ANN supported study on the performance and slurry erosion resistance of thermal sprayed WC20Cr3C27Ni coatings

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Abstract

The thermal spray coatings are commonly employed in slurry pump components and hydrodynamic turbine blades, where wear progression is an intricate phenomenon. In this research work, the performance analysis of HVOF and APS sprayed WC20Cr3C27Ni coatings for slurry erosion wear is carried out by using artificial neural networks (ANN). The influence of time, particle size, impact angle, speed, and slurry concentration on wear performance of coatings and turbine steel substrate are evaluated. Under the experimental settings, slurry erosion wear rates and mass loss for both coatings and substrate were determined. When ASTM A743 steel was coated with thermal sprayed WC20Cr3C27Ni coatings, the slurry erosion wear resistance of the steel was enhanced by 2 and 3.5 times for APS and HVOF coatings, respectively. The design of ANN made it possible to examine the interactions between the seven input variables. A robust model was formed by the two outputs that followed. This model enables the prediction of slurry erosion wear rate and mass loss of WC20Cr3C27Ni coatings and substrate.

1. Introduction

The field of tribology known as erosive wear studies how solid-liquid interactions affect metal or composite surfaces [1–3]. Slurry particles degrade the metal surface as a result of mechanical action brought on by the transfer of kinetic energy from the particles to the metal surface during the interaction between slurry and metal. This phenomenon is most commonly investigated in a variety of sectors such as mining, food processing, power plants, and chemical. The erosive issue brought on by liquids or solid liquids adversely affects the functioning of hydraulic machinery and its components [4, 5]. Three solid materials, including fly ash, bottom ash, and coal for electricity generation, are transported using centrifugal slurry pumps in thermal power plants. Heavy-duty slurry pumps are used in the mining sector to transfer sand and silt. Solid particles in numerous sectors create erosive wear in slurry pumps that primarily reduce their effectiveness [6]. Industries utilise a variety of coatings and their deposition processes to minimise degradation of hydraulic machinery's materials.

The hard phases commonly utilised in coatings to improve erosion resistance are WC or Cr3C2. WC-based coatings, such as WC-Co, WC-Ni, and WCCoCr, are typically employed in erosion and abrasive phenomena [7–10]. When chemical stability is necessary, Cr3C2-based coatings are frequently employed. For example, Cr3C2-NiCr coatings are used in engineering applications due to their strong tribological characteristics under severe working environments [11, 12]. According to recent findings, the coating processed by spraying WC20Cr3C27Ni powder outperformed the coating formed by spraying powder containing only tungsten carbide or chromium carbide [7–16]. Thermal spray is a family of deposition techniques used in coating fabrication that deposit finely fragmented non-metallic or metallic materials in a molten or semi-molten state [17]. The atmospheric plasma spray (APS) and high-velocity oxy-fuel method (HVOF) are recognised as the most efficient processes for applying high-performance coatings at a low cost [18].

A smart machine, Artificial Intelligence (AI), works similarly to humans. The notion of AI incorporates all advances in computer science, with an emphasis on intelligence and developing activities. An advanced
Artificial intelligence is powerful and reliable, and it interacts like a human in the sense that its intellectual layers are similar to the human brain [19]. A family of communication technology that uses artificial neural networks (ANN), which are built on learning [20]. To develop the learning process, ANN imitates the functioning of neurons found in the human brain. ANN is a two-component simple mathematical model. The first component is the input layer that accepts input, while the second component is the output layer which anticipates outputs [21]. The fundamental problem of this model is that having one fundamental issue is that it lacks a learning mechanism because no weights are allocated. Another model created by Rosenblatt in 1958, is called a perceptron, which has weights allocated. An added weight allows the perceptron to do learning in the Backpropagation sense. Through training and learning, ANN can identify and integrate a diversity of nonlinear systems in data series, offering a high-quality and effective technique to determine the ideal conditions for industrial applications [22]. When there is a complicated correlation between the variables being researched or when there is an inadequate understanding of physical correlations, this approach is typically adopted [23, 24]. A sophisticated computational model, like the ANN model, is required for the understanding of variations involving the tribological behaviour of thermal spray coatings because they include intricate chemical and thermodynamic interactions.

However, gathering adequate data on thermal spraying procedures and coatings is expensive, particularly gathering enough information about the tribological characteristics of coatings. This has led to growing interest in the thermal spraying technique's use of the shallow ANN model, which usually has less than three hidden layers for applications that do use very little data.

In this research work, the HVOF and APS sprayed WC20Cr3C27Ni coatings were deposited and slurry erosion-associated tests were conducted to produce the data set for the ANN model's training, validation, and testing. The developed ANN model is capable of predicting erosive wear under variable operating conditions. Additional trials have confirmed the developed ANN model's accuracy and predictability. Additionally, a mean impact value-based study has been carried out to quantitatively evaluate the relative relevance of each input variable for the enhancement of the tribological performance of coatings in the slurry of various compositions. The outcome of the current investigation is that researchers could estimate the life of thermal sprayed WC20Cr3C27Ni coatings under given operating conditions, that can minimise erosion wear in the case of slurry pumps, turbine blades, and short-range pipelined circuits.

2. Materials And Methods

2.1 Materials

ASTM A743 steel was chosen as the substrate material for the current investigation, and an optical emission spectroscope was used to confirm its actual composition. The nominal composition of ASTM A743 steel is presented in Table 1.
Spherical thermal spray powder WC$_2$O$_3$Cr$_3$C$_2$7Ni was purchased from MECPL in Jodhpur, India, and used as the spraying raw material. The diameter distribution of the powder was in the range of 5–35 µm. The nominal chemical composition of the WC$_2$O$_3$Cr$_3$C$_2$7Ni powder offered by the supplier is presented in Table 2.

2.2 Coating Deposition

High-velocity oxygen fuel and atmospheric plasma spray processes were used to deposit coating. Spraying parameters are listed in Table 3. Shot-blasting was done to prepare the specimen's surface for adhesion before the coating procedure was started. A 5 mm aperture was utilised to shoot quartz (30–80 mm) from 200 mm away from the specimens as an abrasive during shot blasting.
<table>
<thead>
<tr>
<th>Process Parameters</th>
<th>HVOF</th>
<th>APS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Blasting pressure (Bar)</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Blasting distance (mm)</td>
<td>150</td>
<td>150</td>
</tr>
<tr>
<td>Blasting angle (degree)</td>
<td>90</td>
<td>90</td>
</tr>
<tr>
<td>Standoff distance (mm)</td>
<td>150</td>
<td>127</td>
</tr>
<tr>
<td>Particle velocity (m/s)</td>
<td>534</td>
<td>131</td>
</tr>
<tr>
<td>Powder feed rate (g/min)</td>
<td>45</td>
<td>40</td>
</tr>
<tr>
<td>Gun traverse speed (m/s)</td>
<td>0.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Plasma arc current (A)</td>
<td>—</td>
<td>500</td>
</tr>
<tr>
<td>Ar gas flow rate (SLPM)</td>
<td>—</td>
<td>40</td>
</tr>
<tr>
<td>H\textsubscript{2} gas flow rate (SLPM)</td>
<td>—</td>
<td>4</td>
</tr>
<tr>
<td>Oxygen flow rate (SLPM)</td>
<td>240</td>
<td>—</td>
</tr>
<tr>
<td>Propane flow rate (SLPM)</td>
<td>60</td>
<td>—</td>
</tr>
</tbody>
</table>

2.3 Powder and as-deposited coating characterization methods

Using a Malvern Panalytical X-ray diffractometer, the phases of powder feedstock and as-deposited coating samples were detected (XRD) with Cu-K\(\alpha\) radiation performed at 40 kV and 40 mA. Other parameters included a 0.01° step size, a 2\(\theta\) scanning range of 25–80°, and an 8°/min scan rate. A ZEISS Gemini was used to conduct research utilising scanning electron microscopy (SEM) to examine the morphology of as-sprayed coatings, coating cross-sections, and eroded coating surfaces. A Vickers hardness tester (HVS-1000Z, Shanghai Zhongyan Instrument Manufacturing Factory) was used to conduct microhardness tests on both substrate and coatings with a 300 g load and a dwell period of 15 s. Six tests were conducted in order to satisfy the reproducibility. Using SEM micrographs of the coating cross-sections and ImageJ as imaging software, the quantity of voids in the coatings was estimated. A magnification of 1000X, a surface roughness of 0.1 µm, and fields of view 15 are the best values for measuring porosity by the image analysis approach [25].

2.4 Slurry erosion test

On slurry erosion pot tester (Ducom Instruments, Bengaluru, TR-41) with change in time, particle size, impact angle, speed, and slurry concentration, erosive wear experiments were conducted. A specific concentration of slurry was put into the tester pot and trials were conducted. The samples were immersed in a pot that contained a slurry of alumina. Thereafter, the jack was used to adjust the pot's height while
the rectangular specimen was put into the propeller shaft. In order to conduct each experiment and evaluate wear, this pot tester was operated for the pre-specified duration. The specimens were cleaned with ultrasonic technology, dried, and weighed using a weight balance of 0.1 mg precision before and after the slurry erosion test. The cleaning procedure makes sure that any bonded erodent particles, or loosely bound dirt, debris, or other particles are removed from the surfaces of specimens.

### 2.5 Range of parameters

Experiments on slurry erosion were carried out under various conditions of particle size, impact angle, speed, time, and slurry concentration. Table 4 provides a summary of the experimentation parameters layout that the present research prefers. The velocities generated by the propeller shaft for this investigation are 500, 1000, 2000, and 3000 rpm. The impact angle was changed during the erosive tests to examine its effect on slurry erosion. The two-phase slurry’s mass flux concentration was maintained between 5 and 20 weight percent. By using 100 µm, 200 µm, and 300 µm alumina erodent, this series of studies are carried out on ASTM A743 steel and both the coatings.

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Time (Hours)</th>
<th>Speed (rpm)</th>
<th>Concentration (% weight)</th>
<th>Impact angle</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
<td>500</td>
<td>5</td>
<td>0</td>
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<tr>
<td>2</td>
<td>3</td>
<td>1000</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>3</td>
<td>2000</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
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<td>3000</td>
<td>5</td>
<td>0</td>
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<tr>
<td>5</td>
<td>10</td>
<td>3000</td>
<td>5</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>10</td>
<td>3000</td>
<td>10</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>10</td>
<td>3000</td>
<td>15</td>
<td>0</td>
</tr>
<tr>
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<td>3000</td>
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<tr>
<td>9</td>
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<td>5</td>
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<td>10</td>
<td>3000</td>
<td>20</td>
<td>45</td>
</tr>
<tr>
<td>16</td>
<td>10</td>
<td>3000</td>
<td>20</td>
<td>60</td>
</tr>
</tbody>
</table>
2.6 Slurry preparation

The erodent materials utilised to explore the erosive wear phenomenon were alumina particles of varied particle sizes. The specified weight percentage of erodent alumina in water, such as 5 weight percent, was used to manufacture the slurry. The slurry was stirred for 30 to 60 seconds at a speed of 18000 rpm only after the necessary weight percentage of erodent was added. The experimentation was then carried out by adding the blended slurry to the slurry pot.

3. Neural Network-based Model Methodology

Different thermal spraying processes have been modelled using ANNs due to their effectiveness in predicting complicated input-output interactions [26]. When conditions of operations and attributes are taken into account, thermal spray is seen as a non-linear phenomenon. In complicated modelling problems related to industrial applications, such as the recognition of patterns and identification and analysis of the nonlinear system, a model built by ANN is an effective statistical tool for identifying correlations between the characteristics and their responses [27]. An ANN is useful to address issues that are challenging to resolve using conventional methods since it replicates the basic principles of how the human brain processes. Additionally, ANN analysis is quicker compared to every other model, including finite element models [28]. An ANN model that can predict the tribological characteristics of coating has been set up and trained. This methodology's implementation includes learning the database to anticipate the specified answers based on changes to the input parameters. The input variables and output responses that will comply with the ANN-based model must be specified for this purpose.

The variables and desired responses to be modelled are used to establish the initial number of inputs and outputs for the ANN. A database is built using the experimental data of the specified input-output variables to enable the learning of the ANN. Weights (w), each of which has a particular impact, interconnect the neurons in the network. A total of seven input units namely erodent particle size, rotational speed, impact angle, slurry concentration, material, time, microhardness that make up the input layer. A hidden layer that is connected to the input layer by weighted connections processes the data coming from the input layer. The output layer then computes the output vector. Before the start of ANN model training, it is essential to pre-process the input variables by normalisation and standardisation techniques in the range 0 to 1. Eq. (1) given below is used to estimate the output from the build ANN model.

\[ Y = f \left( w_2 \left( f \left( w_1 X + b_1 \right) + b_2 \right) \right) \]

where, \( w_1 \) and \( w_2 \) are weights applied to the neurons of input-hidden and output-hidden layers, respectively and \( b_1 \) and \( b_2 \) are biases of every neuron in output layer and hidden layer, respectively. Y and X are output and input vectors of the ANN network. Table 5 presents the specific parameters used to construct the ANN model.
Table 5
Parameters used in training of ANN model

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Learning rate</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>Input layer neurons</td>
<td>7</td>
</tr>
<tr>
<td>3</td>
<td>Number of hidden layers</td>
<td>2</td>
</tr>
<tr>
<td>4</td>
<td>Hidden layer neurons</td>
<td>10</td>
</tr>
<tr>
<td>5</td>
<td>Output layer neurons</td>
<td>2</td>
</tr>
<tr>
<td>6</td>
<td>Hidden layer activation function</td>
<td>relu- rectified linear unit</td>
</tr>
<tr>
<td>7</td>
<td>Output layer activation function</td>
<td>relu- rectified linear unit</td>
</tr>
<tr>
<td>8</td>
<td>Performance function</td>
<td>MSE</td>
</tr>
<tr>
<td>9</td>
<td>Performance goal</td>
<td>$10^{-3}$</td>
</tr>
<tr>
<td>10</td>
<td>Number of epochs</td>
<td>1000</td>
</tr>
</tbody>
</table>

A total of 192 input-output patterns made up the experimentally collected data that was employed. The standard practice is to first split the data into three categories before training the multi-layered ANN model. The first subset of data is 70% of the total data, which is used to train the ANN model. The second subset containing 15% of the total data is used to comprehend the interconnections between input and output, and to modify the number of neurons in each layer and for the verification that enables the formulation of the final ANN structure. The last subset of the balance 15% normally enables verification of training outcomes. A variety of ANN configurations were examined, each with hyperparameter tuning using changes in parameters like the number of hidden layers, number of neurons in the hidden layer, activation functions and weight initialisers. Both output layer and hidden layers neurons govern by rectified linear unit (relu) activation function.

The back-propagation approach, one of the popular training methods for learning multi-layer networks, is used in this study to train the ANN model in a supervised manner. With the aim of optimising the network performance throughout the training phase, the values of weights and biases are updated during every epoch of training. The mean square error (as given in Eq. (2)) the difference between outcomes of the experiment and ANN model output, is used in this study as the measure of network performance.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_{exp} - y_{pred})^2$$
where, \(n\) = number of data points under investigation, \(y_{exp}\) = experimental results and \(y_{pred}\) = results predicted by fully trained ANN model. Root Mean Square Error (RMSE), coefficient of determination \((R^2)\), Mean Absolute Error (MAE), and Pearson correlation coefficient \((R)\) were used to evaluate the developed ANN model.

4. Results And Discussions

4.1 As-deposited coating characterisation

XRD, microhardness, porosity analysis, and cross-sectional and surface microstructure studies are all part of coating characterisation.

4.1.1 Compositional analysis of coating powder and coatings

Figure 1 depicts the XRD patterns of WC20Cr3C27Ni powder, as-deposited HVOF and APS coatings. The indicated crystalline phases, WC, \((W, Cr)_2C\), Cr3C2, Ni, and Cr2O3 were visible in the XRD patterns of WC20Cr3C27Ni coatings. The current WC20Cr3C27Ni coatings XRD findings were in good accord with the literature [29–32]. The micrograph of as-sprayed coatings shown in Fig. 2, demonstrated a drop in Cr3C2, producing a cluster of these phases, likely as a result of the extended holding time in the flame. In this regard, these kinds of coatings discussed by researchers [32] gives insights on Cr rich phases like Cr3C2 decreases during the deposition of the coatings, with a development complex carbides \((W, Cr)_2C\). It is because of the interaction between these phases and the high solubility of Cr3C2 and WC in Ni at high temperatures. The XRD data supported the hypothesis that the high process temperature and quick cooling were responsible for the development of WC\(_{1-x}\) in the APS coating. As a result, as-sprayed coatings consisting compositional variations because of the various cooling rates used in the deposition process by APS and HVOF techniques.

4.1.2 Microhardness and porosity

Since coating hardness is a determining element in wear resistance, slurry erosion resistance of coatings is proportional to coating hardness. Throughout the cross-section of the specimens, the coatings' microhardness was tested. In terms of the highest microhardness, APS and HVOF coatings had values of 930 and 1162 HV, respectively. In comparison to APS sprayed coatings, WC20Cr3C27Ni coatings deposition by HVOF often showed greater microhardness values. This is most likely connected to the presence of WC and the repeated propensity for Cr3C2 to cluster when complex carbides \((W, Cr)_2C\) are transformed. When compared to the WC phase, the \((W, Cr)_2C\) matrix found in the APS coating is softer. One more reason for the change in hardness of both coatings is percent porosity, which is discussed in a subsequent paragraph. Additionally, the ASTM A743 steel substrate's microhardness was measured and reported to be 217 ± 9.3 HV.
In comparison to the APS coating, which has 1.7±0.3% of pores, the HVOF has less porosity level and it is reported as 0.6±0.3%. The values are in line with the porosity % for thermal sprayed tungsten carbide-based coatings published in the literature. The micro-hardness of the as-sprayed coatings is influenced by the degree of porosity and splat adherence. The HVOF coating produced better micro-hardness because it has relatively strong splat adherence and a reduced porosity level. WC20Cr3C27Ni coating has less porosity than WC-10Co-4Cr coatings [33, 34].

4.1.3 Cross-sectional and surface analysis of coatings

The coating thickness and substrate-coating interface were examined using cross-section SEM micrographs. The cross-sectional microstructures of as-sprayed coatings are shown in Fig. 2. Consistent contact between the substrate and both coatings is seen in SEM micrographs presented in Figs. 2 (a) and (c), resulting in interfacial adhesion. In thermal spray coatings, inter-lamellae splats are frequently seen developed on the substrate. Inter-lamellae splats make sure that the substrate and the coating are interlocked, demonstrating an extended coating life, a strong bonding, and improved mechanical characteristics [35, 36]. The thickness of the coatings was determined to be between 355 and 397 µm. Laminar splat-like microstructure, which is evident in Figs. 2 (c) and (d), is a common feature of any thermal spray coating. The two coatings exhibit strong adherence to the substrate and a dense microstructure, without interface detachment and the cracks development, as may be seen in general.

The surface microstructure of the APS and HVOF-deposited WC20Cr3C27Ni is shown in Fig. 3. The mixture of partially melted and fully melted particles and that make up the globules microstructure, which is visible in 2000X magnification SEM micrographs. Additionally, the as-deposited coated surface shows few micro-voids and unmelted particles. The SEM micrographs confirm the excellent quality of both coatings because there are no cracks to be seen in both coating.

4.2 Erosion wear rate

The coating WC20Cr3C27Ni that had been sprayed with the HVOF technique showed the lowest wear rates in the outcomes of the slurry erosion experiments as presented in Fig. 4. In the circumstances encountered, these coatings combine decreased porosity content and high hardness to promote optimal behaviour against the mechanism that creates erosive wear. Additionally, these WC20Cr3C27Ni coatings have a higher WC carbide content and a lower metallic matrix content, which increases their resistance to this sort of mixed wear with the development of micro-cuts and micro-grooves as well as carbide fracture in the matrix and detachment of carbides. The literature reports similar outcomes [37, 38]. The tungsten carbides in the coating, which frequently have a micro-hardness greater compared to the erodent, are responsible for the best resistance to slurry erosion. Therefore, HVOF coatings consisting of more tungsten carbide content exhibited more resistance to slurry erosion. It requires more impact force from the erodent to break up the hard coating, notably the tungsten carbide phase. A higher concentration of WC carbides, High microhardness values, and lower porosity content are all factors that contribute to the HVOF coating's good performance against slurry erosion. These factors resulted in less wear of the micro-groove and micro-cut type and increased fracture resistance of the hard tungsten carbide phases.
4.3 Training and validation of neural network model

After 57 epochs, the training of the ANN model was terminated with just an error of 0.00145. Figure 5 (a) depicts the performance during the training of the ANN model. The error distribution presented in Fig. 5 (b) provides an explanation for the error curves overlap, which is additionally verifying the performance of the developed neural network. The orange bars in this instance, as displayed, stand in for training data, the purple bars for testing data and the pink bars for validation data. Outliers are data points when the correction is much poorer than the majority of the data, and the histogram can indicate these data points. Since the majority of the errors in this instance are between 0.05 and −0.05, there are no obvious outliers, which most important parameter to improve the accuracy of results predicted by the ANN model. Because the validation set error and test set error to have comparable features, the overall mean square error is minimal, and there has not been overfitting, the outcome of the developed ANN model in this scenario is acceptable.

4.4 Testing of neural network model

After training, the ANN model's predicted outcomes were reverse-normalized to allow comparison with the experimental results. Figure 6 presents a comparison between predicted values by the trained ANN model and experimental values. This examination demonstrated that there is a significant resemblance between the ANN model predicted results and results obtained from the experiments. The built-in ANN model in this study makes it feasible to make 99.1% correct predictions. The capacity to predict new values using the model's input parameters and generalizability is a major benefit of the values derived using ANN. The trained result matches the targets appropriately since all of the data showing slurry erosion rates and the mass losses of both coatings are dispersed around the y = T line. The predicted output values and the experimental results are in good agreement. The overall Pearson correlation value was 0.98365, indicating a strong correlation between the predicted and actual values.

A very low number is displayed for the ANN model's relative error for both training and testing. The errors for each output from the developed ANN model output are shown in Fig. 7. The outcomes demonstrate that the existing artificial neural network model is sufficient to forecast the coating's attributes. In summary, Fig. 7 demonstrates that all ANN-base model outputs showed extremely low relative errors, ranging from −0.031% to +0.24%. The estimation error will be displayed with a normal distribution in the two outputs of the ANN model, mass loss and slurry erosion wear rate. The investigation of the relative errors demonstrates the viability of the developed ANN model to predict the behaviour of the outputs under study.

5. Conclusions

An ANN model for slurry wear resistance with strong predictability is developed in this study. The following is a list of the key findings:
1. Both APS and HVOF deposited WC20Cr3C27Ni coatings had minimal porosity, were dense, and had strong adherence to ASTM A743 steel.

2. According to erosive wear data, the application of thermal sprayed WC20Cr3C27Ni coatings increased ASTM A743 steel's slurry erosion wear resistance by 2 and 3.5 times for APS and HVOF coatings, respectively, at a zero-impingement situation with an increase in rotational speed.

3. The built-in ANN model in this study makes it feasible to make 99.1% correct predictions. With a coefficient of correlation value of 0.98365, the ANN model was successful in predicting the outcomes of slurry erosion wear resistance and mass loss. The model's average regression value of 0.9791 and maximum performance value of 0.053317 both demonstrate that the correlation it produced was adequate.

4. The primary contribution of the newly developed artificial intelligence model is the capability to forecast wear rates and mass loss due to slurry erosion while taking working parameters influences into accounts such as erodent particle size, rotational speed, impact angle, slurry concentration, material, time, and micro-hardness. The developed ANN model makes a significant practical contribution by making it possible to choose the kind of coating that is best for the wear that happens in industrial environments, saving cost and time in the process. Furthermore, it is also useful to estimate the life of the coatings under specified operating conditions for a given industrial application.

Declarations

Acknowledgements

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References


Figures

**Figure 1**

XRD analysis of a) HVOF as-sprayed WC20Cr3C27Ni coating and b) APS as-sprayed WC20Cr3C27Ni coating
Figure 2

Micrographs of cross-section of as-deposited (a, b) APS and (c, d) HVOF coatings at low 400 X and 5000 X magnifications.
Figure 3

Surface morphology of as-deposited (a) APS and (b) HVOF coatings.

Figure 4

Influence of materials on mass loss due to erosion.
Figure 5

Performance of developed ANN model (a) mean square error (MSE) and (b) histogram of errors
Figure 6

Pearson’s coefficient for (a) training data, (b) testing data and (c) overall data.
Figure 7

Error histogram of prediction of outputs by developed ANN model for (a) Slurry Erosion Wear Rate and (b) Slurry Erosion mass loss