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Improving Food Safety and Traceability Using Optimization of Barcodes

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Abstract: There is significant attention on traceability systems in the context of monitoring in the food industry. Although, this has focused increasingly on food safety, agro-food and non-food sectors have also instituted traceability requirements for product identification, differentiation and historical monitoring. This study utilizes the powerful technique of Design of Experiments (DOE) to study the effect of several process parameters on the response or quality characteristics of a process or product. The application of DOE avoids specialist knowledge of statistical analysis by replacing it with a graphical methodology, applied here in the production process of barcodes for food and agricultural products.

Key words: Food safety, design of experiments, traceability, barcode, response surface regression

INTRODUCTION

Traditionally, packaging design has had a subordinate role with respect to product design and production systems design, however, its impact on supply chain costs and performances can be devastating. Only in the past few years its strategic role has been recognized both in theory and in practice (Azzi *et al*., 2012). Food package manufacturing is an important segment of the food supply chain that links the agricultural production stage with consumers. Therefore, economic development trends of food manufacturing impacts on consumers, agricultural producers and the performance of the food supply chain as a whole (Asiseh *et al*., 2010). Food production and distribution systems are becoming more interdependent, integrated and globalized. At the same time, escalating numbers of heavily publicized outbreaks of foodborne diseases and contamination have raised public awareness of the need to ensure food quality and safety. This need drives much of the technological innovation to trace food consistently and efficiently from the point of origin to the point of consumption. The selection of product innovation projects by food and agribusiness companies is only part of the entire innovation process. The innovation process starts with developing and maintaining a culture of innovation within the company (Roucan-Kane *et al*., 2011). Small-scale farmers may lack the resources to comply with increasingly strict food safety standards, particularly traceability requirements. Given the role of traceability in protecting consumers, ensuring food safety and managing reputational risks and liability, it is vital to integrate and empower small-scale agricultural producers in the food supply chain through barcode optimization.

In recent years, consumers' concerns about environmental and health issues related to food products have risen; consequently, the demand for organically grown products has increased (Haghjou *et al*., 2013). Food packaging plays an important role in attracting consumers' attention and generating expectations in the consumer that in turn affect their product perception and buying behaviour. In the present study, categorizing' and perceptual mapping' diametrically opposed methods (predefined criteria vs. consumer criteria) were used to study the influence of packaging design on consumer perceptions of dairy products (Gelici-Zeko *et al*., 2013). And also many food companies have developed and marketed foods packages in response to increasing consumer concern about diet and healthiness (Kohansal and Firoozzare, 2013).

The adoption of food safety and quality practices differs among varying enterprises. This variation reveals incentives as understood by each business to supply safe food products. These incentives may be externally driven (e.g., to meet legal requirements or to meet the needs of major customers) or internally driven (e.g., to improve operational efficiency or to reduce error rates, wastage and costs) (Cobanoglu *et al*., 2012).

Traceability is a concept developed in industrial engineering and was originally seen as a tool to ensure

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the quality of products and production. Economics literature from supply-chain management defines traceability as the information system necessary to provide the history of a product or a process from origin to point of final sale (Wilson and Clarke, 1998; Jack *et al*., 1998; Timon and O'Reilly, 1998). Specific standards for food traceability have been mandated internationally by law in the European Union (EU), Japan and more recently the United States and also by private firms and associations.

Food is a complex product (Golan *et al*., 2004) and modern food production, processing and distribution systems may integrate (and combine) food and package from multiple sources, farms, regions and countries (Cannavan A). The environmental impacts of packages have been found to be relatively small compared with the food items they contain. Furthermore, from the environmental and operational point of view, the most significant task of the package is to protect the product which is important to acknowledge in the packaging design process. Food products covered by traceability standards include fresh produce such as mangoes, avocados and asparagus; bulk foods such as milk, soybeans, specialty coffee and olive oil; fish and seafood and livestock for meat and dairy. It also plays a vital role in animal identification, a prerequisite for implementing livestock traceability in the meat and dairy sectors.

Traceability data are recorded through a variety of media including but not limited to barcodes, pen/paper, Radio Frequency Identification Devices (RFIDs), wireless sensor networks, mobile devices and applications, Enterprise Resource Planning (ERP) applications and internet-based applications. Information related to product tracing may be recorded and transmitted through management information systems or in the case of smaller operations, paperwork such as invoices, purchase orders and bills of lading. Traceability data may also be captured directly from products such as fresh produce, seafood and livestock. Products may be tagged with barcodes or RFIDs which store product and associated data. Wireless sensors may transmit data on temperature, spoilage or location to RFIDs tagged to products.

Now a days, DOE has gained 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 yet so widespread. 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 (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 (Beran and Macik, 2009) in the area of cost optimization. Furthermore, this issue was applied to areas of synergy effects in the food distribution industry (Gros *et al*., 2009) and in the field of economic optimization was dealt with by Tomsik and Svoboda (2010).

This study is focused on one significant factor of traceability systems the application of design of experiments to optimize barcodes for food packaging.

MATERIALS AND METHODS

The following methodology (for designing, performing and analyzing experiments) was used for the purpose of obtaining the results for this study:

- 1st phase: identify the potential factors by brainstorming a cause and effect design diagram
- 2nd phase: choosing suitable factors from a basic set for their investigation
- 3rd phase: Selecting the appropriate working range for each potential factor which were considered in the 2nd phase
- 4th phase: select the experimental levels for each factor from within the extremes explored in the 3rd phase
- 5th phase: if possible, trial run or dry run the experiments with all possible combinations within the range of each factor selected in an extremely short run, to guard against a process failure owing to interactions
- 6th phase: choose an orthogonal array for experiments or an appropriate experimental design (full factorial or fractional factorial)
- 7th phase: run experiments as designed. Experiments must be performed randomly
- 8th phase: analyze the experimental results for the objective of the project and verify them with the objective evidence
- 9th phase: perform more advanced methods such as response surface methods (path of steepest ascent or central composite design) by adding center points and axial points to the current design

- 10th phase: if the results do not seem to be meeting the objective of the study, it could be owing to inappropriate factors considered in the study

This presents two choices which are either to completely restart the experimentation with different factors or the part design or processes design need to be modified. Additionally, one could potentially use a different technique using the knowledge gained in phases 1 through 9 to achieve the objectives set. Identify the potential factors by brainstorming a cause and effect design diagram.

Theoretical framework: Response Surface Methodology (RSM) is a collection of mathematical techniques useful for the modeling and analysis of problems in which a response of interest is influenced by several variables and the objective is to optimize this response. Thus, RSM allows one to optimize a response of interest by determining the best settings for the controllable factors. The first step in RSM is to find a suitable approximation for the true functional relationship between y and the set of independent variables. The basic goal in RSM is to identify the optimal settings of the key factors. The three basic steps of RSM are:

- Factor screening experiments
- Follow the path of steepest ascent/descent
- Fit a quadratic regression model and optimize it

After performing a screening experiment and obtaining a linear model of the response with only main effects (Hron, 2012), it is necessary to move in a direction that quickly improves the response. The path of steepest ascent should be followed to maximize the response and to minimize the response, the path of steepest descent should be followed.

To calculate the path of steepest ascent, it is first necessary to fit a model. In the case that an experiment has only two main factors and the interaction between factor x_1 and x_2 is not significant. The model equation for this experiment is:

$$\hat{Y} = f(x) = b_0 + b_1x_1 + b_2x_2 + \varepsilon \quad (1)$$

Where:
b_0 = The intercept estimate
b_1, b_2 = The coefficients for factors
x_1 and x_2 = The coefficients for factors, respectively

If the experiment employs k number of significant factors, then Eq. 1 is modified into the following general form:

$$\hat{Y} = f(x) = b_0 + b_1x_1 + b_2x_2 + \ldots + b_kx_k + \varepsilon \quad (2)$$

According to Eq. 2, the steepest ascent is proportional to the signs and magnitudes of the regression coefficients in the fitted First-Order Model. If there is curvature in the system, a polynomial of higher degree must be used such as the Second-Order Model:

$$\hat{Y} = f(x) = b_0 + \sum_{i=1}^{k} b_ix_i + \sum_{i=1}^{k} b_{ii}x_i^2 + \sum_{i<j} b_{ij}x_ix_{ji} + \varepsilon \quad (3)$$

After obtaining this model Eq. 3:

- One process variable can be chosen as the base factor and indicate the step size or increment (Δx_i) for the base factor
- The increment in the other process variables can be determined using the Eq. 4:

$$\Delta x = \frac{b_j}{b_i}\Delta x_i \quad (4)$$

- The increments can be transformed from coded to uncoded units

Experimental design: The experiment was conducted in the laboratory of the new Czech factory of Alcan Packaging and focused on optimizing EAN Barcodes. Alcan Packaging is engaged in the manufacturing of printed flexible packaging for the food industry. This production takes place in three shift operations 6 days a week. Technology can be divided into several major operations and associated support processes which are: printing; lamination; cutting; importing substrates, packaging and storage of products; washing; installation of cylinders; the preparation and mixing of colors and disposal of waste gases.

Internationally, there are several barcode systems, so before starting adjustment of factors for the experiment, it is appropriate to explain the differences between the two most commonly used in the food retail industry: UPCBarcodes and EANBarcodes. The requirement for a universal price code system was addressed in the early 1970s by an association of retailers and other food industry players, named the Uniform Product Code Council. The code which was adopted in 1974 was known as the Universal Product Code (UPC) which later became known as UPC-A. As requirements developed and as the need to adopt a code which could be applied internationally, the European Article Numbers (EAN) System was also adopted (also known as the International

Article Number). These systems are now administered by a non-profit international organization named Global Systems One or GS-1.

Figure 1 illustrates the differences between the EAN-13 code and the UPC-A code. The EAN contains a 13 digit number and the UPC contains a 12 digit number. The US and Canada have a country code of zero which is not printed under the barcode nor is it entered in the US and Canadian Inventory and Point of Sale Databases. The two graphics in Fig. 1 are exactly the same; the width of the bars and the width of the spaces between the bars are exactly the same, though the lengths of the bars differ. The only major difference is the placement of the numbers below (the human readable numbers) which are there only as a back-up in case the barcode does not scan properly and the information has to be manually entered into the point of sale system.

Optimization of the barcode printing processes on food packaging will be based on an effective application of DOE techniques in order to discover the significant process parameters which affect the means of the Z-module (which defines the nominal width of the narrow elements), GS-1 international (defines certain size ranges), PCS measurement (means Print Contrast Signal measurement) and also in order to discover the key parameters which affect their variabilities.

Fig. 1: Comparison of EAN-13 and UPC-A barcodes

Table 1 presents a 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 barcode quality printed on the foil. The purpose of a first designed experiment is not just to obtain good results but 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 study due to the confidentiality agreement between the researchers 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, the following interactions of interest have been identified:

- A<=>B
- B<=>D
- C<=>D
- A<=>C

The quality characteristic of interest for this study was the level of quality EAN code: ANSI/CEN are:

- Very good A4
- Good B3
- Sufficient C2
- Readable D1
- Insufficient F0

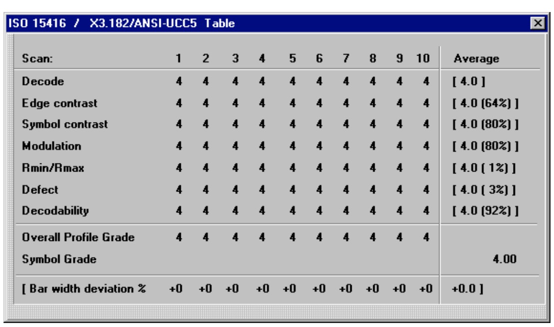
Minimum values: For customers with unspecified quality code D1. There are customers' own specifications based on minimum B3 value required for producers such as for: Aldi and Lidl, Bastin and Kuchemeister, Van Netten, Manner, Coppenrath, Schumann.

Table 1: List of process parameters for experiment

Process parameter	Units	Low level setting	High level setting	Lower level setting (coded units)	High level setting (coded units)
A: feed-rate	m/min	200	250	-1	+1
B: operation temperature	°C	200	220	-1	+1
C: contact pressure	kPa	45	55	-1	+1
D: kinematic viscosity	mm^2/sec	90	110	-1	+1

To obtain the barcode quality responses a Barcode and REA PC-Scan device with laser measuring was used. The REA PC-Scan is a precision measuring device for the verification of printed bar codes of different types and accurate measurement of barcode film masters. The unit consists of a measuring head (laser device) and software to evaluate and display the results. The measuring head is motor-powered and is controlled by the evaluation software. The measurement results must be reproducible and comparable. All measurements must, therefore be performed under constant conditions. In the CEN/ANSI evaluation for the individual parameters, the quality will be specified as a percentage and as a grade from 4-0 or A-F. The grades are allocated to certain ranges of percentage values (e.g., symbol contrast of 40-55% is grade 3 or B) in Fig. 2. In multiple measurements, an average value will then be calculated from the results of the individual measurements (scan reflectance profile grade). The average value is the arithmetic average of the individual scan reflectance profile grades. The result is designated as the overall symbol grade (Table 2). The aggregate indicator of the barcode quality provided by the REA PC-Scan was subsequently converted to a numeric value (percentage of total level of quality). This conversion (Table 2) was done because of the possibility to express the response of the barcode quality as numeric (continuous) variables, instead of text variables.

The quality characteristic of interest for this analysis was barcode quality measured in percentage of total level of quality. Having identified the quality characteristic and the list of process parameters, the next step was to select an appropriate design matrix for the experiment. The design matrix shows all the possible combinations of process parameters at their respective levels. The choice of design matrix or experimental layout is based on the degree of freedom required for studying the main and interaction effects. The total degrees of freedom required for studying the four main effects and four interaction effects is equal to eight. A $2^{(5-1)}$ factorial design was selected to study all the main and interaction effects stated above. The degree of freedom associated with this design is 8.



ISO 15416 / X3.182/ANSI-UCC5 Table

Scan:	1	2	3	4	5	6	7	8	9	10	Average
Decode	4	4	4	4	4	4	4	4	4	4	[4.0]
Edge contrast	4	4	4	4	4	4	4	4	4	4	[4.0 (64%)]
Symbol contrast	4	4	4	4	4	4	4	4	4	4	[4.0 (80%)]
Modulation	4	4	4	4	4	4	4	4	4	4	[4.0 (80%)]
Rmin/Rmax	4	4	4	4	4	4	4	4	4	4	[4.0 (1%)]
Defect	4	4	4	4	4	4	4	4	4	4	[4.0 (3%)]
Decodability	4	4	4	4	4	4	4	4	4	4	[4.0 (92%)]
Overall Profile Grade	4	4	4	4	4	4	4	4	4	4	
Symbol Grade											4.00
[Bar width deviation %	+0	+0	+0	+0	+0	+0	+0	+0	+0	+0	+0.0]

Fig. 2: CEN/ANSI barcode evaluation with 4 (or A) results

Table 2: Conversion REA PC-Scan of response to numerical values

REA PC-Scan: ANSI	REA PC-Scan: CEN	Range	Mean (central point) of response
A	4	<100-60>	90
B	3	<80-60>	70
C	2	<60-40>	50
D	1	<40-20>	30
E	0	<20-0>	10

In order to minimize the effect of interference noise factors induced into the experiment, each trial condition was randomized. Randomization is a process of performing experimental trials in a random order, rather than that in which they are logically listed. The idea is to evenly distribute the effect of noise across the total number of experimental trials (i.e., those that are difficult to control or expensive to control under standard production conditions).

RESULTS AND DISCUSSION

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 barcode quality. The results of the analysis are shown in Table 3. For the significance test, it was decided to select significance levels of a = 5% (0.05). If the p-value is less than the significance level (0.05), the factor or interaction effect can then be regarded to be statistically significant. For the present experiment, the main effects were feed-rate, operational temperature, contact pressure and kinematic viscosity and no interaction effects were statistically significant. It is important to note that these effects have a significant impact on the average barcode quality. This finding is further supported by a Pareto plot (Fig. 3) of factor and interaction effects. In the Pareto plot, any factor or interaction effect which 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 Table 3. 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. Those factors of the model which can be used to predict the quality of printing (EAN) barcodes on the food

Table 3: Estimated effects and coefficients for EAN code quality (coded units)

Terms	Effect	Coefficient	SE coefficient	t-values	p-values
Constant	-	48.75	2.562	19.03	0.000
Feed rate	-17.50	-8.75	2.562	-3.42	0.019
Oper. temperature	22.50	11.25	2.562	4.39	0.007
Contact pressure	-27.50	-13.75	2.562	-5.37	0.003
Viscosity	-22.50	-11.25	2.562	-4.39	0.007
Feed rate x Oper. temperature	-2.50	-1.25	2.562	-0.49	0.646
Feed rate x Contact pressure	-2.50	-1.25	2.562	-0.49	0.646
Feed rate x Viscosity	2.50	1.25	2.562	0.49	0.646
Oper. temperature x Contact pressure	-2.50	-1.25	2.562	-0.49	0.646
Oper. temperature x Viscosity	2.50	1.25	2.562	0.49	0.646
Contact pressure x Viscosity	-7.50	-3.75	2.562	-1.46	0.203

S = 10.247; PRESS = 5376; R^2 = 94.28%; R^2 (pred) = 41.41% and R^2 (adj) = 82.83%

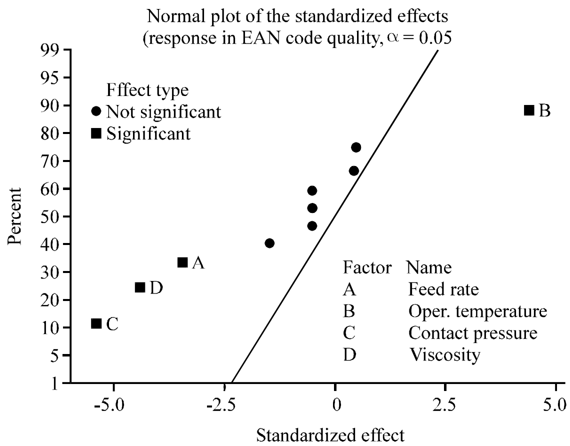


Fig. 3: Normal plot of the standardized effect showing Table 3 results as a Pareto plot

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.) can be computed using the Eq. 5:

$$I_{A,\ B} = \frac{1}{2} \times \left(E_{A,\ B\ (+1)} - E_{A,\ B\ (-1)}\right) \tag{5}$$

Where:

$E_{A,\ B\ (+1)}$ = The effect of parameter (factor) A at high level of factor B

$E_{A,\ B\ (-1)}$ = The effect of factor A at low level of factor B

Table 4 shows the calculation of the coefficients to determine the predictive equations of the barcode quality responses.

Model development and prediction of barcode quality: This stage involves the development of a mathematical model which depicts the relationship between the barcode quality and the key factors or interactions which influence it. For this study, it was found that the main effects were feed-rate, operational temperature, contact pressure and kinematic viscosity and no interaction effects were statistically significant. The predicted model was based

Table 4: Estimated coefficients for EAN code quality using data in uncoded units

Terms	Coefficients
Constant	-470
Feed rate	0.7
Oper. temperature	2.25
Contact pressure	12.25
Viscosity	-1.125
Feed rate x Oper. temperature	-0.005
Feed rate x Contact pressure	-0.01
Feed rate x Viscosity	0.005
Oper. temperature x Contact pressure	-0.025
Oper. temperature x Viscosity	0.0125
Contact pressure x Viscosity	-0.075

on these four significant effects. The average barcode quality based on the current process settings was C3 (50% of the barcode quality maximum). The predicted barcode quality is given by Eq. 6 of a regression model for n number of significant factors at 2-levels:

$$\hat{Y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \ldots + \beta_{1n} x_1 x_n + \varepsilon \tag{6}$$

Where:

$\beta_1, \beta_2, \ldots, \beta_n$ = The regression coefficients

β_0 = The average response in the factorial experiment

ε = The random error component with is approximately normally independently distributed with mean zero and constant variance σ^2

The regression coefficient β_{12} corresponds to the interaction between the process parameters x_1 and x_2. The average Barcode Quality (BCQ) based on the current process settings is C3 (50% of the barcode quality maximum). The predicted barcode quality is after substituting actual values of the significant factors and interactions in the general Eq. 6 given by the following equation:

$$BCQ = -470 + 0.7A + 2.25B + 12.25C - 1.125D - 0.075\ (C \times D) + \varepsilon \tag{7}$$

The coefficient of multiple determination R^2(adj) = 82.83% indicates that this equation is well suited to the response data obtained. The model is able to explain the variability to 82.9%. With non-negligible interactions the following figures show the optimal settings for printing food packaging. The optimal process settings for maximizing quality of barcodes were:

- Feed-rate 200 m min^{-1}
- Operating temperature 220°C
- Contact pressure 45 kPa
- Kinematic viscosity 90 mm^2/sec

The next phase of the research was to perform more advanced methods such as Response Surface Methodology (RSM) by adding center points and axial points to the current design. As can be seen from Fig. 3 for the normal plot of the standardized effect, there are two main factors influencing the value of response-pressure and temperature. In another part of the design of experiments, therefore, focus is on the optimization of these two factors. Setting of the other factors will be at their optimum which was found using a full factorial design. This procedure could be considered ideal because it shows no interaction of factors such as being significant. The code results of the experiment using the RSD Method are shown in Table 5.

From the analysis of variance, the pure quadratic check implies that the first-order model is not an adequate approximation. Moreover, it is possible to calculate the curvature using the ratio between the average responses at the four corners of the experimental squares:

$$\text{Yield (B, C)}_{\text{corners}} = \frac{1}{4}\times\sum_{j=1}^{4}\left(\text{Yield (B, C)}\right)_j = 47.5 \quad (8)$$

and between the average responses of five central points:

$$\text{Yield (B, C)}_{\text{center}} = \frac{1}{5}\times\sum_{i=1}^{5}\left(\text{Yield (B, C)}\right)_i = 36.4 \quad (9)$$

The relative difference of the average of responses is >23%. This value represents the significant curvature of the system. If there is curvature in the system, then a polynomial of higher degree must be used such as the following second-order model (or central composite design) which is represented by Eq. 3. At this point, this additional analysis must be performed to locate the optimum more precisely. A Second-Order Model in variables B and C can not be fit using the design in Table 1. The experimenters decided to augment this design with enough points to fit a Second-Order Model. Four observations were obtained at (B = {42.9289; 57.0711; 50.0000}) and (C = {195.000; 159.645; 230.355}). The complex experiment is shown in Table 4 and 5. The design is displayed in Fig. 4 and 5.

In this case, the experimenters wished to find the level of C and B factors that optimize the predicted

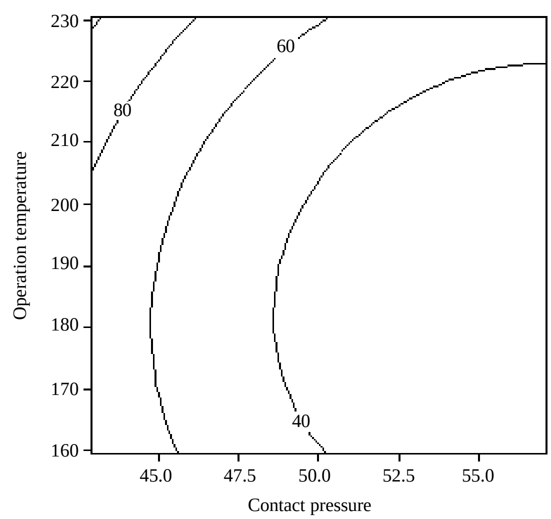


Fig. 4: The contour plot of EAN code quality vs. operation temper; contact pressure

Table 5: Results of the experiment

StdOrder	RunOrder	CenterPt point	Blocks	B	C	Yield (EAN) code	Description
2	1	1	1	55	170	25	Factorial experiment
8	2	0	1	50	195	37	Steepest ascent experiment
7	3	0	1	50	195	36	
3	4	1	1	45	220	75	Factorial experiment
5	5	0	1	50	195	35	Steepest ascent experiment
6	6	0	1	50	195	37	
9	7	0	1	50	195	37	
1	8	1	1	45	170	50	Factorial experiment
4	9	1	1	55	220	45	
10	10	-1	2	42.9289	195	82	Central composite design
11	11	-1	2	57.0711	195	21	
12	12	-1	2	50	159.645	48	
13	13	-1	2	50	230.355	57	

response. This point if existing would be the set of C, B factors for which the partial derivatives are equal to zero:

$$\frac{\partial(\text{yield})}{\partial B} = \frac{\partial(\text{yield})}{\partial C} = 0 \quad (10)$$

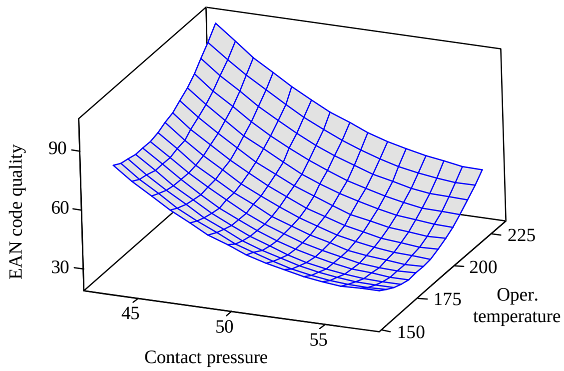


Fig. 5: Response surface plot of EAN code quality; surface plot of EAN code qualit vs. operation temper; contract pressure

This point, say B_{opt}, C_{opt} was called the stationary point. Generally, the stationary point could represent a point of maximum response but also a point of minimum response or a saddle point. For the purpose of distinguishing these stationary points, the second partial derivate could be computed or the graphical tool used. This graphical tool is the contour plot represented by Fig. 4 which is according to the most straightforward way if there are only two or three process variables. From this contour plot and surface plot of yield, it is relatively easy to see that the optimum is very near 230°C and 42 MPa of pressure and that the response is a maximum at this point. From watching the counter plot, it can be noted that the process may be slightly more sensitive to changes of contact pressure than to changes in temperature. To find the exact optimum the Minitab 16 Software was used. The exact optimum is shown in Fig. 6 and Table 6.

The optimum provide by the response optimizer of EAN code quality is very close to what was found by visual inspection of the contour and surface plot.

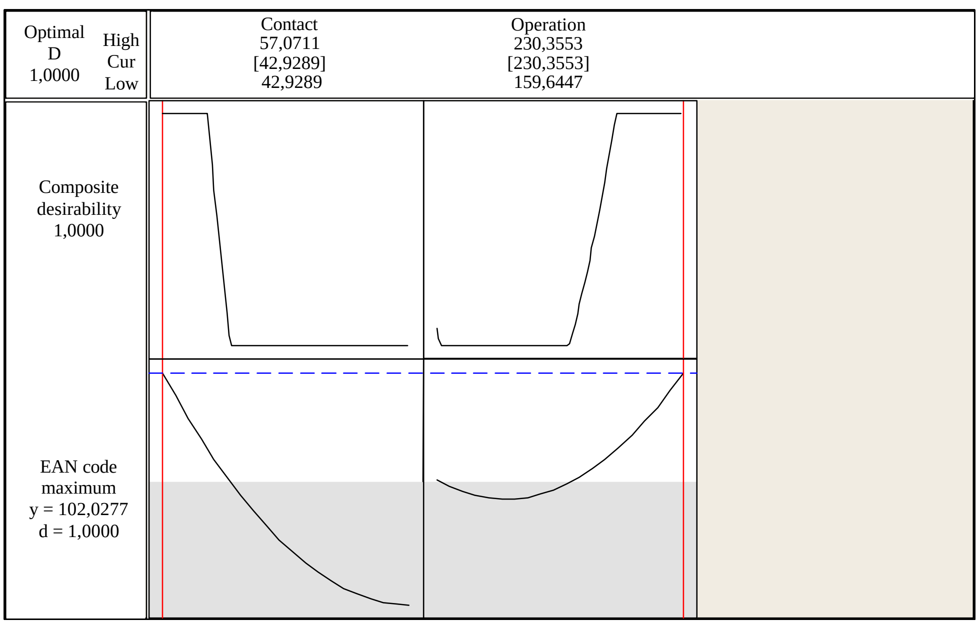


Fig. 6: Response optimizer of EAN code quality

Table 6: Response surface regression: EAN code quality versus contact pressure and operation temperature

Terms	Coefficient	SE coefficient	t-values	p-values
Constant	36.400	2.812	12.946	0.000
Contact pressure	-17.658	2.223	-7.944	0.000
Operation temperature	7.216	2.223	3.246	0.014
Contact pressure x Contact pressure	6.737	2.384	2.826	0.026
Operation temperature x Operation temperature	7.237	2.384	3.036	0.019
Contact pressure x Operation temperature	-1.250	3.144	-0.398	0.703

S = 6.28734; PRESS = 1949.99; R^2 = 92.71%; R^2(pred) = 48.63%; R^2(adj) = 87.50%; the analysis was performed using coded units; estimated regression coefficients for EAN quality

CONCLUSION

The purpose of this study was to illustrate an application of DOE to a barcode printing process. The objectives of the experiment in this study were 2 fold. The first objective was to identify the critical barcode printing process parameters which influence the response quality of printing. The second objective was to identify the process parameters that affect the variability in the quality. The barcode quality has been increased by 28%. The final phase of the experiment was to perform more advanced methods such as Response Surface Methodology (RSM) by adding center 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 DOE in other core processes for performance improvement and variability reduction.

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