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RESEARCH ARTICLE

OPTIMIZATION of ATMOSPHERIC PLASMA SPRAY PROCESS PARAMETERS for DEPOSITION of THERMAL BARRIER COATINGS

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ABSTRACT

In the production of thermal barrier coating (TBC) with the atmospheric plasma spray coating system, the process parameters directly affect the production cost and performance of the coatings. In this study, a comprehensive modeling-design-optimization study was conducted to improve the analytical performance of TBC. For this purpose, the data were taken from a literature study that included an extensive experimental design application. The modeling study prepared first, second, and third-order polynomial, trigonometric, and logarithmic-based models for each process output. Model selections were made with neuro-regression and a statistical method. The selected models were run on four different stochastic optimization algorithms for the coatings' deposition efficiency, bond strength, porosity, and hardness value outputs. Thirty-six neuro-regression models prepared in the modeling study have high $R^2_{training}$ values. The second-order logarithmic nonlinear (SOLN) models were successful in the coatings' deposition efficiency and bond strength, and the polynomial nonlinear models were successful for the four process outputs. Therefore, they were chosen as the objective functions of the optimization algorithms. In addition, the selected models were run at the parameters determined by numerical optimization in the reference publication, and the prediction abilities of the models in the two studies were compared. SOLN models for deposition efficiency and bond strength values, second-order nonlinear model for hardness value, and reference study' model predicted more closely to the validation test result for porosity values of coating. In the optimization studies, three or more algorithms suggested the same results with the same parameter sets for the deposition efficiency and hardness values. The optimization results show that these points can be a global optimum point for optimizing these two coating properties.

Keywords: *Plasma spray coating, Thermal barrier coating, Neuro-regression, Optimization*

1. INTRODUCTION

Gas turbine engines are widely used in power plants and aircraft engines. Turbine engines used in power plants operate for extended periods (100-500 days) at high temperatures under constant thermal stresses. Although the ones used in aircraft engines work for shorter periods, they operate under variable thermal stresses due to different conditions intake off-landing and flight [1]. More dynamic and stable flight of airplanes is ensured by having a sizeable thrust-weight ratio. Increasing the turbine inlet temperature is an efficient approach to increase the thrust-weight ratio. However, increasing the temperature will also increase the condition of the turbine components to undergo hot corrosion, high stresses, and oxidation. The most effective method to eliminate this problem is to coat turbine engine components with ceramic TBC with low thermal conductivity [1-3]. TBC are deposited in the form of a metallic bond coating and a ceramic top coating on nickel-based superalloy parts that are resistant to the operating conditions of turbine engines. The bond coating provides oxidation and corrosion resistance to the structure and balances the thermal properties and tensions between the ceramic coating and the substrate. The ceramic top coating provides thermal insulation, strain tolerance, and thermal shock resistance for hot components by reducing heat transfer. Generally, in TBC, 40-200 μm thick MCrAlY (M= Ni, Co) is used as the bond coating, while 100-400 μm thick yttrium-stabilized zirconia (YSZ) is used as the top coating [1, 2, 4].

TBCs are mainly produced using either electron beam physical vapor deposition (EB-PVD) or atmospheric plasma spraying (APS) [5, 6]. In EB-PVD, the raw materials are deposited on the substrate surface after heated and evaporated with a high-energy electron beam. Coatings are deposited as columnar grains containing closed and open pores perpendicular to the substrate in a typical EB-PVD system. Microstructures of PVD coatings have good strain tolerance due to their low elastic modulus. In this way, the thermal cycle life of the coated engine components is extended. However, the EB-PVD technique is more complex and costly than other coating techniques [5]. Metalic or ceramic coating powders in APS coatings are injected into the plasma jet with a carrier gas. The coating powders are converted into semi-molten form by heating in the plasma, and at the same time, they are accelerated and sprayed onto the substrate surface. When semi-molten powders hit the substrate surface, they spread on the surface and form coating layers called splats. Therefore, APS coatings are relatively less costly and have lower thermal conductivity than EB-PVD coatings [1, 2, 5, 6].

Optimization of APS coatings begins with the mathematical modeling of process parameters and responses. Many microstructural and physical properties of TBC, such as the amount of porosity, bond strength, and hardness, are affected by more than fifty factors such as plasma characteristics, substrate properties, coating powder properties, atmosphere, device and user properties [7]. These parameters can affect the properties of coatings both individually and together. Many researchers have studied various experimental and statistical methods to optimize these effects of parameters. Chen et al. investigated the effects of plasma power, process gas flow values, and coating distance on the thermal shock resistance of the coating by using Range analysis [8]. Bertrand et al. statistically investigated the effects of plasma power, coating distance, gas flow rates, speed, and angle of movement of the coating gun on the surface roughness, deposition efficiency, amount of porosity, and thermal conductivity properties of coatings [9]. Ning et al. investigated the effects of process parameters on thermal stress estimation of coatings using Artificial Neural Networks (ANN) [10]. Ramachandran et al. investigated the effects of primary and carrier gas flow rates, plasma power, coating distance, and powder feed rate on coatings' deposition efficiency and bond strength by response surface analysis (RSA) [11]. Kim et al. investigated the change of oxide growth in the bond layer of TBC with thermal cycle tests and process temperature and time with regression analysis (RA) [12]. Karthikeyan et al. investigated the effects of plasma power, coating distance, and powder feed rate on their coatings' porosity and hardness values with RSA. They modeled the data with RA [13].

Optimization of the physical, mechanical, and thermal properties of APS coatings has been investigated by many researchers using various optimization algorithms [4, 14-18]. Lin et al. obtained the optimal plating distance, plasma current, argon, and hydrogen gas flow rates using an ANN and

Genetic Algorithm (GA). They performed validation tests using these parameters and obtained approximately 40% reduction in the porosity value of the coatings, high-temperature stability, and high hardness [4]. Tonkonogy et al. investigated the effects of grinding parameters on the surface properties of coatings by using ant colony, particle swarm, scatter search, and genetic algorithm. They stated that the surfaces of the coatings deposited with the parameters suggested by the genetic algorithm would have lower surface defects and roughness [17]. Ye et al. investigated the microstructural properties of coatings such as porosity, pore-crack ratio, and maximum ferret diameter with the Cuckoo Search Algorithm. They noted that there was no significant relationship between porosity, pore-crack ratio, maximum Feret diameter, and aspect ratio, but the coating powder size had a significant effect on the microstructure properties of the coatings [18]. Shi et al. investigated the effects of the microstructural properties of the coatings on the thermal diffusivity behavior with Random Generation Algorithm. They suggested that the best thermal insulation achieved in a 50 µm coating with porosity widths from 0.54 µm to 2.56 µm [15]. Sankar et al. investigated the effects of coating thickness on thermal conductivity with GA and suggested the optimum coating thickness as 125 µm [16]. Rajesh et al. used Teaching Learning Based Optimization Algorithm to obtain optimum microhardness, porosity, wear and surface roughness values of their coatings. They determined that parameters such as carrier gas flow rate, coating distance, arc current, and powder feed rate are directly related to coating properties [14].

The APS process optimization studies are examined, it is seen that only one first or second-order regression model is used in the preparation of the objective functions. In these studies, the data obtained with the process parameters were estimated by the models prepared with the same parameters. The ability of the models to predict the actual values was checked with the R^2 calculation. After this evaluation, models with high R^2 values were stated as successful. However, in this approach, while the models successfully predict the results obtained only in those parameters, they may not predict the whole process correctly. Such problems have been somewhat resolved with ANN-based modeling and optimization studies [4]. Another critical issue is the limitation of models as objective functions. System parameters can be used within a certain operating range in engineering applications. This situation requires that the functions that define the systems also have boundaries. In addition, the security, sensitivity, and robustness of the algorithm used in stochastic search systems should also be considered [19].

In this study, a modeling-design-optimization technique was conducted to optimize the process parameters in the production of TBCs with the APS system. This method was organized using data from a literature study [11], which organized the experimental work with a factorial experimental design set to optimize the deposition efficiency, tensile bond strength, hardness, and porosity of the coatings. Firstly, in modeling and optimization studies, neuro-regression models in different forms (linear, polynomial, trigonometric and logarithmic) were made. Secondly, the prepared models were selected for each process output by checking the statistical analyzes and limit values. Finally, Differential Evolution (DE), Nelder-Mead (NM), Random Search (RS), and Simulated Annealing (SA) stochastic optimization algorithms were run with selected models to solve the same problems. In this way, optimum operating parameters for the APS process were obtained.

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2. MATERIAL AND METHOD

2.1. Modelling

In the modeling stage, a hybrid method combining the benefits of RA and ANN was used to test the accuracy of the predictions. In this method, four-fifths of all data are randomly allocated for training. The rest is used for testing. The purpose of the training process is to minimize the difference between the experimental and predicted values by adjusting the regression models and coefficients listed in Table 1. Finally, in the testing phase, the ability of the models prepared with the training data to predict the test data is checked.

Statistical analyses of the coefficient of determination ($R^2_{training}$, $R^2_{testing}$), root mean square error (RMSE), mean absolute error (MAE), and model efficiency (ME) of training and test data for each model were used to determine the relationships between neuro-regression models and experimental data (see Eq. 1-4). In addition, the lowest and highest predictive values of all models were calculated under experimental limit conditions.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(X_{A,i}-X_{P,i})^2}{\sum_{i=1}^{n} X_{P,i}^2} \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_{A,i} - X_{P,i})^2} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(X_{A,i} - X_{P,i}) \tag{3}$$

$$ME = 1 - \frac{\sum_{i=1}^{n}(X_{A,i}-X_{P,i})^2}{\sum_{i=1}^{n}(X_{A,i}-\bar{X}_{P,i})^2} \tag{4}$$

where X_A is the actual value and X_P is the estimated value.
To determine the objective functions in the optimization algorithms, the statistical calculations and limit values of the nine neuro-regression models were calculated, and model selections were made. Model selection is carried out in three steps. In the first step, $R^2_{training}$ and $R^2_{testing}$ values are checked, and those with values greater than 0.9 will be selected. In the second step, the limit values of the models are checked, and the models with less than 100% difference to the experimental data will be selected. In the third step, the models' RMSE, MA, and ME values are checked. Models with RMSE and MA values close to zero and ME values close to one will be determined as target functions.

Table 1. Multiple regression model forms.

Models	Nomenclature	Formula
First Order Multiple linear	FOL	$Y = \sum_{i=1}^{3}(a_i x_i) + c$
Second order multiple nonlinear	SON	$Y = \sum_{k=1}^{3}\sum_{j=1}^{3}(a_j x_j x_k) + \sum_{i=1}^{3}(a_i x_i) + c$
Third order multiple nonlinear	TON	$Y = \sum_{l=1}^{3}\sum_{m=1}^{3}\sum_{p=1}^{3}(\beta_l x_l x_m x_p) + \sum_{k=1}^{3}\sum_{j=1}^{3}(a_j x_j x_k) + \sum_{i=1}^{3}(a_i x_i) + c$
First order trigonometric multiple nonlinear	FOTN	$Y = \sum_{i=1}^{3}(a_i Sin[x_i] + a_i Cos[x_i]) + c$
Second order trigonometric multiple	SOTN	$Y =$

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nonlinear		$\sum_{i=1}^{3}(a_i Sin[x_i] + a_i Cos[x_i]) + \sum_{j=1}^{3}(\beta_j Sin^2[x_j] + \beta_j Cos^2[x_j]) + c$
Third order trigonometric multiple nonlinear	TOTN	$Y = \sum_{i=1}^{3}(a_i Sin[x_i] + a_i Cos[x_i]) + \sum_{j=1}^{3}(\beta_j Sin^2[x_j] + \beta_j Cos^2[x_j]) + \sum_{k=1}^{3}(\gamma_k Sin^3[x_k] + \gamma_k Cos^3[x_k]) + c$
First order logarithmic multiple nonlinear	FOLN	$Y = \sum_{i=1}^{3}(a_i Log[x_i]) + c$
Second order logarithmic multiple nonlinear	SOLN	$Y = \sum_{k=1}^{3}\sum_{j=1}^{3}(a_j Log[x_j x_k]) + \sum_{i=1}^{3}(a_i Log[x_i]) + c$
Third order logarithmic multiple nonlinear	TOLN	$Y = \sum_{l=1}^{3}\sum_{m=1}^{3}\sum_{p=1}^{3}(\beta_l Log[x_l x_m x_p]) + \sum_{k=1}^{3}\sum_{j=1}^{3}(a_j Log[x_j x_k]) + \sum_{i=1}^{3}(a_i Log[x_i]) + c$

2.2. Optimization

Structural optimization is defined as reaching the optimum value by minimizing or maximizing the specified single or multiple targets, considering all constraints. For this purpose, two types of optimization techniques called traditional and non-traditional are used. Traditional optimization techniques only work for continuous and differentiable functions. However, some engineering design problems have characteristic properties that conventional optimization techniques, which only work for continuous and differentiable functions, cannot be used. For this reason, only non-traditional methods can be used to solve these problems. For this purpose, many optimization algorithms such as Ant Colony, Particle Swarm, and Genetic Algorithm were developed and used in many engineering applications [17, 20, 21]. However, since the exact solution cannot be reached with stochastic methods, it is beneficial to use more than one algorithm with various technical infrastructure for the same optimization problem solution to increase the reliability of the result [19].

Some objective function-based problems can be encountered in solving mathematical optimization problems by stochastic algorithms. The problems of objective functions are expressed in general titles as non-multilinearity, having many local optimum points, mixed-integer design variables, and nonlinear constraints [19]. In this study, DE, NM, SA, and RS optimization algorithms, which have been successfully applied in many engineering applications, were used to solve the same APS coating problems to overcome the difficulties encountered in the optimization study. Detailed information and operating parameters of these algorithms are available in [19, 20].

2.3. Problem Definition

In this study, the deposition efficiency, bond strength, porosity, and set values of TBC produced by the APS process were optimized. Firstly, the data used to determine the objective functions were taken from the literature study [11]. The data including coating process inputs (Input Power (P), Primary Gas Flow Rate (PGFR) Coating Distance (D), Powder Feed Rate (PFR), Carrier Gas Flow Rate (CGFR) and outputs (Deposition Efficiency (E), Bond Strength (BS), Porosity (P), Hardness (H)) are presented in Table 2. Next, nine candidate functional structures are proposed to express the relationship between each process output and inputs mathematically. Then, the selection of the most suitable model for each output was made in two steps: the calculation of the $R^2_{training}$, $R^2_{testing}$, RMSE, MAE, ME, limit values of the models, and the selection of those that satisfy the conditions. Finally, all coating problems are solved by four different direct search algorithms with the selected models.

In this optimization study, the objective functions define the deposition efficiency, bond strength, porosity, and hardness values of the coating of YSZ powder as TBC in the APS system. The objectives of the optimization study are to maximize the deposition efficiency, bond strength, and hardness values and minimize the porosity value. The search space is continuous in the optimization setup, and the design variables are integers. Design values for this process were determined as 22 kW≤ P ≤ 30 kW, 25lpm ≤ PGFR ≤ 45 lpm, 90 mm ≤ D ≤ 130 mm, 15 gpm ≤ PFR ≤ 35 gpm, and 3 lpm ≤ CGFR ≤ 11 lpm.

Table 2. Process parameters and responses in the factorial experimental design set of thermal barrier coatings [11].

	Process parameters					Responses			
Run	P (kW)	PGFR(lpm)	D (mm)	PFR(gpm)	CGFR(lpm)	E (%)	BS(MPa)	P (%)	H ($Hv_{0.3}$)
1	24	30	100	15	9	44	9	20	710
2	28	30	100	15	5	59	17	8	954
3	24	40	100	15	5	49	7	11	792
4	28	40	100	15	9	67	21	4	1082
5	24	30	40	15	5	42	5	25	675
6	28	30	40	15	9	39	7	22	683
7	24	40	40	15	9	47	10	23	757
8	28	40	40	15	5	60	14	11	966
9	24	30	100	30	5	42	4	25	675
10	28	30	100	30	9	58	13	14	943
11	24	40	100	30	9	47	9	19	757
12	28	40	100	30	5	63	16	9	1024
13	24	30	40	30	9	32	4	25	512
14	28	30	40	30	5	40	5	24	652
15	24	40	40	30	5	41	6	25	663
16	28	40	40	30	9	45	8	17	733
17	22	35	110	25	7	41	6	23	663
18	30	35	110	25	7	64	19	6	1036
19	26	25	110	25	7	38	8	23	617
20	26	45	110	25	7	53	15	11	861
21	26	35	90	25	7	66	16	7	1071
22	26	35	130	25	7	48	7	23	780
23	26	35	110	15	7	58	18	12	943
24	26	35	110	35	7	48	13	21	780
25	26	35	110	25	3	58	10	13	943
26	26	35	110	25	11	53	11	14	861
27	26	35	110	25	7	70	23	5	1129
28	26	35	110	25	7	72	22	4	1164
29	26	35	110	25	7	70	23	5	1129
30	26	35	110	25	7	71	22	4	1140
31	26	35	110	25	7	70	23	5	1129

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32	26	35	110	25	7	72	22	4	1164

3. RESULTS AND DISCUSSION

In the reference study [11], the experimental setup of TB production with the APS system was organized according to the factorial experimental design set:

I. The results were modeled by RA.

II. They obtained the optimum values graphically with response surface analysis and numerically via the models. In both calculations, the input power 26.3 kW, coating distance 110.5 mm, carrier gas flow rate 36.15 lpm, powder feed rate 23.35 gpm, and carrier gas flow rate 7.8 lpm were found as optimum values of process parameters. They determined the deposition efficiency as 71.0825%, the bond strength as 22.999 MPa, the porosity as 4.0009%, and the hardness as 1148.92 $HV_{0.3}$ via graphical optimization.

III. They calculated the deposition efficiency as 71.0837%, the bond strength as 22.9997 MPa, the porosity as 4.0001%, and the hardness as 1148.94 $Hv_{0.3}$ via numerical optimization.
The statistical results and limit values of neuro-regression models of deposition efficiency, bond strength, porosity, and hardness values of TBC produced with the APS system are given in Table 3-6, respectively. The objective functions for each coating response were selected by examining these values.

Table 3. Results of Neuro-Regression models prepared for deposition efficiency of coatings.

Models	$R^2_{training}$	$R^2_{testing}$	RMSE	MAE	ME	Maximum (%)	Minimum (%)
FON	0.982	0.0575	7.2345	5.9144	0.5966	81.4711	32.8749
SON	0.9977	0.8176	2.5516	1.8566	0.9498	81.8114	9.2366×10^{-7}
TON	0.9999	**0.9599**	0.3202	0.1025	0.9992	81.313	19.3512
FOTN	0.9853	0.4183	6.537	4.7106	0.6706	114.393	4.2758×10^{-6}
SOTN	0.9999	0.1365	0.3202	0.1025	0.9992	76.1162	10.4223
TOTN	0.9999	-0.404	0.3202	0.1025	0.9992	62	1.1014×10^{-12}
FOLN	0.9827	0.1407	7.0935	5.76	0.6121	78.7856	32.1459
SOLN	0.9975	**0.9122**	1.6487	0.9137	0.9459	86.798	21.1729
TOLN	0.9999	0.687	0.3202	0.1025	0.9992	117.494	9.1199×10^{-11}

All models had $R^2_{training}$ values greater than 0.98 as shown in Table 3. However, only the TON and SOLN models have $R^2_{testing}$ values greater than 0.9. The maximum and minimum values are 81.313%, 19.3512% for TON and 86.798%, and 21.1729% for SOLN. Therefore, it was determined that the limit values of both models were compatible with the experimental results. In the final model selection step, it was seen that both models met the criteria for RMSE, MAE, and ME values. Therefore, the TON and SOLN models, which were successful in all evaluations, were chosen as objective functions for the optimization of the deposition efficiency of the coatings.

Table 4. Results of Neuro-Regression models for bond strength value of coatings.

Models	$R^2_{training}$	$R^2_{testing}$	RMSE	MAE	ME	Maximum (MPa)	Minimum (MPa)

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FON	0.9264	-0.0812	3.7064	2.9298	0.6312	28.2771	0.7685
SON	0.9941	**0.9192**	1.0416	0.798	0.9708	26.6069	1.1248
TON	0.9998	0.6835	0.1601	0.0512	0.9993	27.8997	$3.4416\ x10^{-7}$
FOTN	0.9511	0.352	3.0225	2.0048	0.7547	56.6733	$8.0577\ x10^{-11}$
SOTN	0.9998	0.3426	0.1601	0.0512	0.9933	27.0203	$1.1242\ x10^{-8}$
TOTN	0.9998	0.4154	0.1802	0.0633	0.9993	11.0614	$2.1811\ x10^{-7}$
FOLN	0.9269	-0.0078	3.6955	2.9044	0.6334	27.0397	0.679
SOLN	0.9924	**0.9325**	1.1858	0.9116	0.9626	28.5923	1.8785
TOLN	0.9998	0.5425	0.1601	0.0511	0.9993	41.3351	$8.1877\ x10^{-8}$

Table 4 shows the statistical results and limit values for the neuro regression models prepared for the bond strength of the coatings. It is seen that the $R^2_{training}$ values of all models are greater than 0.92, and even the 2nd and 3rd-degree models are greater than 0.99. However, only the $R^2_{testing}$ values of the SON and SOLN models were greater than the limit value of 0.9 (0.9192 and 0.9325). These two models also satisfied the other two criteria and were chosen as objective functions for optimizing the bond strength of the coatings.

Table 5. Results of Neuro-Regression models for porosity value of coatings.

Models	$R^2_{training}$	$R^2_{testing}$	RMSE	MAE	ME	Maximum (%)	Minimum (%)
FON	0.9579	0.0221	3.5559	2.7711	0.7768	31.5121	$1.8892\ x10^{-7}$
SON	0.9929	0.7831	1.4061	0.89	0.965	42.7176	$9.4926\ x10^{-11}$
TON	0.9999	**0.9358**	0.1601	0.0512	0.9995	36.562	0.8587
FOTN	0.9546	0.0927	3.5683	2.2883	0.7752	57.9335	1.2801 x10-7
SOTN	0.9999	0.3032	0.1601	0.0512	0.9995	30.9089	$1.9072\ x10^{-7}$
TOTN	0.9999	-0.3731	0.1601	0.0512	0.9995	27.925	$5.7252\ x10^{-8}$
FOLN	0.99525	0.1219	3.6484	2.8352	0.765	31.0363	$1.7474\ x10^{-8}$
SOLN	0.993	0.8218	1.3967	0.8633	0.9655	47.5996	3.6005
TOLN	0.9999	-0.1294	0.1601	0.0512	0.9995	91.9325	$2.0571\ x10^{-7}$

Table 5 shows the statistical results and limit values for the neuro-regression models for the porosity values of the coatings. It is seen that the $R^2_{training}$ values of all models are greater than 0.95, but only the $R^2_{testing}$ value 0.9358 of the TON model is greater than the limit value of 0.9. Therefore, the maximum and minimum values that can be reached with the TON model are 36.562% and 0.8587%, respectively, which meet the limit criteria. Finally, the RMSE, MAE, and ME values were examined. It was seen that the RMSE and MAE values were close to zero (0.1601 and 0.0512), and the ME values were close to 1 (0.9995). Therefore, the TON model met all the criteria and was chosen as the objective function for optimizing the porosity of the coatings.

Table 6. Results of Neuro-Regression models for hardness value of coatings.

Models	$R^2_{training}$	$R^2_{testing}$	RMSE	MAE	ME	Maximum ($Hv_{0.3}$)	Minimum ($Hv_{0.3}$)
FON	0.9871	0.042	8.876	78.4129	0.6553	1358.58	487.096
SON	0.9991	**0.9694**	3.7793	2.4316	0.9792	1238.91	280.1352
TON	0.9999	0.4552	5.6044	1.7948	0.999	1410.46	301.154
FOTN	0.9918	0.4106	78.9978	49.7294	0.8055	2091.45	$5.088\ x10^{-6}$
SOTN	0.9999	-0.0912	5.6044	1.7948	0.999	1248.3	178.491

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TOTN	0.9999	0.796	5.6044	1.7948	0.999	1193.6	15.2357 $x10^{-6}$
FOLN	0.9866	0.1243	100.966	80.0364	0.6823	1312.47	498.078
SOLN	0.9989	0.043	28.2528	17.5079	0.9751	1313.19	3.6379 $x10^{-12}$
TOLN	0.9999	0.522	5.6044	1.7948	0.999	1760.2	2.8323 $x10^{-8}$

Table 6 shows the statistical results and limit values for the neuro-regression models for the hardness values of the coatings. It is seen that the $R^2_{training}$ values of all models are greater than 0.98, but only the $R^2_{testing}$ value 0.9694 of the SON model is greater than the limit value of 0.9. Therefore, the SON model also satisfied the other two criteria and was chosen as objective functions to optimize the hardness of the coatings. As a result of the model selections, TON and SOLN models for deposition efficiency, SON and SOLN models for bond strength, TON model for porosity values, and SON model for hardness value were selected as the objective functions in the optimization of the coatings.

In the reference study, regression models were prepared for each coating process response, and then a numeric optimization study was carried out using these models. For all coating process responses, an optimum experimental set was determined as input power 26.3 kW, primary gas flow rate 36.15 lmp, coating distance 110.5 mm, powder feed rate 23.35 gpm, and carrier gas flow rate 7.8 lpm. The results of validation tests, the predicted values of the regression models of the reference, and current studies are given in Table 7.

Table 7. Comparison of Neuro-Regression model results with reference study.

Responses	Validation	Reference Study	Current Study Objective functions TON	SOLN
Deposition efficiency (%)	72	71.0837	73.0561	71.2686
Bond strength (MPa)	21	22.9997	24.1362	22.3709
Porosity (%)	4	4.0001	3.9404	
Hardness ($HV_{0.3}$)	1153	1148.94	1149.37	

When Table 7 is examined, it is seen that the estimated values of regression models of both the reference and the current studies have very close to the validation results. For example, while the error rates in the estimations of the deposition efficiency of coatings were 1.72% in the reference study, it was 1.466 % with the TON model and 1.025 % with the SOLN model in the current study. These values for the bond strength of the coatings were 9.522% in the reference study, 14.934% with the SON model, and 6.528% with the SOLN model in the current study. For the porosity and hardness values of the coatings, the rates were 0.0025% and 0.3521% in the reference study and 1.49% and 0.314% in the current study, respectively.

Four different optimization algorithms were used to maximize the deposition efficiency, bond strength, and hardness values and minimize the coatings' porosity value. Table 8 shows the objective functions, optimization constraints, suggested process parameters, and estimated values of algorithms for each coating response.

Table 8. Optimization results of thermal barrier coating.

Responses	Objective	Constraints	Opt.	Suggested	Suggested Design Parameters

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	Functions		Algorithms	Values	
Deposition efficiency (%)	TON		DE SA NM	81.312	X_1= 28.6369 kW, X_2= 39.4152 lpm, X_3=99.4844 mm, X_4= 22.3357 gpm, X_5= 8.1161 lpm
			RS	124.755	X_1= 30, X_2= 25 lpm, X_3= 130 mm, X_4=35 gpm, X_5=3 lpm
	SOLN		DE SA NM RS	86.798	X_1= 27.4608 kW, X_2= 36.0565 lpm, X_3=90 mm, X_4=21.3869 gpm, X_5=7.1047 lpm
Bond strength (MPa)	SON		DE NM	27.8997	X_1= 29.0027 Kw, X_2= 40.6943 lpm, X_3= 105.441 mm, X_4=21.2947 gpm, X_5=7.1047 lpm
			RS SA	73.5196	X_1= 30 Kw, X_2= 25 lpm, X_3= 130, X_4=35 gpm, X_5=3 lpm
	SOLN	22 kW<P<30 kW 25lpm<PGFR<45 lpm 90 mm<D<130 mm 15 gpm<PFR< 35 gpm 3 lpm<CGFR<11 lpm	DE NM	28.5923	X_1= 27.8652 Kw, X_2= 36.711 lpm, X_3= 90 mm, X_4=19.6789 gpm, X_5=6.2139 lpm
			RS	47.3729	X_1= 30, X_2= 25, X_3= 130, X_4=35 gpm, X_5=11 lpm
			SA	40.0992	X_1= 22 Kw, X_2= 45 lpm, X_3= 130 mm, X_4=35 gpm, X_5=3 lpm
Porosity (%)	TON		DE	2.0568	X_1= 27.3598 kW, X_2= 36.5172 lpm, X_3= 93.8257 mm, X_4=15.6061 gpm, X_5=6.1185 lpm
			SA	1.1018	X_1= 27.9016 kW, X_2= 34.893 lpm, X_3=105.305 mm, X_4=15.0098 gpm, X_5=3 lpm
			NM	0.8881	X_1= 27.6482 kW, X_2= 37.0504 lpm, X_3=106.634 mm, X_4=22.8431 gpm, X_5=6.6352 lpm
			RS	2.0694	X_1= 29.8778 kW, X_2= 42.2386 lpm, X_3= 95.307 mm, X_4=23.7204 gpm, X_5=5.3439 lpm
Hardness ($HV_{0.3}$)	TON		DE SA NM RS	1313.19	X_1= 27.8464 kW, X_2= 36.755 lpm, X_3= 90 mm, X_4=20.2408 gpm, X_5=5.7636 lpm

*(X_1:Input Power, X_2:Primary Gas Flow Rate, X_3: Coating Distance, X_4: Powder Feed Rate, X_5: Carrier Gas Flow Rate)

When Table 8 is examined, the highest value for maximizing the deposition efficiency of the coatings was predicted as 124.755% by the TON model with the RS algorithm. However, this value was considered an unrealistic result. Other algorithms of the TON model predicted as 81.312% with the same design parameters (X_1=28.6369 kW, X_2=39.4152 lpm, X_3=99.4844 mm, X_4=22.3357 gpm, X_5=8.1161 lpm). Similarly, by the SOLN model, the four algorithms predicted as 86.798% with same design parameters (X_1=27.4608 kW, X_2=36.0565 lpm, X_3=90 mm, X_4=21.3869 gpm, X_5=7.1047 lpm). The fact that more than three algorithms give the same result with the same parameters for the deposition efficiency of the coatings is interpreted as that the objective functions are consistent and that these parameter sets can have local maximum points. In the maximization studies, the bond strength values of the coatings were predicted as 27.8997 MPa by DE and NM algorithms in the TON model with the parameters set as X_1=29.0027 kW, X_2=40.6943 lpm, X_3=105.441 mm, X_4=21.2947 gpm, and X_5=7.1047 lpm. In the same model, it was predicted as 73.5196 MPa by the RS and SA algorithms with the parameters X_1=30 kW, X_2=25 lpm, X_3=130 mm, X_4=35 gpm, and X_5=3 lpm. Nevertheless, this value was considered an unrealistic result. The DE and NM algorithms of the SOLN model estimated 28.5923 MPa with the parameter set X_1=27.8652 kW, X_2=36.711 lpm, X_3=90 mm, X_4=19.6789 gpm, X_5=6.2139 lpm. The values estimated by the RS and SE algorithms are 47.3729 MPa and 40.0992 MPa, about twice the maximum experimental result, so they did not meet the criterion. To minimize the porosity value of the coatings, DE, SA, NM, and RS algorithms were run with the TON model and predicted as 2.0568%, 1.1018%, 0.8881%, and 2.0694%, respectively. To maximize the hardness values of the coatings, four algorithms were run with the TON model and predicted as 1313.19 $HV_{0.3}$ with the same design parameters (X_1=27.8464 kW, X_2=36.755 lpm, X_3=90 mm, X_4=20.2408 gpm, X_5=5.7636 lpm). It is interpreted that these parameters, which are suggested to give the same result by all four algorithms, can indicate a global optimum point. The optimization results of the TBC are evaluated in general, both polynomial and logarithmic models were successful, but trigonometric models were not.

4. CONCLUSIONS

The deposition efficiency, adhesion strength, porosity, and hardness values are the properties that affect both the production costs and the performance of TBCs. The optimization studies of TBC were carried out in two steps in the study. In the first step, first, second, and third-order polynomial, logarithmic and trigonometric regression models were prepared by fitting from the coating process data. Then, model selection was made for each coating output. The selected models were run with four different optimization algorithms for the same problem solutions in the second step. Based on the studies carried out, the following results have been obtained:

• $R^2_{training}$ values of thirty-six models prepared for four different process outputs are greater than 0.92. However, only six models have $R^2_{testing}$ values greater than 0.9. This situation shows the inadequacy of the classical R^2 calculation.

• In the regression model selections, 2nd and/or 3rd-order nonlinear polynomial and logarithmic models successfully described the process, while trigonometric models were not successful in solving any problem.

• A design parameter set was proposed for the optimum values of all coating outputs in the reference study, and a validation test was performed according to the parameter set. Calculations were made using this proposed design set with the regression models in both the reference study and the current study. The closeness of the results in the two studies to the validation test results was compared. The present study models gave better results for the deposition efficiency, adhesion strength, and hardness values.

• In the optimization studies, the same result was estimated for the deposition efficiency value with the same design parameters by three algorithms with the TON model and four algorithms with the SOLN model. Similarly, for the hardness value of the coatings, the four algorithms predicted the same result with the same design parameters. Therefore, these results are interpreted as showing the global optimum of the proposed parameters for the two outputs.

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REFERENCES

[1] Boyce, M.P., (2011), Gas turbine engineering handbook, Elsevier.

[2] Darolia, R., (2013), Thermal barrier coatings technology: critical review, progress update, remaining challenges and prospects, International Materials Reviews, 58(6), 315-348.

[3] Mutasim, Z. and Brentnall, W, (1997), Thermal barrier coatings for industrial gas turbine applications: An industrial note, Journal of Thermal Spray Technology, 6(1), 105-108.

[4] Lin, C.M., Yen, S.H. and Su, C.Y., (2016), Measurement and optimization of atmospheric plasma sprayed CoMoCrSi coatings parameters on Ti-6Al-4V substrates affecting microstructural and properties using hybrid abductor induction mechanism, Measurement, 94, 157-167.

[5] Guo, H., Gong, S., Khor, K.A. and Xu, H., (2003), Effect of thermal exposure on the microstructure and properties of EB-PVD gradient thermal barrier coatings, Surface and Coatings Technology, 168(1), 23-29.

[6] Liu, Q., Huang, S. and He, A., (2019), Composite ceramics thermal barrier coatings of yttria stabilized zirconia for aero-engines, Journal of Materials Science And Technology, 35(12), 2814-2823.

[7] Matejka, D. and Benko, B., (1989), Plasma spraying of metallic and ceramic materials, John Wiley and Sons.

[8] Chen, H., Hao, Y., Wang, H. and Tang, W., (2010), Analysis of the microstructure and thermal shock resistance of laser glazed nanostructured zirconia TBCs, Journal of Thermal Spray Technology, 19(3), 558-565.

[9] Bertrand, G., Bertrand, P., Roy, P., Rio, C. and Mevrel, R., (2008), Low conductivity plasma sprayed thermal barrier coating using hollow psz spheres: Correlation between thermophysical properties and microstructure, Surface and Coatings Technology, 202(10), 1994-2001.

[10] Ning, L., Cai, Z., Zhao, X., Liu, Y. and Wang, W., (2021), Fast stress evaluation of the top coat of thermal barrier coatings under CaO–MgO–Al2O3–SiO2 penetration based on image recognition and an artificial neural network, Ceramics International, 47(13), 18252-18261.

[11] Ramachandran, C., Balasubramanian, V. and Ananthapadmanabhan, P., (2011), Multiobjective optimization of atmospheric plasma spray process parameters to deposit yttria-stabilized zirconia coatings using response surface methodology, Journal of Thermal Spray Technology, 20(3), 590-607.

[12] Kim, K., Kim, D., Park, K., Yun, J., Jun, N. and Seok, C.S., (2021), A cumulative oxide growth model considering the deterioration history of thermal barrier coatings, Corrosion Science, 182, 1-8.

[13] Karthikeyan, S., Balasubramanian, V. and Rajendran, R., (2014), Developing empirical relationships to estimate porosity and microhardness of plasma-sprayed YSZ coatings, Ceramics International, 40(2), 3171-3183.

[14] Rajesh, T.S. and Rao, R.V., (2016), Parameter Optimization of Amalgamated Al2O3-40%TiO2 Atmospheric Plasma Spray Coating on SS304 Substrate Using TLBO Algorithm, Journal of Surface Engineered Materials and Advanced Technology, 6(03), 89-105.

[15] Shi, H., Zhao, C. and Wang, B., (2016), Modeling the thermal radiation properties of thermal barrier coatings based on a random generation algorithm, Ceramics International, 42(8), 9752-9761.

[16] Sankar, V., Thampi, B.G. and Panicker, M.R., (2020), Optimization of thermal barrier coatings in a single cylinder diesel engine using thermal analysis and genetic algorithm, Journal of Physics: Conference Series, IOP Publishing.

[17] Tonkonogyi, V., Dasic, P., Rybak, O. and Lysenko, T., (2019), Application of the modified genetic algorithm for optimization of plasma coatings grinding process, International Conference New Technologies, Development and Applications, Springer.

[18] Ye, D., Wang, W., Xu, Z., Yin, C., Zhou, H. and Li, Y., (2020), Prediction of thermal barrier coatings microstructural features based on support vector machine optimized by cuckoo search algorithm, Coatings, 10(7), 1-13.

[19] Aydin, L., Artem H.S. and Oterkus, S., (2020), Designing engineering structures using stochastic optimization methods, CRC Press, Taylor & Francis Group.

[20] Ozturk, S., Aydin, L. and Celik, E., (2018), A comprehensive study on slicing processes optimization of silicon ingot for photovoltaic applications, Solar Energy, 161, 109-124.

[21] Ozturk, S., Aydin, L., Kucukdogan, N., and Celik, E, (2018), Optimization of lapping processes of silicon wafer for photovoltaic applications, Solar Energy, 164, 1-11.