INVESTIGATION OF BENDING OVER SHEAVE FATIGUE LIFE OF STRANDED STEEL WIRE ROPE BY ARTIFICIAL NEURAL NETWORKS

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Abstract— Steel wire ropes are used in elevators, cranes, mine hoistings, bridges, offshore and aerial ropeway systems. In this study, bending over sheave (BoS) fatigue lifetimes of 6 × 36 Warrington-Seale steel wire ropes have been determined experimentally. The artificial neural networks (ANN) was trained using experimental data through the back propagation algorithm containing double input and single output parameters. The results showed that there has been rather good correlation between predicted results by using ANN and the measured BoS fatigue life experimental data.

Keywords— Bending Over Sheave Fatigue, Steel Wire Rope, Artificial Neural Networks.

I. INTRODUCTION

Steel wire ropes are frequently used in elevators, cranes, mine hoistings, bridges, offshore and aerial ropeway systems. Steel wire ropes include many wires that wrapped to the fibre or wire core in order to form a strand. Several of strands are then twisted together to form rope. There has been great interest in rope technology area since application area of steel wire ropes becomes vast. In the application area, steel wire ropes are mainly subjected to fatigue since either ropes incur to the altering loads with time such as bridge or repetitive move on the sheaves such as cranes. First issue is called by tension-tension fatigue where ropes incur to the altering tensile load. Second issue is called by BoS fatigue where ropes incur to the repetitive bending combined with static tensile load.Many investigations have been conducted to identifying the effect of BoS fatigue to the lifetime of the steel wire ropes [1-5]. In addition, researchers used ANN to analyze the characteristics of wire ropes [6].The reasons of the use of ANN in process modeling are listed in Ye et al. [7] as the following: First, the recent advances in computer technology and parallel processing have made the use of ANN more economically feasible. Second, since the ANN is composed of nets of non-linear basis functions, it has the ability to evolve good process models from example data and require little or no a priori knowledge of the task to be performed. Third, ANN has the potential to solve certain types of complex problems that have not been satisfactorily handled by more traditional methods.

In this paper, effects of tensile load (S) and sheave diameter (D) to the BoS fatigue lifetimes of 6 × 36 Warrington-Seale steel wire ropes have been determined experimentally. Eight different tensile loads and two sheaves with different diameters have been employed for BoS fatigue tests. Then, artificial neural network model has been devised by using experimental test data and back propagation learning algorithm is used to predict the data obtained from the experimental tests. The results indicate that BoS fatigue life has been predicted with a good performance by the usage of designed neural network model.

II. ARTIFICIAL NEURAL NETWORKS: A BRIEF OVERVIEW

The artificial neural networks are basically computational models, which simulate the function biological networks, composed of neurons. In the literature most papers on the use of artificial neural networks apply a multilayered, feed forward, fully connected network of perceptions. Among the reasons for using this kind of ANN is the simplicity of its theory, ease of programming and good results. The system has three layers of neurons: input layer, a hidden layer and an output layer. The neurons or units of the network are connected by the weights. The input layer consists of all the input factors, information from the input layer is then processed through one hidden layer, and following output vector is computed in the final (output) layer. The scheme of ANN used in this paper is shown in **Fig. 1.**

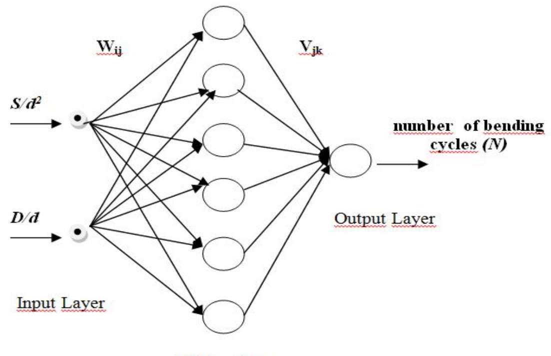

Fig.1. The scheme of ANN

Back propagation (BP), which is one of the most famous training algorithms for multi-layer perceptions, is a gradient descent technique to minimize the error for particular training pattern. Although BP training algorithm has some drawbacks, this method was preferred due to its simplicity and reliability. Each input unit of the input layer receives input signal X_i and broadcasts this signal to all units in the hidden layer. Each hidden unit Y_j sums its weighted input signal and applies its activation function to compute output signal.

$$Y_j = f\left(\sum_{i=1} W_{ij} X_i + b_j\right) \quad (1)$$

where f is the activation function, W_{ij} is the weight of the connection from the ith input unit to the jth hidden unit, $b_j$is the weight of bias connection for jth hidden unit. The output signal of the hidden unit Y_j is sent to all units in the output layer. Each output unit O_k sums its weighted input signal and applies its activation function to compute its output signal.

$$O_k = f\left(\sum_{j=1} V_{jk} Y_j + b_k\right) \quad (2)$$

whereV_{jk} is the weight of the connection from the jth hidden unit to the kth output unit. The parameter of bias (b) in Eqs. (1) and (2), also called the threshold value, is permanently set to 1 in hidden layer as well as output layer so that corresponding weight shifts the activation function along the X axis. The activation function used in this study is a logistic sigmoid function defined as,

$$f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

The BP training algorithm is an iterative gradient descent algorithm, designed to minimize the sum of square error (E) which is averaged over all patterns and is calculated as follows,

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{k=1}^{K}(de_{pk} - O_{pk})^2 (4)$$

where$de_{pk}$is the desired or actual output, O_{pk} is the predicted output for the pth k pattern. During training, an ANN is presented by the data for thousands of times, which is referred to as cycles. After each cycle the error between the ANN output and desired values are propagated backward to adjust the weight in a manner to mathematically guarantee to converge. Detailed description of the mathematical formulation of the BP can be found in [8].

In this paper, the available data set is partitioned into three parts. Those are corresponding to training, testing and validation of the model. Using experimental data, an optimized ANN model was developed to predict the BoS fatigue lifetimes of the 6 × 36 Warrington-Seale steel wire ropes. All simulations were performed in the MATLAB environment using its ANN toolbox. In order to stop training automatically, there is a need for error evaluation. Mean square error (MSE) which is the average squared difference between outputs and targets was calculated by using following expression,

$$MSE = \frac{1}{m}\sum_{k=1}^{m}(de_i - O_i)^2 (5)$$

wherede_i is desired or actual value, O_i the predicted output value and m is the number of data.

The experimental data sets consist of 8 samples of which 45% were used for training the network and 30% were selected randomly to test the performance of the trained network. A final check on the performance of the trained network is made using a validation set [9].

III. EXPERIMENTAL STUDY

Experimental tests have been performed in the Rope Technology Laboratory of Institute of Mechanical Handling and Logistics (Institut für Fördertechnik und Logistik (IFT), University of Stuttgart, Germany) so as to determine effects of tensile load and sheave diameter to the BoS fatigue life of steel wire rope running with sheaves.

In this study, steel wire rope samples with 10 mm in diameter (d) have been used. Investigated steel wire rope construction is 6 × 36 Warrington-Seale (WS) rope with Independent Wire Rope Core (IWRC). Investigated rope construction has six strands around a steel core which is a wire rope itself. 6 × 36 Warrington-Seale rope with IWRC can be used by mine hoisting, oil industry, cranes etc. 6 × 36 Warrington-Seale rope construction offers optimum resistance in fatigue and crushing. Cross-section of 6 × 36 Warrington-Seale rope with IWRC used in this study is shown in **Fig. 2.**

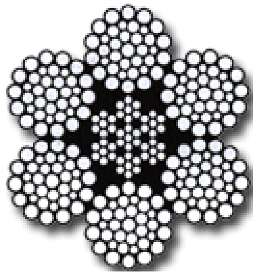

Fig.2. Cross section of rope sample used: 6 x 36 Warrington-Seale with IWRC [2]

Rope samples were moulded by lead casting cones on each end and connected to backing rope so as to form a loop which is necessary for the test[2]. In this study, eight different tensile loads and two sheaves with different diameters have been employed for BoS fatigue tests to determine effects of tensile load and sheave diameter to the BoS fatigue lifetimes of 6 × 36 WS rope with 10 mm diameter. Sheaves with 250 mm and 100 mm in diameters have been used. Tensile loads which are 15 kN, 20 kN, 25 kN and 30 kN have been employed when sheave with 250 mm in diameter is used and tensile loads which are 10 kN, 15 kN, 20 kN and 25 kN have been employed when sheave with 100 mm in diameter is used in the BoS fatigue tests. Test results are given in **Table 1**.

IV. RESULTS AND DISCUSSION

In this ANN model, two variables groups, specific tensile load (S/d^2) and diameter ratio (D/d) parameters have been chosen as the input parameters, and number of bending cycles (N) has been regarded as the output parameter. In order to decide the optimum structure of neural network, the rate of error convergence was checked by changing the number of hidden neurons. The networks were trained up to cycles where the level of MSE is satisfactory and further cycles had no significant effect on error reduction. Some of the parameters used for ANN and obtained values were given in **Table 2**. Results obtained from ANN and experimental results were given in **Table 1**.

Table 1: Experimental and ANN BoS fatigue life results for 6 × 36 Warrington-Seale rope

6 × 36 Warrington-Seale rope					
D = 250 mm (D/d=25)			D = 100 mm (D/d=10)		
Tensile load	N_{test} (cycles)	N_{ANN} (cycles)	Tensile load	N (cycles)	N_{ANN} (cycles)
S=15 kN	163456	174693	S=10 kN	32516	32515.07
S=20 kN	86792	86791.7	S=15 kN	27774	28832.4
S=25 kN	69619	70295.4	S=20 kN	13170	15469.4
S=30 kN	38505	35504.9	S=25 kN	4684	4682.4

Table 2: Network details and results

Network parameters	*Output parameters*
Hidden neuron number-	18
number of iterations	1000
MSE (test)	0.0036577
MSE (training)	0.0029135
MSE (validation)	0.0001987

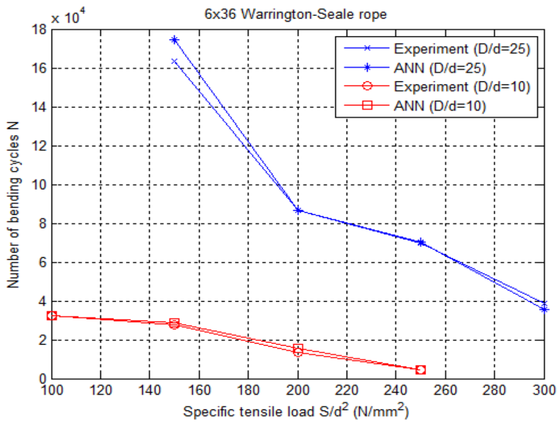

Fig.3. Experimental and ANN BoS fatigue lifetime results

As shown in **Fig. 3**, the results are very close to the experimental data. It can be seen in **Fig. 3** that ANN results exhibit a good agreement with experimental results both for sheaves with 250 mm and 100 mm in diameters. These findings demonstrate that artificial neural networks produce proper prediction and useful results.

CONCLUSIONS

This paper aimed to evaluate the artificial neural network in predicting Bos fatigue lifetime. Although there are some more theoretical estimations and analysis for BoS fatigue lifetime predictions they require substantial expertise in the mathematical definitions of equations. As an alternative to the existing references, an attempt has been made to model predicting BoS fatigue lifetimes of 6 × 36 Warrington-Seale steel wire ropes employing feed forward artificial neural networks. For this purpose an optimum neural network has been constructed and its predictions were compared with the existing experimental data. The results showed rather good correlation with the experimental data and it has been concluded that the ANN model can be effectively utilized as a prediction tool for such a purpose.

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