



ANALYSIS, MODELING AND IMPROVEMENT OF STAMPED PARTS QUALITY USING GENERALIZED LINEAR MODELS

Foad Hassanmirzaei, *hassanmf@uwindsor.ca* Department of Industrial and Manufacturing Systems Engineering, University of Windsor, Windsor, Canada

Zbigniew J. Pasek, *zjpasek@uwindsor.ca* Department of Industrial and Manufacturing Systems Engineering, University of Windsor, Windsor, Canada

ABSTRACT

This paper presents an approach used for improving the visual quality of body panels produced in an automated press shop of a car manufacturer. To solve the complex problem of panels' visual defects, the optimal values of process parameters based on Generalized Linear Models (GLZ) were identified and deployed. The project focused on parts exhibiting excessive rejection rates. To deal effectively with the case in which the distribution function representing the number of defects in the panels was found to be binomial with presence of some covariates in the model, the research approach focused on development of Logit Models.

After identifying the potential causes of defects and selecting the most significant process factors from typical factor sets varying from 20 to 40 for each part, the levels of factors, number of replications and appropriate methods for running the experiments regarding to practical limitations and shop floor scheduling were established. Finally, the optimal values for process variables minimizing number of defects and used effectively to set up action plans for improving the panels' quality were identified. Implementing the plans, the process capability was increased by 0.25 for those non-satisfactory parts and production costs fell between 3-7% among them.

Keywords: Stamping process; Design of experiments; Generalized Linear Model; Process improvement

1. INTRODUCTION

Use of an internal frame covered with non-load-bearing skin is today a prevailing technology used in building passenger car bodies. To create a car's unique visual appearance, steel welded structural components (constituting the frame) are covered with body panels designed and shaped according to the requirements of the desired styling. As a material for the non-load-bearing skin, use of steel is still prevalent, but alternative solutions based on aluminum alloys, composites and plastics are also gaining



on popularity. The car's outer skin is usually made out of stamped sheet metal panels. Typically, 100 to 150 panels comprise a car body, with 40 to 50 panels considered critical.

Stamping processes to be used for a particular panel depend on its design. However, normally the processes used extensively are blanking, drawing, piercing, forming, notching, trimming, hemming, etc. Blanking prepares the initial approximate form of the part in flat sheet. Drawing is generally the first operation to attain depth related form. Piercing, notching, hemming, are product design related operations. Trimming generally removes the extra material on the periphery of the panel provided for blankholding during draw operation. Decision on trim line is very important and becomes deciding factor to obtain good draw.

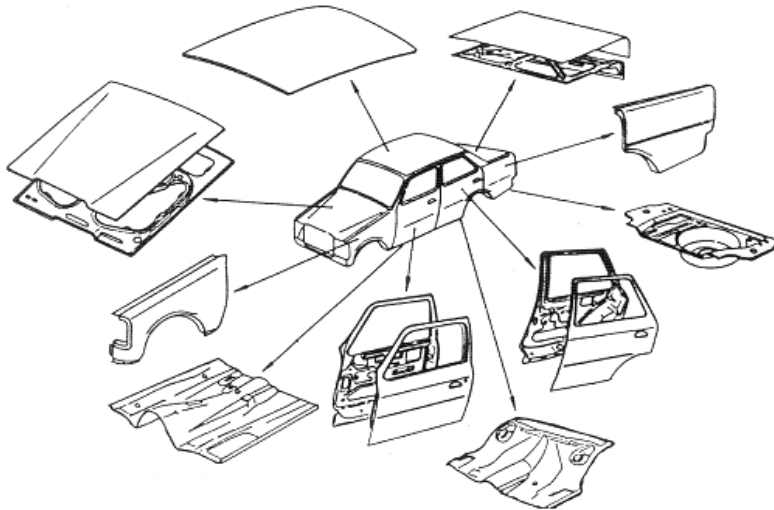


Figure 1 Major panels of a car body.

For each automotive body panel, the sheet metal stamping process requires two distinct types of equipment: the stamping press and a set of stamping dies. While the die set is specific to the panel geometry, the press is a general-purpose equipment. Production of automotive body panels is usually carried out in batches, i.e., production runs divided into discrete lots, allowing for making of various components with the same presses and exchangeable sets of dies.

Batch manufacturing processes have been widely used in making of various products, such as electrical goods, furniture, clothing, newspapers, books and sample products. Since in the batch manufacturing process, products are produced in limited batch quantities, total process variation is generally attributed to two sources: either to batch-to-batch variation due to inherent process variability among different batches, or within-batch variation due to inherent process variability. Since different variation components are usually caused by different root causes, separation and estimation



of each of them is critical for determining an effective variation reduction strategy [Jionghua and Huairui, 2003].

Efforts to improve quality require that the factors affecting it be identified, and the relationship between the factors and the investigated response be modeled. The output of this effort allows either identification of root causes responsible for low quality, or the determination of optimal settings in the framework of robust parameter design, the Taguchi approach, [Phadke, and Taguchi, 1987] or response surface methodology, product or process optimization, [Box *et al.*, 1978]. When the common assumptions associated with a typical scenario (i.e., additivity of effects, constant error variance, normality of errors) are not met, two alternative approaches are commonly pursued: normalization of data (through use of some normalizing transformation) or the use of generalized linear modeling (GLZs). Recently, a third alternative (Inverse Normalizing Transformation) has been developed, that models a response subject to self generated random variation and externally generated systematic and random variation [Shore, 2000]. It is then assumed that the relationship between the response and the externally generated variation is uniformly either convex or concave.

The second approach does not require normality of errors; however the first two conditions (i.e., additivity of effects, constant error variance) are replaced by two separate decisions. The first decision relates to the choice of the error distribution or, alternatively, to specifying the variance-function (modeling of the variance in terms of the mean). The second decision regards the scale needed to achieve additivity of the systematic effects (transforming of the mean, via a link function, to obtain the linear predictor). Thus, unlike the normalization approach which attempts to achieve all of the above three conditions for a normal scenario by a single transformation, GLZ does not transform the data and does not strive for normality. Instead, it models the given response by separating modeling of the error from modeling of the mean. Good recent introductions of the GLZ approach, as related to quality improvement efforts, may be found in [Myers and Montgomery, 1997; Hamada and Nelder, 1997].

2. AUTO PANELS STAMPING PROCESS

The company uses a new automated press shop for the body panels' production. The process includes a washing unit and six stamping presses. Figure 1 shows a block diagram of the press shop process. The first stamping machine has a capacity of 2,000 tons, the second – 1,000 tons, and the four remaining can deliver 800 tons each. The blanks, coming from a preceding process are fed to the washing unit and then transferred to the presses. At the first stamping machine the blanks are subjected to a deep drawing process. Consecutive stamping stations perform the trimming, edge-bending and punching. At the end of the last stamping line, the blanks are fully transformed into panels and undergo a thorough inspection before being moved to the inventory area. Out of all the



panels comprising the car body, the company decided to produce just around twenty five key parts in this stamping shop and outsource the other panels to suppliers. The panels produced in-house included, but were not limited to, for example, all large outer parts like trunks, doors, fenders, roof, and hood outer parts.

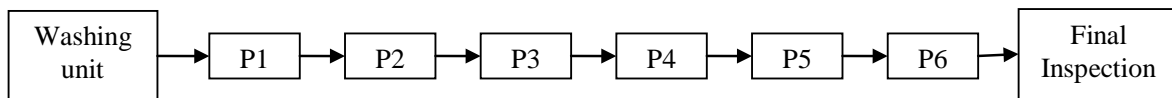


Figure 1 Press shop process

3. QUALITY ISSUES IN PANEL STAMPING

Quality performance is of high significance in the automotive stamping operations due to complexity of the process, high cost of machinery and tooling, and high cost of any scrap. Primarily, however, stamped parts quality tracking follows their conformance with dimensional specification, as they are readily quantifiable [Majeske and Hammet, 2003]. The visual defects, however, are much more difficult to track and quantify, and often times they are not becoming apparent until later stages for the manufacturing process, such as painting. Identification and assessment of visual defects often has to rely heavily on operator's experience and contains significant subjective component.

Introduction of any new product initially goes through a ramp-up phase, where production gradually reaches expected throughput and allows to debug and fine-tune the production system. IN the case described here, the majority of parts have reached the minimum acceptance rate before mass production phase. However, because of process complexity, its novelty for workers and supervisors, and initial instability of the process, solving the problem of low yield level seemed unattainable for nearly 20% of parts in the ramp-up phase. Figure 2 shows the acceptance rate for press shop parts over time. Moreover, there were some complaints from press-shop customers, including consecutive downstream processes such as body shops or paint shops for those products. High level of parameter variations and existence of different effective process and raw material parameters made process experts to use practical statistical techniques for detection of parameters effects.

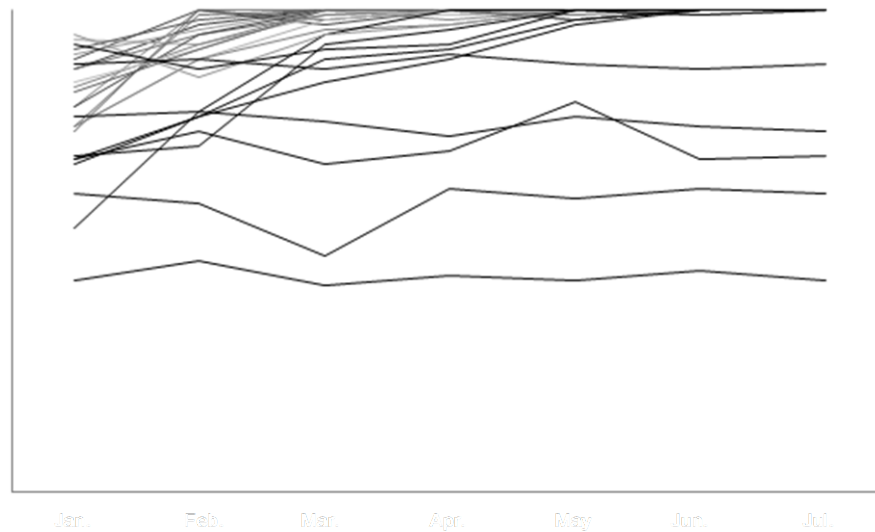


Figure 2 Trends of first acceptance rate of press shop panels

The majority of nonconformities were related to visual defects appearing on the surface of stamped parts. The surface quality of a product - particularly in the automotive industry - constitutes an important criterion for the customer and is generally seen as closely tied to the overall quality of the vehicle. Even inevitable defects at the early production stages that occur prior to painting (e.g., in the press shop), may cause defects such as dents, bumps, sink marks, etc. Some of those also remain invisible to the naked eye while the vehicle remains unpainted. The intense competition among manufacturers pushes them to increase the surface quality in conjunction with continuously decreasing production costs.

The type and occurrence frequency of each defect category vary with the part design. Because each stamped parts has its specific process, it is essential that each be considered separately. Figure 3 shows some examples of these defects:

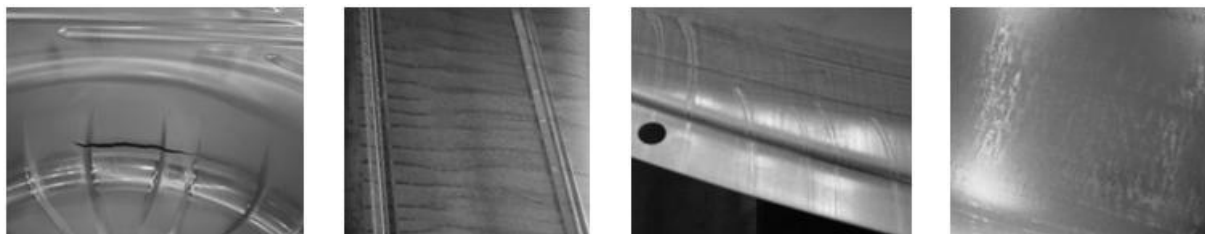


Figure 3 Examples of visual defects on parts, a-split, b-wave, c-galling, d-orange peel

The first obstacle to use simple process optimization techniques like ANOVA was that the rate of visual defects did not follow normal distribution. Some type of discrete distribution e.g., binomial, better describes the occurrence of the phenomena. The second barrier was the existence of some uncontrollable variables in the process itself and its environment, such as, for example, air temperature



and a few mechanical characteristics of metal sheets, which affected the rate of defects. To deal better with these two problems, related mathematical techniques were reviewed.

4. GENERAL AND GENERALIZED LINEAR MODELS

Generalized Linear Models (GLZ) are an extension of the linear modeling process that allows models to be fit to data that follow probability distributions other than the Normal distribution [Rodriguez, 2003]. The generalized linear model can be used to predict responses both for dependent variables with discrete distributions and for dependent variables which are nonlinearly related to the predictors.

Generalized Linear Models also relax the requirement of equality or constancy of variances that is required for hypothesis tests in traditional linear models. There are many relationships that cannot adequately be summarized by a simple linear equation, for two major reasons: (i) the dependent variable of interest may have a non-continuous distribution, or (ii) the effect of the predictors on the dependent variable may not be linear in nature.

The GLZ approach is a generalized regression procedure, unifying the linear and nonlinear regression, that enables modeling of responses from many different distributions. Because the GLZ uses maximum likelihood to fit the model, when a specific model is chosen, the model obtained is equivalent to that obtained by OLS. The GLZ can be used to model a response variable that is a member of the exponential family. This family of response distributions includes the normal, binomial, exponential, Poisson, and gamma distributions. Assuming a random sample of N observations, y_1, y_2, \dots, y_N , if y_i is a member of the exponential family, its probability density function can be expressed generally as [Myers, 1990].

$$f(y_i, \theta_i, \phi) = \exp\{r(\phi)[y_i, \theta_i - g(\theta_i)] + h(y_i, \phi)\} \quad (1)$$

where $r(\cdot)$, $b(\cdot)$, and $h(\cdot)$ are known functions, θ_i is the natural location parameter, and ϕ denotes the dispersion parameter. The model is constructed by setting the link function, $g(\cdot)$, equal to the linear predictor as follows:

$$g(\mu_i) = \eta_i \quad (2)$$

The link function, $g(\cdot)$, is assumed to be monotone and differentiable and $g^{-1}(\cdot)$ is its inverse function. There are many possible choices for the link function, but if we choose $g(\mu_i) = \theta_i$ for model construction, the link is said to be the canonical link. The parameters θ_i are not necessarily constant between data points and link the density function to the regressor



variables through the linear function $x_i'\beta$, which is a linear predictor of $\mu_i = E(y_i)$. The link function tying μ_i and $x_i'\beta$ together is accomplished through θ_i and is given by

$$x_i'\beta = s(\mu_i) \quad (3)$$

5. DOE APPLICATION IN A PRESS SHOP

The intent of experimental design is to minimize the number of experiments required to identify which causes are significantly related to important effects. This allows for a large number of variables to be studied and analyzed just as easily and as economically as if only one variable was studied and analyzed. A lot of research effort was involved in development of these concepts, and is well reported in literature [Box *et al.*, 1978; Taguchi, 1997; Montgomery, 1997].

The appropriate use of DOE and other quality improvement techniques lead to higher quality and more reliable products. The understanding of the processes underlying manufactured products resulting from the use of DOE could also increase productivity and reduce costs. Many quality techniques and concepts such as statistical process control (SPC) are directed toward improving quality at the downstream processes and operations by emphasizing control charts and inspection. DOE, on the other hand, emphasizes the upstream processes and operations, focusing on developing products and processes that are well-designed, thereby improving quality at the initial stages of the product and process development. It is generally accepted to carry out the following steps for experimental design projects [Montgomery, 1997].

Phase I – Problem Recognition and Statement

The stamping shop produces twenty five of the main parts for vehicle body, including five that did not satisfy quality levels. Of those five panels, two (see Figure 4) were selected for detailed analysis, based on the: (i) cost of production, (ii) level of quality, and (iii) detectability of defects.



Figure 4- Pilot parts for 1st DOE project: hood outer (L) and front left door inner panels (R)

Then, the visual defects of panels were analyzed and based on possible rates of improvement, the target level of yield was determined for each part independently. For example, for Left Front Door



Inner (LFDI), First Throughput Yield at the beginning of the project was 79%, while the Target was set at 90%.

Phase II - Choice of Factors, Levels, and Ranges

There are some preliminary steps before building the best model for press shop parts' processes. First of all, it is essential to identify the causes of defects separately for each part.

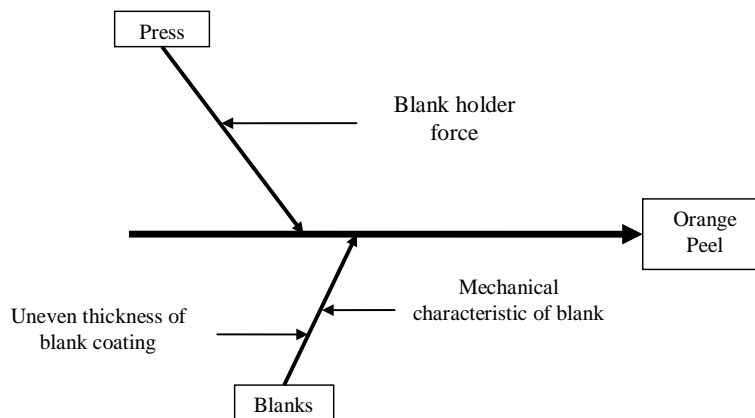


Figure 5 - Cause and Defect Diagram for orange peel defect

Separate Cause and Defect (Fishbone) Diagrams were developed for each type of defect; an example for the orange peel defect is shown in Figure 5. Identification of the customers and their needs, and using QFD-based analysis for selection of factors and their ranges was also considered in this phase. The quality team selected the most significant process factors from typical factor sets varying from 20 to 40 for each part. In the next step, the levels of factors, number of replications and methods for running the experiments regarding to practical limitations and shop floor scheduling were established.

For Left front door Inner, one of nominated parts, four parameters were selected in the end, and two of those were covariates. Those four parameters include:

- Rate of oil flow in washing unit (m^3/s) – F1
- Age of blank (day) – F2
- Reciprocal of relative elongation of blanks (1/%) – 1/C1
- Temperature of environment ($^{\circ}\text{C}$) – C2

The first two parameters are the primary factors in model. Their levels are:

- Rate of oil flow: Level I – $5 \text{ m}^3/\text{s}$, Level II – $10 \text{ m}^3/\text{s}$



- Age of blank: Level I – 200 days, Level II – 300 days

Phase III- Selection of the Response Variable

Percentage of high-quality products in a produced batch was considered as the best response variable for determining the quality level of parts. This variable sometimes called First Throughput Yield (FTY), which is not only a good indicator of quality level for each part, but also has significant relationship with production cost, inasmuch as producing unacceptable parts imposes more cost for the company.

Phase IV- Choice of Experimental Design

The first aspect of modeling the quality problems in press shop relates to existence of some uncontrollable parameters in the model. The second one relates to the fact that the distribution function of the number of accepted parts in a produced batch is binomial, not normal, which is due to the distribution function of number of visual defects. The particular model structure can be selected only on a case-by-case basis. For the presented example, Left Front Door Inner, the selected model was:

- Two-way GLZ model with two factors and two covariates, including center points.
- Two experiments (batch production) for each treatment.

Based on above selected model, ten experiments should be run. However, the definition of experiments for a batch production process like press shop when GLZ models are selected is very different from other process types. In this type of experiment, the total or a part of a batch, the process factors which are stable during the experiments, should be considered as one experiment. Thus, running ten experiments here is equivalent to running ten batches of products. These needs were reported to production planning department for future production scheduling.

The designed batch size for most of panels includes more than 500 parts, which is quite satisfactory for the statistical analysis. It is necessary, however, that the process factors be fixed during experiments. When that condition was not met, the experiment (e.g., data collection) was stopped, but production stream was continuing. Another constraint was due to excessively low quality levels, that required stopping of the experiment after collecting minimum number of data, and subsequently changing factors by production team. By this collaboration, running experiments can be handled with minimum cost, but collecting enough data.

Phase V- Performing the Experiments

The table 1 shows the experimental data for Left front door Inner. The experiment runs were run randomized. During near two months, ten experiments were conducted, each including one batch of production. The level of factors and value of covariates were calculated based on accurate measuring



system in stamping process. Using experimental design data based on methods requires major changes in shop floor planning. Moreover, there were some limitations with regard to parameters modification. The values of factors are showed as coded.

Table 1- The data from ten experiments for Left Front Door Inner panel

		Input Variables				Results						
		Factors		Covariates		Parts			Defects			
No.	Date	F1	F2	C1	C2	Yield	Accepted	Rejected	Split	Wave	Galling	other
1	628	1	1	45	33	0.919	542	48	0	0	0	48
2	705	-1	-1	43	32	0.999	1533	1	0	0	0	1
3	726	-1	1	44	18	0.910	822	81	71	0	0	10
4	729	0	0	44	16	0.924	585	48	29	2	7	10
5	803	1	-1	46	14	0.394	37	57	57	0	0	0
6	803	0	0	45	14	0.929	650	50	35	3	9	3
7	808	1	-1	44	13	0.704	202	85	61	24	0	0
8	814	1	1	45	9	0.954	887	43	41	0	0	2
9	820	-1	1	44	4	0.916	757	69	13	0	56	0
10	820	-1	-1	43	4	0.916	545	50	9	0	40	1

As it is apparent from Table 1, the number of accepted and rejected parts and type of failures were calculated during each experiment. This separation of failures provides better chance for performing analysis for each type of failure separately, because the significant factors for each of them are not unique.

Phase VI- Statistical Analysis of the data

Statistical analysis software was employed for data analysis. This software can handle large amount of data and are produce sufficient flexibility to construct the appropriate model. Figure 6 shows some analytical results for left front door inner. This analysis is done for the split, main defect.

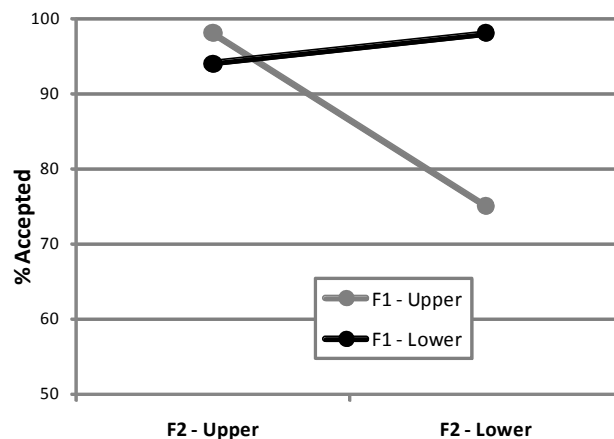


Figure 6 - Treatment yield averages for left front door inner



Table 2- Parameter estimation of GLZ model

Effect	Response Variable - Parameter estimates (Spreadsheet1.sta) Distribution : BINOMIAL, Link function: LOGIT Modeled probability that Response Variable = 0					
	Level of Effect	Column	Estimate	Standard Error	Wald Stat.	p
Intercept		1	-31.846	6.0273	27.91583	0.000000
1 / Elongation		2	1499.151	265.6916	31.83720	0.000000
Temperature		3	0.091	0.0092	97.97303	0.000000
Oil Flow	-1	4	0.423	0.1425	8.80592	0.003003
Blank Age	-1	5	-0.376	0.1154	10.60581	0.001127
Oil Flow*Blank Age	1	6	0.865	0.1076	64.55929	0.000000
Scale			1.000	0.0000		

Table 2 shows the significant effect in GLZ model and parameter estimation for related factors and covariates and their effects. It is assumed there is no interaction between covariates and between covariates and factors. Figure 7 shows predicted rate of acceptance against elongation of blanks in each treatment in normal temperature, for example -1 +1 consider first factor is set in lower level and second factor in higher level. The same analysis for percentage of parts not having any scratch, which is another main defect on mentioned part, against environment temperature is showed in figure 8.

The results of this step allow determining which combination of factors' levels and covariates' values should be selected to maximize FTY. After finding the best values for process improvement including factors and covariates, the previously mentioned steps should be repeated time after time to deal with unexpected changes occurring in the process and original unsettledness of the process. However, after certain level of quality is reached, some quality plans need to be modified by considering new process parameters, leading to a new quality zone.

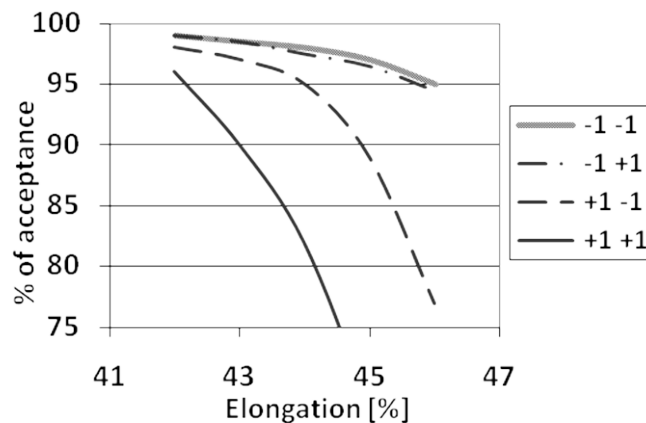


Figure 7 – Acceptance rate vs. elongation of blanks for each treatment

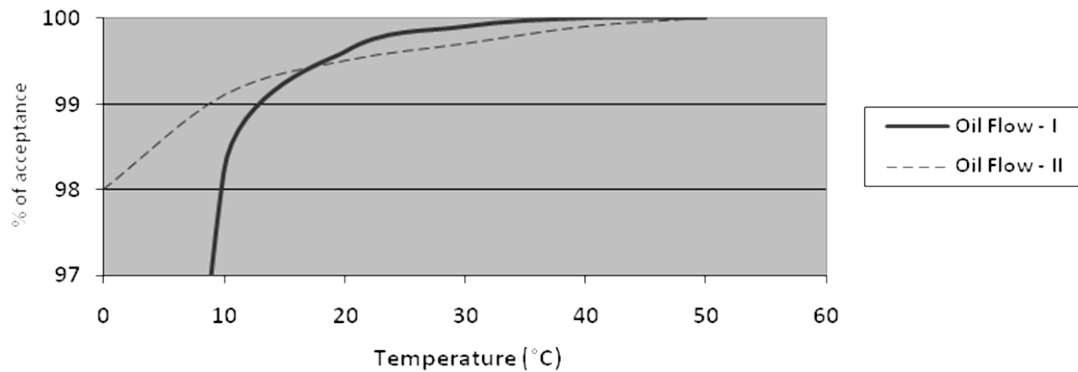


Figure 8 – rate of acceptance for scratch vs. temperature for each treatment

5. CONCLUSIONS

After finding the best values for process parameters based on the selected models, the procedure needs to be fully repeated over for analysis of each type of defect. Going over each specification provides two important advantages in DOE models:

- Providing more control on model and variables
- Finding more relations between variables (seems that there is more Degree of Freedom in the model).

This last advantage compensates for the one of the major limitations in experimental design. It means that with smaller amount of data, one may get more information while providing the necessary data is a big problem in DOE.

After improving the process based on GLZ models, Process Capability was increased by 0.25 on average. This improvement shows the way to increased productivity which lead to production cost reduction on average by nearly 5% for selected parts. It is essential to say that process improvement based on GLZ models was done for the first time and the results are very significant for first trial.

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