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Parameter Optimization of Amalgamated Al_2O_3-40% TiO_2 Atmospheric Plasma Spray Coating on SS304 Substrate Using TLBO Algorithm

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Abstract

SS304 is a commercial grade stainless steel which is used for various engineering applications like shafts, guides, jigs, fixtures, etc. Ceramic coating of the wear areas of such parts is a regular practice which significantly enhances the Mean Time Between Failure (MTBF). The final coating quality depends mainly on the coating thickness, surface roughness and hardness which ultimately decides the life. This paper presents an experimental study to effectively optimize the Atmospheric Plasma Spray (APS) process input parameters of Al_2O_3-40% TiO_2 ceramic coatings to get the best quality of coating on commercial SS304 substrate. The experiments are conducted with a three-level L_{18} Orthogonal Array (OA) Design of Experiments (DoE). Critical input parameters considered are: spray nozzle distance, substrate rotating speed, current of the arc, carrier gas flow and coating powder flow rate. The surface roughness, coating thickness and hardness are considered as the output parameters. Mathematical models are generated using regression analysis for individual output parameters. The Analytic Hierarchy Process (AHP) method is applied to generate weights for the individual objective functions and a combined objective function is generated. An advanced optimization method, Teaching-Learning-Based Optimization algorithm (TLBO), is applied to the combined objective function to optimize the values of input parameters to get the best output parameters and confirmation tests are conducted based on that. The significant effects of spray parameters on surface roughness, coating thickness and coating hardness are studied in detail.

Keywords

Atmospheric Plasma Spray (APS) Coating, SS304 Steel, Teaching Learning Based Optimization (TLBO), Design of Experiments (DoE), Analytic Hierarchy Process (AHP), Al_2O_3-40% TiO_2

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1. Introduction

Alumina (Al_2O_3) and Titania (TiO_2) ceramics are the most popular materials used for plasma spray coating of machine components in polyester manufacturing sector. The selection of the coating material directly depends on the application. Al_2O_3 is corrosion resistant and is mostly used on mating surface to resist abrasive wear and adhesive wear. TiO_2 is being increasingly used as a thermal barrier coating especially in textile/polyester/man-made fiber applications. Effective ceramic coating exhibits low thermal diffusivity, strong adherent to the substrate, phase stability and thermal shock resistance during thermal cycling and provides oxidation wear and corrosion protection to the substrate. Al_2O_3 ceramic is stable with less solubility and shows good corrosion resistance but possesses less toughness. Therefore, it is beneficial to choose ceramic composites rather than individual ceramics. The use of Al_2O_3 composite rather than individual Al_2O_3 has certain advantages. Ramachandran *et al.* [1] stated that TiO_2 has a lower melting point and effectively binds alumina grains, contributing to high density. Further, studies, particularly in optimizing the critical input on parameters of Al_2O_3/TiO_2 coatings in various applications were identified and analyzed in detail. The effects of various parameters and the final coated surface properties of some of the oxides were also studied in depth, for the last one decade.

SS304 has high chromium content, to the range of 18% to 20%, commonly supplied in the form of bar or rolled condition. It can be flame or induction hardened to produce a high surface hardness with excellent wear resistance for an alloy steel grade. Applying a harder material as a thin coating on an SS304 steel surface can provide superior protection against abrasive wear and can be used effectively in the case of bearing seating applications. Addition of TiO_2 in the range of 3%, 13% and 40% to alumina powder is widely used for ceramic coating applications using thermal spray process. Increasing the TiO_2 content in the sprayed powder leads to a decrease in the melting temperature of the Al_2O_3-TiO_2 coating and has a linear tendency to diminish the porosity and increasing the fracture toughness of coating. The percentage of porosity of the 40% TiO_2 mixtures is lower than other compositions like 97/3 and 87/13. This clearly justifies the use for Al_2O_3-40% TiO_2 for the current experiment.

Despite increased interest in the fundamentals of plasma spraying there is still a lack of reliable models that relate engineering properties of coatings, such as hardness or roughness, to variations in process parameters or deposition geometry. Due to extremely rapid cooling after coating, the surface properties of plasma sprayed oxides are not necessarily the same as those for non-sprayed items, which make the scenario more complex. This gap between the need to understand a process to optimize it and a growing demand for good plasma sprayed coatings can be filled temporarily by various engineering analysis approach.

A number of researchers worked on different types of special coatings on various types of substrates which are important to manufacturing processes. Yong *et al.* [2] studied the coating degradation mechanisms of AlSi coated boron steel after the hot bending process. It was concluded that the bending deformation affected the coating layer behavior the most. Parisa *et al.* [3] studied the erosion performance of laser cladded Ni-60% WC coatings subjected to a controllable Abrasive Water Jet (AWJ). The chemical composition of coatings was modified by nanocrystalline WC powder and the rare earth element (La_2O_3). The tribological evaluation of the erosion scars showed a log-linear relationship between coating hardness and volume loss under erosion. Zalnezhad *et al.* [4] had conducted an optimization study on the parameters of titanium nitride coating on aerospace Al7075-T6 alloy, using magnetron sputtering technique. The effects of the temperature, DC bias voltage, rate of nitrogen, and DC power on the surface hardness, adhesion, surface roughness, and microstructure of the coated samples were investigated. Taguchi optimization method was used with the L_{16} orthogonal array.

Zalnezhad *et al.* [5] coated Titanium Nitride (TiN) on aerospace Al7075-T6 in different conditions using PVD magnetron sputtering technique, and the surface hardness of TiN-coated specimens was measured using a micro hardness machine. A fuzzy logic model is offered to predict the surface hardness of TiN coating on AL7075-T6 with respect to changes in input process parameters, Direct Current (DC) power, DC bias voltage, and nitrogen flow rate. Toko *et al.* [6] performed the sensitivity analysis in the process for Mg/Al cladding model in order to evaluate the influences of extrusion parameters on the coating thickness uniformity. The sensitivities of initial thickness of the coating material plate, extrusion temperature, ram speed, die angle, and ratio of simulated flow stress to the experimental one for pure Al were evaluated. Results had shown that the initial thickness of the coating material plate and die angle influence on the uniformity most. Amir *et al.* [7] studied by modeling the coating characteristics of yttria-stabilized zirconia. The properties such as deposition efficiency, adhesion strength, surface roughness, and hardness in plasma spray process are studied in detail. Binu *et al.* [8] examined the characteristics of multilayer Ti, TiN, and Diamond-Like Carbon (DLC) coatings deposited on standard tool substrates at varying sputtering parameters and conditions, such as power density, partial pressure, substrate temperature, and reactive gases. The results indicated that a graded multilayer coating showed better adhesion to the substrates. Bor *et al*. [9] proposed a method to develop a robust Partially Stabilized Zirconia (PSZ) performance for the plasma spraying process with applications of surface response methodology and fractional factorial experiment. Experimental results showed that a quadratic model with the proposed two-step design make it a simple, effective, and efficient way to a robust process. Weiming *et al.* [10] presented Computational Fluid Dynamics (CFD) simulation for analyzing fluid flow patterns and heat transfer stimulations of plasma spray gun. It was concluded that the optimal velocity and direction of cooling water, which efficiently cools the nozzle improves the service life of the plasma jet. Azarmi *et al.* [11] introduced an advanced production technique for manufacturing foam core sandwich structures with high temperature constituents. It is a rapid technique which eliminates joining process. It was concluded that there is a good adhesion between skin and core due to mechanical and metallurgical bonds.

Saravanan *et al.* [12] carried out experimental investigations to produce high-quality Al_2O_3 coatings by optimizing the detonation spray process parameters following a factorial design approach. Yugeswaran *et al.* [13] studied the influence of Critical Plasma Spraying Parameter (CPSP) on plasma sprayed Al_2O_3-TiO_2 composite coatings. Al_2O_3-TiO_2 composite coatings in different compositions (Al_2O_3-3% TiO_2, Al_2O_3-13% TiO_2, and Al_2O_3-40% TiO_2) were prepared by 40 kW atmospheric plasma spray torch at three different CPSP conditions (833.33, 1000 and 1166.66) and their influence on coatings and plasma jet temperature were studied. Singh *et al.* [14] studied the sliding and erosive wear behaviour of atmospheric plasma sprayed conventional and nanostructured Al_2O_3 coatings. Sathish *et al.* [15] [16] studied the plasma sprayed nanoceramic coatings for biomedical applications. Datta *et al.* [17] tried to correlate input process parameters with various responses of a plasma spray coating process. They had developed mathematical models based on MINITAB which is comparable with the current work. They have used a design of experiment similar to the current work. As a part of current work, the resulted mathematical models were tried by substituting values. But the result obtained were negative values, which concludes that the mathematical modelling done by Datta *et al.* was not correct. The performances of the developed approaches had been tested on different cases obtained through real experiments. Palanivelu *et al.* [18] studied the scratch and wear behaviour of plasma sprayed nano ceramics bilayer Al_2O_3-13% TiO_2/hydroxyapatite coated on medical grade titanium substrates. The aim of their work was to design and produce a bilayer coating on the non-toxic commercially pure titanium (denoted as CP-Ti) implant substrate in order to improve the biocompatibility and surface properties. Perumal *et al.* [19] compared the relative wear resistance of three candidate coatings for titanium alloy-based orthopaedic applications using a reciprocating test method. Micrometer-sized powders of the following compositions were plasma sprayed on to Ti-6Al-4V (TAV) alloy: 1) Al_2O_3 (AO), 2) 8 mol% yttria stabilized zirconia (8YSZ) and 3) Al_2O_3-40% 8YSZ (A4Z). The composite coating A4Z was reported as having superior wear resistance.

Mishra *et al.* [20] deposited Al_2O_3-13% TiO_2 coating on nickel-based Superni 718 and AE 435 super alloys using a low-velocity oxy-fuel (LVOF) process. The coating was characterized for SEM, XRD and surface roughness. The LVOF sprayed Al_2O_3-13% TiO_2 coating had shown good oxidation resistance as well as adherence to the substrates under the tested environment. Bolleddu *et al.* [21] deposited air plasma sprayed nanostructured Al_2O_3-13% TiO_2 coatings as a function of critical plasma spray parameter (CPSP), defined as the ratio of arc power to primary gas flow rate, using nitrogen and argon as the primary plasma gases. Effect of CPSP on microstructural and wear characteristics of coatings deposited with nitrogen was found to be relatively small.

Yang *et al.* [22] presented the aspects of preparing of nanostructured Al_2O_3-TiO_2-ZrO_2 composite powders and plasma spraying nanostructured composite coating. Forghani *et al.* [23] studied the coating of Al_2O_3-TiO_2 on mild steel as substrate and coating material. A design of experiment was used to conduct the experiment. Two of the output measurement of their study were similar to the current experiment which are, microhardness and thickness. The results were comparable with the current work. The design of experiment used to conduct the experiment was much similar to the current work. Yusoff *et al.* [24] studied the effect of plasma spray parameters of amalgamated Al_2O_3-13% TiO_2 powder on mild steels. A two-level factorial design of experiment was used to optimize the operational spray parameters. One of the input parameter was same as used in current work, powder feed rate. The conclusion of the paper says that input parameters potentially affect the microhardness and surface roughness, which is well proven by the current work. Sure *et al.* [25] used Al_2O_3-40% TiO_2 for coating of high density graphite substrate. In the current experiment also, Al_2O_3-40% TiO_2 is used for coating.

The advantages of this particular coating powder is justified by the results in this experiment. Yilmaz *et al.* [26] had used SS 316 L substrate for coating. In this work, four different nanometric mono and multi Al_2O_3 and TiO_2 layers had been applied on Stainless Steel substrates by Atomic Layer Depositions (ALD) in order to improve their intrinsic corrosion resistance.Vergas *et al.* [27] had used SS304 for comparing the strength of coating, with Al_2O_3-43% TiO_2 and Al_2O_3-13% TiO_2. This is the only work seen during the entire literature review, where the researcher had used SS304 substrate for coating with Al_2O_3-TiO_2. This clearly shows that there is only a little work happened in this field, where SS304 is used as substrate for Al_2O_3-TiO_2 coating through atmospheric plasma spray rout.

Kang *et al.* [28] studied the influences of parameters such as spraying voltage, spraying current, primary gas feed rate and spraying distance on the properties of plasma-sprayed Al_2O_3-40% TiO_2 composite ceramic coating by using orthogonal experimental design. The influence sequences of the parameters on the properties of plasma-sprayed Al_2O_3-40% TiO_2 coating were reported as spraying distance, spraying voltage, spraying current and argon gas flow rate.

It is observed from the survey of research across the years that different researchers had conducted experimental investigations on plasma spraying of Al_2O_3-TiO_2 coatings on different substrates. The research was mostly experimental and only very few attempts were made to develop the mathematical models to depict the relationships between the input and output parameters that can be used for prediction as well as for determining the optimum values of the output parameters. Few researchers [29]-[31] had applied neural networks also for prediction purpose. Furthermore, it is observed that only a few researchers had experimented on plasma spraying of Al_2O_3-TiO_2 coatings on stainless steel substrates [32] [33]. Research literature in manufacturing [34]-[43] had already proved the usefulness of the mathematical models for predicting the output parameters and for determining the value of input parameters. Hence in the present work, experimental investigation in to spraying of Al_2O_3-40% TiO_2 on SS304 substrate is carried out. Following section presents the experimental design and procedure.

2. Experimental Design and Procedure

The experimental design is carried out using L_{18} orthogonal array of Taguchi's design of experiments (DoE). Distance of spray gun, substrate rpm, arc current, carrier gas flow and coating power flow rate are considered as independent input parameters. Selected responses in this study are surface roughness, coating thickness and hardness. All process parameters including the experimental ranges and the levels of the plasma spray formation are shown in **Table 1**.

The Design of Experiments is shown in **Table 2**.

2.1. Preparation and Testing of Al_2O_3-40% TiO_2 Coating

Amalgamated powder of Al_2O_3-40% TiO_2 supplied by H C Starck, USA is used for coating. SS304 steel is sectioned with a dimension of 27.5 mm dia and 3 mm thickness to make test substrate samples. Each experiment is conducted with three samples. Total three samples are assembled in one cartridge. The sample pieces are surface ground up to mirror finish, so as to avoid non-uniformity in thickness and later blasting is carried out in all the sample coupons. Fused Alumina of grit size 60 µm is used as the sand blasting material and supplied by Carborandum Universal. Al_2O_3-40% TiO_2 powder from H C Starck USA was deposited on the substrates by using an SG 100 Plasma Gun from Metco USA. The nano powders are preheated in an oven up to 110˚C to ensure the removal of moisture.

The experiments are conducted according to the design of experiments shown in **Table 2**. The parameters which are kept constant during the experiment are:

Spray nozzle	GP, 5.43 mm
Grind blasting pressure	2 Kg/cm^2
Substrate exposure to gun	30 Sec
Primary gas pressure	100 Psi
Secondary gas pressure	80 Psi

Table 1. Ranges of parameters.

No	Parameter	Low level	Middle level	High level
1	Spray distance of gun, mm	75	100	125
2	Carrier gas flow, Lit./min.	20	30	50
3	Powder flow rate, Gms./min.	25	35	50
4	RPM of the substrate	150	250	350
5	Arc current, A	350	400	500

Table 2. DoE for conducting the experiments.

Experiment No	Spray distance mm	Substrate rpm	Arc current A	Carrier gas flow Lit./min.	Powder flow rate Gms./min.
1	75	150	300	20	25
2	75	250	400	30	35
3	75	350	500	40	50
4	125	150	300	30	35
5	125	250	400	40	50
6	125	350	500	20	25
7	175	150	400	20	50
8	175	250	500	30	25
9	175	350	300	40	35
10	75	150	500	40	35
11	75	250	300	20	50
12	75	350	400	30	25
13	125	150	400	40	25
14	125	250	500	20	35
15	125	350	300	30	50
16	175	150	500	30	50
17	175	250	300	40	25
18	175	350	400	20	35

After the coating, test samples are cleaned in ethanol and dried to avoid accumulation of moisture. The coating thickness is measured using Ultrasonic thickness gauge. The surface roughness is measured by a SV-C3100 from Mitutoyo and was applied on the coating surface for a length of 15 mm with a pitch of 0.001 mm and at a scanning speed of 2.0 mm/sec. The hardness of the coated surface is measured by Hardness tester make Equotip 3, with range of up to 1000 HV.

2.2. Coating Output Parameter Details

The mean values of the measured coating thickness, roughness and hardness are given in **Table 3**.

3. Mathematical Modelling and Optimization

Excel data analysis is used to generate mathematical model for each of the output parameters. Regression modelling is applied for this purpose. The mathematical models for all the output parameters are shown below as Equations (1)-(3).

Table 3. The values of measured output parameters.

Experiment No	Mean thickness μm	Mean roughness μm	Mean hardness HV
1	400.00	4.60	211.00
2	500.00	5.44	210.67
3	530.00	4.70	209.00
4	386.67	4.99	218.67
5	366.67	4.78	213.67
6	193.33	4.28	205.00
7	376.67	4.67	201.67
8	213.33	5.52	201.33
9	390.00	6.00	208.33
10	416.67	4.27	318.00
11	196.67	3.70	219.00
12	416.67	4.07	226.00
13	530.00	4.28	319.33
14	450.00	5.20	263.67
15	420.00	5.76	255.33
16	373.33	4.68	334.33
17	253.33	5.23	247.00
18	266.67	4.39	267.67

$$\begin{aligned} T\text{, Thickness } \mu\text{m} = {} & 664.0403 - 14.6665 * D - 8.14021 * N - 0.39756 * A + 133.092 * G \\ & - 25.1872 * P + 0.015751 * D * N + 0.025697 * D * A - 0.25612 * D * G \\ & + 0.151304 * D * P + 0.004293 * N * A + 0.067524 * N * G + 0.077343 * N * P \\ & - 0.17902 * A * G + 0.050092 * A * P - 0.97816 * G * P. \end{aligned} \tag{1}$$

$$\begin{aligned} R\text{, Roughness } \mu\text{m} = {} & 9.58062 + 0.07514 * D + 0.01450 * N + 0.04042 * A + 0.27645 * G \\ & - 0.07835 * P - 0.00003 * D * N + 0.00009 * D * A - 0.00198 * D * G \\ & - 0.00133 * D * P - 0.00010 * N * A + 0.00074 * N * G + 0.00011 * N * P \\ & - 0.00109 * A * G + 0.00002 * A * P + 0.00590 * G * P \end{aligned} \tag{2}$$

$$\begin{aligned} H\text{, Hardness HV} = {} & 252.845 - 0.32851 * D + 2.22996 * N + 0.0997 * A - 1.05367 * G \\ & - 17.302 * P - 0.0033 * D * N - 0.00445 * D * A + 0.06521 * D * G \\ & + 0.03511 * D * P - 0.00293 * N * A - 0.05658 * N * G + 0.02746 * N * P \\ & + 0.01995 * A * G + 0.02211 * A * P - 0.07336 * G * P 136.0 - 0.349 \end{aligned} \tag{3}$$

where

D = spray distance;
N = substrate RPM;
A = arc current;
G = carrier gas flow; and
P = powder flow rate.

The values of roughness are considered non-beneficial and the values of thickness and hardness are considered as beneficial. ANOVA is carried out on each of these models to check the adequacy as shown in **Tables 4-6**.

Table 4. Regression details and ANOVA of thickness model.

Regression statistics thickness model					
Multiple R			0.991017		
R square			0.982115		
Adjusted R square			0.847978		
Standard error			41.55112		
Observations			18		
ANOVA					
	df	SS	MS	F	Significance F
Regression	15	189,613.7	12,640.91	7.321716	0.126591
Residual	2	3452.991	1726.496		
Total	17	193,066.7			

Table 5. Regression details and ANOVA of roughness model.

Regression statistics roughness model					
Multiple R			0.96137		
R square			0.92423		
Adjusted R square			0.35598		
Standard error			0.49587		
Observations			18		
ANOVA					
	df	SS	MS	F	Significance F
Regression	15.00000	5.99886	0.39992	1.62644	0.44619
Residual	2.00000	0.49178	0.24589		
Total	17.00000	6.49064			

Table 6. Regression details and ANOVA of hardness model.

Regression statistics hardness model					
Multiple R			0.982208		
R square			0.964733		
Adjusted R square			0.700233		
Standard error			23.94703		
Observations			18		
ANOVA					
	df	SS	MS	F	Significance F
Regression	15	31374.44	2091.63	3.647383	0.236068
Residual	2	1146.921	573.4603		
Total	17	32,521.36			

3.1. Confirmation Experiments

Five trial samples for SS304 are made for confirmation tests. The random values for all the input parameters, in between the maximum and minimum levels are taken to conduct the confirmation tests. The measured output parameters and the predicted values using the proposed mathematical models for three samples for SS substrate are given in **Tables 7-9** and % variation between actual and predicted values are also shown in the tables.

3.2. SN Analysis

To determine the effect of each variable on the output, the signal-to-noise ratio, or the SN ratio, needs to be calculated for each experiment conducted. Once SN ratio values are calculated for each factor and level, they are tabulated as shown in **Table 10** and the range R (R = high SN − low SN) of the SN for each parameter is calculated and entered in the table. The larger the R value for a parameter, the larger the effect the variable has on the process. This is because the same change in signal causes a larger effect on the output variable being measured.

SN ratio values for coating thickness on SS304 substrate are calculated for each parameter and level. The values are tabulated for thickness as shown in **Table 11**. The larger the ΔR value for a parameter, the larger the effect the variable has on the process.

Table 7. Measured and predicted values—thickness.

Distance mm	Substrate rpm	Current A	Carrier gas flow Lit./Min.	Power flow rate Gms./Min.	Thickness µm	Predicted values µm	% Variation
100	200	350	25	40	309.00	342.92	9.89
90	175	375	35	45	428.00	476.04	10.09
80	190	425	35	40	562.00	508.72	9.48

Table 8. Measured and predicted values—hardness.

Distance mm	Substrate rpm	Current A	Carrier gas flow Lit./Min.	Power flow rate Gms./Min.	Hardness HV	Predicted values HV	% Variation
150	300	450	35	30	213	206.13	3.23
160	225	325	25	30	238	243.68	2.33
80	190	425	35	40	203	222.91	8.93

Table 9. Measured and predicted values—roughness.

Distance mm	Substrate rpm	Current A	Carrier gas flow Lit./Min.	Power flow rate Gms./Min.	Hardness µm	Predicted values µm	% Variation
100	200	350	25	40	4.89	5.26	7.09
150	300	450	35	30	4.96	4.46	10.14
160	225	325	25	30	5.48	6.05	9.46

Table 10. Levels and parameters SN ratio.

Level	**P1**	**P2**	**P3**	**P4**
1	$SN_{P1,1}$	$SN_{P2,1}$	$SN_{P3,1}$	$SN_{P4,1}$
2	$SN_{P1,2}$	$SN_{P2,2}$	$SN_{P3,2}$	$SN_{P4,2}$
3	$SN_{P1,3}$	$SN_{P2,3}$	$SN_{P3,3}$	$SN_{P4,3}$
Δ	R_{P1}	R_{P2}	R_{P3}	R_{P4}
Rank	….	….	….	….

Here, the R value clearly shows that carrier gas flow has a significant effect on the coating thickness. The next dominant parameter in the case of coating thickness is rpm of the substrate. The sequence of dominance is shown as rank. Similarly, SN ratio values are calculated for surface roughness for each parameter and level for all the output parameters as shown in **Table 12**. It is found that spray distance has a significant effect on the surface roughness. The next dominant parameter in the case of surface roughness is carrier gas flow. In the case of surface hardness, the substrate rpm has a significant effect on the coating hardness as shown in **Table 13**. The next dominant parameter in the case of hardness is arc current. All the effects related to coating thickness, roughness and hardness are plotted as graphs in **Figures 1-3**.

3.3. Application of Teaching Learning Based Optimization (TLBO)

Now, to determine the optimum values of output parameters, an advanced optimization method, known as Teaching-learning-based optimization (TLBO) is applied individually to each of these mathematical models given by Equation (1) to (3). TLBO is a teaching-learning process inspired algorithm proposed by Rao *et al.* [44], based on the effect of influence of a teacher on the output of learners in a class. The algorithm mimics teaching-learning ability of teacher and learners in a class room. Teacher and learners describes two basic modes of the learning, through teacher (known as teacher phase) and interacting with the other learners (known as learner phase). The algorithm-specific parameter-less concept of the algorithm is one of the attracting features of the algorithm in addition to its simplicity and the ability to provide the global or near global optimum solutions in comparatively less number of function evaluations. More details about the TLBO algorithm can be found in [45] and https://sites.google.com/site/tlborao.

Table 11. SN ratio matrix and ΔR values of coating thickness.

	Distance mm	rpm	Current A	Carrier gas flow Lit./Min.	Powder flow rate Gms./Min.
Level 1	51.86	52.27	50.34	49.46	49.88
Level 2	51.46	49.81	52.03	51.44	51.92
Level 3	49.66	50.9	50.62	52.09	51.18
ΔR	2.2	2.46	1.69	2.63	2.04
Rank	3	2	5	1	4

Table 12. SN ratio matrix and ΔR values of coating roughness.

	Distance mm	rpm	Current A	Carrier gas flow Lit./Min.	Powder flow rate Gms./Min.
Level 1	12.93	13.21	13.95	12.97	13.32
Level 2	13.72	13.86	13.23	14.05	14.01
Level 3	14.07	13.65	13.54	13.7	13.4
ΔR	1.14	0.65	0.73	1.09	0.69
Rank	1	5	3	2	4

Table 13. SN ratio matrix and ΔR values of coating hardness.

	Distance mm	rpm	Current A	Carrier gas flow Lit./Min.	Powder flow rate Gms./Min.
Level 1	47.22	48.33	47.08	47.1	47.3
Level 2	47.71	47.04	47.48	47.51	47.78
Level 3	47.57	47.13	47.94	47.89	47.42
ΔR	0.5	1.29	0.87	0.79	0.47
Rank	4	1	2	3	5

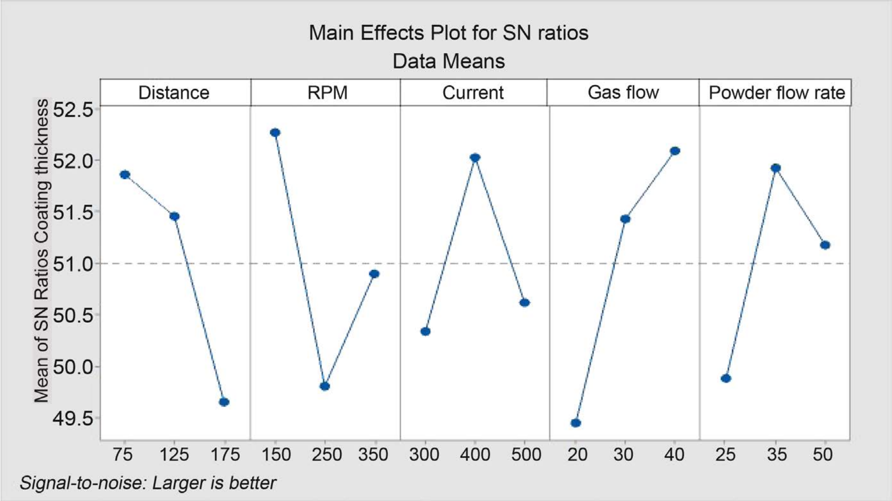

Figure 1. SN ratio vs input parameter in the case of coating thickness.

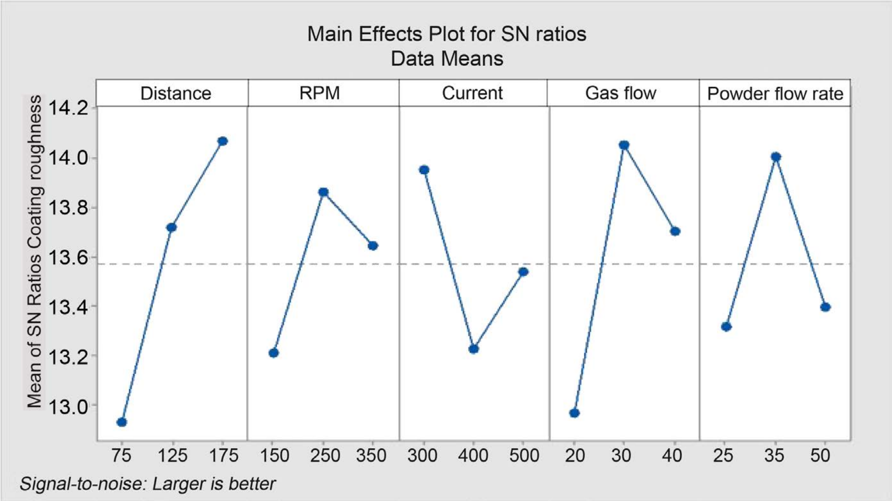

Figure 2. SN ratio vs input parameter in the case of coating roughness.

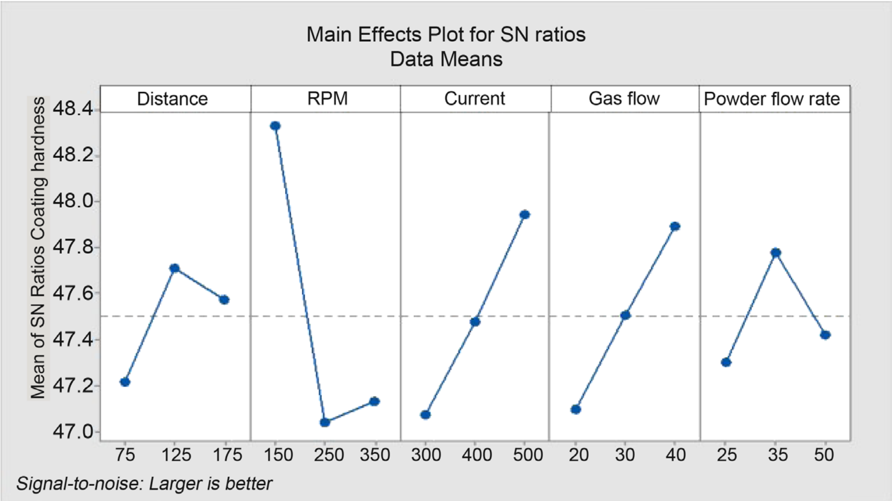

Figure 3. SN ratio vs input parameter in the case of coating hardness.

Pickard *et al*. [46] mentioned that the TLBO algorithm has origin bias affecting the population convergence and success rates of benchmark objective functions with origin solutions. But they had overlooked the fact that the TLBO algorithm provided better results even for the benchmark functions whose solutions were not located at the origin [47] [48]. Many researchers had obtained better results with TLBO algorithm for different objective functions with different characteristics [45]. Moreover, the results shown by Pickard *et al*. [46] in **Table 1** of their paper are checked by the first author of this paper under the same conditions and it is found that the results shown by Pickard *et al*. [46] for non-origin based objective functions were incorrectly reported. The TLBO algorithm has obtained the optimum results irrespective of whether the solution to the objective function is located at the origin or not. It seems that Pickard *et al*. [46] attempted to justify the work of Črepinšek *et al*. [49] which was commented upon by Waghmare *et al*. [50]. However, Rao [51] had already mentioned that the justification made by Črepinšek *et al*. [52] was not convincing and many of the statements made by them on the work of Waghmare [50] were questionable and there was no such inexact replication of computational experiments by Waghmare [50]. Comments were also made by Rao [51] on the unusual concept of function evaluations required for duplicate removal. An interesting point here is that even though the TLBO algorithm has already proved its better performance for many of the standard benchmark functions whose solutions are located at the origin or somewhere else, Pickard *et al*. [46] are cautioning the researchers while using the TLBO algorithm. Why and for what benefit the caution is required is not clear. Furthermore, Pickard *et al*. [46] mentioned that the bias is occurring when teaching factor takes the value of 2. But in the original TLBO algorithm, the value of teaching factor varies randomly during each iteration either as 1 or 2 and it will not remain as 2 during all the iterations and Pickard *et al*. [46] had not considered this fact. Pickard *et al*. [46] proposed two modifications to the original TLBO algorithm and the second modification uses the "biasing" property to "assist in locating better solutions"! Any way, the TLBO algorithm has been applied by many researchers to many real life applications (whose solutions are not located at origin) in different engineering disciplines and obtained better results as compared to the other advanced optimization algorithms [45].

A population size of 10 and 100 number of iterations with 30 independent runs is considered for executing the TLBO algorithm for the optimisation of individual objective functions. Values obtained by applying TLBO algorithm for the individual objective functions of T (Thickness), R (Roughness) and H (Hardness) are 1326.1 µm, 1.8194 µm and 411.886 HV respectively. Convergence graphs of TLBO for each of these output parameters are shown in **Figures 4-6**.

3.4. Formation of Combined Objective Function

In this paper, a pirori approach is used by forming a combined objective function, involving all the three objectives and this function is solved by applying TLBO algorithm for the given ranges of the input parameters. The optimized values for individual output parameters T, R and H are obtained by applying TLBO, by considering only one objective at a time. However, in actual practice, optimization of all these output parameters is required simultaneously. Hence the problem becomes a multi-objective problem, as shown in Equation (4).

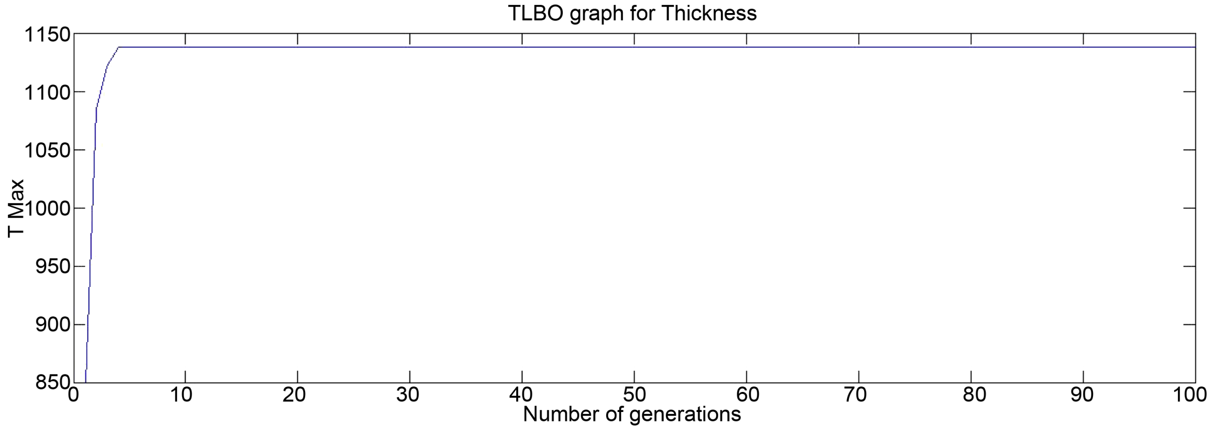

Figure 4. Convergence graph of TLBO for coating thickness.

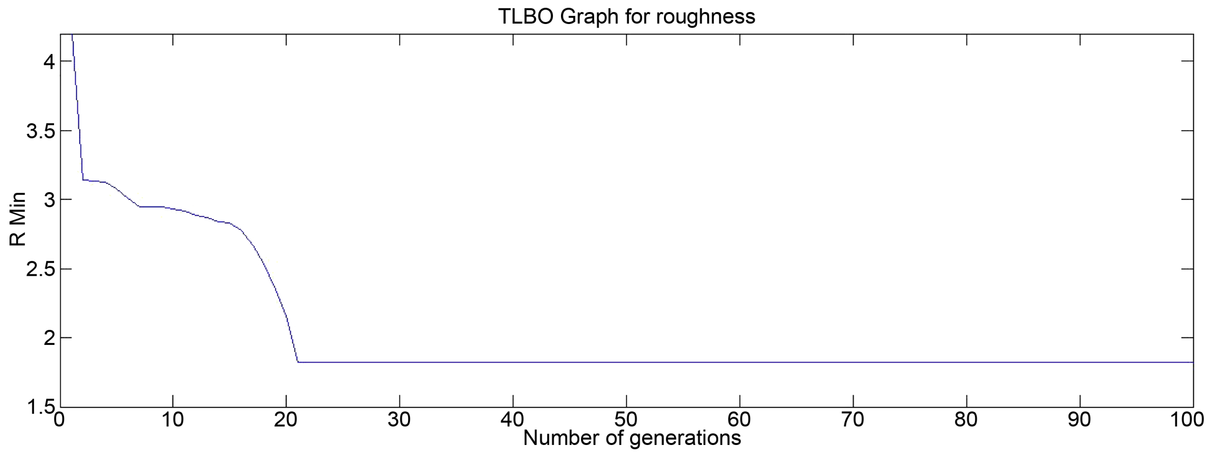

Figure 5. Convergence graph of TLBO for coating roughness.

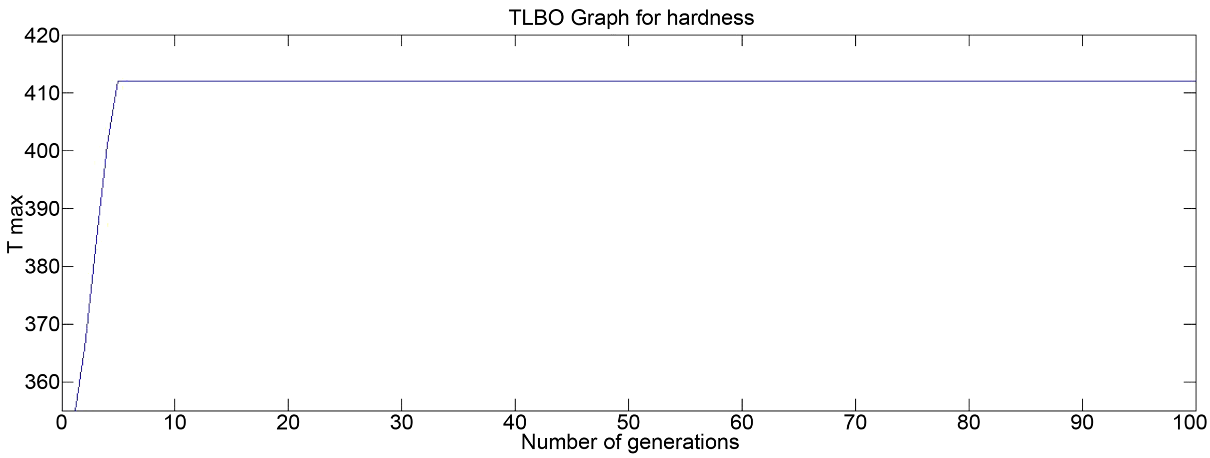

Figure 6. Convergence graph of TLBO for coating hardness.

$$Z_{\text{Max}} = W_2 * \frac{T}{T_{\text{Max}}} + W_3 * \frac{H}{H_{\text{Max}}} - W_1 * \frac{R}{R_{\text{Min}}} \quad (4)$$

In the above Equation (4) W_1, W_2 and W_3 represents the weightings assigned to the objective functions. T_{max}, R_{min} and H_{max} represents the optimum desired values T, R and H when solved individually for the given range of input parameters. These values are, 1326.1 µm, 1.8194 µm and 411.886 HV respectively. The weights W_1, W_2 and W_3 can be assigned by the decision maker based on his preferences. In this paper, a systematic approach of assigning the weights is presented. This method is known as Analytic Hierarchy Process (AHP) [53], which lets the decision maker to assign the weights by following the theory of relative importance relation. A parameter compared with itself is always assigned the value 1 so the main diagonal entries of the pair-wise comparison matrix are all 1. The numbers 3, 5, 7, and 9 correspond to the verbal judgments "moderate importance", "strong importance", "very strong importance", and "absolute importance". Comparisons of output parameters like Coating thickness (T), Surface roughness (R) and Hardness (H) are done and decision making matrix was made as shown below

$$\begin{array}{cc} \text{Criterion} & T \quad R \quad H \end{array}$$

$$A_1 = \begin{matrix} T \\ R \\ H \end{matrix} \begin{bmatrix} 1 & 1/3 & 1/5 \\ 3 & 1 & 1/3 \\ 5 & 3 & 1 \end{bmatrix}$$

The normalized weights of each criterion are calculated following the procedure and these are $W_T = 0.1048$, $W_R = 0.2583$ and $W_H = 0.6370$. The value of maximum Eigen value (λ_{max}) is 3.0385 and consistency ratio (CR) =

0.036712, which is much less than the allowed CR value of 0.1. Thus, there is good consistency in the judgments made. The weights calculated through the AHP are applied to combined objective function as given below in Equation (5).

$$\begin{aligned} Z_{\max} = {} & 0.1048/1326.1*\big(664.032-14.667*D-8.14*N-0.398*A+133.094*G \\ & -25.186*P+0.016*D*N+0.026*D*A-0.256*D*G+0.151*D*P \\ & +0.004*N*A+0.068*N*G+0.077*N*P-0.179*A*G+0.05*A*P \\ & -0.978*G*P+0.6370/411.886\ (252.845-0.32851*D+2.22996*N \\ & +0.0997*A-1.05367*G-17.302*P-0.0033*D*N-0.00445*D*A \\ & +0.06521*D*G+0.03511*D*P-0.00293*N*A-0.05658*N*G \\ & +0.02746*N*P+0.01995*A*G+0.02211*A*P-0.07336*G*P\big) \\ & -0.2583/1.8194\big(-9.58062+0.07514*D+0.01450*N+0.04042*A \\ & +0.27645*G-0.07835*P-0.00003*D*N+0.00009*D*A \\ & -0.00198*D*G-0.00133*D*P-0.00010*N*A+0.00074*N*G \\ & +0.00011*N*P-0.00109*A*G+0.00002*A*P+0.00590*G*P\big) \end{aligned} \tag{5}$$

Now, the TLBO algorithm is applied on the combined objective function and the optimum value of coefficient *Z* max is achieved after 100 iterations with 30 independent runs is 0.2155 and the corresponding values of the optimum input parameters are:

Spray distance: 175 mm.
Carrier Gas Flow: 40 Lit./min.
Powder flow rate: 50 Gms./min.
RPM of the substrate: 150 rpm.
Arc current: 500 A.

These values are simultaneously, satisfying all the three objectives considered for Al_2O_3-40% TiO_2 coating on SS304 substrate. The convergence graph of TLBO is shown as **Figure 7**.

Considering equal weights, *i.e.*, $W_T = 0.33$, $W_R = 0.33$ and $W_H = 0.33$, the combined objective function is generated and TLBO algorithm is applied on the combined objective function and the optimum values of coefficient *Z* max is 0.0399 and the corresponding values of optimum input parameters are:

Spray distance: 175 mm.
Carrier Gas Flow: 40 Lit./min.
Powder flow rate: 50 Gms./min.
RPM of the substrate: 350 rpm.
Arc current: 500 A.

The convergence graph of TLBO is shown as **Figure 8**.

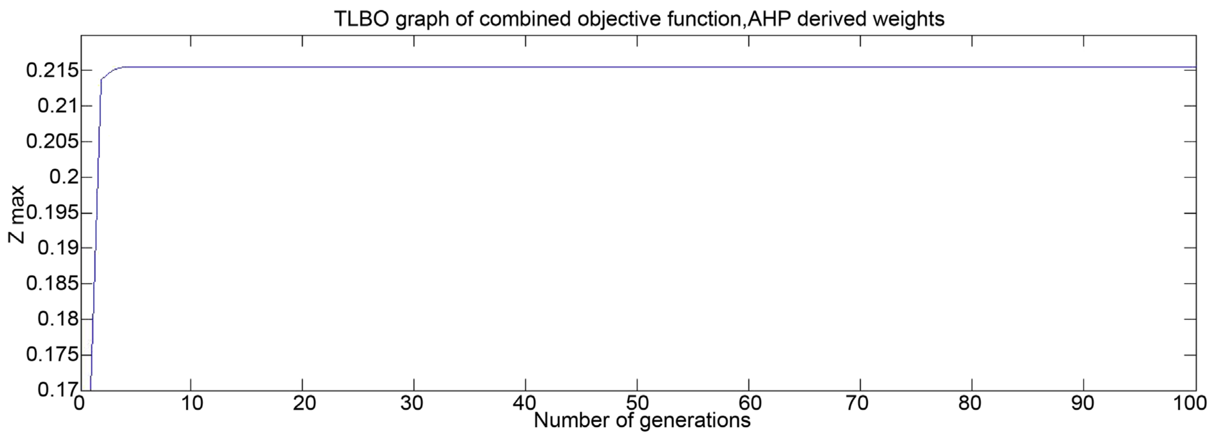

Figure 7. Convergence graph of TLBO for the combined objective function.

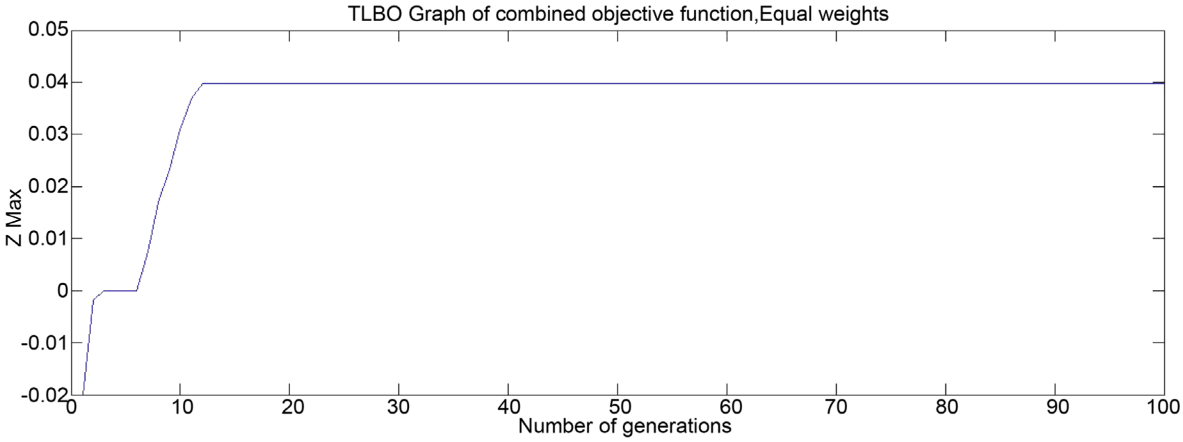

Figure 8. Convergence graph of TLBO for combined objective function with equal weights of objectives.

4. Conclusions

In the field of surface coating with Al_2O_3-40% TiO_2, mathematical modeling and optimization are rarely found. There is a direct relationship between the output parameters of the coating characteristics with respect to the input parameters. In the present work, mathematical models are generated using regression analysis for all the output parameters in terms of input parameters. The optimization is carried out using a latest advanced optimization technique called TLBO algorithm for each output parameters and confirmation tests are also carried out. The confirmation tests have given near about the same values compared to the predicted values and the % of error is not significant. A combined objective function is generated and it is effectively optimized using TLBO algorithm to get the global optimum values of input parameters. TLBO algorithm has proved its effectiveness in solving the multi objective optimization problems. AHP method is used to decide weights for the individual objective functions in the combined objective function and it takes into account the preferences of the decision maker. SN analyses are carried out to understand the significance of the process input parameters on each of the output parameters considered. The proposed approach can be used for different types of substrates and more number of input and output parameters can be easily optimized using the approach. This approach can be applied to similar surface coating engineering techniques like metalizing, HVOF, cold spraying, hard chrome coating, nirtiding, carbide coating, etc. Another recently developed algorithm specific parameter-less algorithm known as Jaya [54] may also be attempted for optimization.

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