this technique and after training *ANN*, the variance of each column of weight in the best weight matrix is determined which is representing the variance of weights between each input frequency/neuron with all neuron in the first hidden layer. The input frequency/neuron with the low variance weights in the best weight matrix has less effect on the model; therefore this frequency/neuron is removed from the training, testing, and validation data sets permanently. In the next attempt, the *ANN* will be training again with the new input data sets after removing one of the input frequency/neuron from the input data sets. Then the variance of each column of weight in the best weight matrix is determined. Next, the input frequency/neuron with the minimum variance in the weight matrix is eliminated from the training, testing, and validation data sets permanently. The explained procedures continue until the satisfactory reduction number of frequencies/neurons in the input layer of the *NN*.

These techniques are applied to amplitude of *FRFs* data sets to achieve an acceptable data reduction level which significantly reduces the amount of required input data sets. The new data sets of amplitude of *FRFs* along *x*, *y*, and *z*-directions are used such as input vectors to the *ANN* models as an alternative of using the original data sets. Such truncation of data sets has very little effect on the accuracy of the classifier results but considerably reduces the number of inputs into the model.

For crack identification in the runner and estimates the turbine operation conditions, changes in amplitude of *FRFs* along one direction may not be sufficient, because the change in a particular frequency could be attributed to different damage size and turbine operation conditions. It is expected that the overall accuracy can be improved by combining the network models trained with the amplitude of *FRFs* along *x*, *y* and *z*-directions.

B. Multiple Artificial Neural Networks

In this section, instead of training several networks and choosing the best network (i.e. *ANN*-1 and *ANN*-2), all individual networks are combined into a multiple neural networks-*MNN* (*ANN*-3). Vibrations data are aggregated together for training *ANN*-3 to improve the overall estimation error that could be smaller than the individual errors for each individual *ANN* (*ANN*-1 and *ANN*-2). Integrating the information of two input data sets for the construction of multiple *ANN* models makes the identification to be more accurate than the decision obtained from an individual neural network. The combination of multiple neural networks by using data fusion techniques is implemented in the MATLAB code.

IV. RESULTS AND DISCUSSION

From the numerical results, the values of amplitude of *FRFs* are quite similar along *x* and *y*-directions, therefore amplitude of *FRFs* along *y*-direction are not taken into consideration. Two different amplitude of *FRFs* data sets along *x* and *z*-directions are used to train two different models of *ANN* to estimate the turbine operation conditions and crack length in the runner. First, data sets of amplitude of *FRFs* along *x* and *z*-directions are used separately for training two different *ANN* models (*ANN*-1 and *ANN*-2). Then, both of the amplitude of *FRFs* data sets along *x* and *z*-directions have been used together to train multiple *ANN* (*ANN*-3).

For learning classifier models, amplitude of *FRFs* data sets are used as input parameters and the corresponding turbine conditions and runner damage state are used as output parameters. The complete data sets (264 patterns) are divided into three subsets. The first subset, 80% (212 patterns) of the complete data sets selected randomly, is used for training, while the remaining (20%) are used for validation 10% (26 patterns) and testing 10% (26 patterns). The testing data sets are used to verify the accuracy and the effectiveness of the classified model, while the validation data sets are used to optimise the performance of the *ANN* model by stopping the training process when the validation error starts to increase as the classifier model becomes over-fitted [4], [6].

During the learning process, different multi-layer neural network arrangements have been investigated in order to determine the best possible number of hidden layers and the neurons number in each hidden layer. It was revealed from experiments that the neural network may not be able to represent the system adequately if the number of hidden layers and neurons in the hidden layer in the neural network is too small. On the other hand, it becomes over-trained if the network is too big [18]. During the training process, the *ANNs* have been tested for all combinations of training rates: 0.005, 0.01, 0.05, 0.1, and 0.3 and momentum: 0.6, 0.7, 0.8 and 0.9. The simulation results show that simultaneous changes of all training parameters (training rate, momentum) can reduce the training time. The training process is terminated when there is no improvement for a limited number of cycles, or when the mean square error (*MSE*) for training samples falls below a specified limit, typically below 0.001 [8], [10], or when it reaches the maximum number of iterations. The maximum number of training epochs is set to be 10000 epochs.

For the *NN* model using amplitude of *FRFs* along *x* and *z*-directions (*ANN*-1 and *ANN*-2), it was found that the minimum of *MSE* could be further reduced by decreasing the learning rate value to 0.001; the momentum rate was considered as 0.6. Hyperbolic tangent function is used as activation function for hidden layer neurons and sigmoid function is used as activation function for output layer neurons.

A. Testing of ANN Using Amplitude of FRFs along x-direction

In order to select the suitable number of neurons in the hidden layer, the performance of *FFANN* with one hidden layer (*ANN*-1) with different number of neurons in the hidden layer (from 1 neuron to 40) has been examined. As a result, the correlation coefficient (*CC*) and *MSE* values for estimation of the turbine operation conditions (Power output-*P*, Net Head - *H*, and Discharge - *Q*) and crack length (*L*) in the turbine runner for different numbers of the neurons in the hidden layer have been determined, and the results are shown in Fig 4 and Fig 5.

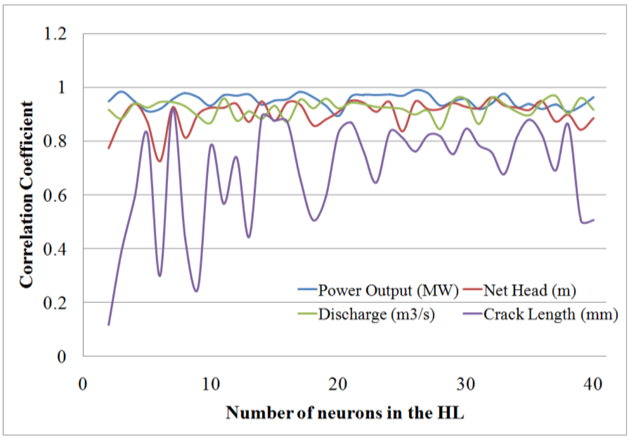

Fig 4: Correlation coefficient for estimation of the turbine operation conditions and crack length by using amplitude of FRFs along x-direction (500 spectral lines)

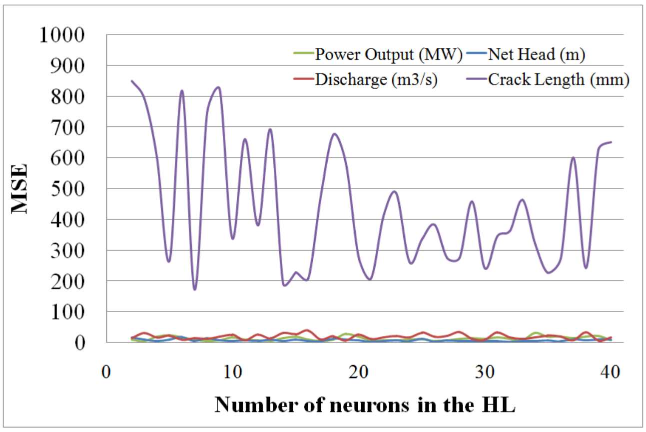

Fig 5: MSE for estimation of the turbine operation conditions and crack length by using amplitude of FRFs along x-direction (500 spectral lines)

During the training process of the *NN* using amplitude of *FRFs* along *x*-direction, it was found that the *FFANN* with one hidden layer *NN* consist of 7 neurons in the hidden layer produce the best identifications for the damage size in the runner and turbine operation conditions. The best attained correlation coefficients are around (0.95, 0.93, 0.94, and 0.92) and for *MSE* are around (9.41, 5.55, 15.01, and 172.7)

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for estimation of the turbine operation conditions (*P*, *H*, and *Q*) and crack length (*L*) respectively.

After are successful training of the *FFANN* (*ANN*-1), new data set of the amplitude of *FRFs* along *x*-direction are fed to the trained model, where these new data sets were not used during the *FFANN* training stage. The results obtained from testing this model are presented in Fig 6. The figure shows a scatter plot between the identified results of the *ANN* model with the actual values of the turbine operation conditions and crack length. As displayed in the figure, it can be seen that the estimation for the crack length and operation parameters by the trained model show good agreement with the actual parameters values.

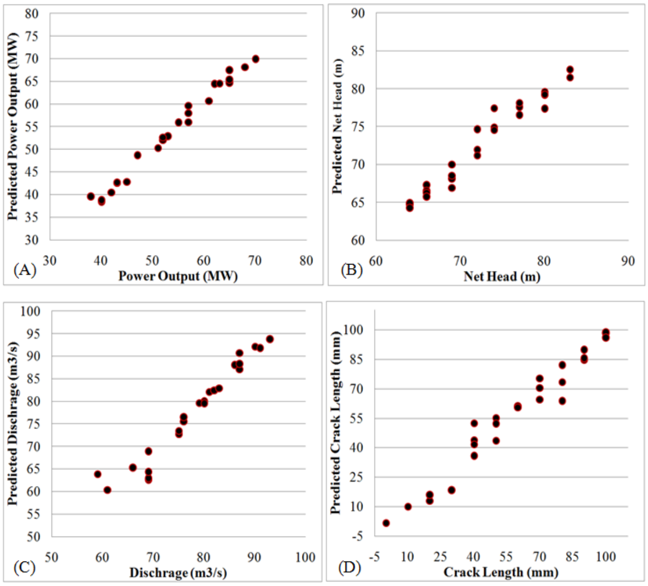

Fig 6: Estimation of the power output (A) net head (B) discharge (C) and crack length (D) by using amplitude of FRFs data sets along x-direction (500 spectral lines)

The size of the used amplitude of *FRFs* data sets along *x*-direction, which are obtained from numerical analysis, is take 500 spectral lines in each test. Using whole spectral lines of the *FRFs* data sets had caused long training time. To avoid long time operation and over-fitting, the size of input amplitude of *FRFs* data is reduced using data reduction method. The reduction technique was applied for amplitude of *FRFs* matrix (264x500) to achieve an acceptable data reduction level.

In this section, the suitable number of spectral lines/neurons in the input layer of *ANN*-2 had been investigated. In order to reduce the number of spectral lines/neurons in the input layer to a satisfactory number of neurons, second data reduction technique has been implemented. Based on this technique, different *ANN* arrangements have been examined with different input data sets, where the number of input amplitude of *FRFs* data samples is gradually reduced by 1. The results of attempted sets are shown in Fig 7.

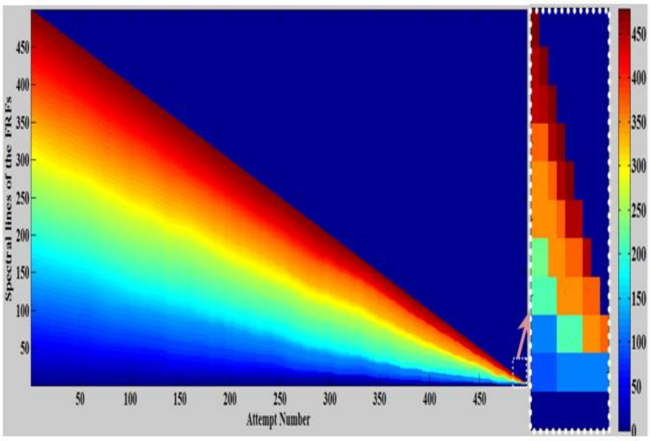

Fig 7: Reducing spectral lines of the FRFs along x-direction using the second data reduction technique

At the right side of the figure a close view of the results of last 10 attempts (from 488 to 497) of reduced data of the amplitude of *FRFs* data sets are shown. The correlation coefficient and *MSE* for the trained *NN* which corresponds to certain set reduced spectral line of the *FRFs* were determined and the results are presented in Fig 8 and Fig 9.

The investigations show that the last 7 spectral lines of the *FRFs* data sets are sufficient to identify the crack length and turbine operation conditions. Fig 10 shows the last 10 attempts (from 488 to 497) for reducing dimensionality of the amplitude of *FRFs* data along *x*-direction. As indicated in the figure, the use of only 7 spectral lines of the amplitude of *FRFs* data sets captured the largest amount of variations in the original data and they have been used further on. Therefore the original amplitude of *FRFs* data array of 264x500 is reduced to 264x7.

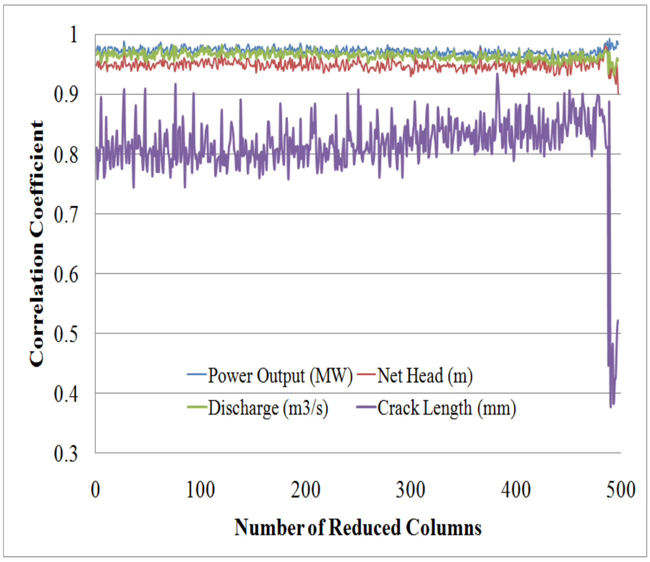

Fig 8: The correlation coefficients for estimated and actual crack length and turbine operation conditions using amplitude of FRFs data sets along x-direction (500 spectral lines)

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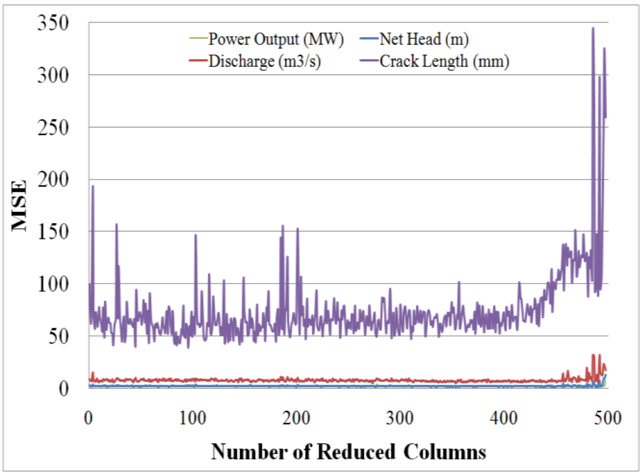
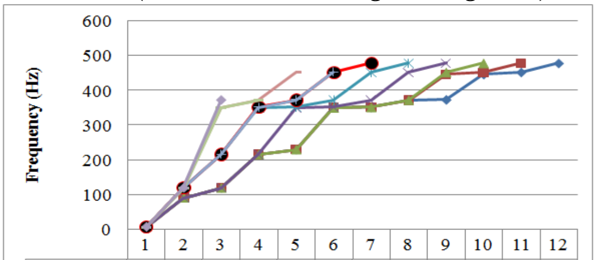


Fig 9: MSE for estimation crack length and turbine operation conditions using amplitude of FRFs data sets along x-direction (500 spectral lines)

The reduced data sets of the amplitudes *FRFs* along *x*-direction have been used as input vectors to the classifier *ANN*-1 as an alternative of the original amplitude of *FRFs* data sets. Such reduction of data sets has little effect on the accuracy of the classifier results but considerably reduces the operation time (weather in the training or recognition).



	1	2	3	4	5	6	7	8	9	10	11	12
Series1	7	91	119	216	230	350	351	372	373	446	452	478
Series2	7	91	119	216	230	350	351	372	446	452	478	
Series3	7	91	119	216	230	350	351	372	452	478		
Series4	7	91	119	216	350	351	372	452	478			
Series5	7	119	216	350	351	372	452	478				
Series6	7	119	216	351	372	452	478					
Series7	7	119	216	351	372	452						
Series8	7	119	351	372	452							
Series9	7	119	351	372								
Series10	7	119	372									

Fig 10: The 10 attempts (from 488 to 497) for reducing dimensionality of the amplitude of FRFs data along x-direction

In the following section, different number of neurons is taken in the hidden layer (i.e., from 1 to 40 neurons). The *FFANN* (*ANN*-1) was trained the reduced input data sets, to determine the best number of neurons in the hidden layer. While, the number of neurons in the input layer is fixed to 7 spectral lines/neurons, the learning rate and momentum are set 0.005 and 0.9 respectively. The correlation coefficient and *MSE* values for identification of the crack length and location for testing *NN* using reduced natural frequencies data sets with different numbers of the neurons in the hidden layer have been determined and the results are presented in Fig 11 and Fig 12.

As illustrated in the figures, the correlation coefficient is around 0.835 for the identification of crack length. The investigations showed that a one hidden layer *NN* with 4 neurons in the hidden layer leads to best acceptable results, where the correlation coefficients are 0.93 and (0.985, 0.95, and 0.93) for the identification of the crack length and turbine operation conditions (*P*, *H*, and *Q*), respectively. Additionally, the corresponding *MSE* to estimate the crack length and turbine operation conditions (*P*, *H*, and *Q*) are 130.59 and (6.69, 2.67, and 15.69) respectively.

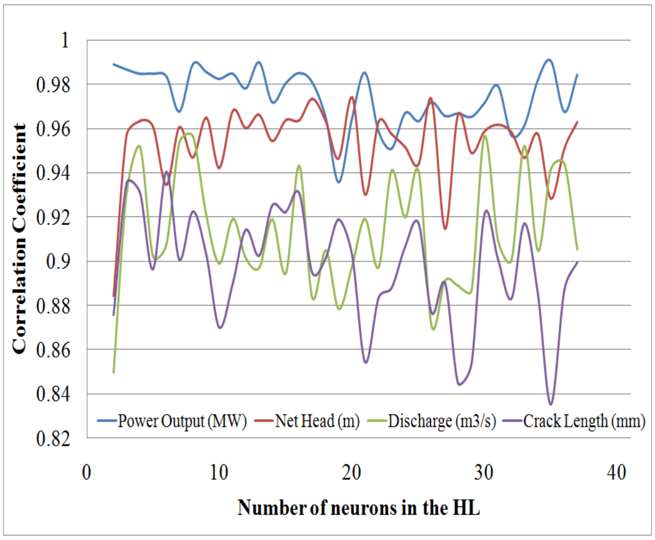


Fig 11: Correlation Coefficient for estimation of the turbine operation conditions and crack length by using amplitude of FRFs along x-direction (7 spectral lines)

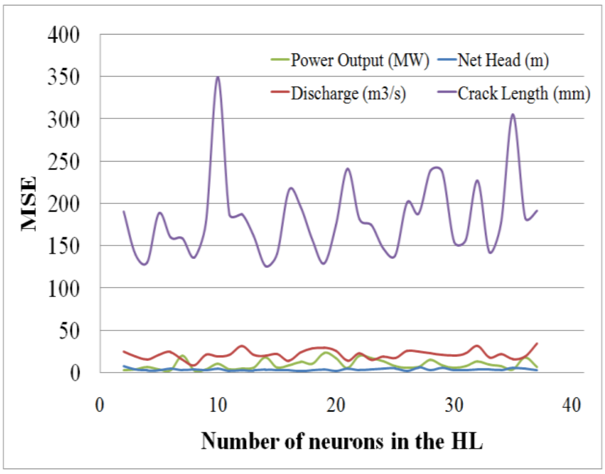


Fig 12: MSE for estimation of the turbine operation conditions and crack length by using amplitude of FRFs along x-direction (7 spectral lines)

So, the tests indicate that the required numbers of spectral lines /neurons in the input layer, it can be concluded that one hidden layer *NN* (*ANN*-1) with 4 neurons in the hidden layer is sufficient to estimate the crack length and operation conditions effectively. Therefore, the performances of one hidden layer *NN* for the identification of the crack length and operation conditions have been tested and the results are illustrated in Fig 13. So, the number of neurons in the input layer is fixed to 7 spectral lines/neurons and the number of neurons in the hidden layer is fixed to 4. The testing results reveal that this model can estimate the turbine operation condition and this model can identify the existence of a crack in the turbine runner.

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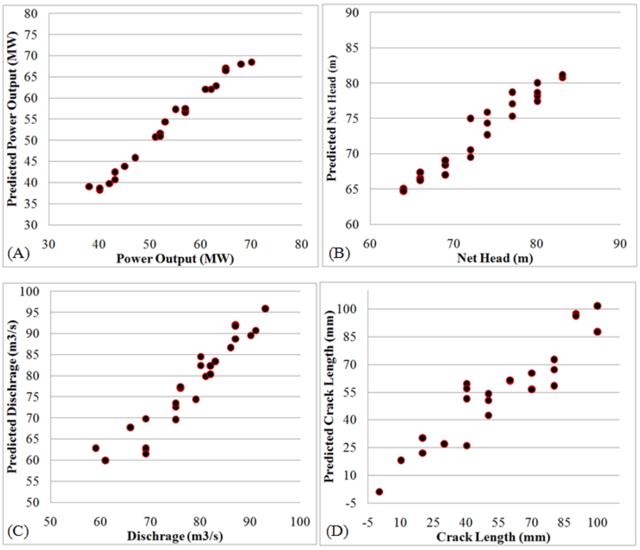

Fig 13: The identification results of the power output (A) net head (B) discharge (C) and crack length (D) using amplitude of FRFs data sets along x-direction (7 spectral lines)

B. Testing of ANN Using Amplitude of FRFs along z-direction

In order to determine the required number of neurons in the hidden layer using amplitude of *FRFs* (along *z*-direction) data sets; *FFANN* with one hidden layer consist of different number of neurons in the hidden layer (from 1 neuron to 40) have been tested. In consequence, the correlation coefficient and *MSE* values for estimation of the turbine operation conditions and crack length in the turbine runner have been determined. The obtained results are shown in Fig 14 and Fig 15.

During the training and testing process of the *NN* using amplitude of *FRFs* along *z*-direction, it was found that the three layers *FFANN* with 4 neurons in the hidden layer had produced the best identifications for the damage size in the runner and monitoring turbine conditions. The correlation coefficients are more than 0.90 for the identification of the turbine operation conditions and crack length. The correlation coefficients and *MSE* are more than (0.97, 0.97, 0.89, and 0.92) and (9.16, 2.59, 36.20, and 152.15) for the identification of the turbine operation conditions (P, H, and Q) and crack length (L), respectively.

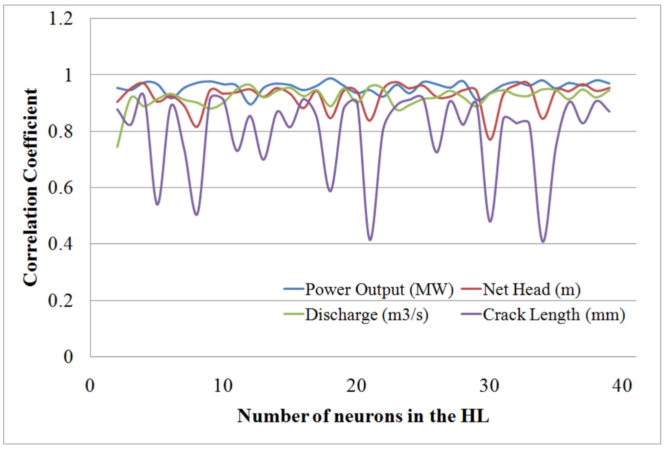

Fig 14: Correlation coefficient for estimation of the turbine operation conditions and crack length by using amplitude of FRFs along z-direction (500 spectral lines)

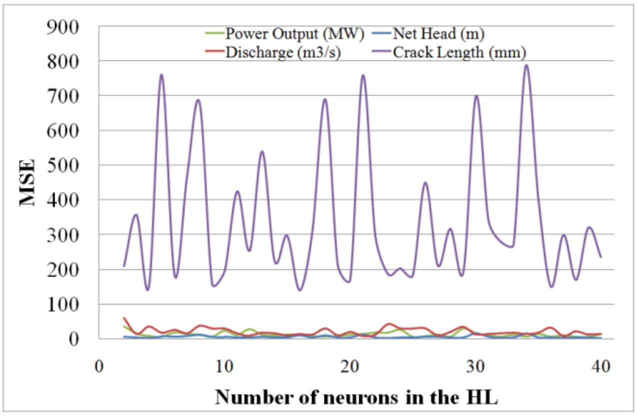

Fig 15 : MSE for the estimated crack length and turbine operation conditions using amplitude of FRFs data sets along z-direction (500 spectral lines)

The size of the amplitude of *FRFs* data sets along *z*-direction obtained from the numerical analysis is represented by 500 spectral lines in each measurement. The spectral lines of the *FRFs* data cause very long training time. To avoid large operation time and over-fitting, the data reduction mechanism was used to reduce dimensionality of the spectra. This technique allows to significantly reducing the amount of amplitude of *FRFs* data. The reduction technique is applied on amplitude of *FRFs* matrix (264x500) to achieve an acceptable data reduction level. The new data sets of amplitudes *FRFs* along *z*-direction are used as input vectors to the classifier (*ANN*-2) as an alternative for using the original amplitude of *FRFs* data sets.

In order to investigate the required number of spectral lines/neurons in the input layer of the *ANN*, second data reduction technique has been applied. Based on this technique, different *FFANN* have been trained with different input data sets, where the number of input data was gradually reduced from 1 spectral line to 497 spectral lines, the obtained results are shown in Fig 16.

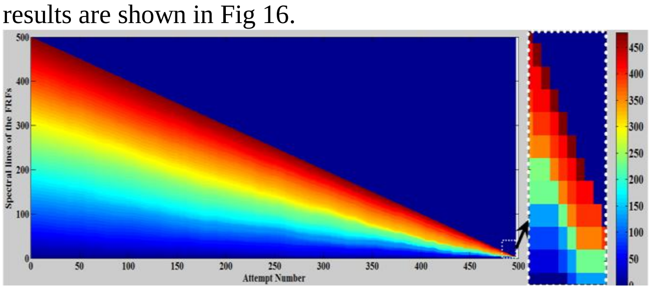

Fig 16: Reducing spectral lines of the FRFs along z-direction using the second data reduction technique

The figure at the right side shows a close view of the last 10 attempts (from 488 to 497) of the reduced amplitude of *FRFs* data sets. The correlation coefficients and *MSE* have been determined for all trained *FFANN* and the results are presented in Fig 17 and Fig 18.

The above figures indicate that the accuracy of the crack identification and the estimation of turbine operation conditions is decrease with the increase of the number of reduced spectral lines in the input layer, particularly after reducing the number spectral lines by 490 lines as illustrated in Fig 17 and Fig 18. The 17 attempts (from 470 to 486) for reducing dimensionality of the amplitude of *FRFs* data sets are

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shown in Fig 19.

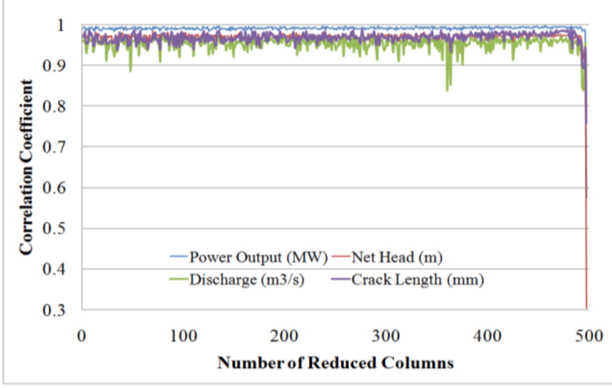


Fig 17: Correlation coefficients for the estimated crack length and turbine operation conditions using amplitude of FRFs data sets along z-direction (500 spectral lines)

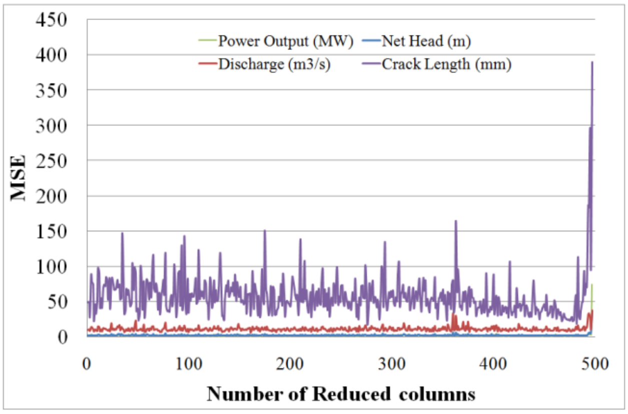
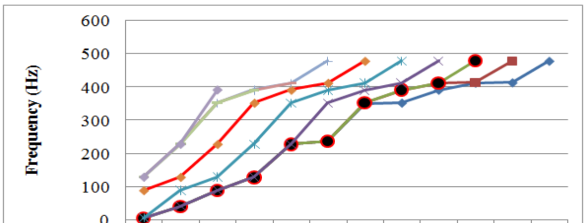


Fig 18: MSE for the estimated crack length and turbine operation conditions using amplitude of FRFs data sets along z-direction (500 spectral lines)



	1	2	3	4	5	6	7	8	9	10	11	12
Series1	7	41	89	129	228	237	349	352	391	412	413	478
Series2	7	41	89	129	228	237	352	391	412	413	478	
Series3	7	41	89	129	228	237	352	391	412	478		
Series4	7	41	89	129	228	352	391	412	478			
Series5	7	89	129	228	352	391	412	478				
Series6	89	129	228	352	391	412	478					
Series7	129	228	352	391	412	478						
Series8	129	228	352	391	412							
Series9	129	228	352	391								
Series10	129	228	391									

Fig 19: The 15 attempt (from 470 to 484) for reducing dimensionality of amplitude of FRFs data along z-direction

The test set shows that the 10 spectral lines of the *FRFs* (along *z*-direction) data sets, as indicated in the figure, is sufficient to estimate the crack length and operation conditions in the Francis turbine. The remained 10 spectral lines of the *FRFs* data are shown in Fig 19. These spectral lines capture the largest amount of variations in the original data and they have been used further on. Therefore, the original amplitude of *FRFs* array of 541x500 is reduced to 541x10. Such truncation of data sets has little effect on the accuracy of the classifier results but considerably reduces the input data. The reduced data sets of amplitude of *FRFs* along *z*-direction are used as input vectors to the classifier models as an alternative to the original amplitude of *FRFs* data sets.

In the following, different number of neurons in the hidden layer (from 1 to 40 neurons) have been examined for training *FFANN* (*ANN*-2) by using the reduced input data sets, to determine the best number of neurons in the hidden layer. While, the number of neurons in the input layer is set equal to 10 spectral lines/neurons, the learning rate and momentum are fixed at 0.005 and 0.9 respectively.

The correlation coefficient and *MSE* values for identification results of the crack length and turbine operation conditions when the trained *FFANN* is fed with reduced input data sets are determined, and the results are presented in Fig 20 and Fig 21.

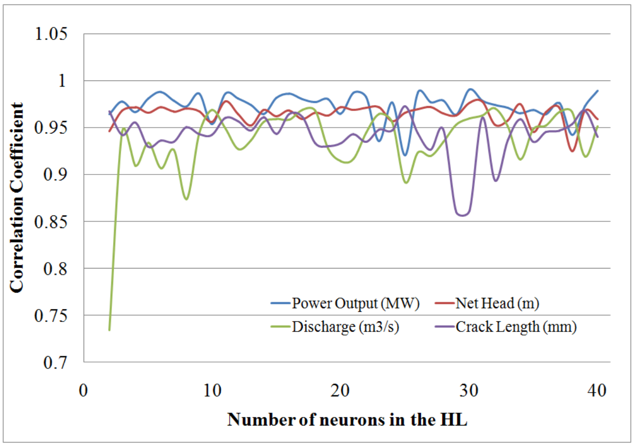


Fig 20: Correlation coefficients for estimated crack length and turbine operation conditions using amplitude of FRFs data sets along z-direction (10 spectral lines)

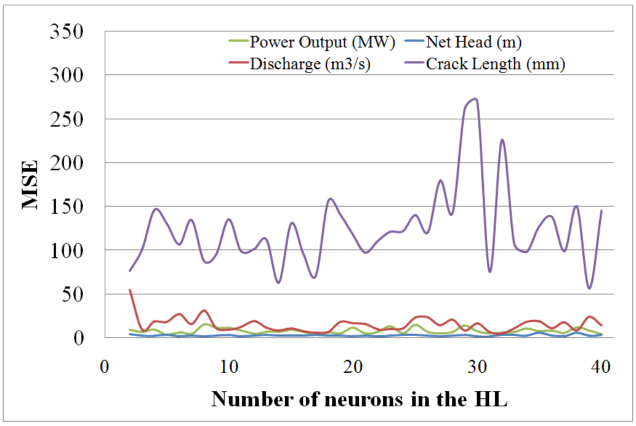


Fig 21: MSE for the estimated crack length and turbine operation conditions using amplitude of FRFs data sets along z-direction (10 spectral lines)

During the training process of the *NN* using the reduced amplitude of *FRFs* data sets, it was found that three layer *FFANN* with 3 neurons in the hidden layer had produced the best identifications for the damage size in the runner and turbine operation conditions. The correlation coefficients and *MSE* are around (0.978, 0.968, 0.945, and 0.942) and (6.43, 2.55, 9.60, and 101.11) for the

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estimation of the turbine operation conditions (*P*, *H*, and *Q*) and crack length (*L*), respectively.

For testing a trained *FFANN* a new data set of reduced amplitude of *FRFs* data sets along *z*-direction are introduced to the system, this new data set was not used in the *FFANN* training stage, the obtained results are presented in Fig 22. The number of neurons in the input layer is set 10 spectral lines/neurons and the number of input neurons is set 3. The figure shows the scatter plots between the estimated results of the trained *FFANN* model with the actual values of the turbine operation conditions and crack length. As displayed in the figure, it can be seen that the estimation for the crack length and the operation parameters by the trained *FFANN* model show good agreement with the actual parameters.

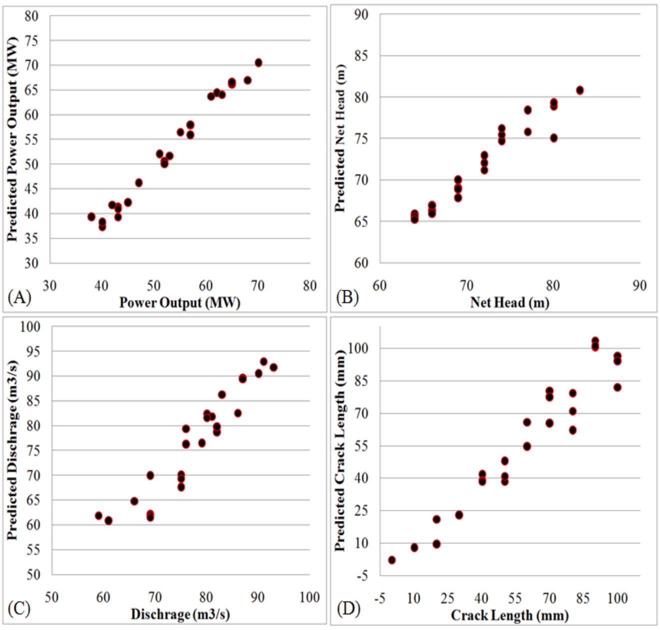

Fig 22: Identification of the power output (A) net head (B) discharge (C) and crack length(D) by using amplitude of FRFs data sets along z-direction (10 spectral lines)

After successful training of the *FFANN* classifier models (i.e. *ANN*-1 and *ANN*-2); new data sets (26 data sets) of the reduced amplitude of *FRFs* data sets (along *x* and *z*-directions) corresponding to both healthy and damaged runner conditions, and under different operation conditions, were selected and fed simultaneously into the *FFANN* classifier models. The obtained results from the classifier models (i.e., *ANN*-1 and *ANN*-2) are presented in Fig 22 and Fig 13. Where *ANN*-1 and ANN-2 are trained using the reduced amplitude of *FRFs* (along *x* and *z*-directions) data sets, the number of spectral lines are taken 7 and 10, respectively. These figures presents the scatter plots between the identified crack length and operation parameters using the classifier models versus the actual crack length, taken into consideration that in ideal situations it should lie on the straight line. As evident from the figures, the identified results are in good agreement with the actual turbine condition parameters.

The high value of correlation coefficients and low values of *MSE* for the identifying of crack parameters showed that *FFANN* have good identification performance. The sufficient number of neurons in the hidden layer is 4 for *ANN*-1 and 3 neurons for *ANN*-2, where the correlation coefficients and *MSE* for *NN* using amplitude of *FRFs* data sets along *x*-direction are (0.93, 0.985, 0.95, and 0.93) and (6.69, 2.67, 15.69, and 130.59) and for *NN* using amplitude of *FRFs* data sets along *z*-direction are (0.978, 0.968, 0.945, and 0.942) and (6.43, 2.55, 9.60, and 101.11) for the identification of the *P*, *H*, *Q*, and *L* respectively. Based on obtained results, one can conclude that by knowing the amplitude of *FRFs* data sets along *x* and *z*-directions the trained classifier models are able to adequately identify the crack length and operation parameters in the Francis turbine. By comparison between the presented results, as shown in Fig 22 and Fig 13, it's concluded that *ANN*-2 more accurate than *ANN*-1 for identification the crack length and turbine operation conditions.

The implementations of the existence techniques such as ultrasound, *X* ray, dye penetrants, magnetic particle and acoustic emission, for damage identification are limited [7] and also these techniques are costly and time consuming [17]. On the other hand, because a limited number of samples are used for training of the neural network, *ANN* is not so sensitive as compared with these techniques. Therefore, *ANN* can be used as an initial assessment, which can be followed by one of the other methods to determine the crack characteristics more precisely. To provide improved model for the crack identification, multiple *FFANN* (*MNN*) model had been proposed.

C. Implementation of MNN Using Amplitude of FRFs along x and z-directions

In this section, instead of training two networks and choosing the best network, *ANN*-1 and *ANN*-2 are combined into one scheme (called *ANN*-3). The data sets of amplitude of *FRFs* along *x*-direction (7 spectral lines) and along *z*-direction (10 spectral lines) are assumed as input vector elements, and they used for training *ANN*-3 to improve the overall estimation. The trained *FFANN* was able to learn the relationship between amplitude of *FRFs* along *x* and *z*-directions with the corresponding damage and operation state. The number of neurons in the hidden layer is taken 4 and 3 for 1st *ANN* and 2nd *ANN*, respectively. The learning rate and momentum are assumed to be 0.001 and 0.6 respectively for 1st *ANN* and 2nd *ANN*, while the value of learning rate and momentum are set 0.1 and 0.6 for the 3rd ANN. The convergence has been achieved after 10000 epochs.

After the successful training of the *FFANN* (*ANN*-3), a new data set, which was not used for training the *FFANN*, is tested by the trained net. Reduced data sets of amplitude of *FRFs* along *x*-direction (7 spectral lines) and along *z*-direction (10 spectral lines) were fed simultaneously into the 1st *ANN* and 2nd *ANN* respectively. The results obtained from the testing *ANN*-3 are presented in Fig 23. The figure shows the scatter plots between the identified results of the proposed models and turbine state. As displayed in the figure, it can be seen that the crack estimation by the trained *ANN*-3 shows good agreement with the existence of the crack length and turbine operation conditions.

A new data set (26 data sets) of amplitude of *FRFs* along *x* and *z*-directions corresponding to both healthy and damaged runner cases have been selected and fed simultaneously into the trained classifier models (*ANN*-3). The results obtained from testing the trained *ANN*-3 for the identification of the crack length in the runner and turbine operation condition are presented in Fig 23.

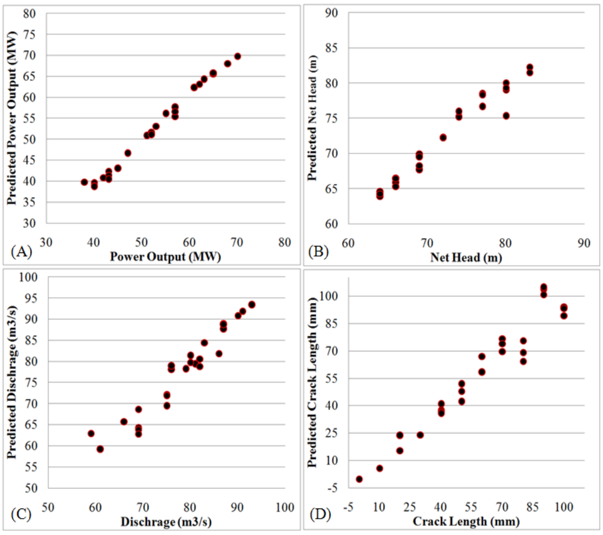

Fig 23: Identification of the power output (A) net head (B) discharge (C) and crack length(D) by using reduced amplitude of FRFs data sets along x and z-directions

The obtained results, as shown in Fig 23, revealed that *ANN*-3 shows improved identification performance in comparison with performance of both *ANN*-1 and *ANN*-2. The figure presents the scatter plots between the identified crack lengths and operation conditions versus the actual parameters, where for perfect performance the points should lie on the straight line. The correlation coefficients and *MSE* are around (0.996, 0.978, 0.964, and 0.97) and (1.24, 1.62, 8.03, and 54) for the identification of the turbine operation conditions (*P*, *H*, and *Q*) and crack length (*L*), respectively. As evident from the figure, it can be noticed that the estimation of the turbine operating parameters (*P*, *H* and *Q*) by the trained multiple *ANN* model show good agreement with the actual turbine operating parameters. The identification results of multiple *ANN* models for the crack length in the turbine runner indicate that these models can identify the crack accurately even if the turbine operating conditions are changed.

Based on obtained results one can conclude that, by knowing the amplitude of *FRFs* along *x* and *z*-directions the trained *FFANNs* are able to adequately identify the crack length in the turbine runner. Also these models can be applied for evaluating turbine operating parameters (power output *P*, head *H* and discharge *Q*) effectively.

V. CONCLUSIONS

From the analysis of conducted simulation results the following conclusions are drawn:

1. *FFANN* which have single and multiple arrangements have been successfully employed for crack identification in the runner and estimating turbine conditions using amplitude of *FRFs* data sets.
2. The data reduction techniques have effectively reduced the input data (spectral lines of the *FRFs*). The results revealed that the pruning mechanism which is based on the data reduction mechanism can led to satisfactory results.
3. The comparison between the results of the *FFANN* models indicates that the *ANN*-2 is more accurate than *ANN*-1 for the estimation of crack and operation parameters in the Francis turbine.
4. The results show that the multiple *FFANN* (*ANN*-3) can improve the precision and can provide better results compared to the single *ANN*.
5. The identified results of multiple *ANN* model for estimating the crack length in the turbine runner demonstrate that these models can identify the crack accurately even if the turbine operating conditions are changed.

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