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Paper

DESIGN OF EXPERIMENTS BASED WATERBLAST PROCESS MODELING AND OPTIMIZATION USED IN EQUIPMENT DESIGN AND SETUP FOR SPECIFIC APPLICATIONS

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ABSTRACT

There are many process parameters available for adjustment with waterblasting equipment. Understanding the significance of these parameters, their relative contribution, and interactions can yield order-of-magnitude increases in productivity. Modeling of these processes can also open up new applications for waterblasting that would otherwise be prohibitively expensive or otherwise unsuitable. This presentation will focus on applying Design of Experiments (DOE) based methodologies to model a dual-head Epi-Centric Waterjet Deck Blaster. Real-world results will be shown for extending waterblasting for removal of hard coatings from sensitive substrates and optimal setup of equipment for common applications.

1. INTRODUCTION TO EXPERIMENTAL DESIGN

Design of Experiments (DOE) is a scientific approach to experimentation. The goal of the experimentation is to optimize, maximize, or minimize one or more process outputs (Responses). Researchers choose those input variables (Factors) and ranges which may be controlled for the process of interest. The DOE approach to experimental design enables researchers to extract the maximum amount of information from a minimal number of trials. There are several types of experimental Designs researchers can utilize, having such uninformative names as: D-Optimal, Box-Behnken, Plackett-Burman, Taguchi OA, and others. All of these Designs have specific strengths and weaknesses. The general goal is to use a Design having a minimum number of trials to generate a mathematical function (Model) describing the process. The DOE process will inform researchers as to which factors, the order of those factors, interaction effects, and statistical significance of the model for each Response of interest.
A well-designed, or robust DOE experiment will:

- Aid in the selection and isolation of important variables
- Minimize the required number of experiments needed to yield meaningful results
- Maximize the amount of information extracted from the experiments
- Minimize the cost of product development and process control
- Provide statistical information on model accuracy and repeatability
- Characterize or account for random variability (noise) of process being modeled

1.1 Setting Range of Process Parameters

To better discern the relationship between machine or process input parameters (Factors) and outputs (Responses), it is helpful to widen the range over which experiments are performed. Rather than operating within a narrow range of pressures, flow rates, standoff distance, etc., expand the ranges beyond those typically seen in a 'normal' production environment. This strategy allows process cause-and-effect relationships to stand out against normal variability associated with measurement error, non-controlled environmental factors, normal process variability, etc. The series of graphs shown in
Figure 1 illustrate the benefit of expanding the range of a single Factor. The points plotted in
Figure 1 were generated using a known polynomial function (continuous orange line). This polynomial is analogous to a mathematical function that precisely describes a particular process. To these results are added a random number between -5 and 5 to provide an artificial source of variability, or 'noise' to point within range evaluated (blue points). This 'artificial noise' represents effects of imprecise machine settings, effects of extraneous uncontrolled variables such as temperature and humidity, measurement error, etc. The best fit a polynomial function through the artificially-randomized points (black line in range of data points). Repeating this example and calculating a cumulative average to illustrate convergence over 100 iterations shown in
Figure 2. Curve fitting for 'Normal' range had an average R^2 of 0.492 ± 0.178, the wider range had an average R^2 of 0.794 ± 0.076, and the full process range had an average R^2 of 0.960 ± 0.012. Using 'normal' (narrow) process ranges, researchers would only be able to 'see' about 50% (R^2 = 0.492) of the underlying cause-and-effect relationship governing the process. Expanding it slightly beyond the normal range would enable researcher to 'see' almost 80% of the underlying relationship (R^2 = 0.794) between Responses (e.g., production rate) and Factors (e.g., machine and process settings used). Dramatically opening up the range, as has been done in the graph on the far

right, allows researchers to understand and mathematically explain 96% (R2 = 0.960) of the variation seen in the Response variable (production process output of interest) resulting from various machine settings and other process parameter settings.

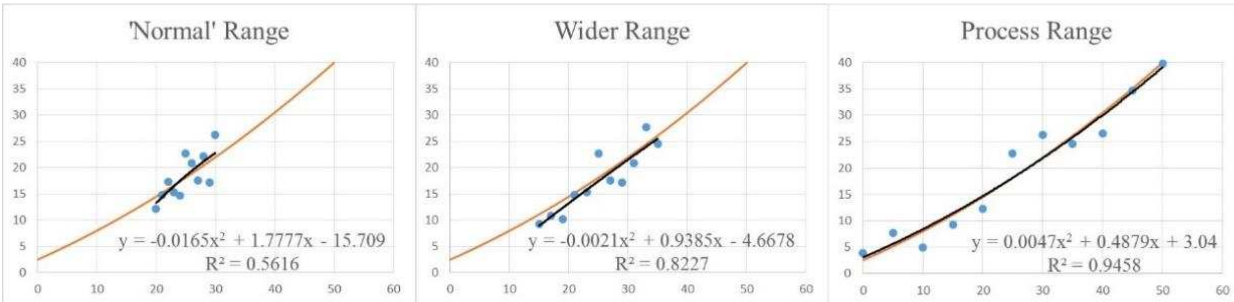

Figure 1. Effects of fitting curves to noisy data over different varible ranges. Know curve (orange) for generating ponts (blue) with random noise between limits and best fit polynomial (black). Best fit polynomial equation and fit shown for each.

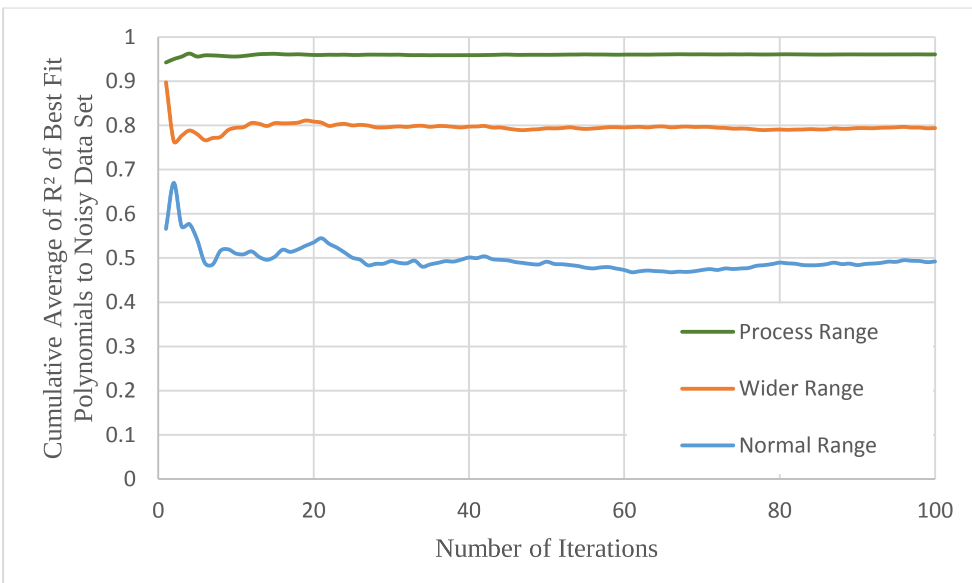

Figure 2. Convergence of best fit polynomial R2 to the three example ranges.

There are additional benefits associated with expanding the range beyond some (arbitrary) narrow range typically used in production as can be seen in Figure 3. An experimenter ‘nibbling around the edges’ of a typical production range (green region in Figure 3) might conclude that performance drops off if he or she moves too far away from their production ‘comfort zone’. However, those researchers will not find dramatic improvements (red region in Figure 3) that can only be found by dramatically increasing the range of the variables studied. Even when a wide process range evaluated the region highlighted in red would be identified, however further experimentation may be required to generate an accurate model and find local optima.

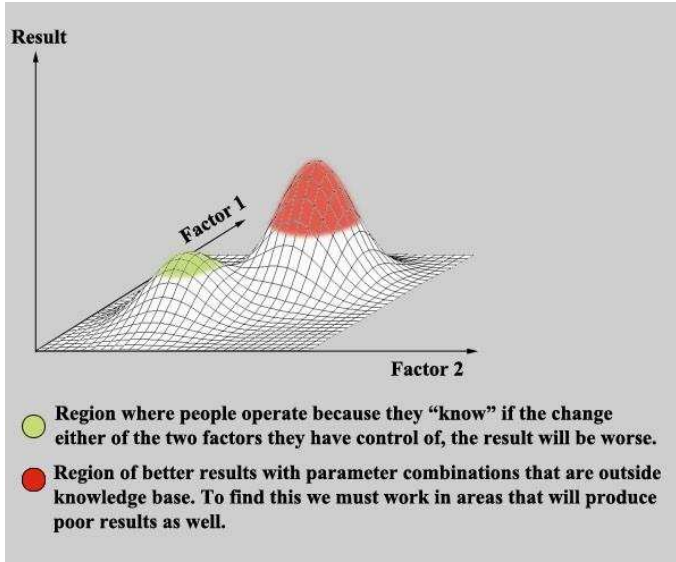

Figure 3. Local & global maxima & minima

1.2 Sizing an Experiment

Generating mathematical functions requires one data point more than the order of curvature. Any two points make a line (for which order=1). For a quadratic, or 2nd order polynomial, three points are required. One point to determine the endpoints of the curve, and one interior to the endpoints to create curvature. Clearly, using the minimum number of points in this way is statistically meaningless. The slope of a line created using only two points might provide information on a general trend, but the slope will vary wildly depending upon how much random error or noise is present, and the researcher would have no way to ascertain how much variation is present. To obtain useful, statistically-significant information, additional points must be included in the experimental design. Typically, quadratic designs (second order) are chosen as a starting point because they help to identify localized maxima (without large misrepresentation around points that are coincidently located on maxima or when extrapolated). An example of a quadratic (2nd order) single-Factor (one variable) Factor Response graph is shown in
Figure 1. The value of the factors appears on the x-axis and Responses on the y-axis. As above, 3 data points are required for fit and additional points are required for statistical significance. A second order polynomial best-fit to the data points will take the form of Equation 1.

$$y = Ax^2 + Bx + C$$

Equation 1. Basic form of second order polynomial for modeling Response from 1 Factor experiment

A quadratic design is needed to identify curvature in a process. This means a minimum of 3 levels (low, medium, high) must be investigated for each variable studied. To fully 'map-out' a design space (full factorial design) trials would need to be run for each variable at each level. The number of experiments that must be performed quickly becomes large and unwieldy, as shown in Figure 3. A 4-Factor full-factorial design (Figure 4C) would require 81 trials. Additional trials are needed to assess lack of fit and statistical accuracy. Pure replicates (exact duplicates of some of the trials) are used to assess process variability, while additional trials (with Factor levels located at points other than the low, medium, and high levels of each variable) would also be needed to assess model lack of fit. Full-factorial designs are commonly done out of ignorance or at the behest of regulatory requirements, where the whole parameter space is evaluated for each permutation of each selected level for each Factor - with replicates. This rapidly becomes overwhelming, as the number of trials increase by 3 to the exponent of number of factors plus replicated trials for evaluation of error and additional trials to assess lack of fit. However, systematic changes of multiple factors with each trial allows one to generate a mathematic matrix of equations of factors and responses which can be simultaneously solved. This dramatically reduces the number of trials required to generate functions relating factors to responses. For a 5-Factor D-Optimal DOE the number of trials required for a determinate matrix drops from 243 trials to 15. An additional 10 trials would be required (5 pure replicates, 5 for lack of fit) to determine statistical significance and lack of fit for a total of 25 experimental trials. The additional trials provide for statistical analysis of variance to determine how strongly each Factor contributes to a particular Response, correlation of the model to the data, and confidence level the models will predict an accurate Response. Continuous factors can be varied continuously over the Factor range(s). Ordinal factors are similar to continuous factors that have discrete set-points, and Categorical variables are discrete, non-numerical variables (e.g., apples & oranges, Jack & Jill, etc.) Categorical factors require all other factors to be varied for each category group. Ordinal factors must be evaluated at each level for each other Factor being evaluated.

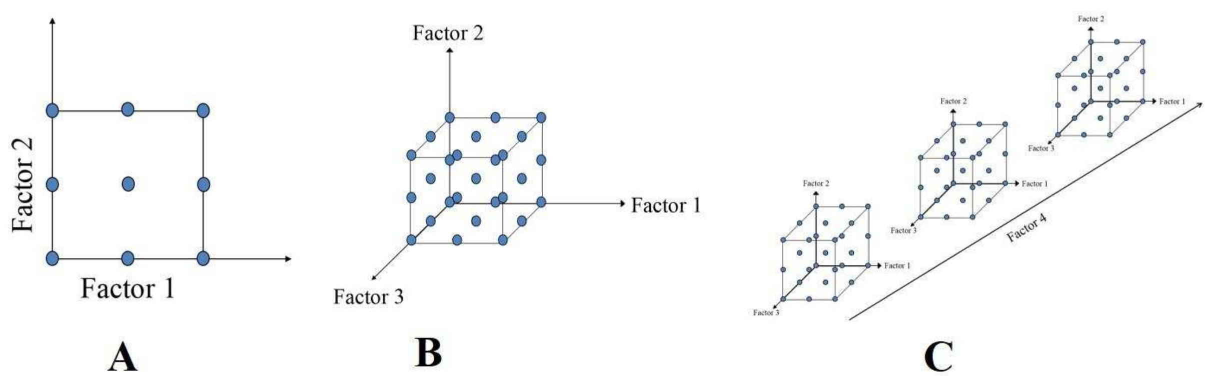

Figure 4. Experimental point reprenstation for 2 Factor (A), 3 Factor (B), and 4 Factor (C)

1.3 Challenges and Shortcomings of Design of Experiments Based Process Modeling

There are few shortcomings to DOE based strategies and techniques and most of these can be addressed with proper planning for robustness and quantification. DOE modeling should be avoided when a process may have true singularities discontinuities or kinks (sections of very high curvature) in the Response curve. This is rare, but electromagnetic fields and quantum effects are two possible examples. . Other shortcoming include: when the cost of each experiment is too high to replicate; when the cost of failed experiments is unacceptable (e.g., human trials); and when experiments have unique components that cannot be accurately quantified or reproduced (behavioral or complex societal factors).

The biggest challenge in using DOE is getting production personnel on-board with the Experimental Design process. Researchers on production lines are tolerated at best, and generally reviled when they start to turn knobs or otherwise mess with the equipment and process. The expertise and experience of production personnel is invaluable when scoping out and conducting experiments, but detrimental if they are allowed to alter subsequent trials based on individual / preliminary results. It is also difficult for production personnel who are unfamiliar with DOE to move out of their comfort zone with regard to expanding ranges of current processes. Production workers and managers are often confident in the process they currently use due to historical experience. Production personnel and product developers also need to understand and accept that obtaining 'bad results' in the course of the optimization is not a 'bad thing'. To uncover and understand the cause-and-effect relationships between input parameters and final surface quality (for example), it is necessary to have a wide range of results. Education and inclusion of production personnel (and others) in the experimental design process is crucial. As is ensuring reasonable expectations with regard to trial-to-trial results when it is time to perform the experiments.

1.4 Software

Full-feature packages allow for process managers with working knowledge of statistics to be successful with minimal training. There are a number of open-source software products that can be used in combination to obtain accurate results with more effort and knowledge of DOE processes and statistical analysis. JMP, Minitab, and Design-Expert are the most recognizable software packages for Multifactor DOE.

2. DOE APPLICATION TO WATERBLASTING

Waterblasting incorporates several complex and non-linear phenomena such as: water traveling through air; and material Response to water impacts. As such, the DOE approach is an excellent tool to understand how machine settings and other process parameters affect output parameter(s) of interest. The DOE method can be used to optimize equipment for specific applications, inform equipment/component design, or evaluate efficacy of new equipment claims.

3. EXAMPLE OF DOE FOR SELECTIVE COATING REMOVAL

ARL was contracted to develop a tool and process to remove durable anti-slip coatings from an elastomeric substrate. For discussion purposes the title 'Rubber' with a following letter designation differentiate the substrates evaluated. Rubber "A" has a relatively firm durometer but can still be gouged or cut with sharp metal tools. Rubber "B" is ~20% softer and is more easily damaged. Both materials have thin seams with a compatible seam filler that is softer than either material. In some areas, the anti-slip coatings overlie patches of much firmer material that cannot be detected until the anti-slip coating is removed. Currently, the only approved process for coating removal is manual hand-sanding using an orbital air sander with 36 grit or finer abrasive. Current reported production rates average ~1 man hour per 0.93 m^2 (1 ft^2) removed, with typical job-size between 74 m^2 and 111 m^2 (800 ft^2 and 1,200 ft^2). The slowness of the current removal method has resulted in schedule delays and interruption of other work. Based on previous experiments for optimizing destruction of the same rubber, it was hypothesized that specialized waterblasting equipment could be optimized to remove the nonskid coating without causing damage to the rubber and to do so at a substantially improved production rate.

3.1 Equipment

The Epi-Jet, produced by Terrydon Inc. shown in Figure 5, was used to test the above hypothesis.

Figure 5. Epi-jet prototyper equipment (Left), View of underside showing nozzle carriers (Right)

Key features of the Epi-Jet that make it ideally suitable for the application are:

- The nozzle carriers are mounted at a uniform distance from the axis of rotation and maintain consistent angle if incidence to surface
- Controllable rotation of nozzle carriers
- Rotation of large central plate eliminates spray-bar stalling on substrate
- Ability to set the overlap of subsequent passes of rotating nozzle carriers
- Adjustable standoff distance between nozzle and substrate

An example of the path traced (epi-centric motion) is shown in Figure 6.

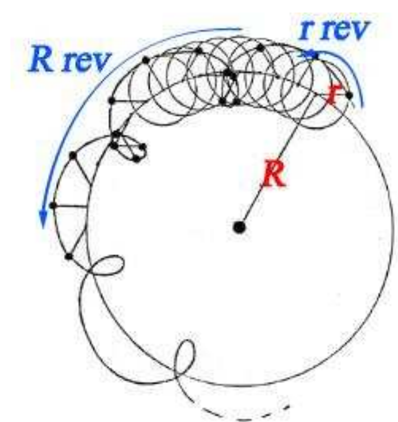

Figure 6. Epi-cyclic motion as primary rotation rate increases

In Figure 6, the rotation speed of the prime centroid (large disc) is increasing with time. The amount of energy delivered to a surface by a waterjet depends upon pressure, flow rate, dwell time, and extent to which tracks overlap. To model this, ARL created a single-jet representation of the planetary-motion jetting pattern using JAVA. The JAVA-based software creates an energy-density map, similar to a heat map, of the process. To better understand the energy intensity map, envision marbles streaming out of a tube as it moves over a grid of cups. The more marbles that end up in a cup, the more intense the energy imparted to that region. The software provides a visual map of the relative energy intensity experienced by the surface. The user inputs rotation speed of the large plate, rotation speed of the small spray nozzles, the radius of the large plate, radius of the nozzle carriers, etc. ARL used this tool to rapidly explore potential designs and provide as uniform surface energy intensity as possible. The program can model both single symmetric bar head and 2-planet epicyclical motion. The nozzle carriers and are evenly spaced around the perimeter of a circle. Input terms are as follows:

R:	Radius of large disk
R rev:	Rate at which nozzle carriers 'orbit' around the centroid of the large disk
r:	Radius of small-head / nozzle-carrier
r rev:	small-head / nozzle-carrier rotation rate
x rate:	Forward translation of the system (left-to-right motion on the screen)
hole count:	Number of nozzles in each nozzle carrier
marbles/sec:	Rate term representing how fast 'marbles' are dropped onto the grid
x length:	Left-to-right display size of grid
y length:	Top-to-bottom display size
x grid count:	Number of cups in a row
y grid count:	Number of cups in a column
time inc:	Time increment

Extending the basic example shown in Figure 6, two small-head nozzle carriers with two jets per nozzle carrier rotate about a central axis (large plate) as the entire system moves from left to right at constant speed is dynamic motion basis for epi-centric water blasting as shown in Figure 7. While this type of pattern appears complicated at first, the basic principles of machine tool path determination apply. There needs to be a minimum number of tooth paths (jets) per inch based on tool diameter. For water jets there can be spacing between adjacent jet paths as direct impact of a jet on a surface is not needed to effect coating removal. The tool head (nozzle carrier) overlap is kept at some known percentage (per head-pass) to produce uniform surface coverage. For common machining this is analogous to a mill-facing operation where a facing to meet surface finish requires the head to split the previous pass by some fraction of the facing-head diameter.

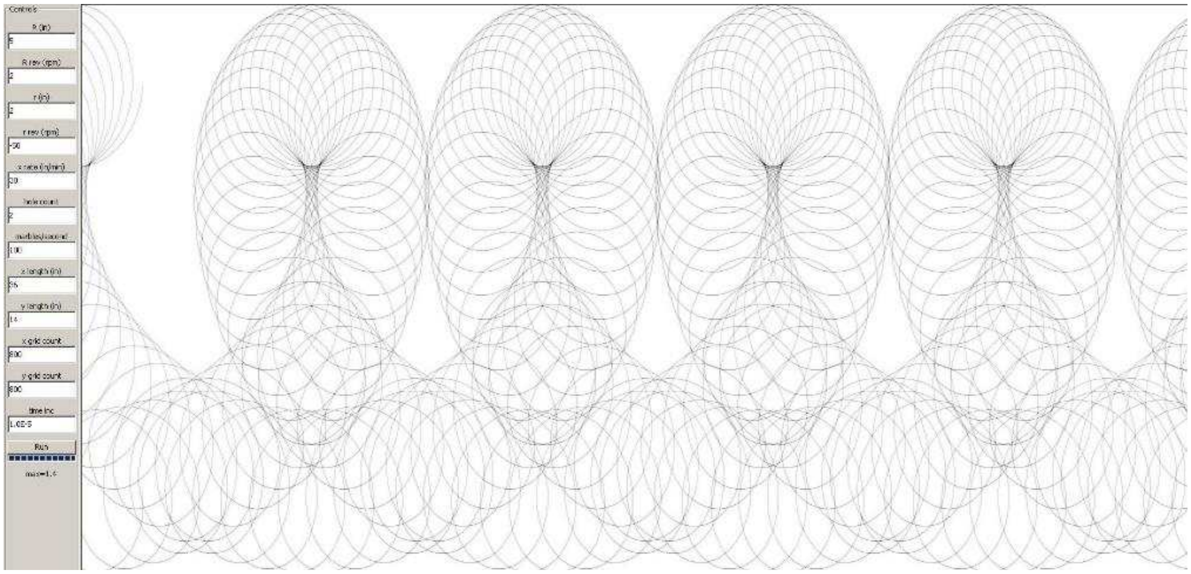

Figure 7. Exagerated epi-cyclic motion example by increasing ration of translation speed to rotation rates

The additional degree of freedom of the epi-cyclic motion results in a fundamentally different jetting pattern from conventional deck-blasters. The jetting patterns of a common deck-blaster and epi-cyclic blast system appear in Figure 8.

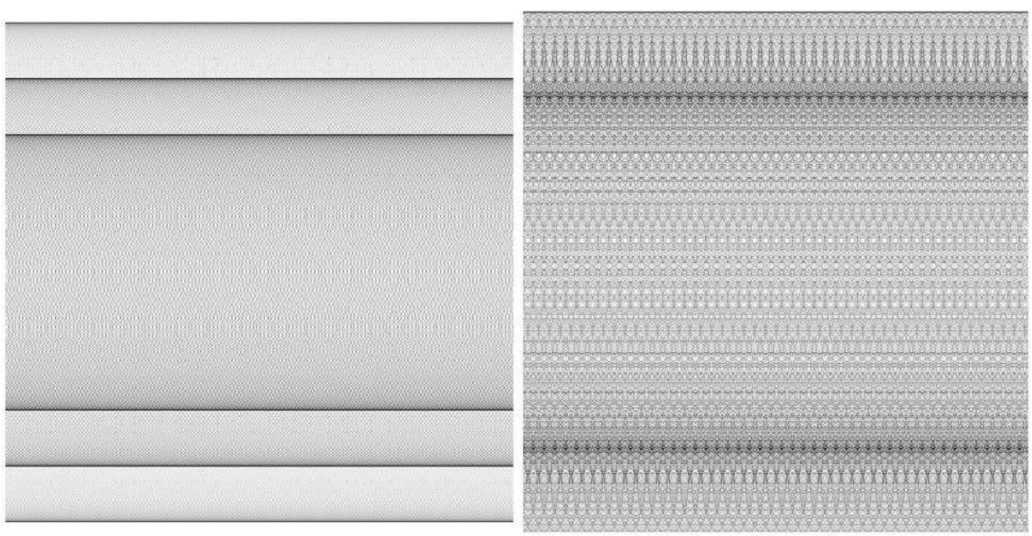

Figure 8. Jetting patterns of conventional 6-jet deck blaster (left) and 4-jet epi-jet (right)

In Figure 8, areas where the jet has passed multiple times or dwell appear. The darker a spot, the greater energy intensity / dwell time that spot has received. Regardless of rotation rate, a deck-blaster with a single axis of rotation will always have high-energy-intensity path lines at distances from center where individual jets are located (shown as the dark horizontal lines on left side of Figure 8). The epi-cyclic blasting pattern (right side of Figure 8) has two higher-energy paths appearing as slightly diffuse darker bands near top and bottom of graphic. These more diffuse higher-energy tracks have less than half the maximum intensity of a typical deck blaster.

3.2 Conducting the Experiments and Process Optimization

A 2nd order, 4-Factor 'D-Optimal' experimental design was chosen for both Rubber 'A' and Rubber 'B' experiments. This resulted in a total of 25 trials for each series of experiments. The 2nd order design will identify curvature and interaction effects within the design space.

Pressure, nozzle size, and flow through the nozzle are coupled. Any two of these variables can be used to calculate the third. Pressure and flow-per-nozzle were chosen as factors for the design, making it easier to limit total flow to the 6 gpm limit imposed by the pump. Nozzles are supplied in integer multiples of 0.1 mm or 0.001". Flow-charts were used to identify the nozzle size providing the 'closest match' in inches to the target flow for a given pressure, and the flow-per-nozzle value in the design was replaced with the theoretical flow through that nozzle.

As mentioned previously, the DOE process generates results outside of what would be considered 'acceptable', and damage to the rubber during trials was expected. Consequently, all trials were performed on rubber scheduled for removal.

Removal Percentage and Post-Blast Surface Condition were the Response (output) parameters of interest. It is difficult to accurately estimate coating removal percentage visually. High-quality photographs and specialized software can be used to accurately estimate removal percentage, but high-quality photographs were not immediately available to ARL personnel.

ARL consulted with Puget Sound Naval Shipyard and Intermediate Maintenance Facility (PSNSY&IMF) rubber and paint engineering authorities to rate the test patches for acceptable condition of rubber and acceptable condition for applying a new coating. ARL then created a combined parameter (rating between -5 and +5) that incorporated relative removal efficiency and post-blast rubber surface condition. At a rating of +5 no coating was removed. At a ranking of zero (0) no coating remained and the rubber was completely unscathed. At a rating of less than zero (0) damage occurred to the rubber ranging from very minor cosmetic scratches to major erosion/gouging. While subjective in nature, the results are valid as long as the rating or ranking system is consistent.

For all trials, the surface condition of the pattern center and pattern edges differed due to the fact that the energy density of the pattern Center is lower than the energy density of the pattern Edge. To account for this, the Edge and Center conditions were rated separately for each trial, representing two distinct and independent outputs.

Rubber "A"

Experiment Design

Factors studied and their ranges are shown in Table 1.

	Range Minimum				Range Maximum			
Factor 1: Pressure	1034	bar	(15.0	Ksi)	2068	bar	(30.0	Ksi)
Factor 2: Flow	2.16	l/min	(0.57	gpm)	5.68	l/min	(1.50	gpm)
Factor 3: Standoff*	0.00	mm	(0.00	in)	25.40	mm	(1.00	in)
Factor 4: Head Rotation	1200	rpm			2000	(rpm)		
*(distance between orifice and surface is an additional 1.344 inches to the standoff)								

Table 1. Experimental Design Space for Rubber A

Trial run sheet with actual/correct values and evaluated responses is shown in Table 2.

Conducting and Evaluation of DOE Trials

Trials for Rubber A were conducted at PSNSY&IMF on a US Navy asset in areas where rubber was to be removed for maintenance. Total Area for testing was limited to < 3.7 m^2 (40 ft^2). Aluminum sheet metal was used as a mask to frame 457 mm (18") wide by 203 mm (8") long test patches for each trial.

Results

	Factor 1		Factor 2		Factor 3		Factor 4	Response 1	Response 2
Run	Pressure		Flow		Standoff		Rotation	Edge Rating	Center Rating
	bar	(Ksi)	l/min	(gpm)	mm	(in)	(rpm)	(- damage, 0 best, + paint remains)	
1	2068	(30.0)	2.16	(0.57)	19.05	(0.75)	2000	-0.2	0.0
2	1034	(15.0)	5.64	(1.49)	12.19	(0.48)	1200	4.0	2.5
3	2068	(30.0)	2.16	(0.57)	0.00	(0.00)	1200	-4.0	0.5
4	1034	(15.0)	5.64	(1.49)	12.19	(0.48)	1200	4.5	5.0
5	2068	(30.0)	2.16	(0.57)	19.05	(0.75)	2000	0.0	1.0
6	1034	(15.0)	5.64	(1.49)	25.15	(0.99)	1200	3.0	3.0
7	1207	(17.5)	3.48	(0.92)	19.05	(0.75)	1204	3.0	2.5
8	1841	(26.7)	5.30	(1.40)	11.68	(0.46)	1630	-1.0	-0.5
9	1712	(24.8)	4.66	(1.23)	19.05	(0.75)	1200	-2.5	1.5
10	2068	(30.0)	2.16	(0.57)	0.00	(0.00)	1200	-1.0	0.5
11	1407	(20.4)	2.35	(0.62)	13.21	(0.52)	1200	4.0	5.0
12	2068	(30.0)	5.64	(1.49)	5.08	(0.20)	1200	-2.0	-1.0
13	1432	(20.8)	5.60	(1.48)	26.16	(1.03)	1636	2.0	3.0
14	2068	(30.0)	5.64	(1.49)	0.00	(0.00)	2015	-1.5	0.5
15	1241	(18.0)	3.56	(0.94)	10.41	(0.41)	1672	3.0	3.0
16	1034	(15.0)	3.97	(1.05)	0.00	(0.00)	1200	3.0	3.0
17	2068	(30.0)	2.88	(0.76)	25.15	(0.99)	1200	-3.0	-1.5
18	2068	(30.0)	5.64	(1.49)	0.00	(0.00)	2000	-3.0	-1.0
19	1407	(20.4)	5.56	(1.47)	0.00	(0.00)	1582	2.0	2.0
20	1034	(15.0)	2.31	(0.61)	0.00	(0.00)	2000	4.0	5.0
21	1034	(15.0)	2.31	(0.61)	25.15	(0.99)	1620	5.0	5.0
22	2068	(30.0)	3.67	(0.97)	9.91	(0.39)	1690	-2.0	-1.0
23	1412	(20.5)	4.20	(1.11)	25.91	(1.02)	2000	2.5	4.0
24	1034	(15.0)	2.31	(0.61)	0.00	(0.00)	2000	5.0	5.0
25	2068	(30.0)	5.64	(1.49)	25.40	(1.00)	1848	-0.5	0.5

Table 2. Design of Experiments table of of experiments and responses for Rubber A

Test patch ratings for Edge and Center were the two Responses for this experiment and equations were generated with a best fit regression.

$$
\begin{aligned}
&Rubber\ A\ Edge\ Rating \\
&\quad = 15.7895 - 0.4382 * Pressure(ksi) - 12.5503 * Standoff(in) + 0.0005 \\
&\quad * Head\ Rotation\ (rpm) + 0.0025 * Standoff(in) * Head\ Rotation(rpm) \\
&\quad + 5.7139 * Flow\ per\ Nozzel(gpm) * Flow\ per\ Nozzel(gpm) - 3.2484 \\
&\quad * Standoff(in) * Standoff(in)
\end{aligned}
$$

Equation 2. Best fit regression equation of model to relate inspector rating of pattern edge to process parameters of experimental equipment for Rubber A

$$
\begin{aligned}
&Rubber\ A\ Center\ Rating \\
&\quad = 5.8785 + .06418 * Pressure(ksi) - 13.4912 * Flow\ per\ Nozzel(gpm) \\
&\quad - 0.0276 * Pressure(ksi) * Pressure(ksi) + 5.8168 \\
&\quad * Flow\ per\ Nozzel(gpm) * Flow\ per\ Nozzel(gpm)
\end{aligned}
$$

Equation 3. Best fit regression equation of model to relate inspector rating of pattern center to process parameters of experimental equipment for Rubber B

All terms are statistically significant (95% confidence level). The resulting models had F-values of less than 0.0001. The F-value provides a measure of model significance, and can be interpreted as the likelihood that correlations between factors and responses are due to chance alone. For an F-value of 0.0001 there is less than one chance in 10,000 that the correlation between model inputs and the resulting surface condition are due to chance. The Edge Ranking model explained ~90% of the variation seen in the data (Adjusted $R^2 = 0.9008$). The Center Ranking model explained ~84% of the variation seen in the data (Adjusted $R^2 = 0.8404$).

These models are shown graphically in Figure 9. In Figure 9 the full ranges of Pressure and Flow per Nozzle appear on the primary axes at fixed values of the other 2 factors. Thus, these represent a 'slice' of the design space. Graphs are color shaded with the same Response scale with green being in the coating completely removed range and rubber undamaged.

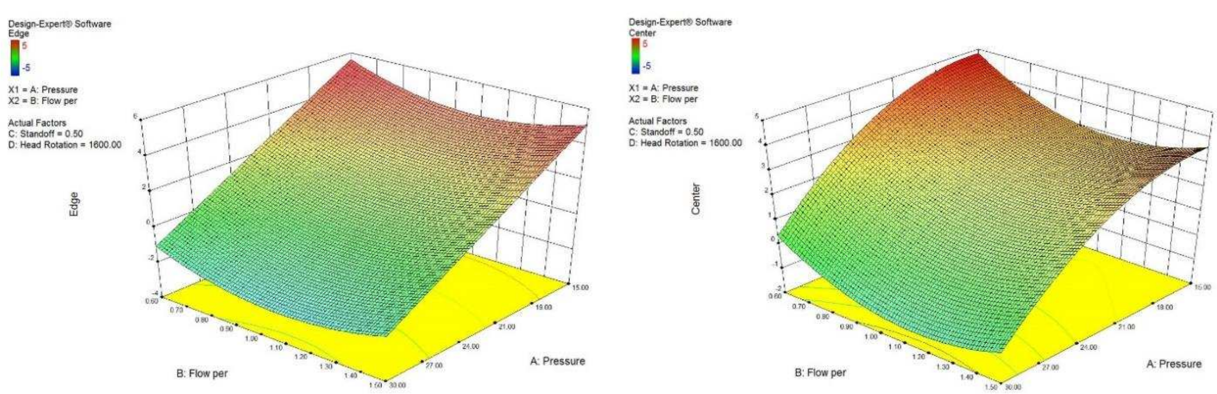

Figure 9. 3D Surface plots of Edge (Left) and Center (Right) Rankings for coating removal from Rubber A.

It should be noted that additional Responses can be measured (power consumption, water consumption, run cost, etc.) and models for these quantities calculated in order to further optimize the process by minimizing cost or water consumption. There are a number of strategies for weighted simultaneous solving to achieve the most acceptable aggregate of responses. A simple method for limited number of responses is to graphically solve by overlaying contour plots as shown in Figure 10. Inside the design space, maximum Flow per Nozzle, 1896 bar (27.5 ksi) Pressure, 20.4 mm (0.805") Standoff, and maximum Rotation provided a perfect rating for both responses is found by the intersection of the blue and black zero level contour lines. This trial was run as a validation patch for the same PSNSY&IMF engineers. All nonskid was removed. Only trace amount of primer and construction paint markings remained. There was no visible scarring or cutting damage to Rubber A. PSNSY&IMF engineers adjudged the surface to be undamaged and "paint-ready". These process parameters on this test equipment produce an instantaneous removal rate of 16.7 m^2/hour (180 ft^2/hour). Because factors needed to be set to maximums to achieve an optimum results, additional improvements in the responses may be achieved by expanding the design space further. To further optimize an additional set of trials should be conducted to augment the design. Time, equipment limitations and services available at test site prevented augmentation of design. Using the mathematical model and extrapolating (accuracy of any model degrades rapidly with extrapolation) a solution can be found at a considerably lower Flow per Nozzle as shown in the intersection of the red and black zero-level contour lines in Figure 10. This result was validated as acceptable at a later date on a mockup.

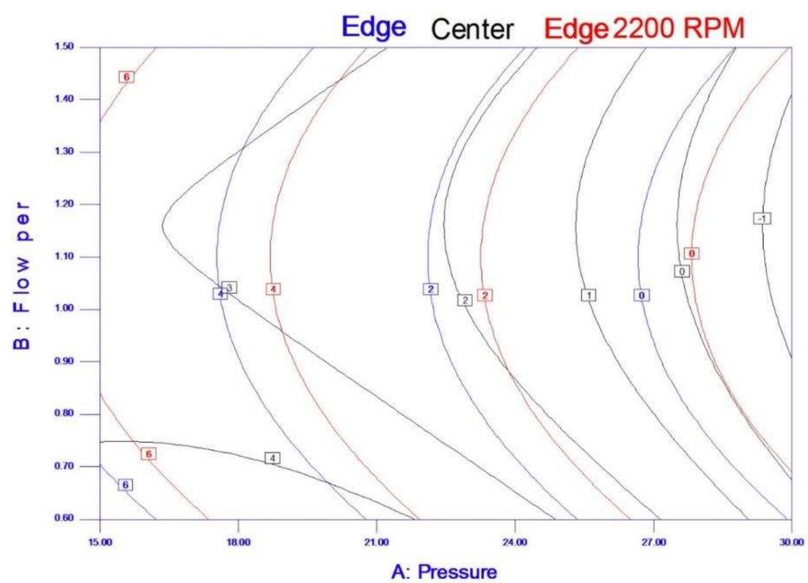

Figure 10. Overlay of 3 contour plots for Pressure and Flow per Nozzle. Standoff is fixed at 0.805" inches, Edge Rating, Center Rating, and Edge Rating with head rpm increased from 2000 to an extrapolated 2200 rpm.

Process Optimization Rubber "B"

Experiment Design

The ranges of the process space were modified based on results obtained during testing of Rubber 'A'. The factors and ranges selected for the Rubber 'B' Trials are shown in Table 3.

	Range Minimum				Range Maximum			
Factor 1: Pressure	1344	bar	(19.5	Ksi)	2103	bar	(30.5	Ksi)
Factor 2: Flow	2.16	l/min	(0.57	gpm)	5.94	l/min	(1.57	gpm)
Factor 3: Standoff*	0.00	mm	(0.00	in)	23.88	mm	(0.94	in)
Factor 4: Head Rotation		1700	rpm			3000	(rpm)	
*(distance between orifice and surface is an additional 1.344 inches to the standoff)								

Table 3. Experimental Design Space for Rubber B

Trial run sheet with actual/correct values and evaluated responses is shown in Table 4. Additional trials were conducted due to errors in setup and unplanned variations in vacuum supply.

Conducting and Evaluation of DOE Trials for Rubber 'B'

Trials for Rubber B were conducted at Pearl Harbor Naval Shipyard and Intermediate Maintenance Facility (PHNSY&IMF) on a US Navy asset in areas where rubber was to be removed for maintenance. Area for testing was limited to < 2.79 m2 (30 ft2). Aluminum sheet metal was used as a mask to frame 457 mm (18") wide by 152 mm (6") long test patches for each trial. Difficulties in maintaining adequate vacuum service to the job site existed and some trials were run with little or no vacuum adding additional noise to results. The range of ratings differed compared to experiments performed on Rubber 'A' due to more severe damage observed on the softer rubber.

Results

	Factor 1		Factor 2		Factor 3		Factor 4	Response 1	Response 2
Run	Pressure		Flow		Standoff		Rotation	Edge Rating	Center Rating
	bar	(Ksi)	l/min	(gpm)	mm	(in)	(rpm)	(- damage, 0 best, + paint remains)	
1	1820	(26.4)	2.35	(0.62)	9.65	(0.38)	2311	-0.3	1.5
2	1662	(24.1)	5.53	(1.46)	15.24	(0.60)	2610	-2.0	0.0
3	2075	(30.1)	2.16	(0.57)	22.61	(0.89)	3000	0.0	0.3
4	2034	(29.5)	5.56	(1.47)	17.78	(0.70)	2935	-6.0	-4.0
5	2027	(29.4)	5.56	(1.47)	17.78	(0.70)	2935	-6.0	-3.0
6	2103	(30.5)	5.68	(1.50)	0.00	(0.00)	1960	-10.0	-7.0
7	2075	(30.1)	2.88	(0.76)	0.00	(0.00)	1700	-1.5	-0.3
8	1379	(20.0)	2.35	(0.62)	0.00	(0.00)	1700	3.0	3.0
9	1386	(20.1)	2.35	(0.62)	0.00	(0.00)	3000	4.5	4.0
10	1386	(20.1)	2.35	(0.62)	23.11	(0.91)	1700	4.0	5.0
11	2048	(29.7)	5.07	(1.34)	18.29	(0.72)	1700	-7.0	-4.0
12	1441	(20.9)	4.24	(1.12)	0.00	(0.00)	2942	-5.0	-2.0
13	2062	(29.9)	5.11	(1.35)	0.00	(0.00)	2942	-4.0	-3.5
14	1958	(28.4)	4.96	(1.31)	14.48	(0.57)	1707	-6.0	-4.0
15	1344	(19.5)	4.13	(1.09)	10.16	(0.40)	2330	4.0	5.0
16	2062	(29.9)	3.26	(0.86)	19.05	(0.75)	1710	-5.0	-2.0
17	2082	(30.2)	3.29	(0.87)	0.00	(0.00)	2942	-3.0	-2.0
18	2082	(30.2)	3.29	(0.87)	0.00	(0.00)	2942	-4.0	-2.0
19	1965	(28.5)	4.50	(1.19)	10.41	(0.41)	2454	-1.5	-0.3
20	1800	(26.1)	4.28	(1.13)	22.61	(0.89)	2318	-2.0	0.0
21	1800	(26.1)	4.28	(1.13)	22.61	(0.89)	2318	-4.0	-2.0
22	1551	(22.5)	3.18	(0.84)	0.00	(0.00)	1700	-2.5	-1.0
23	1613	(23.4)	3.63	(0.96)	16.00	(0.63)	3000	-0.5	2.0
24	1613	(23.4)	5.94	(1.57)	0.00	(0.00)	2935	-3.0	2.0
25	1558	(22.6)	5.87	(1.55)	18.80	(0.74)	1700	-2.0	-0.5
26	1475	(21.4)	5.72	(1.51)	0.00	(0.00)	1700	-3.0	-1.0
27	1344	(19.5)	5.45	(1.44)	23.88	(0.94)	3000	1.0	1.0
28	1379	(20.0)	2.35	(0.62)	0.00	(0.00)	3000	0.0	0.3
29	1379	(20.0)	2.35	(0.62)	22.61	(0.89)	1700	0.5	1.0
30	2103	(30.5)	5.68	(1.50)	0.00	(0.00)	1960	-7.0	-10.0
31	1379	(20.0)	2.35	(0.62)	0.00	(0.00)	3000	3.0	2.5

Table 4. Design of Experiments table of of experiments and responses for Rubber B

$$
\begin{aligned}
&Rubber\ B\ Edge\ Rating \\
&\quad = 15.5377 - 0.4948 * Pressure(ksi) - 4.8048 * Flow\ per\ Nozzel(gpm)
\end{aligned}
$$

Equation 4. Best fit regression equation of model to relate inspector rating of pattern edge to process parameters of experimental equipment for Rubber B

$$
\begin{aligned}
&Rubber\ B\ Center\ Rating \\
&\quad = 6.3243 + .0834 * Pressure(ksi) + 8.8472 * Standoff(in) - 0.0021 \\
&\quad * Head\ Rotation\ (rpm) + 3.1192 * Flow\ per\ Nozzel(gpm) - 0.5462 \\
&\quad * Pressure(ksi) * Flow\ per\ Nozzel(gpm) + 0.0027 * Head\ Rotation\ (rpm) \\
&\quad * Flow\ per\ Nozzel(gpm) - 9.48264 * Standoff(in) * Standoff(in)
\end{aligned}
$$

Equation 5. Best fit regression equation of model to relate inspector rating of pattern center to process parameters of experimental equipment for Rubber B

All terms appearing in the preceding equations are statistically significant at the 95% confidence level. Non-significant terms have been eliminated. Both models had F-values less than 0.0001. There is less than one chance in 10,000 that the correlation between model inputs and the resulting surface condition could be due to chance. The Rubber B model was able to explain ~71% of the variation seen in the data (Adjusted R2 = 0.7122). The Rubber 'B' Center model was able to explain ~76% of the variation seen in the data (Adjusted R^2 = 0. 7566). These models are shown graphically in Figure 11.

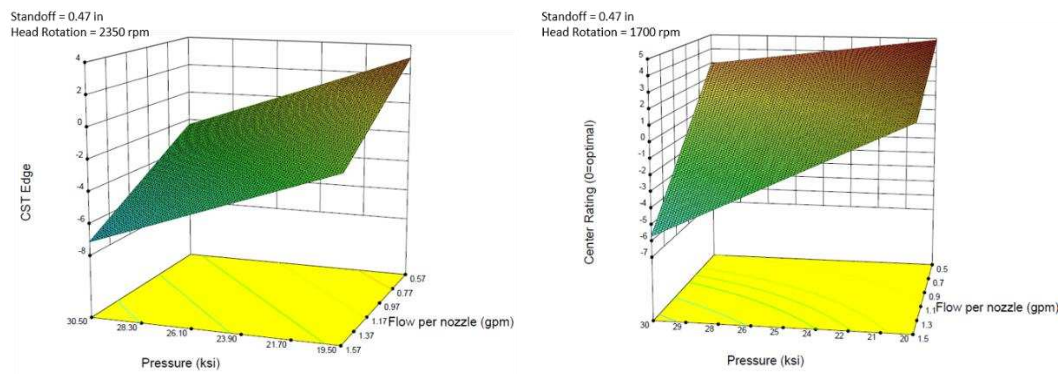

Figure 11. 3D Surface plots of Edge and Center Rating for Rubber B anti-skid coating removal

PHNSY&IMF asked ARL to optimize the process to leave the bottom-most layer of anti-skid coating intact, even though this would require secondary sanding to get to a paint-ready surface. After optimizing to achieve the desired condition, ARL performed a dozen validation trials. In some of these, ARL went over the same area 2-3 times to assess the effect of multiple passes. ARL consistently achieved the requested single-pass surface condition. With multiple passes nearly all anti-skid coating was removed without causing damage to the surface. The single-pass removal rate (leaving most of the lower layer of anti-skid coating) is ~16.7 m^2/hour (180 ft^2/hour). At three passes, the removal rate to a (nearly) paint-ready surface is ~ 5.6 m^2/hour (60 ft^2/hour). A process maps was generated to aid in equipment setup and use for shipyard workers, shown in Figure 12.

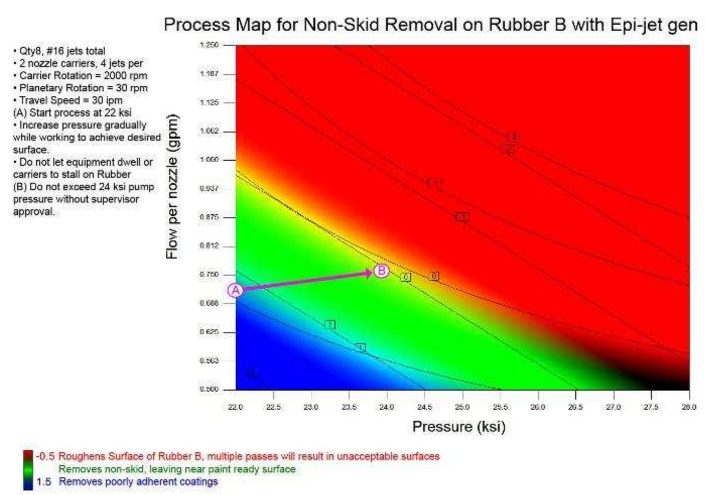

Figure 12. Process map for opperators removing anti-skid coatings from Rubber B

4. CONCLUSIONS

The Design of Experiments process can be a powerful tool to model the waterblasting process. The mathematical models produced can be used to optimize for applications that would otherwise be prohibitive to try. Models can also be used to identify process parameter ranges when results become unacceptable, which is very useful in establishing acceptable process windows. Additional responses on water usage, equipment wear, production rate, and operating costs can be used to predict job costs and size support equipment.