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Non-destructive evaluation of ceramic candle filters using artificial neural networks

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ABSTRACT

Ceramic candle filters play an important role in coal-based turbine system for a modern power plant. However, after exposure to the high pressure and high temperature in the gas turbine chamber, the effectiveness of the filters deteriorates over time. Their failure to perform may create catastrophic consequences for the multi-million dollar equipment downstream. A non-destructive evaluation procedure using artificial neural networks is proposed to examine the filters. In lieu of experimental data, the vibration signatures of filters damaged to various degrees are created by means of analytical simulation. Then, a feed-forward artificial neural network and a radial basis function neural network are built and trained to evaluate the signatures for the purpose of determining the filters' degree of deterioration. Good results are obtained and presented here. The application of the proposed procedure should not be confined to the ceramic candle filters alone. It is a general procedure that will find many applications on the evaluation of other structural components and engineering products in the industry.

KEYWORDS

Neural Network, Structural Identification, Non-destructive, Finite Element Methods.

1 Introduction

About one half of the electricity in the United States and one third worldwide is generated with coal, thus it is extremely important to develop advanced power generating systems to produce very clean, efficient and affordable electricity. The National Energy Technology Laboratory of the U. S. Department of Energy (NETL/DOE) is developing two such systems: Integrated Gasification Combined Cycles (IGCC) and Pressurized Fluidized Bed Combustion (PFBC), and has demonstrated with a pilot power plant for their commercialisation at the Southern Company Services located in Wilsonville, Alabama [1]. However, successful implementation of IGCC and PFBC in power generation gas turbine depends critically on the performance of a key element that is the ceramic candle filter. A typical filter assemblage made by Westinghouse is shown in Fig. 1.

These filters are a type of hot gas particulate filter. They serve to clean the gas for meeting the particulate emission requirements and hence to protect the downstream heat exchanger and gas turbine components from particle fouling and erosion effects [2]. The ceramic candle filters are composed of silicon carbide and are constantly subjected to high temperature 927°C (1,700°F) and high pressure 2.07 MPa (300 psi) conditions throughout their service life.

The material strength of ceramic filters deteriorates after exposure to the high temperatures and high pressures in their plenum [4]. Their failure may create catastrophic consequences for the multi-million dollars equipment downstream and may result in unscheduled shutdown of the power plant. Hence, it is important to examine the filters frequently to detect their imminent failure. The maintenance shutdown period of the power plant offers a good opportunity for such an examination. The NETL recognised the importance of this filter evaluation and has supported a study to develop a non-destructive evaluation technique based on the measurements of vibration response [3]. They evaluated virgin filter as well as several used filters damaged to various degrees by using a traditional modal analysis procedure. In this procedure, the used filters were first dismounted from the plenum, brought to a laboratory and suspended on a tripod with elastic strings. After attaching an accelerometer to the filter, impact dynamic vibration was induced and acceleration signatures were recorded. The Fast Fourier Transform was then performed to transform the signatures in the time domain to those in the frequency domain. Deterioration of the filters could be determined based on the changes of their natural frequencies. Since the filter is confined in its plenum and subjected to the relatively homogeneous loads of high temperature and high pressure, the change in its natural frequency is largely attributed to a decrease in the modulus of elasticity caused by the loads [4].

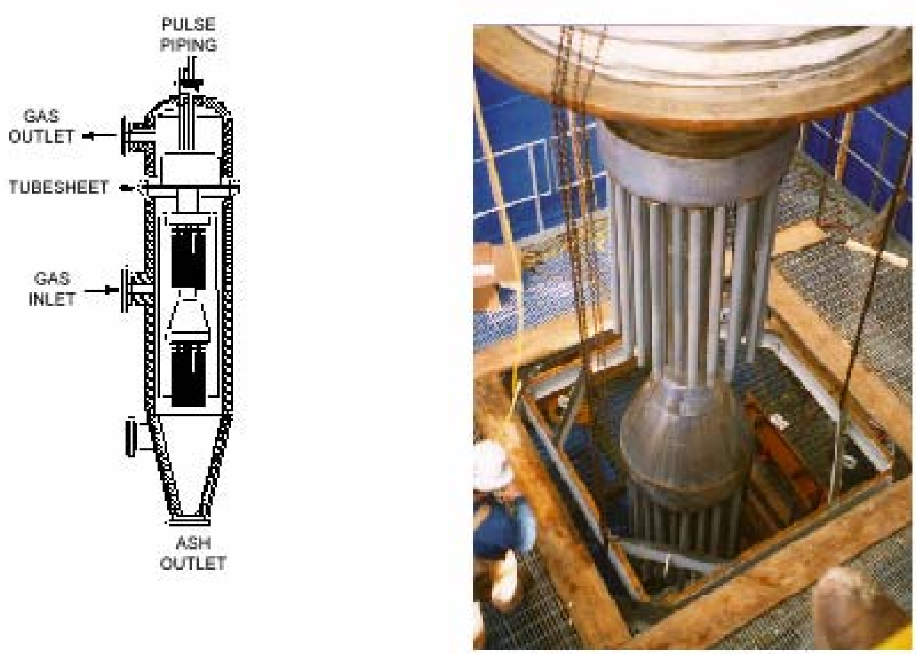

Fig. 1 Westinghouse Filter System

In view of the above description, it is found that physically dismounting the filters and transporting them to a laboratory for a test are time consuming. Hence, we propose an in situ evaluation procedure using the artificial neural networks, which is more convenient to carry out and thus increases the efficiency of the filter evaluation.

2 In situ Non-destructive Evaluation

The proposed in situ evaluation procedure may be described as follows:

- Select a number of ceramic candle filters from the laboratory and the pilot power plant, which are at various degrees of degradation due to the lengths of their exposure to the loads and due to the intensity of their service loads. Consequently they have different moduli of elasticity [4]. Their vibration signatures will be collected and employed as training examples.
- An artificial neural network (ANN) will be built and trained by using the collected signatures in order to have the capability in recognising the physical state of a filter from its vibration signature.
- The well-trained ANN will be loaded onto a laptop computer, which can be brought to the site of the filter. The filter in its original hanging position is given a non-contact excitation and its vibration signature is remotely collected using a laser vibrometer. Finally, this signature is fed into the laptop computer and the resident ANN will produce an instant evaluation of the current state of the filter. Thus, an informed decision can be made on whether the filter needs to be replaced.

The success of the proposed procedure is hinged on whether the ANN can perform the task of the evaluation promptly and accurately, which will be discussed in subsequent paragraphs.

3 Artificial Neural Networks

ANN is a richly connected network of simple computational elements, which can carry out complex cognitive and computational tasks [5]. A special feature of an ANN is that it can learn from examples through training without prior knowledge of the model structures. Therefore, once the networks are designed and properly trained, they can read the vibration signature and give an instantaneous evaluation of the filter. Two types of ANN will be presented: feedforward artificial neural network and radial basis function neural network.

4 Feed-forward Artificial Neural Network

Feed-forward artificial neural network (FANN) is perhaps the most popular neural network used in engineering applications. A standard FANN is shown in Fig. 2 that consists of an input layer, two hidden layers, and an output layer. Although the figure demonstrates a FANN with two hidden layers, we can change the number of hidden layers depending upon the FANN performance.

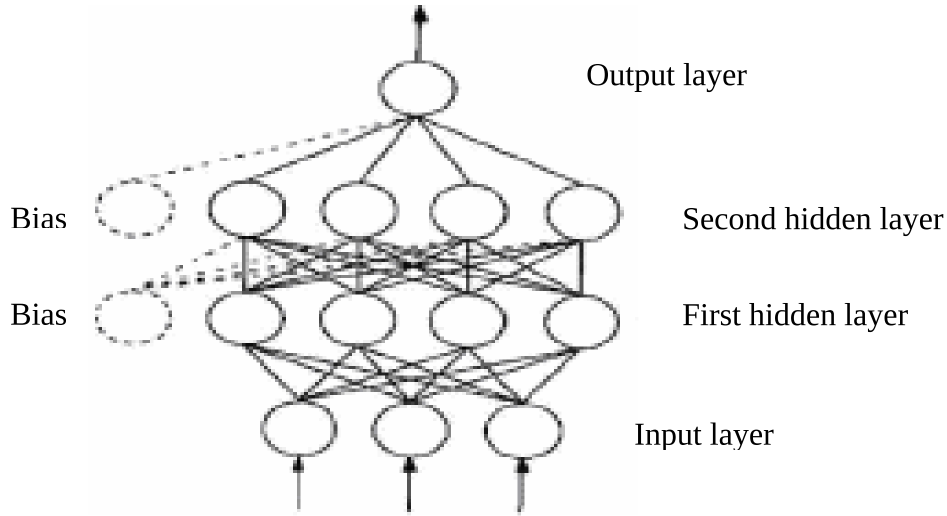

Fig. 2 Feed-forward Artificial Neural Network

Once the number of hidden layers and the number of neurons of each layer are selected, a training process is begun. The weights and bias for the node connections are determined through processing a set of training examples, which allows the FANN to learn the information about the system to be recognised. After the FANN is trained, then it is able to produce an approximate solution to a given set of fresh data not hitherto seen by the FANN.

Specifically, NEWFF in software MATLAB[7] is used to create the FANN for this work. One hidden layer with five neurons is selected. A linear function is chosen as the transfer function for the hidden layer and the output layer. For back-propagation, a network training function that updates weight and bias values according to Levenberg-Marquart procedure is used.

5 Radial basis function neural network

Radial basis function neural network (RBFN) can be used for a wide range of application primarily because it can approximate any regular function and its training is faster than that of FANN. This faster learning speed comes from the fact that RBFN has only two layers of weights and each layer can be determined sequentially. The main difference between a basic FANN and a RBFN is the non-linear transfer function used in the hidden layer nodes. Instead of the sigmoid function, radial basis function is used, which employs a type of symmetrical Gasssian Function.

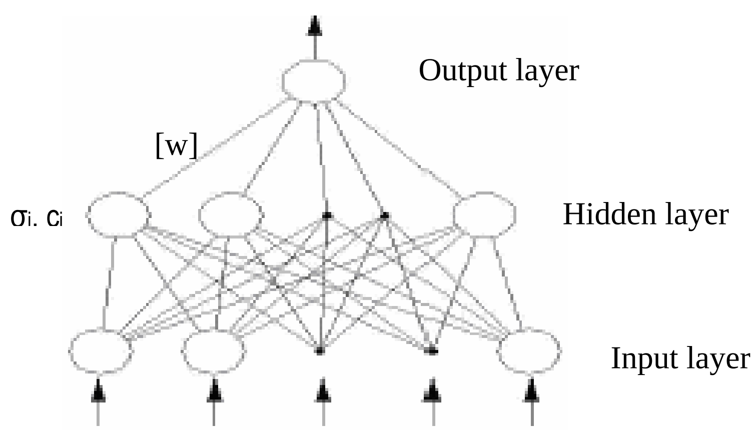

Fig. 3 Radial Basis Function Network

The RBFN also uses a clustering process on the input data before presenting them to the network. It uses activation functions [6] that are locally tuned to cover a region of the input space. The network structure is shown in Fig. 3 that consists of an input layer, a single hidden layer, and an output layer. Only the connections from the hidden layer to the output layer are weighted, leading to a much faster training rate than FANN.

Specifically, NEWRB in software MATLAB[7] is used to create the RBFN for this work. In a radial basis network, neurons are added to the hidden layer one by one until the specified mean squared error goal is met. The goal used here is 0.15. The radial basis function has a spread. The spread chosen here is 40 [7].

6 Finite Element Method Simulation

The vibration signatures of the virgin and the used filters may be collected in the laboratory [3]. However, for the purpose of demonstrating that the ANN are capable to do the evaluation, a set of training signatures as well as a set of testing signatures are created by computer simulations. Finite Element Methods and SAP2000 [8] are used for this simulations.

We build 11 finite element models of the filters. Their dimensions are identical but their moduli of elasticity are different to reflect the degradation of the filter at various stages. Each model has a length of 1,514 mm (59.625 inch), an outside radius of 60 mm (2.363 inch), and an inside radius of 30 mm (1.181 inch), with a closed end that has a thickened wall thickness of 36 mm (1.417 inch) and a length of 15mm (0.591 inch). These are the actual measurements of a ceramic candle filter. Their moduli of elasticity are varied from 6,895mpa (1,000,000 psi) to 41,370 mpa (6,000,000 psi) with an interval of 3,448 mpa (500,000 psi).

The model with the highest modulus of elasticity represents the virgin filter. The others represent filters damaged to various degrees. 960 hexahedral isoparametric elements are used to build the model, see Fig. 4. An impulse was applied at the model and the velocity signatures at the free end are recorded through dynamic analysis. The reason for using velocity signatures instead of acceleration signatures as used in the laboratory tests [3] is due to the characteristics of the laser vibrometer. Laser vibrometer, which is available in NETL and also available commercially, is a device designed to remotely collect velocity signatures, not acceleration signatures. A sample velocity signature is shown in Fig. 5. A collection of such signatures is a set of valid training examples. Then, a FANN and a RBFN are built as mentioned in previous paragraphs. They are taught [7] with the said training examples.

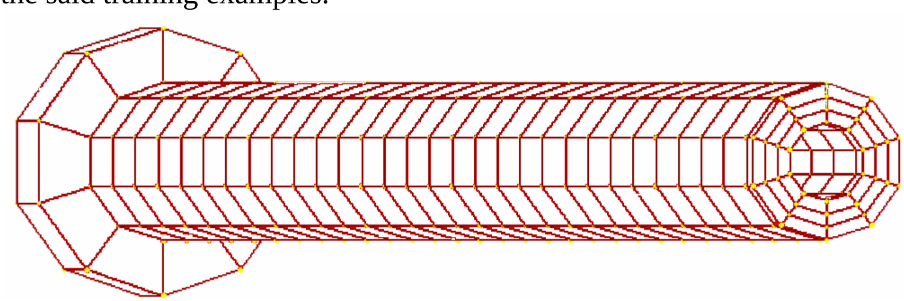

Fig. 4 Finite Element Model of Ceramic Filter

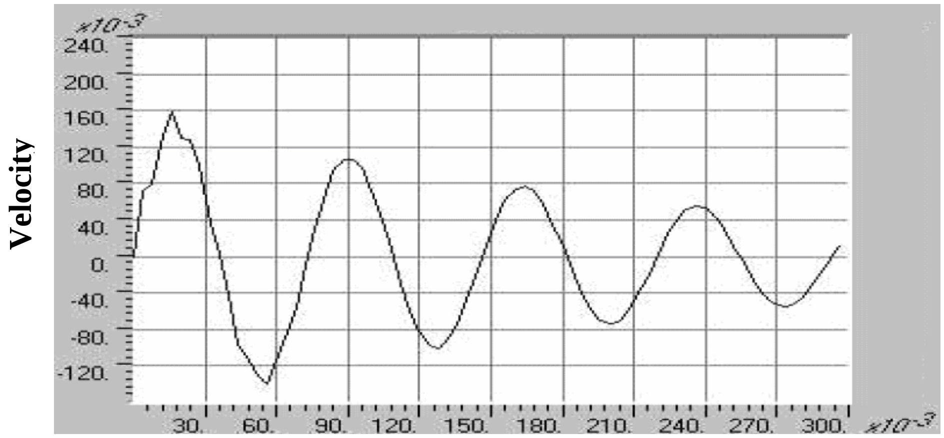

Fig. 5 Time-Velocity Wave for Filter with E= 20,685 mpa (3,000,000 psi)

7 Evaluations and Comparisons

Next, we select some new models representing the filters to be evaluated, which have moduli of elasticity of 7,585 mpa (1,100,000 psi), 9,653 mpa (1,400,000 psi), 15,859 mpa (2,300,000 psi), 24,822 mpa (3,600,000 psi), 28,270 mpa (4,100,000psi), 32,407 mpa (4,700,000 psi),
35,854 mpa (5,200,000 psi), and 39,991mpa (5,800,000 psi). Based on these inputs, fresh velocity signatures are generated as before, which are not hitherto seen by the ANN. Namely, these signatures are not among the training examples and thus completely unknown to the ANN. We feed the signatures to the FANN and the RBFN respectively; then, each network produces a set of evaluations of the moduli of elasticity. The results are shown in Table 1.

Table 1 Comparison of ANN's Evaluation

Ea	mpa	7,585	9,653	15,859	24,822	28,270	32,407	35,854	39,991
	$x10^6$ psi	1.1000	1.4000	2.3000	3.6000	4.1000	4.7000	5.2000	5.8000
Ef	mpa	7,164	9,545	16,037	24,812	28,259	32,431	35,838	40,017
	$x10^6$ psi	1.0390	1.3844	2.3259	3.5986	4.0985	4.7035	5.1977	5.8038
Er	mpa	7,815	9,297	16,036	25,199	27,987	31,709	36,230	40514
	$x10^6$ psi	1.1335	1.3483	2.3258	3.6547	4.0590	4.5988	5.2545	5.8758
Erf(%)		-5.5455	-1.1143	1.1261	-0.0389	-0.0366	0.0745	-0.0442	0.0655
Err(%)		3.0455	-3.6929	1.1217	1.5194	-1.0000	-2.1532	1.0481	1.3069

Ea: actual elastic modulus.
Ef: elastic modulus estimated by FANN.
Er: elastic modulus estimated by RBFN.
Erf: error of the FANN.
Err: error of the RBFN

From Table 1, the differences between the true modulus of elasticity and the ANN evaluations are indeed very small; the percentage errors are varied from 0.04% to 5.5% for FANN and 1% to 3.69% for RBFN. They have assured that both neural networks can recognise velocity signatures and give accurate evaluations of the filters. Their performances point out that the proposed in situ evaluation procedure is viable. From our record, FANN takes two minutes for the training and evaluation while RBFN responds instantly. Their efficiency is indeed excellent.

8 Concluding Remarks

Two types of artificial Neural Networks, FANN and RBFN, are used to analyse the vibration signatures of the filters for the determination of their degree of deterioration. Both networks can perform the evaluation of the filter directly and accurately. But RBFN takes a much shorter time than FANN for the evaluation. This result shows that the proposed in situ non-destructive evaluation for the filter is a viable procedure, which is much more efficient and convenient than the traditional procedure. It also shows that ANN is an effective tool for non-destructive evaluation. The method presented here is a general method; it should not be confined to one application. It works for the ceramic candle filter; it should also work for any other similar engineering structural elements or engineering products in the industry.

9 Acknowledgements

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10 References

[1]. Ruth, Lawrence A., Advanced Pulverized Coal Combustion, Proceedings of the Advanced Coal-Based Power and Environmental System' 98 Conference, Morgantown, WV, July 1998.
[2]. Lipper, T.E., Bruck, G.J., Sanjana, Z.Alvin, M.A. and Newby, R.A., Performance of the Westinghouse APF in Pilot Scale Test Facilities, Proceedings of the Advanced Coal-Based Power and Environmental System' 98 Conference, Morgantown, WV, July 1998.
[3]. Roger H.L. Chen, Evaluation of Ceramic Candle filters Degradation and Damage Location, Final Report, Federal Energy Technology Center, US Department of Energy, January 1998.
[4]. Alvin, M.A., Tressler, T.E., Lippert, E.S., and Smeltzer, E.E., Durability of Ceramic Filters, Proceeding of Coal-Fired Power System'94, Advanced in IGGG and PFBC Review Meeting, Morgantown WV, June,1994.
[5]. Mark R. Warnes, Jarmila Glassey, Gray A. Montague, Bo Kara, Application of radial basis function and feedforward artificial neural network to Escherichia Coli fermentation process. Neurocomputing 20, 1998.
[6]. J.Moody, C.J. Darken, Fast learning in networks of locally-tuned processing units, Neural Comput. 1 (1989) 281-294.
[7] MathWorks, The Users' Manual of MATLAB, Version 5, MathWorks, Natick, MA.
[8] Computers and Structures, the Users' Manual of SAP2000, Computers and Structures, Inc., Berkeley, CA.