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APPLICATION OF DESIGN OF EXPERIMENTS TO WELDING PROCESS OF FOOD PACKAGING

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Abstract

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Design of experiments is one of the many problem-solving quality tools that can be used for various investigations such as finding the significant factors in a process, the effect of each factor on the outcome, the variance in the process, troubleshooting the machine problems, screening the parameters, and modeling the processes. The objectives of the experiment in this study are two-fold. The first objective is to identify the parameters of food packaging welding, which influence the response strength of a weld. The second objective is to identify the process parameters that affect the variability in the weld strength. The results of the experiment have stimulated the engineering team within the company to extend the applications of DOE in other core processes for performance improvement and variability reduction activities.

food packaging, welding process, 2^k full factorial design, optimization, interaction in processes

Experimental methods are widely used in research as well as in industrial settings, however, sometimes for very different purposes. The primary goal in scientific research is usually to show the statistical significance of an effect that a particular factor exerts on the dependent variable of interest. In many cases, it is sufficient to consider the factors affecting the production process at two levels. For example, the temperature for a chemical process may either be set a little higher or a little lower, the amount of solvent in a dyestuff manufacturing process can either be slightly increased or decreased, etc. The experimenter would like to determine whether any of these changes affect the results of the production process. The most intuitive approach to study those factors would be to vary the factors of interest in a full factorial design, that is, to try all possible combinations of settings. This would work fine, except that the number of necessary runs in the experiment (observations) will increase geometrically. For example, if you want to study 7 factors, the necessary number of runs in the experiment would be 2**7 = 128. To study 10 factors you would need 2**10 = 1,024 runs in the experiment. Because each run may require time-consuming and costly setting and resetting of machinery, it is often not feasible to require that many different production runs for the experiment. In these conditions, we have two ways how to reduce experimental trals (and also time a cost of them). The first ways is based on *fractional factorials* are used that "sacrifice" interaction effects so that main effects may still be computed correctly. The second way is based on previous screening of factors for selecting the significant ones. For this purpose we can use the Analysis of ariance (ANOVA) or graphic tools (for example Normal plot of the standardized effect or Pareto chart).

In general, every machine used in a production process allows its operators to adjust various settings, affecting the resultant quality of the product manufactured by the machine. Experimentation allows the production engineer to adjust the settings of the machine in a *systematic* manner and to learn which factors have the greatest impact on the resultant quality. Using this information, the settings can be constantly improved until optimum quality is obtained.

Packaging in food products is a critical process. Robust, airtight seals are required to preserve product freshness and shelf life. The sealing process in packaging is critical. One of the leverage points in this process is seal strength. When wrapping materials are joined together, generally two important leverages are sealing temperature and sealing time. The practical (or experimental) purpose of the paper is to determine optimal seal process requirements (especially the welding process of food packaging) in order to provide maximum tensile strength in the seal.

In this case, many process factors´ optimization strategies exist. One of the appropriate strategies is to find relative broad-based initial experiments that include the variables we think are driving the response. Next, we run the experiment and fit a full factorial response from the results. We then use the 2^k factorial design model to guide us in developing our second experiment, using the so-called path of steepest ascent or central composite design thus moving in closer to the optimal response. This systematic practice tends to work very well with using quantitative factors during its dealing. The usual alternative is more or less haphazard trial-and-error search over our feasible region or study grip. The sequence of experiments may include second-order response surface if a first-order response surface is judge to be inadequate. Nevertheless, the objective remains to close in on our best operating setting as quickly and economically as possible. The theoretical objective of the paper is to demonstrate how can be useful to implicate 2^k full factorial design for getting optimum of the welding process of food packaging.

In our case, the 2^k full factorial design can be a powerful technique used to study the effect of several process parameters affecting the response or quality characteristic of a process/product. The first step in DOE field was created by Sir R. A. Fisher, at the Rothamsted Agricultural Field Research Station in London, UK in the 1930s. His primary goal was to determine the optimum sunshine, water, amount of fertilizer and underlying soil condition needed to produce the best crop. Fisher introduced the technique and demonstrated its use in agricultural experiments, and Fisher's approach to DOE was also a direct replacement of traditional one-variable-at-a-time (OVAT) approach to experimentation. OVAT's approach to experimentation has the following limitations (Konda, 1999):

1. lack of reproducibility;
2. interactions among the process parameters cannot be studied or analysed;
3. risk of arriving at the false optimum conditions for the process; and
4. not cost-effective and time consuming in many cases.

Besides OVAT's approach to experimentation shows DOE approach as one of the powerful tools used to investigate deeply hidden causes of process variation. DOE techniques are useful for surfacing the effects of hidden variables, and studying possible effects of variables during process design and development. Experiments range from uncontrollable factors introduced randomly to carefully controlled factors. A few of the techniques (Antony, 2001) are:

1. trial and error methods;
2. running special lots;
3. pilot runs in which certain elements are set up in expectation of producing predicted results;
4. simple comparison of pairs of methods;
5. complex experiments involving many factors that are arranged in complex pattern.

Today, there are mainly three principal approaches of DOE in practice. They are the classical or traditional methods, Taguchi's methods, and Shainin methods (Antony, 2003). The traditional method is based on the work by Sir Ronald Fisher. Professor Taguchi from Japan has refined the technique with the objective of achieving robust product designs against sources of variation. The Shainin method, designed and developed by Dr. Shainin, uses a variety of techniques with the major emphasis on problem solving for existing products.

Nowadays, DOE has gained an increased attention among many Six Sigma practitioners as it is the key technique employed in the improvement phase of the Six Sigma methodology (Phadke, 1989). It is also recommended that DOE is employed within the optimization phase of Design for Six Sigma (DFSS). It is fair to say that DOE will be a key technique for developing reliable and robust products or processes in the 21st century. Over the last 15 years or so, DOE has gained increased acceptance in the USA and Japan as an important component for improving process capability, driving down quality cost and improving process yield. In Europe, this approach is not as much widespread yet. Nevertheless, a number of successful applications of DOE for improving process performance, product quality and reliability, reducing process variability, improving process capability, developing new products, etc. have been reported by many manufacturers over a decade (Albin, 2001; Antony, 2001; Ellekjaer and Bisgaard, 1998; Green and Launsby, 1995; Sirvanci and Durmaz, 1993). In the Czech Republic, the implementation of DOE methodology was dealt by (Gozora, 2011) in the field of agricultural research and by (Beran & Macik, 2009) in the area of cost optimization. Furthermore, this issue was dealt in areas of synergy effects in the food distribution industry (Grosova & Gros, 2009), and in the field of economic optimization was dealt by (Tomsik & Svoboda, 2010).

RESOURCES AND METHODS

Alcan Packaging Ltd. is engaged in the manufacture of printed flexible packaging for the food industry. This production takes place in three shift operation six days a week. Technology can be divided into several major operations and associated support processes which are: printing; lamination;

cutting; import substrates, packaging and storage of products; washing; and installation of cylinders. Principle of the welding food packaging (seals) is as follows. A sufficiently amount of electrical current pulse (up to 300A) is applied to the resistance strip, which is a part of the welding jaws. Foils are heated to welding temperature generated by thermal pulse and pressure of the welding jaws then caused welded connection between two sheets (jaw specific pressure is 0.1 to 0.15 Mpa).

A frequently used factorial experiment design is known as the 2^k factorial design, which is basically an experiment involving k factors, each of which has two levels ('low' and 'high'). In such a multi-factor two-level experiment, the number of treatment combinations needed to get complete results is equal to 2k. The first objective of a factorial experiment is to be able to determine, or at least estimate, the factor effects, which indicate how each factor affects the process output. Factor effects need to be understood so that the factors can be adjusted to optimize the process output.

The effect of each factor on the output can be due to it alone (a main effect of the factor), or a result of the interaction between the factor and one or more of the other factors (interactive effects). When assessing factor effects (whether main or interactive effects), one needs to consider not only the magnitudes of the effects, but their directions as well. The direction of an effect determines the direction in which the factors need to be adjusted in a process in order to optimize the process output.

In factorial designs, the main effects are referred to using single uppercase letters, e.g., the main effects of factors A and B are referred to simply as 'A' and 'B', respectively. An interactive effect, on the other hand, is referred to by a group of letters denoting which factors are interacting to produce the effect, e.g., the interactive effect produced by factors A and B is referred to as 'AB'. Each treatment combination in the experiment is denoted by the lower case letter(s) of the factor(s) that are at 'high' level (or '+' level). Thus, in a 2-factorial experiment, the treatment combinations are: 1) 'a' for the combination wherein factor A = 'high' and factor B = 'low'; 2) 'b' for factor A = 'low' and factor B = 'high'; 3) 'ab' for the combination wherein both A and B = 'high'; and 4) '(1)', which denotes the treatment combination wherein both factors A and B are 'low'.

The objectives of the experiment were:

1. to identify the key welding process parameters which influence the strength of the weld;
2. to identify the key welding process parameters, which influence variability in weld strength; and
3. to determine the optimal settings of the welding process parameters, which can meet the objectives (1) and (2).

RESULTS AND DISCUSSION

The Tab. I presents the list of significant parameters (which remained in the process after the previous all parameters scan), along with their levels used for the experiment. As part of the initial investigation, it was decided to study the process parameters at two-levels. The purpose of this first experiment was to understand the process, especially the operating range of important process parameters and their impact on the weld strength of the foil. The purpose of a first designed experiment is not just to obtain good results rather to understand the worst and best operating conditions so that small sequential experiments can be conducted to gain more process knowledge. The actual values of settings of the parameters are not revealed in the paper due to confidentiality agreement between the authors and the company where the experiment was carried out. However, the data collected from the experiment are real and have not been modified in this study.

Interactions of interest

Further to a thorough brainstorming session, has been identified the following interactions of interest.

1. A <=> B
2. B <=>D
3. C <=> D
4. A <=> C.

The quality characteristic of response for this study was welding strength measured in [MPa] (marked as yield). In order to minimize the effect of noise factors induced into the experiment, each trial condition was randomized. Randomization is a process of performing experimental trials in a random order, not that in which they are logically listed. The idea is to evenly distribute the effect of noise across (those that are difficult to control or expensive to control under standard production conditions) the total number of experimental trials.

The analysis of experimental data and interpretation of results are essential to meet the objectives of the experiment. If the experimenter has designed and performed the experiment correctly, the statistical analysis would then provide effective and statistically valid conclusions. The first step in the analysis was to identify the factors and interactions which influence the mean weld strength.

The results of the analysis are shown in Tab. III. For significance test, it was decided to select significance levels of a = 5 per cent (0.05). If the p-value is less than the significance level (0.05), the factor or interaction effect is then regarded to be statistically significant. For the present experiment, main effects 1. type of used technology; 2. operation time, 3. welding temperature; welding pressure; and interaction effects time × technology are statistically significant. It is important to note that these effects

I: *List of process parameters for the experiment*

Process parameter	Units	Low level setting	High level setting	Lower level setting (coded units)	High level setting (coded units)
A: Welding pressure	MPa	0.10	0.15	–1	+1
B: Operation time	sec	2	4	–1	+1
C: Welding temperature	^0C	190	220	–1	+1
D: Type of used technology	A /B	seam welding	seamless welding	–1	+1

II: *Results of the experiment*

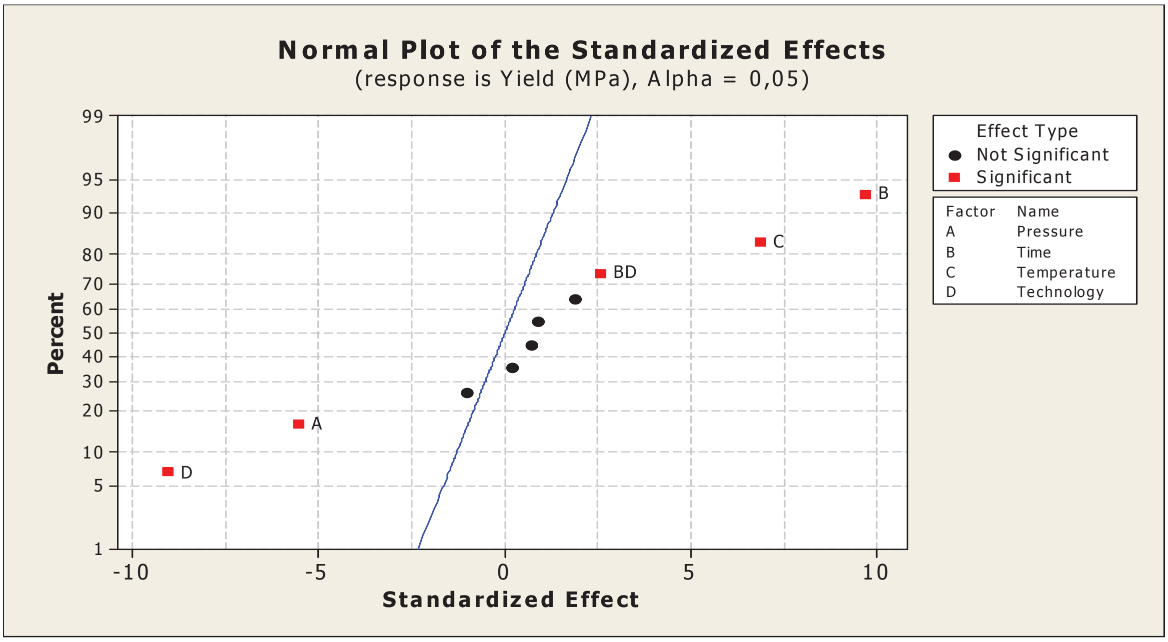
StdOrder	RunOrder	A	B	C	D	Yield (MPa)
2	1	1	–1	–1	–1	2.589
10	2	1	–1	–1	1	0.493
12	3	1	1	–1	1	2.147
14	4	1	–1	1	1	1.981
3	5	–1	1	–1	–1	3.984
13	6	–1	–1	1	1	2.275
16	7	1	1	1	1	3.285
8	8	1	1	1	–1	4.274
9	9	–1	–1	–1	1	1.701
5	10	–1	–1	1	–1	3.820
11	11	–1	1	–1	1	3.008
7	12	–1	1	1	–1	4.456
6	13	1	–1	1	–1	2.901
4	14	1	1	–1	–1	3.266
1	15	–1	–1	–1	–1	3.064
15	16	–1	1	1	1	4.249

III: *Project report: main effects, interaction effects and p-values*

Factors:	4	Base Design:	4;	16	
Runs:	16	Replicates:		1	
Blocks:	1	Center pts (total):		0	
Factorial Fit: Yield (MPa) versus Pressure; Time; Temperature; Technology					
Estimated Effects and Coefficients for Yield (MPa) (coded units)					
Term	Effect	Coef	SE Coef	T	P
Constant		2,9683	0,06363	46,65	**0,000**
Pressure	–0,7026	–0,3513	0,06363	–5,52	**0,003**
Time	1,2306	0,6153	0,06363	9,67	**0,000**
Temperature	0,8736	0,4368	0,06363	6,86	**0,001**
Technology	–1,1519	–0,5759	0,06363	–9,05	**0,000**
Pressure*Time	0,0214	0,0107	0,06363	0,17	0,873
Pressure*Temperature	0,1129	0,0564	0,06363	0,89	0,416
Pressure*Technology	–0,1291	–0,0646	0,06363	–1,01	0,357
Time*Temperature	0,0911	0,0456	0,06363	0,72	0,506
Time*Technology	0,3291	0,1646	0,06363	2,59	**0,049**
Temperature*Technology	0,2366	0,1183	0,06363	1,86	0,122
S = 0,254530		PRESS = 3,31703			
R-Sq = 98,15%		R-Sq(pred) = 81,07%		R-Sq(adj) = **94.46%**	

have a significant impact on the average weld strength.

This finding is further supported by a Pareto plot (see Fig. 2) of factor and interaction effects. In the Pareto plot, any factor or interaction effect which



1: *Normal plot of the standardized effect shows the same results as Pareto plot*

extends past the reference line is considered to be significant.

The calculated effect factor in the coded values (response factor to change from −1 to +1) is in the first column of Tab. III. The second column is represented by the regression coefficient (that is a half effect of each factor). The statistical significance of each factor or interaction, expressed as a p-value, is noted in the fifth column (significant factors and interactions are highlighted). Full members of the model to predict the quality of welding process of the food package are those that have relatively large (statistical) significance. This would mean that their p-value is close to zero. The interaction between two process parameters (say A and B i.e. $I_{A,B}$) can be computed using the following equation:

$$I_{A,B} = \frac{1}{2} \times (E_{A,B(+1)} - E_{A,B(-1)}), \quad (1)$$

where $E_{A,B(+1)}$ is the effect of parameter (factor) 'A' at high level of factor 'B' and where $E_{A,B(-1)}$ is the effect of factor 'A' at low level of factor 'B'.

Model development and prediction of welding process quality

This stage involves the development of a simple mathematical model, which depicts the relationship between the weld strength and the key factors or interactions which influence it. For this study, it was found following main effects:

- type of used technology;
- operation time;
- welding temperature;
- welding pressure;
- and interactions effects time × technology;
- and time × temperature are statistically significant.

The predicted model is based on these four significant effects a one interaction. The predicted weld strength (yield) is given by the following formula:

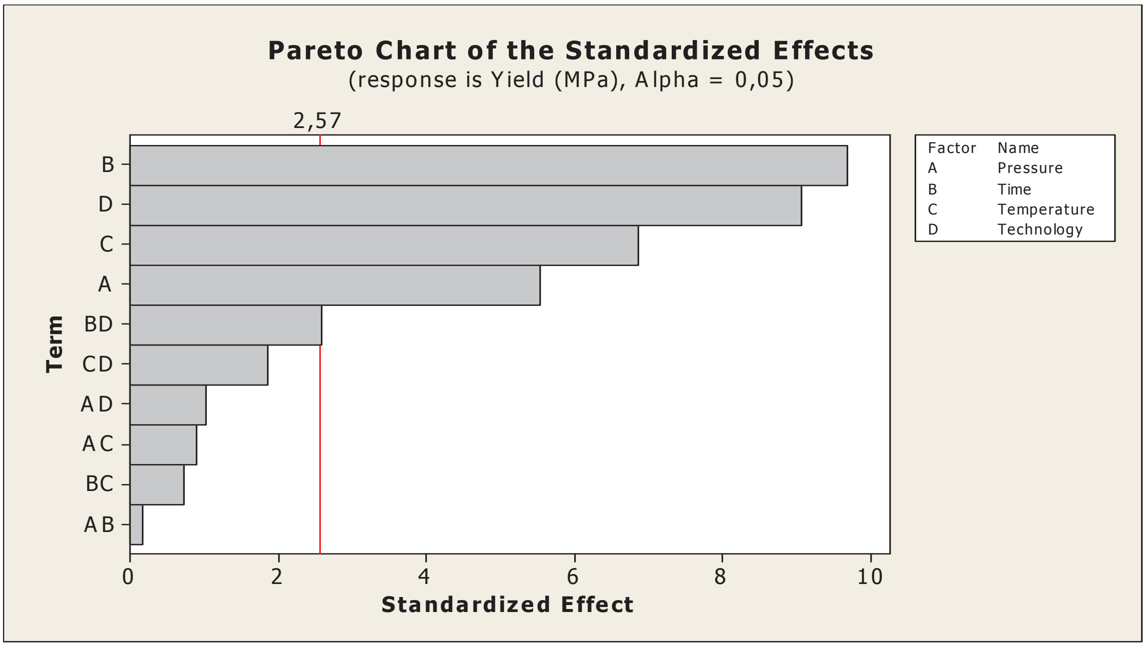
$$\begin{aligned} \text{yield} = {} & 2.9683 - 0.3513\ \text{pressure} + 0.6153\ \text{time} + \\ & + 0{,}4363\ \text{temperature} - 0{,}5759\ \text{technology} + \\ & + 0.3291\ (\text{time} \times \text{technology}). \end{aligned}$$

The coefficient of multiple determination R-Sq(adj) = 94.46 % indicates that this equation is well suited to the acquired response data. Model is able to explain the variability to 94.46 %.

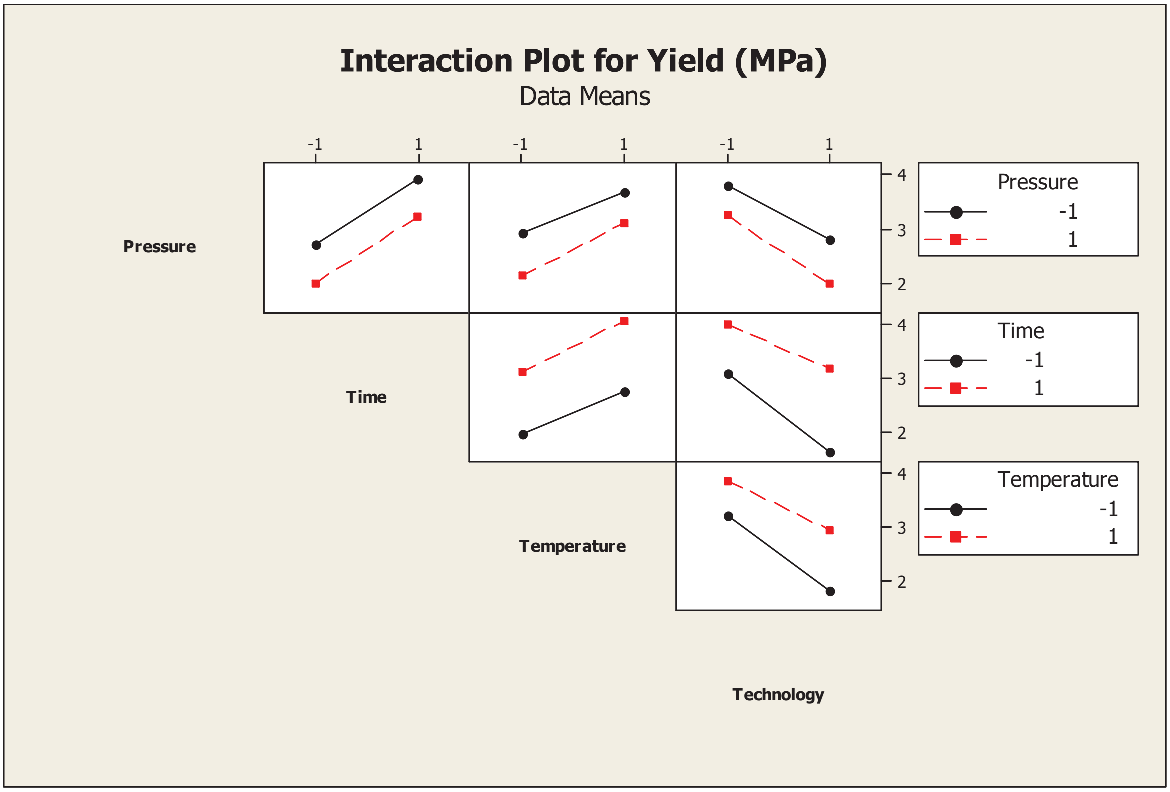
Wit non-negligible interactions the following figures show us the optimal settings for weld strength of food packaging. The optimal process settings for maximizing weld strength were:

- A: Welding pressure = 0.10 MPa;
- B: Operation time = 4 sec;
- C: Welding temperature = 220 ^{0}C;
- D: Type of used technology = seam welding (B).

In order to determine whether two process parameters are interacting or not, it could be used a simple but powerful graphical tool called interaction graph. If lines in the interaction plot are parallel, there is no interaction between the processes parameters. This implies that the change in the mean response from low to high level of a factor does not depend on the level of the other factor. On the other hand, if the lines are non-parallel, an interaction exists between the parameters (factors). The Fig. 3 illustrates the moderate interaction plots between time × technology and time × temperature.



2: *Pareto plot shows 4 significant parameters and B × D significant interaction*



3: *Interactions graph for the experiment*

SUMMARY

The purpose of this paper is to use an application of full factorial design to a welding process of food packaging. To achieve this purpose the paper offers a seven-step strategy to apply design of experiment technique in studying a process and optimizing the welding process performance.

In step 1, the key welding process parameters which influence the strength of the weld were identified using brainstorming and effect analysis. In step 2, the main factors are selected that are used for further

investigation. In step 3, the factors and their levels are chosen for the full-factorial experimentation. In step 4, an experimental design is selected. In step 5, a randomized run of all the combinations of experiments was done. In step 6, to ensure success while running the full-fledged experiments. In step 7, the optimal settings of the welding process parameters were chosen.

The welding process of food packaging has been increased by 34 per cent. The next phase of the research is to perform more advanced methods such as response surface methodology by adding centre points and axial points to the current design. The results of the experiment have stimulated the engineering team within the company to extend the applications of design of experiments in other core processes for performance improvement and variability reduction activities.

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