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RESPONSE SURFACE OPTIMIZED ROBOTIC SPRAY-PAINTING METAMODELING FOR FANUC PAINT ROBOT P-250IB/15

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Abstract

Because of the widespread use of spray-painting in the automotive industry, the automated spray-painting method has recently sparked attention in industry and research. The benefits of automating the spray-painting process include enhanced quality, efficiency, less labour, a cleaner environment, and, most importantly, affordability. The statistical tool Taguchi's DOE method is used in this study to evaluate the performance characteristics of an industrial robot Fanuc 250ib for an automated painting operation. The Taguchi method with L25 orthogonal array is utilized for the creation of the experiment, which takes includes 3 input parameters and 5 different levels for each input parameters. The goal of this research is to explore and optimise the primary controlling factors for enhanced paint coating quality as evaluated by Dry Film Thickness, leads to lower refusal. This is achieved using response surface methodology (RSM) metamodeling to optimized the spray-painting parameters used by Fanuc Paint Robot P-250iB/15. This research work helps to develop the mathematical correlations of input and response parameters to achieve the optimized paint work through Robot.

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1. Introduction

Because of the widespread use of spray-painting in the automotive industry, the automated spray-painting method has recently sparked attention in industry and research. The benefits of automating the spray-painting process include enhanced quality, efficiency, less labour, a cleaner environment, and, most importantly, affordability. The statistical tool Taguchi's DOE method is used in this study to evaluate the performance characteristics of an industrial robot Fanuc 250ib for an automated painting operation. The Taguchi method with L25 orthogonal array is utilized for the creation of the experiment, which takes includes 3 input parameters and 5 different levels for each input parameters. The goal of this research is to explore and optimise the primary controlling factors for enhanced paint coating quality as evaluated by Dry Film Thickness, leads to lower refusal. This is achieved using response surface methodology (RSM) metamodeling to optimized the spray-painting parameters used by Fanuc Paint Robot P-250iB/15. This research work helps to develop the mathematical correlations of input and response parameters to achieve the optimized paint work through Robot.

2. Experimental Procedure and Optimization

The studies were conducted out on a Fanuc 250ib automated robotic spray painting system with a specifically built Titanium spray end-effector, as shown in Figure 1. This is a six-axis industrial manipulator with articulated arms. With a resolver or feedback, each axis is servo controlled. The end wrist's payload capacity is 15kg, and the reach is 2800mm. The Fanuc 30ib controller is used to control the robot. The tests were carried out in accordance with ISO 9001 and ISO/TS 16949 standards.

Figure 1. Robotic spray painting Fanuc 250ib.

Design of experiments (DOE). Paint flow, air shaping, turbine speed, high voltage, and viscosity are all factors that influence robotic spray painting. The output quality of robotic spray painting is measured in terms of Dry film thickness in this study (DFT). Elcometer is used to measure DFT in microns. Taguchi's Design of Experiment technique was used to create the experiment.

Table 1. Design Factor.

S. No.	Control factor	Units	Level 1	Level 2	Level 3	Level 4	Level 5
1	Paint flow	cc/min	200	250	300	350	400
2	Shaping air	bar	2	4	6	8	10
3	Viscosity	sec	16	16.5	17	17.5	18

A suitable orthogonal array (OA) must be chosen for the experiments based on the total number of degrees of freedom (DOF) [13]. Because the current study takes into account three components with five levels, the total number of DOF is equal to (No of levels - 1) x No of Main factors $= (5-1) \times 3 = 12,$ ignoring the interaction between the factors. As a result, the minimal number of experiments is equal to the total number of DOF plus one. As a result, an appropriate OA is one that uses response technique and includes a number of experiments equal to or larger than the total number of DOF. As a result, L25 OA was chosen, and the physical architecture of the experiment is shown in Table 2.

Table 2. Experimental value based on DOE.

S. No.	Paint flow	Shaping air	Paint Viscosity	Dry film Thickness
1	200	2	16.0	55
2	200	4	16.5	57
3	200	6	17.0	59
4	200	8	17.5	61
5	200	10	18.0	63
6	250	2	16.5	53
7	250	4	17.0	55
8	250	6	17.5	57
9	250	8	18.0	59
10	250	10	16.0	60
11	300	2	17.0	58
12	300	4	17.5	60
13	300	6	18.0	62
14	300	8	16.0	63
15	300	10	16.5	65
16	350	2	17.5	71
17	350	4	18.0	72
18	350	6	16.0	74
19	350	8	16.5	75
20	350	10	17.0	77

21	400	2	18.0	90
22	400	4	16.0	92
23	400	6	16.5	94
24	400	8	17.0	95
25	400	10	17.5	97

RSM Regression metamodeling.

Backward Elimination of Terms α to remove = 0.1

Model Summary of the RS regression metamodeling is given below:

S	R-sq	R-sq(adj)	R-sq(pred)
0.257226	99.97%	99.97%	99.96%

This shows the 99% curve fitting for the prediction model. Table 3 shows the Analysis of variance table.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	5	4811.70	962.34	14544.47	0.000
Linear	3	3841.11	1280.37	19351.02	0.000
Paint flow	1	3715.22	3715.22	56150.48	0.000
Shaping air	1	125.17	125.17	1891.71	0.000
Paint Viscosity	1	0.72	0.72	10.88	0.004
Square	1	943.56	943.56	14260.58	0.000
Paint follow* Paint follow	1	943.56	943.56	14260.58	0.000
2-Way interaction	1	0.83	0.83	12.48	0.002
Paint follow* Paint Viscosity	1	0.83	0.83	12.48	0.002
Error	19	1.26	0.07		
Total	24	4812.96			

The figure 2 show the pareto chart for dry film thickness.

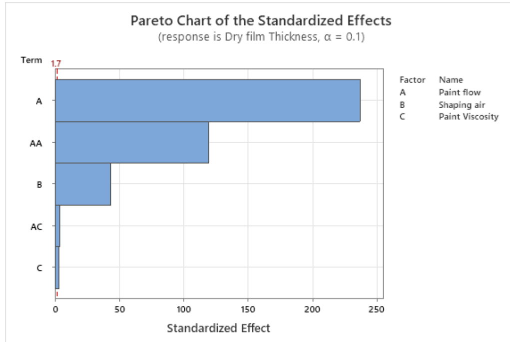

Figure 2. Pareto chart for Dry film thickness.

Regression Equation in Uncoded Units for dry film thickness is shown in equation 1.

Dry film Thickness = 113.10 - 0.6427 Paint flow + 0.8457 Shaping air + 1.406 Paint Viscosity + 0.001469 Paint flow*Paint flow-0.00389 Paint flow* Paint Viscosity (1)

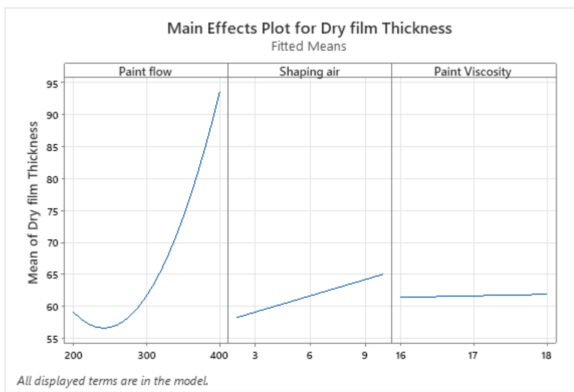

Figure 3. Parameter effect plot for Dry film Thickness.

The figure 3 shows the input parameter effect on output response. The paint flow carries very important effect on response parameter.

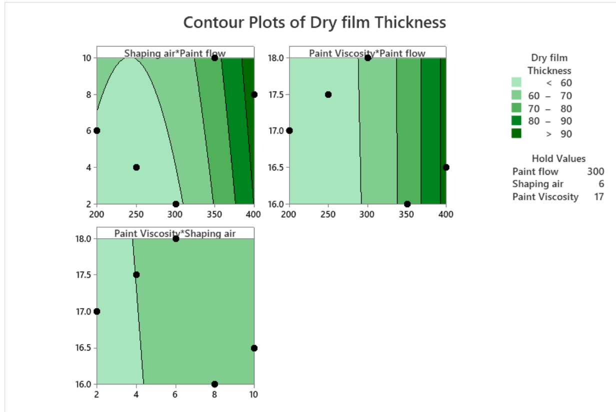

Figure 4. Surface plot for response parameter.

Figure 4 shows the contour plot of dry film thickness with respect to input parameters. Then composite desirability function is implemented for surface response optimizer to optimize the process with given limits, weights and target values.

Solution

Solution	Paint flow	Shaping air	Paint Viscosity	Dry film Thickness Fit	Composite Desirability
1	240.404	2	16	52.7043	1

Parameters

Response	Goal	Lower	Target	Upper	Weight	Importance
Dry film Thickness	Minimum		53	97	1	1

Multiple Response Prediction

Variable	Setting
Paint flow	240.404
Shaping air	2
Paint Viscosity	16

Response	Fit	SE Fit	95% CI	95% PI
Dry film Thickness	52.704	0.130	(52.432, 52.976)	(52.101, 53.307)

Figure 5 shows the optimization results, and a confirmation test was performed to evaluate the design parameters that influence the automated spray painting process. The best levels of paint flow were 200cc/min, 2bar of shaping air, and 17.5secs of viscosity for this control parameter. The outcomes of the tests were compared to the projected value acquired through statistical analysis. The results of the confirmation test were quite close to the predicted values, with the maximum error percentage being less than 10%.

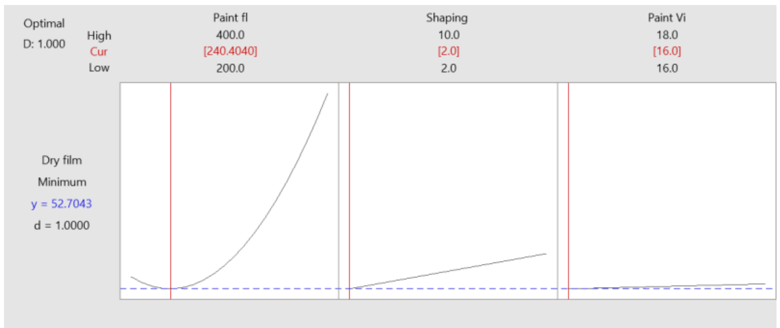

Figure 5. RSM optimizer plot for response parameter.

3. Conclusion

Using Taguchi's DOE, the robotic spray painting of plastic components was successfully investigated in this work. The goal was to increase DFT as much as possible. Paint flow, air shaping, and viscosity were all taken into account. Paint flow and Shaping air were the most influential parameters, and they were investigated and optimised to get the most favourable value of the response variable, DFT, utilising L25 OA. DFT was mainly influenced by shaping air, which contributed 51.05 percent, and paint flow, which contributed 30.78 percent, according to Anova findings. Viscosity was also discovered to be a non-significant effect. The optimal values of the designed parameters were used in a later confirmation test. When the outcomes of the confirmation experiments were compared to the projected model values, the error percentage was less than 10%.

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