Neural Network Prediction of Slurry Erosion Wear of Ni-WC Coated Stainless Steel 420

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Abstract: In the present study, Erosion wear of stainless steel 420 was predicted using an artificial neural network (ANN). Stainless steel 420 is used for making slurry transportation components, such as pump impellers and casings. The erosion wear performance was analyzed by using a slurry pot tester at the rotational speed of 600–1500 rpm with a time duration of 80–200 min. Fly ash was used as an erodent medium, and the solid concentration varied from 20 to 50%. The particle size of erodent selected for the erosion tests was <53 µm, 53–106 µm, 106–150 µm, 150–250 µm. A standard artificial neural network (ANN) for the prediction of erosion wear was designed using the MATLAB program. Erosion wear results obtained from experiments showed a good agreement with the ANN results. This technique helps in saving time and resources for a large number of experimental trials and successfully predicts the erosion wear rate of the coatings both within and beyond the experimental domain.

Keywords: slurry erosion; stainless steel fly ash; artificial neural network

1. Introduction

Slurry pipelines are commonly utilized to transport solid goods across short and large distances using carrier fluids. Solid minerals are transported in industrial applications utilizing carrier fluids, such as air, water, and oil [1,2]. As water is less costly and more easily accessible, it is commonly used as a carrier fluid in slurry transportation. Pipelines convey solid materials in a variety of particle shapes and sizes. Other factors that impact solid-liquid flow behavior include particle size, solid material concentration, flow velocity, slurry viscosity and density [3–5]. Researchers have been working on the successful transportation of slurry with high solid concentrations and investigating the head loss characteristics of slurry flow in pipelines over the past decade. The slurry tends to cause erosion wear of various components of the hydraulic system handling the slurry which includes the hydraulic machines as well. Erosion wear of these machine components tends to reduce the reliability of the hydraulic system and in the process increases the related maintenance cost and affects component working life [6]. To avoid erosion, and wear-related issues in slurry handling hydraulic components, material selection is very important. A literature review of available research was conducted before experimenting and it was found that several different surface coatings and methods of deposition were used by different researchers to increase the erosion and corrosion resistance of pump and turbine component materials. The HVOF (high velocity oxyfuel) method of surface coating is widely used by different industries. HVOF process coated material gives better erosion,
corrosion, and abrasion resistance to hydraulic machinery [7,8]. High hardness is a significant parameter that participates in the improvement of erosion performance [7–10]. Further, the addition of various feedstocks helps improve different properties of coating [9–12]. Artificial neural networks (ANN) models are increasingly being employed as a trustworthy modeling tool for accurate prediction and online monitoring of actual process data, which arises in a variety of engineering applications. ANNs are made up of several interconnected processing pieces called neurons or cells that are linked by weighted connections. The system of biological neurons, whose connections are provided by synapses, inspired neural networks [13,14]. Many researchers have used different kinds of ANN models. Modeling of multiphase reactors [15], applications in process control [16–22], predictions from experiments in catalysis [23–25] to estimate the composition of a mixture [26–31], modeling of pump-mixer characteristics [32,33], chemical reactor modeling [34], experimental investigation of wastewater treatment applications [35–38], and so on have all been successfully applied with ANNs.

2. Experimental Investigation

A slurry erosion pot tester (Ducom: TR-401, Bangalore, India) was used to perform the slurry erosion wear experiments. The schematic diagram of the slurry erosion pot tester is depicted in Figure 1. It consists of a cylindrical container which is known as a pot, a rotating spindle and a screwed jaw. The capacity of the pot was about 2000 mL, which was used for pouring the slurry into it for performing slurry tests. A mark is made inside the cylindrical pot. The slurry is filled into the pot up to that mark so that the test specimen is completely dipped into the slurry for the accurate results of erosion tests. A screw jack is used for the height adjustments of the cylindrical pot and also used for the loading and unloading of the pot during experimentation. An impeller was fixed at the bottom of the spindle with screw threads which helps in the complete movement of slurry particles and also helps in the prevention of slurry settling at the bottom of the pot during experimentation. The test specimen is tightened horizontally, i.e., at a 0° impact angle in the spindle with the help of the impeller so that the test specimen and the impeller both rotate at the same speed. The mass of the test specimen was measured before and after the erosion experiment and the change in mass was considered as the loss of eroded material. The mass loss measurements were performed with the use of an electronic micro-balancer having the least count of 0.0001 gm. For the mass loss measurements of the test specimen, it was completely washed with acetone and dried for some time and a reading is noted during each cycle.

Figure 1. Photograph of slurry pot tester.
2.1. Slurry Preparation

To make the accurate and appropriate solid concentration of fly ash slurry, solid particles of fly ash were added to a fixed amount of water. The weight of the water and the solid particles of fly ash were measured with the help of a weighing machine (Ducom instruments limited, Bangalore, India) having a resolution of 0.1 gm. After adding fly ash particles into the water, the slurry was well mixed so that the solid particles do not settle down in the container.

2.2. Operational Conditions

Experiments of slurry erosion were performed at different levels of solid concentration, impact velocity (rotational speed), particle-size range of erodent and time duration of the experiment. The solid concentration of erodent was taken from 20 to 50% (by weight). The erosion tests were conducted at four rotational speeds namely 600, 900, 1200 and 1500 rpm with the time duration of 80, 120, 160 and 200 min. The particle size of erodent selected for the erosion tests was <53 µm, 53–106 µm, 106–150 µm, and 150–250 µm.

3. Materials and Methods

3.1. Specimen

Stainless steel (SS) 420 was taken as a base material which is utilized as slurry transportation material. The chemical configuration of SS-420 is given in Table 1. Rectangular-shaped specimens of 60 mm × 25 mm × 6 mm dimensions with an 8 mm diameter central hole were cut from the substrate material for erosion tests. The isometric view of the test specimen is depicted in Figure 2.

Table 1. Chemical composition of SS-420 (wt. %).

| Element | C  | Cr  | Mn  | Si  | P   | Ni  | S   | Fe  | Others |
|---------|----|-----|-----|-----|-----|-----|-----|-----|--------|
| wt. %   | 0.13 | 12.55 | 0.85 | 0.95 | 0.04 | 13.95 | 0.035 | 61.65 | Rest   |

Figure 2. Geometry of test specimen.

3.2. Deposition of Coating Powders

The high-velocity oxy-fuel (HVOF) system was used for the deposition of different combinations of coating powders of Nickel (Ni), Chromium oxide (Cr$_2$O$_3$) and Yttrium oxide (Y$_2$O$_3$) on the substrate material SS-420 at Harsha Welding and Coatings Private Limited, Panchkula, Haryana (India). The particle size of all the powder was less than 40 µm. Scanning Electron Microscopy (SEM) analysis of the powder was performed to verify the purity of the powder to be used in the coating. The analysis of the SEM results highlights that the coating powder was almost 100% pure. The SEM image of the powder is shown in Figure 3. These powders were used to study and analyze the tribological behavior of SS-420. Before the deposition of coating powders on SS-420 specimens, these specimens were cleaned with acetone to obtain the appropriate deposition thickness of coating powders on the specimens. The surfaces of the substrate specimens were blasted by using sand or abrasive particles before the deposition of coating powders which helped in improving the strength between the surface of the substrate specimen and the coating layer. The process parameters of the HVOF spraying technique during the deposition process are...
listed in Table 2. Process parameters remained constant for the deposition of all coating powders on the substrate specimens. After deposition of coating powders, compressed air was used for the cooling of specimens. The Microhardness and roughness of values of the base materials with the coating are shown in Table 3.

**Table 2. HVOF process parameters.**

| Type                        | Value  |
|-----------------------------|--------|
| Oxygen Pressure (MPa)       | 1.471  |
| LPG fuel Pressure (MPa)     | 0.6865 |
| Air Pressure (MPa)          | 0.6374 |
| Spray Distance (mm)         | 145    |
| Oxygen flow rate (SPLM)     | 255    |
| LPG fuel flow rate (SPLM)   | 65     |
| Airflow rate (SPLM)         | 640    |
| Coating Powder feed rate (g/min) | 35    |

**Figure 3.** SEM image of powder (a) Nickel (b) Chromium (c) Yttrium.
Table 3. Microhardness and roughness of samples.

| Specimen                             | Microhardness | Roughness |
|--------------------------------------|---------------|-----------|
| SS 420                               | 240           | 1.35      |
| Ni – 30Cr coated SS 420              | 1135          | 5.28      |
| Ni – 30Cr + 3% Y₂O₃ coated SS 420    | 1280          | 5.44      |

3.3. Erodent Material

Fly ash was used as an erodent material. Fly ash was collected from Tata steel long products Ltd., Gamharia, Jamshedpur, India. Before the use of fly ash, the moisture content was removed from the collected samples by the use of a microwave oven. Particle-size distribution of erodent particles was obtained by carrying out a sieve analysis. For sieve analysis, standard British sieves were used with the different mesh numbers ranging from 500 µm to <53 µm. Fly ash particles are very fine. So, the quantity of large-sized particles was very low in the fly ash. In the fly ash sample, about 52.25% of particles were found below 53 µm. Approximately 22.70%, 6.83%, 6.50%, 8.42%, 2.12% and 1.17% particles were lying in the range of 53–75 µm, 75–106 µm, 106–150 µm, 150–250 µm, 250–355 µm and 355–500 µm, respectively. The microstructural characterization was performed by using SEM and Energy-Dispersive X-Ray Spectroscopy (EDS) analysis. Scanning Electron Microscopy (SEM) was used to observe the surface characterization of erodent by using a scanning electron microscope [JEOL, The Netherlands (Model: JSM-6510LV), Gamharia, Jamshedpur, India]. It was observed from the morphology of fly ash as shown in Figure 4, that its particles have no sharp edges and are spherical. EDS was used to find the composition of various elements present in erodent material. From the EDS of fly ash, it was found that SiO₂ and Al₂O₃ were the major constituents present in fly ash at 51.42% and 38.60%, respectively. Additionally, CO₂, MgO, CaO, FeO and TiO₂ were present at 3.09%, 2.09%, 2.20%, 1.55% and 1.05%, respectively.

Figure 4. SEM image of Fly ash.

4. Result and Discussion

4.1. Effect of Rotational Speed

Rotational speed significantly affects the erosion wear on the surface of the coated and non-coated samples and to determine its effect, the experiment was performed at a rotational speed of 600, 900, 1200 and 1500 rpm. All other parameters remain constant so that only the effect of rotational speed can be observed. Other parameters were taken as
the time duration for the experiment was 200 min, the concentration of solids was 50% and the particle size of fly ash was 150–250 µm. A graph of the erosion wear is shown in Figure 5. It was observed that Ni – 30Cr + 3% Y₂O₃ gives the best erosion wear resistance as compared to Ni – 30Cr and uncoated SS-420. It is because the solid particles gain high momentum which in turn gets transferred to the specimen under pot slurry conditions and similar results have been found by other investigators [6–8] who depict that a surge in rotational speed increases erosion wear.

4.2. Effect of Time Duration

The experiment was performed for the time duration of 200 min and readings were taken every 40 min and rotational speed was fixed at 1500 rpm and the concentration of erodent material was taken at 50% and particle sizes were taken at 150–250 µm. A graph of the effect of time duration is shown in Figure 6. Erosion wear increases when time increases for both the coatings and uncoated SS-420. Curves show a linear increase with an increase in the time duration and minimum erosion wear was found for the Ni – 30Cr + 3% Y₂O₃ coating when fly ash is used as erodent material and the highest erosion wear occurs at 200 min on uncoated SS-420.
4.3. Effect of Solid Concentration

The concentration of solids in the slurry varied from 20% to 50% by increasing the weight of fly ash in water and time duration; rotational speed and particle size were taken at 200 min, 1500 rpm and 150–250 µm, respectively. The effect of solid concentration is shown in Figure 7. Erosion wear increases with solid concentration at 20% solid concentration with the Ni – 30Cr + 3% Y₂O₃ coating.

![Figure 7](image-url)

**Figure 7.** Effect of solid concentration of the moving particles on erosion wear.

4.4. Effect of Particle Size

The particle size of fly ash cannot be the constant in an actual power generation scenario and to observe the effect of different particle sizes, the experiment was performed on the particle size of <53 µm, 53–106 µm, 106–150 µm, 150–250 µm. It has been shown that when particle size grows, erosion wear increases which are owing to the significant momentum or energy transfer associated with large particles as compared to small particles which are coherent with the findings of the authors [4,7,8]. The effect of particle size is shown in Figure 8. Ni – 30Cr + 3% Y₂O₃ gives the best results in every particle size as compared to Ni – Cr and uncoated SS-420.

![Figure 8](image-url)

**Figure 8.** Effect of particle size of the moving particles on erosion wear.

Figure 9 shows the micrograph of the eroded stainless steel 420. It can be observed that eroded surfaces accumulated mainly with crater lip, micro-cutting, pull out and micropores. It may be due to slope boundaries and melted particles of coatings. The deep dark color shows the presence of the tungsten carbide phase. Tungsten carbide is the
hardest element, and the presence of cobalt increases its binding capacity which may tend to high erosion resistance.

![Figure 9. SEM micrograph of eroded SS-420 (Fly ash).](image)

5. Artificial Neural Network (ANN) Model

On a computer, neural network simulations were run on the input data in the current study. In MATLAB 2021a (Version-2021a, MathWorks, Natick, MA, USA), an artificial neural network was created. The simulations were performed on a PC (with Intel i5 with 11th generation processor, 16 GB RAM, and 512 SSD). Figures 10 and 11 demonstrate the structure and network of the constructed multi-layer NN model, respectively. ANN models consist of input, hidden and output layers. During the creation of the neural network, a feed-forward back-propagation approach was chosen. To measure the influence of changing weights on the total error in a NN model, a backpropagation learning approach is used.

\[(p)^a = wn^{a-1} + b\]  

where \(W\) denotes the assigned weight and \(b\) denotes the bias. In the end, generated output was matched with the experimental value. The ANN model was evaluated based on mean absolute error, coefficient of determination \((R^2)\), root mean square error, etc. It shows how much each weight contributes to the total inaccuracy. Larger variations will be seen in the weights that contribute the most to the total error. Ten neurons make up the hidden layer, which is followed by the output layer. Certain objective functions are used to determine the weights.

![Figure 10. 4-layer model of neural network.](image)
The ANN model was developed by taking rotational speed, time duration, solid concentration and particle size as the input parameters and mass loss due to erosion as the output parameter. Table 4 lists the many hyper-parameters utilized to construct the ANN. The ideal learning rate ($\mu$) of 0.01 is used by the developed ANN.

![Network arrangement of ANN model.](image)

**Figure 11.** Network arrangement of ANN model.

**Table 4.** Hyper-parameter set of ANN model.

| Sl. No | Parameters                        | Values         |
|-------|-----------------------------------|----------------|
| 1     | Learning rate                     | 0.01           |
| 2     | No. of layers                     | 3              |
| 3     | Number of neurons                 | 25             |
| 4     | Epochs                            | 17             |
| 5     | Adaptive learning function        | Levenberg-Marquardt |
| 6     | Performance function              | MSE            |
| 7     | Training set                      | 80%            |
| 8     | Validation set                    | 10%            |
| 9     | Testing set                       | 10%            |

The developed model has three layers, each with 25 neurons, and the adaptive function utilized was Levenberg-Marquardt [23], a popular fitting approach for regression issues. The model was run for 17 epochs and the performance function utilized was mean square error (MSE). The data was separated into three categories: training, validation, and testing. For training, a total of 80% of the data was provided to the ANN model, which was then verified with 10% of the data. In between, the validation set is used to ensure that the training is progressing well. Overfitting mistakes can be eliminated with the use of a validation set. If the validation set isn’t functioning as expected, something may be incorrect, which may be fixed by tweaking the model’s hyperparameters. The anticipated values are returned by the proposed ANN model. To assess the model’s robustness, these values are noted and compared to the ground truth values. The Coefficient of determination ($R^2$) [23], Mean Absolute Error (MAE) [24], Root Mean Square Error (RMSE) [25], Pearson correlation coefficient (R) [26], and Lin’s Concordance (C) [39] are used to evaluate the created model and these are defined as:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (o_i - p_i)^2}$$  \hspace{1cm} (2)

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |o_i - p_i|$$  \hspace{1cm} (3)

where $x$ is the total observations, $p_n$ is the predicted value and on is the original value.

$$R^2 = 1 - \frac{E(S)}{T(S)}$$  \hspace{1cm} (4)
where $E(S)$ is the sum of squares of the errors and $T(S)$ is the total sum of squares.

$$
r = \frac{X \sum AB - (\sum A \sum B)}{\sqrt{[X \sum a^2 - (\sum a)^2][X \sum b^2 - (\sum b)^2]}}$$

(5)

where $X$ is the pair scores, $\sum AB$ is the product of paired scores, $\sum a$ is the sum of scores, and $\sum a^2$ is the sum of squared scores.

$$\rho_C = \frac{2CV_aV_b}{V_a^2 + V_b^2 + (M_a - M_b)^2}$$

(6)

where $C$ is the correlation coefficient, $V$ is the variance, and $M$ is the mean.

The generated model was evaluated using the coefficient of determination ($R^2$), mean absolute error (MAE), root mean square error (RMSE), Pearson correlation coefficient ($R$), and Lin’s Concordance ($\rho_C$). A two hidden layers ANN model of the architecture 4-25-25-3-3 was shown to be the best model for predicting mass loss due to fly ash slurries using a trial-and-error method. The network is highly trained once the value of $R$ is close to 1 and can be trusted with the results. Figure 12 depicts the training, validation, and testing correlation coefficients. Similarly, Figure 13 shows the comparison of the predicted values to the actual values. Figure 14 shows that the intended ANN model has been properly trained because the mean square error on the epoch is quite low. The projected values using the developed model are quite close to the experimentally observed values. Table 5 shows the comparison of experimental values to ANN predicted values. The ANN model’s efficiency is determined by the error percentage, which ranges from 0% to 5%.

Figure 12. Correlation coefficient in (a) training, (b) validation, (c) testing, and (d) overall.
Figure 13. Actual versus predicted comparison of ANN.

Figure 14. Mean square error of the designed ANN.

Table 5. Compression of experimental and ANN predicted results of mass loss due to erosion.

| Sl. No | Experimental Result | ANN Predicted Result | Error (%) |
|-------|----------------------|-----------------------|-----------|
| 1     | 0.0083               | 0.008329484           | 0.355230506 |
| 2     | 0.0079               | 0.007824601           | 0.95441329  |
| 3     | 0.0089               | 0.008545091           | 3.987741689 |
| 4     | 0.0032               | 0.003116069           | 2.622854455 |
| 5     | 0.0121               | 0.011577823           | 4.315511447 |
| 6     | 0.0039               | 0.003931927           | 0.818648631 |
| 7     | 0.0019               | 0.00187093            | 1.530005067 |
| 8     | 0.0042               | 0.00419516            | 0.115229551 |

6. Conclusions

Erosion wear analysis of SS 420, Ni – 30Cr and Ni – 30Cr + 3% Y2O3 was studied in the present work by performing the experiments on slurry pot testers. Erosion wear depends on the parameters as well as the properties of the material. Effects of some different parameters were observed in this study and by analyzing all the results following conclusion can be made:
• By applying the Ni – 30Cr and Ni – 30Cr + 3% Y₂O₃ coating on SS 420, microhardness increases significantly but the roughness of the surface also increases. Microhardness of bare SS 420 and SS 420 coated with Ni – 30Cr and Ni – 30Cr + 3% Y₂O₃ coatings were found to be 240, 1135 and 1280, respectively.

• Order of erosion wear resistance by varying solid concentration, rotational speed, time duration and particle size is found as Ni – 30Cr + 3% Y₂O₃ > Ni – 30Cr > bare SS 420.

• Wear results obtained from experiments showed a good agreement with the ANN results. Therefore, it can be said that the ANN is a useful tool to optimize and evaluate the effect of influence parameters on the erosion wear of materials.

• The ANN model’s efficiency is determined by the error percentage, which ranges from 0% to 5%.

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