Monitoring of the Crack Propagation in Welded Joint of the Tank Using Multi-Class Recognition

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Abstract

The numerical analysis of the vertical weld-fabricated steel tank is carried out taking into account the defects of the welds in the form of through-the-thickness cracks of different lengths and numbers, which are located in different zones of the object's ring. The influence of defects on the stress of the tank is estimated in the places of sensors installation under the action of vertical load. The usage of multi-class recognition is proposed by classifier based on Probabilistic Neural Network for monitoring of the crack propagation. Multidimensional vectors of diagnostic features are used for multi-class recognition. The training set of vectors is formed for defect-free and defect conditions, the classifier is trained and tested, the analysis of recognition efficiency is carried out by using the probability of correct multi-class recognition.

Keywords: welded tank, stress, crack propagation, multi-class recognition, neural network classifier

1. Introduction

Modern monitoring systems of complex spatial objects and their structural elements implement the concept of Structural Health Monitoring (SHM) in the principles of their construction and operation [1, 2]. SHM systems are developed as extensive information networks that are similar to the human nervous system. The systems provide measurement, recording, conversion, transmission and complex analysis of data for recognition of the objects' current technical condition and the forecasting of its future changes. The development of monitoring systems is important for ensuring reliable and trouble-free operation of complex spatial objects of aeronautical engineering, energetic, oil-and-gas industry, which are characterized by multi-site damages in welded or riveted joining [3]. In general, the existence of such damages leads to multi-class technical condition of the objects in the temporal and spatial dimensions. Therefore, the actual problems of monitoring include multi-class diagnosis, evaluation and forecasting technical condition of objects at the multi-site damages. These problems can be solved by developing the multi-class recognition system based on artificial neural networks.

This paper is a continuation of the previous researches [4, 5] dedicated to development of the complex monitoring system of vertical weld-fabricated tanks with environmentally hazardous substances, whose operation is associated with various internal and external influences. The development of monitoring system is based on the complex application of data on the vibration state, stress-strain state parameters and the spatial position of the object together with the application of multi-class recognition system (classifier) based on Probabilistic Neural Network (PNN) [6, 7]. In general, the PNN-based classifier can solve the following problems of multi-class recognition: (a) localization of single crack or multi-site damages, (b) monitoring of cracks propagation, and (c) structure degradation is caused by cracks propagation. The results of solving the above mentioned problem (c) are given in [7].

The purposes of this work are: a) numerical analysis of the vertical weld-fabricated tank at the presence and propagation of single crack and several cracks, and b) analysis of the efficiency of multi-class recognition of tank condition at the crack propagation by PNN-based classifier.

2. Numerical analysis of tank at the presence and propagation of cracks in welded joining

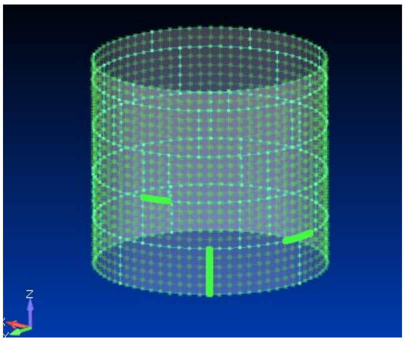
For the above purposes it is important to research the change of parameters of the stress-strain state of the tank structural elements under the influence of operational loads and possible damage to the surface integrity of the tank. It will allow to determine the sensitivity of the parameters of the stress-strain state to the appearance and propagation of cracks in the welds of the tank structure.

We use Finite Element (FE) Analysis to design the discrete model of the tank, which can be representative of an actual object as in paper [3]. For this purpose we consider the wall of tank shell made from steel with the following properties: Density 7850 kg/m^3; Modulus of Elasticity $2.06\cdot10^5$ N/m^2; Poison's ratio 0.3; Shear Modulus $0.79\cdot10^5$ N/m^2. The shell wall is welded from sheets of 5 mm thick. It is modeled in the form of rings, consisting of surfaces, the size of which corresponds to the tank sheets.

The wall is modeled by the set of the quadrangle plane FE with six degrees of freedom. Mechanical data of weld joints are accepted the same as for the material of the walls. Therefore, additional finite elements for simulation of weld joints are not used. The circumference of the shell is divided into 72 parts, and in height the shell is divided into 22 parts. The following defects models are constructed: one vertical (L1) and two horizontal (L2, L3) cracks of identical length, which occur consecutively one after another and are located in the first and second rings of the shell. Cracks in welds are modeled using a set of triangular and quadrangular flat FE. The width of all cracks is equal to the diameter of the weld 5 mm. The relative size of the cracks $\Delta l_i/l_i$ (i = 1, 2, 3) varies from 0 to 0,5, where Δl_i is the length of the crack, and l_i is the length of the weld where the crack is propagated. The discrete model of tank with cracks is presented in Figure 1a, and Figure1b shows the scheme of cracks location and the places of sensors installation (marked by 1-

5). The arrows indicate the various possible directions of the cracks propagation, which occur in a T-butt welds.

a)



b)

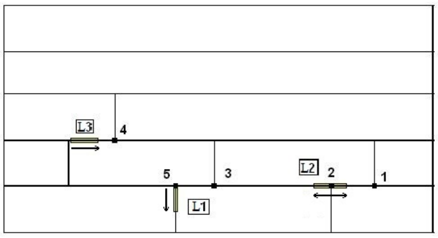


Figure 1. Discrete model of vertical weld-fabricated tank with cracks (a) and scheme of cracks location and the places of sensors installation (b)

Loads from the weight of the roof and other elements are modeled in the form of concentrated forces applied to the nodes of the upper edge of the model. The characteristic value of the load per node is 680.14 N, and the boundary design value of the load is 897.78 N.

Maxima of stress are obtained in the places of sensors installation at the occurrence and propagation of cracks. The results of the researches are presented in Table 1 for the case of the occurrence and propagation of one crack (L1), in Table 2 for the case of the simultaneous occurrence and propagation of two cracks (L1 and L2), and in Table 3 for the case of the simultaneous occurrence and propagation of three cracks (L1, L2 and L3).

Table 1. Stress in the places of sensors installation at the occurrence and propagation of one crack (L1)

Number of sensor	Stress, MPa				
	$\Delta l_1/l_1 = 0$	$\Delta l_1/l_1 = 0.05$	$\Delta l_1/l_1 = 0.1$	$\Delta l_1/l_1 = 0.2$	$\Delta l_1/l_1 = 0.5$
1	0.62140	0.62116	0.62141	0.62145	0.62182
2	1.30410	1.30410	1.09380	1.09400	1.09460
3	0.59157	0.59155	0.60189	0.60268	0.59856
4	0.71968	0.71981	0.69143	0.69121	0.69117
5	0.76733	0.83244	0.97446	1.19560	1.46780

Received results show that the stress values in the places of installation of sensors 1-4 change insignificantly or ambiguously as a function of relative size and number of cracks. The stress value increases at the location of sensor 5 in case of occurrence and propagation of the crack L1, as well as in cases of simultaneous occurrence and propagation of two and three cracks.

Table 2. Stress in the places of sensors installation at the simultaneous occurrence and propagation of two cracks (L1 and L2)

Number of sensor	Stress, MPa				
	$\Delta l_i/l_i = 0$	$\Delta l_i/l_i = 0.05$	$\Delta l_i/l_i = 0.1$	$\Delta l_i/l_i = 0.2$	$\Delta l_i/l_i = 0.5$
1	0.62140	0.62142	0.62170	0.62459	0.67330
2	1.30410	0.81758	0.61915	2.55720	0.97679
3	0.59157	0.60238	0.60224	0.60412	0.61870
4	0.71968	0.72340	0.69156	0.69167	0.69571
5	0.76733	0.83219	0.97372	1.19590	1.51340

Table 3. Stress in the places of sensors installation at the simultaneous occurrence and propagation of three cracks (L1, L2 and L3)

Number of sensor	Stress, MPa				
	$\Delta l_i/l_i = 0$	$\Delta l_i/l_i = 0.05$	$\Delta l_i/l_i = 0.1$	$\Delta l_i/l_i = 0.2$	$\Delta l_i/l_i = 0.5$
1	0.62140	0.62146	0.62176	0.62488	0.67814
2	1.30410	0.81750	0.61922	2.55830	0.98487
3	0.59157	0.60234	0.60241	0.60493	0.63228
4	0.71968	0.72420	0.69189	0.69305	2.22080
5	0.76733	0.83215	0.97360	1.20310	1.60160

The values of stress at the location of sensor 5 are practically identical for the same relative crack size $\Delta l_i/l_i$ in the cases of one, two or three cracks. This does not allow to recognize the tank conditions caused by different numbers of cracks according to the readings of sensor 5. However, the change of stress value at the location of sensor 5 can be used for the monitoring of propagation of one crack L1.

3. Multi-class recognition of tank condition at the crack propagation

We associate the diagnostic feature a_i with the coordinates of the location of each sensor. Generally, the spectral, correlation, statistical, fractal or other characteristics of the measured signals can be used as diagnostic features. According to the above mentioned results, the stress values in the places of installation of sensors are considered as diagnostic features. Thus, to determine the condition of the object we use a multidimensional vector of diagnostic features, which for our example contains five components:

$$A = (a_1; a_2; a_3; a_4; a_5)^T \; . \tag{1}$$

We will consider the problem of monitoring of the propagation of crack L1. Then we define the following five classes of the technical condition of the object for the data given in Table 1:

- class S_0 characterizes the defect-free condition ($\Delta l_1/l_1 = 0$);
- class S_1 characterizes the condition of crack propagation when relative crack size is $\Delta l_1/l_1 < 0.1$;
- class S_2 characterizes the condition of crack propagation when relative crack size is in the interval $0.1 \le \Delta l_1/l_1 < 0.2$;

- class S_3 characterizes the condition of crack propagation when relative crack size is in the interval $0.2 \le \Delta l_1/l_1 < 0.5$;
- class S_4 characterizes the condition of crack propagation when relative crack size is $\Delta l_1/l_1 \ge 0.5$.

Thus, the monitoring of the crack propagation in welded joint of the tank will be performed by means of the multi-class recognition of the technical condition of tank using the multidimensional vector of diagnostic features (1). We use a PNN-based classifier for recognition [7, 8]. The PNN is based on the architecture of a radial basis network, which consists of two layers. Neurons of the first layer have radial basis activation functions, and the second layer is called a competition layer. It estimates the probability of membership of the input vector with a particular class and compares the input vector with that class, the probability of membership with which is higher [8]. Each input vector of the PNN corresponds to a certain initial or target value, and an "input/target" membership vector is formed for a set of input and output values. The training set contains M pairs of "input/target" vectors. There are N classes of possible membership of the input vector. The number of neurons in the first layer is formed by the number of M pairs of "input/target" vectors of the training set. The output layer of competition contains N neurons, according to N classes.

One of the important elements of this classifier is the training set of diagnostic feature vectors (images). The algorithm presented in Figure 2 illustrates the process of formation of training and test sets of diagnostic feature vectors for multi-class recognition for the purpose of monitoring the crack propagation.

By using the presented algorithm and data given in Table 1, the training vectors of diagnostic features are formed for classes $S_0 - S_4$.

The training vectors of diagnostic features for class S_0 are as follows:

- one vector $A_0 = (a_{01};a_{02};a_{03};a_{04};a_{05})^T$, where a_{0i} are the stress values in the location of the sensors 1-5 for the defect-free condition ($\Delta l_1/l_1 = 0$);

- ten vectors formed from A_0 by using the permissible deviation $\Delta_0 = \pm 2.5\%$, the component of which a_{05} takes values from $0.975a_{05}$ to $1.025a_{05}$ with a step of 0.005;

- one vector A_0, the component of which a_{05} takes boundary value for the defect-free condition $a_{05} = 0.79$.

The occurrence and propagation of crack L1 causes the change of the stress value only at the location of sensor 5. Therefore, for the formation of the training vectors of diagnostic features that characterize the classes $S_1 - S_4$ of defective conditions of the object we use data for the features $a_1 - a_4$ shown in the Table 1, and for the component a_5 we will use the following range of values:

- for class S_1 the value of feature a_5 varies from 0.8 to 0.89 with a step of 0.01;
- for class S_2 the value of feature a_5 varies from 0.9 to 1.05 with a step of 0.01;
- for class S_3 the value of feature a_5 varies from 1.06 to 1.41 with a step of 0.05;
- for class S_4 the value of feature a_5 varies from 1.42 to 1.48 with a step of 0.01.

The total number of training vectors is 53 vectors for all conditions $S_0 - S_4$.

Multi-class recognition of tank condition was performed on the input test vectors of stress values after training the neural network classifier. We use data for the features

$a_1 - a_5$ shown in the Table 1 as the test sets of diagnostic feature vectors, the total number of test vectors is 5 vectors for all conditions $S_0 - S_4$.

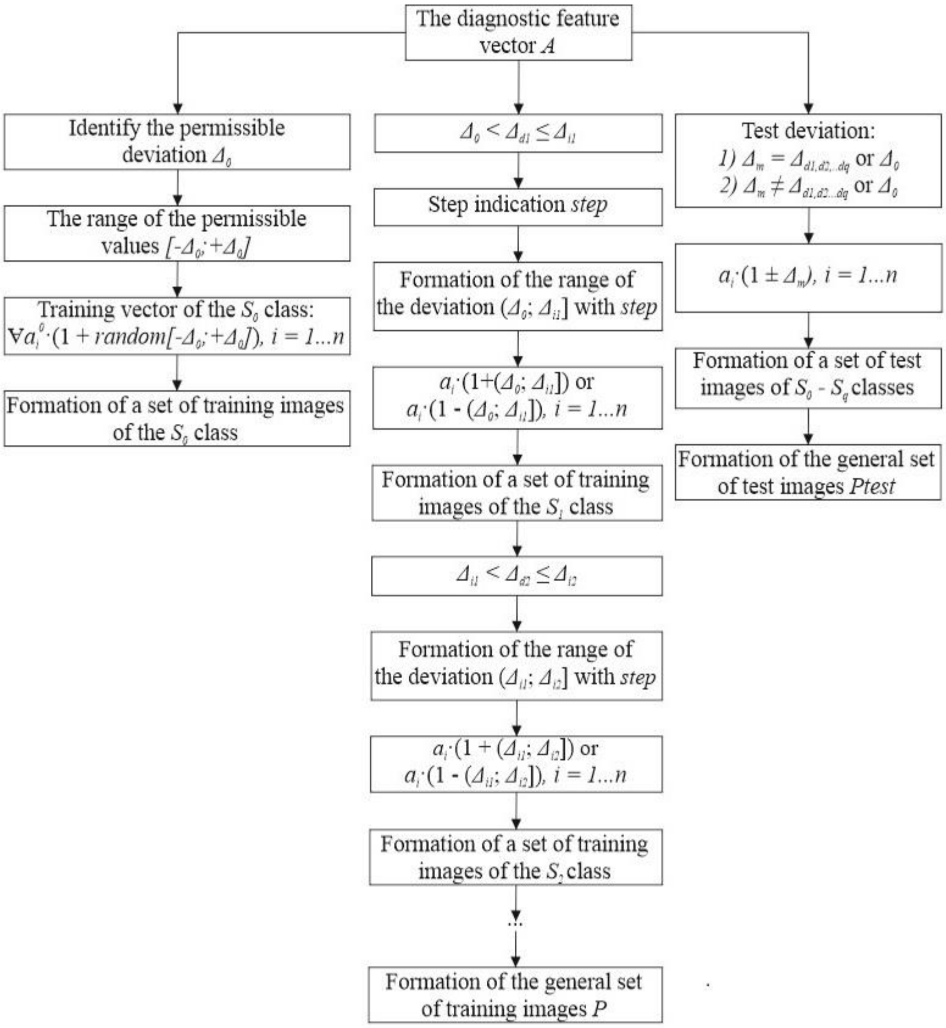


Figure 2. Algorithm of formation of training and test sets of diagnostic feature vectors

We evaluate the efficiency of multi-class recognition by the indicator K, which is determined in percentage as the ratio of the number of correctly classified vectors to the total number of input vectors [7]. Practically, the indicator K is a percentage of the probability of correct classification. However, as noted in [7], the probabilistic neural network parameter *spread* imposes functional conditions on classification accuracy. In the software implementation of PNN, this parameter is related to the mean square deviation of the Gaussian function, which specifies the width of the activation functions of neurons and determines their influence on the estimation of the total probability density. Therefore, the parameter *spread* affects the result of classification, during the network learning its value is taken without additional justification. The optimum value of the parameter *spread* is determined experimentally during the network testing and directly in the process of classification of test vectors as such that provides error-free recognition or with minimum possible errors.

According to the above, it is important to study the influence of the PNN parameter *spread* on the efficiency indicator *K*. For this aim the multi-class recognition of tank condition is performed for different values of parameter *spread*. The value of the *spread* parameter is changing in the range of values from 0.005 to 0.01 with an increment of 0.001, in the range of values from 0.01 to 0.1 – with an increment of 0.01, and in the range of values from 0.1 to 0.5 – with an increment of 0.1. Figure 3 shows the graph of the dependence of the recognition efficiency indicator *K* on the value of the PNN parameter *spread*.

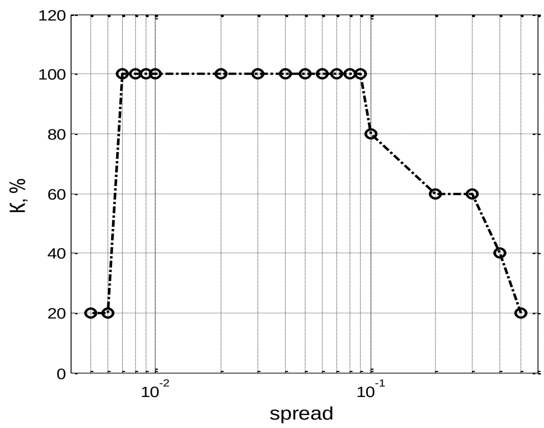


Figure 3. Graph of the dependence of the multi-class recognition efficiency indicator *K* on the Probabilistic Neural Network parameter *spread*

The presented results of the study of the influence of the PNN parameter *spread* on the efficiency indicator *K* have shown the possibility of error-free multi-class recognition of the object condition by the developed classifier. It is ensured if the value of the network influence parameter *spread* is in the range of [0.007; 0.09].

4. Conclusions

The numerical analysis of the vertical weld-fabricated steel tank is carried out taking into account the defects of the welds in the form of through-the-thickness cracks of different lengths and numbers, which are located in different zones of the object's ring. Maxima of stress are obtained in the places of 1-5 sensors installation under the action of vertical load at the occurrence and propagation of cracks. Received results show that the stress value increases at the location of sensor 5 in case of occurrence and propagation of the crack L1, as well as in cases of simultaneous occurrence and propagation of two and three cracks. The change of stress value at the location of sensor 5 is used for the monitoring of propagation of one crack L1.

The usage of multi-class recognition is proposed by classifier based on Probabilistic Neural Network for monitoring of the crack propagation. For recognition, multidimensional diagnostic feature vector that characterize the defect-free (S_0 class) and defective ($S_1 – S_4$ classes) object conditions is used. The algorithm of formation of training and test sets of diagnostic feature vectors for multi-class recognition is carried out for the purpose of monitoring the crack propagation. The developed PNN-based classifier is trained and tested.

The analysis of recognition efficiency, depending on the PNN parameter *spread*, is carried out by using the probability of correct multi-class recognition. It is found that the developed classifier provides error-free multi-class recognition of test vectors, if the value of the network influence parameter *spread* is in the range of [0.007; 0.09].

The received results indicate the possibility and efficiency of using the multi-class recognition by PNN-based classifier for monitoring of the crack propagation in welded joint of the tank. These results can be used for the further research taking into account the random values of relative sizes of the cracks at the time of cracks propagation.

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