Neural modelling of cavitation erosion process of 34CrNiMo6 steel

M Szala\(^1\) and M Awtoniuk\(^2\)

\(^1\) Lublin University of Technology, Faculty of Mechanical Engineering, Department of Materials Engineering, 36 Nadbystrzycka Street, 20-618 Lublin, Poland

\(^2\) Warsaw University of Life Sciences, Institute of Mechanical Engineering, Nowoursynowska 164, 02-787 Warsaw, Poland

m.szala@pollub.pl

Abstract. Artificial neural networks (ANN) are commonly used to solve many industrial problems. However, their application for cavitation erosion evaluation is a quite new attempt. Thus, the aim of this work was to elaborate the neural model of the cavitation erosion process of 34CrNiMo6 steel. Cavitation erosion tests were conducted with a usage of the ultrasonic vibratory method with stationary specimen that relies on the ASMT G32 standard. The proceeding damage of marked steel surface area was observed by means of a scanning electron microscope. Wear was evaluated with profiler measurements, image analysis of cavitation worn surface areas and weighing done in stated time intervals. The cavitation erosion results were analysed with Matlab software by Neural Network Toolbox. The developed neural model of cavitation erosion process that combines exposure time, roughness, area fraction of worn surfaces, and mass loss gives promising results.

1. Introduction

The process of cavitation erosion (CE) of structural materials still seems to be a phenomenon, which is not entirely understood. Cavitation consists in formation and subsequent implosion of vapour bubbles due to local pressure fluctuations in liquid that affects the solid surface, resulting in the material surface layer deterioration. Wear due to cavitation is a common problem in fluid machinery, diesel engines, propellers, pipelines, valves and many more machine components [1–8].

The cavitation erosion is considered as a fatigue process which does not present a constant erosion rate [9,10]. Thus, cavitation wear intensity was divided into four stages: incubation, acceleration, deceleration and terminal, schematically plotted in Figure 1. Even though the main goal of CE testing is to calculate the material mass or volume loss, many researchers focus on investigating the incubation process, first initial stage of erosion. Literature on the subject reports that many researchers take an attempt to characterise CE long-time resistance on the basis of the incubation period or discuss behaviour of the material in the initial period of erosion. For instance, Dybowski et al. [11] analysed the incubation period of the magnesium alloy, as well as the incubation period of Al-Si based alloys [12]. Dular et al. [13] developed the original cavitation erosion model on results of study conducted in the incubation period of CE. Franc et al. [14] investigated the incubation period of work hardened materials, while Garcia et al. [15] observed the initial stage of epoxy coatings erosion, and Ning et al. [16] described the initial period of erosion of epoxy resin, ceramic and Polyurethane coatings. It is worth to mention that the incubation stage is easy to observe for metal alloys due to their plastic deformation...
[17–20]. Therefore, ceramic materials or thermally sprayed coatings present a limited incubation period of erosion; thus, thermally sprayed ceramic containing coatings exhibits a negligible incubation stage [21–24]. On the other hand, it is acknowledged by the literature that physical vapor deposited ceramic hard films presents superior to steel cavitation erosion [25–27]. It can be concluded that material factors play a crucial role in wear behaviour or materials.

Generally, investigating erosion resistance with a usage of standard test rigs such as vibratory, rotating disc or liquid jet test stand and standardised procedures is time-consuming [28]. Therefore, there still is a demand for elaboration of method that allows to estimate or predict cavitation erosion behaviour of structural metal alloys in a short period of time. Especially, the analysis of wear process done in the incubation period of erosion is considered as a promising solution. The previous paper [1] gave auspicious results for application of computer image analysis software for cavitation erosion description. Thus, in present work the artificial neural network (ANN) was implemented to model CE processes. Especially, that ANN is a promising method for solving problems in various branches and has different applications. ANNs allow to obtain satisfying results for biomedical engineering [29], electrical engineering [30], mechanical engineering [31,32], materials engineering [33,34], pharmacology and pharmacy [35], nutrition and food technology [36]. In addition, Nasiri et al. [37] employed the ANN for cavitation erosion prediction in a centrifugal pump.

Literature on the subject presents application of the ANN for various wear processes prediction [19,38–40]. Even though there are some works presenting its application for modelling the cavitation erosion processes [19] with usage of roughness and residual stress, modelling on the basis of image analysis was not reported in the literature. Therefore, this paper presents the analysis of the cavitation erosion results published in previous paper [1], with the usage of artificial intelligence i.e. ANN.

This paper has two major objectives. First, the main one, is to develop a neural model of the cavitation erosion process of 34CrNiMo6 steel. Second one is to investigate possibilities to use the image analysis as an effective method of creating a useful signal in a process of modelling this phenomenon. The application combination of artificial intelligence with the image analyses processing cavitation damaged worn areas is a new idea, which has not been previously reported in the literature.

2. Material and methods

2.1. Cavitation erosion test of 34CrNiMo6 steel

The description of cavitation erosion experiment is given in the previous work [1]. The 34CrNiMo6 steel was used as a representative material. Total test time lasted for 120 minutes and during time intervals the material mass loss, roughness development and fraction area of damaged surface were

![Figure 1. Cavitation erosion curves with typical period names (∆m – mass loss, ∆V – volume loss) [1].](image-url)
The mass loss $\Delta m$ was estimated with 0.1 mg accuracy and the roughness profile parameter $Ra$ (arithmetic mean of absolute departures form the mean line) was measured with surface profiler. The image analysis was conducted with ImagePro software, which allows to estimate the fraction area of damaged surface $vf$. Observations were done in the marked sample surface, measurement procedure is described in reference [1]. These three quantitative results were used for the ANN procedure. In addition, the damaged surface was observed with usage of the scanning electron microscope (SEM) equipped with BSE and Topo modes. Observation was conducted in the marked area after stated time intervals of cavitation testing.

2.2. Development of artificial neutrons network model

The ANN model was elaborated with usage of Matlab environment (2017a) and Neural Network Toolbox. The model block diagram is shown in Figure 2. The input signals were cavitation exposure time $t$ [min], roughness parameter $Ra$ [$\mu$m] and volume fraction of damaged surface $vf$ [%]. The output signal was the mass loss $\Delta m$ [mg] measured after each cavitation erosion testing time-interval. Mass loss is a parameter describing the degree of cavitation wear [1].

The neural model consisted of an input layer, a hidden layer and an output layer. Each of layers was characterized by a certain number of neurons. For example, the model described as 3-2-1 means a network with 3 input neurons, 2 hidden neurons and 1 output neuron. The number of neurons in the input and output layers was related to the number of input and output signals of the model. The number of neurons in the hidden layer was determined experimentally by evaluating the performance of neural networks with different numbers of hidden neurons. Details of this analysis will be described in the Results and discussion section. Learning took place according to Levenberg-Marquardt backpropagation algorithm. The maximum number of epochs to train the network was equal to 15. As a result of the research, $n = 8$ measurement samples were received. Due to the limited data set, k-fold cross validation was decided to be performed. A predicate $k = n$ was assumed, so it was a type of the so-called leave-one-out cross validation [41].

Two model performance evaluation indexes were used: normalised root mean square error NRMSE (informally called fit, which was the name used hereinafter) and root mean square error RMSE. By and large, the model describes the phenomenon in more detail, if the fit value is higher and the RMSE value is lower. The indexes were calculated as follows:

$$\text{fit} = \left( 1 - \frac{\|y - \hat{y}\|_2}{\|y - \bar{y}\|_2} \right) \times 100\%$$

$$\text{RMSE} = \frac{\|y - \hat{y}\|_2}{Ns}$$

where: $y$ – output signal (measured), $\hat{y}$ – predicted output signal, $\bar{y}$ – mean of output (measured) signal, $Ns$ – the number of samples.
3. Results and discussion

Cavitation erosion results

Table 1 presents the results of mass loss, roughness measurements and volume fraction of damaged surface areas. The cavitation worn surface of steel is presented in Figures 3 and 4. It is obvious that the incubation period of erosion lasted for 20 minutes of cavitation testing. On the basis of analysis of data from Table 1 and morphology of surface (Figure 3 and 4) versus time, results may be assumed as complementary. Wear parameters were increasing nonlinearly with time. The scanning electron microscope SEM observations allowed qualitative evaluation of damaged surfaces. The results indicate development of cavitation pits, with visible plastic deformation and surfaces roughening that proceeded along with time. The quantitative results form Table 1 were used to build up the ANN model of the cavitation erosion process of 34CrNiMo6 steel.

Table 1. The values of cavitation erosion experiment.

| Cavitation exposure time, \( t \) [min] | Surface roughness, Ra [\( \mu m \)] | Volume fraction, \( vf \) [%] | Mass loss, \( \Delta m \) [mg] |
|----------------------------------------|-----------------------------------|----------------------------|---------------------|
| 0                                     | 0.065                             | 1.55                       | 0                   |
| 5                                     | 0.070                             | 5.77                       | 0                   |
| 10                                    | 0.100                             | 7.34                       | 0                   |
| 20                                    | 0.100                             | 19.64                      | 0                   |
| 40                                    | 0.140                             | 50.42                      | 3                   |
| 60                                    | 0.170                             | 60.18                      | 8                   |
| 90                                    | 0.205                             | 62.50                      | 13                  |
| 120                                   | 0.230                             | 70.20                      | 15                  |

Figure 3. Development of the selected surface area observed after 0, 20, 40, 120 minutes of cavitation testing. Scanning electron microscope (SEM), BSE mode, 5000x.
Figure 4. Development of the selected surface area observed after 0, 20, 40, 120 minutes of cavitation testing. Scanning electron microscope (SEM), SEM-Topo mode (lower row), 5000x.

Modelling the cavitation erosion with ANN

Figures 5-7 show how the model performance has changed depending on the number of neurons in the hidden layer and selected input signals. All networks in the studied range had a high model performance for learning data, i.e. fit index value above 99% and RMSE below 0.013. For this reason, selection of the number of neurons in the hidden layer depended on fitting to the test data. When selecting the size of the hidden network layer, the principle of savings was followed, i.e. network with the highest fit to data with the smallest possible structure was chosen. Finally, neural models $M_1$, $M_2$, and $M_3$ were chosen, having following structures:

- $M_1$: 3-5-1 for net with time $t$, roughness $Ra$, and volume fraction $vf$ as inputs signals (Figure 5),
- $M_2$: 2-6-1 for net with time $t$, and roughness $Ra$ as inputs signals (Figure 6),
- $M_3$: 2-3-1 for net with time $t$, and volume fraction $vf$ as inputs signals (Figure 7).

Table 2 shows the values of fit and RMSE indexes for selected neural models.

Figure 5. Model performance indexes for model $M_1$ with 3 inputs (time $t$, volume fraction $vf$, and roughness $Ra$) and different numbers of neurons in hidden layer.
The network with three input signals (model M1) captures cavitation wear most accurately. The model can be reduced to two input signals (M2 and M3 models). This will result in a decrease in the fit index by approximately 2.4 percentage points and an increase in the RMSE value (more than 3 times). M2 and M3 models differ in one input signal. In the M2 model, roughness at the input was considered while in the M3 model it was volume fraction.

Using roughness as a network input is a popular solution. For example, in [19] also a neural model was built with two input signals, i.e. cavitation time and roughness. The network has reached the RMSE value of 0.13. Unfortunately, authors do not specify whether this is a value for learning or testing dataset, so it is difficult to accurately compare the results.
Nevertheless, replacing roughness with a parameter resulting from image analysis, i.e. volume fraction, is a novelty. The results show that it is impossible to clearly judge which version of the network gives more accurate results, M_2 (with roughness as an input) or M_3 (with volume fraction as an input). Therefore, it can be assumed that image analysis is an alternative method of determining cavitation wear.

4. Conclusions
Current paper presents the usage of ANN for describing the cavitation erosion process. The ANN seems to be an auspicious tool for modelling this phenomenon owing to high model performance.

This new attempt that relies on usage of image analysis results i.e. volume fraction (vf) can be successfully used for cavitation erosion phenomena modelling.

Model performance analysis has shown that the most accurate model was the one with three input signals. However, the structure of the model can be successfully reduced to two input signals, i.e. exposure time and roughness or exposure time and volume fraction. Both reduced models have achieved an acceptable performance (fit index was approx. 96.5% and RMSE index 0.204 for testing dataset). It indicates that the models created on the basis of roughness, as well as image analysis results (vf) can be effectively build up and implemented for cavitation erosion process simulation.

ANN model that considers the volume area fraction damaged due to cavitation erosion is an original attempt for description of cavitation erosion process and will be developed in future works.

5. References
[1] Szala M 2017 Application of computer image analysis software for determining incubation period of cavitation erosion – preliminary results ITM Web of Conferences 15 06003
[2] Krella A K and Zakrzewska D E 2018 Cavitation Erosion – Phenomenon and Test Rigs Advances in Materials Science 18 15–26
[3] Francis T & 2014 Cavitation And The Centrifugal Pump: A Guide For Pump Users (Hardback) - Taylor & Francis
[4] Franc J-P and Michel J-M 2004 Fundamentals of Cavitation vol 76 (New York, Boston, Dordrecht, London, Moscow: Kluwer Academic Publishers)
[5] Brennen C E 1995 Cavitation and Bubble Dynamics (Oxford: Oxford University Press)
[6] Chmiel J, Jasionowski R and Zasada D 2015 Cavitation Erosion and Corrosion of Pearlitic Gray Cast Iron in Non-Standardized Cavitation Conditions Solid State Phenomena
[7] Zhang L, Liu Y-H, Luo K-Y, Zhang Y-K, Zhao Y, Huang J-Y, Wu X-D and Zhou C 2018 Tensile Property of ANSI 304 Stainless Steel Weldments Subjected to Cavitation Erosion Based on Treatment of Laser Shock Processing Materials 11 805
[8] Jasionowski R, Przetakiewicz D and Przetakiewicz W 2014 Cavitation Erosion Resistance of Alloys Used in Cathodic Protection of Hulls of Ships Archives of Metallurgy and Materials 59 241–245
[9] Richman R H and McNaughton W P 1990 Correlation of cavitation erosion behavior with mechanical properties of metals Wear 140 63–82
[10] Anon 2010 ASTM G32-10: Standard Test Method for Cavitation Erosion Using Vibratory Apparatus (PA, USA: ASTM International: West Conshohocken, Philadelphia)
[11] Dybowski B, Szala M, Kielbus A and Hejwowski T J 2015 The mechanisms of cavitation erosion of the Elektro21 magnesium alloy Solid State Phenomena 229 99–104
[12] Dybowski B, Szala M, Hejwowski T J and Kielbus A 2015 Microstructural phenomena occurring during early stages of cavitation erosion of Al-Si aluminium casting alloys Solid State Phenomena 227 255–8
[13] Dular M, Stoffel B and Sirok B 2006 Development of a cavitation erosion model Wear 261 642–655
[14] Franc J-P 2009 Incubation Time and Cavitation Erosion Rate of Work-Hardening Materials J. Fluids Eng 131
[15] García G L, López-Ríos V, Espinosa A, Abenojar J, Velasco F and Toro A 2014 Cavitation resistance of epoxy-based multilayer coatings: Surface damage and crack growth kinetics during the incubation stage Wear 316 124–32

[16] Qiu N, Wang L, Wu S and Likhachev D S 2015 Research on cavitation erosion and wear resistance performance of coatings Engineering Failure Analysis 55 208–23

[17] Romo S A, Santa J F, Giraldo J E and Toro A 2012 Cavitation and high-velocity slurry erosion resistance of welded Stellite 6 alloy Tribology International 47 16–24

[18] Bregliozzi G, Schino A D, Ahmed S I-U, Kenny J M and Haefke H 2005 Cavitation wear behaviour of austenitic stainless steels with different grain sizes Wear 258 503–10

[19] Gao G, Zhang Z, Cai C, Zhang J and Nie B 2019 Cavitation Damage Prediction of Stainless Steels Using an Artificial Neural Network Approach Metals 9 506

[20] Krawczyk J, Jasionowski R, Ura D, Goły M and Frocisz Ł 2018 The effect of cavitation erosion on austenitic-ferritic steel Zeszyty Naukowe Akademii Morskiej w Szczecinie 56

[21] Szala M and Hejwowski T 2018 Cavitation Erosion Resistance and Wear Mechanism Model of Flame-Sprayed Al2O3-40%TiO2/NiMoAl Cermet Coatings Acta Phys. Pol. A 136 342–7

[22] Szala M, Walczak M, Pasierbiewicz K and Kamiński M 2019 Cavitation Erosion and Sliding Wear Mechanisms of AlTiN and TiAlN Films Deposited on Stainless Steel Substrate Coatings 9 340

[23] Krella A and Czyżniewski A 2008 Cavitation erosion resistance of nanocrystalline TiN coating deposited on stainless steel Wear 265 963–70

[24] Krella A K 2011 The new parameter to assess cavitation erosion resistance of hard PVD coatings Engineering Failure Analysis 18 855–67

[25] Winiczenko R, Salat R and Awtoniuk M 2013 Estimation of tensile strength of ductile iron friction welded joints using hybrid intelligent methods Transactions of Nonferrous Metals Society of China 23 385–391

[26] Kosowski K, Tucki K and Kosowski A 2010 Application of Artificial Neural Networks in Investigations of Steam Turbine Cascades Journal of Turbomachinery 132

[27] Zagórski I and Kulisz M 2019 Effect of technological parameters on vibration acceleration in milling and vibration prediction with artificial neural networks ed M Kulisz, M Szala, M Badurowicz, W Cel, M Chmielewska, Z Czyz, K Falkowicz, J Kujawska and T Tulwin MATEC Web of Conferences 252 03015

[28] Zagórski I, Kulisz M, Klonica M and Matuszak J 2019 Trochoidal Milling and Neural Networks Simulation of Magnesium Alloys Materials 12 2070

[29] Salat R and Salat K 2015 Modeling analgesic drug interactions using support vector regression: a new approach to isobolographic analysis. Journal of pharmacological and toxicological methods 71 95–102
[36] Winiczenko R, Górnicki K, Kaleta A and Janaszek-Mańkowska M 2018 Optimisation of ANN topology for predicting the rehydrated apple cubes colour change using RSM and GA Neural Comput & Applic 30 1795–809

[37] Nasiri M R, Mahjoob M J and Vahid-Alizadeh H 2011 Vibration signature analysis for detecting cavitation in centrifugal pumps using neural networks 2011 IEEE International Conference on Mechatronics 2011 IEEE International Conference on Mechatronics pp 632–5

[38] Kurt H I and Oduncuoglu M 2015 Application of a Neural Network Model for Prediction of Wear Properties of Ultrahigh Molecular Weight Polyethylene Composites International Journal of Polymer Science

[39] Humelnicu C, Ciortan S and Amortila V 2019 Artificial Neural Network-Based Analysis of the Tribological Behavior of Vegetable Oil–Diesel Fuel Mixtures Lubricants 7 32

[40] D’Addona D M, Ullah A M M S and Matarazzo D Tool-wear prediction and pattern-recognition using artificial neural network and DNA-based computing Journal of Intelligent Manufacturing 1–17

[41] Tangirala A K 2015 Principles of system identification : theory and practice (Boca Raton: CRC Press)