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Coating Adherence Optimization for 67Ni18Cr5Si4B Alloy Powder by High-Velocity Oxygen Fuel Spray Based on the Grey Wolf Algorithm Method

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ABSTRACT

Adhesion engineers increasingly use coatings in industrial equipment on gas turbine blades and vanes because of the benefits of protection against thermal stresses, oxidation, and hot corrosion. However, the coating process has suffered sub-optimal value determination, posing a serious threat to the economics of coating. While the prevailing approach of introducing the Taguchi method appears effective in resolving this issue, it sacrifices convergence speed and multiple optimization solutions. Thus, the grey wolf algorithm is proposed to optimize the coating of 67Ni18Cr5Si4B alloy powder process parameters, including powder feed rate, spray velocity, and spray distance. The high-velocity oxygen fuel spray was used, and the objectives were good microhardness, adhesion strength, and porosity. The optimal value to obtain the best coating for each of the responses was given as 85MPa for the adhesion strength, 0.684909% porosity, and 583.04HV microhardness. The present study offers important insights into the optimization thresholds to help the components development process. The quantitative form of this work is new. Fast convergence solutions offered by metaheuristics such as the grey wolf optimization algorithm are rarely found in the literature.

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1. INTRODUCTION

The rapid advancement in product manufacture has been motivated by the unprecedented tastes and preferences of consumers globally. This has necessitated an increase in the use of industrial equipment and machinery. Among the utilities used in manufacturing industries, the gas turbine is a central focus of many manufacturers. The gas turbine is used for combustion in power plants, translating natural gas to mechanical energy. The generated energy propels a generator, which creates electrical energy that is responsible for moving along power lines to service the manufacturing industry. Within the gas turbine, the blades and vanes ascertain an adequate flow of air within the whole turbine. These blades, which are appended to a shaft, facilitate the extraction of energy obtainable in the air. While using blades and vanes in gas turbines, thermal stresses, oxidation, and hot corrosion are usually experienced and affect the lifespan of these blades and vanes. To mitigate this problem, adhesion engineers increasingly use coatings in industrial equipment in gas turbine blades and vanes since they protect them against thermal stresses, oxidation, and hot corrosion.

Furthermore, investments in coating equipment, such as the high-velocity oxygen fuel spray, are demanding and elevated. The challenge is even the wide sides, capabilities, and complexity required by the coating system to function effectively. This stresses the need to optimize the coating process for cost-effectiveness and to guarantee the sustainability of the process and the manufacturing process as a whole.

However, the coating process has suffered sub-optimal value determination, which poses a serious threat to the economics of coating. While the prevailing approach of introducing the Taguchi method appears effective in resolving this issue, it sacrifices convergence speed and multiple optimization solutions. But the grey wolf algorithm has these attributes and many more. For instance, it is implemented easily, exhibiting a limited number of parameters and abiding by simple principles to operate. Thus, the grey wolf algorithm is proposed to optimize the coating of 67Ni18Cr5Si4B alloy powder process parameters in chiding powder feed rate, spray velocity, and spray distance. While using the powder specified in this work, of interest to the researcher are the following objectives: adhesion strength, porosity, and good microhardness. It is agreed that coating in utilities such as gas turbine blades and various components is a great way to protect components and help them withstand extremely high temperatures. This happens as components are thermally insulated. It is also known that the high-velocity oxygen fuel spray is the coating trend of the future. However, no study has covered straightforward mathematics in his implementation of the 67Ni18Cr5Si4B alloy powder to choose the best parameters in the spray process. Moreover, despite the diverse usage of the grey wolf algorithm, most studies to date have focused mainly on the modified Taguchi method (Danthala et al., 2021). Given the foregoing information as motivation, the optimization of the spray process parameters was pursued using the 67Ni18Cr5Si4B alloy powder. This optimization is of great significance to the associated studies since it could enrich researchers with this new knowledge.

Contribution: In this work, we proposed a metaheuristic optimization method based on the grey wolf algorithm. The following states the principal contributions of this work:

1. A new heuristic is presented, which can optimize the spray process parameters using the grey wolf algorithm. The adoption of this method allows us to overcome the drawback of the Taguchi method, which is a relatively poor convergence ability and an inability to produce multiple solutions at the same time.
2. The method of the grey wolf algorithm attains satisfactory performance and serves as a forerunner in its implementation in other processes.

In this study, the grey wolf optimisation, which is a non-traditional optimisation and not a traditional method, was employed for the following reasons: First, differently from other optimization tools such as the Taguchi method, integer programming, and linear programming methods, it offers insights into the optimization process of 67Ni18Cr5Si4B alloy powder. This is done as it uses a population of points, which mimics the different recognizable classes of grey involved (i.e., alpha, beta, and delta) in their social and hunting behaviour for prey devouring. It uses these points during searching, generates random positions, and explores the search space. Secondly, by offering a quick optimization procedure, it indirectly reduces the cost of coating the 67Ni18Cr5Si4B alloy powder and improves the efficiency of the fabrication process.

In the remaining part of the article, section 2 discusses the literature review in a detailed account. Section 3 states the methodology of the process. Section 4 discusses the results and discussion. Section 5 is the concluding remarks.

2. LITERATURE REVIEW

In modern industrial thermal spraying technologies, the high-velocity oxygen-fuel (HVOF) is located as a central process aimed at controlling the complex phenomenon of physicochemical scheme while coating materials. In this section, the various literature associated with thermal spraying technology is discussed regarding previous literature contributed by authors. In the area of HVOF, Ren et al. (2021) suggested a discontinuous cycle optimization representation. The attribute-based CAD/CFD was built to represent the conceptual structure. It was found that the spray coating was improved by handling the in-flight particle trend. Cheng et al. (2022) applied the Taguchi Optimisation technique to HVOF parameters to optimize them. It was found that the optimized coating illustrated better corrosion resistance relative to other coatings.

Notwithstanding, Murugan et al. (2014) suggested the optimization of HVOF spray parameters and found that WC-based cermet coatings are effective in the tested procedure. Ren et al. (2023) utilized a parametric coating treatment forecast prototype, the Nelder-Mead approach.

Hong et al. (2023) considered cermet coatings generated through HVOF spraying to improve cavitation silk erosion prevention in ocean power systems. It was found that two types of carbide-based cermet HVOF spray coating sets using commercial Cr3Cr2-2S(NiCr) and WC-10(N_i) powers as the on-process powders. Russell et al. (2023) used sodium alginate as a gelation assistant for producing spherical cement feedstock powders from ceramic metal particles. It was found that spherical particles enhanced activities within the HVOF gas stream. Meghwal et al. (2022) fabricated an AlCoCrFeNi high entropy alloy coating utilizing the HVOF process. In the aspect of improving the wear resistance of AlCoCrFeMo high entropy coatings, Patel et al. (2024) considered the material for applications in aerospace.

Dinh et al. (2018) used OCE and Taguchi to optimize process parameters for polishing using high-velocity oxygen fuel spray. The ANOVA analysis noted the spray distance as the parameter having the most effect standing at 53.18%, next is velocity at 32.72% and the least being the power feed rate standing at 13.45% while the values to make the most of the microhardness are velocity at 1000m/s, 40g/min power feed pace and a spray length 0.2m. in the vain, to decrease the polishing porosity a velocity of 900m/s is suggested, power feed rate 30g/min as well spray distance 0.1. The wear characteristic of crankshaft journal bearing coated using the HVOF method was the study carried out by Nursoy et al. (2008). Several reaction optimizations of the method factor for a small force cold spray polishing practice with the aid of the Taguchi value model were studied by Goyal et al. (2014). The outcome of the studies shows an enhancement in the Utility function (raw data), such as CT and CD.

Pukasiewicz et al. (2017) examined the impact of face-off length, power feed rate, as well as the proportion of fuel to oxygen on stress, microstructure as well and cavitation on the polishing of FeMnCrSi. Nguyen et al. (2021) determine the most favourable variable to obtain greater velocity in oxygen fuel spray employing 16Mn substance sprayed by a WC-12 Co. Spray distance appears to be the most prominent for the porosity and strength. Ribu et al. (2022b) studied water jet washing away performance as regards HVOF-sprayed WC-10Co polishing when used on 35CrMo grade steel using trials. The highest force on the coating erosion was from the impingement angle. Danthala et al. (2021) pointed out that productivity, lower expenses on labour, quality, and a clean environment can be achieved using robotic techniques of spraying. The call-in parameters for the optimal result are pressure, distance, and speed. An easily improved Taguchi method is employed to reduce surface roughness and thickness variation and to maximize the film adhesion in robotic spraying.

Górnik et al. (2021) used statistical methods to examine the microstructure of WC-Co-Cr coatings accumulation along with HVOF. From the outcome, the porosity lies between 5.01% to 5.38% in volume, and a coating size of 0.1-1.0 μm was noticed to be dominant. Ribu et al. (2022a) used a usual polished HVOF composite WC-10Co coating on steel support. Coating wasted several experimental models have been formulated. The author concluded that speed is the most significant, followed by impinging angle, slurry composition, and time being the least.

Prasad et al. (2021) focus on comparison analysis and examination of HVOF feed invariable to get the most out of the hardness and bring down the porosity as relates to the WC-10Co-4Cr coatings. An acceptable reduced value of 0.2% was obtained, and 1325.26 HVx was maximized in contrast with the rest forms of coating as established through response graphs and contours. Chi et al. (2021) pointed out that, as a result of increased hardness of the unprocessed material, a usual method of coating was brought in to enhance the slurry erosion-resistant ability. Al-Abboodi et al. (2022) studied the arid amorphous coating made of iron deposited on mild steel with the aid of the HVOF heat technique of spraying. Yang et al. (2022) examined the deposition of Ni-Mo alloy coating on nodular cast iron substrate using the HVOF spraying technique. The outcome shows the possibility of using HVOF to achieve 58.8 MPa bonding strength, as well as a Ni-Mo coating not subjected to corrosion with 0.62% porosity. Oksa et al. (2014) in the study of nickel-based HVOF coating behaviour pointed out the special ability of HVOF coating made of Nickel under varying temperatures below 800^0C in a biomass CFB boiler.

Wang et al. (2020) suggested the manufacturing of completely densified as well as a complete circular WC-Co particle to be utilized in thermal spraying using a novel alumina-aided treatment technique. Mosayebi et al. (2020) investigated the impact of Ni-Mo as well as Ni concerning their ability to resist corrosion in chloride media. The outcome shows a higher corrosion ability for 3v/v% HCl and 3.5wt%.% NaCl for the Ni-Mo and an utmost polarization resistance in Ni-15 wt% when the two coating methods are analyzed. The study of Hong et al. (2021) subjected high-velocity fuel (HVOF) sprayed nanostructured WC-10Co-4Cr coatings to seawater at different intervals under the influence of bacteria aimed at bringing down the surface. The outcome of the study shows a reduction in current density associated with corrosion, an increase in resistance parameters up to one magnitude, and elevated penetration ability of the sealant into the sprayed coating as a result of the ultrasound–aided sealing method. Henao et al. (2020) investigated the activity of behaviour of HVOF-sprayed HAp/TiO_2 graded coatings on a Ti-6Al-4V alloy. They concluded that the HVOF-sprayed Hap-based coating has a superior advantage over the uncoated Ti-6Al-4V alloy. Mahade et al. (2021) deposited a Cr3C2eNiCr-based coating using the High-Velocity Oxy Fuel as well as High-Velocity Air Fuel to study how feasible it is to adopt Cr3C2eNiCr-based coating on the brakes of automobiles, as regards sliding wear performance when dry under varying examination processes.

From the reviews conducted in this section, the focus of the various articles was declared, and the associated shortcomings of the papers were discussed. However, despite convincing evidence of extensive studies on fabrication, mechanical property modification, and enhancement of coating properties of HVOF coatings, among others, the aspect of parametric optimization during the HVOF coating process is less tackled in the literature. In light of this research gap, the objective of this article is to optimize the parameters of the HVOF thermal spray coating process while processing the 67Ni18Cr5Si4B alloy powder using the grey wolf optimization specifically, the novel grey wolf optimization was chosen for the present study based of its outstanding advantage of fast computational ability and the unique material of 67Ni18Cr5Si4B was used. The grey wolf optimization was introduced and satisfied the condition that, despite the paucity of data that may confront the coating process, the grey wolf algorithm thrives, providing a rich set of information to which further managerial decisions could be made.

3. METHODOLOGY

In this paper, the data by Dinh et al. (2018) was utilized, which proposed the optimization of 67Ni18Cr5Si4B coating using the Taguchi-OEC method. This requires first defining the orthogonal array and then proceeding to evaluate the objective function of the grey wolf optimization through the combination of the orthogonal array entries. Thus, the procedure followed in the present paper is as follows:

Step 1: Establish the factor level to propose an orthogonal array from this table: After establishing the HVOF coating process, the key components of the process essential to achieve the goal of the coating process in terms of efficiency and quality of outputs are established. These components are referred to as parameters. In all, three process parameters are identified to influence the HVOF coating process. These are the standoff distance, powder feed rate, and particle velocity. Given these three parameters, specific levels are chosen, which are levels 1, 2, and 3 in this case, obtainable from the data provided by Dinh et al. (2018), which is the coating of 67Ni18Cr5Si4B substance on C45 steel substrate. Then, by entering the number of parameters and levels into software such as Minitab 18 (2020), an orthogonal array of a particular run is returned as the result of the inputs of the parameter number and level. The Minitab 18 (2020) is a statistical package with an orthogonal array design facility that employs rules for the specification of the orthogonal array for a problem.

Step 2: Use the orthogonal array and the data on factors and levels to obtain the translated orthogonal array, which is the replacement of the initially generated orthogonal entries with the specific values obtained from the factor level table.

Step 3: For each objective function, identify the constraints and variables and determine if the function is in a minimization or maximization context.

Step 4: Apply the grey wolf algorithm.

Step 4.1: Randomly initializes the grey wolf population: Here, the parameters, namely the standoff distance, powder feed rate, and particular velocity, are assigned some initial values in no order.

Step 4.2: Find the positions of the alpha, beta, and omega wolves. It is assumed that their positions relative to the prey being hunted are important and are determinants in catching and killing the prey.

Step 4.3: Find the first, second, and third positions of the wolves.

Step 4.4: Obtain the new position of the wolves as they move towards the same targeted prey.

Step 4.5: Carry out greedy selection.

4. RESULTS AND DISCUSSIONS

In this section, the discussion only centred on the grey wolf algorithm since the Taguchi techniques, which involve the development of an orthogonal array, have been reported by Dinh et al. (2018). The results and discussion section is structured according to four segmentations: (1) the Pre-grey wolf application stage, (2) the grey wolf prey-searching stage, (3) The prey-encycling stage (4) the prey-killing stage. The corresponding steps for these stages in the methodology are as follows: steps 1 to 3 are the pre–grey wolf application stage. Step 4.1 shows the searching stage for the prey. Step 4.2 of the methodology stage shows the encyling stage for the prey, while steps 4.3 to 4.5 are implemented for the grey killing stage.

Phase 1 - The prey-grey wolf application stage: At this prey-grey wolf application stage, factors (parameters) and their levels are extracted from the original data presented by Dinh et al. (2018). In a case where those data are not available in the form presented by Dinh et al. (2018), the most important parameters that should represent the coating process are identified. Then data is collected multiple times and grouped according to some preferred classes, which are called the levels. The data obtained from levels and factors form the basis of the selection of orthogonal arrays, which were picked from the generated data of the Minitab software. The orthogonal array provides a set of experimental trials upon which the regression equation is generated. This forms the ending point of the first phase of the result generation. The output of this phase is Equation (1), which expresses the adhesive strength in terms of stand-off distance, powder feed rate, and particle velocity. Moreover, two other progression equations were generated, similar to Equation (1). However, the details are not shown here, but only the results are used for further processing in the work. Thus, regression equations related to porosity and microhardness were generated and used for further processing in the grey wolf optimization procedure. New, starting the second phase, Equation (2) is deployed.

Moreover, three empirical models were developed in the work, each of which focuses on the objective function. Formulation, where the adhesion strength (A) is the dependent variable of the linear programming formulation while. The standoff distance, powder feed rate, and particle velocity are the independent variables. These independent variables are also maintained in the second and third objectives, where porosity (P) and Microhardness (M) are the dependent variables.

Moreover, these three empirical models, which were obtained, will be used for the optimization using the grey wolf optimization algorithm. The optimization process is achieved with the help of a C++ program. The optimization process is conducted to help determine the output variables. Furthermore, starting the working of the process with objective 1, it is known that the adhesion strength (A) should be maximized. Therefore, by extracting data from the orthogonal array and feeding it into the Minitab 18 (2020) software, Equation (1) is formulated as follows:

$$A = 216 - 0.248V - 8.22Q + 1187L + 0.01052VQ - 0.809VL - 9.63QL \quad (1)$$

From Equation (1), the inputs, which are the standoff distance, powder feed rate, and particle velocity, have the units of measurement as metres, grams/min, and metres/second, respectively. Equation (1) is for the output named Adhesion strength (MPa), symbolized as A, and should be maximized. Furthermore, as the analysis will be done in this section, the expected objectives of porosity (%), named P, are minimization, while microhardness (HV), named M, should be maximization. Moreover, for the experimentation conducted in this section, the population size used is a wolf of seven, while the number of iterations is fixed at 180.

Phase 2: The grey wolf prey-searching stage - Next, each parameter is defined as per their boundaries in the lower and upper aspects. These boundaries are obtained from the generated orthogonal arrays (translated), which show 800 and 1000 metres/second as the lower and upper boundaries for particle velocity, respectively. The lower and upper boundaries for powder feed rate are 30 and 50 grams/min, while for the standoff distance, the lower and upper boundaries are 0.1 and 0.3, respectively. Notice that from the steps indicated in the methodological section, the application of the grey wolf algorithm is the next phase of action after defining the objective function stated in Equation (1). For this application step, the sub-step to implement is the randomization and initialization of the grey wolf algorithm. To achieve this objective, Equation (2) is used:

$$X = L + r\,(U - L) \quad (2)$$

Note that L is the lower boundary value of the parameter of interest U is the upper boundary value for the parameter. r is the randomly generated number between 0 and 1.

The boundaries defined for this problem show where the values of a parameter begin (i.e., lower boundary) and where it ends (i.e., upper boundary). By setting boundaries for the parameters, the various goals for the coating process could be prioritized. This means that the decision-maker chooses either the efficiency of the coating process on the substrate C45 steel or the quality of the coating should be considered first. This protects the processing time and the energy expenditure of the decision-maker in the process. Overall, the sustainability of the process is promoted. The format used in running the C++ program is to generate values in rows, with each row having process parametric values of the upper and lower boundaries. This represents a wolf. This consists of a matrix (wolf). The wolf contains values falling within the specified boundaries. These values can randomly be determined with Equation (2) yields a value of 0.287322.

In summary, from calculations, V, Q, and L are obtained as 827.442, 48.4716, and 0.287323, respectively. These values provide a basis to be substituted into equation (1), which is the objective function that defines the adhesive strength of the coats on the C45 steel substrate. By substituting the values of V, Q, and L mentioned above into Equation (1), the predicted value of the adhesive strength, AD, is obtained as 48.8891MPa. This is an intermediate value that should be used for further processing. The calculated random variable generated is 0.137211, and the upper boundary is 1000 metres/second. By substituting these values into equation (2), V is obtained as 827.4422. Also, knowing the lower limit of Q is 30g/min, the upper limit is 50 g/min, the random variable is 0.923582, and the value of Q, using equation (2), is calculated as 48.47164. Furthermore, L may be calculated using Equation (2). However, there is a need to introduce the lower boundary as 0.1 metres, the upper boundary as 0.3 metres, and the random variable used is 0.936613, and then introduce these values into aid of equation (2). For the first wolf, the random variables generated are as follows: 1st wolf 0.137211 0.923582 0.936613.

Now, for this first wolf, the values of all the inputs, namely particle velocity (V), powder feed rate (Q), and standoff distance (L), could be predicted and substituted into the objective function (i.e., equation (1) to establish the output value, AD. The next calculation involves determining the value of V using Equation (2). Notice that the lower boundary is given as 800 metres/second; the two are also repeated for wolves 2 to 7 using newly generated random values. The summary of these results is shown in Table 1.

The calculations in Table 1 set the scene for the more intensive evaluations through several iterations until convergence is achieved. In the analysis that follows, the representative detail of each iteration is shown, and this is repeated until very close or the same values of outputs are generated each time, which is the convergence of the results. The iterations start with iteration 1 and proceed to iteration 180, which is considered the terminating iteration. Furthermore, this paper highlights the method of the grey wolf algorithm to propose optimization for the coating of 67Nil8Cr5Si4B alloy powder process parameters. However, for a deeper understanding of the methodology and implementation of the grey wolf algorithm in the practical scenario discussed in this research, some important questions need to be answered, such as the following: What is the likelihood that the grey wolf algorithm will lead to the correct result? How many initial guesses are essential to affect the convergence result for the algorithm? By deeply understanding these questions and attempting to answer them, there is a pointer to the need to add information about the stopping rule for the algorithm. Moreover, the stopping condition forces the grey wolf algorithm to terminate the process. In the literature, the popular and meaningful conditions could be any of the following: the use of a random termination key, an external /internal condition, the quality of the solution, and the number of interactions.

Table 1. The result summary

V	Q	L	AD
827.442	48.4716	0.287323	48.8891
846.004	40.1169	0.149709	50.8736
938.865	43.6534	0.139827	56.4785
865.908	30.5042	0.259673	78.4293
807.343	44.6733	0.230076	51.8345
929.337	42.2208	0.255913	58.5604
965.032	36.5505	0.205087	58.4305

Table 2. The information of the 1st, 2nd, and 3rd wolf

X1	X2	X3
A_1 = 2a.r-a	A_2 = 2a.r-a	A_3 = 2a.r-a
C_1 = 2.r	C_2 = 2.r	C_3 = 2.r
$D_\alpha = \mid C_1 X_\alpha - X(t) \mid$	$D_\beta = \mid C_2 X_\beta - X(t) \mid$	$D_\delta = \mid C_3 X_\delta - X(t) \mid$
$X_1 = X_\alpha - A_1 D_\alpha$	$X_2 = X_\beta - A_2 D_\beta$	$X_3 = X_\delta - A_3 D_\delta$

However, based on the nature of the grey wolf algorithm, the number of iterations is used as a unique criterion in this work. It is fixed at 180 iterations. The motivation to use the number of iterations as a stopping criterion in this work is the opportunities it provides to reach convergence. Higher iterations provide higher opportunities for feedback and chances to adjust and fine-tune the outcome, yielding enhanced overall results. Furthermore, the number of iterations of 180 was decided based on several initial multiple independent runs of the program with random initialization. It was found that at 180 runs, the results show the capability of the grey wolf optimization to track the counting problem being solved in the present study.

Commencement of iteration 1

Here, the appropriate step to implement is to find the positions of the alpha, beta, and omega wolves. In this step, each of these wolves represents the best, second, and third-best values of the seven wolves, respectively. Notice that the objective of the decision maker is to maximize the value of A, which implies that the best position is the wolf with the highest value of A. The second-best position has the second-highest value of the serial number, and the third-best value of A is with the wolf having the third largest value of A from the seven wolves. Recall that with Equations (1) and (2), the values of inputs, V, Q, and L, were simulated with the corresponding output, AD. Now, the three outputs AD, which yield the best results, are recalled and labeled as alpha, beta, and delta wolves. The corresponding values of the outputs, which give the best, are 78.4.293, with the inputs of V, Q, and L as 865.908, 30.5042, and 0.259673, respectively. This is the 4th wolf in the set of results. The second best has an AD value. 58.5604 that has corresponding values of V, Q, and L as 929.337, 42.2208, and 0.255913, respectively. Next, the third best output is 58.4305 and has the values of V, Q, and L as 965.032, 36.5505, and 0.205087, respectively.

Phase 3 - The prey-encycling stage: The next stage is to calculate X_1, X_2, and X_3. However, this is achieved by first determining the value of "a", Equation (3).

$$a = 2\left(1 - \frac{iteration}{\max iter}\right) \tag{3}$$

Now, to evaluate the value of "a", the iteration number is 1, and the Maxiter is given as 180. The value of "a" is 1.98. However, it is known that for the first, second, and third wolf, the following information is useful (Table 2):

Now, obtaining the value of X_1, the expression for A_1 is obtained by substituting the values "a", and r as 1.99, and 0.137516, respectively. Thus, A_1 is 1.4427. Also, C_1 is obtained by substituting r as 0.137516, and C_1 yields 0.275032. Now, having obtained the value of C_1, the value of D alpha is computed as C1 is introduced as 0.275032, X alpha is.

X_1, X_2, X_3,

Using the values 865.908 30.5042 0.259673

X(t) = 827.442 48.4716 0.287323

D_α = |0.275032 (865.908 30.5042 0.259673) - (827.442 48.4716 0.287323) |

D_α = 589.2896 40.082 0.215903

X_1 = 865.908 30.5042 0.259673 – [-1.4427(589.2896 40.082 0.215903)]

X_1 = 1716.0761 88.3305 0.571153

Following the same procedure, the C++ programming language is used to derive the values of and

X_1: 1720.34 88.6204 0.57272

X_2: -472.109 -3.70879 -0.0330428

X_3: 885.218 34.6325 0.1899

The next step involves finding X_{new}, the average of X_1, X_2, and X_3. Thus, X_{new} is obtained as follows:

X_{new}: 711.149 39.848 0.243192

Phase 4 - The prey-killing stage: Next, the greedy selection is conducted, where the researcher inputs the values of X_{new} into the objective function to obtain the required output value. In the present objective, we are expected to optimize as such when the value obtained X_{new} surpasses the previous value for the output. We replace the wolf, but if the reserve is the case, the wolf remains unchanged. The process undergone above is called greedy selection.

The previous value of adhesion strength is 48.8891, but X_{new} is 63.3636.

Then $F(X_{new})$ of adhesion strength is 63.3636.

The objective demands that the $F(X_{new})$ produces a value above the initial value of F. However, we noticed

Table 3. The updated values

V	Q	L	AD
800.000	39.8480	0.243192	63.3636
846.004	40.1169	0.149709	50.8736
938.865	43.6534	0.139827	56.4785
865.908	30.5042	0.259673	78.4293
807.343	44.6733	0.230076	51.8345
929.337	42.2208	0.255913	58.5604
965.032	36.5505	0.205087	58.4305

Table 4. The output summary of the 1st iteration

Iteration	Output
Iteration 1	: 78.4293
Iteration 2	: 78.4293
Iteration 3	: 78.4293
…	
Iteration 177	: 85.82
Iteration 178	: 85.82
Iteration 179	: 85.82
Iteration 180	: 85.82

that in this case, the new value is above the previous value, i.e., $F(X_{new}) > F(X)$. Since this satisfies our needed condition, the new wolf is desirable, and the wolf is replaced. The updated values are shown in Table 3.

A similar operation is repeated for the rest of the wolves. At the end of each iteration, the best values with the highest S/N value will be taken as X alpha. Moreover, a total of 180 iterations were processed for the problem. In this situation, the optimal input in terms of particle velocity, powder feed rate, and stand-off distance was obtained with their corresponding output of adhesion strength, porosity, and microhardness. After running several iterations, it was observed that iterations one, two, and three yielded 78.4293 each. Further iterations yielded different values, which increased over time for the adhesion strength. Furthermore, little increases were observed in adhesion strength for iteration 4 to iteration 176. Finally, the value of 85.82 was obtained consecutively for iterations 177,178,179, and 180. This gives the motivation to terminate the iteration at 120 because it converges at this point. Notice that the values continue to increase because maximization of the objective function is desired. Two other sets of iterations were worked on in the iteration concerning porosity, minimization of the objective function is pursued, and the minimum value converges at 0.684909. Also, for the output named microhardness, maximization of the output yielded a value of 583.04, which was truncated at 180 iterations. However, in this work, only a brief detail of iterations for the adhesion strength is shown, covering iterations 1 to 3 and 177 to 180. Details of iterations for other outputs are not indicated here. In summary, the output of the first iteration, which is adhesion strength, is shown Table 4.

Furthermore, the best fit, which is taken as the values for the adhesion strength after 180 iterations, yielded values of V, Q, L, and A at the 180th iteration as 80m/s, 30g/min, 0.248465m, and 85.82MPa, respectively. Moreover, for the best feet of X alpha for porosity at the end of 180 iterations, the values of V, Q, L, and P are 800m/s, 30g/min, 0.229903m, respectively. The corresponding porosity is 0.684909 percent. Moreover, for the micro-hardness output, the best feet X alpha values at the end of 180 iterations are V=180m/s, Q=30g/min, L=0.3m, while the microhardness is 583.04 HV.

In practice, several instances occur where the addition of layers of coating is made to the surfaces of solid objects such as pipes, car bodies, and other applications. The result of this study provides information on the appropriate position to stand while handling the nozzle with respect to the surface being coated, i.e., stand-off distance. In addition, it educates the decision maker on the powder feed rate, which should not be above the one specified in this work. Besides, the particle velocity of the nozzle of the spray unit should be discharged at the maximum threshold displayed in this work. If all conditions are satisfied, the efficiency of the coating process is guaranteed. In addition, the quality of the coat should also be desirable.

5. CONCLUSIONS

This study focuses on the optimization of coating by the HVOF spraying technique. To obtain stand-out responses for the adhesive strength, porosity, and micro-hardness, the grey wolf optimization approach was adopted as the optimization method. The input parameters were found jointly to have an outstanding performance on the responses when alternated within the given range of 800-1000 for the velocity (V), 30-50 for the feed rate (Q), and 0.1-0.3 for the distance (L). The optimal coating condition for the adhesion strength is at a particle velocity of 800m/s, at a 30g/min power feed rate, and a standoff distance of 0.229903m. Undertaking the coating at a particle velocity of 800m/s, 30g/m power feed rate, and 0.3 standoff distance provides the best condition for the micro-hardness and an optional condition for porosity at 800m/s particle velocity, 30g/m power feed rate, and 0.229903 standoff distance. This is the first time grey wolf optimization is used to optimize coating parameters of

67NiCrS5i4B on C45 steel substrate. In further work, the merging of fuzzy and VIKOR to the grey wolf optimization model for combined selection and optimization of parameters, to demonstrate the impact of uncertainties in selecting among the coating process parameters, should be discussed. This study can also be extended with practical data obtained from practice, in which the optimal quantities suggested in this work are further optimized by methods such as ant colony optimization and whale optimization.

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