COMPARISON OF METHODS FOR ROBUST PARAMETER DESIGN OF PRODUCTS AND PROCESSES WITH AN ORDERED CATEGORICAL RESPONSE

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ABSTRACT

COMPARISON OF METHODS FOR ROBUST PARAMETER DESIGN OF PRODUCTS AND PROCESSES WITH AN ORDERED CATEGORICAL RESPONSE

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Robust design of products or processes with categorical response has more momentous role in industrial experiments for quality improvements, because ordinal categorical quality characteristics are encountered more frequent than continuous ones in industry. In this study, five optimization methods for an ordered categorical response are compared with each other: Logistic Regression Model Optimization (LRMO), Accumulation Analysis (AA), Weighted Signal-to-noise Ratio (WSNR), Scoring Scheme (SS), and Weighted Probability Scoring Scheme (WPSS). In order to compare performance of these methods for different types of robust design problems, each method is individually applied on two different types of problems: smaller-the-better and larger-the-better. All examples are studied to find the optimal parameter settings of statistically significant controllable factors and trying to optimize both location and dispersion of the results. To compare the optimal levels derived from these five methods, three performance criteria are used: SNR at optimal parameter settings, estimated by ANOVA model of continuous version of data or true model (if applicable); probability of observing target category, estimated by LR models; and that of observing target category estimated by ANOVA models of cumulative percentage of categories. According to the results, LRMO and AA methods have the best performance results in most of the examples analyzed in this study. Since AA is criticized as not allowing analysis of location and dispersion effects separately but not LRMO, WPSS and SS, more examples and further analysis might be studied to show this discrepancy of the methods.

KEY WORDS: Robust Parameter Design; Ordinal Categorical Response; Ordinal Logistic Regression; Accumulation Analysis; Signal-to-noise Ratio.

ÖZ

SIRALI KATEGORİK ÇIKTILI ÜRÜN VE PROSES PARAMETRE TASARIMI İÇİN YÖNTEM KARŞILAŞTIRMASI

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Kategorik çıktısı olan ürün veya prosesin robust tasarımın kalite iyileştirmeleri için yapılan endüstriyel deneylerde önemli rolü vardır. Çünkü endüstride sıralı kategorik kalite karakteristiklerine sürekli kalite karakteristiklerinden daha sık rastlanır. Bu çalışmada, sıralı kategorik çıktılar için kullanılan beş optimizasyon metodu birbiriyle karşılaştırılmıştır: Lojistik Regresyon Model Optimizasyonu (LRMO), Birikim Analizi (AA), Ağırlıklı Sinyal Gürültü Oranı (WSNR), Skor Tasarısı (SS), ve Ağırlıklı Olasılık Skor Tasarısı (WPSS). Bu metotların farklı robust tasarım problemlerinde davranışlarını gözlemlemek için herbir metot iki farklı tip problem üzerinde uygulanmıştır: en küçük-en iyi ve en büyük-en iyi. Kontrol edilebilir faktörlerin istatistiksel olarak anlamlı en uygun parametre değerlerini bulabilmek ve konum ve dağılım sonuçlarını optimize edebilmek için bütün örnekler çalışılmıştır. Bu beş metodun elde ettiği en uygun seviyeleri karşılaştırmak için üç performans kriteri kullanılmıştır: Sürekli verilerin (eğer uygulanabilirse) en uygun parametre değerlerindeki ANOVA modeli veya doğru model ile tahmin edilmiş SNR; hedef kategorinin LR modeli ile tahmin edilmiş görülme olasılığı; ve kategorilerin kümülatif yüzdeleri üzerinde ANOVA modeli ile tahmin edilmiş hedef kategorilerin görülme olasılığı. Sonuçlara dayanarak, bu çalışmada LRMO ve AA metotları çoğu örnekte en iyi performans sonuçlarını vermiştir. AA metodu LRMO, WPSS ve SS metotlarının aksine, konum ve dağılım etkilerinin ayrı analizine izin vermediği için eleştirildiğinden dolayı metotların farklılığını gösterebilmek için daha fazla örnek çalışılabilir ve ileri analizler yapılabilir.

ANAHTAR KELİMELER: Robust Parametre Tasarımı; Sıralı Kategorik Çıktı; Sıralı Lojistik Regresyon; Birikim Analizi; Sinyal Gürültü Oranı

To My Husband

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CHAPTER 1

INTRODUCTION

In industry, experiments are conducted in order to analyze and improve product quality and process performance by considering economical requirements. If quality responses (characteristics) are continuous variables, measuring and analyzing such characteristics are relatively easier than that of categorical variables. However, in many industries quality characteristics are measured as ordered categorical responses, because collecting such data is easier and cost-effective as mentioned by Wu and Yeh (2006). Due to these facts, it is important to find out ways to analyze ordered categorical data effectively. In this study, some design optimization methods that can be applied on naturally ordered categorical response data are compared.

While optimizing the design, methods deal with two types of factors that affect the quality characteristics: controllable and uncontrollable (noise) factors. All robust design methods focus on location effects of the controllable factors which help adjusting the mean of the quality responses to the target value. In addition to the location effects, methods also focus on dispersion effects of the controllable factors which help minimizing the variance of the quality characteristics. Considering these two effects, optimal parameter settings are detected, which lead to the robustness of the quality characteristics. In other words, reaching these goals minimizes the effects of uncontrollable factors on the quality of products and processes.

In order to analyze ordered categorical response data for the purpose of design optimization, several different methods are proposed as presented in Chapter 2. In this study, five such methods are selected for comparison. These optimization methods are Logistic Regression Model Optimization (LRMO), Accumulation Analysis (AA), Weighted Signal-to-noise Ratio (WSNR), Scoring Scheme (SS), and Weighted Probability Scoring Scheme (WPSS).

The selected methods are applied on five different example problems that are chosen from the following types; smaller-the-better and larger-the better. Three of them are of smaller-the-better type and two of them are of larger-the-better type, since, it is aimed to compare performance of these methods for different types of problems. These examples, called as surface defect, thick-film resistor, simulation, inkjet printer and duplicator examples are explained in Chapter 3.

LRMO differs from the other methods by also providing empirical models of the response location and dispersion in order to evaluate the performance of a given parameter setting.

LRMO also estimates the probability of observing each response category and signal-to-noise ratio for the given parameter settings to determine the performance. For the purpose of comparing the methods to each other, the optimal settings estimated by five different methods are evaluated using the estimated probabilities of observing target response category and estimated signal-to-noise ratios at optimal parameter settings found. In addition to the use of LR's prediction models, ANOVA models of cumulative percentage of categories is used for the comparison of five methods. In this latter model, predicted percentages of categories for the given parameter settings, calculated from the raw collected data, are used as the performance measure. Moreover, SNRs at optimal parameter settings, estimated by ANOVA model of continuous version of data (if applicable) are used for the comparison of five methods.

All these three performance criteria are used to compare the methods and the methods that have the best performance steadily are determined in the study. All the results derived from the analysis are given in Chapter 3. According to these results, methods are discussed, and the advantages and weaknesses of methods are mentioned in Chapter 4. Then, in the light of all these studies and results, some conclusions are presented and some further studies are proposed in Chapter 5.

CHAPTER 2

LITERATURE SURVEY

As ordered categorical response data may need to be analyzed more frequently than continuous response data, some robust design methods are developed suitable for such data.

Taguchi (1974) is the pioneer in introducing a robust design method for ordered categorical response data, which is the AA method. This method uses cumulative frequencies of each category and each parameter setting to analyze data, determine optimal levels and apply analysis of variance (ANOVA). In addition to the location effects of the factors, Taguchi proposed to focus on dispersion effects of the predictor variables as well. It is tried to determine factors that minimize variance of the response. In AA method, it is claimed that both location and dispersion effects of factors are focused on and aims of making the mean close to target value and minimizing variance are tried to be achieved simultaneously.

However, Taguchi's accumulation analysis method is criticized by Nair (1986) claiming that this method does not allow analysis of location and dispersion effects separately for a given set of parameter settings (or controllable factor levels). Moreover, Nair (1986), Box and Jones (1986) criticize that accumulation analysis method is unnecessarily complicated. Furthermore, Hamada and Wu (1989) show that spurious effects can be determined. In other words, significance of factors can be wrongly detected. For instance, among all factors introduced, factor A may be detected as significant factor on response data even though factor A has no effect on response data actually. In addition, in their study it is concluded that accumulation analysis may reverse the order of factor importance. As illustrated in study of Hamada and Wu (1989) AA detects so called factor E as the second most important factor even though that factor is the least important one.

Nair (1986) proposes the SS method instead of AA due to his criticism that accumulation analysis method does not allow analysis of location and dispersion effects separately for a given set of parameter settings. Nair (1986) proposes two types of scores for location and dispersion effects in order to identify these effects separately. However, Jeng and Guo (1996), and Wu and Yeh (2006) criticize scoring scheme method about having complicated computation. Furthermore, this method does not propose a way to compromise between optimal levels found depending on location and dispersion effects of predictor variables.

Jeng and Guo (1996) develop the WPSS method in order to recover from the complexity of the SS method. In this method, two types of scores for location and dispersion effects are introduced in order to identify these effects separately similar to the SS method. This method determines weights of categories depending on the importance of categories as distinct from scoring scheme method. Moreover, in order to avoid compromising between optimal levels found depending on location and dispersion effects, mean square deviation (MSD) is calculated using location and dispersion scores.

Chipman and Hamada (1996) develop Bayesian Analysis method in order to avoid difficulties like inaccurate results and infinite factor effect predictions in modeling. In this method, Gibbs sampler is used and complex computation applications are done to fit the model. This method is strong in analyzing location and dispersion effects of factors.

Wu and Yeh (2006) introduce a WSNR method claiming that it was presented by Taguchi to make the AA simpler. The original source of this method is not given by Wu and Yeh (2006). In this method, weights are given to categories proportional to the quality loss. Then, by using these weights and frequencies of occurrence of categories signal-to-noise ratios are calculated, which are used to find the optimal levels of factors.

Asiabar and Ghomi (2006) develop minimization of expected loss (MEL) method which is determined as being more accurate than the AA method. In this method, probability distribution function of data in categories is determined. Then, proportional to the quality loss, coefficients of categories are defined. By using these probabilities and coefficients, expected loss for levels of factors are calculated and used to find the optimal levels of the factors.

Köksal et al. (2006) develop a design optimization method based on logistic regression for a categorical response. In this method, an ordinal logistic regression model is fit to response data. Then, by using this model probability of observing each category, mean and variance of response data for each set of parameter settings are estimated. Then, by using estimated mean and variance, signal-to-noise ratios for each set of parameter settings are calculated. Both signal-to-noise ratios and the estimated probability of target category are used to find the optimal levels of controllable factors. One of the advantages of this method is that this method can allow analysis of location and dispersion effects separately for a given set of parameter settings. Another advantage is that without compromising it can find the optimal levels by the help of signal-to-noise ratios and estimated probabilities. The final advantage is that this method can use response surface optimization to find better parameter settings than the methods choosing the best design from only possible combinations of tested parameter levels especially if design parameters are defined on a continuous scale.

2.1. BACKGROUND ON METHODS

Among all these methods given in literature survey, Logistic Regression Model Optimization, Accumulation Analysis, Weighted Signal-to-noise Ratio, Scoring Scheme, and Weighted Probability Scoring Scheme methods are selected to compare in this study.

2.1.1. Logistic Regression Model Optimization

The method is developed by Köksal et al. (2006) and it is based on logistic regression models of the categorical response, mean and variance. A model is fit for the probability of observing each category using ordinal logistic regression. It allows the analysis of location and dispersion effects separately for a given set of parameter settings by estimating expected response category and variance of the categories. Using this method, it is possible to find the parameter design solution following an approach similar to Taguchi's signal-to-noise ratio approach as well as a response surface optimization approach. This method's performance depends on adequacy of the fitted models and the optimization method used. It is applied in the following steps.

Step 1. By using ordinal logistic regression, fitting a model for the probability of observing a category

Since the response data are ordered categorical, ordinal logistic regression is used to fit a model to the data. In this method, full enumeration approach can be used. In other words, using logistic regression models, estimates of probabilities of observing the response categories at each of the parameter settings generated by a full factorial design are obtained. In this estimation, equations (2.1) and (2.2) are used. Then, optimal parameter settings among all possible parameter settings generated are found.

$$\hat{P}(Y_i \le j) = \hat{\pi} = \frac{e^{(\hat{\beta}_j+\hat{\beta}_1 x_{1i}+\hat{\beta}_2 x_{2i}+\cdots++\hat{\beta}_k x_{ki})}}{1+e^{(\hat{\beta}_j+\hat{\beta}_1 x_{1i}+\hat{\beta}_2 x_{2i}+\cdots++\hat{\beta}_k x_{ki})}}, \qquad i=1,\ldots,m, \quad j=1,\ldots,J-1 \qquad (2.1)$$

$$\hat{P}(Y_i = j) = \hat{P}(Y_i \le j) - \hat{P}(Y_i \le j-1), \qquad i=1,\ldots,m, \quad j=1,\ldots,J \qquad (2.2)$$

where,

Y_i: Quality response at a given set i of parameter settings (or controllable factor levels)

$x_{1i}, x_{2i}, \ldots, x_{ki}$, $i=1,\ldots,m$.

j: Response category , $j=1,\ldots,J$

$\hat{P}(Y_i \le j)$: Estimator for probability of observing the quality response at category j or below for set i of parameter settings.

$\hat{\beta}_j$: Intercept for the probability model for category j.

$\hat{\beta}_l$: Coefficient estimate for the probability models of all categories for factor x_l, $l=1,2,\ldots,k$.

Step 2. Estimating expected category and variance of the category

For each set of parameter settings generated in the full factorial design, expected category and variance of the category are estimated by using equations (2.3) and (2.4), respectively. Expected category shows the location effect of factors whereas variance of the category represents the dispersion effect of these factors. By this way, this method can observe location and dispersion effects of factors, separately.

$$\hat{E}(Y_i) = \sum_{j=1}^{J} j\hat{P}(Y_i = j), \qquad i=1,\ldots,m \tag{2.3}$$

$$\hat{V}(Y_i) = \hat{E}\left[{Y_i}^2\right] - \left(\hat{E}[Y_i]\right)^2 = \left[\sum_{j=1}^{J} j^2\hat{P}(Y_i = j)\right] - \left(\hat{E}[Y_i]\right)^2, \quad i=1,\ldots,m \tag{2.4}$$

$\hat{E}(Y_i)$= Estimator for the expected category at set *i* of parameter settings.

$\hat{V}(Y_i)$= Estimator for the variance of the category at set *i* of parameter settings.

Step 3. Find the optimal factor levels for target category and minimum deviation from the target category

By using one of the following alternate ways, the optimal levels for the factors can be determined.

Way 1. Calculating signal-to-noise ratios (SNRs) for each set of parameter settings generated in full factorial design and finding the set of parameter settings based on the SNR values

As it is mentioned before, the robust design problem can be one of the following two types: smaller-the-better and larger-the-better. If smaller-the-better or larger-the-better type of a response is considered, then signal-to-noise ratio for each set *i* of parameter settings can be calculated by using equation (2.5) or (2.6), respectively.

$$SNR_i = -10 \times \log(\left(\hat{E}[Y_i]\right)^2 + \hat{V}(Y_i)) \tag{2.5}$$

$$SNR_i = -10 \times \log\left[\left(\frac{1}{(\hat{E}[Y_i])^2}\right) \times \left(1 + 3 \times \left(\frac{\hat{V}(Y_i)}{(\hat{E}[Y_i])^2}\right)\right)\right] \tag{2.6}$$

For both types of the robust design problem, the set of parameter settings that has the maximum SNR value among all parameter settings in the full factorial design gives the optimal solution.

Way 2. Finding the set of parameter settings that has the maximum estimated probability for target category

For two different types of problems, another way to find out the optimal levels is to maximize the probability of the target category. Therefore, the probabilities of observing each response category for each set of parameter settings generated in full factorial design are estimated by using equations (2.1) and (2.2). After this estimation, the set of parameter settings that has the maximum probability of target category is selected as the optimal solution.

Estimated probability $\hat{P}_t^{LR(P)}$ of observing target category and estimated signal-to-noise ratio are also used in this study as performance measures for the optimal solutions found by the methods.

Way 3. Finding the optimal solution using a response surface optimization approach

This method can find a better solution in the feasible space of design parameters by using a response surface optimization method. In this method, problem is formulated as a nonlinear multi-objective optimization problem. In other words, optimization model is formulated in order to make the mean category close to the target and minimize the variance of the response. This model can be formulated according to the following two types of the problem; smaller-the-better and larger-the-better. The design parameters that achieve estimated desired mean and minimum variance give the optimal solution.

<u>Optimization Model for Smaller-the-better Type of Problem</u>

$Min\ \hat{E}(Y) = f_1(x_1, x_2, \ldots, x_k)$

$Min\ \hat{V}(Y) = f_2(x_1, x_2, \ldots, x_k)$

s.t.

$\vec{\boldsymbol{x}} = (x_1, x_2, \ldots, x_k) \in D \qquad \hat{E}(Y) \geq 0$

$\hat{V}(Y) \geq 0$

where,

x_i: Setting of parameter (control factor) i, i=1,2, … , k settings

f_1 & f_2: Empirical model for $\hat{E}(Y)$ and $\hat{V}(Y)$, respectively.

D: Design space for parameters 1,2, … , k

<u>Optimization Model for Larger-the-better Type of Problem</u>

$Max\ \hat{E}(Y) = f_1(x_1, x_2, \ldots, x_k)$

$Min\ \hat{V}(Y) = f_2(x_1, x_2, \ldots, x_k)$

s.t.

$\vec{\boldsymbol{x}} = (x_1, x_2, \ldots, x_k) \in D$

$\hat{E}(Y) \geq 0$

$\hat{V}(Y) \geq 0$

In this study, all the other methods used in the comparison search for the best solution among all possible combinations of given control factor levels, even though a factor (or design parameter) is defined on a continuous scale. In order to compare the methods, this third approach is not utilized, in spite of the fact that it would be more advantageous for especially continuous design parameters.

2.1.2. Accumulation Analysis Method

Accumulation analysis method is developed by Taguchi (as cited in Box & Jones, 1986) and it is based on analyzing cumulative frequencies of categories. It is also explained by Logothetis and Wynn (1989). Generally it is not necessary to have dependency between the categories for a given data. This method tries to detect the factors affecting the outputs of the experiment by creating dependency between these categories. By accumulating frequencies of category occurrences for the given parameter settings, it is able to prepare a data structure elements of which are dependent. Based on this principle, AA method consists of five steps.

Step 1. Creating cumulative frequency table by summing the frequencies of occurrence.

In this step, the response data is arranged by adding frequencies of occurrence for one category to the frequencies for the next category. These sums which are cumulative frequencies are created for each set of parameter settings.

Step 2. Creating frequency and cumulative frequency table for each level

In this step, frequencies and cumulative frequencies of each level for each factor are individually summed. By this way, aggregate frequencies and cumulative of levels for each factor are calculated. If interactions of factors are considered, frequencies and cumulative frequencies are individually summed for each level combinations of interacting factors. For instance, let interaction of factors A and B be taken into consideration and each factor has two levels. Then, frequencies and cumulative frequencies are individually summed for A_1B_1, A_1B_2, A_2B_1 and A_2B_2.

Step 3. Applying analysis of variance (ANOVA) for all factors.

In order to determine significance of factors, analysis of variance calculations are implemented by using these aggregate cumulative frequencies as given in the procedure below. In these calculations, cumulative frequencies of last category are not used, due to their being the aggregate of whole frequencies.

First of all, weights of each category are calculated by using equation (2.7) where *P(i)* is the proportion of cumulative frequency in category *i*.

$$W_{(i)} = \frac{1}{P(i)(1-P(i))} \qquad (2.7)$$

Then the correction factor CF_i of each category i and overall correction factor CF are calculated by using equations (2.8) and (2.9), respectively.

$$CF_i = \frac{Total\ Cumulative\ Frequency\ of\ Category\ i}{Total\ Cumulative\ Frequency} \tag{2.8}$$

$$CF = \sum_{i=1}^{I} CF_i \times W_i \tag{2.9}$$

Sum of squares S_{ij} for each factor i and category j and sum of squares S_i for each factor i are calculated by using equations (2.10) and (2.11), respectively. In addition, degree of freedom df_i for each factor i is calculated as shown in equation (2.12).

$$S_{ij} = \sum_{k=1}^{K} \frac{CFR_{ijk}{}^2}{CFR_{iJk}} - \frac{\left(\sum_{k=1}^{K} CFR_{ijk}\right)^2}{\left(\sum_{k=1}^{K} CFR_{iJk}\right)^2} \tag{2.10}$$

where,

CFR_{ijk} = Cumulative frequency for factor i, category j and level k

CFR_{iJk} = Cumulative frequency for factor i, category J (the last category) and level k

$$S_i = \sum_{j=1}^{J} S_{ij} \times W_j \tag{2.11}$$

$$df_i = (Number\ of\ categories - 1) \times (Number\ of\ Levels - 1) \tag{2.12}$$

If interactions of factors are considered, sum of squares $S_{i\times t}$ for interaction of factors i and t are calculated by using equations (2.13). In addition, degree of freedom $df_{i\times t}$ for interaction of factors i and t is calculated as shown in equation (2.14).

$$S_{i\times t} = \left(\sum_{j=1}^{J}\left[\sum_{k=1,l=1}^{K,L} \frac{CFR_{i\times tjk\times l}{}^2}{CFR_{i\times tJk\times l}}\right] \times W_j\right) - CF - S_i - S_t \tag{2.13}$$

where,

$CFR_{i\times tjk\times l}$ = Cumulative frequency for factor i and level k of factor i, and factor t and level l of factor t in category j.

$CFR_{i\times tJk\times l}$ = Cumulative frequency for factor i and level k of factor i, and factor t and level l of factor t in category J (the last category).

$$df_{i\times t} = (Number\ of\ categories - 1) \times (Number\ of\ Levels\ for\ factor\ i - 1) \times (Number\ of\ Levels\ for\ factor\ t - 1) \tag{2.14}$$

Total sum of squares TSS is calculated by using equation (2.15). Furthermore, total degree of freedom df_T is calculated as shown in equation (2.16).

$$TSS = (Number\ of\ categories - 1) \times (Number\ of\ experiments) \times (Number\ of\ repetitions) \tag{2.15}$$

$$df_T = (Number\ of\ categories - 1) \times ((Number\ of\ experiments \times Number\ of\ repetitions) - 1) \tag{2.16}$$

Sum of squares S_e and degrees of freedom df_e for error are calculated by using equations (2.17) and (2.18).

$$S_e = TSS - \sum_{i=1}^{I} S_i \tag{2.17}$$

$$df_e = df_T - \sum_{i=1}^{I} df_i \tag{2.18}$$

Mean sum of squares MS_i for each factor i is calculated as given in equation (2.19). Moreover, critical F value F_i for each factor i is calculated by using equation (2.20).

$$MS_i = \frac{S_i}{df_i} \tag{2.19}$$

$$F_i = \frac{MS_i}{MS_e} \tag{2.20}$$

If F value of a factor is greater than $F^{dfi}_{dfe(0.10)}$, then the relevant factor has a significant effect on the quality characteristic.

Step 4. Determining the optimal factor levels

After significant factors are detected by the help of ANOVA, for these significant factors the set of parameter settings that has the maximum frequencies among all levels of significant factors in target category give the optimum conditions for each factor. For interactions of factors, which are detected as significant, set of parameter settings that has the maximum frequencies among all level combinations of interacting factors in target category give the optimum conditions for these factors.

Step 5. Estimating long-run performance of optimal levels of factors

In addition to LRMO's prediction model, another prediction model is used for comparison of five methods. This model, calculations of which are given in this step, is used also by the AA method in order to estimate the long-run performance.

Estimated frequency $\widehat{FR}_{ij}$ for each category j and each factor i is calculated by using equation (2.21).

$$\widehat{FR}_{ij} = \frac{CFR_{ij}}{CFR_{iJ}} \qquad \text{for optimal levels} \tag{2.21}$$

J : Number of categories

Overall estimated frequency $\hat{T}_j$ for each category j is calculated by using equation (2.22).

$$\hat{T}_j = \frac{\sum_{k=1}^{K} CFR_{ij}}{\sum_{k=1}^{K} CFR_{iJ}} \qquad \text{for optimal levels} \tag{2.22}$$

J : Number of categories

By using logit (omega) transformation (equation (2.23)) estimated frequency and overall estimated frequency for each category are transformed into decibels.

$$LT = -10\log_{10}\left\{\frac{1}{p} - 1\right\} \quad (2.23)$$

where

p : Estimated cumulative frequency for each category j and each factor i or overall estimated frequency for each category j

Then, by using equation (2.24) long –run performance (model prediction for category *j*) $\hat{\mu}_j$ is estimated for each category j in decibels. $\hat{\mu}_j$ is estimated cumulative percentage for category *j*. Then, again by using logit (omega) transformation, these estimations are transformed into cumulative percentages $\widehat{CP}_j$ for each category *j*. Then, cumulative estimated percentage $\widehat{CP}_j$ value is converted to estimated percentage $\hat{P}_j$ for each category *j* by using equation (2.25).

$$\hat{\mu}_j = \hat{T}_j + \sum_{i=1}^{I}(\widehat{FR}_{ij} - \hat{T}_j) + \sum_{i=1,k=1}^{I,K}\left[\left(\widehat{FR}_{ikj} - \hat{T}_j\right) - \left(\widehat{FR}_{ij} - \hat{T}_j\right) - (\widehat{FR}_{kj} - \hat{T}_j)\right] \quad (2.24)$$

where

$\widehat{FR}_{ijk}$: Estimated frequency for each category *j* and each interaction of factors *i* and *k*

$$\hat{P}_j = \widehat{CP}_j - \widehat{CP}_{j-1} \quad (2.25)$$

J= Number of significant factors

If $\widehat{CP}_j \le \widehat{CP}_{j-1}$, then $\widehat{CP}_j = \widehat{CP}_{j-1}$. Therefore, according to equation (2.25), $\hat{P}_j = \widehat{CP}_{j-1} - \widehat{CP}_{j-1} = 0$.

The logit (omega) transformation is used in this method because values of estimated cumulative frequencies are between 0 and 1, which does not satisfy normality assumption of ANOVA. By using logit transformation range of percentages is widen from [0, 1] to [-∞, ∞]

Estimated percentage $\hat{P}_t^{ANOVA(CP)}$of target category is chosen as the performance criterion for optimal solutions.

2.1.3. Weighted Signal-to-noise Ratio Method

Weighted signal-to-noise ratio method is also developed by Taguchi. Then, Wu and Yeh (2006) introduced this method and compared it with four other robust parameter design methods. WSNR method consists of five steps. Weights of categories are added to the traditional SNR method in order to represent quality loss in each category. Then, this method tries to determine the optimal parameter settings that can reach the category with minimum quality loss.

Step 1. Giving each category a weight

In this step, weights are given to categories proportional to the quality loss. In other words, the targeted category has the smallest weight due to having the smallest quality loss, whereas the least desired category has the largest weight. If equal weights are assigned to the categories, this method cannot be used properly. However, there is no guidance given for determining scale of weights and spacing between weights.

Step 2. Calculating signal-to-noise ratios for each set of parameter settings

After weights are given to categories, signal to noise ratios are calculated for each set of parameter settings by using these weights and frequencies of the categories. The signal to noise ratio formula is given in equation (2.26).

$$\eta_i = -10 \times \log\left(\frac{1}{n}\sum_{j=1}^{J} w_j^2 f_{ij}\right) \quad (2.26)$$

where,

η_i=Signal-to-noise ratio for set *i* of parameter settings.

w_j=Weight for category *j*.

f_{ij}=Frequency for category *j* at set *i* of parameter settings.

n=Total number of experiments conducted for each set of parameter settings.

Step 3. Applying analysis of variance (ANOVA) for all factors.

In this method, originally, ANOVA is not applied in order to determine significant factors and interactions of factors. Therefore, optimal parameter settings for all factors are found by ignoring significance of factors. Moreover, no way is introduced for determining optimal parameter settings for interacting factors. However, in this study ANOVA is applied on weighted signal-to-noise ratios in order to detect the significant factors and their optimal levels.

Step 4. Calculating average signal-to-noise ratios for each level among all parameter settings

In order to see how signal to noise ratio behaves for each level of significant factors, the averages of signal to noise ratios for each significant factor are calculated for each level. In addition, for significant interactions of factors, the averages of signal to noise ratios for each level combination of interacting factors are calculated. By this way, signal to noise ratio data which represent each level for each significant factor and each level combination for interacting factors, can be obtained.

Step 5. Determining the optimal factor levels

The level for each significant factor and the level combination for interacting factors that have the maximum signal noise is the optimal level for that factor.

Moreover, for this method, no way is introduced for estimating performance of the optimal solution. Even though ANOVA prediction model could be used here, too, it has not been utilized to compare the model performances.

2.1.4. Scoring Scheme Method

Scoring scheme method is developed by Nair (1986). This method consists of eight steps. The major steps of this method are calculating two sets of scores that represent location and dispersion effects of factors. These two scores allow analysis of location and dispersion effects separately for a given set of parameter settings. This method can find out optimal parameter settings that shift mean close to the target by the help of location effects whereas it can determine the optimal solution that minimize variance of the category.

Step 1. Calculating the midrank for each category

The midrank τ_p for each category p is calculated by using equation (2.27).

$$\tau_p = \sum_{i=1}^{p-1} q_i + q_p/2 \tag{2.27}$$

where

q_i=Overall proportion of observations that is involved in category i.

Step 2. Calculating the set of location scores

In order to observe location effects of factors, first of all location score l_p for each category p is calculated by using equations (2.28) and (2.29).

$$l_p = \frac{\tilde{\tau}_p}{\left[\sum_{i=1}^{P} q_i \tilde{\tau}_i^{\,2}\right]^{1/2}} \tag{2.28}$$

where,

$$\tilde{\tau}_p = \tau_p - \sum_{i=1}^{P} q_i \tau_i = \tau_p - 0.5 \tag{2.29}$$

Step 3. Calculating location pseudo-observations

By using the set of location scores l_p calculated and frequencies of occurrence f_{ip} for each category p, location pseudo-observation L_i for the i^{th} set of parameter settings is calculated as seen in equation (2.30).

$$L_i = \sum_{p=1}^{P} f_{ip} l_p, \qquad i=1,\ldots,P \tag{2.30}$$

Step 4. Calculating the set of dispersion scores

In order to observe dispersion effect of factors, first of all dispersion score d_p for each category p is calculated by using equations (2.31) and (2.32).

$$d_p = \frac{e_p}{\left[\sum_{i=1}^{P} q_i e_i^2\right]^{1/2}} \tag{2.31}$$

where,

$$e_p = l_p(l_p - \sum_{i=1}^{P} q_i l_i{}^3) - 1 \tag{2.32}$$

Step 5. Calculating dispersion pseudo-observations

By using the set of dispersion scores calculated and frequencies for each category, dispersion pseudo-observation D_i for the i^{th} set of parameter settings is calculated as seen in equation (2.33).

$$D_i = \sum_{p=1}^{P} f_{ip} d_p,\ \ i=1,\ldots,P \tag{2.33}$$

Step 6. Applying analysis of variance (ANOVA) for all factors.

In this method, originally ANOVA is not applied in order to determine significant factors and interactions of factors. Therefore, optimal parameter settings for all factors are found by ignoring significance of factors. Moreover, no way is introduced for determining optimal parameter settings for interacting factors. However, in this study ANOVA is applied on both location and dispersion pseudo-observations in order to detect the significant factors on location and dispersion effects separately.

Step 7. Calculating average location and dispersion pseudo-observations of each level for each factor among all location and dispersion pseudo-observations

In order to see how location and dispersion pseudo-observations of each level behave for each significant factor, the averages of location and dispersion pseudo-observations for each factor are calculated according to each level. Similarly, for each significant interaction of factors, the averages of location and dispersion pseudo-observations for each level combination of interacting factors are calculated. By this way, location and dispersion pseudo-observation data which represent each level of factors and level combination of interacting factors, can be obtained.

Step 8. Determining the optimal parameter settings

If the problem is smaller-the-better type, then the level of a factor that has both the minimum location and dispersion pseudo-observations is the optimal level for that factor. On the contrary, if the problem is larger-the-better type, then the level of a factor that has the maximum location and minimum dispersion pseudo-observations is the optimal level for that factor.

If an interaction of factors have significant effects on location or dispersion pseudo-observations, in this study prediction equation for averages of location and dispersion pseudo-observations are used to find optimal parameter settings by using equations (2.34) and (2.35).

$$\hat{L} = \bar{L} + \sum_{k=1}^{K}(\overline{L_k} - \bar{L}) + \sum_{i=1,j=1}^{I,J}\left[\left(\overline{L_{ij}} - \bar{L}\right) - (\bar{L_i} - \bar{L}) - (\bar{L_j} - \bar{L})\right] \quad (2.34)$$

$$\hat{D} = \bar{D} + \sum_{k=1}^{K}(\overline{D_k} - \bar{D}) + \sum_{i=1,j=1}^{I,J}\left[\left(\overline{D_{ij}} - \bar{D}\right) - (\bar{D_i} - \bar{D}) - (\bar{D_j} - \bar{D})\right] \quad (2.35)$$

where

$\hat{L}$: Predicted location pseudo-observation

$\hat{D}$: Predicted dispersion pseudo-observation

$\bar{L}$: Average of all location pseudo-observations

$\overline{L_k}$: Average of location pseudo-observations for factor *k* at optimal level

$\overline{L_{ij}}$: Average of location pseudo-observations for interaction of factors *i* and *j* at these factors' optimal levels

$\bar{D}$: Average of all dispersion pseudo-observations

$\overline{D_k}$: Average of dispersion pseudo-observations for factor *k* at optimal level

$\overline{D_{ij}}$: Average of dispersion pseudo-observations for interaction of factors *i* and *j* at these factors' optimal levels

By using full enumeration approach, predicted location and dispersion pseudo-observations are calculated for all possible level combinations of interacting factors. Then, if the problem is smaller-the-better type, the parameter settings of interacting factors that lead to the minimum predicted location and dispersion pseudo-observations are selected. If the problem is larger-the-better type, the parameter settings of interacting factors that lead to the maximum predicted location and the minimum predicted dispersion pseudo-observations are selected.

If a factor has significant effect on both location and dispersion pseudo-observations and both of these observations give the same optimal parameter setting for that factor, then these setting is the exact solution. However, if the optimal parameter setting of a factor according to location and dispersion pseudo-observations differ, then it is required to compromise between these two different levels of the factor. No method is suggested for compromising between two such different levels and estimating the performance of the optimal solution. In this study, a way is introduced for compromising between two different levels as explained below. Moreover, if an interaction of factors has significant effect on both location and dispersion pseudo-observations and the optimal parameter setting of that interaction according to predicted location and dispersion pseudo-observations differ, then the same way is used in this study.

Way of reaching a compromise between two different optimal levels based on predicted location and dispersion pseudo-observations

If a factor or an interaction has significant effect on both location and dispersion pseudo-observations and the optimal parameter settings for that factor or interaction according to location and dispersion pseudo-observations differ, predicted location and dispersion pseudo-observations for all possible parameter settings of that factor or interaction are calculated. Then, predicted location pseudo-observations versus predicted dispersion pseudo-observations graph is drawn. For smaller-the-better type of problem, the elbow point that decrease both predicted location and dispersion pseudo-observations give the selected efficient solution as shown on Figure 2.1. For larger-the-better type of problem, the elbow point that increase predicted location and decrease predicted dispersion pseudo-observations give the selected efficient solution as shown on Figure 2.2.

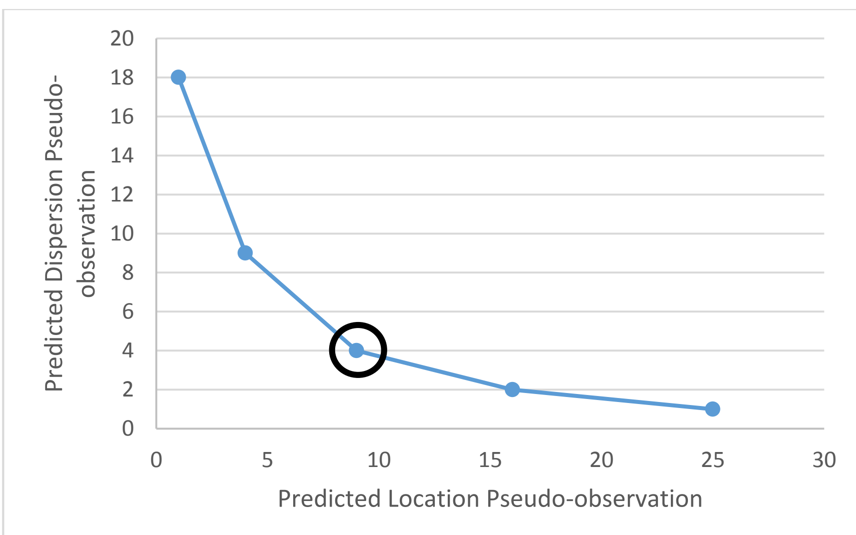

Figure 2.1. Predicted location pseudo-observations versus predicted dispersion pseudo-observations graph & selected efficient solution for smaller-the-better type of problem

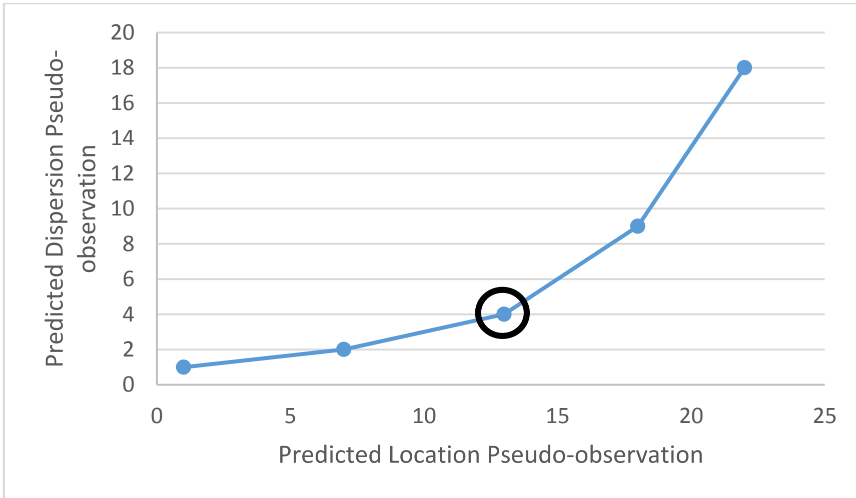

Figure 2.2. Predicted location pseudo-observations versus predicted dispersion pseudo-observations graph & selected efficient solution for larger-the-better type of problem

2.1.5. Weighted Probability Scoring Scheme Method

Weighted probability-scoring scheme method is recommended by Jeng and Guo (1996). Similar to SS method, this method calculates two sets of scores that represent location and dispersion effects of factors. These two scores allow analysis of location and dispersion effects separately for a given set of parameter settings. In addition to Nair's scoring scheme method, this method merges two scores for location and dispersion effects in one score, mean square deviation (MSD). By this way, it introduces a way to compromise between optimal levels detected depending on location and dispersion effects of factors. This method has seven steps which are explained below.

Step 1. Determining the weights of the categories

This method gives the target category the largest weight, thus location effect behaves as larger-the-better type. Therefore, the weights decrease as the categories move away from the target category.

Step 2. Calculating location scores for each set of parameter settings

In this step, location score L_j for each set j of parameter settings are calculated as seen in equation (2.36) by using weights w_i given and proportion p_{ij} of observation j for each category i.

$$L_j = \sum_{i=1}^{I} w_i p_{ij} \tag{2.36}$$

Step 3. Calculating dispersion scores for each set of parameter settings

Before calculating dispersion scores, a target value set is determined. In this set, a value is given to each category directly proportional to total number of desired observations. Hence, total number of observations at each set of parameter settings is given to target category whereas zero value is given to other categories. For example, a smaller-the-better type of problem has five response categories. Therefore, weight set of categories should be defined as {5, 4, 3, 2, 1} and desired proportions of observations should be as {1, 0, 0, 0, 0}. Hence, the target value set should be defined as {5, 0, 0, 0, 0} by multiplying weights given and desired proportions of observations. Then, dispersion scores D_j are calculated as seen in equation (2.37) by using weights w_i, proportion p_i of observation and target value for each category i.

$$D_j^2 = \sum_{i=1}^{I} [w_i p_i - (Target\ Value)_i]^2 \quad (2.37)$$

Step 4. Calculating Mean Square Deviation (MSD) Scores

Instead of compromising between optimal levels depending on location and dispersion scores, in this method mean square deviation scores MSD_j are calculated by using location and dispersion scores as seen in equation (2.38) in order to determine the selected efficient solution.

$$E(MSD_j) = E\left[\frac{1}{n}\sum_{i=1}^{I}\frac{1}{y_i^2}\right] \cong \frac{1}{\mu^2}\left(1+\frac{3\sigma^2}{\mu^2}\right) \cong \frac{1}{L_j^2}\left(1+\frac{3D_j^2}{L_j^2}\right) \quad (2.38)$$

Step 5. Applying analysis of variance (ANOVA) for all factors.

In this method, originally ANOVA is not applied in order to determine significant factors and interactions of factors. Therefore, optimal parameter settings for all factors are found by ignoring significance of factors. Moreover, no way is introduced for determining optimal parameter settings for interacting factors. However, in this study ANOVA is applied on mean square deviation scores in order to detect the significant factors.

Step 6. Calculating average of mean square deviation scores for each level of factors among all mean square deviation scores

In order to see how mean square deviation scores of each level behaves for each significant factor, the averages of them for each factor are calculated according to each level. In addition, for significant interactions of factors, the averages of mean square deviation scores for each level combination of interacting factors are calculated. By this way, mean square deviation scores which represent each level of significant factor and each level combination for interacting factors, can be obtained.

Step 7. Determining the optimal factor levels

The levels for each significant factor and the level combination for interacting factors that have the minimum mean square deviation scores are the optimal levels for that factor.

For this method, no way is introduced about estimating performance of the optimal solution. Even though ANOVA prediction model could be used here, too, it has not been utilized to compare the model performances.

CHAPTER 3

APPLICATION AND COMPARISON OF METHODS ON EXAMPLE PROBLEMS

Comparisons of methods are illustrated on five different examples as explained in the following subsections. Three of these examples are chosen to be of smaller-the-better type and two of them larger-the-better type. In addition, while choosing examples, problems are preferred in which sets of parameter settings of 8, 16 or 18 experimental runs are designed and analyzed. Moreover, while choosing examples, problems are preferred in which different numbers of factors are considered. Furthermore, in these problems factors have two or three levels. These choices are made to be able to see how the methods behave on data that have different properties.

3.1. SURFACE DEFECT EXAMPLE

Polysilicon deposition process is analyzed by using Taguchi's robust design method by Phadke (1989). In this experiment, number of surface defects, which is the quality characteristic, is detected on the wafers after the polysilicon deposition process is applied. In this case, six controllable factors are considered and their levels are tabulated in Table 3.1.

Table 3.1. Controllable Factors and Their Levels for the Surface Defect Example

FACTORS		**LEVELS**		
		1	**2**	**3**
A	Deposition Temperature (^oC)	T_0 - 25	T_0	T_0 + 25
B	Deposition Pressure (mtorr)	P_0 - 200	P_0	P_0 + 200
C	Nitrogen Flow (sccm)	N_0	N_0 - 150	N_0 - 75
D	Silane Flow (sccm)	S_0 - 100	S_0 - 50	S_0
E	Settling Time (min)	t_0	t_0 + 8	t_0 + 16
F	Cleaning Method	*None*	CM_2	CM_3

For these factors, a total of 18 experimental runs are designed and conducted at the selected factor levels according to the L_{18} orthogonal array shown in Table 3.2.

Table 3.2. Experimental Design for the Surface Defect Example

Exp. No	A	B	C	D	E	F
1	1	1	1	1	1	1
2	1	2	2	2	2	2
3	1	3	3	3	3	3
4	2	1	1	2	2	3
5	2	2	2	3	3	1
6	2	3	3	1	1	2
7	3	1	2	1	3	3
8	3	2	3	2	1	1
9	3	3	1	3	2	2
10	1	1	3	3	2	1
11	1	2	1	1	3	2
12	1	3	2	2	1	3
13	2	1	2	3	1	2
14	2	2	3	1	2	3
15	2	3	1	2	3	1
16	3	1	3	2	3	2
17	3	2	1	3	1	3
18	3	3	2	1	2	1

As a result of the experiments, the number of surface defects measured on three areas of three wafers are given in Table 3.3.

In this example, it is targeted to achieve wafers that have minimum number of surface defects. Therefore, this is a smaller-the better type of problem.

Before explaining the optimization methods for ordered categorical data, Taguchi’s robust design method is demonstrated to be able to obtain a benchmark solution to be used in the comparison of the selected methods. It should be noted that the original data are continuous and Taguchi’s robust design method can be applied on this continuous response data set. On the other hand, ordered categorical data sets are under consideration it this study. Because of this reason, these continuous data are converted to ordered categorical data as explained later in this subsection. Due to this categorization, Taguchi’s robust design method is expected to yield better results than all of the other methods applied on the categorical data.

Table 3.3. Surface Defect Data of the Surface Defect Example

Exp. No	**Test Wafer 1**			**Test Wafer 2**			**Test Wafer 3**		
	Top	**Center**	**Bottom**	**Top**	**Center**	**Bottom**	**Top**	**Center**	**Bottom**
1	1	0	1	2	0	0	1	1	0
2	1	2	8	180	5	0	126	3	1
3	3	35	106	360	38	135	315	50	180
4	6	15	6	17	20	16	15	40	18
5	1720	1980	2000	487	810	400	2020	360	13
6	135	360	1620	2430	207	2	2500	270	35
7	360	810	1215	1620	117	30	1800	720	315
8	270	2730	5000	360	1	2	9999	225	1
9	5000	1000	1000	3000	1000	1000	3000	2800	2000
10	3	0	0	3	0	0	1	0	1
11	1	0	1	5	0	0	1	0	1
12	3	1620	90	216	5	4	270	8	3
13	1	25	270	810	16	1	225	3	0
14	3	21	162	90	6	1	63	15	39
15	450	1200	1800	2530	2080	2080	1890	180	25
16	5	6	40	54	0	8	14	1	1
17	1200	3500	3500	1000	3	1	9999	600	8
18	8000	2500	3500	5000	1000	1000	5000	2000	2000

3.1.1. Taguchi's Robust Design Method for the Surface Defect Example

In this method, signal to noise ratio of surface defects for each set of parameter settings is calculated and tabulated in Table 3.4 by using equation (3.1);

$$\eta = -10\log_{10}\left[\frac{1}{9}\sum_{i=1}^{3}\sum_{j=1}^{3} y_{ij}^2\right] \tag{3.1}$$

Table 3.4. Signal to Noise Ratios of Surface Defects

Exp. No	A	B	C	D	E	F	SNR
1	1	1	1	1	1	1	0.5115
2	1	2	2	2	2	2	-37.3042
3	1	3	3	3	3	3	-45.1685
4	2	1	1	2	2	3	-25.7609
5	2	2	2	3	3	1	-62.5372
6	2	3	3	1	1	2	-62.2312
7	3	1	2	1	3	3	-59.8819
8	3	2	3	2	1	1	-71.6858
9	3	3	1	3	2	2	-68.1543
10	1	1	3	3	2	1	-3.46787
11	1	2	1	1	3	2	-5.08155
12	1	3	2	2	1	3	-54.8543
13	2	1	2	3	1	2	-49.3814
14	2	2	3	1	2	3	-36.5371
15	2	3	1	2	3	1	-64.1759
16	3	1	3	2	3	2	-27.3051
17	3	2	1	3	1	3	-71.5052
18	3	3	2	1	2	1	-71.9957

By taking averages of SNR values for each level of factors, the average signal to noise ratios given in Table 3.5 are determined. According to Taguchi's robust design method, the largest average SNR values among three levels give the optimal levels for each factor. Hence, Taguchi finds the optimum conditions as $A_1B_1C_1D_1E_2F_2$ which can be seen in Table 3.5.

Table 3.5. Analysis of Surface Defect Data

Factor	Average η by Factor Level			Degree of Freedom	Sum of Squares	Mean Square	F	p
	1	2	3					
A	**-24.2275**	-50.1039	-61.7547	2	4427.2384	2213.6192	27.2585	0.0020
B	**-27.5476**	-47.4418	-61.0967	2	3415.5487	1707.7743	21.0295	0.0037
C	**-39.0277**	-55.9925	-41.0659	2	1029.5174	514.7587	6.3387	0.0423
D	**-39.2027**	-46.8477	-50.0357	2	371.9324	185.9662	2.2900	0.1962
E	-51.5244	**-40.5367**	-44.0250	2	378.2794	189.1397	2.3291	0.1922
F	-45.5585	**-41.5763**	-48.9513	2	163.5189	81.7595	1.0100	0.4283
Error				5	404.9398	60.3535		
Total				17	10190.9751	564.8370		

Although, Taguchi finds the optimal levels for all factors, analysis of variance (ANOVA) also presented in Table 3.5 shows that factors D, E and F cannot be found significant with 90% confidence.

According to these conditions, the optimum predicted signal to noise ratio η_{opt} is calculated by using the equation (3.2). The optimal parameter settings determined and the signal to noise ratio estimated at these optimal parameter settings are given in Table 3.6.

$$\eta_{opt} = m + (m_{A_1} - m) + (m_{B_1} - m) + (m_{C_1} - m) \tag{3.2}$$

where

m : Average of all SNRs = -45.3620,

m_{i_j}: Average of SNRs belonging to j^{th} level of i^{th} factor

It should be noted that Phadke (1989) assumes a different prediction model by including D and E effects also in the model.

Table 3.6. Optimum Levels of Factors and Predicted Signal to Noise Ratio for Surface Defect Example

A	B	C	SNR
1	1	1	-0.0788

Since the methods that are compared in this study are robust design methods for ordered categorical response data, continuous data given in Table 3.3 are categorized. While categorizing, the ranges which are introduced by Phadke (1989) and given in Table 3.7 are used.

Table 3.7. Range of Surface Defect Numbers for Each Category

Categories	Range of Surface Defect Numbers
I	0-3
II	4-30
III	31-300
IV	301-1000
V	≥1001

Depending on these ranges, the categorized surface defect data are tabulated in Table 3.8. This process created naturally ordered response data: quality improves while category decreases. Hence, this problem is of smaller-the-better type.

Table 3.8. Categorized Surface Defect Data

Exp. No	**Number of Observations by Categories**				
	I	**II**	**III**	**IV**	**V**
1	9	0	0	0	0
2	5	2	2	0	0
3	1	0	6	2	0
4	0	8	1	0	0
5	0	1	0	4	4
6	1	0	4	1	3
7	0	1	1	4	3
8	3	0	2	1	3
9	0	0	0	4	5
10	9	0	0	0	0
11	8	1	0	0	0
12	2	3	3	0	1
13	4	2	2	1	0
14	2	3	4	0	0
15	0	1	1	1	6
16	3	4	2	0	0
17	2	1	0	2	4
18	0	0	0	2	7

3.1.2. Logistic Regression Model Optimization for Surface Defect Example

Before applying the method, the order of levels of factor C is changed. The original levels of factor C are not increasing or decreasing order. Since the levels of factors should be ordered in order to use ordinal logistic regression model, levels of factor C are arranged as given in Table 3.9. Hence, this modified factor is referred to C′.

Table 3.9. Modified Levels of Factor C

Level	Taguchi	LRMO
N_o-150	2	1
N_o-75	3	2
N_o-0	1	3

As explained in step 1 of subsection 2.1, an ordinal logistic regression model is fit to the response data by using MINITAB. Then, it is observed that factors D and F have no significant effect on the surface defect categories as shown in Figure 3.1, because the other factors' p values are smaller than 0.10 depending on 90% confidence. Also, on this figure the intercept of this model and coefficients of each factor are given.

```
Logistic Regression Table

                                                   Odds     95% CI
Predictor        Coef   SE Coef      Z      P     Ratio  Lower  Upper
Const(1)      5.42467  0.895899   6.06  0.000
Const(2)      6.62957  0.947982   6.99  0.000
Const(3)      7.87702   1.00259   7.86  0.000
Const(4)      8.95482   1.04769   8.55  0.000
A            -1.81619  0.235898  -7.70  0.000    0.16   0.10   0.26
B            -1.60309  0.229317  -6.99  0.000    0.20   0.13   0.32
C'           0.470517  0.200074   2.35  0.019    1.60   1.08   2.37
E           -0.477380  0.186217  -2.56  0.010    0.62   0.43   0.89


Log-Likelihood = -194.815
Test that all slopes are zero: G = 118.754, DF = 4, P-Value = 0.000
```

Figure 3.1. Ordinal Logistic Regression Results for Categorized Surface Defect Data

Although some factors are found to be significant, the model does not fit the data adequately according to Pearson and Deviance test results as shown in Figure 3.2. Because, p-values of both tests are smaller than 0.10 as seen on Figure 3.2. The tests reject the null hypothesis that the model fits the response data adequately at α=0.10. Hence, interactions of factors are tried to be involved in the model, but no interaction is found as significant. In addition, it is observed that involvement of interactions in the model does not improve the goodness-of-fit.

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	102.184	64	0.002
Deviance	111.623	64	0.000

Figure 3.2. Goodness-of-fit for the Model for Surface Defect Example

Parameter settings for significant factors in a full factorial design are generated by MATLAB as tabulated in Table 3.10. Then, probability of observing each response category and signal-to-noise ratios are estimated by using these parameter settings based on the model fit to the response data. Equations (2.1) and (2.2) are used in estimation of probability of observing each response category. These calculations are illustrated below for the first trial.

$$\hat{P}(Y_1 \leq 1) = \frac{e^{(5.42467-1.81619\times 1-1.60309\times 1+0.470517\times 1-0,477380\times 1)}}{1+e^{(5.42467-1.81619\times 1-1.60309\times 1+0.470517\times 1-0,477380\times 1)}}$$

$$\hat{P}(Y_1 \leq 1) = 0.8806$$

$$\hat{P}(Y_1 \leq 2) = \frac{e^{(6.62957-1.81619\times 1-1.60309\times 1+0.470517\times 1-0,477380\times 1)}}{1+e^{(6.62957-1.81619\times 1-1.60309\times 1+0.470517\times 1-0,477380\times 1)}}$$

$$\hat{P}(Y_1 \leq 2) = 0.9609$$

$$\hat{P}(Y_1 = 2) = 0.9609 - 0.8806 = 0.0803$$

$$\hat{P}(Y_1 \leq 3) = \frac{e^{(7.87702-1.81619\times 1-1.60309\times 1+0.470517\times 1-0,477380\times 1)}}{1+e^{(7.87702-1.81619\times 1-1.60309\times 1+0.470517\times 1-0,477380\times 1)}}$$

$$\hat{P}(Y_1 \leq 3) = 0.9884$$

$\hat{P}(Y_1 = 3) = 0.9884 - 0.9609 = 0.0275$

$$\hat{P}(Y_1 \leq 4) = \frac{e^{(8.95482-1.81619\times1-1.60309\times1+0.470517\times1-0,477380\times1)}}{1+e^{(8.95482-1.81619\times1-1.60309\times1+0.470517\times1-0,477380\times1)}}$$

$\hat{P}(Y_1 \leq 4) = 0.9960$

$\hat{P}(Y_1 = 4) = 0{,}9960 - 0{,}9884 = 0.0076$

$\hat{P}(Y_1 = 5) = 1 - 0.9960 = 0.0040$

In addition, since it is smaller-the-better type of problem, equations (2.3), (2.4) and (2.5) are used to calculate the signal-to-noise ratios.

$$\hat{E}(Y_1) = 1\times0.8806 + 2\times0.0803 + 3\times0.0275 + 4\times0.0076 + 5\times0.0040 = 1.1741$$

$$\hat{V}(Y_1) = [1^2\times0.8806 + 2^2\times0.0803 + 3^2\times0.0275 + 4^2\times0.0076 + 5^2\times0.0040] - (1.1741)^2 = 0.2924$$

$$SNR_1 = -10\times\log((1.1741)^2 + 0.2924) = -2.2295$$

Table 3.10. Estimated Probabilities and Signal to Noise Ratios based on Ordinal Logistic Regression Models of Categorized Surface Defect Data

TRIAL *i*	FACTORS				P(Yi=j)					SNR
	A	B	C′	E	I	II	III	IV	V	
1	1	1	1	1	0.8806	0.0803	0.0275	0.0076	0.0040	-2.2295
2	2	1	1	1	0.5455	0.2547	0.1329	0.0431	0.0238	-6.0702
3	3	1	1	1	0.1633	0.2311	0.2995	0.1756	0.1305	-9.9368
4	1	2	1	1	0.5976	0.2345	0.1131	0.0354	0.0193	-5.5686
5	2	2	1	1	0.1945	0.2517	0.2910	0.1546	0.1082	-9.5416
6	3	2	1	1	0.0378	0.0781	0.1975	0.2595	0.4272	-12.2940
7	1	3	1	1	0.2301	0.2692	0.2771	0.1343	0.0893	-9.1286
8	2	3	1	1	0.0464	0.0932	0.2213	0.2630	0.3761	-12.0470
9	3	3	1	1	0.0078	0.0179	0.0584	0.1284	0.7875	-13.4921
10	1	1	2	1	0.9219	0.0533	0.0175	0.0048	0.0025	-1.5559
11	2	1	2	1	0.6577	0.2074	0.0921	0.0279	0.0150	-4.9656
12	3	1	2	1	0.2381	0.2723	0.2736	0.1303	0.0857	-9.0405
13	1	2	2	1	0.7039	0.1841	0.0770	0.0228	0.0122	-4.4752
14	2	2	2	1	0.2788	0.2845	0.2546	0.1117	0.0704	-8.6067

Table 3.10 (cont'd) Estimated Probabilities and Signal to Noise Ratios based on Ordinal Logistic Regression Models of Categorized Surface Defect Data

15	3	2	2	1	0.0592	0.1143	0.2487	0.2600	0.3178	-11.7205
16	1	3	2	1	0.3236	0.2912	0.2327	0.0948	0.0577	-8.1568
17	2	3	2	1	0.0722	0.1339	0.2686	0.2517	0.2735	-11.4273
18	3	3	2	1	0.0125	0.0280	0.0877	0.1735	0.6983	-13.2526
19	1	1	3	1	0.9498	0.0346	0.0111	0.0030	0.0015	-1.0530
20	2	1	3	1	0.7546	0.1566	0.0616	0.0178	0.0094	-3.9019
21	3	1	3	1	0.3334	0.2919	0.2279	0.0915	0.0553	-8.0613
22	1	2	3	1	0.7919	0.1351	0.0509	0.0145	0.0076	-3.4497
23	2	2	3	1	0.3823	0.2914	0.2041	0.0769	0.0452	-7.5935
24	3	2	3	1	0.0915	0.1600	0.2876	0.2355	0.2254	-11.0463
25	1	3	3	1	0.4337	0.2850	0.1802	0.0642	0.0368	-7.1129
26	2	3	3	1	0.1108	0.1828	0.2977	0.2182	0.1904	-10.7092
27	3	3	3	1	0.0199	0.0435	0.1272	0.2183	0.5912	-12.9250
28	1	1	1	2	0.8207	0.1178	0.0430	0.0121	0.0064	-3.0784
29	2	1	1	2	0.4268	0.2862	0.1834	0.0658	0.0379	-7.1777
30	3	1	1	2	0.1080	0.1797	0.2967	0.2207	0.1948	-10.7553
31	1	2	1	2	0.4795	0.2750	0.1600	0.0546	0.0308	-6.6879
32	2	2	1	2	0.1303	0.2030	0.3018	0.2013	0.1636	-10.4015
33	3	2	1	2	0.0238	0.0514	0.1454	0.2335	0.5459	-12.7695
34	1	3	1	2	0.1564	0.2258	0.3007	0.1806	0.1364	-10.0290
35	2	3	1	2	0.0293	0.0622	0.1680	0.2478	0.4928	-12.5705
36	3	3	1	2	0.0049	0.0112	0.0378	0.0895	0.8566	-13.6618
37	1	1	2	2	0.8799	0.0808	0.0277	0.0076	0.0040	-2.2372
38	2	1	2	2	0.5438	0.2553	0.1336	0.0434	0.0240	-6.0863
39	3	1	2	2	0.1624	0.2304	0.2997	0.1762	0.1313	-9.9492
40	1	2	2	2	0.5959	0.2352	0.1137	0.0357	0.0195	-5.5847
41	2	2	2	2	0.1935	0.2511	0.2913	0.1553	0.1089	-9.5546
42	3	2	2	2	0.0376	0.0776	0.1967	0.2592	0.4289	-12.3016
43	1	3	2	2	0.2289	0.2687	0.2776	0.1350	0.0898	-9.1421
44	2	3	2	2	0.0461	0.0927	0.2206	0.2630	0.3777	-12.0553
45	3	3	2	2	0.0078	0.0177	0.0581	0.1278	0.7886	-13.4950
46	1	1	3	2	0.9214	0.0536	0.0176	0.0048	0.0025	-1.5644
47	2	1	3	2	0.6561	0.2081	0.0926	0.0281	0.0151	-4.9816
48	3	1	3	2	0.2368	0.2719	0.2741	0.1309	0.0863	-9.0542
49	1	2	3	2	0.7025	0.1849	0.0775	0.0229	0.0123	-4.4908

Table 3.10 (cont'd) Estimated Probabilities and Signal to Noise Ratios based on Ordinal Logistic Regression Models of Categorized Surface Defect Data

50	2	2	3	2	0.2775	0.2842	0.2552	0.1122	0.0709	-8.6210
51	3	2	3	2	0.0588	0.1137	0.2480	0.2602	0.3193	-11.7296
52	1	3	3	2	0.3221	0.2911	0.2334	0.0953	0.0581	-8.1716
53	2	3	3	2	0.0717	0.1333	0.2681	0.2520	0.2749	-11.4371
54	3	3	3	2	0.0124	0.0278	0.0872	0.1728	0.6998	-13.2567
55	1	1	1	3	0.7396	0.1650	0.0660	0.0192	0.0102	-4.0764
56	2	1	1	3	0.3160	0.2905	0.2364	0.0975	0.0597	-8.2324
57	3	1	1	3	0.0699	0.1305	0.2656	0.2534	0.2806	-11.4773
58	1	2	1	3	0.3637	0.2923	0.2131	0.0821	0.0488	-7.7699
59	2	2	1	3	0.0851	0.1517	0.2825	0.2412	0.2396	-11.1672
60	3	2	1	3	0.0149	0.0331	0.1014	0.1910	0.6596	-13.1399
61	1	3	1	3	0.1032	0.1742	0.2946	0.2250	0.2030	-10.8374
62	2	3	1	3	0.0184	0.0404	0.1198	0.2112	0.6103	-12.9872
63	3	3	1	3	0.0030	0.0070	0.0241	0.0600	0.9059	-13.7758
64	1	1	2	3	0.8197	0.1185	0.0433	0.0122	0.0064	-3.0918
65	2	1	2	3	0.4251	0.2865	0.1841	0.0662	0.0381	-7.1933
66	3	1	2	3	0.1074	0.1790	0.2964	0.2213	0.1959	-10.7664
67	1	2	2	3	0.4778	0.2755	0.1607	0.0550	0.0310	-6.7038
68	2	2	2	3	0.1295	0.2022	0.3017	0.2020	0.1645	-10.4132
69	3	2	2	3	0.0236	0.0511	0.1447	0.2329	0.5476	-12.7756
70	1	3	2	3	0.1555	0.2251	0.3009	0.1813	0.1373	-10.0413
71	2	3	2	3	0.0291	0.0618	0.1673	0.2474	0.4945	-12.5773
72	3	3	2	3	0.0048	0.0111	0.0376	0.0890	0.8574	-13.6638
73	1	1	3	3	0.8792	0.0813	0.0279	0.0077	0.0040	-2.2483
74	2	1	3	3	0.5421	0.2559	0.1343	0.0436	0.0242	-6.1025
75	3	1	3	3	0.1614	0.2297	0.2999	0.1769	0.1321	-9.9616
76	1	2	3	3	0.5943	0.2359	0.1144	0.0359	0.0196	-5.6009
77	2	2	3	3	0.1924	0.2505	0.2917	0.1559	0.1095	-9.5676
78	3	2	3	3	0.0373	0.0772	0.1959	0.2590	0.4306	-12.3091
79	1	3	3	3	0.2277	0.2682	0.2781	0.1356	0.0904	-9.1557
80	2	3	3	3	0.0458	0.0922	0.2198	0.2630	0.3793	-12.0636
81	3	3	3	3	0.0077	0.0176	0.0577	0.1272	0.7898	-13.4979

Since quality improves as the category decreases, probability of observing category 1 is desired to be maximized. Likewise, signal-to-noise ratio is tried to be maximized, too.

As seen in Table 3.10, 19^{th} set of parameter settings gives both maximum SNR value with -1.0530 and maximum estimated probability of observing category 1 with 0.9498. Therefore, the optimal levels are found as $A_1B_1C'_3\,E_1$.

Due to the changes made in order of the levels for factor C, the optimum settings for the original data set are $A_1B_1C'_3E_1$. By using Taguchi's prediction equation (3.2), the predicted SNR values for these optimal parameter settings are found as given in Table 3.11.

Table 3.11. Predicted SNR Values for Optimal Parameter Settings Found by LRMO and Taguchi based on Taguchi's Prediction Equation

FACTORS			**SNR**	**METHODS**
A	**B**	**C**		
1	1	1	-0.0788	LRMO
1	1	1	-0.0788	Taguchi's Method

According to these predictions, LRMO has the same optimal parameter settings and estimated SNR value as ones found by Taguchi's method.

In addition to comparison according to Taguchi's prediction equation, results are compared according to performance criteria chosen by Logistic Regression Model Optimization. As it is mentioned before, estimated probability $\hat{P}_t^{LR(P)}$ of observing target category and signal-to-noise ratio are the performance measure to evaluate the performance of optimal levels. Hence, probability of observing category 1 and signal-to-noise ratio for optimal levels found by Taguchi's method and LRMO are given in Table 3.12. Since Taguchi finds factor E as insignificant, alternative levels of factor E are tried. Then, the alternative levels that give the best results of estimated probability of target category and estimated SNR are tabulated in Table 3.12.

Table 3.12. Estimated Probability for each Category and Signal-to-noise Ratio for Optimal Levels for the Surface Defect Example

FACTORS				$\hat{P}_i^{LR(P)}$					**SNR**	**METHOD**
A	**B**	**C′**	**E**	**1**	**2**	**3**	**4**	**5**		
1	1	3	1	**0.9498**	0.0346	0.0111	0.0030	0.0015	**-1.0530**	Taguchi
1	1	3	1	**0.9498**	0.0346	0.0111	0.0030	0.0015	**-1.0530**	LRMO

According to estimated probability of target category and signal-to-noise ratio, LRMO shows equal performance with Taguchi's method.

3.1.3. Accumulation Analysis Method for Surface Defect Example

In accumulation analysis method, as explained in subsection 2.2, cumulative frequencies are created by adding frequencies of occurrence given in Table 3.8 for one category to the frequencies for the next category as seen in Table 3.13.

Table 3.13. Cumulative Frequencies for the Cumulative Categories

Exp. No	**Cumulative Frequencies for the Cumulative Categories**				
	I	**II**	**III**	**IV**	**V**
1	9	9	9	9	9
2	5	7	9	9	9
3	1	1	7	9	9
4	0	8	9	9	9
5	0	1	1	5	9
6	1	1	5	6	9
7	0	1	2	6	9
8	3	3	5	6	9
9	0	0	0	4	9
10	9	9	9	9	9
11	8	9	9	9	9
12	2	5	8	8	9
13	4	6	8	9	9

Table 3.13 (cont'd) Cumulative Frequencies for the Cumulative Categories

14	2	5	9	9	9
15	0	1	2	3	9
16	3	7	9	9	9
17	2	3	3	5	9
18	0	0	0	2	9

Frequencies and cumulative frequencies of each level of each factor given in Tables 3.8 and 3.13, respectively, are individually summed. By this way, aggregate frequencies and cumulative frequencies of levels for each factor are calculated as given in Table 3.14.

Table 3.14. Cumulative Rate of Occurrences for the Cumulative Categories for Surface Defect Example

	FREQUENCIES					**CUMULATIVE FREQUENCIES**				
Factors \ Categories	**I**	**II**	**III**	**IV**	**V**	**I**	**II**	**III**	**IV**	**V**
A_1	**34**	6	11	2	1	34	40	51	53	54
A_2	7	15	12	7	13	7	22	34	41	54
A_3	8	6	5	13	22	8	14	19	32	54
B_1	**25**	15	6	5	3	25	40	46	51	54
B_2	20	8	8	7	11	20	28	36	43	54
B_3	4	4	14	10	22	4	8	22	32	54
C_1	**19**	11	2	7	15	19	30	32	39	54
C_2	11	9	8	11	15	11	20	28	39	54
C_3	**19**	7	18	4	6	19	26	44	48	54
D_1	**20**	5	9	7	13	20	25	34	41	54
D_2	13	18	11	2	10	13	31	42	44	54

Table 3.14 (cont'd) Cumulative Rate of Occurrences for the Cumulative Categories for Surface Defect Example

D_3	16	4	8	13	13	16	20	28	41	54
E_1	**21**	6	11	5	11	21	27	38	43	54
E_2	16	13	7	6	12	16	29	36	42	54
E_3	12	8	10	11	13	12	20	30	41	54
F_1	**21**	2	3	8	20	21	23	26	34	54
F_2	**21**	9	10	6	8	21	30	40	46	54
F_3	7	16	15	8	8	7	23	38	46	54

In order to determine significance of factors, as illustrated in Step 3 of subsection 2.2, ANOVA is preferred. First of all, weights, correction factors and proportions of cumulative frequencies in relevant category are calculated by using equations (2.7), (2.8) and (2.9) as given in Table 3.1.

In order to determine significance of factors, as illustrated in Step 3 of subsection 2.2, ANOVA is preferred. First of all, weights, correction factors and proportions of cumulative frequencies in relevant category are calculated by using equations (2.7), (2.8) and (2.9) as given in Table 3.15.

Table 3.15. Weights, Correction Factors and Proportions of Cumulative Frequencies in Relevant Category for Surface Defect Example

VALUES	CATEGORIES			
	I	II	III	IV
Weights (W)	4.7398	4.0153	4.3508	5.7857
Correction Factors (CF)	14.8210	35.6543	66.7654	98.0000
Proportions of cumulative frequency in relevant category (P)	0.3025	0.4691	0.6420	0.7778

Then, sum of squares for each factor and category are calculated by using equation (2.10) as given in Table 3.16.

Table 3.16. Sum of Squares for Each Factor and Category for Surface Defect Example

Factors \ Categories	I	II	III	IV
A	23.5000	42.2222	76.2593	102.1111
B	19.2778	45.3333	72.1481	101.3704
C	15.6111	36.5926	69.3333	99.0000
D	15.2778	36.7778	68.5926	98.1111
E	15.5741	36.4815	67.4074	98.0370
F	17.2407	36.2593	68.8889	99.7778

Then, by using these sum of squares as shown in equation (2.11), sum of squares for each factor are calculated. Furthermore, by using equation (2.15), total sum of squares is calculated. Moreover, by using equations (2.17) and (2.19), sum of squares for error and mean sum of squares are calculated. Finally, critical F values for each factor are calculated by using equation (2.20). All these results are given in Table 3.17.

Table 3.17. Analysis of Variance (ANOVA) Results for AA Method in Surface Defect Example

Factors	df	S	MS	F
A	8	132.5999	16.5750	29.9869
B	8	102.9073	12.8634	23.2721
C	8	24.4706	3.0588	5.5339
D	8	15.2685	1.9086	3.4529
E	8	9.8981	1.2373	2.2384
F	8	33.4225	4.1778	7.5584
Error	596	329.4331	0.5527	
Total	644	648	1.0062	

Since $F^{8}_{596(0.10)}$ is equal to 1.6805 and all the critical F values given in Table 3.17 are greater than 1.6805, all the factor effects are determined as significant. Therefore, the levels for factors that have maximum frequencies in category 1 as seen in Table 3.14 give the optimal solution alternatives as tabulated in Table 3.18. Factors C and F have two alternative optimal levels due to having same frequencies at these levels.

Table 3.18. Optimal Solution Alternatives found by AA Method for Surface Defect Example

FACTORS					
A	**B**	**C**	**D**	**E**	**F**
1	1	1	1	1	1
1	1	1	1	1	2
1	1	3	1	1	1
1	1	3	1	1	2

By using Taguchi's prediction equation (3.2), the predicted SNR values for these optimal parameter settings are found as given in Table 3.19.

Table 3.19. Predicted SNR Values for Optimal Parameter Settings Found by AA and Taguchi according to Taguchi's Method

FACTORS			SNR	METHODS
A	**B**	**C**		
1	1	1	-0.0788	AA (C=1)
1	1	3	-2.1170	AA (C=3)
1	1	1	-0.0788	Taguchi's Method

Since Taguchi determines factors D, E and F as insignificant, in comparison by using Taguchi's prediction equation, optimal levels of factor D, E and F found in accumulation analysis method are not used. According to these predictions, optimal levels with C=1 found by AA method has the same optimal parameter settings and estimated SNR value as the ones found by Taguchi's method.

In addition to comparison according to Taguchi's prediction equation, results are compared according to performance criterion explained in step 5 of subsection 2.1.2. As it is mentioned before, estimated percentage of target category is the performance criterion for the optimal parameter settings. In order to calculate this percentage, estimated frequency for each category and each factor and total estimated frequencies for each category are calculated by using equations (2.21) and (2.22), respectively. These results are tabulated in Table 3.20. In this method, until this part all calculations are made in MATLAB.

Table 3.20. Estimated Frequency for each Category and each Factor and Total Estimated Frequencies for each Category for Surface Defect Example

FACTORS	LEVELS	CATEGORIES				
		I	II	III	IV	V
A	1	62.9630	74.0741	94.4444	98.1481	100.0000
	2	12.9630	40.7407	62.9630	75.9259	100.0000
	3	14.8148	25.9259	35.1852	59.2593	100.0000
B	1	46.2963	74.0741	85.1852	94.4444	100.0000
	2	37.0370	51.8519	66.6667	79.6296	100.0000
	3	7.4074	14.8148	40.7407	59.2593	100.0000
C	1	35.1852	55.5556	59.2593	72.2222	100.0000
	2	20.3704	37.0370	51.8519	72.2222	100.0000
	3	35.1852	48.1481	81.4815	88.8889	100.0000
D	1	37.0370	46.2963	62.9630	75.9259	100.0000
	2	24.0741	57.4074	77.7778	81.4815	100.0000
	3	29.6296	37.0370	51.8519	75.9259	100.0000
E	1	38.8889	50.0000	70.3704	79.6296	100.0000
	2	29.6296	53.7037	66.6667	77.7778	100.0000
	3	22.2222	37.0370	55.5556	75.9259	100.0000
F	1	38.8889	42.5926	48.1481	62.9630	100.0000
	2	38.8889	55.5556	74.0741	85.1852	100.0000
	3	12.9630	42.5926	70.3704	85.1852	100.0000
TOTAL		30.2469	46.9136	64.1975	77.7778	100.0000

By using logit (omega) transformation (equation (2.23)) estimated frequencies and overall estimated frequencies for each category are transformed into decibels as tabulated in Table 3.21.

Table 3.21. Logit Transformation Values for Estimated Frequencies and Overall Estimated Frequencies for each Category for Surface Defect Example

FACTORS	LEVELS	CATEGORIES				
		I	II	III	IV	V
A	1	2.3043	4.5593	12.3049	17.2440	∞
	2	-8.2691	-1.6267	2.3043	4.9882	∞
	3	-7.5958	-4.5583	-2.6518	1.6277	∞
B	1	-0.6436	4.5593	7.5968	12.3049	∞
	2	-2.3033	0.3218	3.0103	5.9210	∞
	3	-10.9683	-7.5958	-1.6267	1.6277	∞
C	1	-2.6518	0.9690	1.6277	4.1499	∞
	2	-5.9200	-2.3033	0.3218	4.1499	∞
	3	-2.6518	-0.3208	6.4346	9.0311	∞
D	1	-2.3033	-0.6436	2.3043	4.9882	∞
	2	-4.9872	1.2963	5.4405	6.4346	∞
	3	-3.7558	-2.3033	0.3218	4.9882	∞
E	1	-1.9620	0.0000	3.7603	5.9210	∞
	2	-3.7558	0.6446	3.0103	5.4405	∞
	3	-5.4395	-2.3033	0.9690	4.9882	∞
F	1	-1.9620	-1.2953	-0.3208	2.3043	∞
	2	-1.9620	0.9690	4.5593	7.5968	∞
	3	-8.2691	-1.2953	3.7603	7.5968	∞
TOTAL		-3.6276	-0.5357	2.5365	5.4405	∞

Then, by using equation (2.24) long–run performance is estimated for each category in decibels for optimal solutions found by Taguchi’s method and AA method as tabulated in Table 3.22.

To illustrate, calculation for optimal parameter settings found by AA, where levels of factors C and F are 1, is shown as follows.

For Category 1:

$$\hat{\mu}_1 = -3.6276 + \left(2.3043 - (-3.6276)\right) + \left(-0.6436 - (-3.6276)\right) + \left(-2.6518 - (-3.6276)\right) + \left(-2.3033 - (-3.6276)\right) + \left(-1.9620 - (-3.6276)\right) + (-1.9620 - (-3.6276))$$

$$\hat{\mu}_1 = 10.9196$$

Table 3.22. Estimated Percentage in decibels for each Category for Optimal Levels for Surface Defect Example

FACTORS						ESTIMATED CUMULATIVE PERCENTAGES					METHODS
A	**B**	**C**	**D**	**E**	**F**	**I**	**II**	**III**	**IV**	**VI**	
1	1	1	1	1	1	10.9196	10.8272	14.5907	19.7098	∞	AA (C=1) & (F=1)
1	1	1	1	1	2	10.9196	13.0915	19.4708	25.0023	∞	AA (C=1) & (F=2)
1	1	3	1	1	1	10.9196	9.5374	19.3976	24.5910	∞	AA (C=3) & (F=1)
1	1	3	1	1	2	10.9196	11.8017	24.2777	29.8835	∞	AA (C=3) & (F=2)

Then, these estimates are transformed back by using again logit transformation as tabulated in Table 3.23. To illustrate, calculations for estimation of percentages are shown below for the first level combination of AA method where levels of factors C and F are 1.

For Category 1:

$\hat{\mu}_1 = 10.9196\ decibels \rightarrow \widehat{CP}_1 = \hat{P}_1 = 92.5137\%$

For Category 2:

$\hat{\mu}_2 = 10.8272\ decibels \rightarrow \widehat{CP}_2 = 92.3758\%$

However, since $\widehat{CP}_2 = 92.3758\%$ is smaller than $\widehat{CP}_1 = 92.5137\%$, $\hat{P}_2$ is assumed to be equal to $\widehat{CP}_1$.

Then, by using equation (2.25);

$\hat{P}_2 = 92.5137 - 92.5137 = 0\%$

For Category 3:

$\hat{\mu}_3 = 14.5907\ decibels \rightarrow \widehat{CP}_3 = 96.6416\%$

By using equation (2.25);

$\hat{P}_3 = 96.6416 - 92.5137 = 4.1279\%$

For Category 4:

$\hat{\mu}_4 = 19.7098\ decibels \rightarrow \widehat{CP}_4 = 98.9411\%$

By using equation (2.25);

$\hat{P}_4 = 98.9411 - 96.6416 = 2.2995\%$

For Category 5:

$\hat{\mu}_5 = \infty\ decibels \rightarrow \widehat{CP}_5 = 100\%$

By using equation (2.25);

$\hat{P}_5 = 100 - 98.9411 = 1.0589\%$

Table 3.23. Estimated Percentage $\hat{P}_i^{ANOVA(CP)}$ for each Category for Optimal Levels for Surface Defect Example

FACTORS						$\hat{P}_i^{ANOVA(CP)}$					**METHODS**
A	**B**	**C**	**D**	**E**	**F**	**I**	**II**	**III**	**IV**	**VI**	
1	1	1	1	1	1	**92.5137**	0.0000	4.1279	2.2995	1.0589	AA (C=1) & (F=1)
1	1	1	1	1	2	**92.5137**	2.8082	3.5605	0.8006	0.3170	AA (C=1) & (F=2)
1	1	3	1	1	1	**92.5137**	0.0000	6.3495	0.7870	0.3498	AA (C=3) & (F=1)
1	1	3	1	1	2	**92.5137**	1.2912	5.8203	0.2711	0.1037	AA (C=3) & (F=2)

3.1.4. Weighted Signal-to-noise Ratio for Surface Defect Example

In this method, first of all weights are given to categories proportional to the quality loss. However, there is no guidance given for determining scale of weights and spacing between weights. Therefore, two different weight sets are compared to see the effect of choosing different weights on the optimal solution.

$W_1 = (1 \quad 2 \quad 3 \quad 4 \quad 5)$

$W_2 = (0 \quad 4 \quad 31 \quad 301 \quad 1001)$

By using equation (2.26), signal-to-noise ratios are calculated for each set of parameter settings by using both weight alternatives and numbers of observations by category as tabulated in Table 3.24.

Table 3.24. Weighted Signal to Noise Ratios for Surface Defects

Exp. No	**Number of Observations by Categories**					**SNR_1**	**SNR_2**
	I	**II**	**III**	**IV**	**V**		
1	9	0	0	0	0	0.0000	0.5012
2	5	2	2	0	0	-5.3712	-23.3668
3	1	0	6	2	0	-9.8528	-43.1752
4	0	8	1	0	0	-6.5854	-20.8279
5	0	1	0	4	4	-12.7107	-56.8628
6	1	0	4	1	3	-11.5297	-55.3718
7	0	1	1	4	3	-12.2760	-55.7331
8	3	0	2	1	3	-10.9498	-55.3691
9	0	0	0	4	5	-13.2222	-57.7593
10	9	0	0	0	0	0.0000	0.5012
11	8	1	0	0	0	-1.2494	-2.4988
12	2	3	3	0	1	-8.6530	-50.4789
13	4	2	2	1	0	-7.0852	-40.1216
14	2	3	4	0	0	-7.4473	-26.3593
15	0	1	1	1	6	-12.9861	-58.3134
16	3	4	2	0	0	-6.1396	-23.4374
17	2	1	0	2	4	-11.8564	-56.6789
18	0	0	0	2	7	-13.6173	-59.0280

Before ANOVA is applied, residual normality assumption is checked for SNR_1 and SNR_2 as shown on Figures A.1 and A.3, respectively. As seen on these figures, normality assumption is not violated for neither of the SNR values. Then, residual's homogeneity of variance assumption is checked for SNR_1 and SNR_2 as shown on Figures A.2 and A.4, respectively. As seen on these figures, residuals do not show any pattern, therefore homogeneity of variance assumption is not unrealistic for both SNR values.

Then, ANOVA is applied on SNR_1 and SNR_2 in order to detect the significant factors as shown in Figures 3.3 and 3.4, respectively. Factors A, B and C have significant effects on numbers of surface defects for both SNR_1 and SNR_2 with 90% confidence.

Analysis of Variance for SNR1, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	168.959	168.959	84.479	23.99	0.000
B	2	119.126	119.126	59.563	16.92	0.000
C	2	21.172	21.172	10.586	3.01	0.091
Error	11	38.729	38.729	3.521		
Total	17	347.987				

S = 1.87639 R-Sq = 88.87% R-Sq(adj) = 82.80%

Figure 3.3. Analysis of Variance (ANOVA) Results according to SNR_1 for WSNR Method in Surface Defect Example

Analysis of Variance for SNR2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	2	3213.1	3213.1	1606.6	14.39	0.001
B	2	2864.6	2864.6	1432.3	12.83	0.001
C	2	830.4	830.4	415.2	3.72	0.058
Error	11	1228.4	1228.4	111.7		
Total	17	8136.5				

S = 10.5674 R-Sq = 84.90% R-Sq(adj) = 76.67%

Figure 3.4. Analysis of Variance (ANOVA) Results according to SNR_2 for WSNR Method in Surface Defect Example

Then, the averages of signal to noise ratios for each significant factor are calculated according to each level as tabulated in Table 3.25. In this method, all calculations are made in MATLAB.

Table 3.25. Averages of Signal-to-noise Ratios for each Significant Factor and Level for Surface Defect Example

	FACTORS		
For Weight Set 1			
LEVELS	**A**	**B**	**C**
1	-4.1877	-5.3477	-7.6499
2	-9.7240	-8.2641	-9.9522
3	-11.3435	-11.6435	-7.6532
For Weight Set 2			
LEVELS	**A**	**B**	**C**
1	-19.7529	-23.1862	-32.5962
2	-42.9761	-36.8560	-47.5985
3	-51.3343	-54.0211	-33.8686

As seen in Table 3.25, parameter settings that have the maximum weighted signal-to-noise ratios are same for both weight sets. This fact shows that changes in scale of weights and spacing between weights have not had impact on optimal levels which are $A_1B_1C_1$.

By using Taguchi's prediction equation (3.2), the predicted SNR values for these optimum levels are found as given in Table 3.26.

Table 3.26. Predicted SNR Values for Optimal Parameter Settings Found by WSNR and Taguchi according to Taguchi's Method for Surface Defect Example

FACTORS			**SNR**	**METHODS**
A	**B**	**C**		
1	1	1	-0.0788	Taguchi's Method
1	1	1	-0.0788	WSNR

According to Table 3.26, WSNR method can find same result as parameter settings found by Taguchi's method.

3.1.5. Scoring Scheme Method for Surface Defect Example

In this method first of all, midranks for each category are calculated by using equation (2.27). Then, location score for each category is calculated by using equations (2.28) and (2.29). These calculated data are tabulated in Table 3.27. To illustrate, these calculations for category 1 is shown below.

For Category 1;

As seen in Table 3.28, sum of numbers of observations in category 1 is 49 and overall sum of numbers of observations is 162. Then,

$$q_1 = {}^{49}/_{162} = 0.3025$$

$$\tau_1 = {}^{0.3025}/_{2} = 0.1512$$

$$\tilde{\tau}_1 = 0.1512 - 0.5 = -0.3488$$

$$l_1 = \frac{-0.3488}{(0.3025\times(-0{,}3488)^2+0.1667\times(-0.1142)^2+0.1728\times0.0556^2+0.1358\times0.2099^2+0.2222\times0.3889^2)^{1/2}}$$

$$l_1 = -1.2402$$

Table 3.27. Calculated Data and Location Scores

	CATEGORIES				
	I	**II**	**III**	**IV**	**V**
q_i	0.3025	0.1667	0.1728	0.1358	0.2222
τ_i	0.1512	0.3858	0.5556	0.7099	0.8889
$\tilde{\tau}_i$	-0.3488	-0.1142	0.0556	0.2099	0.3889
l_i	-1.2402	-0.4061	0.1975	0.7463	1.3828

Table 3.28. Sum of Numbers of Observation in each Category and Overall Sum of Numbers of Each Category for Surface Defect Example

Exp. No	Numbers of Observations by Categories				
	I	II	III	IV	V
1	9	0	0	0	0
2	5	2	2	0	0
3	1	0	6	2	0
4	0	8	1	0	0
5	0	1	0	4	4
6	1	0	4	1	3
7	0	1	1	4	3
8	3	0	2	1	3
9	0	0	0	4	5
10	9	0	0	0	0
11	8	1	0	0	0
12	2	3	3	0	1
13	4	2	2	1	0
14	2	3	4	0	0
15	0	1	1	1	6
16	3	4	2	0	0
17	2	1	0	2	4
18	0	0	0	2	7
Total	49	27	28	22	36
Overall Sum	162				

Then, by using equation (2.30), location pseudo-observations are calculated as tabulated in Table 3.30 for each set of parameter settings.

Moreover, by using equations (2.31) and (2.32) dispersion scores are calculated for each category as shown in Table 3.29. To illustrate, these calculations for category 1 is shown below.

For Category 1;

$$e_1 = -1.2402 \times (-1.2402 - (0.3025 \times (-1.2402)^3 + 0.1667 \times (-0.4061)^3 + 0.1728 \times 0.1975^3 + 0.1358 \times 0.7463^3 + 0.2222 \times 1.3828^3)) - 1$$

$e_1 = 0.6091$

$d_1 =$

$$\frac{0.6091}{(0.3025\times(0.6091)^2+0.1667\times(-0.8118)^2+0.1728\times(-0.9723)^2+0.1358\times(-0.4858)^2+0.2222\times0.8330^2)^{1/2}}$$

$d_1 = 0.8056$

Table 3.29. Calculated Data and Dispersion Scores

	CATEGORIES				
	I	**II**	**III**	**IV**	**V**
e_i	0.6091	-0.8118	-0.9723	-0.4858	0.8330
d_i	0.8056	-1.0737	-1.2859	-0.6425	1.1017

In addition, by using equation (2.33), dispersion pseudo-observations are calculated as tabulated in Table 3.30 for each set of parameter settings.

Table 3.30. Location and Dispersion Pseudo-observations for each Experiment

Exp. No	**A**	**B**	**C**	**D**	**E**	**F**	**L_i**	**D_i**
1	1	1	1	1	1	1	-11.169	7.254
2	1	2	2	2	2	2	-6.616	-0.69
3	1	3	3	3	3	3	1.44	-8.196
4	2	1	1	2	2	3	-3.05	-9.878
5	2	2	2	3	3	1	8.11	0.762
6	2	3	3	1	1	2	4.447	-1.675
7	3	1	2	1	3	3	6.925	-1.626
8	3	2	3	2	1	1	1.571	2.509
9	3	3	1	3	2	2	9.899	2.938
10	1	1	3	3	2	1	-11.16	7.254
11	1	2	1	1	3	2	-10.326	5.374
12	1	3	2	2	1	3	-1.721	-4.366
13	2	1	2	3	1	2	-4.63	-2.139

Table 3.30 (cont'd) Location and Dispersion Pseudo-observations for each Experiment

14	2	2	3	1	2	3	-2.906	-6.754
15	2	3	1	2	3	1	8.836	3.609
16	3	1	3	2	3	2	-4.948	-4.45
17	3	2	1	3	1	3	4.138	3.66
18	3	3	2	1	2	1	11.173	6.428

After residual normality and homogeneity of variance assumptions are checked for L and D scores, ANOVA is applied for L and D as shown on Figure 3.5 and 3.6, respectively.

```
Analysis of Variance for Li, using Adjusted SS for Tests

Source  DF  Seq SS  Adj SS  Adj MS      F      P
A        2  418.03  418.03  209.01  15.63  0.000
B        2  330.53  330.53  165.26  12.36  0.001
Error   13  173.83  173.83   13.37
Total   17  922.39


S = 3.65670   R-Sq = 81.15%   R-Sq(adj) = 75.36%
```

Figure 3.5. Analysis of Variance (ANOVA) Results according to L Scores for SS Method in Surface Defect Example

As seen on Figure 3.5, only factors A and B have significant effect on location scores with p values smaller than 0.10.

```
Analysis of Variance for Di, using Adjusted SS for Tests

Source  DF   Seq SS   Adj SS   Adj MS      F      P
A        2   65.306   65.306   32.653   4.58  0.043
C        2   49.751   49.751   24.875   3.49  0.076
D        2   45.886   45.886   22.943   3.22  0.088
F        2  251.968  251.968  125.984  17.66  0.001
Error    9   64.189   64.189    7.132
Total   17  477.099


S = 2.67060   R-Sq = 86.55%   R-Sq(adj) = 74.59%
```

Figure 3.6. Analysis of Variance (ANOVA) Results according to D Scores for SS Method in Surface Defect Example

As seen on Figure 3.6, factors A, C, D and F have significant effect on dispersion scores with p values smaller than 0.10.

Then, the averages of location and dispersion pseudo-observations for each significant factor are calculated according to each level as seen in Table 3.31. In this method, all calculations are made in MATLAB.

Table 3.31. Averages of Location and Dispersion Pseudo-observations for each Factor

Level	**A**	**B**	**C**	**D**	**F**
Location					
1	-6.592	-4.672			
2	1.801	-1.005			
3	4.793	5.679			
Dispersion					
1	1.103		2.160	1.500	4.636
2	-2.679		-0.272	-2.211	-0.107
3	1.576		-1.885	0.713	-4.526

Since this is smaller-the-better type of a problem, the minimum average value for both location and dispersion pseudo-observations for each significant factor gives the optimal parameter settings. Hence, as seen in Table 3.31, optimal parameter settings are estimated to be A_1B_1 and $A_2C_3D_2F_3$ according to location and dispersion results, respectively. Since the optimal parameter settings of factor A for location and dispersion results differ, it is necessary to compromise between two different levels for the factor A. No method is suggested for compromising between two such different levels. Therefore, as explained in subsection 2.1.4, estimated location and dispersion scores are calculated for all possible levels of factor A by using equations (2.34) and (2.35), respectively. To illustrate, these calculations are shown below for level of 1 for factor A.

For Level of A = 1;

$$\bar{L} = {\sum_{i=1}^{18} L_i}/{18} = 0.0007$$

$$\bar{D} = {\sum_{i=1}^{18} D_i}/{18} = 0.0008$$

$$\hat{L} = 0.0007 + (-6.592 - 0.0007) + (-4.672 - 0.0007) = -11.2646$$

$$\hat{D} = 0.0008 + (1.103 - 0.0008) + (-1.885 - 0.0008) + (-2.211 - 0.0008) + (-4.526 - 0.0008) = -7.5224$$

When the calculations are done for all possible (1, 2, 3) levels of factor A, predicted location versus dispersion scores graph are shown on Figure 3.7.

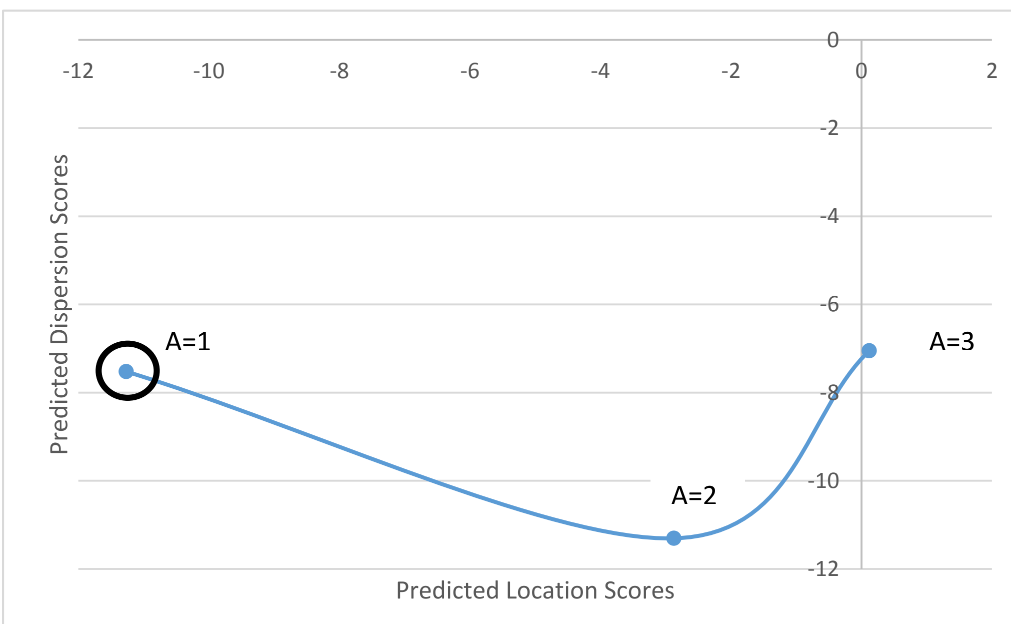

Figure 3.7. Predicted Location versus Dispersion Scores for Surface Defect Example

It is tried to determine the point that reduce both predicted location and dispersion scores. Hence, as seen on this figure there is too much difference between predicted location scores for level 1 and 2 of factor A whereas there is not too much difference between predicted dispersion scores for level 1 and 2. Therefore, it is better to choose the level 1 of A which has minimum predicted location score.

According to these results, the optimal parameter settings are $A_1B_1C_3D_2F_3$.

The predicted SNR values found by using Taguchi's prediction equation (3.2), for these optimum levels are given in Table 3.32.

Table 3.32. Predicted SNR Values for Optimal Parameter Settings Found by SS and Taguchi according to Taguchi's Method

FACTORS			SNR	METHODS
A	B	C		
1	1	3	-2.1170	SS
1	1	1	-0.0788	Taguchi's Method

As seen in Table 3.32, SS method cannot find the optimal parameter settings same as ones found by Taguchi.

3.1.6. Weighted Probability Scoring Scheme Method for Surface Defect Example

First of all, this method gives the target category the largest weight, thus location effect behaves as larger-the-better type. Therefore, since category 1 is the most desired category, the weights are chosen as given below.

$$Weights = (5 \quad 4 \quad 3 \quad 2 \quad 1)$$

Then, proportions of observation p_{ij} for each category i and set j of parameter settings are calculated as tabulated in Table 3.33. To illustrate, proportions of observations for first experiment are calculated as shown below.

$$p_{11} = \frac{9}{9} = 1$$

$$p_{21} = p_{31} = p_{41} = p_{51} = \frac{0}{9} = 0$$

Table 3.33. Proportions of observations p_{ij} for each category i and set j of parameter settings for Surface Defect Example

Exp. No	CATEGORIES				
	I	**II**	**III**	**IV**	**V**
1	1.00	0.00	0.00	0.00	0.00
2	0.56	0.22	0.22	0.00	0.00
3	0.11	0.00	0.67	0.22	0.00
4	0.00	0.89	0.11	0.00	0.00
5	0.00	0.11	0.00	0.44	0.44
6	0.11	0.00	0.44	0.11	0.33
7	0.00	0.11	0.11	0.44	0.33
8	0.33	0.00	0.22	0.11	0.33
9	0.00	0.00	0.00	0.44	0.56
10	1.00	0.00	0.00	0.00	0.00
11	0.89	0.11	0.00	0.00	0.00
12	0.22	0.33	0.33	0.00	0.11
13	0.44	0.22	0.22	0.11	0.00
14	0.22	0.33	0.44	0.00	0.00
15	0.00	0.11	0.11	0.11	0.67
16	0.33	0.44	0.22	0.00	0.00
17	0.22	0.11	0.00	0.22	0.44
18	0.00	0.00	0.00	0.22	0.78

Then, location scores are calculated depending on equation (2.36) as tabulated in Table 3.34 by using these weights and proportions of observations. To illustrate, location score is calculated for first set of parameter settings as shown below.

$$L_1 = 5 \times 1 + 4 \times 0 + 3 \times 0 + 2 \times 0 + 1 \times 0 = 5$$

Before calculating dispersion scores, target value set is determined as given below. In this set, all the observations are expected to be in category 1, therefore 5 is assigned for category 1.

$$Target = (5 \quad 0 \quad 0 \quad 0 \quad 0)$$

Then, dispersion scores are calculated as tabulated in Table 3.34 according to equation (2.37) by using weights, proportion of observation for each category and target value set. To illustrate, dispersion score is calculated for first set of parameter settings as shown below.

$$D_1^2 = (5 \times 1 - 5)^2 + (4 \times 0 - 0)^2 + (3 \times 0 - 0)^2 + (2 \times 0 - 0)^2 + (1 \times 0 - 0)^2 = 0$$

Instead of compromising between optimal levels for location and dispersion scores, mean square deviation (MSD) scores are calculated based on equation (2.38) by using location and dispersion scores in order to determine the optimal solution as given in Table 3.34. To illustrate, MSD score is calculated for first set of parameter settings as shown below.

$$E(MSD_1) \cong \frac{1}{5^2}\left(1 + \frac{3 \times 0^2}{5^2}\right) = 0.04$$

Table 3.34. Location, Dispersion and Mean Squared Deviation Scores for each Experiment

Exp. No	A	B	C	D	E	F	L_i	d_i^2	MSD
1	1	1	1	1	1	1	5.0000	0.0000	0.0400
2	1	2	2	2	2	2	4.3333	6.1728	0.1058
3	1	3	3	3	3	3	3.0000	23.9506	0.9982
4	2	1	1	2	2	3	3.8889	37.7531	0.5613
5	2	2	2	3	3	1	1.7778	26.1852	8.1808
6	2	3	3	1	1	2	2.4444	21.6914	1.9899
7	3	1	2	1	3	3	2.0000	26.2099	5.1644
8	3	2	3	2	1	1	2.8889	11.7160	0.6245
9	3	3	1	3	2	2	1.4444	26.0988	18.4654
10	1	1	3	3	2	1	5.0000	0.0000	0.0400
11	1	2	1	1	3	2	4.8889	0.5062	0.0445
12	1	3	2	2	1	3	3.5556	17.9136	0.4154
13	2	1	2	3	1	2	4.0000	9.0000	0.1680
14	2	2	3	1	2	3	3.7778	18.6790	0.3452
15	2	3	1	2	3	1	1.6667	25.8025	10.3920
16	3	1	3	2	3	2	4.1111	14.7160	0.2137
17	3	2	1	3	1	3	2.4444	15.7160	1.4879
18	3	3	2	1	2	1	1.2222	25.8025	35.3576

After residual normality and homogeneity of variance assumptions are checked for MSD scores, ANOVA is applied for MSD as shown on Figure 3.8.

```
Analysis of Variance for MSD, using Adjusted SS for Tests

Source  DF    Seq SS   Adj SS   Adj MS      F      P
A        2    307.47   307.47   153.73   7.99  0.016
B        2    390.25   390.25   195.13  10.14  0.009
C        2    172.06   172.06    86.03   4.47  0.056
E        2    212.15   212.15   106.07   5.51  0.037
F        2    186.75   186.75    93.38   4.85  0.048
Error    7    134.73   134.73    19.25
Total   17   1403.41


S = 4.38711   R-Sq = 90.40%   R-Sq(adj) = 76.69%
```

Figure 3.8. Analysis of Variance (ANOVA) Results according to MSD Scores for WPSS Method in Surface Defect Example

As seen on Figure 3.8, only factor D has no significant effect on MSD scores with 90% confidence.

In order to see how MSD scores for each level of significant factors behave, the averages of them for each significant factor are calculated according to each level as shown in Table 3.35.

Table 3.35. Averages of Mean Square Deviation Scores for each Significant Factor in Surface Defect Example

	FACTORS				
LEVELS	**A**	**B**	**C**	**E**	**F**
1	0.2740	1.0312	5.1652	0.7876	9.1058
2	3.6062	1.7981	8.2320	9.1459	3.4979
3	10.2189	11.2698	0.7019	4.1656	1.4954

Since levels that have the lowest MSD give the optimal levels, optimal levels are $A_1B_1C_3E_1F_3$.

The predicted SNR values found by using Taguchi's prediction equation (3.2), for these optimal parameter settings are given in Table 3.36. In this method, all calculations are made in MATLAB.

Table 3.36. Predicted SNR Values for Optimal Parameter Settings Found by WPSS and Taguchi according to Taguchi's Method

Factors			SNR	Methods
A	**B**	**C**		
1	1	3	-2.1170	WPSS
1	1	1	-0.0788	Taguchi's Method

As seen in Table 3.36, WPSS method cannot find the optimal parameter settings same as the ones found by Taguchi.

The methods are compared according to three different performance measures which are predicted SNRs calculated depending on Taguchi's Method, estimated probability $\hat{P}_t^{LR(P)}$ of observing target category calculated depending on LRMO and estimated percentage $\hat{P}_t^{ANOVA(CP)}$ of target category as tabulated in Tables 3.37, 3.38 and 3.39, respectively.

As seen in Table 3.37, LRMO, AA and WSNR show the best performance according to performance criterion of Taguchi's method.

As seen in Table 3.38, LRMO, AA and WSNR show the best performance according to performance criteria of LRMO.

As seen in Table 3.39, LRMO, AA and WSNR show the best performance according to performance criterion which is target category's percentage. In this comparison, since all factors are found as significant depending on ANOVA results depending on frequencies of categories and LRMO, WSNR, SS and WPSS find some factors as insignificant, some alternative optimal solutions for these methods are considered. In Table 3.39, optimal solution alternatives that give the best percentage of target category among all possible alternatives are tabulated for these methods.

Table 3.37. Comparison Table According to Prediction Depending on Taguchi's Method in Surface Defect Example

Factors			SNR	Methods
A	B	C		
1	1	1	-0.0788	Taguchi's Method
1	1	1	-0.0788	LRMO
1	1	1	-0.0788	AA (C=1)
1	1	1	-0.0788	WSNR
1	1	3	-2.1170	SS
1	1	3	-2.1170	WPSS

Table 3.38. Comparison Table According to Prediction Depending on LRMO in Surface Defect Example

FACTORS				$\hat{P}_i^{LR(P)}$					SNR	METHODS
A	B	C′	E	1	2	3	4	5		
1	1	3	1	0.9498	0.0346	0.0111	0.0030	0.0015	-1.0530	LRMO
1	1	3	1	0.9498	0.0346	0.0111	0.0030	0.0015	-1.0530	AA (C′=3)
1	1	3	1	0.9498	0.0346	0.0111	0.0030	0.0015	-1.0530	WSNR (E=1)
1	1	2	1	0.9219	0.0533	0.0175	0.0048	0.0025	-1.5559	SS (E=1)
1	1	2	1	0.9219	0.0533	0.0175	0.0048	0.0025	-1.5559	WPSS

Table 3.39. Comparison Table According to Prediction Depending on Observed Percentages of a Category in Surface Defect Example

FACTORS						$\hat{P}_i^{ANOVA(CP)}$					METHODS
A	B	C	D	E	F	I	II	III	IV	V	
1	1	1	1	1	1	92.5137	0.0000	6.3495	0.7870	0.3498	LRMO (D=1) & (F=1)
1	1	1	1	1	2	92.5137	1.2912	5.8203	0.2711	0.1037	LRMO (D=1) & (F=2)
1	1	1	1	1	1	92.5137	0.0000	4.1279	2.2995	1.0589	AA (C=1) & (F=1)
1	1	1	1	1	2	92.5137	2.8082	3.5605	0.8006	0.3170	AA (C=1) & (F=2)

Table 3.39 (cont'd). Comparison Table According to Prediction Depending on Observed Percentages of a Category in Surface Defect Example

1	1	3	1	1	1	92.5137	0.0000	6.3495	0.7870	0.3498	AA (C=3) & (F=1)
1	1	3	1	1	2	92.5137	1.2912	5.8203	0.2711	0.1037	AA (C=3) & (F=2)
1	1	1	1	1	1	92.5137	0.0000	4.1279	2.2995	1.0589	WSNR (D=E=F=1)
1	1	3	2	1	3	60.9242	32.4319	6.4232	0.2207	0.0000	SS (E=1)
1	1	3	1	1	3	74.3068	15.6836	9.5599	0.3460	0.1037	WPSS (D=1)

3.2. THICK-FILM RESISTOR PRODUCTION EXAMPLE

In this case, another data set, which is analyzed by Jeng and Guo (1996), is used to make another comparison of the methods. In this experiment, quality of chip resistor RC06 is tried to be improved. Manufacturers of resistors target to produce resistors that have resistance of 10Ω. Then, in this problem, amount of deviation from this target value is chosen as quality characteristics. Therefore, eight controllable factors that affect the amount of deviation from this target value are determined, and tabulated in Table 3.40. Moreover, percentage deviations from this target value are calculated and categorized into six categories by using Table 3.41 for different set of parameter settings.

Table 3.40. Controllable Factors and Their Levels for the Thick-film Resistor Production Example

FACTORS		LEVELS		
		1	**2**	**3**
A	Paste blends	70%:30%	80%:20%	-
B	Printing speed	62 mm/s	123mm/s	183mm/s
C	Printing height	2×0.5mm	2×0.64mm	3×0.5mm
D	Squeegee pressure	Scale 1	Scale 2	Scale 3
E	Screen tension	25 psi	22 psi	19 psi
F	Temperature	Profile 1	Profile 2	Profile 3
G	Conveyor speed	80 mm/min	100 mm/min	120 mm/min
H	Operator shift	1	2	3

Table 3.41. Percentage Deviation Range from Target

Category	**Percentage Deviation Range from Target**		**Degree of Modification**
I	0	-15	slightly
II	-16	-30	moderately
III	-31	-45	fairly
IV	-46	-60	heavily
V	-60	-∞	none (scrapped)
VI	∞	0	none (scrapped)

Numbers of occurrence of each category for 18 experimental runs are tabulated in Table 3.42. In addition, set of parameter settings of these 18 experimental runs are designed and applied at the selected factor levels according to the L_{18} orthogonal array as given in Table 3.43. Factor H is not taken into consideration by Jeng and Guo (1996) in their study. Factor H is not included while applying the methods in this study.

Table 3.42. Numbers of occurrences of each category for each set of parameter settings in the Thick-film Resistor Production Example

Exp. No	**CATEGORIES**					
	I	**II**	**III**	**IV**	**V**	**VI**
1	256	2250	2791	337	5	31
2	0	51	1791	3825	3	0
3	1	180	2404	3081	4	0
4	0	70	2085	3504	1	10
5	9	233	3665	1733	3	27
6	32	616	3878	1104	37	3
7	3	116	2945	2378	208	20
8	0	1	176	5477	16	0
9	17	325	5299	25	0	4
10	448	4323	892	6	0	1
11	1993	2798	559	14	0	306
12	1362	4226	38	1	0	43
13	13	1072	4570	6	0	9

Table 3.42 (cont'd) Numbers of occurrences of each category for each set of parameter settings in the Thick-film Resistor Production Example

14	2020	2723	486	74	2	365
15	768	4382	485	11	0	24
16	313	2735	2591	19	0	12
17	19	3997	1067	2	0	18
18	249	3755	1613	53	0	0

Table 3.43. Experimental Design for the Thick-film Resistor Production Example

Exp. No	A	B	C	D	E	F	G	H
1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3
4	1	2	1	1	2	2	3	3
5	1	2	2	2	3	3	1	1
6	1	2	3	3	1	1	2	2
7	1	3	1	2	1	3	2	3
8	1	3	2	3	2	1	3	1
9	1	3	3	1	3	2	1	2
10	2	1	1	3	3	2	2	1
11	2	1	2	1	1	3	3	2
12	2	1	3	2	2	1	1	3
13	2	2	1	2	3	1	3	2
14	2	2	2	3	1	2	1	3
15	2	2	3	1	2	3	2	1
16	2	3	1	3	2	3	1	2
17	2	3	2	1	3	1	2	3
18	2	3	3	2	1	2	3	1

In this example, since it is targeted to achieve minimum percentage deviation from target, the most desired category is category 1. Therefore, it is smaller-the-better type of a problem.

3.2.1. Logistic Regression Model Optimization for Thick-film Resistor Production Example

As explained in step 1 of subsection 2.1, an ordinal logistic regression model is fit by using MINITAB and all factors and three interactions except factor B have significant effect on the percentage deviation from the target value as shown in Figure 3.9. Because these factors' *p* values are smaller than 0.10 depending on 90% confidence. Since interaction of factors A and B has significant effect on the percentage deviation from target value, factor B is not omitted from the model. Also, on this figure the intercept of this model and coefficients of each factor are given.

Logistic Regression Table

						95% CI	
Predictor	Coef	SE Coef	Z	P	Odds Ratio	Lower	Upper
Const(1)	-9.58516	0.0974090	-98.40	0.000			
Const(2)	-5.98730	0.0932686	-64.19	0.000			
Const(3)	-2.28962	0.0921678	-24.84	0.000			
Const(4)	1.79114	0.0949946	18.86	0.000			
Const(5)	2.06968	0.0964670	21.45	0.000			
A	6.89476	0.0749910	91.94	0.000	987.09	852.16	1143.38
B	-0.0151971	0.0257878	-0.59	0.556	0.98	0.94	1.04
C	1.78355	0.0422295	42.23	0.000	5.95	5.48	6.46
D							
2	-2.02961	0.0218809	-92.76	0.000	0.13	0.13	0.14
3	-2.37854	0.0283523	-83.89	0.000	0.09	0.09	0.10
E	-0.756388	0.0135812	-55.69	0.000	0.47	0.46	0.48
F							
2	-2.62132	0.0827509	-31.68	0.000	0.07	0.06	0.09
3	1.68207	0.0825131	20.39	0.000	5.38	4.57	6.32
G	-0.989784	0.0086576	-114.32	0.000	0.37	0.37	0.38
A*B	-0.381750	0.0166596	-22.91	0.000	0.68	0.66	0.71
A*C	-0.902215	0.0277063	-32.56	0.000	0.41	0.38	0.43
F*A							
2	1.79222	0.0539103	33.24	0.000	6.00	5.40	6.67
3	-1.11130	0.0536476	-20.71	0.000	0.33	0.30	0.37

Log-Likelihood = -86301.322
Test that all slopes are zero: G = 93988.025, DF = 13, P-Value = 0.000

Figure 3.9. Ordinal Logistic Regression Results for Thick-film Resistor Production Example

Although some factors are found to be significant, the model does not fit the data adequately according to Pearson and Deviance test results as shown in Figure 3.10. Because, p-values of both tests are smaller than 0.10 as seen on Figure 3.10. The tests reject the null hypothesis that the model fits the response data adequately at $\alpha=0.10$.

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	2363357	72	0.000
Deviance	20422	72	0.000

Figure 3.10. Goodness-of-fit for the model for Thick-film Resistor Production Example

Parameter settings for significant factors in a full factorial design are generated by MATLAB as tabulated in Table B.1. Then, probability of observing each response category and signal-to-noise ratios are estimated by using these parameter settings based on the model fit to the response data. Equations (2.1) and (2.2) are used in estimation of probability of observing each response category. In addition, since it is smaller-the-better type of problem, equation (2.5) is used to calculate the signal-to-noise ratios. Both estimated probabilities of observing each category and the SNR values are tabulated in Table B.1.

As it is mentioned before, estimated probability $\hat{P}_t^{LR(P)}$ of observing target category and the signal-to-noise ratio are the performance measure to evaluate the performance of optimal levels. Therefore, 164^{th} trial gives both the maximum SNR value with -0.8406 and maximum estimated probability of observing category 1 with 0.9322 as seen in Table B.1 in Appendix. Therefore, the optimal parameter settings are found as $A_2B_1C_1D_1E_1F_2G_1$ as given in Table 3.44.

Table 3.44. Estimated Probability for each Category and Signal-to-noise Ratios for Optimal Levels for the Thick-film Resistor Production Example

FACTORS							$\hat{P}_i^{LR(P)}$						**SNR**
A	**B**	**C**	**D**	**E**	**F**	**G**	**I**	**II**	**III**	**IV**	**V**	**VI**	
2	1	1	1	1	2	1	0.9322	0.0658	0.0019	0	0	0	-0.8406

3.2.2. Accumulation Analysis Method for Thick-film Resistor Production Example

In accumulation analysis method, as explained in subsection 2.2 cumulative frequencies are created by adding frequencies of occurrence given in Table 3.42 for one category to the frequencies for the next category as shown in Table B.2.

Frequencies and cumulative frequencies are calculated by summing the frequencies in Table 3.42 and cumulative frequencies in Table B.2 for relevant level of each factor as given in Table B.3. Before determining the optimal parameter settings, analysis of variance (ANOVA) calculations are implemented as shown in Table B.4, B.5 and ANOVA table is given in Table 3.45. Since $F^{5}_{\infty(0.10)}$ is equal to 1.85 and critical F values for factor A given in Table 3.45 is greater than 1.85, factor A effect is determined as significant. Similarly, due to the fact that $F^{10}_{\infty(0.10)}$ is equal to 1.60 and critical F values for other factors given in Table 3.45 are greater than 1.60, other factor effects are determined as significant.

Table 3.45. Analysis of Variance (ANOVA) Results for Thick-film Resistor Production Example

Factors	df	S	MS	F
A	5	77069.6764	15413.9353	21688.8777
B	10	6092.1994	609.2199	857.2306
C	10	9913.8922	991.3892	1394.9792
D	10	5962.9123	596.2912	839.0387
E	10	15129.0110	1512.9011	2128.7962
F	10	928.9801	92.8980	130.7164
G	10	12708.1811	1270.8181	1788.1623
A×B	10	3269.6908	326.9691	460.0767
A×C	10	12652.5378	1265.2538	1780.3328
A×F	10	3161.8036	316.1804	444.8959
Error	507365	360576.1154	0.7107	
Total	507460	507465	1.0000	

Since the parameter settings that have the maximum frequencies in category 1 give the optimal solution, optimal levels are $A_2B_1C_2D_1E_1F_3G_1$ as seen in Table B.3.

Estimated frequencies for each category and factor and total estimated frequencies for each category are calculated by using equations (2.21) and (2.22), respectively. These results are tabulated in Table B.6.

By using logit (omega) transformation (Equation (2.23)) estimated frequencies and overall estimated frequencies for each category transformed into decibels as tabulated in Table B.7.

Then, by using equation (2.24) long–run performance is estimated for each category in decibels. Then, these estimates are transformed back by using again logit transformation.

The long-run performances in decibels and percentages $\hat{P}_i^{ANOVA(CP)}$ are tabulated in Table 3.46. Percentage of category 1 gives the performance of optimal parameter settings given in Table 3.46.

In this method, calculations are made in MATLAB.

Table 3.46. Estimated Percentage for each Category for Optimal Levels for Thick-film Resistor Production Example

	FACTORS							$\hat{P}_i^{ANOVA(CP)}$					
	A	**B**	**C**	**D**	**E**	**F**	**G**	**I**	**II**	**III**	**IV**	**V**	**VI**
In dB	2	1	2	1	1	3	1	4.8110	16.5295	22.2551	5.7897	3.5637	0.000
In %	2	1	2	1	1	3	1	**75.1708**	22.6536	1.5835	0.5921	0.0000	0.000

3.2.3. Weighted Signal-to-noise Ratio for Thick-film Resistor Production Example

In this method, first of all weights are given to categories proportional to the quality loss. However, there is no guidance given for determining scale of weights and spacing between weights. But, in the surface defect example the results are not changed when two different weight sets are compared to see the effect of choosing different weights on the optimal solution. Therefore, the weights are given to categories as shown below.

$W = (1 \quad 2 \quad 3 \quad 4 \quad 5 \quad 6)$

By using equation (2.26), signal-to-noise ratios are calculated for each set of parameter settings by using weights and number of observations by category as tabulated in Table B.8.

Before ANOVA is applied, residual assumptions are checked for SNR values. Normality and residual's homogeneity of variance assumptions are not violated for SNR values.

Then, ANOVA is applied on SNR values in order to detect the significant factors as shown on Figure 3.11. As seen on this figure, factors A, C, D and G have significant effects on response data with 90% confidence.

Analysis of Variance for SNR, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	1	51.9367	51.9367	51.9367	106.11	0.000
C	2	3.5113	3.5113	1.7557	3.59	0.067
D	2	2.8883	2.8883	1.4442	2.95	0.098
G	2	6.1533	6.1533	3.0766	6.29	0.017
Error	10	4.8946	4.8946	0.4895		
Total	17	69.3842				

S = 0.699611   R-Sq = 92.95%   R-Sq(adj) = 88.01%

Figure 3.11. Analysis of Variance (ANOVA) Results according to SNR Scores for WSNR Method in Thick-film Resistor Production Example

Then, the averages of signal to noise ratios for each significant factor are calculated according to each level as tabulated in Table B.9. In this method, all calculations are made in MATLAB.

As seen in Table B.9, parameter settings that have the maximum averages of signal-to-noise ratios give the optimal solution which is $A_2C_3D_1G_1$.

3.2.4. Scoring Scheme Method for Thick-film Resistor Production Example

In this method first of all, midranks for each category are calculated by using equation (2.27). Then, location score for each category is calculated by using equations (2.28) and (2.29). These calculated data are tabulated in Table B.10. Then, by using equation (2.30), location pseudo-observations are calculated as tabulated in Table B.12 for each set of parameter settings.

Moreover, by using equations (2.31) and (2.32) dispersion scores are calculated for each category as shown in Table B.11. In addition, by using equation (2.33), dispersion pseudo-observations are calculated as tabulated in Table B.12 for each set of parameter settings.

After residual normality and homogeneity of variance assumptions are checked for L and D scores, ANOVA is applied for L and D as shown on Figure 3.12 and 3.13, respectively.

Analysis of Variance for Li, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	1	268017276	268017276	268017276	345.41	0.000
B	2	10754701	10754701	5377350	6.93	0.028
C	2	9372164	9372164	4686082	6.04	0.037
D	2	16189241	16189241	8094620	10.43	0.011
E	2	16431201	16431201	8215600	10.59	0.011
G	2	32390510	32390510	16195255	20.87	0.002
Error	6	4655617	4655617	775936		
Total	17	357810709				

S = 880.872   R-Sq = 98.70%   R-Sq(adj) = 96.31%

Figure 3.12. Analysis of Variance (ANOVA) Results according to L Scores for SS Method in Thick-film Resistor Production Example

As seen on Figure 3.12, only factor F has no significant effect on location scores with 90% confidence.

Analysis of Variance for Di, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
C	2	42948045	42948045	21474023	4.22	0.039
E	2	45875472	45875472	22937736	4.51	0.032
Error	13	66078811	66078811	5082985		
Total	17	154902328				

S = 2254.55   R-Sq = 57.34%   R-Sq(adj) = 44.22%

Figure 3.13. Analysis of Variance (ANOVA) Results according to D Scores for SS Method in Thick-film Resistor Production Example

As seen on Figure 3.13, factors C and E have significant effect on dispersion scores with p values smaller than 0.10.

Then, the averages of location and dispersion pseudo-observations for each significant factor are calculated according to each level as seen in Table B.13. In this method, all calculations are made in MATLAB.

Since this experiment is smaller-the-better type of problem, the minimum average value for both location and dispersion pseudo-observations for each significant factor gives the optimal parameter settings. Hence, as seen in Table B.13, optimal parameter settings are estimated to be $A_2B_1C_3D_1E_1G_1$ and C_1E_3 according to location and dispersion results, respectively. Since the optimal parameter settings of factors C and E for location and dispersion results differ, it is necessary to compromise between two different levels for the factors C and E. No method is suggested for compromising between two such different levels. Therefore, as explained in subsection 2.1.4, estimated location and dispersion scores are calculated for all possible levels of factors C and E by using equations (2.34) and (2.35), respectively.

When the calculations are done for all possible (1, 2, 3) levels of factors C and E, predicted location versus dispersion scores graph are shown on Figure 3.14.

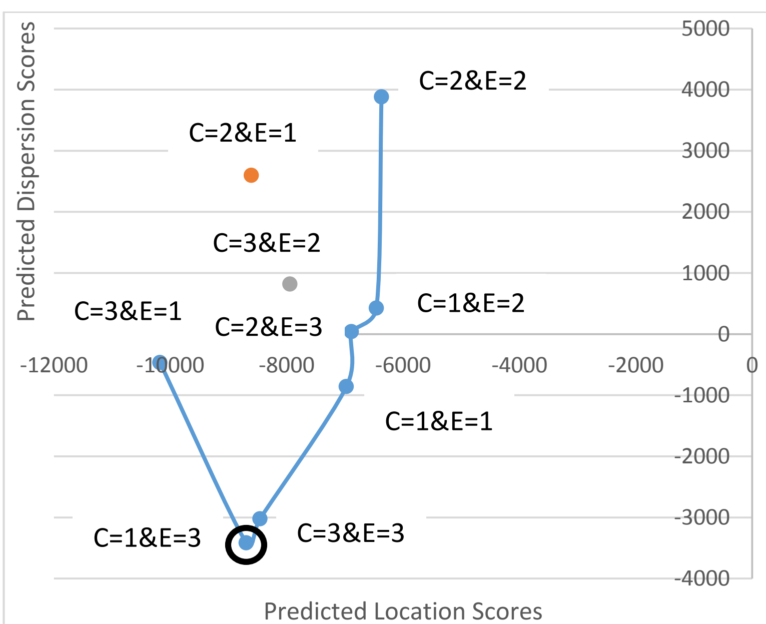

Figure 3.14. Predicted Location versus Dispersion Scores for Thick-film Resistor Production Example

It is tried to determine the point that achieve minimize both predicted location and dispersion scores. Hence, as seen on Figure 3.14 there is too much difference between predicted dispersion scores for point 1 (C=3&E=1) and 2 (C=1&E=3) whereas there is not too much difference between predicted location scores for point 1 and 2. Therefore, it is better to choose the level 1 and 3 of factors C and E respectively.

According to these results, the optimal parameter settings are $A_2B_1C_1D_1E_3G_1$.

3.2.5. Weighted Probability Scoring Scheme Method (WPSS) for Thick-film Resistor Production Example

First of all, this method gives the target category the largest weight, thus location effect behaves as larger-the-better type. Therefore, since category 1 is the most desired category, the weights are chosen as given below.

$$Weights = (6 \quad 5 \quad 4 \quad 3 \quad 2 \quad 1)$$

Then, proportions of observation p_{ij} for each category i and set j of parameter settings are calculated as tabulated in Table B.14. Then, location scores are calculated depending on equation (2.36) as tabulated in Table B.15 by using these weights and proportions of observations. Before calculating dispersion scores, target value set is determined as given below. In this set, all the observations are expected to be in category 1, therefore 6 is assigned for category 1.

$$Target = (6 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0)$$

Then, dispersion scores are calculated as tabulated in Table B.15 according to equation (2.37) by using weights, proportion of observation for each category and target value set.

Instead of compromising between optimal levels for location and dispersion scores, mean square deviation (MSD) scores are calculated based on equation (2.38) by using location and dispersion scores in order to determine the optimal solution as given in Table B.15.

After residual normality and homogeneity of variance assumptions are checked for MSD scores, ANOVA is applied for MSD as shown on Figure 3.15.

Analysis of Variance for MSD, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	1	1.71100	1.71100	1.71100	152.27	0.000
B	2	0.12795	0.12795	0.06398	5.69	0.041
C	2	0.13698	0.13698	0.06849	6.10	0.036
D	2	0.14803	0.14803	0.07401	6.59	0.031
E	2	0.36144	0.36144	0.18072	16.08	0.004
G	2	0.41613	0.41613	0.20807	18.52	0.003
Error	6	0.06742	0.06742	0.01124		
Total	17	2.96895				

S = 0.106002   R-Sq = 97.73%   R-Sq(adj) = 93.57%

Figure 3.15. Analysis of Variance (ANOVA) Results according to MSD Scores for WPSS Method in Thick-film Resistor Production Example

As seen on Figure 3.15, only factor F has no significant effect on MSD scores with 90% confidence.

In order to see how MSD scores for each level of significant factors behaves, the averages of them for each factor are calculated according to each level as shown in Table B.16. As seen in this table, levels that have the lowest MSD scores give the optimal levels. Then, the optimal parameter settings are $A_2B_1C_3D_1E_1G_1$. In this method, all calculations are made in MATLAB.

The methods are compared according to two different performance measures which are estimated probability $\hat{P}_i^{LR(P)}$ of observing target category calculated depending on LRMO and estimated percentage $\hat{P}_i^{ANOVA(CP)}$ of target category as tabulated in Table 3.47 and 3.48 respectively.

As seen in Table 3.47, LRMO shows the best performance according to performance criteria of LRMO.

Table 3.47. Comparison Table According to Prediction Depending on LRMO in Thick-film Resistor Production Example

FACTORS							$\hat{P}_i^{LR(P)}$						SNR	METHODS
A	**B**	**C**	**D**	**E**	**F**	**G**	**1**	**2**	**3**	**4**	**5**	**6**		
2	1	1	1	1	2	1	**0.9322**	0.0658	0.0019	0.0000	0.0000	0.0000	-0.8406	LRMO
2	1	2	1	1	3	1	0.7497	0.2412	0.0088	0.0002	0.0000	0.0000	-2.5473	AA
2	1	3	1	1	2	1	0.9296	0.0684	0.0020	0.0001	0.0000	0.0000	-0.8709	WSNR (B=1&E=1 &F=2)
2	1	1	1	3	2	1	0.7519	0.2391	0.0087	0.0002	0.0000	0.0000	-2.5300	SS (F=2)
2	1	3	1	1	2	1	0.9296	0.0684	0.0020	0.0001	0.0000	0.0000	-0.8709	WPSS (F=2)

Table 3.48. Comparison Table According to Prediction Depending on Percentages of Observing a Category in Thick-film Resistor Production Example

FACTORS							$\hat{P}_i^{ANOVA(CP)}$						METHODS
A	**B**	**C**	**D**	**E**	**F**	**G**	**1**	**2**	**3**	**4**	**5**	**6**	
2	1	1	1	1	2	1	27.6800	64.9877	7.3323	0.0000	0.0000	0.0000	LRMO
2	1	2	1	1	3	1	**75.1708**	22.6536	1.5835	0.5921	0.0000	0.0000	AA
2	1	3	1	1	2	1	56.6300	42.0517	1.1465	0.0000	0.0000	0.1718	WSNR (B=1&E=1 &F=2)
2	1	1	1	3	2	1	3.6519	82.1264	14.2217	0.0000	0.0000	0.0000	SS (F=2)
2	1	3	1	1	2	1	56.6300	42.0517	1.1465	0.0000	0.0000	0.1718	WPSS (F=2)

As seen in Table 3.48, AA shows the best performance according to performance criterion which is target category's percentage.

In this comparison, since all factors are found as significant depending on ANOVA results depending on frequencies of categories and depending on LRMO and WSNR, SS and WPSS find some factors as insignificant, some alternative optimal solutions for these methods are considered. In Table 3.47 and 3.48, optimal solution alternatives that give the best performance measure among all possible alternatives are tabulated for these methods.

3.3. SIMULATED EXAMPLE IN FOAM MOLDING EXPERIMENT

In this case, quality of urethane-foam product is tried to be improved and experiment is formed to decrease voids in this product. These data are originally analyzed by Jinks (1987). Then, Bayesian analysis method is applied on these data by Chipman and Hamada (1996). Later on, Logistic Regression Model Optimization is applied on these data by Köksal et al. (2006). In this data set, response data, which is quality of urethane-foam product, contain three levels which are very good (I), acceptable (II), needs repair (III). In addition, controllable and uncontrollable (noise) factors considered in this experiment are given in Table 3.49. In this example, it is targeted to achieve to produce product included in category 1. Therefore, it is smaller-the-better type of a problem. In addition to this, H and I are the uncontrollable (noise) factors.

Table 3.49. Controllable and Uncontrollable Factors and Their Levels for Simulated Example

CONTROLLABLE FACTORS		**LEVELS**	
		0	**1**
A	Shot Weight	185	250
B	Mold Temperature	70 ^{o}F	120 ^{o}F
C	Foam Block	use	do not use
D	RTV Insert	use	do not use
E	Vent Shell	vented	unvented
F	Spray Wax Viscosity	2:1	4:1
G	Tool Elevation	level	elevated
UNCONTROLLABLE FACTORS		**0**	**1**
H	Shift	Second	Third
I	Shell quality	Good	Bad

8 different experimental runs are conducted for different parameter settings of controllable and uncontrollable factors. For each experimental run, numbers of occurrences are tabulated for different parameter settings of uncontrollable factors (H and I) in Table 3.50. In addition, set of parameter settings of these 8 experimental runs are designed and applied at the selected factor levels according to the L_8 orthogonal array as given in Table 3.50.

Table 3.50. Numbers of Occurrences of Each Category for Each Set of Parameter Settings in Foam Molding Experiment

Exp. No	FACTORS							H (1) / I (1)			H (0) / I (1)			H (1) / I (0)			H (0) / I (0)		
	A	B	C	D	E	F	G	I	II	III	I	II	III	I	II	III	I	II	III
1	0	0	0	0	0	0	0	3	6	1	6	4	0	1	4	5	0	10	0
2	0	0	0	1	1	1	1	0	3	7	3	4	3	0	6	4	0	7	3
3	0	1	1	0	0	1	1	0	0	10	0	1	9	0	0	10	0	0	10
4	0	1	1	1	1	0	0	0	0	10	0	10	0	0	3	7	0	9	1
5	1	0	1	0	1	0	1	3	5	2	3	7	0	3	5	2	1	6	3
6	1	0	1	1	0	1	0	2	8	0	4	5	1	0	5	5	1	5	4
7	1	1	0	0	1	1	0	2	7	1	2	5	3	2	7	1	1	6	3
8	1	1	0	1	0	0	1	0	4	6	1	7	2	0	4	6	0	3	7

Since noise factors cannot be included in calculations, numbers of occurrences are summed for each category as shown in Table 3.51.

Table 3.51. Numbers of Occurrences of Each Category for Each Set of Parameter Settings for Foam Molding Experiment

Exp. No	FACTORS							CATEGORIES		
	A	B	C	D	E	F	G	I	II	III
1	0	0	0	0	0	0	0	10	24	6
2	0	0	0	1	1	1	1	3	20	17
3	0	1	1	0	0	1	1	0	1	39
4	0	1	1	1	1	0	0	0	22	18
5	1	0	1	0	1	0	1	10	23	7

Table 3.51 (cont'd) Numbers of Occurrences of Each Category for Each Set of Parameter Settings for Foam Molding Experiment

6	1	0	1	1	0	1	0	7	23	10
7	1	1	0	0	1	1	0	7	25	8
8	1	1	0	1	0	0	1	1	18	21

When Köksal et al. (2006) fit an ordinal logistic regression model on the response data, the estimated coefficients of model are shown on Figure 3.16. In addition, the optimal parameter settings and the estimated probability of observing each category for these optimal parameter settings are given in Table 3.52. In Köksal's study, it is found that Factor D does not have significant effect on quality characteristics of product. Moreover, the estimated probability of observing targeted category is found as 0.7864.

```
Logistic Regression Table

                                                  Odds     95% CI
Predictor       Coef   SE Coef      Z       P    Ratio   Lower  Upper
Const(1)    -1.13122  0.319809  -3.54   0.000
Const(2)     1.82540  0.330082   5.53   0.000
A
  1          1.38742  0.279459   4.96   0.000    4.00    2.32   6.93
B
  1         -1.82512  0.286177  -6.38   0.000    0.16    0.09   0.28
C
  1        -0.976926  0.276184  -3.54   0.000    0.38    0.22   0.65
E
  1          1.04737  0.276648   3.79   0.000    2.85    1.66   4.90
F
  1         -1.02634  0.277629  -3.70   0.000    0.36    0.21   0.62
G
  1         -1.53620  0.281162  -5.46   0.000    0.22    0.12   0.37


Log-Likelihood = -255.082
Test that all slopes are zero: G = 110.806, DF = 6, P-Value = 0.000
```

Figure 3.16. Ordinal Logistic Regression Results for Foam Molding Experiment

In addition, the model fits the data adequately according to Pearson and Deviance test results. Because, p-values of both tests are larger than 0.10 as seen on Figure 3.17. Hence, the tests fail to reject the null hypothesis that the model fits that data adequately at α=0.10.

```
Goodness-of-Fit Tests

Method    Chi-Square  DF      P
Pearson      4.21124   8  0.838
Deviance     6.38399   8  0.604
```

Figure 3.17. Goodness-of-fit for the model for Data of Foam Molding Experiment

Table 3.52. Optimal Parameter Settings and the Estimated Probabilities Found by Köksal et al. (2006)

FACTORS						P_i			SNR
A	**B**	**C**	**E**	**F**	**G**	**I**	**II**	**III**	
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289

We use the same experimental design of Table 3.51 and take the probability models generated by Köksal et al. (2006) as "true models", and add them random error to generate a new data set, and measure performances of all models on this new data. Standard normally distributed errors are randomly generated as tabulated in Table 3.53. To illustrate, procedure for generation of error values is explained below.

Table 3.53. Standard Normally and Randomly Generated Errors

TRIAL	**EXP. NO**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	-1.0149	-0.4677	0.2696	0.8123	0.1769	-1.2833	-0.4140	0.4759
2	-0.4711	-0.1249	0.4943	0.5455	-0.3075	-2.3290	-0.4383	1.4122
3	0.1370	1.4790	-1.4831	-1.0516	-0.1318	0.9019	2.0034	0.0226

Table 3.53 (cont'd) Standard Normally and Randomly Generated Errors

4	-0.2919	-0.8608	-1.0203	0.3975	0.5954	-1.8356	0.9510	-0.0479
5	0.3018	0.7847	-0.4470	-0.7519	1.0468	0.0668	-0.4320	1.7013
6	0.3999	0.3086	0.1097	1.5163	-0.1980	0.0355	0.6489	-0.5097
7	-0.9300	-0.2339	1.1287	-0.0326	0.3277	2.2272	-0.3601	-0.0029
8	-0.1768	-1.0570	-0.2900	1.6360	-0.2383	-0.0692	0.7059	0.9199
9	-2.1321	-0.2841	1.2616	-0.4251	0.2296	-0.5073	1.4158	0.1498
10	1.1454	-0.0867	0.4754	0.5894	0.4400	0.2358	-1.6045	1.4049
11	-0.6291	-1.4694	1.1741	-0.0628	-0.6169	0.2458	1.0289	1.0341
12	-1.2038	0.1922	0.1269	-2.0220	0.2748	0.0700	1.4580	0.2916
13	-0.2539	-0.8223	-0.6568	-0.9821	0.6011	-0.6086	0.0475	-0.7777
14	-1.4286	-0.0942	-1.4814	0.6125	0.0923	-1.2226	1.7463	0.5667
15	-0.0209	0.3362	0.1555	-0.0549	1.7298	0.3165	0.1554	-1.3826
16	-0.5607	-0.9047	0.8186	-1.1187	-0.6086	-1.3429	-1.2371	0.2445
17	2.1778	-0.2883	-0.2926	-0.6264	-0.7371	-1.0322	-2.1935	0.8084
18	1.1385	0.3501	-0.5408	0.2495	-1.7499	1.3312	-0.3334	0.2130
19	-2.4969	-1.8359	-0.3086	-0.9930	0.9105	-0.4189	0.7135	0.8797
20	0.4413	1.0360	-1.0966	0.9750	0.8671	-0.1403	0.3174	2.0389
21	-1.3981	2.4245	-0.4930	-0.6407	-0.0799	0.8998	0.4136	0.9239
22	-0.2551	0.9594	-0.1807	1.8089	0.8985	-0.3001	-0.5771	0.2669
23	0.1644	-0.3158	0.0458	-1.0799	0.1837	1.0294	0.1440	0.6417
24	0.7477	0.4286	-0.0638	0.1992	0.2908	-0.3451	-1.6387	0.4255
25	-0.2730	-1.0360	0.6113	-1.5210	0.1129	1.0128	-0.7601	-1.3147
26	1.5763	1.8779	0.1093	-0.7236	0.4400	0.6293	-0.8188	-0.4164
27	-0.4809	0.9407	1.8140	-0.5933	0.1017	-0.2130	0.5197	1.2247
28	0.3275	0.7873	0.3120	0.4013	2.7873	-0.8657	-0.0142	-0.0436
29	0.6647	-0.8759	1.8045	0.9421	-1.1667	-1.0431	-1.1555	0.5824
30	0.0852	0.3199	-0.7231	0.3005	-1.8543	-0.2701	-0.0095	-1.0065
31	0.8810	-0.5583	0.5265	-0.3731	-1.1407	-0.4381	-0.6898	0.0645
32	0.3232	-0.3114	-0.2603	0.8155	-1.0933	-0.4087	-0.6667	0.6003
33	-0.7841	-0.5700	0.6001	0.7989	-0.4336	0.9835	0.8641	-1.3615
34	-1.8054	-1.0257	0.5939	0.1202	-0.1685	-0.2977	0.1134	0.3476
35	1.8586	-0.9087	-2.1860	0.5712	-0.2185	1.1437	0.3984	-0.1818
36	-0.6045	-0.2099	-1.3270	0.4128	0.5413	-0.5316	0.8840	-0.9395
37	0.1034	-1.6989	-1.4410	-0.9870	0.3893	0.9726	0.1803	-0.0375
38	0.5632	0.6076	0.4018	0.7596	0.7512	-0.5223	0.5509	-1.8963
39	0.1136	-0.1178	1.4702	-0.6572	1.7783	0.1766	0.6830	-2.1280
40	-0.9047	0.6992	-0.3268	-0.6039	1.2231	0.9707	1.1706	-1.1769

$$Logit[P(Y=1)] = -1.131 + 1.387A - 1.825B - 0.977C + 1.047E - 1.026F - 1.536G + \epsilon$$

$$Logit[P(Y=2)] = 1.825 + 1.387A - 1.825B - 0.977C + 1.047E - 1.026F - 1.536G + \epsilon$$

where $\epsilon \sim N(0,1)$

$$P(Y=1) = \frac{e^{-1.131+1.387A-1.825B-0.977C+1.047E-1.026F-1.536G+\epsilon}}{1+e^{-1.131+1.387A-1.825B-0.977C+1.047E-1.026F-1.536G+\epsilon}}$$

$$P(Y=2) = \frac{e^{1.825+1.387A-1.825B-0.977C+1.047E-1.026F-1.536G+\epsilon}}{1+e^{1.825+1.387A-1.825B-0.977C+1.047E-1.026F-1.536G+\epsilon}}$$

$$P(Y=3) = 1 - P(Y=1) - P(Y=2)$$

For the first error value (-1.0149) and the first trial *{0 0 0 0 0 0}*, probability values of observing each category are calculated as following;

$P(Y=1) = 0.1047$ $\quad P(Y=2) = 0.5875$ $\quad P(Y=3) = 0.3078$

Therefore, for the first trial, the experiment gives response as 2. Because estimated probability of observing category 2 has the maximum value among all three probabilities.

When it is applied for all error values and trials, the response data are determined as given in Table 3.54.

Table 3.54. Modified Foam Molding Experimental Design in Simulated Example

Trial	**A**	**B**	**C**	**E**	**F**	**G**	**I**	**II**	**III**
1	0	0	0	0	0	0	5	32	3
2	0	0	0	1	1	1	0	20	20
3	0	1	1	0	1	1	0	0	40
4	0	1	1	1	0	0	0	20	20
5	1	0	1	1	0	1	4	34	2
6	1	0	1	0	1	0	1	34	5
7	1	1	0	1	1	0	3	34	3
8	1	1	0	0	0	1	0	19	21

Then, all methods are applied on these simulated data, the methods that can have the closest estimated probability and same optimal parameter settings given in Table 3.52, are considered as methods that have the best performance.

3.3.1. Logistic Regression Model Optimization for Simulated Example

As explained in step 1 of subsection 2.1, an ordinal logistic regression model is fit to the response data by using MINITAB. All factors have significant effect on quality of product with 90% confidence as shown in Figure 3.18. Also, on this figure the intercept of this model and coefficients of each factor are given.

```
Logistic Regression Table

                                                    Odds     95% CI
Predictor        Coef    SE Coef       Z       P   Ratio  Lower  Upper
Const(1)    -2.17613   0.459466   -4.74   0.000
Const(2)     2.95922   0.514106    5.76   0.000
A
  1          2.77901   0.443075    6.27   0.000   16.10   6.76  38.38
B
  1         -3.01943   0.459484   -6.57   0.000    0.05   0.02   0.12
C
  1         -1.85186   0.444141   -4.17   0.000    0.16   0.07   0.37
E
  1          1.89602   0.444149    4.27   0.000    6.66   2.79  15.90
F
  1         -2.03791   0.456902   -4.46   0.000    0.13   0.05   0.32
G
  1         -2.83337   0.443649   -6.39   0.000    0.06   0.02   0.14

Log-Likelihood = -171.071
Test that all slopes are zero: G = 171.643, DF = 6, P-Value = 0.000
```

Figure 3.18. Ordinal Logistic Regression Results for Simulated Data

In addition, the model fits to the response data adequately, according to Pearson and Deviance test results. Because, p-values of both tests are larger than 0.10 as seen on Figure 3.19. Hence, the tests fail to rejects the null hypothesis that the model fits to these data adequately at α=0.10. Since these p values are greater than p values given in Figure 3.17, this model fits to the data more adequately.

```
Goodness-of-Fit Tests

Method      Chi-Square  DF      P
Pearson        1.81138   8  0.986
Deviance       2.45634   8  0.964
```

Figure 3.19. Goodness of fit for the model for Simulated Data

Parameter settings for significant factors in a full factorial design are generated by MATLAB as tabulated in Table C.1. Then, probability of observing each response category and signal-to-noise ratios are estimated by using these parameter settings based on the model fit to the response data. Equations (2.1) and (2.2) are used in estimation of probability of observing each response category. In addition, since it is smaller-the-better type of problem, equation (2.5) is used to calculate signal-to-noise ratios. Both estimated probabilities of observing each category and SNR values are tabulated in Table C.1.

As it is mentioned before, estimated probability $\hat{P}_t^{LR(P)}$ of observing target category and signal-to-noise ratio are the performance measure to evaluate the performance of optimal levels. Therefore, 37^{th} trial gives both maximum SNR value with -0.8998 and maximum estimated probability of observing category 1 with 0.9241 as seen in Table C.1. Therefore, the optimal parameter settings are found as $A_1B_0C_0E_1F_0G_0$ by using simulated data as given in Table 3.55 same as the optimal levels found by Köksal et al. (2006) models. This optimal solution is the same as the solution obtained by the true model.

Table 3.55. True Probability for Each Category and Signal-to-noise Ratios for Optimal Levels in Simulated Example

FACTORS						P_i			SNR	DATA ANALYZED
A	B	C	E	F	G	I	II	III		
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289	True model, Simulated Data

3.3.2. Accumulation Analysis Method for Simulated Example

In accumulation analysis method, as explained in subsection 2.2 cumulative frequencies are created by adding frequencies of occurrence given in Table 3.54 for one category to the frequencies for the next category as seen in Table C.2.

Frequencies and cumulative frequencies are calculated by summing the frequencies in Table 3.54 and cumulative frequencies in Table C.2 for relevant level of each factor as given in Table C.3. Before determining the optimal parameter settings, analysis of variance (ANOVA) calculations are implemented as shown in Tables C.4 and C.5 and ANOVA table is given in Table 3.56. Since $F^2_{626(0,10)}$ is equal to 2.31 and critical F values for all factors given in Table 3.56 are greater than 2.31, all factor effects are determined as significant.

Table 3.56. Analysis of Variance (ANOVA) Results

Factors	**df**	**S**	**MS**	**F**
A	2	37.5671	18.7836	23.6486
B	2	43.6631	21.8316	27.4860
C	2	6.1721	3.0861	3.8854
E	2	7.9289	3.9645	4.9913
F	2	8.5996	4.2998	5.4135
G	2	38.8500	19.4250	24.4561
Error	626	497.2190	0.7943	
Total	638	640	1.0031	

Since the parameter settings that have maximum frequencies in category 1 give the optimal solution, optimal levels are $A_1B_0C_0E_1F_0G_0$ as seen in Table C.3.

This optimal solution is the same as the solution obtained by the true model as tabulated in Table 3.57.

Table 3.57. True Probability for Each Category and Signal-to-noise Ratios for Optimal Levels for AA Results in Simulated Example

FACTORS						P_i			SNR	DATA ANALYZED
A	B	C	E	F	G	I	II	III		
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289	True model, Simulated Data

3.3.3. Weighted Signal-to-noise Ratio for Simulated Example

In this method, first of all weights are given to categories proportional to the quality loss. However, there is no guidance given for determining scale of weights and spacing between weights. But, in the surface defect example the results are not changed when two different weight sets are compared to see the effect of choosing different weights on the optimal solution. Therefore, the weights are given to categories as shown below.

$W = (1 \quad 2 \quad 3)$

By using equation (2.26), signal-to-noise ratios are calculated for each set of parameter settings by using weights and number of observations by category as tabulated in Table C.6.

Before ANOVA is applied, residual normality and homogeneity of variance assumptions are checked for SNR scores. Then, ANOVA is applied on SNR values in order to detect the significant factors as shown on Figure 3.20. Factors A, B and G are found significant effects on response data with 90% confidence.

```
Analysis of Variance for SNR, using Adjusted SS for Tests

Source  DF   Seq SS  Adj SS  Adj MS     F      P
A        1   2.9803  2.9803  2.9803  4.30  0.107
B        1   3.6020  3.6020  3.6020  5.19  0.085
G        1   3.0493  3.0493  3.0493  4.40  0.104
Error    4   2.7751  2.7751  0.6938
Total    7  12.4068


S = 0.832938   R-Sq = 77.63%   R-Sq(adj) = 60.86%
```

Figure 3.20. Analysis of Variance (ANOVA) Results according to SNRs for WSNR Method in Simulated Example

Then, the averages of signal to noise ratios for each factor are calculated according to each level as tabulated in Table C.7. In this method, all calculations are made in MATLAB.

As seen in Table C.7, parameter settings that have maximum averages of signal-to-noise ratios give the optimal solution which is $A_1B_0G_0$ same as the optimal levels found by Köksal et al. (2006) models.

Since factors C, E and F are insignificant factors and all factors are included in the logistic regression model, alternative parameter settings are tried for factors C, E and F. The best combination of levels are $C_0E_1F_0$.

This optimal solution is the same as the solution obtained by the true model as tabulated in Table 3.58.

Table 3.58. True Probability for Each Category and Signal-to-noise Ratios for Optimal Levels for WNSR Results in Simulated Example

FACTORS						***P_i***			**SNR**	**DATA ANALYZED**
A	**B**	**C**	**E**	**F**	**G**	**I**	**II**	**III**		
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289	True model, Simulated Data

3.3.4. Scoring Scheme Method for Simulated Example

In this method first of all, midranks for each category are calculated by using equation (2.27). Then, location score for each category is calculated by using equations (2.28) and (2.29). These calculated data are tabulated in Table C.8. Then, by using equation (2.30), location pseudo-observations are calculated as tabulated in Table C.10 for each set of parameter settings.

Moreover, by using equations (2.31) and (2.32) dispersion scores are calculated for each category as shown in Table C.9. In addition, by using equation (2.33), dispersion pseudo-observations are calculated as tabulated in Table C.10 for each set of parameter settings.

After residual normality and homogeneity of variance assumptions are checked for L and D scores, ANOVA is applied for L and D as shown on Figure 3.21 and 3.22, respectively.

```
Analysis of Variance for Li, using Adjusted SS for Tests

Source  DF  Seq SS  Adj SS  Adj MS     F      P
A        1  1369.4  1369.4  1369.4  4.90  0.091
B        1  1617.2  1617.2  1617.2  5.79  0.074
G        1  1438.3  1438.3  1438.3  5.15  0.086
Error    4  1117.3  1117.3   279.3
Total    7  5542.1


S = 16.7129   R-Sq = 79.84%   R-Sq(adj) = 64.72%
```

Figure 3.21. Analysis of Variance (ANOVA) Results according to L Scores for SS Method in Simulated Example

As seen on Figure 3.21, factors A, B and G have significant effect on location scores with 90% confidence.

```
Analysis of Variance for Di, using Adjusted SS for Tests

Source  DF  Seq SS  Adj SS  Adj MS     F      P
A        1  104.70  104.70  104.70  2.16  0.202
G        1   45.24   45.24   45.24  0.93  0.379
Error    5  242.84  242.84   48.57
Total    7  392.78


S = 6.96902   R-Sq = 38.17%   R-Sq(adj) = 13.44%
```

Figure 3.22. Analysis of Variance (ANOVA) Results according to D Scores for SS Method in Simulated Example

As seen on Figure 3.22, all factors are found as insignificant. However, p values of factors A and G are not so much greater than 0.10. Therefore, factors A and G are considered as significant.

Then, the averages of location and dispersion pseudo-observations for each significant factor are calculated according to each level as seen in Table C.11. In this method, all calculations are made in MATLAB.

Since this experiment is smaller-the-better type of problem, the minimum average value for both location and dispersion pseudo-observations for each significant factor gives the optimal parameter settings as seen in Table C.11 which are $A_0B_1G_1$and A_0G_1, respectively.

Furthermore, estimated probabilities of observing each category by SS method after simulation is calculated. In the comparison, since all factors are found as significant depending on true model and SS finds some factors as insignificant, some alternative optimal solutions for these methods are considered. In Table 3.59, optimal solution alternative that gives the best performance measure among all possible alternatives is tabulated for SS methods.

Then, this optimal solution is worse than the solution obtained by the true model as tabulated in Table 3.59.

Table 3.59. True Probability for Each Category and Signal-to-noise Ratios for Optimal Levels for SS Results in Simulated Example

FACTORS						P_i			**SNR**	**DATA ANALYZED**
A	**B**	**C**	**E**	**F**	**G**	**I**	**II**	**III**		
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289	True model
0	1	0	1	0	1	**0.0309**	0.3493	0.6198	-8.4548	Simulated Data

3.3.5. Weighted Probability Scoring Scheme Method for Simulated Example

First of all, this method gives the target category the largest weight, thus location effect behaves as larger-the-better type. Therefore, since category 1 is the most desired category, the weights are chosen as given below.

$Weights = (3 \quad 2 \quad 1)$

Then, proportions of observation p_{ij} for each category i and set j of parameter settings are calculated as tabulated in Table C.12. Then, location scores are calculated depending on equation (2.36) as tabulated in Table C.13 by using these weights and proportions of observations. Before calculating dispersion scores, target value set is determined as given below. In this set, all the observations are expected to be in category 1, therefore 3 is assigned for category 1.

$Target = (3 \quad 0 \quad 0)$

Then, dispersion scores are calculated as tabulated in Table C.13 according to equation (2.37) by using weights, proportion of observation for each category and target value set. Instead of compromising between optimal levels for location and dispersion scores, mean square deviation (MSD) scores are calculated based on equation (2.38) by using location and dispersion scores in order to determine the optimal solution as given in C.13.

Before ANOVA is applied, residual normality and homogeneity of variance assumptions are checked for MSD values. Then, ANOVA is applied on MSD values in order to detect the significant factors. All factors are found insignificant effects on response data with 90% confidence. Therefore, this method should not be applied on this example. Even so, optimal parameter settings are found by ignoring ANOVA results in order to see performance of WPSS method on this data if it found effects of all factors as significant.

In order to see how MSD scores for each level of factors behaves, the averages of them for each factor are calculated according to each level as shown in Table C.14. As seen in this table, levels that have the lowest MSD scores give the optimal levels which are $A_1B_0C_0E_1F_0G_0$ same as the optimal levels found by Köksal et al. (2006) models. In this method, all calculations are made in MATLAB.

This optimal solution is the same as the solution obtained by the true model as tabulated in Table 3.60.

Table 3.60. True Probability for Each Category and Signal-to-noise Ratios for Optimal Levels for WPSS Results in Simulated Example

FACTORS						***P_i***			**SNR**	**DATA ANALYZED**
A	**B**	**C**	**E**	**F**	**G**	**I**	**II**	**III**		
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289	True model, Simulated Data

The methods are compared according to true probabilities calculated by using true model as seen in Table 3.61.

Table 3.61. Comparison Table According to True Models in Simulated Example

FACTORS						P_i			SNR	METHODS
A	**B**	**C**	**E**	**F**	**G**	**1**	**2**	**3**		
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289	True models
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289	LRMO
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289	AA
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289	WSNR
0	1	0	1	0	1	**0.0309**	0.3493	0.6198	-8.4548	SS
1	0	0	1	0	0	**0.7864**	0.1996	0.0139	5.9289	WPSS*

As seen in Table 3.61, all methods except SS method show the best performance according to true models.

In this comparison, since all factors are found as significant depending on true model, and WSNR and SS find some factors as insignificant, some alternative optimal solutions for these methods are considered. In Table 3.61, optimal solution alternative that gives the best performance measure among all possible alternatives is tabulated for SS and WSNR methods.

3.4. INKJET PRINTER EXAMPLE

In this case, another data set, which is analyzed by Logothetis (1992), is used to make another comparison of the methods. In this experiment, an ink mixture that is used in ink-jet printer, is tried to be prepared in order to have high adhesion property. In order to evaluate the quality of ink’s adhesion, ten printed samples are kept overnight for fixed time period under same conditions. Then, the samples are rubbed and the numbers of rubs are counted until prints turn to unreadable writings. If a printer does not turn to unreadable format in 26 rubs, then this ink mixture is considered in good adhesion quality. The controllable factors that affect the quality of adhesion are tabulated in Table 3.62. These factors are the ingredients of ink mixture and levels are the percentage amounts of these substances. When the percentage amounts of these controllable factors are estimated, the remaining percentage amount is accepted for methanol (MeOH).

---

* WPSS finds all factors as insignificant. These optimal parameter settings are found by ignoring ANOVA results.

Table 3.62. Controllable Factors and Their Levels for Inkjet Printer Example

FACTORS		LEVELS	
		1	**2**
A	Dye	1%	3%
B	Carbitol	1.5%	2.5%
C	PM	6.5%	9.5%
D	Resin	8%	12%
E	Water	10%	20%

Sets of parameter settings of 8 experimental runs are designed and applied at the selected factor levels according to the L_8 as given in Table 3.63. In addition, numbers of rubs counted for these 8 experimental runs and 10 samples are tabulated in Table 3.64.

Table 3.63. Experimental Design for the Inkjet Printer Example

Exp. No	A	B	C	D	E
1	0	0	0	0	0
2	0	0	1	1	1
3	0	1	0	1	1
4	0	1	1	0	0
5	1	0	0	0	1
6	1	0	1	1	0
7	1	1	0	1	0
8	1	1	1	0	1

Table 3.64. Numbers of Rubs Counted for Each Sample and Experimental Runs for Inkjet Printer Example

Exp. No	**Samples**									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	2	9	5	25	2	19	15	17	26	13
2	>26	11	20	11	>26	18	11	10	16	6
3	1	2	2	5	>26	11	1	2	4	3
4	15	3	3	19	>26	19	14	3	18	14
5	19	5	2	1	2	2	6	3	>26	4
6	9	6	8	7	3	5	3	7	2	1
7	>26	20	>26	20	>26	>26	>26	>26	24	10
8	>26	>26	1	15	19	>26	>26	26	3	>26

Then, by using ranges for numbers of rubs given in Table 3.65, the response data given in Table 3.64 are categorized. Then, numbers of occurrences of each category for 8 experiments are tabulated in Table 3.66.

Table 3.65. Ranges for Numbers of Rubs in Inkjet Example

Category	**Range**	
	Min	**Max**
I	1	10
II	11	18
III	19	26
IV	26	∞

Table 3.66. Numbers of Occurrences in Each Category for each Set of Parameter Settings in Inkjet Printer Example

Exp. No	**CATEGORIES**			
	I	**II**	**III**	**IV**
1	4	3	3	0
2	2	5	1	2
3	8	1	0	1
4	3	4	2	1
5	8	0	1	1
6	10	0	0	0
7	1	0	3	6
8	2	1	1	6

In this example, it is targeted to have prints that included in category IV, therefore this case is larger-the better type of problem.

3.4.1. Logistic Regression Model Optimization for Inkjet Printer Example

As explained in step 1 of subsection 2.1, an ordinal logistic regression model is fit by using MINITAB and all factors except factors D and E, and two interactions have significant effect on quality of ink adhesion with 90% confidence as seen on Figure 3.23. Also, on this figure the intercept of this model and coefficients of each factor are given.

Logistic Regression Table

Predictor	Coef	SE Coef	Z	P	Odds Ratio	95% CI Lower	Upper
Const(1)	0.0488407	0.528516	0.09	0.926			
Const(2)	1.16995	0.552725	2.12	0.034			
Const(3)	2.20485	0.604785	3.65	0.000			
A							
2	1.66124	0.924073	1.80	0.072	5.27	0.86	32.21
B							
2	0.800176	0.607265	1.32	0.188	2.23	0.68	7.32
C							
2	-1.11110	0.612561	-1.81	0.070	0.33	0.10	1.09
A*B							
2*2	-5.43671	1.12200	-4.85	0.000	0.00	0.00	0.04
A*C							
2*2	2.02185	0.986952	2.05	0.041	7.55	1.09	52.26

Log-Likelihood = -79.301
Test that all slopes are zero: G = 43.089, DF = 5, P-Value = 0.000

Figure 3.23. Ordinal Logistic Regression Results for Inkjet Printer Example

Moreover, the model fits the response data adequately, according to Pearson and Deviance test results. Because, p-values of both tests are larger than 0.10 as seen on Figure 3.24. Hence, the tests fail to reject the null hypothesis that the model fits to these data adequately with 90% confidence.

Goodness-of-Fit Tests

Method	Chi-Square	DF	P
Pearson	20.0683	16	0.217
Deviance	21.5168	16	0.159

Figure 3.24. Goodness-of-fit for the Model for Inkjet Printer Example

Parameter settings for significant factors in a full factorial design are generated by MATLAB as tabulated in Table D.1. Then, probability of observing each response category and signal-to-noise ratios are estimated by using these parameter settings based on the model fit to the data. Equations (2.1) and (2.2) are used in estimation of probability of observing each response category. In addition, since it is larger-the-better type of problem, equation (2.6) is used to calculate the signal-to-noise ratios. Both estimated probabilities of observing each category and SNR values are tabulated in Table D.1.

As it is mentioned before, estimated probability $\hat{P}_t^{LR(P)}$ of observing target category and signal-to-noise ratio are the performance measure to evaluate the performance of optimal levels. Therefore, 7^{th} trial gives both maximum SNR value with 10.1376 and maximum estimated probability for category 4 with 0.6836 as seen in Table D.1. Therefore, the optimal levels are found as $A_1B_1C_0$ as given in Table 3.67.

Table 3.67. Estimated Probability for Each Category and Signal-to-noise Ratios for Optimal Levels in Inkjet Printer Example

FACTORS			$\hat{P}_i^{LR(P)}$				**SNR**
A	**B**	**C**	**I**	**II**	**III**	**IV**	
1	1	0	0.0509	0.0903	0.1752	0.6836	10.1376

3.4.2. Accumulation Analysis Method for Inkjet Printer Example

In accumulation analysis method, as explained in subsection 2.2 cumulative frequencies are created by adding frequencies of occurrence given in Table 3.66 for one category to the frequencies for the next category as seen in Table D.2.

Frequencies and cumulative frequencies are calculated by summing the frequencies in Table 3.66 and cumulative frequencies in Table D.2 for relevant level of each factor as given in Table D.3. Before determining the optimal parameter settings, analysis of variance (ANOVA) calculations are implemented as shown in Table D.4, D.5 and ANOVA table is given in Table 3.68. Since $F^3_{216(0.10)}$ is equal to 2.11 and critical F values for all factors except factors C, D and E given in Table 3.68 are greater than 2.11, all factors except factors C, D and E are determined as significant. Since interaction between factors A and C has significant effect on quality characteristics, C is included in the model.

Table 3.68. Analysis of Variance (ANOVA) Results

Factors	df	S	MS	F
A	3	10.3689	3.4563	4.8615
B	3	21.9629	7.3210	10.2974
A×B	3	43.1543	14.3848	20.2331
C	3	1.0965	0.3655	0.5141
A×C	3	7.6628	2.5543	3.5928
D	3	1.0965	0.3655	0.5141
E	3	1.0926	0.3642	0.5122
Error	216	153.5655	0.7110	
Total	237	240	1.0127	

Since the parameter settings that have maximum frequencies in category 4 give the optimal solution, optimal parameter settings are $A_1B_1C_0$ as seen in Table D.3.

Estimated frequencies for each category and factor and total estimated frequencies for each category are calculated by using equations (2.21) and (2.22), respectively. These results are tabulated in Table D.6.

By using logit (omega) transformation (Equation (2.23)), estimated frequencies and overall estimated frequencies for each category transformed into decibels as tabulated in Table D.7.

Then, by using equation (2.24), long–run performance is estimated for each category in decibels. Then, these estimates are transformed back by using again logit transformation. The long-run performances in decibels and percentages $\hat{P}_i^{ANOVA(CP)}$ are tabulated in Table 3.69. Percentage of category 4 gives the performance of optimal parameter settings given in Table 3.69.

In this method, calculations are made in MATLAB.

Table 3.69. Estimated Percentage for each Category for Optimal Levels for Inkjet Printer Example

	FACTORS			$\hat{P}_i^{ANOVA(CP)}$			
	A	**B**	**C**	**I**	**II**	**III**	**IV**
In decibel	1	1	0	-7.9690	-9.5790	-4.7610	∞
In percentage	1	1	0	13.7622	0.0000	11.2769	74.9609

3.4.3. Weighted Signal-to-noise Ratio for Inkjet Printer Example

In this method, first of all weights are given to categories proportional to the quality loss. However, there is no guidance given for determining scale of weights and spacing between weights. But, in the surface defect example the results are not changed when two different weight sets are compared to see the effect of choosing different weights on the optimal solution. Therefore, the weights are given to categories as shown below.

$W = (4 \quad 3 \quad 2 \quad 1)$

By using equation (2.26), the signal-to-noise ratios are calculated for each set of parameter settings by using weights and number of observations by category as tabulated in Table D.8.

Before ANOVA is applied, residual normality and homogeneity of variance assumptions are checked for SNR values. Normality and residual's homogeneity of variance assumptions are not violated for SNR values.

Then, ANOVA is applied on SNR values in order to detect the significant factors as shown on Figure 3.25. As seen on this figure, factors A, B, C and E, and interactions of factors A and B, A and C have significant effects on response data with 90% confidence.

Analysis of Variance for SNR, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	1	2.7997	2.7997	2.7997	677.66	0.024
B	1	10.4077	10.4077	10.4077	2519.18	0.013
C	1	0.0010	0.0010	0.0010	0.23	0.713
E	1	0.3761	0.3761	0.3761	91.04	0.066
A*B	1	20.0142	20.0142	20.0142	4844.41	0.009
A*C	1	3.3998	3.3998	3.3998	822.91	0.022
Error	1	0.0041	0.0041	0.0041		
Total	7	37.0026				

S = 0.0642760   R-Sq = 99.99%   R-Sq(adj) = 99.92%

Figure 3.25. Analysis of Variance (ANOVA) Results according to SNR Scores for WSNR Method in Inkjet Printer Example

Then, the averages of signal to noise ratios for each significant factor and interaction are calculated according to each level as tabulated in Table D.9. In this method, all calculations are made in MATLAB.

As seen in Table D.9, parameter settings that have maximum averages of signal-to-noise ratios give the optimal solution. However, according to averages of SNRs for actual factor and interaction, the optimal levels for factor C differentiate. Optimal level for factor C is 1 for results of actual factor whereas it is 0 for results of interaction. Since difference between averages of two levels for actual factor is too small, optimal level of factor C is assumed to be 0. Then, the optimal solution is determined as $A_1B_1C_0E_0$.

3.4.4. Scoring Scheme Method for Inkjet Printer Example

In this method first of all, midranks for each category are calculated by using equation (2.27). Then, location score for each category is calculated by using equations (2.28) and (2.29). These calculated data are tabulated in Table D.10. Then, by using equation (2.30), location pseudo-observations are calculated as tabulated in Table D.12 for each set of parameter settings.

Moreover, by using equations (2.31) and (2.32) dispersion scores are calculated for each category as shown in Table D.11. In addition, by using equation (2.33), dispersion pseudo-observations are calculated as tabulated in Table C.12 for each set of parameter settings.

After residual normality and homogeneity of variance assumptions are checked for L and D scores, ANOVA is applied for L and D as shown on Figure 3.26 and 3.27, respectively.

Analysis of Variance for Li, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	1	3.986	3.986	3.986	2.06	0.288
B	1	85.179	85.179	85.179	44.03	0.022
C	1	2.316	2.316	2.316	1.20	0.388
A*B	1	204.546	204.546	204.546	105.73	0.009
A*C	1	38.058	38.058	38.058	19.67	0.047
Error	2	3.869	3.869	1.935		
Total	7	337.953				

S = 1.39092   R-Sq = 98.86%   R-Sq(adj) = 95.99%

Figure 3.26. Analysis of Variance (ANOVA) Results according to L Scores for SS Method in Inkjet Printer Example

As seen on Figure 3.26, factors A, B, C and interactions of A and B, A and C have significant effect on location scores with 90% confidence.

Analysis of Variance for Di, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	1	139.809	139.809	139.809	14.86	0.012
B	1	15.869	15.869	15.869	1.69	0.251
Error	5	47.036	47.036	9.407		
Total	7	202.714				

S = 3.06711   R-Sq = 76.80%   R-Sq(adj) = 67.52%

Figure 3.27. Analysis of Variance (ANOVA) Results according to D Scores for SS Method in Inkjet Printer Example

As seen on Figure 3.27, only factor A has significant effect on dispersion scores with p values smaller than 0.10.

Then, the averages of location and dispersion pseudo-observations for each actual factor and the averages of location pseudo-observations for the interactions are calculated according to each level as seen in Table D.13 and D.14, respectively. In this method, all calculations are made in MATLAB.

Since this experiment is larger-the-better type of problem, the maximum average value for location and the minimum dispersion pseudo-observations for each factor gives the optimal parameter settings. Hence, as seen in Table D.13 and D.14, the optimal levels for location and dispersion results for factor A differ, it is necessary to compromise between two different levels of factor A.

When compromising is implemented based on subsection 2.1.4, estimated location and dispersion scores are calculated for all possible levels of factors A, B and C by using equations (2.34) and (2.35), respectively.

When the calculations are done for all possible (1, 2, 3) levels of factors A, B and C, predicted location versus dispersion scores graph are shown on Figure 3.28.

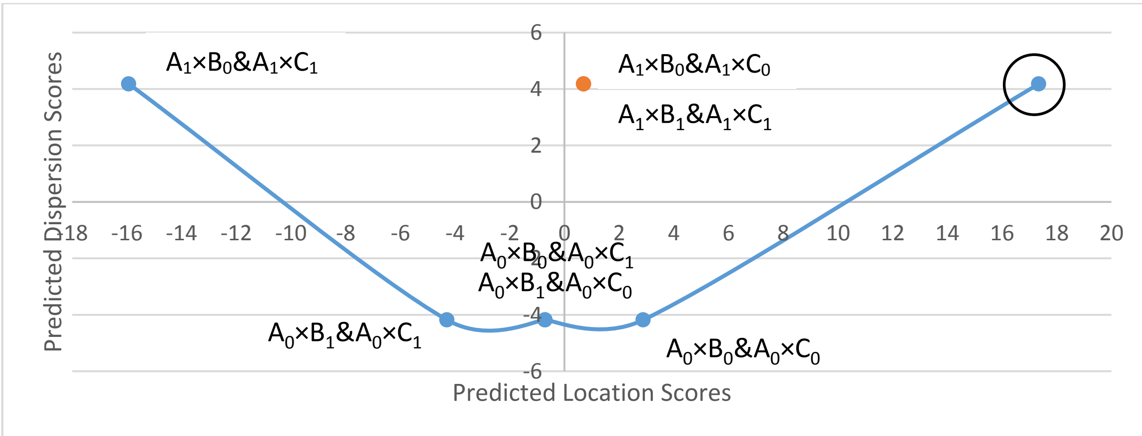

Figure 3.28. Predicted Location versus Dispersion Scores for Inkjet Printer Example

It is tried to determine the point that achieve maximize predicted location and minimize dispersion scores. Hence, as seen on this figure there is too much difference between predicted location scores for point 7 ($A_0 \times B_0 \& A_0 \times C_0$) and 8 ($A_1 \times B_1 \& A_1 \times C_0$) whereas there is not so much difference between predicted dispersion scores for point 7 and 8. Therefore, it is better to choose point 8 ($A_1 \times B_1 \& A_1 \times C_0$).

Then, optimal parameter settings are found as $A_1B_1C_0$ by SS method.

3.4.5. Weighted Probability Scoring Scheme Method for Inkjet Printer Example

First of all, this method gives the target category the largest weight, thus location effect behaves as larger-the-better type. Therefore, the weights are chosen as given below.

$$Weights = (1 \quad 2 \quad 3 \quad 4)$$

Then, proportions of observation p_{ij} for each category i and set j of parameter settings are calculated as tabulated in Table D.15. Then, location scores are calculated depending on equation (2.36) as tabulated in Table D.16 by using these weights and proportions of observations. Before calculating dispersion scores, target value set is determined as given below. In this set, all the observations are expected to be in category 4, therefore 4 is assigned for category 4.

$$Target = (0 \quad 0 \quad 0 \quad 4)$$

Then, dispersion scores are calculated as tabulated in Table D.16 according to equation 2.37 by using weights, proportion of observation for each category and target value set. Instead of compromising between optimal levels for location and dispersion scores, mean square deviation (MSD) scores are calculated based on equation (2.38) by using location and dispersion scores in order to determine the optimal solution as given in Table D.16.

Before ANOVA is applied, residual normality and homogeneity of variance assumptions are checked for MSD scores. Then, it is seen that homogeneity of variance assumption is not satisfied as shown on Figure 3.29.

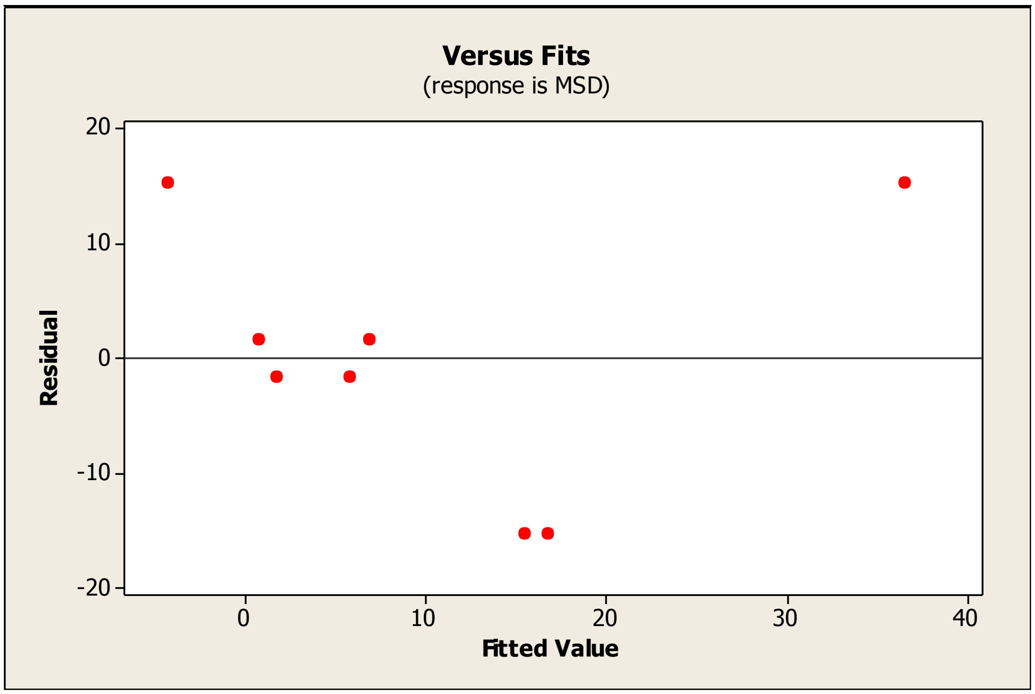

Figure 3.29. Residual vs. Fitted Value Plot for MSD in Inkjet Printer Example

Therefore, logarithm of MSD scores are taken in order to satisfy homogeneity of variance assumption as tabulated in Table D.16. Then, this assumption is not violated as seen on Figure 3.30.

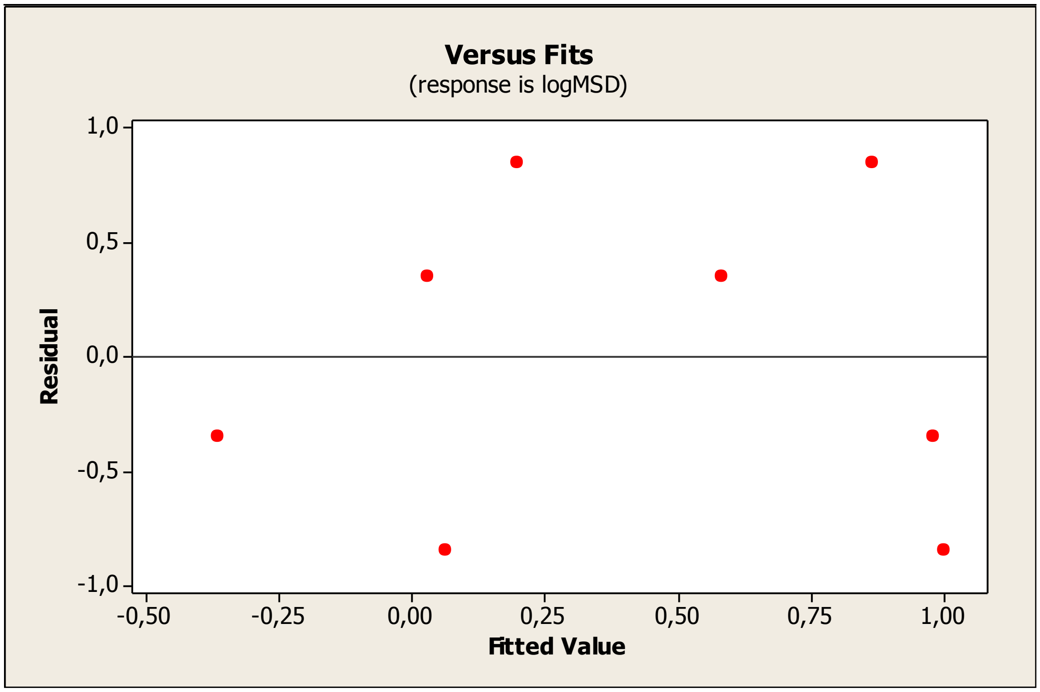

Figure 3.30. Residual vs. Fitted Value Plot for logMSD in Inkjet Printer Example

Then, ANOVA is applied on logMSD scores as shown in Figure 3.31.

Analysis of Variance for logMSD, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	1	0.1409	0.1409	0.1409	2.09	0.285
B	1	1.5353	1.5353	1.5353	22.82	0.041
C	1	0.0107	0.0107	0.0107	0.16	0.729
A*B	1	2.8813	2.8813	2.8813	42.83	0.023
A*C	1	0.5040	0.5040	0.5040	7.49	0.112
Error	2	0.1346	0.1346	0.0673		
Total	7	5.2068				

S = 0.259384   R-Sq = 97.42%   R-Sq(adj) = 90.95%

Figure 3.31. Analysis of Variance (ANOVA) Results according to MSD Scores for WPSS Method in Inkjet Printer Example

As seen on Figure 3.31, factors A, B, C and interactions of A and B, A and C have significant effect on logMSD scores with 90% confidence.

In order to see how logarithm of MSD scores for each level of significant factors behaves, the logarithm of averages of MSD for each significant factor are calculated according to each level as shown in Table D.17. In order to decide the levels of factors A and B interacted and factors A and C interacted, logMSD interaction graphs are drawn for A×B and A×C as shown on Figures 3.32 and 3.33, respectively. Since the point that has the minimum logMSD value, the optimal parameter settings are $A_1B_1C_0$.

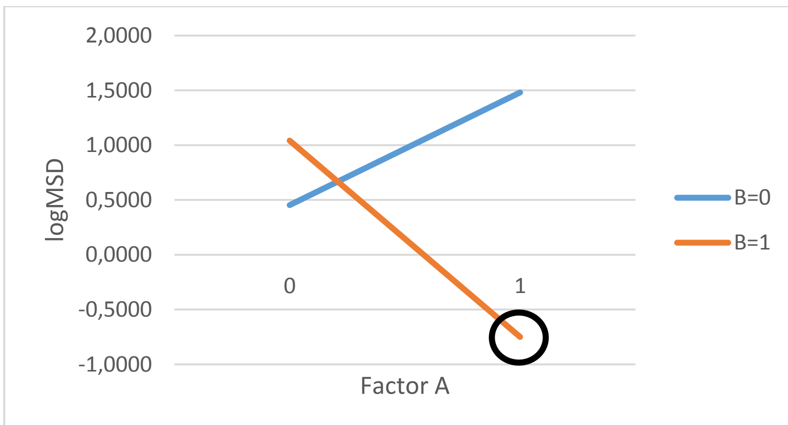

Figure 3.32. Interaction Graph or factors A and B

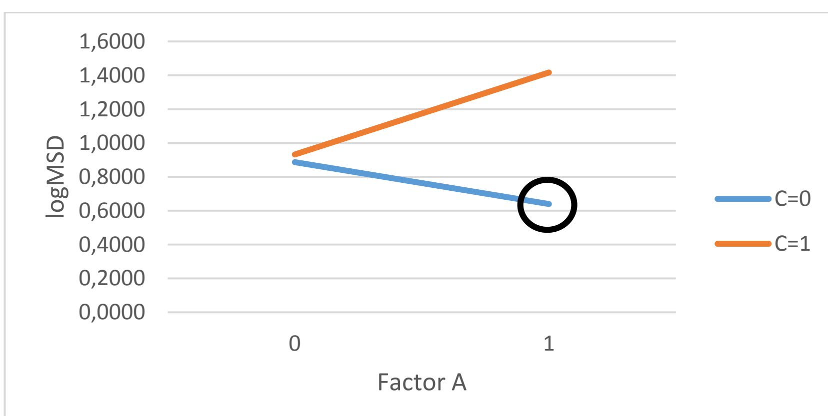

Figure 3.33. Interaction Graph or factors A and C

In this method, all calculations are made in MATLAB. Moreover, according to WPSS method, no way is suggested to examine performance of optimal levels.

The methods are compared according to two different performance measures which are estimated probability $\hat{P}_t^{LR(P)}$ of observing target category calculated depending on LRMO and estimated percentage $\hat{P}_t^{ANOVA(CP)}$ of target category as tabulated in Table 3.70 and 3.71 respectively.

Table 3.70. Comparison Table According to Prediction Depending on LRMO in Inkjet Printer Example

FACTORS			$\hat{P}_i^{LR(P)}$				**SNR**	**METHODS**
A	**B**	**C**	**1**	**2**	**3**	**4**		
1	1	0	0.0509	0.0903	0.1752	**0.6836**	10.1376	LRMO
1	1	0	0.0509	0.0903	0.1752	**0.6836**	10.1376	AA
1	1	0	0.0509	0.0903	0.1752	**0.6836**	10.1376	WSNR
1	1	0	0.0509	0.0903	0.1752	**0.6836**	10.1376	SS
1	1	0	0.0509	0.0903	0.1752	**0.6836**	10.1376	WPSS

As seen in Table 3.70, all methods show the best performance according to performance criteria of LRMO.

Table 3.71. Comparison Table According to Prediction Depending on Estimated Percentage of Target Category in Inkjet Printer Example

FACTORS			$\hat{P}_i^{ANOVA(CP)}$				**METHODS**
A	**B**	**C**	**1**	**2**	**3**	**4**	
1	1	0	13.7622	0.0000	11.2769	**74.9609**	LRMO
1	1	0	13.7622	0.0000	11.2769	**74.9609**	AA
1	1	0	13.7622	0.0000	11.2769	**74.9609**	WSNR
1	1	0	13.7622	0.0000	11.2769	**74.9609**	SS
1	1	0	13.7622	0.0000	11.2769	**74.9609**	WPSS

As seen in Table 3.71, all methods show the best performance depending on this performance measure.

3.5. DUPLICATOR EXAMPLE

In this case, another data set, which is analyzed by Logothetis and Wynn (1989), is used to make another comparison of the methods. In this experiment, paper sheets are fed to the duplicator and it is aimed to detect the optimal operating conditions that provide successful feeding through duplicator. The controllable factors that affect the success of feeding are tabulated in Table 3.72. These factors are the operating conditions for paper feeding operation.

In this problem, sets of parameter settings of 16 experimental runs are designed and applied at the selected factor levels according to the L_{16} orthogonal array as given in Table 3.73. In addition, numbers of successful paper sheet feeds through duplicator for these 16 experimental runs are tabulated in Table 3.74.

Table 3.72. Control Factors and Their Levels for Duplicator Example

FACTORS		**LEVELS**	
		0	**1**
A	Vacuum Header Type	Normal	Lightweight
B	Feed cam type	Normal	Smoothed
C	Master cylinder cam	Smoothed	Normal
D	Air rifle setting	Normal	High
E	Chain gripper release cam	Normal	Advanced
F	Paper weight bar spring	Without	With
G	Release blowdown spray	Off	On
H	Buckle setting	Normal	High
I	Paperweight bar	Light	Heavy
J	Paperweight bar position	Normal	Back
K	Impression roller setting	Normal	High
L	Vacuum setting	Normal	High

Table 3.73. Experimental Design for the Duplicator Example

Exp. No	**A**	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**FxI**	**I**	**J**	**K**	**L**
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	1	1	1	1	1	1	1
3	0	0	0	1	1	1	0	0	0	1	1	1	1
4	0	0	0	1	1	1	1	1	1	0	0	0	0
5	0	1	1	0	0	1	0	0	1	0	0	1	1
6	0	1	1	0	0	1	1	1	0	1	1	0	0
7	0	1	1	1	1	0	0	0	1	1	1	0	0
8	0	1	1	1	1	0	1	1	0	0	0	1	1
9	1	0	1	0	1	0	0	1	0	0	1	0	1
10	1	0	1	0	1	0	1	0	1	1	0	1	0
11	1	0	1	1	0	1	0	1	0	1	0	1	0
12	1	0	1	1	0	1	1	0	1	0	1	0	1
13	1	1	0	0	1	1	0	1	1	0	1	1	0
14	1	1	0	0	1	1	1	0	0	1	0	0	1
15	1	1	0	1	0	0	0	1	1	1	0	0	1
16	1	1	0	1	0	0	1	0	0	0	1	1	0

Table 3.74. Numbers of Successful Paper Sheet Feeds for Duplicator Example

Exp. No	**Tests**			
	1	**2**	**3**	**4**
1	2	9	0	3
2	124	46	0	3
3	21	7	0	2
4	3	9	0	6
5	*377	13	7	7
6	*379	*359	0	*341
7	*372	43	0	184
8	330	5	143	*337
9	2	3	0	4
10	1	3	0	0
11	4	34	3	0
12	1	3	3	3

Table 3.74. (cont'd) Numbers of Successful Paper Sheet Feeds for Duplicator Example

13	*500	*500	219	77
14	*500	*500	*500	*500
15	*500	489	9	8
16	45	46	0	218

Then, by using ranges for numbers of successful paper sheet feeds through duplicator given in Table 3.75, the response data given in Table 3.74 are categorized. Then, numbers of occurrences in each category for each set of parameter settings are tabulated in Table 3.76.

Table 3.75. Ranges for Numbers of Successful Paper Sheet Feeds for Duplicator Example

Category	**Range**	
	Min	**Max**
I	0	0
II	1	168
III	169	336
IV	337	∞

*Test is stopped after these numbers of paper-sheet fed

Table 3.76. Numbers of Occurrences in Each Category for Each Set of Parameter Settings for Duplicator Example

Exp. No	**CATEGORIES**			
	I	**II**	**III**	**IV**
1	1	3	0	0
2	1	3	0	0
3	1	3	0	0
4	1	3	0	0
5	0	3	0	1
6	1	0	0	3
7	1	1	1	1
8	0	2	1	1
9	1	3	0	0
10	2	2	0	0
11	1	3	0	0
12	0	4	0	0
13	0	1	1	2
14	0	0	0	4
15	0	2	0	2
16	1	2	1	0

In this example, it is targeted to have number of successful feeds that included in category IV, therefore this case is larger-the better type of problem.

3.5.1. Logistic Regression Model Optimization for Duplicator Example

As explained in step 1 of subsection 2.1, ordinal logistic regression model is fit by using SPSS program instead of MINITAB. Because an ordinal logistic regression model can include up to 9 factors and 50 covariates in MINITAB and in this example there are twelve factors. One by one all factors except factors B (VAR00002), F (VAR00006), K (VAR000012), and L (VAR000013) are omitted because these factors have no significant effect on number of successful paper fed as shown on Figure 3.34. Also, on this figure the intercept of this model and coefficients of each factor are given.

Parameter Estimates

			Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Threshold	[VAR00014 =	1]	-4,300	,877	24,042	1	,000	-6,019	-2,581
	[VAR00014 =	2]	-,531	,570	,869	1	,351	-1,648	,586
	[VAR00014 =	3]	,012	,568	,000	1	,983	-1,101	1,125
Location	[VAR00002=0]		-3,044	,713	18,204	1	,000	-4,443	-1,646
	[VAR00002=1]		0[a]	.	.	0	.	.	.
	[VAR00006=0]		-1,015	,518	3,833	1	,050	-2,030	,001
	[VAR00006=1]		0[a]	.	.	0	.	.	.
	[VAR00012=0]		,889	,516	2,973	1	,085	-,122	1,900
	[VAR00012=1]		0[a]	.	.	0	.	.	.
	[VAR00013=0]		-,546	,510	1,144	1	,285	-1,545	,454
	[VAR00013=1]		0[a]	.	.	0	.	.	.

Link function: Logit.

a. This parameter is set to zero because it is redundant.

Figure 3.34. Ordinal Logistic Regression Results for Duplicator Example

Although, p value (0.285) of factor L shows that factor L has no significant effect on number of successful paper fed, this factor is assumed to be included in the model. Because 0.285 is not considerably larger than 0.10. Moreover, when factor L is omitted, the Pearson test result shows that model does not fit the data adequately as seen on Figure 3.35 whereas model included factor L can fit the data adequately according to Pearson test as shown on Figure 3.36.

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	29,199	18	,046
Deviance	20,289	18	,317

Link function: Logit.

Figure 3.35. Goodness of fit for the model omitted factor L

Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	50,878	41	,139
Deviance	31,730	41	,850

Link function: Logit.

Figure 3.36. Goodness of fit for the model included factor L

Parameter settings for significant factors in a full factorial design are generated by MATLAB as tabulated in Table D.1. Then, probability of observing each response category and signal-to-noise ratios are estimated by using these parameter settings based on the model fit to the data. Equations (2.1) and (2.2) are used in estimation of probability of observing each response category. In addition, since it is larger-the-better type of problem, equation (2.6) is used to calculate the signal-to-noise ratios. Both estimated probabilities of observing each category and SNR values are tabulated in Table E.1.

As it is mentioned before, estimated probability $\hat{P}_t^{LR(P)}$ of observing target category and signal-to-noise ratio are the performance measure to evaluate the performance of optimal levels. Therefore, 14^{th} trial gives both maximum SNR value with 11.9835 and maximum estimated probability for category 4 with 0.9900 as seen in Table E.1. Therefore, the optimal parameter settings are found as $B_1F_1K_0L_1$ as given in Table 3.77.

Table 3.77. Estimated Probability for Each Category and Signal-to-noise Ratios for Optimal Levels in Duplicator Example

FACTORS				$\hat{P}_i^{LR(P)}$				**SNR**
B	**F**	**K**	**L**	**I**	**II**	**III**	**IV**	
1	1	0	1	0.0001	0.0057	0.0042	**0.9900**	**11.9835**

3.5.2. Accumulation Analysis Method for Duplicator Example

In accumulation analysis method, as explained in subsection 2.2, cumulative frequencies are created by adding frequencies of occurrence given in Table 3.76 for one category to the frequencies for the next category as seen in Table E.2.

Frequencies and cumulative frequencies are calculated by summing the frequencies in Table 3.76 and cumulative frequencies in Table E.2 for relevant level as given in Table E.3. Before determining the optimal parameter settings, analysis of variance (ANOVA) calculations are implemented as shown in Table E.5, E.6 and ANOVA table is given in Table 3.78. Since $F^{3}_{150(0.10)}$ is equal to 2.12, factors B, F and I have significant effect on quality characteristics. In addition, factors D and K are assumed to be significant due to having reasonably small difference between 1.9860 and 2.12.

Table 3.78. Analysis of Variance (ANOVA) Results

Factors	df	S	MS	F
A	3	0,7847	0,2616	0,3360
B	3	45,7079	15,2360	19,5730
C	3	0,7847	0,2616	0,3360
D	3	4,6379	1,5460	1,9860
E	3	1,7122	0,5707	0,7332
F	3	5,5161	1,8387	2,3621
G	3	0,7847	0,2616	0,3360
H	3	0,7847	0,2616	0,3360
I	3	5,5161	1,8387	2,3621
J	3	0,4755	0,1585	0,2036
K	3	4,6379	1,5460	1,9860
L	3	3,1101	1,0367	1,3318
F*I	3	0,7847	0,2616	0,3360
Error	150	116,7628	0,7784	
Total	189	192	1,0159	

Since the levels that have maximum frequencies in category 4 give the optimal solution, optimal levels are $B_1D_0F_1I_1K_0$ as seen in Table E.3.

Estimated frequencies for each category and factor and total estimated frequencies for each category are calculated by using equations (2.21) and (2.22), respectively. These results are tabulated in Table E.6.

By using logit (omega) transformation (Equation (2.23)) estimated frequencies and overall estimated frequencies for each category transformed into decibels as tabulated in Table E.7.

Then, by using equation (2.24) long–run performance is estimated for each category in decibels. Then, these estimates are transformed back by using again logit transformation. The long-run performances in decibels and percentages $\hat{P}_i^{ANOVA(CP)}$ are tabulated in Table 3.79. Percentage of category 4 gives the performance of optimal parameter settings given in Table 3.79.

Table 3.79. Estimated Percentage for each Category for Optimal Levels for Duplicator Example

	FACTORS					$\hat{P}_i^{ANOVA(CP)}$			
	B	**D**	**F**	**I**	**K**	**I**	**II**	**III**	**IV**
In decibel	1	0	1	1	0	-10.5826	-6.1125	-7.3265	0.0000
In percentage	1	0	1	1	0	8.0397	11.6192	0.0000	**80.3411**

3.5.3. Weighted Signal-to-noise Ratio for Duplicator Example

In this method, first of all weights are given to categories proportional to the quality loss. However, there is no guidance given for determining scale of weights and spacing between weights. But, in the surface defect example the results are not changed when two different weight sets are compared to see the effect of choosing different weights on the optimal solution. Therefore, the weights are given to categories as shown below.

$$W = (4 \quad 3 \quad 2 \quad 1)$$

By using equation (2.26), the signal-to-noise ratios are calculated for each set of parameter settings by using weights and number of observations by category as tabulated in Table E.8.

Before ANOVA is applied, residual normality and homogeneity of variance assumptions are checked for SNR values. Normality and residual's homogeneity of variance assumptions are not violated for SNR values.

Then, ANOVA is applied on SNR values in order to detect the significant factors as shown on Figure 3.37. As seen on this figure, factors B, D, F and K have significant effects on response data with 90% confidence. Although, *p* values of factors D and K are greater than 0.10, 0.181 and 0.191 are not considerably larger than 0.10. Therefore, effects of factors D and K are assumed to be significant.

Analysis of Variance for SNR, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
B	1	50,139	50,139	50,139	14,20	0,003
D	1	7,195	7,195	7,195	2,04	0,181
F	1	11,531	11,531	11,531	3,27	0,098
K	1	6,871	6,871	6,871	1,95	0,191
Error	11	38,843	38,843	3,531		
Total	15	114,578				

S = 1,87913   R-Sq = 66,10%   R-Sq(adj) = 53,77%

Figure 3.37. Analysis of Variance (ANOVA) Results according to SNR Scores for WSNR Method in Duplicator Example

Then, the averages of signal to noise ratios for each significant factor are calculated according to each level as tabulated in Table E.9. In this method, all calculations are made in MATLAB.

As seen in Table E.9, parameter settings that have maximum averages of signal-to-noise ratios give the optimal solution which is $B_1D_0F_1K_0$. According to WSNR method, no way is suggested to examine performance of optimal parameter settings.

3.5.4. Scoring Scheme Method for Duplicator Example

In this method first of all, midranks for each category are calculated by using equation (2.27). Then, location score for each category is calculated by using equations (2.28) and (2.29). These calculated data are tabulated in Table E.10. Then, by using equation (2.30), location pseudo-observations are calculated as tabulated in Table D.12 for each set of parameter settings.

Moreover, by using equations (2.31) and (2.32) dispersion scores are calculated for each category as shown in Table E.11. In addition, by using equation (2.33), dispersion pseudo-observations are calculated as tabulated in Table E.12 for each set of parameter settings.

After residual normality and homogeneity of variance assumptions are checked for L and D scores, ANOVA is applied for L and D as shown on Figure 3.38 and 3.39, respectively.

Analysis of Variance for Li. using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
B	1	78.196	78.196	78.196	49.43	0.000
F	1	9.014	9.014	9.014	5.70	0.036
K	1	5.360	5.360	5.360	3.39	0.093
L	1	3.947	3.947	3.947	2.49	0.143
Error	11	17.403	17.403	1.582		
Total	15	113.920				

S = 1.25780   R-Sq = 84.72%   R-Sq(adj) = 79.17%

Figure 3.38. Analysis of Variance (ANOVA) Results according to L Scores for SS Method in Duplicator Example

As seen on Figure 3.38, factors B, F, K and L have significant effect on location scores with 90% confidence. Although, p value of factor L is greater than 0.10, 0.143 is not considerably larger than 0.10. Therefore, effect of factor L is assumed to be significant.

Analysis of Variance for Di, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
B	1	17.402	17.402	17.402	5.50	0.036
K	1	3.321	3.321	3.321	1.05	0.325
Error	13	41.169	41.169	3.167		
Total	15	61.892				

S = 1.77957   R-Sq = 33.48%   R-Sq(adj) = 23.25%

Figure 3.39. Analysis of Variance (ANOVA) Results according to D Scores for SS Method in Duplicator Example

As seen on Figure 3.39, only factor B has significant effect on dispersion scores with p values smaller than 0.10.

Then, the averages of location and dispersion pseudo-observations for each significant factor are calculated according to each level as seen in Table E.13. In this method, all calculations are made in MATLAB.

Since this experiment is larger-the-better type of problem, the maximum average value for location and minimum dispersion pseudo-observations for each significant factor gives the optimal parameter settings. Hence, as seen in Table E.13, the optimal parameter settings for location and dispersion results for factor B differ, it is necessary to compromise between two different levels of factor B.

When compromising is implemented based on subsection 2.1.4, estimated location and dispersion scores are calculated for all possible levels of factor B (0 or 1) by using equations (2.34) and (2.35), respectively.

When the calculations are done for all possible (0, 1) levels of factor B, predicted location versus dispersion scores graph are shown on Figure 3.40.

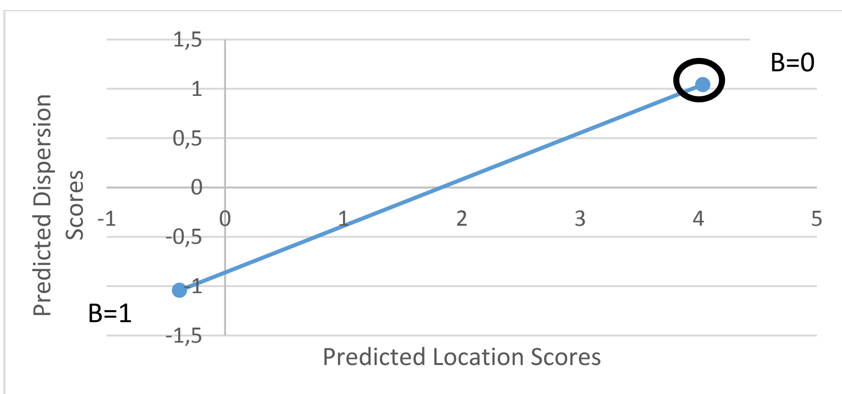

Figure 3.40. Predicted Location versus Dispersion Scores for Duplicator Example

It is tried to determine the point that achieve maximize predicted location and minimize dispersion scores. Hence, as seen on this figure there is too much difference between predicted location scores for point 1 (B=1) and 2 (B=0) whereas there is not so much difference between predicted dispersion scores for point 1 and 2. Therefore, it is better to choose point 2 (B=1).

According to these facts, the overall parameter settings are estimated as $B_0F_0K_1L_0$.

3.5.5. Weighted Probability Scoring Scheme Method for Duplicator Example

This method gives the target category the largest weight, thus location effect behaves as larger-the-better type. Therefore, the weights are chosen as given below.

$$Weights = (1 \quad 2 \quad 3 \quad 4)$$

Then, proportions of observation p_{ij} for each category i and set j of parameter settings are calculated as tabulated in Table E.14. Then, location scores are calculated depending on equation (2.36) as tabulated in Table E.15 by using these weights and proportions of observations. Before calculating dispersion scores, target value set is determined as given below. In this set, all the observations are expected to be in category 4, therefore 4 is assigned for category 4.

$$Target = (0 \quad 0 \quad 0 \quad 4)$$

Then, dispersion scores are calculated as tabulated in Table D.15 according to equation (2.37) by using weights, proportion of observation for each category and target value set. Instead of compromising between optimal levels for location and dispersion scores, mean square deviation (MSD) scores are calculated based on equation (2.38) by using location and dispersion scores in order to determine the optimal solution as given in Table E.15.

Before ANOVA is applied, residual normality and homogeneity of variance assumptions are checked for MSD scores. Then, it is seen that none of these assumptions is violated. Then, ANOVA is applied on MSD values as shown on Figure 3.41.

Analysis of Variance for MSD, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
B	1	125,898	125,898	125,898	102,49	0,000
F	1	7,140	7,140	7,140	5,81	0,035
K	1	7,230	7,230	7,230	5,89	0,034
L	1	5,544	5,544	5,544	4,51	0,057
Error	11	13,513	13,513	1,228		
Total	15	159,325				

S = 1,10834   R-Sq = 91,52%   R-Sq(adj) = 88,43%

Figure 3.41. Analysis of Variance (ANOVA) Results according to MSD Scores for WPSS Method in Duplicator Example

As seen on Figure 3.41, factors B, F, K and L have significant effect on MSD scores with 90% confidence.

In order to see how MSD scores for each level of significant factors behave, the averages of them for each significant factor are calculated according to each level as shown in Table E.16. As seen in this table, levels that have the lowest MSD scores give the optimal parameter settings which are $B_1F_1K_0L_1$. In this method, all calculations are made in MATLAB. Moreover, According to WPSS method, no way is suggested to examine performance of optimal parameter settings.

The methods are compared according to two different performance measures which are estimated probability $\hat{P}_t^{LR(P)}$ of observing target category calculated depending on LRMO and estimated percentage $\hat{P}_t^{ANOVA(CP)}$ of target category as tabulated in Table 3.80 and 3.81 respectively.

Table 3.80. Comparison Table According to Prediction Depending on LRMO in Duplicator Example

FACTORS				$\hat{P}_i^{LR(P)}$				**SNR**	**METHODS**
B	**F**	**K**	**L**	**1**	**2**	**3**	**4**		
1	1	0	1	0.0001	0.0057	0.0042	**0.9900**	11.9835	LRMO
1	1	0	1	0.0001	0.0057	0.0042	**0.9900**	11.9835	AA (L=1)
1	1	0	1	0.0001	0.0057	0.0042	**0.9900**	11.9835	WSNR (L=1)
0	0	1	0	0.0320	0.5566	0.1226	0.2888	7.1775	SS
1	1	0	1	0.0001	0.0057	0.0042	**0.9900**	11.9835	WPSS

Table 3.81. Comparison Table According to Prediction Depending on Estimated Percentage of Target Category in Duplicator Example

FACTORS					$\hat{P}_i^{ANOVA(CP)}$				**METHODS**
B	**D**	**F**	**I**	**K**	**1**	**2**	**3**	**4**	
1	0	1	1	0	8.0397	11.6192	0.0000	**80.3411**	LRMO (D=0 & I=1)
1	0	1	1	0	8.0397	11.6192	0.0000	**80.3411**	AA
1	0	1	1	0	8.0397	11.6192	0.0000	**80.3411**	WSNR (I=1)
0	0	0	1	1	42.8639	57.1361	0.0000	0.0000	SS
1	0	1	1	0	8.0397	11.6192	0.0000	**80.3411**	WPSS

As seen in Table 3.80, LRMO, AA, WSNR and WPSS methods show the best performance according to performance criteria of LRMO.

As seen in Table 3.81, LRMO, AA, WSNR and WPSS methods show the best performance according to this performance measure.

3.6. OVERALL COMPARISON

In the light of these results given above, in order to determine which methods are the best methods in robust parameter design of products and processes with ordered categorical response among these five methods, overall comparison table is given in Table 3.82.

In Table 3.82, performance measure according to probability $\hat{P}_t^{LR(P)}$ of observing target category calculated depending on LR, estimated percentage $\hat{P}_t^{ANOVA(CP)}$ of target category, for all methods and problems except simulated example, and true P_i models for simulated example and Taguchi SNR model of continuous data for surface defect example are tabulated.

As seen in this table, LRMO has the best results for all examples depending on its own performance measure $\hat{P}_t^{LR(P)}$ whereas AA provides the best results in all examples except thick-film resistor example depending on this performance measure. AA has the best results for all examples depending on performance measure which is the estimated percentage $\hat{P}_t^{ANOVA(CP)}$ of target category while LRMO provides the best results in all examples except thick-film resistor example depending on this performance measure. Moreover, LRMO and AA methods are capable of providing the best results with strong steadiness whereas the other methods do not provide similar level of steadiness in the examples of this study.

Moreover, as seen in Table 3.82, LRMO, AA and WSNR can find the best results according to predicted SNR results depending on Taguchi's SNR model and true probability models. Although, WPSS seems to be capable of providing the best result in simulated example, it cannot find any factors significant in this example.

Finally, the goodness-of-fit test results for Pearson and Deviance tests are tabulated in Table 3.83. As seen in this table, ordinal logistic regression model cannot fit the response data adequately for surface defect and thick-film resistor examples.

Table 3.82. Overall Comparison Table According to the Best Results

Examples	**Type**	$\hat{P}_i^{LR(P)}$					$\hat{P}_i^{ANOVA(CP)}$				
		LRMO	**AA**	**WSNR**	**WPSS**	**SS**	**LRMO**	**AA**	**WSNR**	**WPSS**	**SS**
Surface Defect	STB	**0.9498**	**0.9498**	**0.9498**	0.9219	0.9219	**92.5137**	**92.5137**	**92.5137**	74.3068	60.9242
Thick-film Resistor	STB	**0.9322**	0.7497	0.9296	0.9296	0.7519	27.6800	**75.1708**	56.6300	3.6500	56.6300
Inkjet Printer	LTB	**0.6836**	**0.6836**	**0.6836**	**0.6836**	**0.6836**	**74.9609**	**74.9609**	**74.9609**	**74.9609**	**74.9609**
Duplicator	LTB	**0.9900**	**0.9900**	**0.9900**	**0.9900**	0.2888	**80.3411**	**80.3411**	**80.3411**	**80.3411**	0.0000
Examples	**Type**	P_i*					SNR*				
Surface Defect	STB						**-0.0788**	**-0.0788**	**-0.0788**	-2.1170	-2.1170
Simulated	STB	**0.7864**	**0.7864**	**0.7864**	**0.7864****	0.0309					

* Comparison is done using true P_i models for simulated example and Taguchi SNR model of continuous data for surface defect example.

** WPSS finds all factors as insignificant. These optimal parameter settings are found by ignoring ANOVA results.

Table 3.83. Goodness-of-fit Results for Each Example in LRMO

LRMO		**Goodness-of-fit**	
Example	**Type**	**Pearson**	**Deviance**
Surface Defect	**STB**	**0.0020**	**0.0000**
Thick-film Resistor	**STB**	**0.0000**	**0.0000**
Simulated	STB	0.9860	0.9640
Inkjet Printer	LTB	0.2170	0.1590
Duplicator	LTB	0.1390	0.8500

CHAPTER 4

DISCUSSION

In the light of these studies for comparison of optimization methods for ordered categorical data, LRMO method finds the optimal settings for statistically significant parameters, which have the best results in the examples analyzed above depending on its own performance measure. In addition, AA method finds the optimal settings for statistically significant parameters that have the best results in the examples analyzed above depending on estimated percentage of target category by ANOVA model. However, for the thick-film resistor problem, these methods cannot find the optimal solutions that give the best performance measure according to other performance measures. Moreover, for the surface defect example, LRMO, AA and WSNR methods can find the optimal parameter settings that have the best predicted signal to noise ratio results at optimal parameter settings, estimated by ANOVA model of continuous version of data.

These results can be explained with the goodness-of-fit test results for LRMO. In other words, ordinal logistic regression model cannot fit to the response data adequately in surface defect and thick film resistor examples. Although this method can give the best performance measure according to LRMO's performance criteria in thick film resistor example, it cannot give best performance measure according to estimated percentage of target category by ANOVA model in this example. This undesired result may be due to the lack of model fit to the response data. These results show that goodness of fit, existence of which is an important factor for LRMO, can be considered as a weakness of the method.

On the other hand, in surface defect example LRMO can find optimal parameter settings that have the best performance measure depending on all three performance measures even if the model cannot fit the response data adequately. This shows us that the goodness-of-fit is not a significant requirement.

Similar to LRMO, AA method cannot find the best performance measure if LRMO's performance criteria is considered for comparison in thick-film resistor example. These facts can be explained with method's nature. Namely, contrary to LRMO, SS and WPSS methods, AA method cannot allow analysis of location and dispersion effects separately for a given set of parameter settings. Instead, both location and dispersion effects of factors are focused and aims of making mean close to target value and minimizing variance are tried to be achieved simultaneously in this method. However, AA method may not be able to achieve these purposes in the thick film resistor example.

Moreover, as Logothetis (1992) criticizes, independency in frequencies of the cumulative categories cannot be provided in AA method. In addition to this fact, as Hamada and Wu (1989) criticizes, spurious effects of some factors may occur. These weaknesses of this method may cause the low performance in the thick film resistor example.

Another method examined in this study is Scoring Scheme Method. SS method can allow analysis of location and dispersion effects separately for a given set of parameter settings. This may lead to finding two contradicting optimal parameter settings for the same problem. As seen in all examples except simulated example, optimal parameter settings found depending on location and dispersion effects differ. However, in this method no way is introduced to compromise between optimal levels found depending on location and dispersion effects. Therefore, despite the fact that this method shows ways to minimize variance and make mean close to the target value, it cannot introduce a way to find overall optimal solution that achieve these goals simultaneously. Thus, a way to compromise between optimal parameter settings is introduced in this study. As seen in section 3, SS method by using this way can find out the optimal parameter settings that show the best performance according to probability of observing target category, estimated by LR models, and that of observing target category estimated by ANOVA models of cumulative percentage of categories in inkjet printer example whereas it cannot show similar success in other examples.

Furthermore, ANOVA is not introduced for application of SS method. However, factors may not have significant effect or may have different effects on location and dispersion effects. Therefore, ANOVA is suggested and applied in this method for SS method.

Moreover, SS method can find the best performance measure only in one smaller-the-better and one larger-the-better type of problems used in this study after compromising. Therefore, there is no evidence that this method can be successful at a certain type of problem.

In addition, similar to SS method, WPSS method can allow analysis of location and dispersion effects separately for a given set of parameter settings. Contrary to SS method, this method calculates mean squared deviation (MSD) to compromise between the optimal parameter settings found depending on location and dispersion effects. Nevertheless, this method cannot show steady success in examples explained in Section 3. In other words, WPSS can estimate optimal parameter settings that show the best performance in simulated, inkjet printer and duplicator examples whereas it cannot show the similar success in other examples. Although WPSS can estimate optimal parameter settings that show the best performance in simulated example, it cannot find any factors as statistically significant.

Moreover, this method can find the best performance data according to probability of observing target category, estimated by LR models only in one smaller-the-better and two larger-the-better type examples used in this study. In addition, this method can find the best performance data according to estimated percentage of observing target category by ANOVA model only in one smaller-the-better and one larger-the-better type examples used in this study. Therefore, there is no evidence that this method can be successful at a certain type of problem.

Furthermore, ANOVA is not introduced for application of WPSS method. However, factors may not have significant effect on MSD scores. Therefore, ANOVA is suggested and applied in this method for WPSS method.

Same as AA method, WSNR method cannot allow analysis of location and dispersion effects separately for a given set of parameter settings. Instead, both location and dispersion effects of factors are focused and aims of making mean close to target value and minimizing variance are tried to be achieved simultaneously in this method. However, WSNR method can find the optimal parameter settings that illustrate the best performance depending on both performance measures in surface defect, simulated, inkjet printer and duplicator examples except thick-film resistor example. The undesired result in thick-film resistor example may occur due to not being able to achieve purposes of making mean close to target value and minimizing variance simultaneously in these examples.

Moreover, WSNR method gives categories weights proportional to the quality loss, but no rule is suggested for determining scale of weights and spacing between weights. This fact may cause not to be able to define importance of target category sufficiently.

In addition to LRMO and AA methods, WSNR method shows almost same performance as ones of LRMO and AA methods. Furthermore, WSNR is a quite practical method. However, unlike LRMO and AA methods, WSNR cannot find the best result in thick-film resistor example according to both performance measures which are probability of observing target category calculated depending on LR and estimated percentage of observing target category by ANOVA model.

The final fact that should be mentioned is that in some examples factors are categorized in levels. However, some factors such as temperature can be analyzed by using their levels in continuous scale. In order to use such data in comparison of methods, continuous scale of these factor levels are not considered. However, LRMO can analyze continuous data by using response surface optimization method. By the help of this property, this method can improve the performance of optimal parameter settings in thick film resistor example which is the example that has factors that can be considered in continuous scale. This property is the great advantage over against the other methods compared in this study.

CHAPTER 5

CONCLUSION AND FURTHER STUDIES

In this study, it is aimed to find the best robust parameter design method for products and processes with ordered categorical response that can find the best performed optimal parameter settings among five methods; Logistic Regression Model Optimization (LRMO), accumulation analysis method (AA), weighted signal-to-noise ratio method (WSNR), scoring scheme method (SS) and weighted probability scoring scheme method (WPSS). LRMO and AA methods have the best performance among these methods when methods are applied on five different examples.

Moreover, WSNR method shows almost same performance as ones of LRMO and AA methods. However, unlike LRMO and AA methods, WSNR cannot find the best result in thick-film resistor example according to both performance measures. If more examples are analyzed in further studies, WSNR may pass beyond other methods.

In addition, LRMO has clear advantage over AA method, since it can allow analysis of location and dispersion effects separately for a given set of parameter settings. Further analysis might be studied to show this discrepancy of the methods. On the other hand, it is determined that being in need of fitting the model to the data adequately is a weakness of LRMO. Therefore, this fact should be investigated by applying this method on much more examples in further studies. Even so, in the examples that models are not fit the response data adequately, optimal levels found by the method can give the best estimated probability of observing target category among all the optimization methods compared in this study.

Furthermore, in order to investigate methods' behavior on different types of problem, examples are chosen in smaller-the-better and larger-the-better types of problem. However, there is no statement found that a certain method is successful or unsuccessful on a certain type of problem. Hence, in further studies much more examples should be analyzed in these two types of problems to investigate the behaviors of the methods against certain type of problems.

In addition, five different examples which are chosen in comparisons of methods, have different properties such as numbers of experimental runs, numbers of factors. These choices are made to be able to see how the methods behave on data that have different properties. However, when the problems analyzed by using the methods compared in this study, there is no evidence found that the methods can be successful at a certain type of property.

Moreover, all methods can be applied on an ordered response data which means that data should in monotonically decreasing or increasing order. However, sometimes nominal data is needed to be analyzed. For this type of data, Erdural (2006) suggests to use two alternative treatments: binary and ordinal treatment. In the binary treatment, data is clustered in two groups (desired, not desired) depending on target. In the ordinal treatment, data is arranged in order to make data in monotonically decreasing or increasing order. In further studies, an addition to smaller-the-better and larger-the-better examples, nominal-the-best examples can be studied for comparison of these methods by using these treatments.

Since in this study factors that have ordered categorical levels are analyzed, LRMO is also applied on these factors in examples. However, LRMO can also be applied on continuous data by using response surface optimization method which is a great advantage over against other methods. Therefore, this method may find better results if continuous data analyses is performed on the examples by considering factors such as temperature that can take continuous value. Hence, behavior and success of this method on the continuous data can be investigated in further studies.

In addition to these conclusions, as it is mentioned before it may be necessary to compromise between optimal levels for location and dispersion scores found by SS method in order to determine overall optimal levels. However, no way is introduced for compromising between these two optimal levels. In this study, a way is introduced for compromising. Then, performance results found depending on this way do not show steady success in the examples. Hence, alternative compromising methods can be investigated in further studies to find an effective way for choosing the optimal level.

Moreover, in this study comparison is made depending on performance criteria which are SNR at optimal parameter settings, estimated by ANOVA model of continuous version of data (if applicable), probability of observing target category, estimated by LR models, and that of observing target category estimated by ANOVA models of cumulative percentage of categories. In order to strengthen the statements provided in this study, alternative comparison methods can be used in further studies.

In conclusion, five robust parameter design methods for products and processes with ordered categorical response are compared in this study on examples that have categorical parameter settings and among these methods LRMO and AA show the best performance on the ordered categorical data. Therefore, it is better to choose LRMO and AA methods in order to analyze ordered categorical data. In addition, if there is a necessity to analyze continuous data, then LRMO can be used for robust parameter design. To sum up, since LRMO has the best performance in this study similar to AA method and it is able to analyze continuous data, it can be more advantageous to prefer using LRMO in robust parameter design for products and processes.

REFERENCES

Asiabar, M.H., & Ghomi, S. M. T. F. (2006). "Analysis of Ordered Categorical Data Using Expected Loss Minimization". *Quality Engineering. 18*(2), 117-121.

Box, G., & Jones, S. (1986). Discussion of "Testing in industrial experiments with ordered categorical data" *Technometrics*, *28*(4), 295-301.

Chipman, H., & Hamada, M. (1996). "Bayesian analysis of ordered categorical data from industrial experiments." *Technometrics. 35*(1), 1-10.

Erdural, S. (2006). *A Method for Robust Design of Products or Processes with Categorical Response*. Unpublished master's thesis, Middle East Technical University, Ankara, Turkey.

Fowlkes, W.Y., & Creveling, C.M. (1995). *Engineering Methods for Robust Product Design.* Massachusetts: Addison-Wesley Publishing Company.

Green, S.B., & Salkind, N.J. (2005). *Using SPSS for Windows and Macintosh*. New Jersey: Prentice-Hall.

Hamada, M., & Wu, C. F. J. (1989). "A critical look at accumulation analysis and related methods." *Technometrics. 32*(2), 119-130.

Hosmer, D.W., & Lemeshow, S. (2000). *Applied Logistic Regression.* United States of America : Wiley-Interscience Publication.

Jeng, Y. C., & Guo, S. M. (1996). "Quality improvement for RC06 chip resistor." *Quality and Reliability Engineering International, 12*(6), 439-445.

Jinks, J. (1987). "Reduction of Voids in a Urethane-Foam Product," in *Fifth Symposium on Taguchi Methods*. Dearborn, MI: American Suppliers Institute, Inc., pp. 135-148.

Köksal, G., Erdural, S., and İlk, Ö. (2006) "A Method for Analysis of Categorical Data for Robust Product and Process Design", Proceedings in Computational Statistics, *17th Symposium of the IASC*, Rome, Italy, Rizzi, A. and Vichi, M. (Eds.) Physica-Verlag, 573-580, 2006.

Logothetis, N., & Wynn,H.P. (1989). *Quality Through Design.* Oxford: Clarendon Press

Logothetis, N. (1992). *Managing For Total Quality*. United Kingdom: Prentice-Hall.

Minitab (Version 16) [Software]. (2010). State College, PA: Minitab.

Montgomery, D.C. (2009). *Statistical Quality Control: A Modern Introduction.* Asia: John Wiley & Sons, Inc.

Nair, V. N. (1986). “Testing in industrial experiments with ordered categorical data” *Technometrics, 28*(4), 283-291.

Phadke, M.S. (1989). *Quality engineering using robust design.* New York: Prentice-Hall.

Ross, P. J. (1996). *Taguchi Techniques for Quality Engineering.* United States of America: McGraw-Hill.

Roy, R. (1990). *A primier on the Taguchi method.* New York: Van Nostrand Reinhold.

SPSS Statistics (Version 17.0) [Software]. (2008). Armonk, NY: IBM Corporation.

Taguchi, G., Chowdhury, S., & Wu, Y. (2004). *Taguchi’s Quality Engineering Handbook.* New Jersey: Wiley.

Wu, F., & Yeh, C. (2006). “A comparative study on optimization methods for experiments with ordered categorical data”. *Computers & Industrial Engineering. 50*(2006) 220-232.

Zang, C., Friswell, M. I., & Mottershead, J.E. (2004) “A review of robust optimal design and its application in dynamics”. *Computers and Structures. 83*, 315-326.

APPENDIX A

GRAPHS FOR RESIDUAL ASSUMPTIONS OF ANOVA

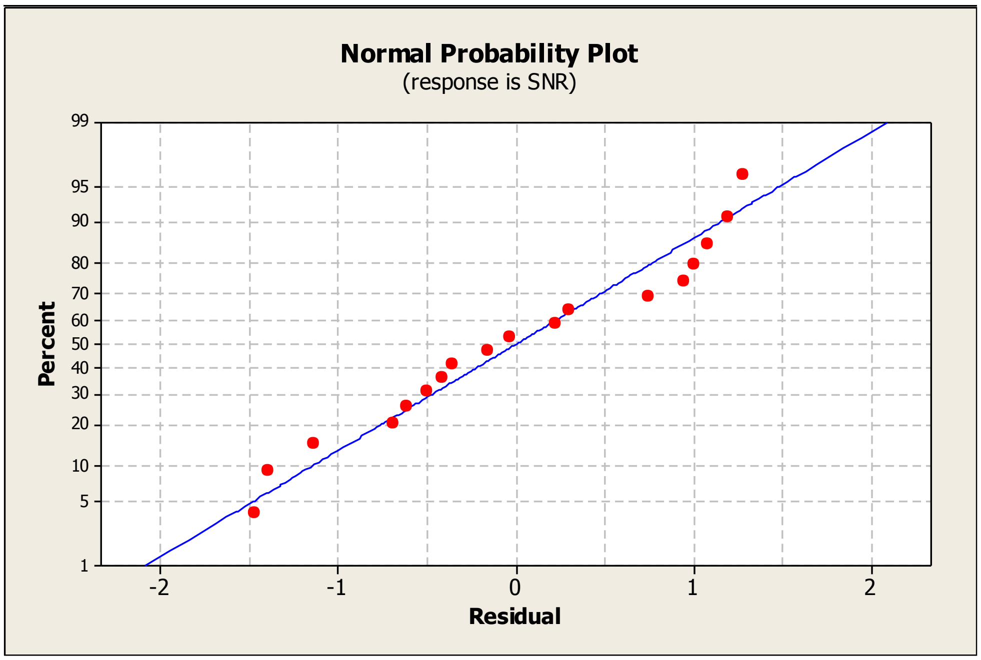

Figure A.1. Normal Probability Plot of Residuals for SNR_1 in Surface Defect Example

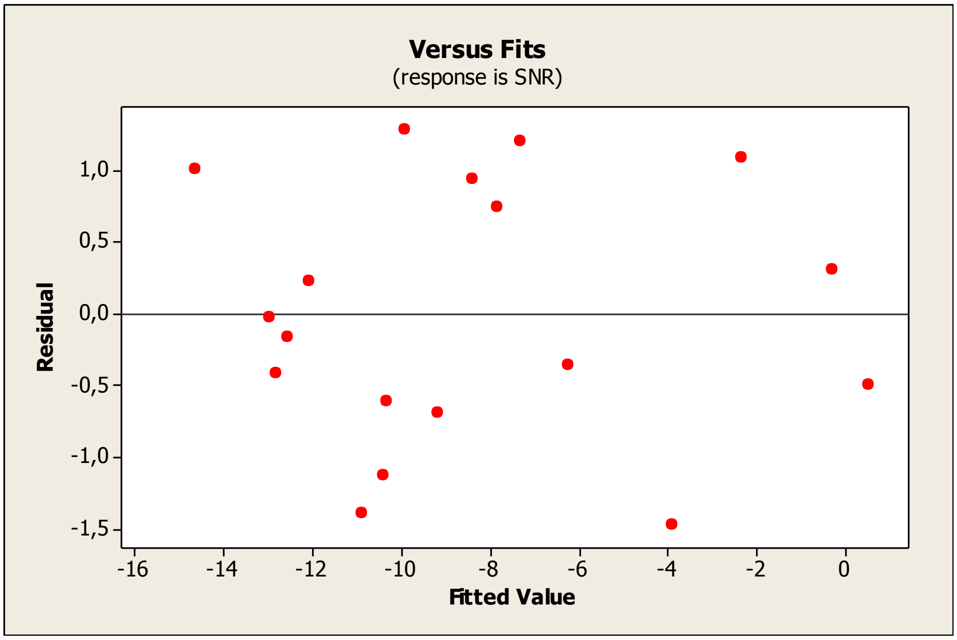

Figure A.2. Residual vs. Fitted Value Plot for SNR_1 in Surface Defect Example

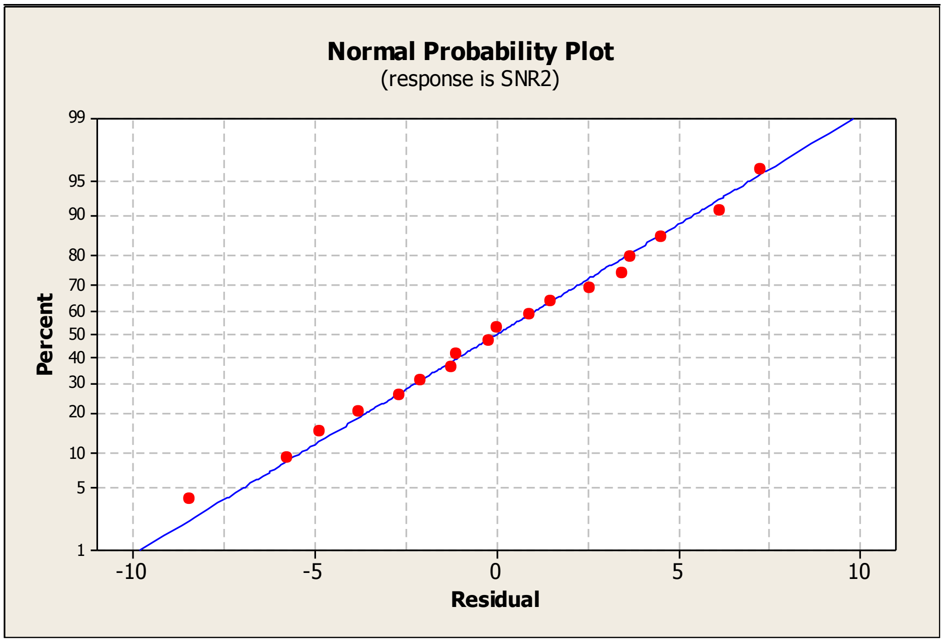

Figure A.3. Normal Probability Plot of Residuals for SNR_2 in Surface Defect Example

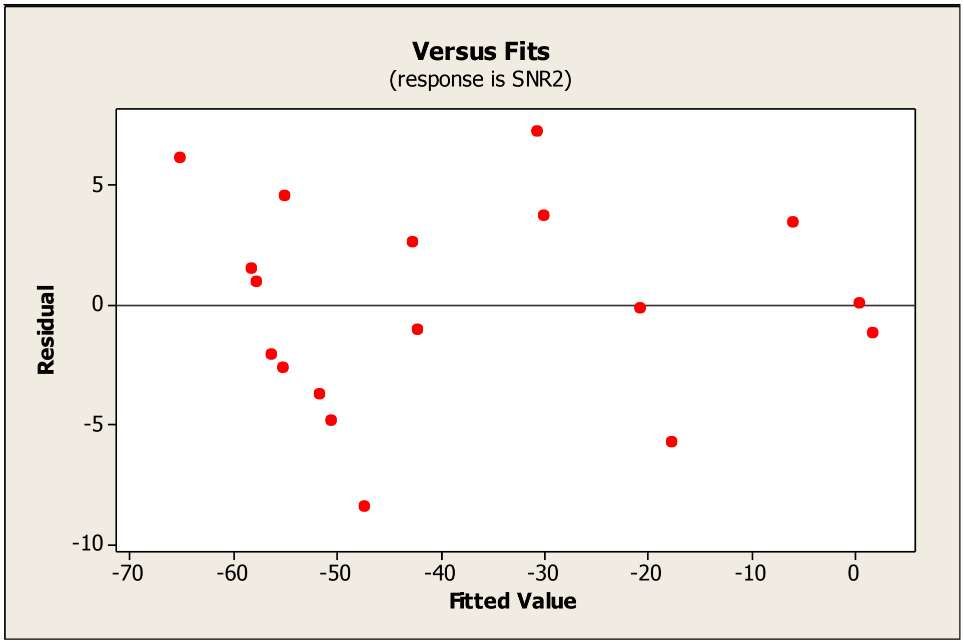

Figure A.4. Residual vs. Fitted Value Plot for SNR_2 in Surface Defect Example

APPENDIX B

RESULTS FOR THICK-FILM RESISTOR PRODUCTION EXAMPLE

B.1 Results of Logistic Regression Model Optimization in Thick-film Resistor Production Example

Table B.1. Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

Trial	FACTORS							$\hat{P}_i^{LR(P)}$						SNR
	A	B	C	D	E	F	G	I	II	III	IV	V	VI	
1	1	1	1	1	1	1	1	0.0189	0.3935	0.5536	0.0335	0.0001	0.0005	-8.5314
2	2	1	1	1	1	1	1	0.8401	0.1548	0.0051	0.0001	0.0000	0.0000	-1.7803
3	1	2	1	1	1	1	1	0.0128	0.3078	0.6295	0.0490	0.0002	0.0007	-8.8783
4	2	2	1	1	1	1	1	0.7068	0.2820	0.0109	0.0003	0.0000	0.0000	-2.8731
5	1	3	1	1	1	1	1	0.0086	0.2322	0.6867	0.0711	0.0003	0.0010	-9.1909
6	2	3	1	1	1	1	1	0.5253	0.4506	0.0235	0.0006	0.0000	0.0000	-4.0643
7	1	1	2	1	1	1	1	0.0443	0.5845	0.3568	0.0142	0.0001	0.0002	-7.6554
8	2	1	2	1	1	1	1	0.8372	0.1575	0.0052	0.0001	0.0000	0.0000	-1.8063
9	1	2	2	1	1	1	1	0.0302	0.5022	0.4462	0.0209	0.0001	0.0003	-8.0634
10	2	2	2	1	1	1	1	0.7025	0.2861	0.0112	0.0003	0.0000	0.0000	-2.9049
11	1	3	2	1	1	1	1	0.0205	0.4131	0.5350	0.0308	0.0001	0.0004	-8.4503
12	2	3	2	1	1	1	1	0.5201	0.4553	0.0240	0.0006	0.0000	0.0000	-4.0952
13	1	1	3	1	1	1	1	0.1007	0.7028	0.1905	0.0059	0.0000	0.0001	-6.7434
14	2	1	3	1	1	1	1	0.8344	0.1602	0.0053	0.0001	0.0000	0.0000	-1.8325
15	1	2	3	1	1	1	1	0.0700	0.6633	0.2578	0.0088	0.0000	0.0001	-7.1505
16	2	2	3	1	1	1	1	0.6981	0.2902	0.0114	0.0003	0.0000	0.0000	-2.9368
17	1	3	3	1	1	1	1	0.0482	0.6008	0.3378	0.0130	0.0001	0.0002	-7.5642
18	2	3	3	1	1	1	1	0.5149	0.4600	0.0245	0.0006	0.0000	0.0000	-4.1260
19	1	1	1	2	1	1	1	0.0025	0.0819	0.7037	0.2073	0.0011	0.0034	-10.0569
20	2	1	1	2	1	1	1	0.4083	0.5535	0.0372	0.0010	0.0000	0.0000	-4.7321
21	1	2	1	2	1	1	1	0.0017	0.0567	0.6560	0.2789	0.0016	0.0051	-10.3417
22	2	2	1	2	1	1	1	0.2405	0.6799	0.0774	0.0021	0.0000	0.0000	-5.6724

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

23	1	3	1	2	1	1	1	0.0011	0.0389	0.5871	0.3629	0.0024	0.0075	-10.6368
24	2	3	1	2	1	1	1	0.1269	0.7146	0.1538	0.0046	0.0000	0.0001	-6.4793
25	1	1	2	2	1	1	1	0.0061	0.1760	0.7178	0.0983	0.0005	0.0014	-9.4476
26	2	1	2	2	1	1	1	0.4033	0.5578	0.0379	0.0010	0.0000	0.0000	-4.7599
27	1	2	2	2	1	1	1	0.0041	0.1261	0.7278	0.1393	0.0007	0.0021	-9.7220
28	2	2	2	2	1	1	1	0.2368	0.6821	0.0789	0.0021	0.0000	0.0000	-5.6952
29	1	3	2	2	1	1	1	0.0027	0.0887	0.7110	0.1935	0.0010	0.0031	-9.9956
30	2	3	2	2	1	1	1	0.1246	0.7141	0.1566	0.0047	0.0000	0.0001	-6.5004
31	1	1	3	2	1	1	1	0.0145	0.3350	0.6064	0.0433	0.0002	0.0006	-8.7686
32	2	1	3	2	1	1	1	0.3983	0.5620	0.0387	0.0010	0.0000	0.0000	-4.7876
33	1	2	3	2	1	1	1	0.0098	0.2556	0.6704	0.0630	0.0003	0.0009	-9.0919
34	2	2	3	2	1	1	1	0.2330	0.6843	0.0805	0.0022	0.0000	0.0000	-5.7179
35	1	3	3	2	1	1	1	0.0066	0.1888	0.7120	0.0909	0.0004	0.0013	-9.3857
36	2	3	3	2	1	1	1	0.1224	0.7135	0.1593	0.0048	0.0000	0.0001	-6.5214
37	1	1	1	3	1	1	1	0.0018	0.0593	0.6630	0.2695	0.0015	0.0048	-10.3067
38	2	1	1	3	1	1	1	0.3274	0.6193	0.0519	0.0014	0.0000	0.0000	-5.1775
39	1	2	1	3	1	1	1	0.0012	0.0407	0.5964	0.3522	0.0023	0.0072	-10.6008
40	2	2	1	3	1	1	1	0.1826	0.7082	0.1061	0.0030	0.0000	0.0000	-6.0423
41	1	3	1	3	1	1	1	0.0008	0.0278	0.5141	0.4433	0.0034	0.0107	-10.8991
42	2	3	1	3	1	1	1	0.0930	0.6963	0.2042	0.0065	0.0000	0.0001	-6.8328
43	1	1	2	3	1	1	1	0.0043	0.1314	0.7280	0.1337	0.0006	0.0020	-9.6891
44	2	1	2	3	1	1	1	0.3228	0.6229	0.0529	0.0014	0.0000	0.0000	-5.2028
45	1	2	2	3	1	1	1	0.0029	0.0926	0.7144	0.1862	0.0010	0.0030	-9.9622
46	2	2	2	3	1	1	1	0.1795	0.7092	0.1081	0.0030	0.0000	0.0000	-6.0639
47	1	3	2	3	1	1	1	0.0019	0.0643	0.6749	0.2529	0.0014	0.0044	-10.2432
48	2	3	2	3	1	1	1	0.0913	0.6945	0.2075	0.0066	0.0000	0.0001	-6.8541
49	1	1	3	3	1	1	1	0.0103	0.2646	0.6638	0.0603	0.0003	0.0008	-9.0546
50	2	1	3	3	1	1	1	0.3183	0.6263	0.0539	0.0014	0.0000	0.0000	-5.2280
51	1	2	3	3	1	1	1	0.0069	0.1962	0.7083	0.0870	0.0004	0.0012	-9.3513
52	2	2	3	3	1	1	1	0.1765	0.7102	0.1101	0.0031	0.0000	0.0000	-6.0853
53	1	3	3	3	1	1	1	0.0047	0.1416	0.7274	0.1239	0.0006	0.0018	-9.6290
54	2	3	3	3	1	1	1	0.0896	0.6927	0.2109	0.0067	0.0000	0.0001	-6.8754
55	1	1	1	1	2	1	1	0.0089	0.2388	0.6823	0.0687	0.0003	0.0010	-9.1626
56	2	1	1	1	2	1	1	0.7114	0.2776	0.0107	0.0003	0.0000	0.0000	-2.8392
57	1	2	1	1	2	1	1	0.0060	0.1753	0.7181	0.0988	0.0005	0.0014	-9.4511
58	2	2	1	1	2	1	1	0.5308	0.4455	0.0230	0.0006	0.0000	0.0000	-4.0312

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

59	1	3	1	1	2	1	1	0.0041	0.1255	0.7277	0.1399	0.0007	0.0021	-9.7254
60	2	3	1	1	2	1	1	0.3418	0.6081	0.0488	0.0013	0.0000	0.0000	-5.0980
61	1	1	2	1	2	1	1	0.0213	0.4216	0.5269	0.0297	0.0001	0.0004	-8.4150
62	2	1	2	1	2	1	1	0.7071	0.2817	0.0109	0.0003	0.0000	0.0000	-2.8709
63	1	2	2	1	2	1	1	0.0144	0.3339	0.6074	0.0435	0.0002	0.0006	-8.7730
64	2	2	2	1	2	1	1	0.5256	0.4502	0.0235	0.0006	0.0000	0.0000	-4.0622
65	1	3	2	1	2	1	1	0.0097	0.2546	0.6711	0.0633	0.0003	0.0009	-9.0958
66	2	3	2	1	2	1	1	0.3371	0.6118	0.0498	0.0013	0.0000	0.0000	-5.1238
67	1	1	3	1	2	1	1	0.0499	0.6075	0.3298	0.0125	0.0001	0.0002	-7.5251
68	2	1	3	1	2	1	1	0.7028	0.2858	0.0112	0.0003	0.0000	0.0000	-2.9027
69	1	2	3	1	2	1	1	0.0341	0.5293	0.4177	0.0185	0.0001	0.0002	-7.9366
70	2	2	3	1	2	1	1	0.5204	0.4550	0.0240	0.0006	0.0000	0.0000	-4.0931
71	1	3	3	1	2	1	1	0.0232	0.4414	0.5077	0.0273	0.0001	0.0004	-8.3316
72	2	3	3	1	2	1	1	0.3325	0.6154	0.0507	0.0013	0.0000	0.0000	-5.1494
73	1	1	1	2	2	1	1	0.0012	0.0403	0.5944	0.3546	0.0023	0.0073	-10.6086
74	2	1	1	2	2	1	1	0.2446	0.6774	0.0759	0.0021	0.0000	0.0000	-5.6479
75	1	2	1	2	2	1	1	0.0008	0.0275	0.5117	0.4458	0.0034	0.0108	-10.9069
76	2	2	1	2	2	1	1	0.1294	0.7150	0.1510	0.0045	0.0000	0.0001	-6.4568
77	1	3	1	2	2	1	1	0.0005	0.0187	0.4220	0.5379	0.0050	0.0159	-11.1986
78	2	3	1	2	2	1	1	0.0639	0.6498	0.2765	0.0097	0.0000	0.0001	-7.2526
79	1	1	2	2	2	1	1	0.0029	0.0917	0.7137	0.1878	0.0010	0.0030	-9.9695
80	2	1	2	2	2	1	1	0.2408	0.6797	0.0773	0.0021	0.0000	0.0000	-5.6708
81	1	2	2	2	2	1	1	0.0019	0.0637	0.6736	0.2549	0.0014	0.0045	-10.2508
82	2	2	2	2	2	1	1	0.1271	0.7146	0.1537	0.0046	0.0000	0.0001	-6.4778
83	1	3	2	2	2	1	1	0.0013	0.0438	0.6107	0.3354	0.0021	0.0067	-10.5431
84	2	3	2	2	2	1	1	0.0626	0.6467	0.2806	0.0099	0.0000	0.0001	-7.2744
85	1	1	3	2	2	1	1	0.0069	0.1945	0.7091	0.0878	0.0004	0.0013	-9.3589
86	2	1	3	2	2	1	1	0.2370	0.6820	0.0788	0.0021	0.0000	0.0000	-5.6936
87	1	2	3	2	2	1	1	0.0046	0.1404	0.7275	0.1251	0.0006	0.0019	-9.6363
88	2	2	3	2	2	1	1	0.1248	0.7141	0.1564	0.0047	0.0000	0.0001	-6.4989
89	1	3	3	2	2	1	1	0.0031	0.0992	0.7191	0.1749	0.0009	0.0028	-9.9089
90	2	3	3	2	2	1	1	0.0614	0.6436	0.2847	0.0101	0.0000	0.0001	-7.2961
91	1	1	1	3	2	1	1	0.0008	0.0288	0.5223	0.4346	0.0033	0.0103	-10.8710
92	2	1	1	3	2	1	1	0.1860	0.7070	0.1041	0.0029	0.0000	0.0000	-6.0192
93	1	2	1	3	2	1	1	0.0006	0.0195	0.4329	0.5270	0.0048	0.0152	-11.1640

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

94	2	2	1	3	2	1	1	0.0949	0.6980	0.2006	0.0063	0.0000	0.0001	-6.8100
95	1	3	1	3	2	1	1	0.0004	0.0132	0.3441	0.6129	0.0070	0.0224	-11.4423
96	2	3	1	3	2	1	1	0.0459	0.5915	0.3487	0.0137	0.0001	0.0002	-7.6167
97	1	1	2	3	2	1	1	0.0020	0.0666	0.6797	0.2460	0.0014	0.0043	-10.2162
98	2	1	2	3	2	1	1	0.1828	0.7081	0.1060	0.0030	0.0000	0.0000	-6.0408
99	1	2	2	3	2	1	1	0.0014	0.0459	0.6194	0.3250	0.0020	0.0064	-10.5073
100	2	2	2	3	2	1	1	0.0931	0.6964	0.2039	0.0065	0.0000	0.0001	-6.8313
101	1	3	2	3	2	1	1	0.0009	0.0313	0.5412	0.4142	0.0030	0.0094	-10.8053
102	2	3	2	3	2	1	1	0.0450	0.5876	0.3532	0.0139	0.0001	0.0002	-7.6385
103	1	1	3	3	2	1	1	0.0048	0.1462	0.7267	0.1199	0.0006	0.0018	-9.6032
104	2	1	3	3	2	1	1	0.1797	0.7092	0.1080	0.0030	0.0000	0.0000	-6.0624
105	1	2	3	3	2	1	1	0.0033	0.1036	0.7215	0.1681	0.0008	0.0026	-9.8757
106	2	2	3	3	2	1	1	0.0914	0.6946	0.2073	0.0066	0.0000	0.0001	-6.8526
107	1	3	3	3	2	1	1	0.0022	0.0722	0.6900	0.2304	0.0013	0.0039	-10.1536
108	2	3	3	3	2	1	1	0.0441	0.5836	0.3578	0.0142	0.0001	0.0002	-7.6602
109	1	1	1	1	3	1	1	0.0042	0.1297	0.7280	0.1355	0.0007	0.0020	-9.6997
110	2	1	1	1	3	1	1	0.5364	0.4405	0.0225	0.0006	0.0000	0.0000	-3.9979
111	1	2	1	1	3	1	1	0.0028	0.0913	0.7133	0.1885	0.0010	0.0030	-9.9730
112	2	2	1	1	3	1	1	0.3469	0.6041	0.0478	0.0013	0.0000	0.0000	-5.0703
113	1	3	1	1	3	1	1	0.0019	0.0634	0.6729	0.2558	0.0014	0.0045	-10.2545
114	2	3	1	1	3	1	1	0.1960	0.7030	0.0982	0.0027	0.0000	0.0000	-5.9519
115	1	1	2	1	3	1	1	0.0101	0.2616	0.6660	0.0612	0.0003	0.0008	-9.0667
116	2	1	2	1	3	1	1	0.5312	0.4452	0.0230	0.0006	0.0000	0.0000	-4.0291
117	1	2	2	1	3	1	1	0.0068	0.1938	0.7095	0.0882	0.0004	0.0013	-9.3625
118	2	2	2	1	3	1	1	0.3421	0.6078	0.0487	0.0013	0.0000	0.0000	-5.0962
119	1	3	2	1	3	1	1	0.0046	0.1397	0.7276	0.1256	0.0006	0.0019	-9.6397
120	2	3	2	1	3	1	1	0.1927	0.7044	0.1001	0.0028	0.0000	0.0000	-5.9737
121	1	1	3	1	3	1	1	0.0241	0.4498	0.4993	0.0263	0.0001	0.0004	-8.2954
122	2	1	3	1	3	1	1	0.5260	0.4499	0.0235	0.0006	0.0000	0.0000	-4.0601
123	1	2	3	1	3	1	1	0.0163	0.3609	0.5835	0.0386	0.0002	0.0005	-8.6641
124	2	2	3	1	3	1	1	0.3375	0.6115	0.0497	0.0013	0.0000	0.0000	-5.1220
125	1	3	3	1	3	1	1	0.0110	0.2784	0.6532	0.0563	0.0002	0.0008	-8.9978
126	2	3	3	1	3	1	1	0.1895	0.7057	0.1019	0.0028	0.0000	0.0000	-5.9954
127	1	1	1	2	3	1	1	0.0006	0.0193	0.4305	0.5294	0.0048	0.0154	-11.1716
128	2	1	1	2	3	1	1	0.1320	0.7154	0.1482	0.0044	0.0000	0.0001	-6.4342

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

129	1	2	1	2	3	1	1	0.0004	0.0131	0.3418	0.6150	0.0071	0.0227	-11.4494
130	2	2	1	2	3	1	1	0.0652	0.6529	0.2722	0.0095	0.0000	0.0001	-7.2294
131	1	3	1	2	3	1	1	0.0003	0.0088	0.2612	0.6861	0.0102	0.0334	-11.7087
132	2	3	1	2	3	1	1	0.0310	0.5081	0.4402	0.0204	0.0001	0.0003	-8.0365
133	1	1	2	2	3	1	1	0.0013	0.0454	0.6175	0.3273	0.0020	0.0064	-10.5151
134	2	1	2	2	3	1	1	0.1296	0.7151	0.1508	0.0045	0.0000	0.0001	-6.4553
135	1	2	2	2	3	1	1	0.0009	0.0310	0.5389	0.4166	0.0030	0.0095	-10.8132
136	2	2	2	2	3	1	1	0.0640	0.6500	0.2762	0.0097	0.0000	0.0001	-7.2511
137	1	3	2	2	3	1	1	0.0006	0.0211	0.4504	0.5093	0.0044	0.0141	-11.1082
138	2	3	2	2	3	1	1	0.0304	0.5035	0.4449	0.0208	0.0001	0.0003	-8.0576
139	1	1	3	2	3	1	1	0.0032	0.1026	0.7210	0.1696	0.0009	0.0027	-9.8830
140	2	1	3	2	3	1	1	0.1272	0.7146	0.1535	0.0046	0.0000	0.0001	-6.4764
141	1	2	3	2	3	1	1	0.0022	0.0715	0.6888	0.2322	0.0013	0.0040	-10.1611
142	2	2	3	2	3	1	1	0.0627	0.6469	0.2803	0.0099	0.0000	0.0001	-7.2729
143	1	3	3	2	3	1	1	0.0015	0.0493	0.6327	0.3088	0.0019	0.0059	-10.4501
144	2	3	3	2	3	1	1	0.0298	0.4989	0.4497	0.0212	0.0001	0.0003	-8.0786
145	1	1	1	3	3	1	1	0.0004	0.0137	0.3522	0.6053	0.0068	0.0216	-11.4168
146	2	1	1	3	3	1	1	0.0969	0.6997	0.1971	0.0062	0.0000	0.0001	-6.7873
147	1	2	1	3	3	1	1	0.0003	0.0093	0.2704	0.6784	0.0098	0.0318	-11.6783
148	2	2	1	3	3	1	1	0.0469	0.5956	0.3438	0.0134	0.0001	0.0002	-7.5934
149	1	3	1	3	3	1	1	0.0002	0.0063	0.2008	0.7321	0.0141	0.0466	-11.9247
150	2	3	1	3	3	1	1	0.0221	0.4300	0.5188	0.0287	0.0001	0.0004	-8.3798
151	1	1	2	3	3	1	1	0.0009	0.0325	0.5492	0.4055	0.0029	0.0091	-10.7771
152	2	1	2	3	3	1	1	0.0950	0.6982	0.2004	0.0063	0.0000	0.0001	-6.8086
153	1	2	2	3	3	1	1	0.0006	0.0221	0.4614	0.4982	0.0042	0.0134	-11.0730
154	2	2	2	3	3	1	1	0.0460	0.5918	0.3484	0.0136	0.0001	0.0002	-7.6152
155	1	3	2	3	3	1	1	0.0004	0.0150	0.3715	0.5871	0.0062	0.0199	-11.3567
156	2	3	2	3	3	1	1	0.0216	0.4253	0.5233	0.0292	0.0001	0.0004	-8.3996
157	1	1	3	3	3	1	1	0.0023	0.0748	0.6941	0.2239	0.0012	0.0038	-10.1269
158	2	1	3	3	3	1	1	0.0933	0.6965	0.2037	0.0064	0.0000	0.0001	-6.8298
159	1	2	3	3	3	1	1	0.0015	0.0516	0.6406	0.2988	0.0018	0.0056	-10.4146
160	2	2	3	3	3	1	1	0.0451	0.5878	0.3529	0.0139	0.0001	0.0002	-7.6370
161	1	3	3	3	3	1	1	0.0010	0.0353	0.5673	0.3854	0.0026	0.0083	-10.7113
162	2	3	3	3	3	1	1	0.0212	0.4206	0.5279	0.0298	0.0001	0.0004	-8.4194
163	1	1	1	1	1	2	1	0.0083	0.2261	0.6907	0.0735	0.0003	0.0010	-9.2172

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

164	2	1	1	1	1	2	1	0.9322	0.0658	0.0019	0.0000	0.0000	0.0000	-0.8406
165	1	2	1	1	1	2	1	0.0056	0.1651	0.7218	0.1054	0.0005	0.0015	-9.5020
166	2	2	1	1	1	2	1	0.8633	0.1324	0.0042	0.0001	0.0000	0.0000	-1.5608
167	1	3	1	1	1	2	1	0.0038	0.1178	0.7266	0.1488	0.0007	0.0023	-9.7753
168	2	3	1	1	1	2	1	0.7435	0.2471	0.0091	0.0002	0.0000	0.0000	-2.5958
169	1	1	2	1	1	2	1	0.0198	0.4052	0.5425	0.0319	0.0001	0.0004	-8.4832
170	2	1	2	1	1	2	1	0.9309	0.0671	0.0020	0.0000	0.0000	0.0000	-0.8556
171	1	2	2	1	1	2	1	0.0134	0.3186	0.6205	0.0466	0.0002	0.0006	-8.8347
172	2	2	2	1	1	2	1	0.8608	0.1348	0.0043	0.0001	0.0000	0.0000	-1.5847
173	1	3	2	1	1	2	1	0.0091	0.2414	0.6805	0.0678	0.0003	0.0009	-9.1515
174	2	3	2	1	1	2	1	0.7395	0.2509	0.0093	0.0002	0.0000	0.0000	-2.6268
175	1	1	3	1	1	2	1	0.0466	0.5943	0.3454	0.0135	0.0001	0.0002	-7.6010
176	2	1	3	1	1	2	1	0.9296	0.0684	0.0020	0.0001	0.0000	0.0000	-0.8709
177	1	2	3	1	1	2	1	0.0318	0.5136	0.4343	0.0199	0.0001	0.0003	-8.0106
178	2	2	3	1	1	2	1	0.8583	0.1372	0.0044	0.0001	0.0000	0.0000	-1.6089
179	1	3	3	1	1	2	1	0.0216	0.4249	0.5237	0.0293	0.0001	0.0004	-8.4011
180	2	3	3	1	1	2	1	0.7355	0.2548	0.0095	0.0002	0.0000	0.0000	-2.6579
181	1	1	1	2	1	2	1	0.0011	0.0376	0.5802	0.3709	0.0025	0.0078	-10.6633
182	2	1	1	2	1	2	1	0.6439	0.3412	0.0145	0.0004	0.0000	0.0000	-3.3159
183	1	2	1	2	1	2	1	0.0007	0.0256	0.4956	0.4628	0.0037	0.0116	-10.9612
184	2	2	1	2	1	2	1	0.4535	0.5146	0.0311	0.0008	0.0000	0.0000	-4.4797
185	1	3	1	2	1	2	1	0.0005	0.0174	0.4054	0.5542	0.0054	0.0171	-11.2506
186	2	3	1	2	1	2	1	0.2758	0.6571	0.0653	0.0017	0.0000	0.0000	-5.4665
187	1	1	2	2	1	2	1	0.0027	0.0859	0.7082	0.1990	0.0010	0.0033	-10.0202
188	2	1	2	2	1	2	1	0.6390	0.3457	0.0148	0.0004	0.0000	0.0000	-3.3482
189	1	2	2	2	1	2	1	0.0018	0.0595	0.6636	0.2687	0.0015	0.0048	-10.3036
190	2	2	2	2	1	2	1	0.4483	0.5191	0.0318	0.0008	0.0000	0.0000	-4.5088
191	1	3	2	2	1	2	1	0.0012	0.0409	0.5972	0.3513	0.0023	0.0072	-10.5976
192	2	3	2	2	1	2	1	0.2717	0.6599	0.0666	0.0018	0.0000	0.0000	-5.4902
193	1	1	3	2	1	2	1	0.0064	0.1836	0.7145	0.0938	0.0004	0.0013	-9.4107
194	2	1	3	2	1	2	1	0.6342	0.3502	0.0152	0.0004	0.0000	0.0000	-3.3804
195	1	2	3	2	1	2	1	0.0043	0.1319	0.7280	0.1332	0.0006	0.0020	-9.6862
196	2	2	3	2	1	2	1	0.4432	0.5236	0.0324	0.0008	0.0000	0.0000	-4.5378
197	1	3	3	2	1	2	1	0.0029	0.0930	0.7147	0.1855	0.0010	0.0030	-9.9592
198	2	3	3	2	1	2	1	0.2676	0.6627	0.0679	0.0018	0.0000	0.0000	-5.5139

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

199	1	1	1	3	1	2	1	0.0008	0.0268	0.5063	0.4516	0.0035	0.0110	-10.9254
200	2	1	1	3	1	2	1	0.5605	0.4185	0.0205	0.0005	0.0000	0.0000	-3.8516
201	1	2	1	3	1	2	1	0.0005	0.0182	0.4163	0.5435	0.0051	0.0163	-11.2163
202	2	2	1	3	1	2	1	0.3692	0.5861	0.0435	0.0011	0.0000	0.0000	-4.9474
203	1	3	1	3	1	2	1	0.0004	0.0123	0.3285	0.6273	0.0075	0.0241	-11.4913
204	2	3	1	3	1	2	1	0.2118	0.6957	0.0900	0.0025	0.0000	0.0000	-5.8495
205	1	1	2	3	1	2	1	0.0019	0.0623	0.6703	0.2595	0.0015	0.0046	-10.2687
206	2	1	2	3	1	2	1	0.5553	0.4232	0.0209	0.0005	0.0000	0.0000	-3.8831
207	1	2	2	3	1	2	1	0.0013	0.0428	0.6062	0.3408	0.0022	0.0068	-10.5616
208	2	2	2	3	1	2	1	0.3644	0.5900	0.0444	0.0012	0.0000	0.0000	-4.9740
209	1	3	2	3	1	2	1	0.0008	0.0292	0.5255	0.4311	0.0032	0.0101	-10.8599
210	2	3	2	3	1	2	1	0.2083	0.6974	0.0917	0.0025	0.0000	0.0000	-5.8716
211	1	1	3	3	1	2	1	0.0045	0.1374	0.7278	0.1278	0.0006	0.0019	-9.6532
212	2	1	3	3	1	2	1	0.5502	0.4279	0.0213	0.0005	0.0000	0.0000	-3.9146
213	1	2	3	3	1	2	1	0.0030	0.0971	0.7177	0.1785	0.0009	0.0028	-9.9259
214	2	2	3	3	1	2	1	0.3596	0.5939	0.0453	0.0012	0.0000	0.0000	-5.0005
215	1	3	3	3	1	2	1	0.0020	0.0675	0.6815	0.2433	0.0013	0.0042	-10.2056
216	2	3	3	3	1	2	1	0.2049	0.6991	0.0934	0.0026	0.0000	0.0000	-5.8936
217	1	1	1	1	2	2	1	0.0039	0.1217	0.7273	0.1442	0.0007	0.0022	-9.7496
218	2	1	1	1	2	2	1	0.8659	0.1299	0.0041	0.0001	0.0000	0.0000	-1.5355
219	1	2	1	1	2	2	1	0.0026	0.0855	0.7078	0.1998	0.0010	0.0033	-10.0238
220	2	2	1	1	2	2	1	0.7477	0.2431	0.0089	0.0002	0.0000	0.0000	-2.5628
221	1	3	1	1	2	2	1	0.0018	0.0592	0.6629	0.2697	0.0015	0.0049	-10.3073
222	2	3	1	1	2	2	1	0.5764	0.4039	0.0192	0.0005	0.0000	0.0000	-3.7532
223	1	1	2	1	2	2	1	0.0094	0.2482	0.6757	0.0655	0.0003	0.0009	-9.1229
224	2	1	2	1	2	2	1	0.8635	0.1322	0.0042	0.0001	0.0000	0.0000	-1.5592
225	1	2	2	1	2	2	1	0.0063	0.1828	0.7148	0.0942	0.0004	0.0014	-9.4143
226	2	2	2	1	2	2	1	0.7438	0.2469	0.0091	0.0002	0.0000	0.0000	-2.5937
227	1	3	2	1	2	2	1	0.0043	0.1313	0.7280	0.1338	0.0006	0.0020	-9.6896
228	2	3	2	1	2	2	1	0.5713	0.4086	0.0196	0.0005	0.0000	0.0000	-3.7850
229	1	1	3	1	2	2	1	0.0224	0.4334	0.5154	0.0282	0.0001	0.0004	-8.3654
230	2	1	3	1	2	2	1	0.8610	0.1346	0.0043	0.0001	0.0000	0.0000	-1.5831
231	1	2	3	1	2	2	1	0.0152	0.3451	0.5976	0.0414	0.0002	0.0006	-8.7279
232	2	2	3	1	2	2	1	0.7398	0.2507	0.0093	0.0002	0.0000	0.0000	-2.6247
233	1	3	3	1	2	2	1	0.0103	0.2644	0.6639	0.0603	0.0003	0.0008	-9.0552

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

234	2	3	3	1	2	2	1	0.5662	0.4133	0.0200	0.0005	0.0000	0.0000	-3.8167
235	1	1	1	2	2	2	1	0.0005	0.0180	0.4139	0.5458	0.0052	0.0165	-11.2238
236	2	1	1	2	2	2	1	0.4590	0.5097	0.0305	0.0008	0.0000	0.0000	-4.4483
237	1	2	1	2	2	2	1	0.0003	0.0122	0.3263	0.6293	0.0076	0.0243	-11.4983
238	2	2	1	2	2	2	1	0.2803	0.6540	0.0639	0.0017	0.0000	0.0000	-5.4410
239	1	3	1	2	2	2	1	0.0002	0.0082	0.2478	0.6970	0.0110	0.0358	-11.7545
240	2	3	1	2	2	2	1	0.1517	0.7155	0.1290	0.0037	0.0000	0.0000	-6.2703
241	1	1	2	2	2	2	1	0.0012	0.0424	0.6042	0.3431	0.0022	0.0069	-10.5695
242	2	1	2	2	2	2	1	0.4538	0.5143	0.0311	0.0008	0.0000	0.0000	-4.4777
243	1	2	2	2	2	2	1	0.0008	0.0289	0.5232	0.4336	0.0032	0.0102	-10.8678
244	2	2	2	2	2	2	1	0.2761	0.6569	0.0652	0.0017	0.0000	0.0000	-5.4648
245	1	3	2	2	2	2	1	0.0006	0.0196	0.4339	0.5260	0.0048	0.0151	-11.1610
246	2	3	2	2	2	2	1	0.1490	0.7158	0.1314	0.0038	0.0000	0.0000	-6.2915
247	1	1	3	2	2	2	1	0.0030	0.0961	0.7171	0.1800	0.0009	0.0029	-9.9332
248	2	1	3	2	2	2	1	0.4487	0.5188	0.0317	0.0008	0.0000	0.0000	-4.5068
249	1	2	3	2	2	2	1	0.0020	0.0669	0.6802	0.2452	0.0014	0.0043	-10.2132
250	2	2	3	2	2	2	1	0.2720	0.6597	0.0665	0.0018	0.0000	0.0000	-5.4886
251	1	3	3	2	2	2	1	0.0014	0.0460	0.6201	0.3241	0.0020	0.0063	-10.5042
252	2	3	3	2	2	2	1	0.1464	0.7159	0.1338	0.0039	0.0000	0.0001	-6.3126
253	1	1	1	3	2	2	1	0.0004	0.0128	0.3365	0.6199	0.0072	0.0232	-11.4661
254	2	1	1	3	2	2	1	0.3744	0.5818	0.0426	0.0011	0.0000	0.0000	-4.9187
255	1	2	1	3	2	2	1	0.0002	0.0086	0.2566	0.6899	0.0105	0.0342	-11.7243
256	2	2	1	3	2	2	1	0.2155	0.6938	0.0882	0.0024	0.0000	0.0000	-5.8258
257	1	3	1	3	2	2	1	0.0002	0.0058	0.1895	0.7395	0.0150	0.0500	-11.9689
258	2	3	1	3	2	2	1	0.1120	0.7096	0.1730	0.0053	0.0000	0.0001	-6.6229
259	1	1	2	3	2	2	1	0.0009	0.0303	0.5336	0.4224	0.0031	0.0098	-10.8318
260	2	1	2	3	2	2	1	0.3696	0.5858	0.0435	0.0011	0.0000	0.0000	-4.9455
261	1	2	2	3	2	2	1	0.0006	0.0206	0.4448	0.5150	0.0046	0.0144	-11.1262
262	2	2	2	3	2	2	1	0.2120	0.6956	0.0899	0.0025	0.0000	0.0000	-5.8480
263	1	3	2	3	2	2	1	0.0004	0.0139	0.3554	0.6022	0.0067	0.0213	-11.4068
264	2	3	2	3	2	2	1	0.1099	0.7086	0.1760	0.0054	0.0000	0.0001	-6.6440
265	1	1	3	3	2	2	1	0.0021	0.0699	0.6860	0.2366	0.0013	0.0041	-10.1787
266	2	1	3	3	2	2	1	0.3647	0.5898	0.0443	0.0012	0.0000	0.0000	-4.9722
267	1	2	3	3	2	2	1	0.0014	0.0482	0.6285	0.3139	0.0019	0.0060	-10.4684
268	2	2	3	3	2	2	1	0.2086	0.6973	0.0916	0.0025	0.0000	0.0000	-5.8701

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

269	1	3	3	3	2	2	1	0.0010	0.0329	0.5522	0.4021	0.0028	0.0089	-10.7660
270	2	3	3	3	2	2	1	0.1079	0.7075	0.1790	0.0055	0.0000	0.0001	-6.6652
271	1	1	1	1	3	2	1	0.0018	0.0614	0.6682	0.2625	0.0015	0.0047	-10.2800
272	2	1	1	1	3	2	1	0.7519	0.2391	0.0087	0.0002	0.0000	0.0000	-2.5300
273	1	2	1	1	3	2	1	0.0012	0.0422	0.6033	0.3442	0.0022	0.0069	-10.5733
274	2	2	1	1	3	2	1	0.5818	0.3989	0.0188	0.0005	0.0000	0.0000	-3.7192
275	1	3	1	1	3	2	1	0.0008	0.0288	0.5221	0.4347	0.0033	0.0103	-10.8716
276	2	3	1	1	3	2	1	0.3897	0.5692	0.0401	0.0010	0.0000	0.0000	-4.8346
277	1	1	2	1	3	2	1	0.0044	0.1356	0.7279	0.1295	0.0006	0.0019	-9.6639
278	2	1	2	1	3	2	1	0.7480	0.2428	0.0089	0.0002	0.0000	0.0000	-2.5607
279	1	2	2	1	3	2	1	0.0030	0.0957	0.7168	0.1807	0.0009	0.0029	-9.9367
280	2	2	2	1	3	2	1	0.5767	0.4036	0.0192	0.0005	0.0000	0.0000	-3.7510
281	1	3	2	1	3	2	1	0.0020	0.0666	0.6796	0.2462	0.0014	0.0043	-10.2168
282	2	3	2	1	3	2	1	0.3848	0.5733	0.0409	0.0011	0.0000	0.0000	-4.8619
283	1	1	3	1	3	2	1	0.0107	0.2716	0.6585	0.0582	0.0003	0.0008	-9.0257
284	2	1	3	1	3	2	1	0.7441	0.2466	0.0091	0.0002	0.0000	0.0000	-2.5916
285	1	2	3	1	3	2	1	0.0072	0.2019	0.7052	0.0841	0.0004	0.0012	-9.3249
286	2	2	3	1	3	2	1	0.5716	0.4083	0.0196	0.0005	0.0000	0.0000	-3.7828
287	1	3	3	1	3	2	1	0.0048	0.1461	0.7267	0.1200	0.0006	0.0018	-9.6038
288	2	3	3	1	3	2	1	0.3798	0.5774	0.0417	0.0011	0.0000	0.0000	-4.8890
289	1	1	1	2	3	2	1	0.0002	0.0085	0.2547	0.6914	0.0106	0.0345	-11.7309
290	2	1	1	2	3	2	1	0.2848	0.6508	0.0626	0.0017	0.0000	0.0000	-5.4153
291	1	2	1	2	3	2	1	0.0002	0.0058	0.1879	0.7405	0.0152	0.0505	-11.9753
292	2	2	1	2	3	2	1	0.1545	0.7152	0.1266	0.0036	0.0000	0.0000	-6.2477
293	1	3	1	2	3	2	1	0.0001	0.0039	0.1352	0.7662	0.0213	0.0733	-12.2175
294	2	3	1	2	3	2	1	0.0774	0.6765	0.2380	0.0079	0.0000	0.0001	-7.0385
295	1	1	2	2	3	2	1	0.0006	0.0204	0.4424	0.5174	0.0046	0.0146	-11.1338
296	2	1	2	2	3	2	1	0.2806	0.6538	0.0639	0.0017	0.0000	0.0000	-5.4393
297	1	2	2	2	3	2	1	0.0004	0.0138	0.3531	0.6044	0.0067	0.0216	-11.4139
298	2	2	2	2	3	2	1	0.1518	0.7155	0.1289	0.0037	0.0000	0.0000	-6.2689
299	1	3	2	2	3	2	1	0.0003	0.0093	0.2712	0.6778	0.0098	0.0317	-11.6756
300	2	3	2	2	3	2	1	0.0759	0.6741	0.2418	0.0081	0.0000	0.0001	-7.0600
301	1	1	3	2	3	2	1	0.0014	0.0477	0.6267	0.3162	0.0019	0.0061	-10.4762
302	2	1	3	2	3	2	1	0.2764	0.6567	0.0651	0.0017	0.0000	0.0000	-5.4632
303	1	2	3	2	3	2	1	0.0010	0.0326	0.5500	0.4045	0.0029	0.0090	-10.7739

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

304	2	2	3	2	3	2	1	0.1492	0.7157	0.1312	0.0038	0.0000	0.0000	-6.2900
305	1	3	3	2	3	2	1	0.0006	0.0222	0.4623	0.4972	0.0042	0.0134	-11.0699
306	2	3	3	2	3	2	1	0.0745	0.6716	0.2455	0.0082	0.0000	0.0001	-7.0816
307	1	1	1	3	3	2	1	0.0002	0.0060	0.1953	0.7358	0.0145	0.0482	-11.9461
308	2	1	1	3	3	2	1	0.2193	0.6919	0.0864	0.0024	0.0000	0.0000	-5.8020
309	1	2	1	3	3	2	1	0.0001	0.0041	0.1409	0.7644	0.0205	0.0701	-12.1878
310	2	2	1	3	3	2	1	0.1142	0.7106	0.1699	0.0051	0.0000	0.0001	-6.6003
311	1	3	1	3	3	2	1	0.0001	0.0027	0.0996	0.7686	0.0282	0.1008	-12.4400
312	2	3	1	3	3	2	1	0.0559	0.6278	0.3050	0.0111	0.0000	0.0001	-7.4009
313	1	1	2	3	3	2	1	0.0004	0.0145	0.3637	0.5945	0.0064	0.0206	-11.3810
314	2	1	2	3	3	2	1	0.2158	0.6937	0.0881	0.0024	0.0000	0.0000	-5.8243
315	1	2	2	3	3	2	1	0.0003	0.0098	0.2805	0.6698	0.0093	0.0303	-11.6449
316	2	2	2	3	3	2	1	0.1121	0.7097	0.1728	0.0053	0.0000	0.0001	-6.6214
317	1	3	2	3	3	2	1	0.0002	0.0066	0.2091	0.7263	0.0134	0.0444	-11.8928
318	2	3	2	3	3	2	1	0.0548	0.6244	0.3093	0.0114	0.0000	0.0001	-7.4227
319	1	1	3	3	3	2	1	0.0010	0.0342	0.5601	0.3934	0.0027	0.0086	-10.7378
320	2	1	3	3	3	2	1	0.2123	0.6955	0.0897	0.0025	0.0000	0.0000	-5.8464
321	1	2	3	3	3	2	1	0.0007	0.0232	0.4733	0.4860	0.0040	0.0128	-11.0346
322	2	2	3	3	3	2	1	0.1101	0.7087	0.1758	0.0054	0.0000	0.0001	-6.6426
323	1	3	3	3	3	2	1	0.0005	0.0158	0.3831	0.5759	0.0059	0.0189	-11.3204
324	2	3	3	3	3	2	1	0.0537	0.6209	0.3136	0.0116	0.0000	0.0002	-7.4445
325	1	1	1	1	1	3	1	0.0329	0.5210	0.4265	0.0192	0.0001	0.0003	-7.9759
326	2	1	1	1	1	3	1	0.7536	0.2375	0.0087	0.0002	0.0000	0.0000	-2.5166
327	1	2	1	1	1	3	1	0.0223	0.4326	0.5162	0.0283	0.0001	0.0004	-8.3686
328	2	2	1	1	1	3	1	0.5840	0.3968	0.0186	0.0005	0.0000	0.0000	-3.7052
329	1	3	1	1	1	3	1	0.0151	0.3444	0.5982	0.0415	0.0002	0.0006	-8.7308
330	2	3	1	1	1	3	1	0.3919	0.5673	0.0397	0.0010	0.0000	0.0000	-4.8226
331	1	1	2	1	1	3	1	0.0759	0.6740	0.2420	0.0081	0.0000	0.0001	-7.0612
332	2	1	2	1	1	3	1	0.7497	0.2412	0.0088	0.0002	0.0000	0.0000	-2.5473
333	1	2	2	1	1	3	1	0.0523	0.6161	0.3195	0.0119	0.0001	0.0002	-7.4740
334	2	2	2	1	1	3	1	0.5790	0.4015	0.0190	0.0005	0.0000	0.0000	-3.7371
335	1	3	2	1	1	3	1	0.0358	0.5396	0.4066	0.0176	0.0001	0.0002	-7.8865
336	2	3	2	1	1	3	1	0.3869	0.5715	0.0405	0.0011	0.0000	0.0000	-4.8500
337	1	1	3	1	1	3	1	0.1654	0.7132	0.1180	0.0034	0.0000	0.0000	-6.1656
338	2	1	3	1	1	3	1	0.7458	0.2450	0.0090	0.0002	0.0000	0.0000	-2.5781

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

339	1	2	3	1	1	3	1	0.1176	0.7119	0.1654	0.0050	0.0000	0.0001	-6.5674
340	2	2	3	1	1	3	1	0.5739	0.4062	0.0194	0.0005	0.0000	0.0000	-3.7689
341	1	3	3	1	1	3	1	0.0822	0.6837	0.2266	0.0074	0.0000	0.0001	-6.9712
342	2	3	3	1	1	3	1	0.3820	0.5756	0.0413	0.0011	0.0000	0.0000	-4.8772
343	1	1	1	2	1	3	1	0.0044	0.1358	0.7279	0.1293	0.0006	0.0019	-9.6627
344	2	1	1	2	1	3	1	0.2867	0.6495	0.0621	0.0017	0.0000	0.0000	-5.4047
345	1	2	1	2	1	3	1	0.0030	0.0959	0.7169	0.1805	0.0009	0.0029	-9.9356
346	2	2	1	2	1	3	1	0.1557	0.7150	0.1256	0.0036	0.0000	0.0000	-6.2384
347	1	3	1	2	1	3	1	0.0020	0.0667	0.6798	0.2459	0.0014	0.0043	-10.2156
348	2	3	1	2	1	3	1	0.0781	0.6776	0.2364	0.0078	0.0000	0.0001	-7.0291
349	1	1	2	2	1	3	1	0.0107	0.2719	0.6582	0.0581	0.0003	0.0008	-9.0244
350	2	1	2	2	1	3	1	0.2824	0.6525	0.0633	0.0017	0.0000	0.0000	-5.4288
351	1	2	2	2	1	3	1	0.0072	0.2022	0.7051	0.0840	0.0004	0.0012	-9.3237
352	2	2	2	2	1	3	1	0.1530	0.7154	0.1279	0.0037	0.0000	0.0000	-6.2596
353	1	3	2	2	1	3	1	0.0049	0.1463	0.7267	0.1198	0.0006	0.0018	-9.6027
354	2	3	2	2	1	3	1	0.0766	0.6752	0.2401	0.0080	0.0000	0.0001	-7.0506
355	1	1	3	2	1	3	1	0.0254	0.4620	0.4872	0.0250	0.0001	0.0003	-8.2428
356	2	1	3	2	1	3	1	0.2782	0.6555	0.0646	0.0017	0.0000	0.0000	-5.4528
357	1	2	3	2	1	3	1	0.0172	0.3728	0.5727	0.0367	0.0002	0.0005	-8.6160
358	2	2	3	2	1	3	1	0.1503	0.7156	0.1302	0.0038	0.0000	0.0000	-6.2808
359	1	3	3	2	1	3	1	0.0116	0.2890	0.6449	0.0535	0.0002	0.0007	-8.9545
360	2	3	3	2	1	3	1	0.0751	0.6727	0.2439	0.0081	0.0000	0.0001	-7.0722
361	1	1	1	3	1	3	1	0.0031	0.1001	0.7196	0.1736	0.0009	0.0027	-9.9023
362	2	1	1	3	1	3	1	0.2209	0.6910	0.0857	0.0023	0.0000	0.0000	-5.7922
363	1	2	1	3	1	3	1	0.0021	0.0697	0.6856	0.2372	0.0013	0.0041	-10.1811
364	2	2	1	3	1	3	1	0.1152	0.7110	0.1686	0.0051	0.0000	0.0001	-6.5911
365	1	3	1	3	1	3	1	0.0014	0.0480	0.6279	0.3147	0.0019	0.0061	-10.4709
366	2	3	1	3	1	3	1	0.0564	0.6293	0.3031	0.0110	0.0000	0.0001	-7.3913
367	1	1	2	3	1	3	1	0.0076	0.2099	0.7007	0.0804	0.0004	0.0011	-9.2889
368	2	1	2	3	1	3	1	0.2173	0.6929	0.0873	0.0024	0.0000	0.0000	-5.8145
369	1	2	2	3	1	3	1	0.0051	0.1523	0.7255	0.1149	0.0005	0.0017	-9.5695
370	2	2	2	3	1	3	1	0.1130	0.7101	0.1716	0.0052	0.0000	0.0001	-6.6122
371	1	3	2	3	1	3	1	0.0034	0.1082	0.7236	0.1615	0.0008	0.0025	-9.8421
372	2	3	2	3	1	3	1	0.0553	0.6259	0.3074	0.0113	0.0000	0.0001	-7.4131
373	1	1	3	3	1	3	1	0.0180	0.3834	0.5629	0.0350	0.0002	0.0005	-8.5726

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

374	2	1	3	3	1	3	1	0.2138	0.6947	0.0890	0.0024	0.0000	0.0000	-5.8368
375	1	2	3	3	1	3	1	0.0122	0.2986	0.6371	0.0512	0.0002	0.0007	-8.9154
376	2	2	3	3	1	3	1	0.1110	0.7091	0.1745	0.0053	0.0000	0.0001	-6.6333
377	1	3	3	3	1	3	1	0.0082	0.2244	0.6918	0.0742	0.0003	0.0010	-9.2245
378	2	3	3	3	1	3	1	0.0542	0.6224	0.3117	0.0115	0.0000	0.0002	-7.4349
379	1	1	1	1	2	3	1	0.0157	0.3525	0.5910	0.0401	0.0002	0.0005	-8.6981
380	2	1	1	1	2	3	1	0.5895	0.3918	0.0182	0.0005	0.0000	0.0000	-3.6711
381	1	2	1	1	2	3	1	0.0106	0.2709	0.6590	0.0584	0.0003	0.0008	-9.0284
382	2	2	1	1	2	3	1	0.3972	0.5629	0.0389	0.0010	0.0000	0.0000	-4.7933
383	1	3	1	1	2	3	1	0.0072	0.2014	0.7055	0.0844	0.0004	0.0012	-9.3274
384	2	3	1	1	2	3	1	0.2322	0.6848	0.0808	0.0022	0.0000	0.0000	-5.7225
385	1	1	2	1	2	3	1	0.0371	0.5474	0.3982	0.0170	0.0001	0.0002	-7.8479
386	2	1	2	1	2	3	1	0.5844	0.3965	0.0186	0.0005	0.0000	0.0000	-3.7030
387	1	2	2	1	2	3	1	0.0252	0.4609	0.4884	0.0251	0.0001	0.0003	-8.2478
388	2	2	2	1	2	3	1	0.3922	0.5671	0.0396	0.0010	0.0000	0.0000	-4.8208
389	1	3	2	1	2	3	1	0.0171	0.3716	0.5737	0.0368	0.0002	0.0005	-8.6205
390	2	3	2	1	2	3	1	0.2285	0.6868	0.0823	0.0022	0.0000	0.0000	-5.7451
391	1	1	3	1	2	3	1	0.0851	0.6875	0.2202	0.0071	0.0000	0.0001	-6.9327
392	2	1	3	1	2	3	1	0.5793	0.4012	0.0190	0.0005	0.0000	0.0000	-3.7349
393	1	2	3	1	2	3	1	0.0589	0.6366	0.2938	0.0106	0.0000	0.0001	-7.3436
394	2	2	3	1	2	3	1	0.3873	0.5712	0.0405	0.0011	0.0000	0.0000	-4.8481
395	1	3	3	1	2	3	1	0.0403	0.5652	0.3785	0.0156	0.0001	0.0002	-7.7575
396	2	3	3	1	2	3	1	0.2249	0.6889	0.0839	0.0023	0.0000	0.0000	-5.7676
397	1	1	1	2	2	3	1	0.0021	0.0690	0.6844	0.2391	0.0013	0.0041	-10.1886
398	2	1	1	2	2	3	1	0.1587	0.7145	0.1232	0.0035	0.0000	0.0000	-6.2157
399	1	2	1	2	2	3	1	0.0014	0.0476	0.6261	0.3169	0.0019	0.0061	-10.4787
400	2	2	1	2	2	3	1	0.0797	0.6801	0.2325	0.0076	0.0000	0.0001	-7.0061
401	1	3	1	2	2	3	1	0.0009	0.0325	0.5493	0.4053	0.0029	0.0091	-10.7765
402	2	3	1	2	2	3	1	0.0382	0.5539	0.3911	0.0165	0.0001	0.0002	-7.8157
403	1	1	2	2	2	3	1	0.0050	0.1510	0.7258	0.1160	0.0005	0.0017	-9.5768
404	2	1	2	2	2	3	1	0.1559	0.7150	0.1254	0.0036	0.0000	0.0000	-6.2370
405	1	2	2	2	2	3	1	0.0034	0.1072	0.7232	0.1629	0.0008	0.0025	-9.8493
406	2	2	2	2	2	3	1	0.0782	0.6777	0.2362	0.0078	0.0000	0.0001	-7.0276
407	1	3	2	2	2	3	1	0.0023	0.0748	0.6942	0.2237	0.0012	0.0038	-10.1263
408	2	3	2	2	2	3	1	0.0375	0.5496	0.3958	0.0168	0.0001	0.0002	-7.8373

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

409	1	1	3	2	2	3	1	0.0121	0.2965	0.6388	0.0517	0.0002	0.0007	-8.9240
410	2	1	3	2	2	3	1	0.1532	0.7153	0.1277	0.0037	0.0000	0.0000	-6.2582
411	1	2	3	2	2	3	1	0.0081	0.2226	0.6929	0.0749	0.0003	0.0011	-9.2323
412	2	2	3	2	2	3	1	0.0767	0.6754	0.2399	0.0080	0.0000	0.0001	-7.0492
413	1	3	3	2	2	3	1	0.0055	0.1624	0.7227	0.1073	0.0005	0.0016	-9.5162
414	2	3	3	2	2	3	1	0.0367	0.5452	0.4006	0.0172	0.0001	0.0002	-7.8588
415	1	1	1	3	2	3	1	0.0015	0.0498	0.6343	0.3068	0.0019	0.0058	-10.4431
416	2	1	1	3	2	3	1	0.1174	0.7119	0.1656	0.0050	0.0000	0.0001	-6.5686
417	1	2	1	3	2	3	1	0.0010	0.0341	0.5594	0.3942	0.0027	0.0086	-10.7403
418	2	2	1	3	2	3	1	0.0576	0.6329	0.2985	0.0108	0.0000	0.0001	-7.3680
419	1	3	1	3	2	3	1	0.0007	0.0232	0.4725	0.4868	0.0040	0.0128	-11.0371
420	2	3	1	3	2	3	1	0.0273	0.4786	0.4705	0.0232	0.0001	0.0003	-8.1698
421	1	1	2	3	2	3	1	0.0036	0.1118	0.7250	0.1565	0.0008	0.0024	-9.8163
422	2	1	2	3	2	3	1	0.1153	0.7111	0.1684	0.0051	0.0000	0.0001	-6.5897
423	1	2	2	3	2	3	1	0.0024	0.0782	0.6990	0.2156	0.0012	0.0036	-10.0922
424	2	2	2	3	2	3	1	0.0564	0.6295	0.3028	0.0110	0.0000	0.0001	-7.3898
425	1	3	2	3	2	3	1	0.0016	0.0541	0.6484	0.2889	0.0017	0.0053	-10.3786
426	2	3	2	3	2	3	1	0.0267	0.4740	0.4752	0.0237	0.0001	0.0003	-8.1905
427	1	1	3	3	2	3	1	0.0085	0.2309	0.6876	0.0716	0.0003	0.0010	-9.1966
428	2	1	3	3	2	3	1	0.1132	0.7102	0.1714	0.0052	0.0000	0.0001	-6.6108
429	1	2	3	3	2	3	1	0.0058	0.1689	0.7205	0.1028	0.0005	0.0015	-9.4827
430	2	2	3	3	2	3	1	0.0553	0.6261	0.3071	0.0113	0.0000	0.0001	-7.4116
431	1	3	3	3	2	3	1	0.0039	0.1207	0.7271	0.1454	0.0007	0.0022	-9.7563
432	2	3	3	3	2	3	1	0.0262	0.4693	0.4799	0.0242	0.0001	0.0003	-8.2111
433	1	1	1	1	3	3	1	0.0074	0.2073	0.7021	0.0815	0.0004	0.0012	-9.3002
434	2	1	1	1	3	3	1	0.4026	0.5584	0.0380	0.0010	0.0000	0.0000	-4.7637
435	1	2	1	1	3	3	1	0.0050	0.1503	0.7259	0.1165	0.0006	0.0017	-9.5803
436	2	2	1	1	3	3	1	0.2362	0.6824	0.0791	0.0022	0.0000	0.0000	-5.6983
437	1	3	1	1	3	3	1	0.0034	0.1067	0.7230	0.1636	0.0008	0.0026	-9.8528
438	2	3	1	1	3	3	1	0.1243	0.7140	0.1569	0.0047	0.0000	0.0001	-6.5032
439	1	1	2	1	3	3	1	0.0178	0.3800	0.5661	0.0355	0.0002	0.0005	-8.5868
440	2	1	2	1	3	3	1	0.3976	0.5626	0.0388	0.0010	0.0000	0.0000	-4.7914
441	1	2	2	1	3	3	1	0.0120	0.2955	0.6397	0.0519	0.0002	0.0007	-8.9281
442	2	2	2	1	3	3	1	0.2325	0.6846	0.0807	0.0022	0.0000	0.0000	-5.7209
443	1	3	2	1	3	3	1	0.0081	0.2218	0.6935	0.0752	0.0003	0.0011	-9.2361

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

444	2	3	2	1	3	3	1	0.1221	0.7134	0.1597	0.0048	0.0000	0.0001	-6.5243
445	1	1	3	1	3	3	1	0.0418	0.5727	0.3702	0.0150	0.0001	0.0002	-7.7185
446	2	1	3	1	3	3	1	0.3926	0.5668	0.0396	0.0010	0.0000	0.0000	-4.8189
447	1	2	3	1	3	3	1	0.0285	0.4888	0.4601	0.0222	0.0001	0.0003	-8.1243
448	2	2	3	1	3	3	1	0.2288	0.6867	0.0822	0.0022	0.0000	0.0000	-5.7435
449	1	3	3	1	3	3	1	0.0194	0.3995	0.5479	0.0327	0.0001	0.0004	-8.5068
450	2	3	3	1	3	3	1	0.1199	0.7127	0.1625	0.0049	0.0000	0.0001	-6.5454
451	1	1	1	2	3	3	1	0.0010	0.0337	0.5572	0.3966	0.0028	0.0087	-10.7482
452	2	1	1	2	3	3	1	0.0813	0.6824	0.2286	0.0075	0.0000	0.0001	-6.9832
453	1	2	1	2	3	3	1	0.0007	0.0229	0.4701	0.4893	0.0041	0.0129	-11.0448
454	2	2	1	2	3	3	1	0.0391	0.5584	0.3861	0.0161	0.0001	0.0002	-7.7927
455	1	3	1	2	3	3	1	0.0004	0.0155	0.3800	0.5789	0.0060	0.0191	-11.3300
456	2	3	1	2	3	3	1	0.0183	0.3869	0.5597	0.0345	0.0001	0.0005	-8.5585
457	1	1	2	2	3	3	1	0.0024	0.0775	0.6980	0.2174	0.0012	0.0036	-10.0997
458	2	1	2	2	3	3	1	0.0798	0.6802	0.2322	0.0076	0.0000	0.0001	-7.0047
459	1	2	2	2	3	3	1	0.0016	0.0535	0.6467	0.2910	0.0017	0.0054	-10.3863
460	2	2	2	2	3	3	1	0.0383	0.5541	0.3908	0.0165	0.0001	0.0002	-7.8143
461	1	3	2	2	3	3	1	0.0011	0.0367	0.5751	0.3766	0.0025	0.0080	-10.6824
462	2	3	2	2	3	3	1	0.0179	0.3822	0.5640	0.0352	0.0002	0.0005	-8.5775
463	1	1	3	2	3	3	1	0.0057	0.1675	0.7210	0.1038	0.0005	0.0015	-9.4901
464	2	1	3	2	3	3	1	0.0783	0.6779	0.2359	0.0078	0.0000	0.0001	-7.0262
465	1	2	3	2	3	3	1	0.0038	0.1196	0.7269	0.1467	0.0007	0.0022	-9.7635
466	2	2	3	2	3	3	1	0.0375	0.5499	0.3955	0.0168	0.0001	0.0002	-7.8358
467	1	3	3	2	3	3	1	0.0026	0.0839	0.7061	0.2030	0.0011	0.0033	-10.0381
468	2	3	3	2	3	3	1	0.0176	0.3776	0.5683	0.0359	0.0002	0.0005	-8.5963
469	1	1	1	3	3	3	1	0.0007	0.0240	0.4810	0.4781	0.0039	0.0123	-11.0093
470	2	1	1	3	3	3	1	0.0588	0.6364	0.2940	0.0106	0.0000	0.0001	-7.3448
471	1	2	1	3	3	3	1	0.0005	0.0163	0.3908	0.5685	0.0057	0.0183	-11.2964
472	2	2	1	3	3	3	1	0.0279	0.4836	0.4654	0.0227	0.0001	0.0003	-8.1476
473	1	3	1	3	3	3	1	0.0003	0.0110	0.3049	0.6485	0.0083	0.0269	-11.5660
474	2	3	1	3	3	3	1	0.0130	0.3116	0.6264	0.0482	0.0002	0.0007	-8.8629
475	1	1	2	3	3	3	1	0.0017	0.0560	0.6541	0.2814	0.0016	0.0052	-10.3510
476	2	1	2	3	3	3	1	0.0576	0.6331	0.2983	0.0108	0.0000	0.0001	-7.3665
477	1	2	2	3	3	3	1	0.0011	0.0384	0.5846	0.3658	0.0024	0.0076	-10.6463
478	2	2	2	3	3	3	1	0.0273	0.4790	0.4701	0.0232	0.0001	0.0003	-8.1684

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

479	1	3	2	3	3	3	1	0.0008	0.0262	0.5006	0.4576	0.0036	0.0113	-10.9444
480	2	3	2	3	3	3	1	0.0127	0.3073	0.6300	0.0491	0.0002	0.0007	-8.8802
481	1	1	3	3	3	3	1	0.0040	0.1247	0.7276	0.1408	0.0007	0.0021	-9.7306
482	2	1	3	3	3	3	1	0.0565	0.6298	0.3025	0.0110	0.0000	0.0001	-7.3883
483	1	2	3	3	3	3	1	0.0027	0.0877	0.7100	0.1954	0.0010	0.0032	-10.0045
484	2	2	3	3	3	3	1	0.0268	0.4743	0.4749	0.0237	0.0001	0.0003	-8.1891
485	1	3	3	3	3	3	1	0.0018	0.0608	0.6668	0.2644	0.0015	0.0047	-10.2872
486	2	3	3	3	3	3	1	0.0125	0.3030	0.6335	0.0501	0.0002	0.0007	-8.8975
487	1	1	1	1	1	1	2	0.0071	0.1997	0.7064	0.0852	0.0004	0.0012	-9.3348
488	2	1	1	1	1	1	2	0.6612	0.3249	0.0135	0.0003	0.0000	0.0000	-3.1973
489	1	2	1	1	1	1	2	0.0048	0.1444	0.7270	0.1215	0.0006	0.0018	-9.6132
490	2	2	1	1	1	1	2	0.4726	0.4978	0.0289	0.0007	0.0000	0.0000	-4.3713
491	1	3	1	1	1	1	2	0.0032	0.1022	0.7208	0.1702	0.0009	0.0027	-9.8857
492	2	3	1	1	1	1	2	0.2914	0.6462	0.0608	0.0016	0.0000	0.0000	-5.3781
493	1	1	2	1	1	1	2	0.0169	0.3694	0.5758	0.0372	0.0002	0.0005	-8.6297
494	2	1	2	1	1	1	2	0.6565	0.3293	0.0138	0.0003	0.0000	0.0000	-3.2295
495	1	2	2	1	1	1	2	0.0115	0.2859	0.6473	0.0543	0.0002	0.0007	-8.9669
496	2	2	2	1	1	1	2	0.4674	0.5024	0.0295	0.0008	0.0000	0.0000	-4.4010
497	1	3	2	1	1	1	2	0.0077	0.2138	0.6984	0.0786	0.0004	0.0011	-9.2712
498	2	3	2	1	1	1	2	0.2871	0.6492	0.0620	0.0017	0.0000	0.0000	-5.4023
499	1	1	3	1	1	1	2	0.0400	0.5632	0.3808	0.0158	0.0001	0.0002	-7.7681
500	2	1	3	1	1	1	2	0.6518	0.3338	0.0141	0.0004	0.0000	0.0000	-3.2618
501	1	2	3	1	1	1	2	0.0272	0.4782	0.4709	0.0233	0.0001	0.0003	-8.1718
502	2	2	3	1	1	1	2	0.4622	0.5070	0.0301	0.0008	0.0000	0.0000	-4.4305
503	1	3	3	1	1	1	2	0.0185	0.3888	0.5579	0.0342	0.0001	0.0005	-8.5507
504	2	3	3	1	1	1	2	0.2829	0.6522	0.0632	0.0017	0.0000	0.0000	-5.4264
505	1	1	1	2	1	1	2	0.0009	0.0322	0.5472	0.4076	0.0029	0.0092	-10.7842
506	2	1	1	2	1	1	2	0.2041	0.6994	0.0938	0.0026	0.0000	0.0000	-5.8987
507	1	2	1	2	1	1	2	0.0006	0.0219	0.4592	0.5004	0.0043	0.0136	-11.0799
508	2	2	1	2	1	1	2	0.1053	0.7060	0.1830	0.0056	0.0000	0.0001	-6.6926
509	1	3	1	2	1	1	2	0.0004	0.0148	0.3694	0.5890	0.0063	0.0200	-11.3632
510	2	3	1	2	1	1	2	0.0513	0.6124	0.3239	0.0122	0.0001	0.0002	-7.4961
511	1	1	2	2	1	1	2	0.0023	0.0741	0.6931	0.2255	0.0012	0.0038	-10.1336
512	2	1	2	2	1	1	2	0.2007	0.7010	0.0956	0.0026	0.0000	0.0000	-5.9206
513	1	2	2	2	1	1	2	0.0015	0.0512	0.6391	0.3008	0.0018	0.0057	-10.4215

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

514	2	2	2	2	1	1	2	0.1034	0.7047	0.1861	0.0058	0.0000	0.0001	-6.7138
515	1	3	2	2	1	1	2	0.0010	0.0350	0.5654	0.3875	0.0027	0.0084	-10.7184
516	2	3	2	2	1	1	2	0.0503	0.6087	0.3283	0.0124	0.0001	0.0002	-7.5179
517	1	1	3	2	1	1	2	0.0054	0.1610	0.7232	0.1083	0.0005	0.0016	-9.5233
518	2	1	3	2	1	1	2	0.1974	0.7024	0.0974	0.0027	0.0000	0.0000	-5.9425
519	1	2	3	2	1	1	2	0.0037	0.1147	0.7258	0.1527	0.0008	0.0024	-9.7963
520	2	2	3	2	1	1	2	0.1014	0.7034	0.1892	0.0059	0.0000	0.0001	-6.7350
521	1	3	3	2	1	1	2	0.0025	0.0803	0.7018	0.2108	0.0011	0.0035	-10.0717
522	2	3	3	2	1	1	2	0.0493	0.6050	0.3328	0.0127	0.0001	0.0002	-7.5397
523	1	1	1	3	1	1	2	0.0007	0.0229	0.4702	0.4892	0.0041	0.0129	-11.0446
524	2	1	1	3	1	1	2	0.1532	0.7153	0.1277	0.0037	0.0000	0.0000	-6.2582
525	1	2	1	3	1	1	2	0.0004	0.0155	0.3801	0.5788	0.0060	0.0191	-11.3299
526	2	2	1	3	1	1	2	0.0767	0.6754	0.2399	0.0080	0.0000	0.0001	-7.0492
527	1	3	1	3	1	1	2	0.0003	0.0105	0.2952	0.6571	0.0087	0.0282	-11.5972
528	2	3	1	3	1	1	2	0.0367	0.5452	0.4006	0.0172	0.0001	0.0002	-7.8588
529	1	1	2	3	1	1	2	0.0016	0.0535	0.6468	0.2910	0.0017	0.0054	-10.3861
530	2	1	2	3	1	1	2	0.1505	0.7156	0.1300	0.0038	0.0000	0.0000	-6.2794
531	1	2	2	3	1	1	2	0.0011	0.0367	0.5751	0.3766	0.0025	0.0080	-10.6823
532	2	2	2	3	1	1	2	0.0752	0.6729	0.2436	0.0081	0.0000	0.0001	-7.0707
533	1	3	2	3	1	1	2	0.0007	0.0250	0.4899	0.4688	0.0038	0.0119	-10.9799
534	2	3	2	3	1	1	2	0.0360	0.5409	0.4053	0.0175	0.0001	0.0002	-7.8803
535	1	1	3	3	1	1	2	0.0038	0.1196	0.7269	0.1466	0.0007	0.0022	-9.7634
536	2	1	3	3	1	1	2	0.1479	0.7158	0.1324	0.0038	0.0000	0.0001	-6.3005
537	1	2	3	3	1	1	2	0.0026	0.0839	0.7061	0.2030	0.0011	0.0033	-10.0379
538	2	2	3	3	1	1	2	0.0738	0.6704	0.2474	0.0083	0.0000	0.0001	-7.0923
539	1	3	3	3	1	1	2	0.0017	0.0581	0.6600	0.2736	0.0016	0.0050	-10.3220
540	2	3	3	3	1	1	2	0.0353	0.5365	0.4100	0.0179	0.0001	0.0002	-7.9018
541	1	1	1	1	2	1	2	0.0033	0.1057	0.7226	0.1650	0.0008	0.0026	-9.8599
542	2	1	1	1	2	1	2	0.4781	0.4929	0.0283	0.0007	0.0000	0.0000	-4.3395
543	1	2	1	1	2	1	2	0.0022	0.0738	0.6925	0.2264	0.0012	0.0038	-10.1372
544	2	2	1	1	2	1	2	0.2960	0.6428	0.0595	0.0016	0.0000	0.0000	-5.3521
545	1	3	1	1	2	1	2	0.0015	0.0509	0.6382	0.3018	0.0018	0.0057	-10.4253
546	2	3	1	1	2	1	2	0.1618	0.7140	0.1207	0.0034	0.0000	0.0000	-6.1924
547	1	1	2	1	2	1	2	0.0080	0.2201	0.6945	0.0760	0.0003	0.0011	-9.2437
548	2	1	2	1	2	1	2	0.4729	0.4975	0.0289	0.0007	0.0000	0.0000	-4.3693

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

549	1	2	2	1	2	1	2	0.0054	0.1603	0.7234	0.1088	0.0005	0.0016	-9.5269
550	2	2	2	1	2	1	2	0.2917	0.6460	0.0607	0.0016	0.0000	0.0000	-5.3764
551	1	3	2	1	2	1	2	0.0036	0.1142	0.7257	0.1534	0.0008	0.0024	-9.7998
552	2	3	2	1	2	1	2	0.1590	0.7145	0.1229	0.0035	0.0000	0.0000	-6.2136
553	1	1	3	1	2	1	2	0.0192	0.3972	0.5501	0.0330	0.0001	0.0004	-8.5163
554	2	1	3	1	2	1	2	0.4677	0.5021	0.0294	0.0008	0.0000	0.0000	-4.3990
555	1	2	3	1	2	1	2	0.0130	0.3112	0.6267	0.0483	0.0002	0.0007	-8.8646
556	2	2	3	1	2	1	2	0.2874	0.6490	0.0619	0.0017	0.0000	0.0000	-5.4007
557	1	3	3	1	2	1	2	0.0088	0.2351	0.6848	0.0701	0.0003	0.0010	-9.1785
558	2	3	3	1	2	1	2	0.1562	0.7149	0.1252	0.0036	0.0000	0.0000	-6.2348
559	1	1	1	2	2	1	2	0.0004	0.0154	0.3777	0.5811	0.0060	0.0193	-11.3372
560	2	1	1	2	2	1	2	0.1074	0.7072	0.1797	0.0055	0.0000	0.0001	-6.6700
561	1	2	1	2	2	1	2	0.0003	0.0104	0.2931	0.6589	0.0088	0.0285	-11.6040
562	2	2	1	2	2	1	2	0.0524	0.6163	0.3192	0.0119	0.0001	0.0002	-7.4728
563	1	3	1	2	2	1	2	0.0002	0.0070	0.2196	0.7187	0.0127	0.0418	-11.8540
564	2	3	1	2	2	1	2	0.0247	0.4561	0.4931	0.0256	0.0001	0.0003	-8.2684
565	1	1	2	2	2	1	2	0.0011	0.0363	0.5730	0.3790	0.0026	0.0081	-10.6902
566	2	1	2	2	2	1	2	0.1055	0.7061	0.1828	0.0056	0.0000	0.0001	-6.6912
567	1	2	2	2	2	1	2	0.0007	0.0247	0.4875	0.4712	0.0038	0.0120	-10.9877
568	2	2	2	2	2	1	2	0.0513	0.6127	0.3236	0.0122	0.0001	0.0002	-7.4946
569	1	3	2	2	2	1	2	0.0005	0.0168	0.3974	0.5621	0.0056	0.0177	-11.2759
570	2	3	2	2	2	1	2	0.0242	0.4514	0.4978	0.0261	0.0001	0.0003	-8.2887
571	1	1	3	2	2	1	2	0.0026	0.0831	0.7052	0.2047	0.0011	0.0034	-10.0453
572	2	1	3	2	2	1	2	0.1035	0.7048	0.1859	0.0057	0.0000	0.0001	-6.7124
573	1	2	3	2	2	1	2	0.0017	0.0576	0.6585	0.2757	0.0016	0.0050	-10.3297
574	2	2	3	2	2	1	2	0.0503	0.6090	0.3280	0.0124	0.0001	0.0002	-7.5164
575	1	3	3	2	2	1	2	0.0012	0.0395	0.5903	0.3593	0.0024	0.0074	-10.6244
576	2	3	3	2	2	1	2	0.0237	0.4467	0.5024	0.0267	0.0001	0.0004	-8.3090
577	1	1	1	3	2	1	2	0.0003	0.0109	0.3028	0.6504	0.0084	0.0272	-11.5728
578	2	1	1	3	2	1	2	0.0783	0.6779	0.2359	0.0078	0.0000	0.0001	-7.0262
579	1	2	1	3	2	1	2	0.0002	0.0074	0.2278	0.7126	0.0121	0.0399	-11.8245
580	2	2	1	3	2	1	2	0.0375	0.5498	0.3955	0.0168	0.0001	0.0002	-7.8358
581	1	3	1	3	2	1	2	0.0001	0.0050	0.1664	0.7531	0.0173	0.0582	-12.0664
582	2	3	1	3	2	1	2	0.0176	0.3776	0.5683	0.0359	0.0002	0.0005	-8.5964
583	1	1	2	3	2	1	2	0.0007	0.0259	0.4983	0.4600	0.0036	0.0114	-10.9520

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

584	2	1	2	3	2	1	2	0.0768	0.6755	0.2396	0.0080	0.0000	0.0001	-7.0477
585	1	2	2	3	2	1	2	0.0005	0.0176	0.4082	0.5515	0.0053	0.0169	-11.2418
586	2	2	2	3	2	1	2	0.0368	0.5455	0.4002	0.0172	0.0001	0.0002	-7.8574
587	1	3	2	3	2	1	2	0.0003	0.0119	0.3209	0.6341	0.0078	0.0250	-11.5151
588	2	3	2	3	2	1	2	0.0172	0.3730	0.5725	0.0366	0.0002	0.0005	-8.6152
589	1	1	3	3	2	1	2	0.0018	0.0602	0.6654	0.2663	0.0015	0.0048	-10.2947
590	2	1	3	3	2	1	2	0.0753	0.6731	0.2434	0.0081	0.0000	0.0001	-7.0693
591	1	2	3	3	2	1	2	0.0012	0.0413	0.5995	0.3486	0.0023	0.0071	-10.5884
592	2	2	3	3	2	1	2	0.0360	0.5412	0.4050	0.0175	0.0001	0.0002	-7.8788
593	1	3	3	3	2	1	2	0.0008	0.0282	0.5177	0.4395	0.0033	0.0105	-10.8867
594	2	3	3	3	2	1	2	0.0169	0.3684	0.5767	0.0374	0.0002	0.0005	-8.6339
595	1	1	1	1	3	1	2	0.0016	0.0528	0.6443	0.2941	0.0017	0.0055	-10.3976
596	2	1	1	1	3	1	2	0.3007	0.6394	0.0583	0.0015	0.0000	0.0000	-5.3259
597	1	2	1	1	3	1	2	0.0011	0.0361	0.5720	0.3801	0.0026	0.0081	-10.6940
598	2	2	1	1	3	1	2	0.1648	0.7133	0.1184	0.0034	0.0000	0.0000	-6.1696
599	1	3	1	1	3	1	2	0.0007	0.0246	0.4864	0.4724	0.0038	0.0121	-10.9915
600	2	3	1	1	3	1	2	0.0831	0.6848	0.2247	0.0073	0.0000	0.0001	-6.9596
601	1	1	2	1	3	1	2	0.0038	0.1180	0.7266	0.1486	0.0007	0.0023	-9.7740
602	2	1	2	1	3	1	2	0.2963	0.6426	0.0594	0.0016	0.0000	0.0000	-5.3504
603	1	2	2	1	3	1	2	0.0025	0.0827	0.7047	0.2055	0.0011	0.0034	-10.0488
604	2	2	2	1	3	1	2	0.1620	0.7139	0.1206	0.0034	0.0000	0.0000	-6.1909
605	1	3	2	1	3	1	2	0.0017	0.0573	0.6577	0.2766	0.0016	0.0050	-10.3334
606	2	3	2	1	3	1	2	0.0815	0.6827	0.2282	0.0075	0.0000	0.0001	-6.9811
607	1	1	3	1	3	1	2	0.0091	0.2417	0.6803	0.0677	0.0003	0.0009	-9.1501
608	2	1	3	1	3	1	2	0.2920	0.6457	0.0606	0.0016	0.0000	0.0000	-5.3748
609	1	2	3	1	3	1	2	0.0061	0.1776	0.7171	0.0973	0.0005	0.0014	-9.4395
610	2	2	3	1	3	1	2	0.1592	0.7145	0.1228	0.0035	0.0000	0.0000	-6.2122
611	1	3	3	1	3	1	2	0.0041	0.1273	0.7278	0.1379	0.0007	0.0021	-9.7141
612	2	3	3	1	3	1	2	0.0799	0.6804	0.2319	0.0076	0.0000	0.0001	-7.0025
613	1	1	1	2	3	1	2	0.0002	0.0073	0.2260	0.7140	0.0123	0.0403	-11.8309
614	2	1	1	2	3	1	2	0.0535	0.6201	0.3146	0.0117	0.0000	0.0002	-7.4495
615	1	2	1	2	3	1	2	0.0001	0.0049	0.1649	0.7538	0.0174	0.0588	-12.0728
616	2	2	1	2	3	1	2	0.0253	0.4611	0.4881	0.0251	0.0001	0.0003	-8.2467
617	1	3	1	2	3	1	2	0.0001	0.0033	0.1176	0.7697	0.0243	0.0850	-12.3182
618	2	3	1	2	3	1	2	0.0118	0.2912	0.6431	0.0530	0.0002	0.0007	-8.9453

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

619	1	1	2	2	3	1	2	0.0005	0.0174	0.4058	0.5538	0.0054	0.0171	-11.2493
620	2	1	2	2	3	1	2	0.0524	0.6165	0.3189	0.0119	0.0001	0.0002	-7.4713
621	1	2	2	2	3	1	2	0.0003	0.0118	0.3187	0.6361	0.0078	0.0252	-11.5221
622	2	2	2	2	3	1	2	0.0248	0.4564	0.4928	0.0256	0.0001	0.0003	-8.2670
623	1	3	2	2	3	1	2	0.0002	0.0079	0.2413	0.7022	0.0113	0.0370	-11.7768
624	2	3	2	2	3	1	2	0.0115	0.2871	0.6464	0.0540	0.0002	0.0007	-8.9622
625	1	1	3	2	3	1	2	0.0012	0.0409	0.5975	0.3509	0.0023	0.0072	-10.5963
626	2	1	3	2	3	1	2	0.0514	0.6129	0.3233	0.0122	0.0001	0.0002	-7.4931
627	1	2	3	2	3	1	2	0.0008	0.0279	0.5154	0.4419	0.0034	0.0106	-10.8946
628	2	2	3	2	3	1	2	0.0243	0.4517	0.4975	0.0261	0.0001	0.0003	-8.2874
629	1	3	3	2	3	1	2	0.0005	0.0190	0.4257	0.5342	0.0049	0.0157	-11.1868
630	2	3	3	2	3	1	2	0.0113	0.2830	0.6497	0.0551	0.0002	0.0008	-8.9790
631	1	1	1	3	3	1	2	0.0001	0.0052	0.1716	0.7502	0.0167	0.0562	-12.0436
632	2	1	1	3	3	1	2	0.0383	0.5544	0.3905	0.0165	0.0001	0.0002	-7.8128
633	1	2	1	3	3	1	2	0.0001	0.0035	0.1227	0.7691	0.0234	0.0813	-12.2879
634	2	2	1	3	3	1	2	0.0180	0.3825	0.5637	0.0351	0.0002	0.0005	-8.5762
635	1	3	1	3	3	1	2	0.0001	0.0023	0.0861	0.7633	0.0318	0.1163	-12.5482
636	2	3	1	3	3	1	2	0.0083	0.2264	0.6905	0.0734	0.0003	0.0010	-9.2161
637	1	1	2	3	3	1	2	0.0004	0.0123	0.3289	0.6269	0.0075	0.0241	-11.4901
638	2	1	2	3	3	1	2	0.0376	0.5501	0.3952	0.0168	0.0001	0.0002	-7.8344
639	1	2	2	3	3	1	2	0.0002	0.0083	0.2500	0.6952	0.0108	0.0354	-11.7468
640	2	2	2	3	3	1	2	0.0176	0.3779	0.5680	0.0359	0.0002	0.0005	-8.5951
641	1	3	2	3	3	1	2	0.0002	0.0056	0.1842	0.7428	0.0155	0.0517	-11.9906
642	2	3	2	3	3	1	2	0.0082	0.2228	0.6928	0.0748	0.0003	0.0011	-9.2316
643	1	1	3	3	3	1	2	0.0008	0.0292	0.5259	0.4307	0.0032	0.0101	-10.8586
644	2	1	3	3	3	1	2	0.0368	0.5458	0.3999	0.0171	0.0001	0.0002	-7.8559
645	1	2	3	3	3	1	2	0.0006	0.0199	0.4367	0.5232	0.0047	0.0150	-11.1521
646	2	2	3	3	3	1	2	0.0172	0.3733	0.5722	0.0366	0.0002	0.0005	-8.6139
647	1	3	3	3	3	1	2	0.0004	0.0135	0.3476	0.6095	0.0069	0.0221	-11.4311
648	2	3	3	3	3	1	2	0.0080	0.2193	0.6950	0.0763	0.0003	0.0011	-9.2471
649	1	1	1	1	1	2	2	0.0031	0.0991	0.7190	0.1751	0.0009	0.0028	-9.9100
650	2	1	1	1	1	2	2	0.8364	0.1582	0.0052	0.0001	0.0000	0.0000	-1.8135
651	1	2	1	1	1	2	2	0.0021	0.0690	0.6843	0.2392	0.0013	0.0041	-10.1891
652	2	2	1	1	1	2	2	0.7012	0.2872	0.0112	0.0003	0.0000	0.0000	-2.9137
653	1	3	1	1	1	2	2	0.0014	0.0475	0.6260	0.3170	0.0020	0.0061	-10.4792

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

654	2	3	1	1	1	2	2	0.5186	0.4566	0.0242	0.0006	0.0000	0.0000	-4.1038
655	1	1	2	1	1	2	2	0.0075	0.2081	0.7017	0.0812	0.0004	0.0012	-9.2969
656	2	1	2	1	1	2	2	0.8336	0.1610	0.0053	0.0001	0.0000	0.0000	-1.8398
657	1	2	2	1	1	2	2	0.0050	0.1509	0.7258	0.1160	0.0005	0.0017	-9.5772
658	2	2	2	1	1	2	2	0.6969	0.2914	0.0115	0.0003	0.0000	0.0000	-2.9456
659	1	3	2	1	1	2	2	0.0034	0.1071	0.7232	0.1630	0.0008	0.0025	-9.8497
660	2	3	2	1	1	2	2	0.5134	0.4613	0.0247	0.0006	0.0000	0.0000	-4.1345
661	1	1	3	1	1	2	2	0.0178	0.3809	0.5652	0.0354	0.0002	0.0005	-8.5827
662	2	1	3	1	1	2	2	0.8306	0.1638	0.0054	0.0001	0.0000	0.0000	-1.8663
663	1	2	3	1	1	2	2	0.0121	0.2964	0.6389	0.0517	0.0002	0.0007	-8.9245
664	2	2	3	1	1	2	2	0.6924	0.2956	0.0117	0.0003	0.0000	0.0000	-2.9776
665	1	3	3	1	1	2	2	0.0081	0.2225	0.6930	0.0749	0.0003	0.0011	-9.2328
666	2	3	3	1	1	2	2	0.5082	0.4660	0.0252	0.0006	0.0000	0.0000	-4.1652
667	1	1	1	2	1	2	2	0.0004	0.0143	0.3616	0.5964	0.0065	0.0208	-11.3875
668	2	1	1	2	1	2	2	0.4019	0.5590	0.0381	0.0010	0.0000	0.0000	-4.7676
669	1	2	1	2	1	2	2	0.0003	0.0097	0.2787	0.6714	0.0094	0.0306	-11.6509
670	2	2	1	2	1	2	2	0.2357	0.6827	0.0794	0.0022	0.0000	0.0000	-5.7015
671	1	3	1	2	1	2	2	0.0002	0.0065	0.2076	0.7274	0.0135	0.0448	-11.8985
672	2	3	1	2	1	2	2	0.1240	0.7139	0.1573	0.0047	0.0000	0.0001	-6.5062
673	1	1	2	2	1	2	2	0.0010	0.0339	0.5581	0.3956	0.0028	0.0087	-10.7449
674	2	1	2	2	1	2	2	0.3969	0.5632	0.0389	0.0010	0.0000	0.0000	-4.7953
675	1	2	2	2	1	2	2	0.0007	0.0230	0.4711	0.4882	0.0041	0.0129	-11.0415
676	2	2	2	2	1	2	2	0.2320	0.6849	0.0809	0.0022	0.0000	0.0000	-5.7242
677	1	3	2	2	1	2	2	0.0004	0.0156	0.3810	0.5779	0.0060	0.0190	-11.3269
678	2	3	2	2	1	2	2	0.1218	0.7133	0.1601	0.0048	0.0000	0.0001	-6.5273
679	1	1	3	2	1	2	2	0.0024	0.0778	0.6984	0.2166	0.0012	0.0036	-10.0965
680	2	1	3	2	1	2	2	0.3919	0.5674	0.0397	0.0010	0.0000	0.0000	-4.8228
681	1	2	3	2	1	2	2	0.0016	0.0538	0.6474	0.2901	0.0017	0.0054	-10.3830
682	2	2	3	2	1	2	2	0.2283	0.6870	0.0824	0.0023	0.0000	0.0000	-5.7467
683	1	3	3	2	1	2	2	0.0011	0.0368	0.5760	0.3756	0.0025	0.0080	-10.6791
684	2	3	3	2	1	2	2	0.1195	0.7126	0.1629	0.0049	0.0000	0.0001	-6.5483
685	1	1	1	3	1	2	2	0.0003	0.0101	0.2881	0.6632	0.0090	0.0292	-11.6200
686	2	1	1	3	1	2	2	0.3216	0.6238	0.0532	0.0014	0.0000	0.0000	-5.2098
687	1	2	1	3	1	2	2	0.0002	0.0068	0.2155	0.7217	0.0130	0.0428	-11.8692
688	2	2	1	3	1	2	2	0.1787	0.7095	0.1087	0.0031	0.0000	0.0000	-6.0698

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

689	1	3	1	3	1	2	2	0.0001	0.0046	0.1566	0.7579	0.0184	0.0623	-12.1106
690	2	3	1	3	1	2	2	0.0908	0.6940	0.2084	0.0066	0.0000	0.0001	-6.8600
691	1	1	2	3	1	2	2	0.0007	0.0241	0.4820	0.4770	0.0039	0.0123	-11.0060
692	2	1	2	3	1	2	2	0.3170	0.6273	0.0542	0.0014	0.0000	0.0000	-5.2350
693	1	2	2	3	1	2	2	0.0005	0.0164	0.3918	0.5675	0.0057	0.0182	-11.2933
694	2	2	2	3	1	2	2	0.1756	0.7105	0.1107	0.0031	0.0000	0.0000	-6.0913
695	1	3	2	3	1	2	2	0.0003	0.0111	0.3058	0.6477	0.0083	0.0268	-11.5631
696	2	3	2	3	1	2	2	0.0891	0.6922	0.2119	0.0068	0.0000	0.0001	-6.8813
697	1	1	3	3	1	2	2	0.0017	0.0562	0.6548	0.2805	0.0016	0.0051	-10.3478
698	2	1	3	3	1	2	2	0.3125	0.6307	0.0553	0.0015	0.0000	0.0000	-5.2600
699	1	2	3	3	1	2	2	0.0011	0.0386	0.5855	0.3648	0.0024	0.0076	-10.6430
700	2	2	3	3	1	2	2	0.1726	0.7114	0.1128	0.0032	0.0000	0.0000	-6.1127
701	1	3	3	3	1	2	2	0.0008	0.0263	0.5016	0.4565	0.0036	0.0113	-10.9411
702	2	3	3	3	1	2	2	0.0874	0.6903	0.2153	0.0069	0.0000	0.0001	-6.9027
703	1	1	1	1	2	2	2	0.0015	0.0492	0.6324	0.3091	0.0019	0.0059	-10.4513
704	2	1	1	1	2	2	2	0.7059	0.2828	0.0110	0.0003	0.0000	0.0000	-2.8797
705	1	2	1	1	2	2	2	0.0010	0.0337	0.5571	0.3967	0.0028	0.0087	-10.7487
706	2	2	1	1	2	2	2	0.5242	0.4516	0.0236	0.0006	0.0000	0.0000	-4.0708
707	1	3	1	1	2	2	2	0.0007	0.0229	0.4700	0.4894	0.0041	0.0130	-11.0453
708	2	3	1	1	2	2	2	0.3359	0.6128	0.0500	0.0013	0.0000	0.0000	-5.1309
709	1	1	2	1	2	2	2	0.0035	0.1107	0.7246	0.1580	0.0008	0.0025	-9.8239
710	2	1	2	1	2	2	2	0.7015	0.2869	0.0112	0.0003	0.0000	0.0000	-2.9115
711	1	2	2	1	2	2	2	0.0024	0.0774	0.6979	0.2175	0.0012	0.0036	-10.1001
712	2	2	2	1	2	2	2	0.5190	0.4563	0.0241	0.0006	0.0000	0.0000	-4.1017
713	1	3	2	1	2	2	2	0.0016	0.0535	0.6466	0.2911	0.0017	0.0054	-10.3867
714	2	3	2	1	2	2	2	0.3312	0.6164	0.0510	0.0013	0.0000	0.0000	-5.1565
715	1	1	3	1	2	2	2	0.0085	0.2290	0.6889	0.0724	0.0003	0.0010	-9.2049
716	2	1	3	1	2	2	2	0.6972	0.2911	0.0115	0.0003	0.0000	0.0000	-2.9435
717	1	2	3	1	2	2	2	0.0057	0.1674	0.7211	0.1039	0.0005	0.0015	-9.4905
718	2	2	3	1	2	2	2	0.5138	0.4610	0.0246	0.0006	0.0000	0.0000	-4.1324
719	1	3	3	1	2	2	2	0.0038	0.1195	0.7269	0.1467	0.0007	0.0022	-9.7639
720	2	3	3	1	2	2	2	0.3266	0.6200	0.0520	0.0014	0.0000	0.0000	-5.1820
721	1	1	1	2	2	2	2	0.0002	0.0068	0.2137	0.7230	0.0131	0.0432	-11.8756
722	2	1	1	2	2	2	2	0.2397	0.6804	0.0777	0.0021	0.0000	0.0000	-5.6772
723	1	2	1	2	2	2	2	0.0001	0.0046	0.1553	0.7585	0.0186	0.0629	-12.1171

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

724	2	2	1	2	2	2	2	0.1264	0.7145	0.1544	0.0046	0.0000	0.0001	-6.4837
725	1	3	1	2	2	2	2	0.0001	0.0031	0.1103	0.7699	0.0258	0.0908	-12.3647
726	2	3	1	2	2	2	2	0.0623	0.6458	0.2817	0.0099	0.0000	0.0001	-7.2804
727	1	1	2	2	2	2	2	0.0005	0.0162	0.3894	0.5698	0.0058	0.0184	-11.3007
728	2	1	2	2	2	2	2	0.2360	0.6826	0.0792	0.0022	0.0000	0.0000	-5.6999
729	1	2	2	2	2	2	2	0.0003	0.0110	0.3037	0.6496	0.0084	0.0271	-11.5700
730	2	2	2	2	2	2	2	0.1242	0.7140	0.1571	0.0047	0.0000	0.0001	-6.5047
731	1	3	2	2	2	2	2	0.0002	0.0074	0.2285	0.7121	0.0121	0.0397	-11.8218
732	2	3	2	2	2	2	2	0.0611	0.6427	0.2859	0.0101	0.0000	0.0001	-7.3021
733	1	1	3	2	2	2	2	0.0011	0.0382	0.5834	0.3671	0.0024	0.0077	-10.6509
734	2	1	3	2	2	2	2	0.2322	0.6848	0.0808	0.0022	0.0000	0.0000	-5.7226
735	1	2	3	2	2	2	2	0.0008	0.0260	0.4993	0.4590	0.0036	0.0114	-10.9489
736	2	2	3	2	2	2	2	0.1219	0.7134	0.1599	0.0048	0.0000	0.0001	-6.5258
737	1	3	3	2	2	2	2	0.0005	0.0176	0.4092	0.5505	0.0053	0.0168	-11.2388
738	2	3	3	2	2	2	2	0.0599	0.6395	0.2900	0.0104	0.0000	0.0001	-7.3239
739	1	1	1	3	2	2	2	0.0001	0.0048	0.1616	0.7555	0.0178	0.0602	-12.0878
740	2	1	1	3	2	2	2	0.1820	0.7084	0.1066	0.0030	0.0000	0.0000	-6.0468
741	1	2	1	3	2	2	2	0.0001	0.0032	0.1151	0.7699	0.0248	0.0869	-12.3339
742	2	2	1	3	2	2	2	0.0927	0.6959	0.2049	0.0065	0.0000	0.0001	-6.8372
743	1	3	1	3	2	2	2	0.0001	0.0022	0.0806	0.7596	0.0336	0.1240	-12.5986
744	2	3	1	3	2	2	2	0.0448	0.5865	0.3545	0.0140	0.0001	0.0002	-7.6445
745	1	1	2	3	2	2	2	0.0003	0.0115	0.3136	0.6408	0.0080	0.0258	-11.5384
746	2	1	2	3	2	2	2	0.1789	0.7095	0.1085	0.0031	0.0000	0.0000	-6.0683
747	1	2	2	3	2	2	2	0.0002	0.0078	0.2369	0.7056	0.0116	0.0379	-11.7921
748	2	2	2	3	2	2	2	0.0909	0.6941	0.2082	0.0066	0.0000	0.0001	-6.8585
749	1	3	2	3	2	2	2	0.0001	0.0052	0.1736	0.7491	0.0165	0.0554	-12.0347
750	2	3	2	3	2	2	2	0.0439	0.5825	0.3591	0.0143	0.0001	0.0002	-7.6663
751	1	1	3	3	2	2	2	0.0008	0.0273	0.5099	0.4477	0.0034	0.0109	-10.9131
752	2	1	3	3	2	2	2	0.1758	0.7104	0.1106	0.0031	0.0000	0.0000	-6.0898
753	1	2	3	3	2	2	2	0.0005	0.0185	0.4201	0.5398	0.0051	0.0161	-11.2045
754	2	2	3	3	2	2	2	0.0892	0.6923	0.2116	0.0068	0.0000	0.0001	-6.8798
755	1	3	3	3	2	2	2	0.0004	0.0125	0.3320	0.6240	0.0074	0.0237	-11.4802
756	2	3	3	3	2	2	2	0.0430	0.5784	0.3637	0.0146	0.0001	0.0002	-7.6880
757	1	1	1	1	3	2	2	0.0007	0.0238	0.4785	0.4807	0.0039	0.0125	-11.0176
758	2	1	1	1	3	2	2	0.5298	0.4465	0.0231	0.0006	0.0000	0.0000	-4.0377

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

759	1	2	1	1	3	2	2	0.0005	0.0161	0.3883	0.5709	0.0058	0.0185	-11.3042
760	2	2	1	1	3	2	2	0.3408	0.6089	0.0490	0.0013	0.0000	0.0000	-5.1034
761	1	3	1	1	3	2	2	0.0003	0.0109	0.3026	0.6505	0.0084	0.0272	-11.5733
762	2	3	1	1	3	2	2	0.1918	0.7047	0.1006	0.0028	0.0000	0.0000	-5.9797
763	1	1	2	1	3	2	2	0.0017	0.0554	0.6524	0.2836	0.0017	0.0052	-10.3592
764	2	1	2	1	3	2	2	0.5246	0.4512	0.0236	0.0006	0.0000	0.0000	-4.0687
765	1	2	2	1	3	2	2	0.0011	0.0380	0.5824	0.3683	0.0025	0.0077	-10.6547
766	2	2	2	1	3	2	2	0.3362	0.6125	0.0500	0.0013	0.0000	0.0000	-5.1292
767	1	3	2	1	3	2	2	0.0007	0.0259	0.4981	0.4602	0.0036	0.0114	-10.9527
768	2	3	2	1	3	2	2	0.1886	0.7060	0.1025	0.0029	0.0000	0.0000	-6.0014
769	1	1	3	1	3	2	2	0.0040	0.1235	0.7275	0.1421	0.0007	0.0022	-9.7382
770	2	1	3	1	3	2	2	0.5193	0.4559	0.0241	0.0006	0.0000	0.0000	-4.0995
771	1	2	3	1	3	2	2	0.0027	0.0868	0.7091	0.1972	0.0010	0.0032	-10.0122
772	2	2	3	1	3	2	2	0.3315	0.6161	0.0510	0.0013	0.0000	0.0000	-5.1548
773	1	3	3	1	3	2	2	0.0018	0.0602	0.6652	0.2665	0.0015	0.0048	-10.2953
774	2	3	3	1	3	2	2	0.1854	0.7072	0.1044	0.0029	0.0000	0.0000	-6.0230
775	1	1	1	2	3	2	2	0.0001	0.0032	0.1141	0.7699	0.0250	0.0878	-12.3406
776	2	1	1	2	3	2	2	0.1289	0.7150	0.1516	0.0045	0.0000	0.0001	-6.4612
777	1	2	1	2	3	2	2	0.0001	0.0021	0.0798	0.7590	0.0338	0.1252	-12.6060
778	2	2	1	2	3	2	2	0.0636	0.6491	0.2774	0.0097	0.0000	0.0001	-7.2572
779	1	3	1	2	3	2	2	0.0000	0.0014	0.0552	0.7239	0.0440	0.1754	-12.9005
780	2	3	1	2	3	2	2	0.0302	0.5022	0.4462	0.0209	0.0001	0.0003	-8.0634
781	1	1	2	2	3	2	2	0.0002	0.0077	0.2351	0.7070	0.0117	0.0383	-11.7986
782	2	1	2	2	3	2	2	0.1266	0.7145	0.1542	0.0046	0.0000	0.0001	-6.4822
783	1	2	2	2	3	2	2	0.0001	0.0052	0.1722	0.7499	0.0167	0.0559	-12.0411
784	2	2	2	2	3	2	2	0.0624	0.6461	0.2815	0.0099	0.0000	0.0001	-7.2789
785	1	3	2	2	3	2	2	0.0001	0.0035	0.1231	0.7690	0.0233	0.0810	-12.2852
786	2	3	2	2	3	2	2	0.0296	0.4976	0.4510	0.0214	0.0001	0.0003	-8.0844
787	1	1	3	2	3	2	2	0.0005	0.0183	0.4177	0.5421	0.0051	0.0162	-11.2121
788	2	1	3	2	3	2	2	0.1243	0.7140	0.1569	0.0047	0.0000	0.0001	-6.5033
789	1	2	3	2	3	2	2	0.0004	0.0124	0.3298	0.6261	0.0075	0.0240	-11.4873
790	2	2	3	2	3	2	2	0.0612	0.6429	0.2856	0.0101	0.0000	0.0001	-7.3006
791	1	3	3	2	3	2	2	0.0002	0.0084	0.2508	0.6946	0.0108	0.0352	-11.7441
792	2	3	3	2	3	2	2	0.0290	0.4930	0.4558	0.0218	0.0001	0.0003	-8.1054
793	1	1	1	3	3	2	2	0.0001	0.0023	0.0834	0.7616	0.0327	0.1200	-12.5725

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

794	2	1	1	3	3	2	2	0.0945	0.6977	0.2013	0.0063	0.0000	0.0001	-6.8145
795	1	2	1	3	3	2	2	0.0000	0.0015	0.0578	0.7294	0.0427	0.1686	-12.8631
796	2	2	1	3	3	2	2	0.0457	0.5907	0.3496	0.0137	0.0001	0.0002	-7.6213
797	1	3	1	3	3	2	2	0.0000	0.0010	0.0396	0.6744	0.0532	0.2317	-13.1856
798	2	3	1	3	3	2	2	0.0215	0.4240	0.5246	0.0294	0.0001	0.0004	-8.4051
799	1	1	2	3	3	2	2	0.0002	0.0054	0.1790	0.7460	0.0160	0.0535	-12.0119
800	2	1	2	3	3	2	2	0.0928	0.6960	0.2046	0.0065	0.0000	0.0001	-6.8357
801	1	2	2	3	3	2	2	0.0001	0.0037	0.1283	0.7680	0.0224	0.0775	-12.2551
802	2	2	2	3	3	2	2	0.0448	0.5867	0.3542	0.0140	0.0001	0.0002	-7.6430
803	1	3	2	3	3	2	2	0.0001	0.0025	0.0903	0.7655	0.0306	0.1111	-12.5125
804	2	3	2	3	3	2	2	0.0211	0.4192	0.5291	0.0300	0.0001	0.0004	-8.4248
805	1	1	3	3	3	2	2	0.0004	0.0130	0.3400	0.6166	0.0071	0.0229	-11.4550
806	2	1	3	3	3	2	2	0.0910	0.6943	0.2080	0.0066	0.0000	0.0001	-6.8570
807	1	2	3	3	3	2	2	0.0002	0.0088	0.2597	0.6873	0.0103	0.0336	-11.7139
808	2	2	3	3	3	2	2	0.0439	0.5827	0.3588	0.0143	0.0001	0.0002	-7.6648
809	1	3	3	3	3	2	2	0.0002	0.0059	0.1920	0.7379	0.0148	0.0492	-11.9589
810	2	3	3	3	3	2	2	0.0207	0.4145	0.5336	0.0306	0.0001	0.0004	-8.4445
811	1	1	1	1	1	3	2	0.0125	0.3033	0.6333	0.0501	0.0002	0.0007	-8.8965
812	2	1	1	1	1	3	2	0.5320	0.4445	0.0229	0.0006	0.0000	0.0000	-4.0241
813	1	2	1	1	1	3	2	0.0084	0.2284	0.6892	0.0726	0.0003	0.0010	-9.2074
814	2	2	1	1	1	3	2	0.3429	0.6072	0.0486	0.0013	0.0000	0.0000	-5.0921
815	1	3	1	1	1	3	2	0.0057	0.1669	0.7212	0.1042	0.0005	0.0015	-9.4928
816	2	3	1	1	1	3	2	0.1932	0.7042	0.0998	0.0028	0.0000	0.0000	-5.9702
817	1	1	2	1	1	3	2	0.0296	0.4974	0.4513	0.0214	0.0001	0.0003	-8.0856
818	2	1	2	1	1	3	2	0.5268	0.4492	0.0234	0.0006	0.0000	0.0000	-4.0551
819	1	2	2	1	1	3	2	0.0201	0.4082	0.5397	0.0315	0.0001	0.0004	-8.4709
820	2	2	2	1	1	3	2	0.3382	0.6109	0.0495	0.0013	0.0000	0.0000	-5.1179
821	1	3	2	1	1	3	2	0.0136	0.3213	0.6182	0.0461	0.0002	0.0006	-8.8236
822	2	3	2	1	1	3	2	0.1900	0.7055	0.1016	0.0028	0.0000	0.0000	-5.9919
823	1	1	3	1	1	3	2	0.0686	0.6604	0.2619	0.0090	0.0000	0.0001	-7.1734
824	2	1	3	1	1	3	2	0.5216	0.4539	0.0239	0.0006	0.0000	0.0000	-4.0861
825	1	2	3	1	1	3	2	0.0472	0.5967	0.3426	0.0133	0.0001	0.0002	-7.5873
826	2	2	3	1	1	3	2	0.3336	0.6146	0.0505	0.0013	0.0000	0.0000	-5.1436
827	1	3	3	1	1	3	2	0.0322	0.5165	0.4313	0.0196	0.0001	0.0003	-7.9973
828	2	3	3	1	1	3	2	0.1868	0.7067	0.1036	0.0029	0.0000	0.0000	-6.0136

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

829	1	1	1	2	1	3	2	0.0017	0.0555	0.6527	0.2833	0.0017	0.0052	-10.3579
830	2	1	1	2	1	3	2	0.1300	0.7151	0.1504	0.0044	0.0000	0.0001	-6.4520
831	1	2	1	2	1	3	2	0.0011	0.0381	0.5828	0.3679	0.0025	0.0077	-10.6534
832	2	2	1	2	1	3	2	0.0642	0.6504	0.2756	0.0096	0.0000	0.0001	-7.2477
833	1	3	1	2	1	3	2	0.0007	0.0259	0.4985	0.4598	0.0036	0.0114	-10.9514
834	2	3	1	2	1	3	2	0.0305	0.5042	0.4442	0.0207	0.0001	0.0003	-8.0542
835	1	1	2	2	1	3	2	0.0040	0.1237	0.7275	0.1419	0.0007	0.0022	-9.7371
836	2	1	2	2	1	3	2	0.1276	0.7147	0.1531	0.0045	0.0000	0.0001	-6.4730
837	1	2	2	2	1	3	2	0.0027	0.0869	0.7093	0.1969	0.0010	0.0032	-10.0110
838	2	2	2	2	1	3	2	0.0629	0.6474	0.2797	0.0098	0.0000	0.0001	-7.2694
839	1	3	2	2	1	3	2	0.0018	0.0603	0.6655	0.2662	0.0015	0.0048	-10.2940
840	2	3	2	2	1	3	2	0.0299	0.4996	0.4489	0.0212	0.0001	0.0003	-8.0753
841	1	1	3	2	1	3	2	0.0096	0.2515	0.6734	0.0644	0.0003	0.0009	-9.1089
842	2	1	3	2	1	3	2	0.1253	0.7142	0.1557	0.0046	0.0000	0.0001	-6.4941
843	1	2	3	2	1	3	2	0.0065	0.1855	0.7136	0.0927	0.0004	0.0013	-9.4014
844	2	2	3	2	1	3	2	0.0617	0.6443	0.2838	0.0100	0.0000	0.0001	-7.2911
845	1	3	3	2	1	3	2	0.0044	0.1334	0.7280	0.1317	0.0006	0.0020	-9.6772
846	2	3	3	2	1	3	2	0.0293	0.4950	0.4537	0.0216	0.0001	0.0003	-8.0962
847	1	1	1	3	1	3	2	0.0012	0.0398	0.5921	0.3571	0.0023	0.0074	-10.6173
848	2	1	1	3	1	3	2	0.0953	0.6984	0.1999	0.0063	0.0000	0.0001	-6.8052
849	1	2	1	3	1	3	2	0.0008	0.0272	0.5092	0.4485	0.0035	0.0109	-10.9156
850	2	2	1	3	1	3	2	0.0461	0.5924	0.3477	0.0136	0.0001	0.0002	-7.6117
851	1	3	1	3	1	3	2	0.0005	0.0184	0.4193	0.5405	0.0051	0.0161	-11.2069
852	2	3	1	3	1	3	2	0.0217	0.4260	0.5226	0.0291	0.0001	0.0004	-8.3965
853	1	1	2	3	1	3	2	0.0028	0.0908	0.7129	0.1895	0.0010	0.0031	-9.9775
854	2	1	2	3	1	3	2	0.0935	0.6968	0.2032	0.0064	0.0000	0.0001	-6.8264
855	1	2	2	3	1	3	2	0.0019	0.0630	0.6720	0.2571	0.0015	0.0045	-10.2592
856	2	2	2	3	1	3	2	0.0452	0.5885	0.3522	0.0139	0.0001	0.0002	-7.6335
857	1	3	2	3	1	3	2	0.0013	0.0433	0.6086	0.3379	0.0021	0.0067	-10.5518
858	2	3	2	3	1	3	2	0.0213	0.4213	0.5271	0.0297	0.0001	0.0004	-8.4162
859	1	1	3	3	1	3	2	0.0068	0.1928	0.7100	0.0887	0.0004	0.0013	-9.3672
860	2	1	3	3	1	3	2	0.0918	0.6950	0.2065	0.0066	0.0000	0.0001	-6.8477
861	1	2	3	3	1	3	2	0.0046	0.1390	0.7276	0.1263	0.0006	0.0019	-9.6442
862	2	2	3	3	1	3	2	0.0443	0.5845	0.3568	0.0142	0.0001	0.0002	-7.6553
863	1	3	3	3	1	3	2	0.0031	0.0982	0.7185	0.1766	0.0009	0.0028	-9.9169

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

864	2	3	3	3	1	3	2	0.0208	0.4166	0.5317	0.0303	0.0001	0.0004	-8.4359
865	1	1	1	1	2	3	2	0.0059	0.1721	0.7193	0.1007	0.0005	0.0015	-9.4666
866	2	1	1	1	2	3	2	0.3479	0.6032	0.0475	0.0012	0.0000	0.0000	-5.0644
867	1	2	1	1	2	3	2	0.0040	0.1231	0.7275	0.1426	0.0007	0.0022	-9.7406
868	2	2	1	1	2	3	2	0.1967	0.7027	0.0978	0.0027	0.0000	0.0000	-5.9469
869	1	3	1	1	2	3	2	0.0027	0.0865	0.7088	0.1977	0.0010	0.0032	-10.0146
870	2	3	1	1	2	3	2	0.1011	0.7031	0.1899	0.0059	0.0000	0.0001	-6.7393
871	1	1	2	1	2	3	2	0.0141	0.3292	0.6114	0.0444	0.0002	0.0006	-8.7918
872	2	1	2	1	2	3	2	0.3432	0.6070	0.0485	0.0013	0.0000	0.0000	-5.0903
873	1	2	2	1	2	3	2	0.0095	0.2506	0.6740	0.0647	0.0003	0.0009	-9.1128
874	2	2	2	1	2	3	2	0.1935	0.7041	0.0996	0.0028	0.0000	0.0000	-5.9687
875	1	3	2	1	2	3	2	0.0064	0.1848	0.7139	0.0931	0.0004	0.0013	-9.4050
876	2	3	2	1	2	3	2	0.0992	0.7017	0.1930	0.0060	0.0000	0.0001	-6.7605
877	1	1	3	1	2	3	2	0.0334	0.5246	0.4228	0.0189	0.0001	0.0003	-7.9591
878	2	1	3	1	2	3	2	0.3385	0.6107	0.0495	0.0013	0.0000	0.0000	-5.1162
879	1	2	3	1	2	3	2	0.0227	0.4364	0.5125	0.0279	0.0001	0.0004	-8.3528
880	2	2	3	1	2	3	2	0.1902	0.7054	0.1015	0.0028	0.0000	0.0000	-5.9904
881	1	3	3	1	2	3	2	0.0154	0.3479	0.5951	0.0409	0.0002	0.0006	-8.7164
882	2	3	3	1	2	3	2	0.0973	0.7001	0.1963	0.0061	0.0000	0.0001	-6.7817
883	1	1	1	2	2	3	2	0.0008	0.0269	0.5069	0.4510	0.0035	0.0110	-10.9234
884	2	1	1	2	2	3	2	0.0655	0.6536	0.2713	0.0094	0.0000	0.0001	-7.2245
885	1	2	1	2	2	3	2	0.0005	0.0183	0.4169	0.5429	0.0051	0.0163	-11.2145
886	2	2	1	2	2	3	2	0.0312	0.5091	0.4391	0.0203	0.0001	0.0003	-8.0317
887	1	3	1	2	2	3	2	0.0004	0.0123	0.3290	0.6267	0.0075	0.0240	-11.4895
888	2	3	1	2	2	3	2	0.0146	0.3359	0.6057	0.0431	0.0002	0.0006	-8.7652
889	1	1	2	2	2	3	2	0.0019	0.0624	0.6706	0.2590	0.0015	0.0046	-10.2668
890	2	1	2	2	2	3	2	0.0642	0.6506	0.2753	0.0096	0.0000	0.0001	-7.2462
891	1	2	2	2	2	3	2	0.0013	0.0429	0.6067	0.3402	0.0022	0.0068	-10.5597
892	2	2	2	2	2	3	2	0.0306	0.5045	0.4438	0.0207	0.0001	0.0003	-8.0528
893	1	3	2	2	2	3	2	0.0008	0.0293	0.5261	0.4305	0.0032	0.0101	-10.8580
894	2	3	2	2	2	3	2	0.0143	0.3314	0.6095	0.0440	0.0002	0.0006	-8.7830
895	1	1	3	2	2	3	2	0.0045	0.1377	0.7277	0.1275	0.0006	0.0019	-9.6514
896	2	1	3	2	2	3	2	0.0630	0.6476	0.2794	0.0098	0.0000	0.0001	-7.2679
897	1	2	3	2	2	3	2	0.0030	0.0973	0.7179	0.1781	0.0009	0.0028	-9.9241
898	2	2	3	2	2	3	2	0.0299	0.4999	0.4486	0.0211	0.0001	0.0003	-8.0738

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

899	1	3	3	2	2	3	2	0.0020	0.0677	0.6818	0.2429	0.0013	0.0042	-10.2037
900	2	3	3	2	2	3	2	0.0140	0.3270	0.6133	0.0449	0.0002	0.0006	-8.8008
901	1	1	1	3	2	3	2	0.0005	0.0191	0.4279	0.5320	0.0049	0.0155	-11.1800
902	2	1	1	3	2	3	2	0.0471	0.5965	0.3428	0.0133	0.0001	0.0002	-7.5885
903	1	2	1	3	2	3	2	0.0004	0.0129	0.3393	0.6173	0.0071	0.0229	-11.4573
904	2	2	1	3	2	3	2	0.0222	0.4311	0.5177	0.0285	0.0001	0.0004	-8.3752
905	1	3	1	3	2	3	2	0.0002	0.0087	0.2591	0.6878	0.0104	0.0337	-11.7160
906	2	3	1	3	2	3	2	0.0103	0.2653	0.6632	0.0600	0.0003	0.0008	-9.0514
907	1	1	2	3	2	3	2	0.0013	0.0449	0.6154	0.3298	0.0021	0.0065	-10.5238
908	2	1	2	3	2	3	2	0.0462	0.5926	0.3473	0.0136	0.0001	0.0002	-7.6103
909	1	2	2	3	2	3	2	0.0009	0.0307	0.5365	0.4193	0.0031	0.0096	-10.8219
910	2	2	2	3	2	3	2	0.0217	0.4264	0.5223	0.0291	0.0001	0.0004	-8.3951
911	1	3	2	3	2	3	2	0.0006	0.0208	0.4478	0.5120	0.0045	0.0143	-11.1166
912	2	3	2	3	2	3	2	0.0101	0.2614	0.6662	0.0612	0.0003	0.0008	-9.0677
913	1	1	3	3	2	3	2	0.0032	0.1016	0.7205	0.1712	0.0009	0.0027	-9.8909
914	2	1	3	3	2	3	2	0.0453	0.5887	0.3519	0.0139	0.0001	0.0002	-7.6320
915	1	2	3	3	2	3	2	0.0021	0.0708	0.6875	0.2343	0.0013	0.0040	-10.1693
916	2	2	3	3	2	3	2	0.0213	0.4216	0.5268	0.0297	0.0001	0.0004	-8.4149
917	1	3	3	3	2	3	2	0.0014	0.0488	0.6307	0.3112	0.0019	0.0060	-10.4587
918	2	3	3	3	2	3	2	0.0099	0.2575	0.6690	0.0624	0.0003	0.0009	-9.0839
919	1	1	1	1	3	3	2	0.0028	0.0895	0.7117	0.1919	0.0010	0.0031	-9.9884
920	2	1	1	1	3	3	2	0.2003	0.7012	0.0959	0.0027	0.0000	0.0000	-5.9236
921	1	2	1	1	3	3	2	0.0019	0.0621	0.6699	0.2600	0.0015	0.0046	-10.2705
922	2	2	1	1	3	3	2	0.1031	0.7045	0.1865	0.0058	0.0000	0.0001	-6.7167
923	1	3	1	1	3	3	2	0.0013	0.0427	0.6057	0.3413	0.0022	0.0068	-10.5634
924	2	3	1	1	3	3	2	0.0501	0.6082	0.3289	0.0125	0.0001	0.0002	-7.5209
925	1	1	2	1	3	3	2	0.0067	0.1904	0.7112	0.0900	0.0004	0.0013	-9.3783
926	2	1	2	1	3	3	2	0.1970	0.7026	0.0977	0.0027	0.0000	0.0000	-5.9454
927	1	2	2	1	3	3	2	0.0045	0.1371	0.7278	0.1280	0.0006	0.0019	-9.6549
928	2	2	2	1	3	3	2	0.1012	0.7032	0.1896	0.0059	0.0000	0.0001	-6.7379
929	1	3	2	1	3	3	2	0.0030	0.0968	0.7176	0.1788	0.0009	0.0028	-9.9276
930	2	3	2	1	3	3	2	0.0491	0.6045	0.3334	0.0127	0.0001	0.0002	-7.5427
931	1	1	3	1	3	3	2	0.0160	0.3561	0.5878	0.0394	0.0002	0.0005	-8.6836
932	2	1	3	1	3	3	2	0.1937	0.7040	0.0995	0.0028	0.0000	0.0000	-5.9672
933	1	2	3	1	3	3	2	0.0108	0.2741	0.6566	0.0575	0.0003	0.0008	-9.0153

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

934	2	2	3	1	3	3	2	0.0993	0.7018	0.1928	0.0060	0.0000	0.0001	-6.7591
935	1	3	3	1	3	3	2	0.0073	0.2040	0.7041	0.0831	0.0004	0.0012	-9.3154
936	2	3	3	1	3	3	2	0.0482	0.6007	0.3379	0.0130	0.0001	0.0002	-7.5645
937	1	1	1	2	3	3	2	0.0004	0.0128	0.3370	0.6194	0.0072	0.0232	-11.4643
938	2	1	1	2	3	3	2	0.0319	0.5140	0.4340	0.0199	0.0001	0.0003	-8.0091
939	1	2	1	2	3	3	2	0.0002	0.0087	0.2571	0.6895	0.0105	0.0341	-11.7227
940	2	2	1	2	3	3	2	0.0149	0.3406	0.6015	0.0422	0.0002	0.0006	-8.7459
941	1	3	1	2	3	3	2	0.0002	0.0058	0.1899	0.7392	0.0150	0.0499	-11.9673
942	2	3	1	2	3	3	2	0.0069	0.1951	0.7088	0.0875	0.0004	0.0013	-9.3560
943	1	1	2	2	3	3	2	0.0009	0.0304	0.5342	0.4217	0.0031	0.0097	-10.8298
944	2	1	2	2	3	3	2	0.0312	0.5094	0.4387	0.0203	0.0001	0.0003	-8.0303
945	1	2	2	2	3	3	2	0.0006	0.0206	0.4454	0.5144	0.0045	0.0144	-11.1243
946	2	2	2	2	3	3	2	0.0146	0.3362	0.6054	0.0431	0.0002	0.0006	-8.7639
947	1	3	2	2	3	3	2	0.0004	0.0140	0.3560	0.6017	0.0066	0.0213	-11.4050
948	2	3	2	2	3	3	2	0.0067	0.1919	0.7104	0.0892	0.0004	0.0013	-9.3709
949	1	1	3	2	3	3	2	0.0021	0.0701	0.6863	0.2361	0.0013	0.0041	-10.1768
950	2	1	3	2	3	3	2	0.0306	0.5048	0.4435	0.0207	0.0001	0.0003	-8.0514
951	1	2	3	2	3	3	2	0.0014	0.0483	0.6289	0.3134	0.0019	0.0060	-10.4665
952	2	2	3	2	3	3	2	0.0143	0.3317	0.6093	0.0440	0.0002	0.0006	-8.7818
953	1	3	3	2	3	3	2	0.0010	0.0330	0.5528	0.4014	0.0028	0.0089	-10.7641
954	2	3	3	2	3	3	2	0.0066	0.1888	0.7120	0.0909	0.0004	0.0013	-9.3858
955	1	1	1	3	3	3	2	0.0003	0.0091	0.2661	0.6820	0.0100	0.0325	-11.6923
956	2	1	1	3	3	3	2	0.0227	0.4361	0.5128	0.0279	0.0001	0.0004	-8.3539
957	1	2	1	3	3	3	2	0.0002	0.0061	0.1973	0.7344	0.0144	0.0476	-11.9381
958	2	2	1	3	3	3	2	0.0105	0.2696	0.6600	0.0588	0.0003	0.0008	-9.0339
959	1	3	1	3	3	3	2	0.0001	0.0041	0.1424	0.7638	0.0202	0.0692	-12.1798
960	2	3	1	3	3	3	2	0.0049	0.1467	0.7266	0.1195	0.0006	0.0018	-9.6005
961	1	1	2	3	3	3	2	0.0006	0.0216	0.4564	0.5033	0.0043	0.0137	-11.0892
962	2	1	2	3	3	3	2	0.0222	0.4314	0.5174	0.0285	0.0001	0.0004	-8.3739
963	1	2	2	3	3	3	2	0.0004	0.0146	0.3666	0.5917	0.0063	0.0203	-11.3720
964	2	2	2	3	3	3	2	0.0103	0.2656	0.6630	0.0600	0.0003	0.0008	-9.0503
965	1	3	2	3	3	3	2	0.0003	0.0099	0.2831	0.6676	0.0092	0.0299	-11.6365
966	2	3	2	3	3	3	2	0.0048	0.1441	0.7270	0.1217	0.0006	0.0018	-9.6148
967	1	1	3	3	3	3	2	0.0015	0.0506	0.6370	0.3034	0.0018	0.0057	-10.4309
968	2	1	3	3	3	3	2	0.0218	0.4267	0.5220	0.0291	0.0001	0.0004	-8.3937

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

969	1	2	3	3	3	3	2	0.0010	0.0346	0.5628	0.3904	0.0027	0.0085	-10.7279
970	2	2	3	3	3	3	2	0.0101	0.2617	0.6660	0.0611	0.0003	0.0008	-9.0666
971	1	3	3	3	3	3	2	0.0007	0.0235	0.4762	0.4830	0.0040	0.0126	-11.0249
972	2	3	3	3	3	3	2	0.0047	0.1416	0.7274	0.1239	0.0006	0.0018	-9.6292
973	1	1	1	1	1	1	3	0.0026	0.0857	0.7080	0.1993	0.0010	0.0033	-10.0218
974	2	1	1	1	1	1	3	0.4204	0.5432	0.0354	0.0009	0.0000	0.0000	-4.6647
975	1	2	1	1	1	1	3	0.0018	0.0594	0.6633	0.2691	0.0015	0.0048	-10.3052
976	2	2	1	1	1	1	3	0.2498	0.6742	0.0740	0.0020	0.0000	0.0000	-5.6174
977	1	3	1	1	1	1	3	0.0012	0.0408	0.5968	0.3518	0.0023	0.0072	-10.5992
978	2	3	1	1	1	1	3	0.1326	0.7155	0.1475	0.0043	0.0000	0.0001	-6.4288
979	1	1	2	1	1	1	3	0.0064	0.1832	0.7146	0.0940	0.0004	0.0014	-9.4122
980	2	1	2	1	1	1	3	0.4154	0.5475	0.0362	0.0009	0.0000	0.0000	-4.6930
981	1	2	2	1	1	1	3	0.0043	0.1316	0.7280	0.1334	0.0006	0.0020	-9.6877
982	2	2	2	1	1	1	3	0.2459	0.6766	0.0754	0.0020	0.0000	0.0000	-5.6404
983	1	3	2	1	1	1	3	0.0029	0.0928	0.7145	0.1859	0.0010	0.0030	-9.9608
984	2	3	2	1	1	1	3	0.1302	0.7152	0.1501	0.0044	0.0000	0.0001	-6.4499
985	1	1	3	1	1	1	3	0.0152	0.3457	0.5970	0.0413	0.0002	0.0006	-8.7254
986	2	1	3	1	1	1	3	0.4103	0.5518	0.0369	0.0010	0.0000	0.0000	-4.7210
987	1	2	3	1	1	1	3	0.0103	0.2650	0.6635	0.0602	0.0003	0.0008	-9.0530
988	2	2	3	1	1	1	3	0.2421	0.6790	0.0768	0.0021	0.0000	0.0000	-5.6633
989	1	3	3	1	1	1	3	0.0069	0.1965	0.7081	0.0868	0.0004	0.0012	-9.3499
990	2	3	3	1	1	1	3	0.1278	0.7148	0.1528	0.0045	0.0000	0.0001	-6.4709
991	1	1	1	2	1	1	3	0.0003	0.0122	0.3269	0.6287	0.0076	0.0243	-11.4964
992	2	1	1	2	1	1	3	0.0870	0.6898	0.2161	0.0069	0.0000	0.0001	-6.9076
993	1	2	1	2	1	1	3	0.0002	0.0083	0.2483	0.6966	0.0109	0.0357	-11.7527
994	2	2	1	2	1	1	3	0.0419	0.5731	0.3697	0.0150	0.0001	0.0002	-7.7162
995	1	3	1	2	1	1	3	0.0002	0.0056	0.1828	0.7437	0.0156	0.0522	-11.9963
996	2	3	1	2	1	1	3	0.0197	0.4034	0.5442	0.0321	0.0001	0.0004	-8.4906
997	1	1	2	2	1	1	3	0.0008	0.0290	0.5238	0.4329	0.0032	0.0102	-10.8657
998	2	1	2	2	1	1	3	0.0854	0.6878	0.2196	0.0071	0.0000	0.0001	-6.9290
999	1	2	2	2	1	1	3	0.0006	0.0197	0.4345	0.5254	0.0048	0.0151	-11.1589
1000	2	2	2	2	1	1	3	0.0411	0.5690	0.3743	0.0153	0.0001	0.0002	-7.7379
1001	1	3	2	2	1	1	3	0.0004	0.0133	0.3456	0.6115	0.0070	0.0223	-11.4375
1002	2	3	2	2	1	1	3	0.0193	0.3987	0.5486	0.0328	0.0001	0.0004	-8.5099
1003	1	1	3	2	1	1	3	0.0020	0.0671	0.6806	0.2447	0.0014	0.0043	-10.2111

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1004	2	1	3	2	1	1	3	0.0838	0.6857	0.2231	0.0072	0.0000	0.0001	-6.9504
1005	1	2	3	2	1	1	3	0.0014	0.0462	0.6206	0.3235	0.0020	0.0063	-10.5020
1006	2	2	3	2	1	1	3	0.0403	0.5648	0.3790	0.0156	0.0001	0.0002	-7.7595
1007	1	3	3	2	1	1	3	0.0009	0.0315	0.5427	0.4125	0.0030	0.0094	-10.8000
1008	2	3	3	2	1	1	3	0.0189	0.3940	0.5530	0.0334	0.0001	0.0005	-8.5292
1009	1	1	1	3	1	1	3	0.0002	0.0087	0.2571	0.6894	0.0105	0.0341	-11.7225
1010	2	1	1	3	1	1	3	0.0630	0.6476	0.2794	0.0098	0.0000	0.0001	-7.2679
1011	1	2	1	3	1	1	3	0.0002	0.0058	0.1900	0.7392	0.0150	0.0499	-11.9671
1012	2	2	1	3	1	1	3	0.0299	0.4999	0.4486	0.0211	0.0001	0.0003	-8.0739
1013	1	3	1	3	1	1	3	0.0001	0.0039	0.1368	0.7657	0.0211	0.0724	-12.2092
1014	2	3	1	3	1	1	3	0.0140	0.3270	0.6133	0.0449	0.0002	0.0006	-8.8009
1015	1	1	2	3	1	1	3	0.0006	0.0206	0.4455	0.5144	0.0045	0.0144	-11.1241
1016	2	1	2	3	1	1	3	0.0618	0.6445	0.2835	0.0100	0.0000	0.0001	-7.2897
1017	1	2	2	3	1	1	3	0.0004	0.0140	0.3561	0.6017	0.0066	0.0213	-11.4048
1018	2	2	2	3	1	1	3	0.0293	0.4953	0.4534	0.0216	0.0001	0.0003	-8.0948
1019	1	3	2	3	1	1	3	0.0003	0.0094	0.2738	0.6756	0.0096	0.0313	-11.6671
1020	2	3	2	3	1	1	3	0.0137	0.3226	0.6171	0.0458	0.0002	0.0006	-8.8186
1021	1	1	3	3	1	1	3	0.0014	0.0483	0.6290	0.3133	0.0019	0.0060	-10.4663
1022	2	1	3	3	1	1	3	0.0606	0.6414	0.2876	0.0102	0.0000	0.0001	-7.3114
1023	1	2	3	3	1	1	3	0.0010	0.0330	0.5528	0.4014	0.0028	0.0089	-10.7639
1024	2	2	3	3	1	1	3	0.0287	0.4907	0.4581	0.0220	0.0001	0.0003	-8.1157
1025	1	3	3	3	1	1	3	0.0006	0.0225	0.4654	0.4941	0.0042	0.0132	-11.0601
1026	2	3	3	3	1	1	3	0.0134	0.3182	0.6208	0.0467	0.0002	0.0006	-8.8361
1027	1	1	1	1	2	1	3	0.0012	0.0423	0.6038	0.3435	0.0022	0.0069	-10.5711
1028	2	1	1	1	2	1	3	0.2540	0.6716	0.0724	0.0020	0.0000	0.0000	-5.5927
1029	1	2	1	1	2	1	3	0.0008	0.0288	0.5227	0.4341	0.0032	0.0103	-10.8695
1030	2	2	1	1	2	1	3	0.1352	0.7158	0.1448	0.0042	0.0000	0.0001	-6.4063
1031	1	3	1	1	2	1	3	0.0006	0.0196	0.4334	0.5265	0.0048	0.0152	-11.1626
1032	2	3	1	1	2	1	3	0.0669	0.6568	0.2669	0.0092	0.0000	0.0001	-7.2006
1033	1	1	2	1	2	1	3	0.0030	0.0960	0.7169	0.1803	0.0009	0.0029	-9.9347
1034	2	1	2	1	2	1	3	0.2501	0.6740	0.0739	0.0020	0.0000	0.0000	-5.6158
1035	1	2	2	1	2	1	3	0.0020	0.0667	0.6800	0.2456	0.0014	0.0043	-10.2147
1036	2	2	2	1	2	1	3	0.1327	0.7155	0.1473	0.0043	0.0000	0.0001	-6.4273
1037	1	3	2	1	2	1	3	0.0014	0.0459	0.6197	0.3246	0.0020	0.0063	-10.5058
1038	2	3	2	1	2	1	3	0.0656	0.6539	0.2709	0.0094	0.0000	0.0001	-7.2223

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1039	1	1	3	1	2	1	3	0.0072	0.2023	0.7050	0.0839	0.0004	0.0012	-9.3229
1040	2	1	3	1	2	1	3	0.2462	0.6765	0.0753	0.0020	0.0000	0.0000	-5.6388
1041	1	2	3	1	2	1	3	0.0049	0.1464	0.7267	0.1197	0.0006	0.0018	-9.6018
1042	2	2	3	1	2	1	3	0.1304	0.7152	0.1500	0.0044	0.0000	0.0001	-6.4484
1043	1	3	3	1	2	1	3	0.0033	0.1038	0.7216	0.1679	0.0008	0.0026	-9.8743
1044	2	3	3	1	2	1	3	0.0644	0.6509	0.2749	0.0096	0.0000	0.0001	-7.2440
1045	1	1	1	2	2	1	3	0.0002	0.0058	0.1884	0.7402	0.0151	0.0504	-11.9735
1046	2	1	1	2	2	1	3	0.0428	0.5775	0.3647	0.0147	0.0001	0.0002	-7.6930
1047	1	2	1	2	2	1	3	0.0001	0.0039	0.1355	0.7661	0.0213	0.0731	-12.2157
1048	2	2	1	2	2	1	3	0.0201	0.4084	0.5395	0.0314	0.0001	0.0004	-8.4699
1049	1	3	1	2	2	1	3	0.0001	0.0026	0.0956	0.7675	0.0292	0.1050	-12.4700
1050	2	3	1	2	2	1	3	0.0093	0.2467	0.6768	0.0659	0.0003	0.0009	-9.1290
1051	1	1	2	2	2	1	3	0.0004	0.0138	0.3538	0.6038	0.0067	0.0215	-11.4120
1052	2	1	2	2	2	1	3	0.0420	0.5734	0.3694	0.0150	0.0001	0.0002	-7.7147
1053	1	2	2	2	2	1	3	0.0003	0.0093	0.2717	0.6773	0.0097	0.0316	-11.6738
1054	2	2	2	2	2	1	3	0.0197	0.4037	0.5439	0.0321	0.0001	0.0004	-8.4893
1055	1	3	2	2	2	1	3	0.0002	0.0063	0.2019	0.7313	0.0140	0.0463	-11.9204
1056	2	3	2	2	2	1	3	0.0091	0.2430	0.6794	0.0672	0.0003	0.0009	-9.1449
1057	1	1	3	2	2	1	3	0.0010	0.0327	0.5506	0.4038	0.0029	0.0090	-10.7718
1058	2	1	3	2	2	1	3	0.0411	0.5693	0.3740	0.0153	0.0001	0.0002	-7.7364
1059	1	2	3	2	2	1	3	0.0006	0.0222	0.4630	0.4966	0.0042	0.0133	-11.0678
1060	2	2	3	2	2	1	3	0.0193	0.3990	0.5483	0.0327	0.0001	0.0004	-8.5086
1061	1	3	3	2	2	1	3	0.0004	0.0151	0.3730	0.5856	0.0062	0.0197	-11.3518
1062	2	3	3	2	2	1	3	0.0090	0.2392	0.6820	0.0686	0.0003	0.0010	-9.1608
1063	1	1	1	3	2	1	3	0.0001	0.0041	0.1412	0.7643	0.0204	0.0699	-12.1861
1064	2	1	1	3	2	1	3	0.0306	0.5048	0.4435	0.0207	0.0001	0.0003	-8.0514
1065	1	2	1	3	2	1	3	0.0001	0.0027	0.0998	0.7687	0.0281	0.1005	-12.4381
1066	2	2	1	3	2	1	3	0.0143	0.3317	0.6093	0.0440	0.0002	0.0006	-8.7819
1067	1	3	1	3	2	1	3	0.0001	0.0019	0.0695	0.7485	0.0375	0.1426	-12.7136
1068	2	3	1	3	2	1	3	0.0066	0.1888	0.7120	0.0909	0.0004	0.0013	-9.3859
1069	1	1	2	3	2	1	3	0.0003	0.0098	0.2811	0.6693	0.0093	0.0302	-11.6431
1070	2	1	2	3	2	1	3	0.0300	0.5003	0.4483	0.0211	0.0001	0.0003	-8.0724
1071	1	2	2	3	2	1	3	0.0002	0.0066	0.2096	0.7259	0.0134	0.0443	-11.8910
1072	2	2	2	3	2	1	3	0.0140	0.3273	0.6131	0.0448	0.0002	0.0006	-8.7997
1073	1	3	2	3	2	1	3	0.0001	0.0045	0.1520	0.7600	0.0190	0.0644	-12.1325

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1074	2	3	2	3	2	1	3	0.0065	0.1856	0.7135	0.0926	0.0004	0.0013	-9.4007
1075	1	1	3	3	2	1	3	0.0007	0.0233	0.4739	0.4854	0.0040	0.0127	-11.0325
1076	2	1	3	3	2	1	3	0.0294	0.4957	0.4530	0.0215	0.0001	0.0003	-8.0934
1077	1	2	3	3	2	1	3	0.0005	0.0158	0.3838	0.5753	0.0059	0.0188	-11.3183
1078	2	2	3	3	2	1	3	0.0137	0.3229	0.6168	0.0457	0.0002	0.0006	-8.8173
1079	1	3	3	3	2	1	3	0.0003	0.0107	0.2985	0.6542	0.0086	0.0277	-11.5865
1080	2	3	3	3	2	1	3	0.0063	0.1826	0.7149	0.0944	0.0004	0.0014	-9.4155
1081	1	1	1	1	3	1	3	0.0006	0.0203	0.4419	0.5179	0.0046	0.0146	-11.1354
1082	2	1	1	1	3	1	3	0.1378	0.7159	0.1420	0.0042	0.0000	0.0001	-6.3837
1083	1	2	1	1	3	1	3	0.0004	0.0138	0.3527	0.6049	0.0067	0.0216	-11.4154
1084	2	2	1	1	3	1	3	0.0683	0.6598	0.2627	0.0090	0.0000	0.0001	-7.1775
1085	1	3	1	1	3	1	3	0.0003	0.0093	0.2708	0.6781	0.0098	0.0318	-11.6770
1086	2	3	1	1	3	1	3	0.0326	0.5189	0.4287	0.0194	0.0001	0.0003	-7.9858
1087	1	1	2	1	3	1	3	0.0014	0.0476	0.6263	0.3166	0.0019	0.0061	-10.4779
1088	2	1	2	1	3	1	3	0.1353	0.7158	0.1446	0.0042	0.0000	0.0001	-6.4048
1089	1	2	2	1	3	1	3	0.0009	0.0325	0.5496	0.4050	0.0029	0.0091	-10.7756
1090	2	2	2	1	3	1	3	0.0670	0.6570	0.2666	0.0092	0.0000	0.0001	-7.1991
1091	1	3	2	1	3	1	3	0.0006	0.0221	0.4618	0.4977	0.0042	0.0134	-11.0715
1092	2	3	2	1	3	1	3	0.0319	0.5144	0.4335	0.0198	0.0001	0.0003	-8.0070
1093	1	1	3	1	3	1	3	0.0034	0.1073	0.7233	0.1627	0.0008	0.0025	-9.8485
1094	2	1	3	1	3	1	3	0.1329	0.7155	0.1472	0.0043	0.0000	0.0001	-6.4259
1095	1	2	3	1	3	1	3	0.0023	0.0749	0.6943	0.2235	0.0012	0.0038	-10.1254
1096	2	2	3	1	3	1	3	0.0657	0.6541	0.2706	0.0094	0.0000	0.0001	-7.2208
1097	1	3	3	1	3	1	3	0.0015	0.0517	0.6409	0.2984	0.0018	0.0056	-10.4131
1098	2	3	3	1	3	1	3	0.0313	0.5099	0.4383	0.0202	0.0001	0.0003	-8.0282
1099	1	1	1	2	3	1	3	0.0001	0.0027	0.0989	0.7684	0.0284	0.1015	-12.4450
1100	2	1	1	2	3	1	3	0.0206	0.4135	0.5347	0.0308	0.0001	0.0004	-8.4490
1101	1	2	1	2	3	1	3	0.0001	0.0018	0.0688	0.7476	0.0378	0.1438	-12.7213
1102	2	2	1	2	3	1	3	0.0095	0.2508	0.6739	0.0646	0.0003	0.0009	-9.1119
1103	1	3	1	2	3	1	3	0.0000	0.0012	0.0474	0.7031	0.0483	0.1999	-13.0289
1104	2	3	1	2	3	1	3	0.0044	0.1347	0.7279	0.1304	0.0006	0.0020	-9.6694
1105	1	1	2	2	3	1	3	0.0002	0.0065	0.2079	0.7272	0.0135	0.0447	-11.8975
1106	2	1	2	2	3	1	3	0.0201	0.4087	0.5392	0.0314	0.0001	0.0004	-8.4685
1107	1	2	2	2	3	1	3	0.0001	0.0044	0.1507	0.7606	0.0191	0.0651	-12.1389
1108	2	2	2	2	3	1	3	0.0094	0.2470	0.6766	0.0659	0.0003	0.0009	-9.1279

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1109	1	3	2	2	3	1	3	0.0001	0.0030	0.1069	0.7697	0.0265	0.0938	-12.3878
1110	2	3	2	2	3	1	3	0.0043	0.1323	0.7280	0.1328	0.0006	0.0020	-9.6837
1111	1	1	3	2	3	1	3	0.0004	0.0156	0.3814	0.5775	0.0060	0.0190	-11.3257
1112	2	1	3	2	3	1	3	0.0197	0.4040	0.5436	0.0320	0.0001	0.0004	-8.4880
1113	1	2	3	2	3	1	3	0.0003	0.0106	0.2964	0.6560	0.0087	0.0280	-11.5933
1114	2	2	3	2	3	1	3	0.0092	0.2432	0.6792	0.0671	0.0003	0.0009	-9.1438
1115	1	3	3	2	3	1	3	0.0002	0.0071	0.2224	0.7167	0.0125	0.0411	-11.8439
1116	2	3	3	2	3	1	3	0.0042	0.1299	0.7280	0.1352	0.0007	0.0020	-9.6980
1117	1	1	1	3	3	1	3	0.0001	0.0019	0.0720	0.7514	0.0366	0.1380	-12.6863
1118	2	1	1	3	3	1	3	0.0146	0.3365	0.6051	0.0430	0.0002	0.0006	-8.7627
1119	1	2	1	3	3	1	3	0.0000	0.0013	0.0496	0.7097	0.0470	0.1923	-12.9899
1120	2	2	1	3	3	1	3	0.0068	0.1922	0.7103	0.0891	0.0004	0.0013	-9.3699
1121	1	3	1	3	3	1	3	0.0000	0.0009	0.0339	0.6464	0.0572	0.2616	-13.3239
1122	2	3	1	3	3	1	3	0.0031	0.0992	0.7191	0.1749	0.0009	0.0028	-9.9090
1123	1	1	2	3	3	1	3	0.0001	0.0046	0.1569	0.7578	0.0184	0.0622	-12.1096
1124	2	1	2	3	3	1	3	0.0143	0.3320	0.6090	0.0439	0.0002	0.0006	-8.7806
1125	1	2	2	3	3	1	3	0.0001	0.0031	0.1115	0.7699	0.0255	0.0898	-12.3568
1126	2	2	2	3	3	1	3	0.0066	0.1890	0.7119	0.0908	0.0004	0.0013	-9.3848
1127	1	3	2	3	3	1	3	0.0001	0.0021	0.0780	0.7575	0.0344	0.1279	-12.6237
1128	2	3	2	3	3	1	3	0.0030	0.0974	0.7179	0.1779	0.0009	0.0028	-9.9235
1129	1	1	3	3	3	1	3	0.0003	0.0111	0.3062	0.6474	0.0083	0.0267	-11.5620
1130	2	1	3	3	3	1	3	0.0140	0.3276	0.6128	0.0448	0.0002	0.0006	-8.7984
1131	1	2	3	3	3	1	3	0.0002	0.0075	0.2306	0.7104	0.0120	0.0393	-11.8143
1132	2	2	3	3	3	1	3	0.0065	0.1859	0.7134	0.0925	0.0004	0.0013	-9.3997
1133	1	3	3	3	3	1	3	0.0001	0.0050	0.1686	0.7518	0.0170	0.0573	-12.0564
1134	2	3	3	3	3	1	3	0.0030	0.0956	0.7167	0.1810	0.0009	0.0029	-9.9379
1135	1	1	1	1	1	2	3	0.0012	0.0394	0.5900	0.3596	0.0024	0.0074	-10.6257
1136	2	1	1	1	1	2	3	0.6552	0.3306	0.0138	0.0004	0.0000	0.0000	-3.2385
1137	1	2	1	1	1	2	3	0.0008	0.0269	0.5067	0.4511	0.0035	0.0110	-10.9239
1138	2	2	1	1	1	2	3	0.4659	0.5036	0.0297	0.0008	0.0000	0.0000	-4.4092
1139	1	3	1	1	1	2	3	0.0005	0.0182	0.4168	0.5430	0.0051	0.0163	-11.2149
1140	2	3	1	1	1	2	3	0.2859	0.6501	0.0623	0.0017	0.0000	0.0000	-5.4090
1141	1	1	2	1	1	2	3	0.0028	0.0899	0.7121	0.1912	0.0010	0.0031	-9.9853
1142	2	1	2	1	1	2	3	0.6505	0.3350	0.0141	0.0004	0.0000	0.0000	-3.2708
1143	1	2	2	1	1	2	3	0.0019	0.0624	0.6705	0.2591	0.0015	0.0046	-10.2672

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1144	2	2	2	1	1	2	3	0.4607	0.5082	0.0303	0.0008	0.0000	0.0000	-4.4387
1145	1	3	2	1	1	2	3	0.0013	0.0429	0.6066	0.3403	0.0022	0.0068	-10.5601
1146	2	3	2	1	1	2	3	0.2817	0.6530	0.0635	0.0017	0.0000	0.0000	-5.4331
1147	1	1	3	1	1	2	3	0.0067	0.1911	0.7109	0.0896	0.0004	0.0013	-9.3751
1148	2	1	3	1	1	2	3	0.6457	0.3395	0.0144	0.0004	0.0000	0.0000	-3.3031
1149	1	2	3	1	1	2	3	0.0045	0.1377	0.7278	0.1275	0.0006	0.0019	-9.6518
1150	2	2	3	1	1	2	3	0.4555	0.5128	0.0309	0.0008	0.0000	0.0000	-4.4681
1151	1	3	3	1	1	2	3	0.0030	0.0972	0.7178	0.1782	0.0009	0.0028	-9.9245
1152	2	3	3	1	1	2	3	0.2775	0.6560	0.0648	0.0017	0.0000	0.0000	-5.4570
1153	1	1	1	2	1	2	3	0.0002	0.0054	0.1777	0.7468	0.0161	0.0539	-12.0177
1154	2	1	1	2	1	2	3	0.1998	0.7014	0.0961	0.0027	0.0000	0.0000	-5.9267
1155	1	2	1	2	1	2	3	0.0001	0.0036	0.1273	0.7682	0.0226	0.0782	-12.2610
1156	2	2	1	2	1	2	3	0.1028	0.7043	0.1869	0.0058	0.0000	0.0001	-6.7197
1157	1	3	1	2	1	2	3	0.0001	0.0024	0.0895	0.7651	0.0308	0.1120	-12.5189
1158	2	3	1	2	1	2	3	0.0500	0.6077	0.3296	0.0125	0.0001	0.0002	-7.5240
1159	1	1	2	2	1	2	3	0.0004	0.0129	0.3380	0.6185	0.0072	0.0231	-11.4613
1160	2	1	2	2	1	2	3	0.1965	0.7028	0.0979	0.0027	0.0000	0.0000	-5.9485
1161	1	2	2	2	1	2	3	0.0002	0.0087	0.2579	0.6888	0.0104	0.0339	-11.7199
1162	2	2	2	2	1	2	3	0.1009	0.7030	0.1901	0.0059	0.0000	0.0001	-6.7409
1163	1	3	2	2	1	2	3	0.0002	0.0059	0.1906	0.7388	0.0149	0.0497	-11.9646
1164	2	3	2	2	1	2	3	0.0490	0.6040	0.3340	0.0128	0.0001	0.0002	-7.5458
1165	1	1	3	2	1	2	3	0.0009	0.0305	0.5352	0.4207	0.0031	0.0097	-10.8265
1166	2	1	3	2	1	2	3	0.1932	0.7042	0.0998	0.0028	0.0000	0.0000	-5.9703
1167	1	2	3	2	1	2	3	0.0006	0.0207	0.4464	0.5134	0.0045	0.0143	-11.1210
1168	2	2	3	2	1	2	3	0.0990	0.7015	0.1933	0.0060	0.0000	0.0001	-6.7621
1169	1	3	3	2	1	2	3	0.0004	0.0140	0.3570	0.6008	0.0066	0.0212	-11.4019
1170	2	3	3	2	1	2	3	0.0480	0.6002	0.3385	0.0130	0.0001	0.0002	-7.5676
1171	1	1	1	3	1	2	3	0.0001	0.0038	0.1327	0.7669	0.0217	0.0748	-12.2310
1172	2	1	1	3	1	2	3	0.1498	0.7157	0.1307	0.0038	0.0000	0.0000	-6.2852
1173	1	2	1	3	1	2	3	0.0001	0.0026	0.0935	0.7668	0.0297	0.1073	-12.4865
1174	2	2	1	3	1	2	3	0.0748	0.6722	0.2447	0.0082	0.0000	0.0001	-7.0767
1175	1	3	1	3	1	2	3	0.0000	0.0017	0.0650	0.7422	0.0394	0.1517	-12.7673
1176	2	3	1	3	1	2	3	0.0358	0.5397	0.4066	0.0176	0.0001	0.0002	-7.8863
1177	1	1	2	3	1	2	3	0.0003	0.0091	0.2670	0.6813	0.0100	0.0324	-11.6895
1178	2	1	2	3	1	2	3	0.1471	0.7159	0.1331	0.0039	0.0000	0.0001	-6.3064

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1179	1	2	2	3	1	2	3	0.0002	0.0061	0.1980	0.7339	0.0143	0.0474	-11.9354
1180	2	2	2	3	1	2	3	0.0734	0.6697	0.2484	0.0084	0.0000	0.0001	-7.0983
1181	1	3	2	3	1	2	3	0.0001	0.0041	0.1430	0.7636	0.0202	0.0690	-12.1770
1182	2	3	2	3	1	2	3	0.0351	0.5353	0.4113	0.0180	0.0001	0.0002	-7.9077
1183	1	1	3	3	1	2	3	0.0006	0.0217	0.4574	0.5023	0.0043	0.0137	-11.0859
1184	2	1	3	3	1	2	3	0.1445	0.7160	0.1355	0.0039	0.0000	0.0001	-6.3275
1185	1	2	3	3	1	2	3	0.0004	0.0147	0.3676	0.5908	0.0063	0.0202	-11.3689
1186	2	2	3	3	1	2	3	0.0720	0.6671	0.2523	0.0085	0.0000	0.0001	-7.1199
1187	1	3	3	3	1	2	3	0.0003	0.0099	0.2840	0.6668	0.0092	0.0298	-11.6336
1188	2	3	3	3	1	2	3	0.0344	0.5308	0.4161	0.0184	0.0001	0.0002	-7.9291
1189	1	1	1	1	2	2	3	0.0005	0.0189	0.4253	0.5345	0.0049	0.0157	-11.1880
1190	2	1	1	1	2	2	3	0.4715	0.4987	0.0290	0.0007	0.0000	0.0000	-4.3775
1191	1	2	1	1	2	2	3	0.0004	0.0128	0.3369	0.6195	0.0072	0.0232	-11.4647
1192	2	2	1	1	2	2	3	0.2905	0.6468	0.0610	0.0016	0.0000	0.0000	-5.3832
1193	1	3	1	1	2	2	3	0.0002	0.0086	0.2570	0.6895	0.0105	0.0341	-11.7231
1194	2	3	1	1	2	2	3	0.1582	0.7146	0.1236	0.0035	0.0000	0.0000	-6.2195
1195	1	1	2	1	2	2	3	0.0013	0.0444	0.6134	0.3322	0.0021	0.0066	-10.5321
1196	2	1	2	1	2	2	3	0.4663	0.5033	0.0296	0.0008	0.0000	0.0000	-4.4072
1197	1	2	2	1	2	2	3	0.0009	0.0303	0.5341	0.4219	0.0031	0.0097	-10.8303
1198	2	2	2	1	2	2	3	0.2862	0.6499	0.0622	0.0017	0.0000	0.0000	-5.4074
1199	1	3	2	1	2	2	3	0.0006	0.0206	0.4453	0.5146	0.0045	0.0144	-11.1247
1200	2	3	2	1	2	2	3	0.1554	0.7150	0.1258	0.0036	0.0000	0.0000	-6.2407
1201	1	1	3	1	2	2	3	0.0032	0.1005	0.7199	0.1728	0.0009	0.0027	-9.8986
1202	2	1	3	1	2	2	3	0.4611	0.5079	0.0302	0.0008	0.0000	0.0000	-4.4367
1203	1	2	3	1	2	2	3	0.0021	0.0701	0.6862	0.2362	0.0013	0.0041	-10.1773
1204	2	2	3	1	2	2	3	0.2820	0.6528	0.0635	0.0017	0.0000	0.0000	-5.4314
1205	1	3	3	1	2	2	3	0.0014	0.0483	0.6288	0.3135	0.0019	0.0060	-10.4669
1206	2	3	3	1	2	2	3	0.1527	0.7154	0.1281	0.0037	0.0000	0.0000	-6.2619
1207	1	1	1	2	2	2	3	0.0001	0.0025	0.0926	0.7665	0.0300	0.1083	-12.4936
1208	2	1	1	2	2	2	3	0.1049	0.7057	0.1836	0.0057	0.0000	0.0001	-6.6971
1209	1	2	1	2	2	2	3	0.0000	0.0017	0.0643	0.7412	0.0397	0.1530	-12.7752
1210	2	2	1	2	2	2	3	0.0511	0.6116	0.3248	0.0122	0.0001	0.0002	-7.5007
1211	1	3	1	2	2	2	3	0.0000	0.0011	0.0442	0.6926	0.0502	0.2118	-13.0886
1212	2	3	1	2	2	2	3	0.0241	0.4501	0.4991	0.0263	0.0001	0.0004	-8.2944
1213	1	1	2	2	2	2	3	0.0002	0.0061	0.1964	0.7350	0.0144	0.0479	-11.9418

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1214	2	1	2	2	2	2	3	0.1030	0.7044	0.1867	0.0058	0.0000	0.0001	-6.7182
1215	1	2	2	2	2	2	3	0.0001	0.0041	0.1417	0.7641	0.0204	0.0696	-12.1835
1216	2	2	2	2	2	2	3	0.0500	0.6080	0.3293	0.0125	0.0001	0.0002	-7.5225
1217	1	3	2	2	2	2	3	0.0001	0.0028	0.1002	0.7687	0.0280	0.1002	-12.4353
1218	2	3	2	2	2	2	3	0.0236	0.4454	0.5037	0.0268	0.0001	0.0004	-8.3146
1219	1	1	3	2	2	2	3	0.0004	0.0146	0.3652	0.5930	0.0064	0.0204	-11.3761
1220	2	1	3	2	2	2	3	0.1011	0.7031	0.1899	0.0059	0.0000	0.0001	-6.7394
1221	1	2	3	2	2	2	3	0.0003	0.0098	0.2819	0.6686	0.0093	0.0301	-11.6403
1222	2	2	3	2	2	2	3	0.0491	0.6042	0.3337	0.0128	0.0001	0.0002	-7.5443
1223	1	3	3	2	2	2	3	0.0002	0.0066	0.2103	0.7255	0.0133	0.0441	-11.8885
1224	2	3	3	2	2	2	3	0.0231	0.4406	0.5084	0.0274	0.0001	0.0004	-8.3347
1225	1	1	1	3	2	2	3	0.0001	0.0018	0.0673	0.7455	0.0384	0.1469	-12.7395
1226	2	1	1	3	2	2	3	0.0764	0.6748	0.2406	0.0080	0.0000	0.0001	-7.0537
1227	1	2	1	3	2	2	3	0.0000	0.0012	0.0463	0.6996	0.0489	0.2039	-13.0490
1228	2	2	1	3	2	2	3	0.0366	0.5443	0.4016	0.0173	0.0001	0.0002	-7.8633
1229	1	3	1	3	2	2	3	0.0000	0.0008	0.0316	0.6327	0.0589	0.2758	-13.3877
1230	2	3	1	3	2	2	3	0.0171	0.3717	0.5737	0.0368	0.0002	0.0005	-8.6204
1231	1	1	2	3	2	2	3	0.0001	0.0043	0.1476	0.7619	0.0195	0.0666	-12.1540
1232	2	1	2	3	2	2	3	0.0749	0.6724	0.2444	0.0082	0.0000	0.0001	-7.0752
1233	1	2	2	3	2	2	3	0.0001	0.0029	0.1046	0.7695	0.0270	0.0959	-12.4038
1234	2	2	2	3	2	2	3	0.0358	0.5400	0.4063	0.0176	0.0001	0.0002	-7.8848
1235	1	3	2	3	2	2	3	0.0001	0.0019	0.0730	0.7525	0.0362	0.1363	-12.6756
1236	2	3	2	3	2	2	3	0.0168	0.3671	0.5779	0.0376	0.0002	0.0005	-8.6390
1237	1	1	3	3	2	2	3	0.0003	0.0103	0.2914	0.6604	0.0089	0.0287	-11.6094
1238	2	1	3	3	2	2	3	0.0735	0.6699	0.2482	0.0083	0.0000	0.0001	-7.0968
1239	1	2	3	3	2	2	3	0.0002	0.0070	0.2182	0.7197	0.0128	0.0421	-11.8591
1240	2	2	3	3	2	2	3	0.0351	0.5356	0.4110	0.0180	0.0001	0.0002	-7.9062
1241	1	3	3	3	2	2	3	0.0001	0.0047	0.1588	0.7569	0.0181	0.0614	-12.1006
1242	2	3	3	3	2	2	3	0.0164	0.3625	0.5820	0.0383	0.0002	0.0005	-8.6576
1243	1	1	1	1	3	2	3	0.0003	0.0090	0.2640	0.6837	0.0101	0.0329	-11.6994
1244	2	1	1	1	3	2	3	0.2951	0.6435	0.0598	0.0016	0.0000	0.0000	-5.3572
1245	1	2	1	1	3	2	3	0.0002	0.0061	0.1956	0.7356	0.0145	0.0481	-11.9449
1246	2	2	1	1	3	2	3	0.1612	0.7141	0.1212	0.0035	0.0000	0.0000	-6.1968
1247	1	3	1	1	3	2	3	0.0001	0.0041	0.1411	0.7643	0.0204	0.0700	-12.1866
1248	2	3	1	1	3	2	3	0.0811	0.6821	0.2292	0.0075	0.0000	0.0001	-6.9870

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1249	1	1	2	1	3	2	3	0.0006	0.0214	0.4538	0.5059	0.0044	0.0139	-11.0973
1250	2	1	2	1	3	2	3	0.2908	0.6466	0.0609	0.0016	0.0000	0.0000	-5.3815
1251	1	2	2	1	3	2	3	0.0004	0.0145	0.3641	0.5940	0.0064	0.0205	-11.3796
1252	2	2	2	1	3	2	3	0.1584	0.7146	0.1234	0.0035	0.0000	0.0000	-6.2180
1253	1	3	2	1	3	2	3	0.0003	0.0098	0.2809	0.6695	0.0093	0.0302	-11.6436
1254	2	3	2	1	3	2	3	0.0795	0.6798	0.2329	0.0077	0.0000	0.0001	-7.0085
1255	1	1	3	1	3	2	3	0.0015	0.0500	0.6352	0.3057	0.0018	0.0058	-10.4391
1256	2	1	3	1	3	2	3	0.2865	0.6497	0.0621	0.0017	0.0000	0.0000	-5.4057
1257	1	2	3	1	3	2	3	0.0010	0.0342	0.5605	0.3930	0.0027	0.0086	-10.7363
1258	2	2	3	1	3	2	3	0.1556	0.7150	0.1257	0.0036	0.0000	0.0000	-6.2393
1259	1	3	3	1	3	2	3	0.0007	0.0233	0.4737	0.4856	0.0040	0.0127	-11.0331
1260	2	3	3	1	3	2	3	0.0780	0.6775	0.2366	0.0078	0.0000	0.0001	-7.0300
1261	1	1	1	2	3	2	3	0.0000	0.0012	0.0459	0.6981	0.0492	0.2056	-13.0577
1262	2	1	1	2	3	2	3	0.0521	0.6155	0.3202	0.0120	0.0001	0.0002	-7.4773
1263	1	2	1	2	3	2	3	0.0000	0.0008	0.0313	0.6307	0.0592	0.2779	-13.3970
1264	2	2	1	2	3	2	3	0.0246	0.4551	0.4941	0.0257	0.0001	0.0003	-8.2727
1265	1	3	1	2	3	2	3	0.0000	0.0005	0.0213	0.5475	0.0666	0.3641	-13.7521
1266	2	3	1	2	3	2	3	0.0115	0.2859	0.6473	0.0543	0.0002	0.0007	-8.9669
1267	1	1	2	2	3	2	3	0.0001	0.0029	0.1036	0.7694	0.0272	0.0968	-12.4107
1268	2	1	2	2	3	2	3	0.0511	0.6119	0.3245	0.0122	0.0001	0.0002	-7.4992
1269	1	2	2	2	3	2	3	0.0001	0.0019	0.0723	0.7517	0.0365	0.1375	-12.6832
1270	2	2	2	2	3	2	3	0.0241	0.4504	0.4988	0.0262	0.0001	0.0004	-8.2930
1271	1	3	2	2	3	2	3	0.0000	0.0013	0.0498	0.7103	0.0469	0.1917	-12.9865
1272	2	3	2	2	3	2	3	0.0112	0.2818	0.6505	0.0554	0.0002	0.0008	-8.9837
1273	1	1	3	2	3	2	3	0.0002	0.0069	0.2165	0.7210	0.0129	0.0425	-11.8655
1274	2	1	3	2	3	2	3	0.0501	0.6082	0.3290	0.0125	0.0001	0.0002	-7.5210
1275	1	2	3	2	3	2	3	0.0001	0.0046	0.1574	0.7575	0.0183	0.0620	-12.1070
1276	2	2	3	2	3	2	3	0.0236	0.4457	0.5034	0.0268	0.0001	0.0004	-8.3132
1277	1	3	3	2	3	2	3	0.0001	0.0031	0.1120	0.7699	0.0254	0.0894	-12.3541
1278	2	3	3	2	3	2	3	0.0110	0.2777	0.6537	0.0565	0.0003	0.0008	-9.0003
1279	1	1	1	3	3	2	3	0.0000	0.0008	0.0328	0.6398	0.0581	0.2684	-13.3547
1280	2	1	1	3	3	2	3	0.0374	0.5489	0.3965	0.0169	0.0001	0.0002	-7.8403
1281	1	2	1	3	3	2	3	0.0000	0.0006	0.0223	0.5582	0.0659	0.3530	-13.7089
1282	2	2	1	3	3	2	3	0.0175	0.3766	0.5692	0.0361	0.0002	0.0005	-8.6003
1283	1	3	1	3	3	2	3	0.0000	0.0004	0.0151	0.4671	0.0694	0.4480	-14.0610

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1284	2	3	1	3	3	2	3	0.0081	0.2218	0.6934	0.0752	0.0003	0.0011	-9.2359
1285	1	1	2	3	3	2	3	0.0001	0.0020	0.0755	0.7552	0.0353	0.1319	-12.6487
1286	2	1	2	3	3	2	3	0.0366	0.5446	0.4012	0.0172	0.0001	0.0002	-7.8618
1287	1	2	2	3	3	2	3	0.0000	0.0014	0.0521	0.7165	0.0456	0.1844	-12.9481
1288	2	2	2	3	3	2	3	0.0171	0.3720	0.5734	0.0368	0.0002	0.0005	-8.6191
1289	1	3	2	3	3	2	3	0.0000	0.0009	0.0357	0.6558	0.0560	0.2516	-13.2785
1290	2	3	2	3	3	2	3	0.0079	0.2183	0.6956	0.0767	0.0003	0.0011	-9.2513
1291	1	1	3	3	3	2	3	0.0001	0.0049	0.1638	0.7544	0.0176	0.0592	-12.0778
1292	2	1	3	3	3	2	3	0.0359	0.5403	0.4060	0.0176	0.0001	0.0002	-7.8833
1293	1	2	3	3	3	2	3	0.0001	0.0033	0.1168	0.7698	0.0245	0.0856	-12.3234
1294	2	2	3	3	3	2	3	0.0168	0.3674	0.5776	0.0375	0.0002	0.0005	-8.6378
1295	1	3	3	3	3	2	3	0.0001	0.0022	0.0818	0.7605	0.0332	0.1222	-12.5871
1296	2	3	3	3	3	2	3	0.0078	0.2148	0.6977	0.0782	0.0004	0.0011	-9.2667
1297	1	1	1	1	1	3	3	0.0047	0.1417	0.7274	0.1238	0.0006	0.0018	-9.6284
1298	2	1	1	1	1	3	3	0.2970	0.6421	0.0593	0.0016	0.0000	0.0000	-5.3465
1299	1	2	1	1	1	3	3	0.0031	0.1002	0.7197	0.1733	0.0009	0.0027	-9.9009
1300	2	2	1	1	1	3	3	0.1624	0.7138	0.1202	0.0034	0.0000	0.0000	-6.1875
1301	1	3	1	1	1	3	3	0.0021	0.0698	0.6858	0.2368	0.0013	0.0041	-10.1797
1302	2	3	1	1	1	3	3	0.0817	0.6830	0.2277	0.0074	0.0000	0.0001	-6.9776
1303	1	1	2	1	1	3	3	0.0112	0.2816	0.6507	0.0555	0.0002	0.0008	-8.9846
1304	2	1	2	1	1	3	3	0.2927	0.6452	0.0604	0.0016	0.0000	0.0000	-5.3709
1305	1	2	2	1	1	3	3	0.0076	0.2102	0.7005	0.0802	0.0004	0.0011	-9.2874
1306	2	2	2	1	1	3	3	0.1596	0.7144	0.1224	0.0035	0.0000	0.0000	-6.2088
1307	1	3	2	1	1	3	3	0.0051	0.1526	0.7254	0.1147	0.0005	0.0017	-9.5681
1308	2	3	2	1	1	3	3	0.0802	0.6808	0.2313	0.0076	0.0000	0.0001	-6.9991
1309	1	1	3	1	1	3	3	0.0266	0.4732	0.4759	0.0238	0.0001	0.0003	-8.1936
1310	2	1	3	1	1	3	3	0.2884	0.6483	0.0616	0.0016	0.0000	0.0000	-5.3952
1311	1	2	3	1	1	3	3	0.0181	0.3839	0.5625	0.0349	0.0002	0.0005	-8.5708
1312	2	2	3	1	1	3	3	0.1568	0.7148	0.1247	0.0036	0.0000	0.0000	-6.2300
1313	1	3	3	1	1	3	3	0.0122	0.2990	0.6368	0.0511	0.0002	0.0007	-8.9138
1314	2	3	3	1	1	3	3	0.0787	0.6785	0.2349	0.0078	0.0000	0.0001	-7.0206
1315	1	1	1	2	1	3	3	0.0006	0.0214	0.4542	0.5055	0.0044	0.0139	-11.0961
1316	2	1	1	2	1	3	3	0.0526	0.6171	0.3182	0.0119	0.0001	0.0002	-7.4678
1317	1	2	1	2	1	3	3	0.0004	0.0145	0.3645	0.5937	0.0064	0.0205	-11.3785
1318	2	2	1	2	1	3	3	0.0248	0.4572	0.4920	0.0255	0.0001	0.0003	-8.2638

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1319	1	3	1	2	1	3	3	0.0003	0.0098	0.2812	0.6692	0.0093	0.0302	-11.6425
1320	2	3	1	2	1	3	3	0.0116	0.2877	0.6459	0.0539	0.0002	0.0007	-8.9595
1321	1	1	2	2	1	3	3	0.0015	0.0501	0.6354	0.3053	0.0018	0.0058	-10.4379
1322	2	1	2	2	1	3	3	0.0516	0.6135	0.3226	0.0121	0.0001	0.0002	-7.4896
1323	1	2	2	2	1	3	3	0.0010	0.0343	0.5608	0.3926	0.0027	0.0086	-10.7350
1324	2	2	2	2	1	3	3	0.0243	0.4525	0.4967	0.0260	0.0001	0.0003	-8.2841
1325	1	3	2	2	1	3	3	0.0007	0.0233	0.4741	0.4852	0.0040	0.0127	-11.0318
1326	2	3	2	2	1	3	3	0.0113	0.2836	0.6491	0.0549	0.0002	0.0008	-8.9763
1327	1	1	3	2	1	3	3	0.0036	0.1125	0.7252	0.1556	0.0008	0.0024	-9.8114
1328	2	1	3	2	1	3	3	0.0506	0.6098	0.3270	0.0124	0.0001	0.0002	-7.5114
1329	1	2	3	2	1	3	3	0.0024	0.0787	0.6997	0.2144	0.0011	0.0036	-10.0872
1330	2	2	3	2	1	3	3	0.0239	0.4478	0.5014	0.0265	0.0001	0.0004	-8.3044
1331	1	3	3	2	1	3	3	0.0016	0.0544	0.6495	0.2875	0.0017	0.0053	-10.3733
1332	2	3	3	2	1	3	3	0.0111	0.2795	0.6523	0.0560	0.0002	0.0008	-8.9931
1333	1	1	1	3	1	3	3	0.0004	0.0152	0.3751	0.5835	0.0061	0.0195	-11.3452
1334	2	1	1	3	1	3	3	0.0377	0.5508	0.3945	0.0167	0.0001	0.0002	-7.8309
1335	1	2	1	3	1	3	3	0.0003	0.0103	0.2908	0.6610	0.0089	0.0288	-11.6115
1336	2	2	1	3	1	3	3	0.0177	0.3787	0.5673	0.0357	0.0002	0.0005	-8.5921
1337	1	3	1	3	1	3	3	0.0002	0.0069	0.2177	0.7201	0.0128	0.0422	-11.8611
1338	2	3	1	3	1	3	3	0.0082	0.2234	0.6925	0.0746	0.0003	0.0011	-9.2292
1339	1	1	2	3	1	3	3	0.0010	0.0359	0.5707	0.3816	0.0026	0.0082	-10.6989
1340	2	1	2	3	1	3	3	0.0369	0.5465	0.3992	0.0171	0.0001	0.0002	-7.8524
1341	1	2	2	3	1	3	3	0.0007	0.0244	0.4849	0.4739	0.0038	0.0121	-10.9963
1342	2	2	2	3	1	3	3	0.0173	0.3740	0.5716	0.0365	0.0002	0.0005	-8.6109
1343	1	3	2	3	1	3	3	0.0005	0.0166	0.3947	0.5646	0.0056	0.0179	-11.2840
1344	2	3	2	3	1	3	3	0.0080	0.2198	0.6947	0.0761	0.0003	0.0011	-9.2446
1345	1	1	3	3	1	3	3	0.0025	0.0823	0.7042	0.2065	0.0011	0.0034	-10.0534
1346	2	1	3	3	1	3	3	0.0362	0.5422	0.4039	0.0174	0.0001	0.0002	-7.8739
1347	1	2	3	3	1	3	3	0.0017	0.0569	0.6568	0.2779	0.0016	0.0051	-10.3381
1348	2	2	3	3	1	3	3	0.0169	0.3694	0.5758	0.0372	0.0002	0.0005	-8.6296
1349	1	3	3	3	1	3	3	0.0011	0.0391	0.5881	0.3618	0.0024	0.0075	-10.6331
1350	2	3	3	3	1	3	3	0.0079	0.2164	0.6968	0.0775	0.0004	0.0011	-9.2600
1351	1	1	1	1	2	3	3	0.0022	0.0723	0.6901	0.2302	0.0013	0.0039	-10.1529
1352	2	1	1	1	2	3	3	0.1655	0.7132	0.1179	0.0034	0.0000	0.0000	-6.1647
1353	1	2	1	1	2	3	3	0.0015	0.0499	0.6346	0.3064	0.0019	0.0058	-10.4416

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1354	2	2	1	1	2	3	3	0.0834	0.6853	0.2238	0.0073	0.0000	0.0001	-6.9547
1355	1	3	1	1	2	3	3	0.0010	0.0341	0.5598	0.3937	0.0027	0.0086	-10.7388
1356	2	3	1	1	2	3	3	0.0401	0.5640	0.3799	0.0157	0.0001	0.0002	-7.7639
1357	1	1	2	1	2	3	3	0.0053	0.1574	0.7242	0.1109	0.0005	0.0016	-9.5422
1358	2	1	2	1	2	3	3	0.1626	0.7138	0.1201	0.0034	0.0000	0.0000	-6.1860
1359	1	2	2	1	2	3	3	0.0036	0.1120	0.7250	0.1562	0.0008	0.0024	-9.8149
1360	2	2	2	1	2	3	3	0.0819	0.6832	0.2274	0.0074	0.0000	0.0001	-6.9762
1361	1	3	2	1	2	3	3	0.0024	0.0784	0.6992	0.2153	0.0011	0.0036	-10.0908
1362	2	3	2	1	2	3	3	0.0393	0.5598	0.3846	0.0160	0.0001	0.0002	-7.7856
1363	1	1	3	1	2	3	3	0.0127	0.3066	0.6305	0.0493	0.0002	0.0007	-8.8829
1364	2	1	3	1	2	3	3	0.1598	0.7143	0.1223	0.0035	0.0000	0.0000	-6.2073
1365	1	2	3	1	2	3	3	0.0086	0.2312	0.6874	0.0715	0.0003	0.0010	-9.1950
1366	2	2	3	1	2	3	3	0.0803	0.6810	0.2310	0.0076	0.0000	0.0001	-6.9976
1367	1	3	3	1	2	3	3	0.0058	0.1692	0.7204	0.1026	0.0005	0.0015	-9.4813
1368	2	3	3	1	2	3	3	0.0385	0.5555	0.3893	0.0164	0.0001	0.0002	-7.8072
1369	1	1	1	2	2	3	3	0.0003	0.0102	0.2887	0.6628	0.0090	0.0291	-11.6183
1370	2	1	1	2	2	3	3	0.0254	0.4622	0.4870	0.0249	0.0001	0.0003	-8.2420
1371	1	2	1	2	2	3	3	0.0002	0.0069	0.2159	0.7214	0.0129	0.0427	-11.8676
1372	2	2	1	2	2	3	3	0.0118	0.2922	0.6423	0.0527	0.0002	0.0007	-8.9415
1373	1	3	1	2	2	3	3	0.0001	0.0046	0.1570	0.7577	0.0184	0.0622	-12.1090
1374	2	3	1	2	2	3	3	0.0055	0.1615	0.7230	0.1079	0.0005	0.0016	-9.5205
1375	1	1	2	2	2	3	3	0.0007	0.0242	0.4826	0.4764	0.0039	0.0123	-11.0041
1376	2	1	2	2	2	3	3	0.0249	0.4575	0.4917	0.0255	0.0001	0.0003	-8.2624
1377	1	2	2	2	2	3	3	0.0005	0.0164	0.3924	0.5669	0.0057	0.0181	-11.2914
1378	2	2	2	2	2	3	3	0.0116	0.2880	0.6456	0.0538	0.0002	0.0007	-8.9584
1379	1	3	2	2	2	3	3	0.0003	0.0111	0.3064	0.6472	0.0083	0.0267	-11.5614
1380	2	3	2	2	2	3	3	0.0053	0.1588	0.7238	0.1099	0.0005	0.0016	-9.5350
1381	1	1	3	2	2	3	3	0.0017	0.0564	0.6552	0.2800	0.0016	0.0051	-10.3458
1382	2	1	3	2	2	3	3	0.0244	0.4528	0.4964	0.0260	0.0001	0.0003	-8.2827
1383	1	2	3	2	2	3	3	0.0011	0.0387	0.5860	0.3642	0.0024	0.0076	-10.6410
1384	2	2	3	2	2	3	3	0.0113	0.2839	0.6489	0.0549	0.0002	0.0008	-8.9752
1385	1	3	3	2	2	3	3	0.0008	0.0263	0.5022	0.4559	0.0036	0.0112	-10.9391
1386	2	3	3	2	2	3	3	0.0052	0.1560	0.7246	0.1120	0.0005	0.0016	-9.5495
1387	1	1	1	3	2	3	3	0.0002	0.0072	0.2240	0.7155	0.0124	0.0407	-11.8381
1388	2	1	1	3	2	3	3	0.0180	0.3836	0.5627	0.0350	0.0002	0.0005	-8.5719

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1389	1	2	1	3	2	3	3	0.0001	0.0049	0.1634	0.7546	0.0176	0.0594	-12.0798
1390	2	2	1	3	2	3	3	0.0084	0.2272	0.6900	0.0731	0.0003	0.0010	-9.2126
1391	1	3	1	3	2	3	3	0.0001	0.0033	0.1164	0.7698	0.0245	0.0859	-12.3256
1392	2	3	1	3	2	3	3	0.0039	0.1200	0.7270	0.1461	0.0007	0.0022	-9.7606
1393	1	1	2	3	2	3	3	0.0005	0.0172	0.4032	0.5564	0.0054	0.0173	-11.2575
1394	2	1	2	3	2	3	3	0.0177	0.3790	0.5670	0.0357	0.0002	0.0005	-8.5908
1395	1	2	2	3	2	3	3	0.0003	0.0116	0.3163	0.6383	0.0079	0.0255	-11.5297
1396	2	2	2	3	2	3	3	0.0082	0.2236	0.6923	0.0745	0.0003	0.0010	-9.2281
1397	1	3	2	3	2	3	3	0.0002	0.0079	0.2392	0.7038	0.0114	0.0375	-11.7840
1398	2	3	2	3	2	3	3	0.0038	0.1179	0.7266	0.1487	0.0007	0.0023	-9.7749
1399	1	1	3	3	2	3	3	0.0012	0.0405	0.5953	0.3535	0.0023	0.0072	-10.6049
1400	2	1	3	3	2	3	3	0.0173	0.3743	0.5713	0.0364	0.0002	0.0005	-8.6096
1401	1	2	3	3	2	3	3	0.0008	0.0276	0.5128	0.4446	0.0034	0.0107	-10.9032
1402	2	2	3	3	2	3	3	0.0080	0.2201	0.6945	0.0760	0.0003	0.0011	-9.2435
1403	1	3	3	3	2	3	3	0.0005	0.0187	0.4231	0.5368	0.0050	0.0159	-11.1951
1404	2	3	3	3	2	3	3	0.0037	0.1157	0.7261	0.1514	0.0007	0.0023	-9.7892
1405	1	1	1	1	3	3	3	0.0010	0.0354	0.5675	0.3851	0.0026	0.0083	-10.7106
1406	2	1	1	1	3	3	3	0.0852	0.6875	0.2201	0.0071	0.0000	0.0001	-6.9319
1407	1	2	1	1	3	3	3	0.0007	0.0241	0.4814	0.4776	0.0039	0.0123	-11.0078
1408	2	2	1	1	3	3	3	0.0410	0.5685	0.3749	0.0154	0.0001	0.0002	-7.7408
1409	1	3	1	1	3	3	3	0.0005	0.0163	0.3912	0.5680	0.0057	0.0182	-11.2950
1410	2	3	1	1	3	3	3	0.0192	0.3981	0.5492	0.0329	0.0001	0.0004	-8.5125
1411	1	1	2	1	3	3	3	0.0025	0.0811	0.7028	0.2091	0.0011	0.0035	-10.0644
1412	2	1	2	1	3	3	3	0.0835	0.6855	0.2236	0.0073	0.0000	0.0001	-6.9533
1413	1	2	2	1	3	3	3	0.0017	0.0561	0.6544	0.2810	0.0016	0.0051	-10.3495
1414	2	2	2	1	3	3	3	0.0402	0.5643	0.3796	0.0157	0.0001	0.0002	-7.7625
1415	1	3	2	1	3	3	3	0.0011	0.0385	0.5850	0.3653	0.0024	0.0076	-10.6448
1416	2	3	2	1	3	3	3	0.0188	0.3934	0.5536	0.0335	0.0001	0.0005	-8.5318
1417	1	1	3	1	3	3	3	0.0060	0.1745	0.7184	0.0993	0.0005	0.0014	-9.4550
1418	2	1	3	1	3	3	3	0.0820	0.6833	0.2272	0.0074	0.0000	0.0001	-6.9747
1419	1	2	3	1	3	3	3	0.0040	0.1249	0.7277	0.1406	0.0007	0.0021	-9.7292
1420	2	2	3	1	3	3	3	0.0394	0.5601	0.3843	0.0160	0.0001	0.0002	-7.7841
1421	1	3	3	1	3	3	3	0.0027	0.0878	0.7101	0.1951	0.0010	0.0032	-10.0030
1422	2	3	3	1	3	3	3	0.0185	0.3887	0.5580	0.0342	0.0001	0.0005	-8.5509
1423	1	1	1	2	3	3	3	0.0001	0.0048	0.1620	0.7553	0.0178	0.0600	-12.0862

Table B.1 (cont'd). Estimated Probabilities of Observing a Category and the Signal to Noise Ratios based on Ordinal Logistic Regression Models for Thick-film Resistor Production Example

1424	2	1	1	2	3	3	3	0.0121	0.2967	0.6387	0.0516	0.0002	0.0007	-8.9233
1425	1	2	1	2	3	3	3	0.0001	0.0032	0.1154	0.7698	0.0247	0.0867	-12.3323
1426	2	2	1	2	3	3	3	0.0056	0.1645	0.7220	0.1058	0.0005	0.0015	-9.5050
1427	1	3	1	2	3	3	3	0.0001	0.0022	0.0808	0.7597	0.0335	0.1237	-12.5967
1428	2	3	1	2	3	3	3	0.0026	0.0834	0.7055	0.2040	0.0011	0.0034	-10.0424
1429	1	1	2	2	3	3	3	0.0003	0.0115	0.3141	0.6403	0.0080	0.0258	-11.5367
1430	2	1	2	2	3	3	3	0.0118	0.2925	0.6421	0.0527	0.0002	0.0007	-8.9403
1431	1	2	2	2	3	3	3	0.0002	0.0078	0.2374	0.7052	0.0116	0.0378	-11.7905
1432	2	2	2	2	3	3	3	0.0055	0.1617	0.7229	0.1078	0.0005	0.0016	-9.5196
1433	1	3	2	2	3	3	3	0.0001	0.0052	0.1740	0.7489	0.0165	0.0553	-12.0331
1434	2	3	2	2	3	3	3	0.0025	0.0819	0.7037	0.2074	0.0011	0.0034	-10.0571
1435	1	1	3	2	3	3	3	0.0008	0.0273	0.5105	0.4471	0.0034	0.0108	-10.9111
1436	2	1	3	2	3	3	3	0.0116	0.2883	0.6454	0.0537	0.0002	0.0007	-8.9572
1437	1	2	3	2	3	3	3	0.0005	0.0185	0.4207	0.5392	0.0050	0.0160	-11.2026
1438	2	2	3	2	3	3	3	0.0054	0.1590	0.7238	0.1098	0.0005	0.0016	-9.5341
1439	1	3	3	2	3	3	3	0.0004	0.0126	0.3326	0.6235	0.0074	0.0237	-11.4785
1440	2	3	3	2	3	3	3	0.0025	0.0803	0.7018	0.2108	0.0011	0.0035	-10.0718
1441	1	1	1	3	3	3	3	0.0001	0.0034	0.1203	0.7694	0.0238	0.0830	-12.3018
1442	2	1	1	3	3	3	3	0.0086	0.2310	0.6875	0.0716	0.0003	0.0010	-9.1959
1443	1	2	1	3	3	3	3	0.0001	0.0023	0.0844	0.7623	0.0323	0.1186	-12.5634
1444	2	2	1	3	3	3	3	0.0039	0.1224	0.7274	0.1434	0.0007	0.0022	-9.7453
1445	1	3	1	3	3	3	3	0.0000	0.0015	0.0585	0.7308	0.0424	0.1668	-12.8530
1446	2	3	1	3	3	3	3	0.0018	0.0604	0.6659	0.2656	0.0015	0.0048	-10.2917
1447	1	1	2	3	3	3	3	0.0002	0.0082	0.2460	0.6984	0.0111	0.0361	-11.7606
1448	2	1	2	3	3	3	3	0.0084	0.2274	0.6899	0.0730	0.0003	0.0010	-9.2115
1449	1	2	2	3	3	3	3	0.0002	0.0055	0.1809	0.7448	0.0158	0.0528	-12.0040
1450	2	2	2	3	3	3	3	0.0039	0.1202	0.7270	0.1460	0.0007	0.0022	-9.7596
1451	1	3	2	3	3	3	3	0.0001	0.0037	0.1298	0.7677	0.0222	0.0766	-12.2469
1452	2	3	2	3	3	3	3	0.0018	0.0593	0.6630	0.2696	0.0015	0.0049	-10.3069
1453	1	1	3	3	3	3	3	0.0006	0.0194	0.4316	0.5283	0.0048	0.0153	-11.1681
1454	2	1	3	3	3	3	3	0.0082	0.2239	0.6921	0.0744	0.0003	0.0010	-9.2270
1455	1	2	3	3	3	3	3	0.0004	0.0132	0.3429	0.6140	0.0070	0.0226	-11.4461
1456	2	2	3	3	3	3	3	0.0038	0.1180	0.7266	0.1486	0.0007	0.0023	-9.7739
1457	1	3	3	3	3	3	3	0.0003	0.0089	0.2622	0.6853	0.0102	0.0332	-11.7056
1458	2	3	3	3	3	3	3	0.0017	0.0581	0.6600	0.2736	0.0016	0.0050	-10.3222

B.2 Results of Accumulation Analysis Method in Thick-film Resistor Production Example

Table B.2. Cumulative Frequencies for the Cumulative Categories for Thick-film Resistor Production Example

Exp. No	Cumulative Frequencies for the Cumulative Categories					
	I	**II**	**III**	**IV**	**V**	**VI**
1	256	2506	5297	5634	5639	5670
2	0	51	1842	5667	5670	5670
3	1	181	2585	5666	5670	5670
4	0	70	2155	5659	5660	5670
5	9	242	3907	5640	5643	5670
6	32	648	4526	5630	5667	5670
7	3	119	3064	5442	5650	5670
8	0	1	177	5654	5670	5670
9	17	342	5641	5666	5666	5670
10	448	4771	5663	5669	5669	5670
11	1993	4791	5350	5364	5364	5670
12	1362	5588	5626	5627	5627	5670
13	13	1085	5655	5661	5661	5670
14	2020	4743	5229	5303	5305	5670
15	768	5150	5635	5646	5646	5670
16	313	3048	5639	5658	5658	5670
17	19	4016	5083	5085	5085	5103
18	249	4004	5617	5670	5670	5670

Table B.3. Cumulative Rates of Occurrences for the Cumulative Categories for Thick-film Resistor Production Example

	Frequencies						Cumulative Frequencies					
Categories / Factors	I	II	III	IV	V	VI	I	II	III	IV	V	VI
A_1	318	3842	25034	21464	277	95	318	4160	29194	50658	50935	51030
A_2	**7185**	30011	12301	186	2	778	7185	37196	49497	49683	49685	50463
B_1	**4060**	13828	8475	7264	12	381	4060	17888	26363	33627	33639	34020
B_2	2842	9096	15169	6432	43	438	2842	11938	27107	33539	33582	34020
B_3	601	10929	13691	7954	224	54	601	11530	25221	33175	33399	33453
C_1	1033	10566	15874	6250	214	83	1033	11599	27473	33723	33937	34020
C_2	**4041**	9803	7744	11125	24	716	4041	13844	21588	32713	32737	33453
C_3	2429	13484	13717	4275	41	74	2429	15913	29630	33905	33946	34020
D_1	**3053**	13822	12286	3893	6	393	3053	16875	29161	33054	33060	33453
D_2	1636	9453	14622	7996	214	99	1636	11089	25711	33707	33921	34020
D_3	2814	10578	10427	9761	59	381	2814	13392	23819	33580	33639	34020
E_1	**4553**	12258	12272	3960	252	725	4553	16811	29083	33043	33295	34020
E_2	2443	11465	7166	12837	20	89	2443	13908	21074	33911	33931	34020
E_3	507	10130	17897	4853	7	59	507	10637	28534	33387	33394	33453
F_1	1682	12162	12520	6927	58	104	1682	13844	26364	33291	33349	33453
F_2	2734	11247	12166	7487	6	380	2734	13981	26147	33634	33640	34020
F_3	**3087**	10444	12649	7236	215	389	3087	13531	26180	33416	33631	34020
G_1	**3977**	12492	14870	2189	10	482	3977	16469	31339	33528	33538	34020
G_2	1270	13485	11058	7326	248	66	1270	14755	25813	33139	33387	33453
G_3	2256	7876	11407	12135	21	325	2256	10132	21539	33674	33695	34020
A_1B_1	257	2481	6986	7243	12	31	257	2738	9724	16967	16979	17010

Table B.3. (cont'd) Cumulative Rates of Occurrences for the Cumulative Categories for Thick-film Resistor Production Example

A_1B_2	41	919	9628	6341	41	40	41	960	10588	16929	16970	17010
A_1B_3	20	442	8420	7880	224	24	20	462	8882	16762	16986	17010
A_2B_1	**3803**	11347	1489	21	0	350	3803	15150	16639	16660	16660	17010
A_2B_2	2801	8177	5541	91	2	398	2801	10978	16519	16610	16612	17010
A_2B_3	581	10487	5271	74	0	30	581	11068	16339	16413	16413	16443
A_1C_1	259	2436	7821	6219	214	61	259	2695	10516	16735	16949	17010
A_1C_2	9	285	5632	11035	22	27	9	294	5926	16961	16983	17010
A_1C_3	50	1121	11581	4210	41	7	50	1171	12752	16962	17003	17010
A_2C_1	774	8130	8053	31	0	22	774	8904	16957	16988	16988	17010
A_2C_2	**4032**	9518	2112	90	2	689	4032	13550	15662	15752	15754	16443
A_2C_3	2379	12363	2136	65	0	67	2379	14742	16878	16943	16943	17010
A_1F_1	288	2867	6845	6918	58	34	288	3155	10000	16918	16976	17010
A_1F_2	17	446	9175	7354	4	14	17	463	9638	16992	16996	17010
A_1F_3	13	529	9014	7192	215	47	13	542	9556	16748	16963	17010
A_2F_1	1394	9295	5675	9	0	70	1394	10689	16364	16373	16373	16443
A_2F_2	2717	10801	2991	133	2	366	2717	13518	16509	16642	16644	17010
A_2F_3	**3074**	9915	3635	44	0	342	3074	12989	16624	16668	16668	17010

Table B.4. Weights, Correction Factors and Proportions of Cumulative Frequencies in Relevant Category for Thick-film Resistor Production Example

VALUES	CATEGORIES				
	I	II	III	IV	V
Weights (W)	14.6068	4.1418	5.7408	89.1130	117.2664
Correction Factors (CF)	554.6689	16851.5931	61011.8282	99202.0758	99754.5092
Proportions of cumulative frequency in relevant category (P)	0.0739	0.4075	0.7753	0.9886	0.9914

Table B.5. Sum of Squares for Each Factor and Category for Thick-film Resistor Production Example

Factors \ Categories	I	II	III	IV	V
A	1024.9931	27756.0932	65251.2288	99203.7682	99759.1715
B	732.7421	17568.7985	61042.8394	99202.6509	99756.9933
C	692.9331	17127.1346	61923.6739	99208.3508	99762.6881
D	590.0612	17398.6992	61527.8410	99202.3295	99756.1719
E	792.4593	17375.2404	62255.2421	99217.5373	99762.7874
F	584.4033	16856.5864	61019.9645	99204.8877	99756.0159
G	662.7367	17498.1014	62424.0393	99202.5816	99757.0640
A×B	1336.0224	28535.8880	65341.2149	99209.7728	99763.7532
A×C	1360.7284	29115.9378	66694.9308	99223.0534	99776.4276
A×F	1112.5932	28224.9936	65263.1948	99208.6878	99762.2587

Table B.6. Estimated Frequencies for each Category and each Factor and Total Estimated Frequencies for each Category for Thick-film Resistor Production Example

Factors	Levels	Categories					
		I	II	III	IV	V	VI
A	1	0.6232	8.1521	57.2095	99.2710	99.8138	100.0000
	2	14.2382	73.7095	98.0857	98.4543	98.4583	100.0000
B	1	11.9342	52.5808	77.4927	98.8448	98.8801	100.0000
	2	8.3539	35.0911	79.6796	98.5861	98.7125	100.0000
	3	1.7966	34.4663	75.3923	99.1690	99.8386	100.0000
C	1	3.0364	34.0947	80.7554	99.1270	99.7560	100.0000
	2	12.0796	41.3834	64.5323	97.7879	97.8597	100.0000
	3	7.1399	46.7754	87.0958	99.6620	99.7825	100.0000
D	1	9.1262	50.4439	87.1701	98.8073	98.8252	100.0000
	2	4.8089	32.5955	75.5761	99.0800	99.7090	100.0000
	3	8.2716	39.3651	70.0147	98.7066	98.8801	100.0000
E	1	13.3833	49.4150	85.4879	97.1282	97.8689	100.0000
	2	7.1811	40.8818	61.9459	99.6796	99.7384	100.0000
	3	1.5156	31.7968	85.2958	99.8027	99.8236	100.0000
F	1	5.0279	41.3834	78.8091	99.5157	99.6891	100.0000
	2	8.0364	41.0964	76.8577	98.8654	98.8830	100.0000
	3	9.0741	39.7737	76.9547	98.2246	98.8566	100.0000
G	1	11.6902	48.4098	92.1193	98.5538	98.5832	100.0000
	2	3.7964	44.1067	77.1620	99.0614	99.8027	100.0000
	3	6.6314	29.7825	63.3128	98.9830	99.0447	100.0000
A×B	1×1	1.5109	16.0964	57.1664	99.7472	99.8178	100.0000
	1×2	0.2410	5.6437	62.2457	99.5238	99.7648	100.0000
	1×3	0.1176	2.7160	52.2163	98.5420	99.8589	100.0000
	2×1	22.3574	89.0653	97.8189	97.9424	97.9424	100.0000
	2×2	16.4668	64.5385	97.1135	97.6484	97.6602	100.0000
	2×3	3.5334	67.3113	99.3675	99.8176	99.8176	100.0000
A×C	1×1	1.5226	15.8436	61.8225	98.3833	99.6414	100.0000
	1×2	0.0529	1.7284	34.8383	99.7119	99.8413	100.0000
	1×3	0.2939	6.8842	74.9677	99.7178	99.9588	100.0000
	2×1	4.5503	52.3457	99.6884	99.8707	99.8707	100.0000
	2×2	24.5211	82.4059	95.2503	95.7976	95.8098	100.0000
	2×3	13.9859	86.6667	99.2240	99.6061	99.6061	100.0000

Table B.6. (cont'd) Estimated Frequencies for each Category and each Factor and Total Estimated Frequencies for each Category for Thick-film Resistor Production Example

A×F	**1×1**	1.6931	18.5479	58.7889	99.4591	99.8001	100.0000
	1×2	0.0999	2.7219	56.6608	99.8942	99.9177	100.0000
	1×3	0.0764	3.1864	56.1787	98.4597	99.7237	100.0000
	2×1	8.4778	65.0064	99.5196	99.5743	99.5743	100.0000
	2×2	15.9730	79.4709	97.0547	97.8366	97.8483	100.0000
	2×3	18.0717	76.3610	97.7307	97.9894	97.9894	100.0000
TOTAL		7.39	40.75	77.53	98.86	99.14	100.00

Table B.7. Logit Transformation Values for Estimated Frequencies and Overall Estimated Frequencies for each Category for Thick-film Resistor Production Example

Factors	**Levels**	**Categories**					
		I	**II**	**III**	**IV**	**V**	**VI**
A	**1**	-22.0349	-10.5168	1.2616	21.3494	27.3971	∞
	2	-7.7972	4.4772	17.0965	18.0432	18.0432	∞
B	**1**	-8.6790	0.4487	5.3692	19.3271	19.4620	∞
	2	-10.4013	-2.6697	5.9345	18.4089	18.8480	∞
	3	-17.3756	-2.7894	4.8622	20.7740	28.1448	∞
C	**1**	-15.0425	-2.8611	6.2285	20.5573	26.2044	∞
	2	-8.6194	-1.5110	2.5991	16.4552	16.6026	∞
	3	-11.1407	-0.5602	8.2924	24.7395	26.6721	∞
D	**1**	-9.9804	0.0769	8.3213	19.1839	19.2523	∞
	2	-12.9646	-3.1539	4.9055	20.3256	25.3749	∞
	3	-10.4482	-1.8753	3.6829	18.8272	19.4620	∞
E	**1**	-8.1093	-0.1005	7.7018	15.2923	16.6216	∞
	2	-11.1135	-1.6013	2.1163	24.9602	25.8938	∞
	3	-18.1277	-3.3136	7.6346	27.0624	27.6925	∞
F	**1**	-12.7616	-1.5110	5.7044	23.1418	25.0793	∞
	2	-10.5845	-1.5626	5.2157	19.4058	19.4731	∞
	3	-10.0077	-1.8007	5.2389	17.4302	19.3722	∞
G	**1**	-8.7811	-0.2753	10.6776	18.3204	18.4010	∞
	2	-14.0373	-1.0278	5.2875	20.2397	27.0624	∞
	3	-11.4850	-3.7237	2.3694	19.8849	20.1625	∞

Table B.7. (cont'd) Logit Transformation Values for Estimated Frequencies and Overall Estimated Frequencies for each Category for Thick-film Resistor Production Example

A×B	**1×1**	-18.1410	-7.1692	1.2540	26.0491	27.5177	∞
	1×2	-26.2564	-12.2312	2.1712	26.3597	26.3597	∞
	1×3	-29.4644	-15.5401	0.3849	18.2881	28.7568	∞
	2×1	-5.4057	9.1094	16.5181	16.7776	16.7776	∞
	2×2	-7.0516	2.6003	15.2692	16.1840	16.2064	∞
	2×3	-14.3449	3.1371	21.9733	27.5116	27.5116	∞
A×C	**1×1**	-18.1078	-7.2516	2.0933	17.8442	24.4812	∞
	1×2	∞	-17.5481	-2.7187	25.4260	28.2262	∞
	1×3	-25.3227	-11.3107	4.7636	25.5302	∞	∞
	2×1	-13.2167	0.4078	25.0705	29.1126	29.1126	∞
	2×2	-4.8819	6.7058	13.0223	13.5784	13.5917	∞
	2×3	-7.8881	8.1293	21.0744	24.0385	24.0385	∞
A×F	**1×1**	-17.6385	-6.4251	1.5430	22.6630	26.9840	∞
	1×2	∞	-15.5305	1.1639	29.8211	∞	∞
	1×3	∞	-14.8254	1.0792	18.0585	25.6343	∞
	2×1	-10.3314	2.6893	23.1797	23.7119	23.7119	∞
	2×2	-7.2096	5.8784	15.1796	16.5548	16.5790	∞
	2×3	-6.5632	5.0926	16.3425	16.8791	16.8791	∞
TOTAL		-10.98	-1.63	5.38	19.39	20.62	∞

B.3 Results of Weighted Signal-to-noise Ratio Method in Thick-film Resistor Production Example

Table B.8. Weighted Signal to Noise Ratios for Resistors for Thick-film Resistor Production Example

Exp. No	**CATEGORIES**						**SNR**
	I	**II**	**III**	**IV**	**V**	**VI**	
1	256	2250	2791	337	5	31	-8.5929
2	0	51	1791	3825	3	0	-11.3627
3	1	180	2404	3081	4	0	-11.0226
4	0	70	2085	3504	1	10	-11.2433

Table B.8. (cont'd) Weighted Signal to Noise Ratios for Resistors for Thick-film Resistor Production Example

5	9	233	3665	1733	3	27	-10.4369
6	32	616	3878	1104	37	3	-9.9534
7	3	116	2945	2378	208	20	-10.9731
8	0	1	176	5477	16	0	-11.9882
9	17	325	5299	25	0	4	-9.4148
10	448	4323	892	6	0	1	-6.5972
11	1993	2798	559	14	0	306	-7.1559
12	1362	4226	38	1	0	43	-5.5117
13	13	1072	4570	6	0	9	-9.0777
14	2020	2723	486	74	2	365	-7.4693
15	768	4382	485	11	0	24	-6.2118
16	313	2735	2591	19	0	12	-7.9429
17	19	3997	1067	2	0	18	-7.1197
18	249	3755	1613	53	0	0	-7.3262

Table B.9. Averages of Weighted Signal-to-noise Ratios for each Level of Factors for Thick-film Resistor Production Example

LEVELS	**FACTORS**			
	A	**C**	**D**	**G**
1	-10.5542	-9.0712	**-8.2897**	**-8.2281**
2	**-7.1569**	-9.2554	-9.1147	-8.7030
3		**-8.2401**	-9.1623	-9.6356

B.4 Results of Scoring Scheme Method in Thick-film Resistor Production Example

Table B.10. Calculated Data and Location Scores for Thick-film Resistor Production Example

	CATEGORIES					
	I	**II**	**III**	**IV**	**V**	**VI**
q_i	0.0739	0.3336	0.3679	0.2133	0.0027	0.0086
τ_i	0.0370	0.2407	0.5914	0.8820	0.9900	0.9957
$\tilde{\tau}_i$	-0.4630	-0.2593	0.0914	0.3820	0.4900	0.4957
l_i	-1.6880	-0.9453	0.3332	1.3925	1.7863	1.8070

Table B.11. Calculated Data and Dispersion Scores for Thick-film Resistor Production Example

	CATEGORIES					
	I	**II**	**III**	**IV**	**V**	**VI**
e_i	1.8809	-0.0887	-0.8952	0.9129	2.1574	2.2314
d_i	2.1130	-0.0997	-1.0057	1.0256	2.4236	2.5067

Table B.12. Location and Dispersion Pseudo-observations for each set of parameter settings for Thick-film Resistor Production Example

Exp. No	A	B	C	D	E	F	G	L_i	D_i
1	1	1	1	1	1	1	1	-1094.71	-2054.81
2	1	1	2	2	2	2	2	5880.31	2123.86
3	1	1	3	3	3	3	3	4926.69	736.01
4	1	2	1	1	2	2	3	5527.81	1517.30
5	1	2	2	2	3	3	1	3453.16	-1837.77
6	1	2	3	3	1	1	2	2264.75	-2664.42
7	1	3	1	2	1	3	2	4585.70	26.11
8	1	3	2	3	2	1	3	7713.10	5478.80

Table B.12. (cont'd) Location and Dispersion Pseudo-observations for each set of parameter settings for Thick-film Resistor Production Example

9	1	3	3	1	3	2	1	1471.82	-5289.96
10	2	1	1	3	3	2	2	-4535.14	-372.76
11	2	1	2	1	1	3	3	-5250.20	4151.50
12	2	1	3	2	2	1	1	-6201.87	2527.20
13	2	2	1	2	3	1	3	512.14	-4646.69
14	2	2	2	3	1	2	1	-5055.47	4503.72
15	2	2	3	1	2	3	2	-5218.15	769.61
16	2	3	1	3	2	3	1	-2202.10	-2167.46
17	2	3	2	1	3	1	2	-3419.39	-1384.22
18	2	3	3	2	1	2	3	-3358.45	-1416.03

Table B.13. Averages of Location and Dispersion Pseudo-observations for each Actual Factor for Thick-film Resistor Production Example

Level	A	B	C	D	E	G
Location						
1	3858.74	**-1045.82**	465.62	**-1330.47**	**-1318.06**	**-1604.86**
2	**-3858.74**	247.37	553.58	811.83	916.52	-73.65
3		798.45	**-1019.20**	518.64	401.55	1678.52
Dispersion						
1			**-1283.05**		424.35	
2			2172.65		1708.22	
3			-889.60		**-2132.57**	

B.5 Results of Weighted Probability Scoring Scheme Method in Thick-film Resistor Production Example

Table B.14. Proportions of observation p_{ij} for each category i and set j of parameter settings for Thick-film Resistor Production Example

Exp. No	CATEGORIES					
	I	II	III	IV	V	VI
1	0.0451	0.3968	0.4922	0.0594	0.0009	0.0055
2	0.0000	0.0090	0.3159	0.6746	0.0005	0.0000
3	0.0002	0.0317	0.4240	0.5434	0.0007	0.0000
4	0.0000	0.0123	0.3677	0.6180	0.0002	0.0018
5	0.0016	0.0411	0.6464	0.3056	0.0005	0.0048
6	0.0056	0.1086	0.6840	0.1947	0.0065	0.0005
7	0.0005	0.0205	0.5194	0.4194	0.0367	0.0035
8	0.0000	0.0002	0.0310	0.9660	0.0028	0.0000
9	0.0030	0.0573	0.9346	0.0044	0.0000	0.0007
10	0.0790	0.7624	0.1573	0.0011	0.0000	0.0002
11	0.3515	0.4935	0.0986	0.0025	0.0000	0.0540
12	0.2402	0.7453	0.0067	0.0002	0.0000	0.0076
13	0.0023	0.1891	0.8060	0.0011	0.0000	0.0016
14	0.3563	0.4802	0.0857	0.0131	0.0004	0.0644
15	0.1354	0.7728	0.0855	0.0019	0.0000	0.0042
16	0.0552	0.4824	0.4570	0.0034	0.0000	0.0021
17	0.0037	0.7833	0.2091	0.0004	0.0000	0.0035
18	0.0439	0.6623	0.2845	0.0093	0.0000	0.0000

Table B.15. Location, Dispersion and Mean Squared Deviation Scores for each set of parameter settings for Thick-film Resistor Production Example

Exp. No	A	B	C	D	E	F	G	L_i	d_i^2	MSD
1	1	1	1	1	1	1	1	4.4095	40.6680	0.3741
2	1	1	2	2	2	2	2	3.3333	41.6942	1.1032
3	1	1	3	3	3	3	3	3.4873	41.5461	0.9250
4	1	2	1	1	2	2	3	3.3887	41.6046	1.0336
5	1	2	2	2	3	3	1	3.7233	43.4538	0.7505
6	1	2	3	3	1	1	2	3.9106	43.7159	0.6262
7	1	3	1	2	1	3	2	3.5182	41.8773	0.9008
8	1	3	2	3	2	1	3	3.0286	44.4132	1.6928
9	1	3	3	1	3	2	1	4.0568	49.8414	0.6128
10	2	1	1	3	3	2	2	4.9189	45.4645	0.2743
11	2	1	2	1	1	3	3	5.0321	21.3863	0.1396
12	2	1	3	2	2	1	1	5.2028	34.6706	0.1789
13	2	2	1	2	3	1	3	4.1878	47.1228	0.5166
14	2	2	2	3	1	2	1	4.9859	20.8076	0.1412
15	2	2	3	1	2	3	2	5.0291	41.9572	0.2363
16	2	3	1	3	2	3	1	4.5831	41.2932	0.3284
17	2	3	2	1	3	1	2	4.7797	51.7695	0.3413
18	2	3	3	2	1	2	3	4.7407	45.1678	0.3128

Table B.16. Averages of Mean Square Deviation for each Factor for Thick-film Resistor Production Example

LEVELS	FACTORS					
	A	**B**	**C**	**D**	**E**	**G**
1	0.8910	**0.4992**	0.5713	**0.4563**	**0.4158**	**0.3977**
2	**0.2744**	0.5507	0.6948	0.6271	0.7622	0.5804
3		0.6981	**0.4820**	0.6646	0.5701	0.7700

APPENDIX C

RESULTS FOR SIMULATED EXAMPLE IN FOAM MOLDING EXPERIMENT

C.1 Results of Logistic Regression Model Optimization for Simulated Example

Table C.1. Estimated Probabilities of Observing a Category and Signal to Noise Ratios based on Ordinal Logistic Regression Models of Simulated Data

Trial	FACTORS						$\hat{P}_i^{LR(P)}$			SNR
	A	B	C	E	F	G	I	II	III	
1	0	0	0	0	0	0	0.1019	0.8488	0.0493	-5.9558
2	0	0	0	0	0	1	0.0066	0.5248	0.4686	-8.0092
3	0	0	0	0	1	0	0.0146	0.7007	0.2847	-7.3076
4	0	0	0	0	1	1	0.0009	0.1279	0.8713	-9.2188
5	0	0	0	1	0	0	0.4304	0.5618	0.0077	-4.3891
6	0	0	0	1	0	1	0.0426	0.8405	0.1169	-6.4904
7	0	0	0	1	1	0	0.0896	0.8540	0.0564	-6.0347
8	0	0	0	1	1	1	0.0058	0.4902	0.5040	-8.1310
9	0	0	1	0	0	0	0.0175	0.7341	0.2484	-7.1511
10	0	0	1	0	0	1	0.0010	0.1501	0.8489	-9.1600
11	0	0	1	0	1	0	0.0023	0.2805	0.7172	-8.7961
12	0	0	1	0	1	1	0.0001	0.0225	0.9773	-9.4872
13	0	0	1	1	0	0	0.1060	0.8467	0.0473	-5.9310
14	0	0	1	1	0	1	0.0069	0.5355	0.4576	-7.9707
15	0	0	1	1	1	0	0.0152	0.7090	0.2758	-7.2699
16	0	0	1	1	1	1	0.0009	0.1329	0.8662	-9.2056
17	0	1	0	0	0	0	0.0055	0.4794	0.5150	-8.1682
18	0	1	0	0	0	1	0.0003	0.0521	0.9475	-9.4135
19	0	1	0	0	1	0	0.0007	0.1086	0.8907	-9.2693
20	0	1	0	0	1	1	0.0000	0.0071	0.9928	-9.5250
21	0	1	0	1	0	0	0.0356	0.8269	0.1375	-6.6096
22	0	1	0	1	0	1	0.0022	0.2673	0.7306	-8.8346
23	0	1	0	1	1	0	0.0048	0.4449	0.5504	-8.2849

Table C.1. (cont'd) Estimated Probabilities of Observing a Category and Signal to Noise Ratios based on Ordinal Logistic Regression Models of Simulated Data

24	0	1	0	1	1	1	0.0003	0.0456	0.9542	-9.4299
25	0	1	1	0	0	0	0.0009	0.1279	0.8713	-9.2188
26	0	1	1	0	0	1	0.0001	0.0086	0.9914	-9.5215
27	0	1	1	0	1	0	0.0001	0.0188	0.9811	-9.4964
28	0	1	1	0	1	1	0.0000	0.0011	0.9989	-9.5397
29	0	1	1	1	0	0	0.0058	0.4902	0.5040	-8.1310
30	0	1	1	1	0	1	0.0003	0.0544	0.9453	-9.4079
31	0	1	1	1	1	0	0.0008	0.1129	0.8863	-9.2580
32	0	1	1	1	1	1	0.0000	0.0074	0.9925	-9.5243
33	1	0	0	0	0	0	0.6463	0.3505	0.0032	-3.1746
34	1	0	0	0	0	1	0.0970	0.8510	0.0519	-5.9862
35	1	0	0	0	1	0	0.1923	0.7836	0.0241	-5.4945
36	1	0	0	0	1	1	0.0138	0.6903	0.2959	-7.3544
37	1	0	0	1	0	0	**0.9241**	0.0755	0.0005	-0.8998
38	1	0	0	1	0	1	0.4172	0.5747	0.0082	-4.4550
39	1	0	0	1	1	0	0.6132	0.3831	0.0037	-3.3821
40	1	0	0	1	1	1	0.0853	0.8553	0.0594	-6.0648
41	1	0	1	0	0	0	0.2229	0.7570	0.0201	-5.3554
42	1	0	1	0	0	1	0.0166	0.7248	0.2586	-7.1962
43	1	0	1	0	1	0	0.0360	0.8279	0.1361	-6.6013
44	1	0	1	0	1	1	0.0022	0.2697	0.7281	-8.8274
45	1	0	1	1	0	0	0.6563	0.3406	0.0031	-3.1098
46	1	0	1	1	0	1	0.1010	0.8492	0.0498	-5.9615
47	1	0	1	1	1	0	0.1993	0.7776	0.0231	-5.4626
48	1	0	1	1	1	1	0.0144	0.6988	0.2868	-7.3164
49	1	1	0	0	0	0	0.0819	0.8562	0.0619	-6.0891
50	1	1	0	0	0	1	0.0052	0.4662	0.5286	-8.2134
51	1	1	0	0	1	0	0.0115	0.6524	0.3361	-7.5173
52	1	1	0	0	1	1	0.0007	0.1034	0.8959	-9.2827
53	1	1	0	1	0	0	0.3727	0.6175	0.0098	-4.6699
54	1	1	0	1	0	1	0.0338	0.8221	0.1441	-6.6458
55	1	1	0	1	1	0	0.0719	0.8575	0.0706	-6.1675
56	1	1	0	1	1	1	0.0045	0.4317	0.5638	-8.3284
57	1	1	1	0	0	0	0.0138	0.6903	0.2959	-7.3544
58	1	1	1	0	0	1	0.0008	0.1219	0.8772	-9.2343

Table C.1. (cont'd) Estimated Probabilities of Observing a Category and Signal to Noise Ratios based on Ordinal Logistic Regression Models of Simulated Data

59	1	1	1	0	1	0	0.0018	0.2349	0.7633	-8.9271
60	1	1	1	0	1	1	0.0001	0.0178	0.9821	-9.4988
61	1	1	1	1	0	0	0.0853	0.8553	0.0594	-6.0648
62	1	1	1	1	0	1	0.0055	0.4769	0.5176	-8.1767
63	1	1	1	1	1	0	0.0120	0.6617	0.3263	-7.4783
64	1	1	1	1	1	1	0.0007	0.1076	0.8917	-9.2719

C.2 Results of Accumulation Analysis Method for Simulated Example

Table C.2. Cumulative Frequencies for the Cumulative Categories for Simulated Example

Exp. No	**Cumulative Frequencies for the Cumulative Categories**		
	I	**II**	**III**
1	5	37	40
2	0	20	40
3	0	0	40
4	0	20	40
5	4	38	40
6	1	35	40
7	3	37	40
8	0	19	40

Table C.3. Cumulative Rates of Occurrences for the Cumulative Categories for Simulated Example

	FREQUENCIES			**CUMULATIVE FREQUENCIES**		
Categories / Factors	**I**	**II**	**III**	**I**	**II**	**III**
$\mathbf{A_0}$	5	72	83	5	77	160

Table C.3. (cont'd) Cumulative Rates of Occurrences for the Cumulative Categories for Simulated Example

A_1	**8**	121	31	8	129	160
B_0	**10**	120	30	10	130	160
B_1	3	73	84	3	76	160
C_0	**8**	105	47	8	113	160
C_1	5	88	67	5	93	160
E_0	6	85	69	6	91	160
E_1	**7**	108	45	7	115	160
F_0	**9**	105	46	9	114	160
F_1	4	88	68	4	92	160
G_0	**9**	120	31	9	129	160
G_1	4	73	83	4	77	160

Table C.4. Weights, Correction Factors and Proportions of Cumulative Frequencies in Relevant Category for Simulated Example

VALUES	**CATEGORIES**	
	I	**II**
Weights (W)	25.6577	4.3604
Correction Factors (CF)	0.5281	132.6125
Proportions of cumulative frequency in relevant category (P)	0.0406	0.6438

Table C.5. Sum of Squares for Each Factor and Category in Simulated Example

Categories / Factors	**I**	**II**
A	0.0281	8.4500
B	0.1531	9.1125
C	0.0281	1.2500

Table C.5. (cont'd) Sum of Squares for Each Factor and Category in Simulated Example

E	0.0031	1.8000
F	0.0781	1.5125
G	0.0781	8.4500

C.3 Results of Weighted Signal-to-noise Ratio Method for Simulated Example

Table C.6. Weighted Signal to Noise Ratios for Simulated Example

Exp. No	CATEGORIES			SNR
	I	II	III	
1	5	32	3	-6.0206
2	0	20	20	-8.1291
3	0	0	40	-9.5424
4	0	20	20	-8.1291
5	4	34	2	-5.9660
6	1	34	5	-6.5801
7	3	34	3	-6.1805
8	0	19	21	-8.2119

Table C.7. Averages of Weighted Signal-to-noise Ratios for each Level of Factors in Simulated Example

LEVELS	FACTORS		
	A	B	G
0	-7.9553	**-6.6740**	**-6.7276**
1	**-6.7346**	-8.0160	-7.9623

C.4 Results of Scoring Scheme Method for Simulated Example

Table C.8. Calculated Data and Location Scores for Simulated Data

	CATEGORIES		
	I	**II**	**III**
q_i	0.0406	0.6031	0.3563
τ_i	0.0203	0.3422	0.8219
$\tilde{\tau}_i$	-0.4797	-0.1578	0.3219
l_i	-1.9378	-0.6375	1.3003

Table C.9. Calculated Data and Dispersion Scores for Simulated Example

	CATEGORIES		
	I	**II**	**III**
e_i	3.3971	-0.3824	0.2599
d_i	4.4565	-0.5016	0.3410

Table C.10. Location and Dispersion Pseudo-observations for each set of parameter settings in Simulated Example

Exp. No	A	B	C	E	F	G	L_i	D_i
1	0	0	0	0	0	0	-26.1887	7.2543
2	0	0	0	1	1	1	13.2553	-3.2119
3	0	1	1	0	1	1	52.0113	13.6402
4	0	1	1	1	0	0	13.2553	-3.2119
5	1	0	1	1	0	1	-26.8262	1.4536
6	1	0	1	0	1	0	-17.1120	-10.8929
7	1	1	0	1	1	0	-23.5881	-2.6619
8	1	1	0	0	0	1	15.1931	-2.3693

Table C.11. Averages of Location and Dispersion Pseudo-observations for each Actual Factor in Simulated Example

Level	A	B	G
Location			
0	**-13.0833**	14.2179	13.4084
1	13.0833	**-14.2179**	**-13.4084**
Dispersion			
0	**-3.6177**		2.3781
1	3.6177		**-2.3781**

C.5 Results of Weighted Probability Scoring Scheme Method for Simulated Example

Table C.12. Proportions of observation p_{ij} for each category i and set j of parameter settings for Simulated Example

Exp. No	CATEGORIES		
	I	II	III
1	0.1250	0.8000	0.0750
2	0.0000	0.5000	0.5000
3	0.0000	0.0000	1.0000
4	0.0000	0.5000	0.5000
5	0.1000	0.8500	0.0500
6	0.0250	0.8500	0.1250
7	0.0750	0.8500	0.0750
8	0.0000	0.4750	0.5250

Table C.13. Location, Dispersion and Mean Squared Deviation Scores for each set of parameter settings for Simulated Example

Exp. No	A	B	C	E	F	G	L_i	d_i^2	MSD
1	0	0	0	0	0	0	2.0500	9.4563	1.8442
2	0	0	0	1	1	1	1.5000	10.2500	6.5185
3	0	1	1	0	1	1	1.0000	10.0000	31.0000
4	0	1	1	1	0	0	1.5000	10.2500	6.5185
5	1	0	1	1	0	1	2.0500	10.1825	1.9676
6	1	0	1	0	1	0	1.9000	11.4613	2.9154
7	1	1	0	1	1	0	2.0000	10.5963	2.2368
8	1	1	0	0	0	1	1.4750	10.1781	6.9105

Table C.14. Averages of Mean Square Deviation for each Factor for Simulated Example

LEVELS	FACTORS					
	A	**B**	**C**	**E**	**F**	**G**
1	11.4703	**3.3114**	**4.3775**	10.6675	**4.3102**	**3.3787**
2	**3.5076**	11.6665	10.6004	**4.3104**	10.6677	11.5992

APPENDIX D

RESULTS FOR INKJET PRINTER EXAMPLE

D.1 Results of Logistic Regression Model Optimization for Inkjet Printer Example

Table D.1. Estimated Probabilities of Observing a Category and Signal to Noise Ratios based on Ordinal Logistic Regression Models for Inkjet Printer Example

Trial	FACTORS			$\hat{\boldsymbol{P}}_{\boldsymbol{i}}^{\boldsymbol{LR(P)}}$				SNR
	A	B	C	I	II	III	IV	
1	0	0	0	0.5122	0.2509	0.1375	0.0993	2.3959
2	0	0	1	0.2569	0.2578	0.2344	0.2509	5.7984
3	0	1	0	0.7004	0.1773	0.0752	0.0472	0.4443
4	0	1	1	0.4349	0.2676	0.1667	0.1308	3.3227
5	1	0	0	0.8468	0.0975	0.0352	0.0205	-0.5989
6	1	0	1	0.9322	0.0447	0.0148	0.0084	-0.7003
7	1	1	0	0.0509	0.0903	0.1752	**0.6836**	10.1376
8	1	1	1	0.1176	0.1726	0.2449	0.4650	8.3888

D.2 Results of Accumulation Analysis Method for Inkjet Printer Example

Table D.2. Cumulative Frequencies for the Cumulative Categories for Inkjet Printer Example

Exp. No	Cumulative Frequencies for the Cumulative Categories			
	I	II	III	IV
1	4	7	10	10
2	2	7	8	10
3	8	9	9	10

Table D.2. (cont'd) Cumulative Frequencies for the Cumulative Categories for Inkjet Printer Example

4	3	7	9	10
5	8	8	9	10
6	10	10	10	10
7	1	1	4	10
8	2	3	4	10

Table D.3. Cumulative Rates of Occurrences for the Cumulative Categories for Inkjet Printer Example

	FREQUENCIES				**CUMULATIVE FREQUENCIES**			
Factors \ Categories	**I**	**II**	**III**	**IV**	**I**	**II**	**III**	**IV**
A_0	17	13	6	4	17	30	36	40
A_1	21	1	5	**13**	21	22	27	40
B_0	24	8	5	3	24	32	37	40
B_1	14	6	6	**14**	14	20	26	40
A_0*B_0	6	8	4	2	6	14	18	20
A_0*B_1	11	5	2	2	11	16	18	20
A_1*B_0	18	0	1	1	18	18	19	20
A_1*B_1	3	1	4	**12**	3	4	8	20
C_0	21	4	7	8	21	25	32	40
C_1	17	10	4	9	17	27	31	40
A_0*C_0	12	4	3	1	12	16	19	20
A_0*C_1	5	9	3	3	5	14	17	20
A_1*C_0	9	0	4	**7**	9	9	13	20
A_1*C_1	12	1	1	6	12	13	14	20
D_0	17	8	7	8	17	25	32	40
D_1	21	6	4	9	21	27	31	40
E_0	18	7	8	7	18	25	33	40
E_1	20	7	3	10	20	27	30	40

Table D.4. Weights, Correction Factors and Proportions of Cumulative Frequencies in Relevant Category for Inkjet Printer Example

VALUES	CATEGORIES		
	I	II	III
Weights (W)	4.0100	4.3956	5.9757
Correction Factors (CF)	18.0500	33.8000	49.6125
Proportions of cumulative frequency in relevant category (P)	0.4750	0.6500	0.7875

Table D.5. Sum of Squares for Each Factor and Category for Inkjet Printer Example

Factors \ Categories	I	II	III
A	0.2	0.8	1.0125
B	1.25	1.8	1.5125
A×B	24.5	39.6	53.65
C	0.2	0.05	0.0125
A×C	19.7	35.1	50.75
D	0.2	0.05	0.0125
E	0.05	0.05	0.1125

Table D.6. Estimated Frequencies for each Category and each Factor and Total Estimated Frequencies for each Category for Inkjet Printer Example

FACTORS	LEVELS	CATEGORIES			
		I	II	III	IV
A	**0**	42.50	75.00	90.00	100.00
	1	52.50	55.00	67.50	100.00
B	**0**	60.00	80.00	92.50	100.00
	1	35.00	50.00	65.00	100.00
A×B	**0×0**	30.00	70.00	90.00	100.00
	0×1	55.00	80.00	90.00	100.00
	1×0	90.00	90.00	95.00	100.00
	1×1	15.00	20.00	40.00	100.00

Table D.6. (cont'd) Estimated Frequencies for each Category and each Factor and Total Estimated Frequencies for each Category for Inkjet Printer Example

C	**0**	52.50	62.50	80.00	100.00
	1	42.50	67.50	77.50	100.00
A×C	**0×0**	60.00	80.00	95.00	100.00
	0×1	25.00	70.00	85.00	100.00
	1×0	45.00	45.00	65.00	100.00
	1×1	60.00	65.00	70.00	100.00
TOTAL		47.50	65.00	78.75	100.00

Table D.7. Logit Transformation Values for Estimated Frequencies and Overall Estimated Frequencies for each Category for Inkjet Printer Example

FACTORS	**LEVELS**	**CATEGORIES**			
		I	**II**	**III**	**IV**
A	**0**	-1.312	4.771	9.542	∞
	1	0.435	0.872	3.174	∞
B	**0**	1.761	6.021	10.911	∞
	1	-2.687	0.000	2.688	∞
A×B	**0×0**	-3.679	3.680	9.542	∞
	0×1	0.872	6.021	9.542	∞
	1×0	9.542	9.542	12.783	∞
	1×1	-7.532	-6.020	-1.760	∞
C	**0**	0.435	2.218	6.021	∞
	1	-1.312	3.174	5.371	∞
A×C	**0×0**	1.761	6.021	12.783	∞
	0×1	-4.770	3.680	7.533	∞
	1×0	-0.871	-0.871	2.688	∞
	1×1	1.761	2.688	3.680	∞
TOTAL		-0.434	2.688	5.689	∞

D.3 Results of Weighted Signal-to-noise Ratio Method for Inkjet Printer Example

Table D.8. Weighted Signal to Noise Ratios for Inkjet Printer Example

Exp. No	CATEGORIES				SNR
	I	II	III	IV	
1	4	3	3	0	-10.1284
2	2	5	1	2	-9.1908
3	8	1	0	1	-11.3988
4	3	4	2	1	-9.6848
5	8	0	1	1	-11.2385
6	10	0	0	0	-12.0412
7	1	0	3	6	-5.3148
8	2	1	1	6	-7.0757

Table D.9. Averages of Weighted Signal-to-noise Ratios for each Level of Factors in Inkjet Printer Example

Levels	Factors			
	A	**B**	**C**	**E**
0	-10.1007	-10.6497	-9.5201	**-9.2923**
1	**-8.9176**	**-8.3685**	**-9.4981**	-9.7259
	Interactions			
	A×B		**A×C**	
0×0	-9.6596		-10.7636	
0×1	-9.7297		-9.1777	
1×0	-11.6399		**-8.2767**	
1×1	**-6.1952**		-9.5585	

D.4 Results of Scoring Scheme Method for Inkjet Printer Example

Table D.10. Calculated Data and Location Scores for Inkjet Printer Example

	CATEGORIES			
	I	II	III	IV
q_i	0.4750	0.1750	0.1375	0.2125
τ_i	0.2375	0.5625	0.7188	0.8938
$\tilde{\tau}_i$	-0.2625	0.0625	0.2188	0.3938
l_i	-0.9720	0.2314	0.8100	1.4579

Table D.11. Calculated Data and Dispersion Scores for Inkjet Printer Example

	CATEGORIES			
	I	II	III	IV
e_i	0.2340	-1.0153	-0.5850	0.6917
d_i	0.3926	-1.7038	-0.9817	1.1607

Table D.12. Location and Dispersion Pseudo-observations for Each Set of Parameter Settings in Inkjet Printer Example

Exp. No	A	B	C	D	E	L_i	D_i
1	0	0	0	0	0	-0.7637	-6.4859
2	0	0	1	1	1	2.9390	-6.3939
3	0	1	0	1	1	-6.0863	2.5979
4	0	1	1	0	0	1.0877	-6.4399
5	1	0	0	0	1	-5.5078	3.3200
6	1	0	1	1	0	-9.7196	3.9262
7	1	1	0	1	0	10.2056	4.4117
8	1	1	1	0	1	7.8451	5.0639

Table D.13. Averages of Location and Dispersion Pseudo-observations for each Actual Factor for Inkjet Printer Example

Level	A	B	C
Location			
0	-0.7058	-3.2630	-0.5380
1	**0.7058**	**3.2630**	**0.5380**
Dispersion			
0	**-4.1804**		
1	4.1804		

Table D.14. Averages of Location Pseudo-observations for Interactions in Inkjet Printer Example

Level	A×B	A×C
Location		
0×0	1.0877	-3.4250
0×1	-0.8967	1.3596
1×0	-7.6137	**2.3489**
1×1	**9.0253**	-0.9372

D.5 Results of Weighted Probability Scoring Scheme Method for Inkjet Printer Example

Table D.15. Proportions of observation p_{ij} for each category i and set j of parameter settings

Exp. No	CATEGORIES			
	I	II	III	IV
1	0.4000	0.3000	0.3000	0.0000
2	0.2000	0.5000	0.1000	0.2000
3	0.8000	0.1000	0.0000	0.1000

Table D.15. (cont'd) Proportions of observation p_{ij} for each category i and set j of parameter settings

4	0.3000	0.4000	0.2000	0.1000
5	0.8000	0.0000	0.1000	0.1000
6	1.0000	0.0000	0.0000	0.0000
7	0.1000	0.0000	0.3000	0.6000
8	0.2000	0.1000	0.1000	0.6000

Table D.16. Location, Dispersion and Mean Squared Deviation Scores for Each Set of Parameter Settings in Inkjet Printer Example

Exp. No	**A**	**B**	**C**	**D**	**E**	L_i	d_i^2	**MSD**	**logMSD**
1	0	0	0	0	0	1.9	17.33	4.2664	0.6301
2	0	0	1	1	1	2.3	11.37	1.4079	0.1486
3	0	1	0	1	1	1.4	13.64	11.162	1.0477
4	0	1	1	0	0	2.1	14.05	2.3941	0.3791
5	1	0	0	0	1	1.5	13.69	8.557	0.9323
6	1	0	1	1	0	1	17	52	1.7160
7	1	1	0	1	0	3.4	3.38	0.1624	-0.7894
8	1	1	1	0	1	3.1	2.73	0.1927	-0.7151

Table D.17. Averages of Mean Square Deviation for each Factor in Inkjet Printer Example

Levels	**Factors**			**Levels**	**Interactions**	
	A	**B**	**C**		**A×B**	**A×C**
0	**0.6819**	1.2190	**0.7808**	**0×0**	0.4529	0.8873
1	1.1826	**0.5413**	1.1461	**0×1**	1.0415	0.9327
				1×0	1.4811	**0.6395**
				1×1	**-0.7506**	1.4166

APPENDIX E

RESULTS FOR DUPLICATOR EXAMPLE

E.1 Results of Logistic Regression Model Optimization for Duplicator Example

Table E.1. Estimated Probabilities of Observing a Category and Signal to Noise based on Ordinal Logistic Regression Models for Duplicator Example

Trial	FACTORS				$\hat{P}_i^{LR(P)}$				SNR
	B	F	K	L	I	II	III	IV	
1	0	0	0	0	0.0134	0.3569	0.1327	0.4970	8.8030
2	0	0	0	1	0.0078	0.2463	0.1155	0.6304	9.7421
3	0	0	1	0	0.0320	0.5566	0.1226	0.2888	7.1775
4	0	0	1	1	0.0188	0.4344	0.1347	0.4122	8.1667
5	0	1	0	0	0.0049	0.1708	0.0927	0.7316	10.4112
6	0	1	0	1	0.0028	0.1070	0.0654	0.8248	10.9983
7	0	1	1	0	0.0118	0.3296	0.1301	0.5285	9.0309
8	0	1	1	1	0.0069	0.2241	0.1098	0.6593	9.9363
9	1	0	0	0	0.0006	0.0266	0.0187	0.9540	11.7744
10	1	0	0	1	0.0004	0.0156	0.0112	0.9728	11.8842
11	1	0	1	0	0.0016	0.0622	0.0412	0.8950	11.4253
12	1	0	1	1	0.0009	0.0371	0.0256	0.9364	11.6709
13	1	1	0	0	0.0002	0.0098	0.0071	0.9828	11.9421
14	1	1	0	1	0.0001	0.0057	0.0042	**0.9900**	**11.9835**
15	1	1	1	0	0.0006	0.0235	0.0167	0.9592	11.8049
16	1	1	1	1	0.0003	0.0138	0.0099	0.9760	11.9024

E.2 Results of Accumulation Analysis Method for Duplicator Example

Table E.2. Cumulative Frequencies for the Cumulative Categories for Duplicator Example

Exp. No	**Cumulative Frequencies for the Cumulative Categories**			
	I	**II**	**III**	**IV**
1	1	4	4	4
2	1	4	4	4
3	1	4	4	4
4	1	4	4	4
5	0	3	3	4
6	1	1	1	4
7	1	2	3	4
8	0	2	3	4
9	1	4	4	4
10	2	4	4	4
11	1	4	4	4
12	0	4	4	4
13	0	1	2	4
14	0	0	0	4
15	0	2	2	4
16	1	3	4	4

Table E.3. Cumulative Rates of Occurrences for the Cumulative Categories for Duplicator Example

	Frequencies				Cumulative Frequencies			
Categories / Factors	**I**	**II**	**III**	**IV**	**I**	**II**	**III**	**IV**
A_0	6	18	2	6	6	24	26	32
A_1	5	17	2	8	5	22	24	32
B_0	8	24	0	0	8	32	32	32
B_1	3	11	4	**14**	3	14	18	32
C_0	5	17	2	8	5	22	24	32
C_1	6	18	2	6	6	24	26	32
D_0	6	15	1	**10**	6	21	22	32
D_1	5	20	3	4	5	25	28	32
E_0	5	20	1	6	5	25	26	32
E_1	6	15	3	8	6	21	24	32
F_0	7	18	3	4	7	25	28	32
F_1	4	17	1	**10**	4	21	22	32
G_0	5	19	2	6	5	24	26	32
G_1	6	16	2	8	6	22	24	32
H_0	6	18	2	6	6	24	26	32
H_1	5	17	2	8	5	22	24	32
I_0	4	21	3	4	4	25	28	32
I_1	7	14	1	**10**	7	21	22	32
J_0	5	18	1	8	5	23	24	32
J_1	6	17	3	6	6	23	26	32
K_0	5	16	1	**10**	5	21	22	32
K_1	6	19	3	4	6	25	28	32
L_0	8	15	3	6	8	23	26	32
L_1	3	20	1	8	3	23	24	32
$F_0 \times I_0$	3	10	2	1	3	13	15	16
$F_1 \times I_0$	4	8	1	3	4	12	13	16
$F_0 \times I_1$	1	11	1	3	1	12	13	16
$F_1 \times I_1$	3	6	0	7	3	9	9	16

Table E.4. Weights, Correction Factors and Proportions of Cumulative Frequencies in Relevant Category for Duplicator Example

VALUES	CATEGORIES		
	I	**II**	**III**
Weights (W)	7.0257	4.9469	5.8514
Correction Factors (CF)	1.8906	33.0625	39.0625
Proportions of cumulative frequency in relevant category (P)	0.1719	0.7188	0.7813

Table E.5. Sum of Squares for Each Factor and Category for Duplicator Example

Factors \ Categories	I	II	III
A	0.0156	0.0625	0.0625
B	0.3906	5.0625	3.0625
C	0.0156	0.0625	0.0625
D	0.0156	0.2500	0.5625
E	0.0156	0.2500	0.0625
F	0.1406	0.2500	0.5625
G	0.0156	0.0625	0.0625
H	0.0156	0.0625	0.0625
I	0.1406	0.2500	0.5625
J	0.0156	0.0000	0.0625
K	0.0156	0.2500	0.5625
L	0.3906	0.0000	0.0625
F×I	2.1875	33.6250	40.2500

Table E.6. Estimated Frequencies for each Category and each Factor and Total Estimated Frequencies for each Category for Duplicator Example

FACTORS	LEVELS	CATEGORIES			
		I	II	III	IV
B	0	25.0000	100.0000	100.0000	100.0000
	1	9.3750	43.7500	56.2500	100.0000
D	0	18.7500	65.6250	68.7500	100.0000
	1	15.6250	78.1250	87.5000	100.0000
F	0	21.8750	78.1250	87.5000	100.0000
	1	12.5000	65.6250	68.7500	100.0000
I	0	12.5000	78.1250	87.5000	100.0000
	1	21.8750	65.6250	68.7500	100.0000
K	0	15.6250	65.6250	68.7500	100.0000
	1	18.7500	78.1250	87.5000	100.0000
TOTAL		17.1875	71.8750	78.1250	100.0000

Table E.7. Logit Transformation Values for Estimated Frequencies and Overall Estimated Frequencies for each Category for Duplicator Example

FACTORS	LEVELS	CATEGORIES			
		I	II	III	IV
B	0	-4.7700	∞	∞	∞
	1	-9.8518	-1.0455	1.0915	∞
D	0	-6.3670	2.8080	3.4240	∞
	1	-7.6978	5.5285	8.4510	∞
F	0	-5.5275	5.5285	8.4510	∞
	1	-8.4500	2.8080	3.4240	∞
I	0	-8.4500	5.5285	8.4510	∞
	1	-5.5275	2.8080	3.4240	∞
K	0	-7.6978	2.8080	3.4240	∞
	1	-6.3670	5.5285	8.4510	∞
TOTAL		-6.8279	4.0748	5.5285	∞

E.3 Results of Weighted Signal-to-noise Ratio Method for Duplicator Example

Table E.8. Weighted Signal-to-noise Ratios for Duplicator Example

Exp. No	CATEGORIES				SNR
	I	II	III	IV	
1	1	3	0	0	-10.3141
2	1	3	0	0	-10.3141
3	1	3	0	0	-10.3141
4	1	3	0	0	-10.3141
5	0	3	0	1	-8.4510
6	1	0	0	3	-6.7669
7	1	1	1	1	-8.7506
8	0	2	1	1	-7.5967
9	1	3	0	0	-10.3141
10	2	2	0	0	-10.9691
11	1	3	0	0	-10.3141
12	0	4	0	0	-9.5424
13	0	1	1	2	-5.7403
14	0	0	0	4	0.0000
15	0	2	0	2	-6.9897
16	1	2	1	0	-9.7772

Table E.9. Averages of Weighted Signal-to-noise Ratios for each Level of Factors for Duplicator Example

Levels	Factors			
	B	D	F	K
0	-10.2995	**-7.8587**	-9.3782	**-7.8740**
1	**-6.7591**	-9.1999	**-7.6804**	-9.1846

E.4 Results of Scoring Scheme Method for Duplicator Example

Table E.10. Calculated Data and Location Scores for Duplicator Example

	CATEGORIES			
	I	**II**	**III**	**IV**
q_i	0.1719	0.5469	0.0625	0.2188
τ_i	0.0859	0.4453	0.7500	0.8906
$\tilde{\tau}_i$	-0.4141	-0.0547	0.2500	0.3906
l_i	-1.5833	-0.2091	0.9560	1.4937

Table E.11. Calculated Data and Dispersion Scores for Duplicator Example

	CATEGORIES			
	I	**II**	**III**	**IV**
e_i	1.6596	-0.9361	-0.1783	1.0872
d_i	1.5068	-0.8499	-0.1618	0.9871

Table E.12. Location and Dispersion Pseudo-observations for Each Set of Parameter Settings for Duplicator Example

Exp. No	A	B	C	D	E	F	G	H	I	J	K	L	L_i	D_i
1	0	0	0	0	0	0	0	0	0	0	0	0	-2.2107	-1.0429
2	0	0	0	0	0	0	1	1	1	1	1	1	-2.2107	-1.0429
3	0	0	0	1	1	1	0	0	1	1	1	1	-2.2107	-1.0429
4	0	0	0	1	1	1	1	1	0	0	0	0	-2.2107	-1.0429
5	0	1	1	0	0	1	0	0	0	0	1	1	0.8664	-1.5626
6	0	1	1	0	0	1	1	1	1	1	0	0	2.8978	4.4680
7	0	1	1	1	1	0	0	0	1	1	0	0	0.6572	1.4821
8	0	1	1	1	1	0	1	1	0	0	1	1	2.0315	-0.8746
9	1	0	1	0	1	0	0	1	0	1	0	1	-2.2107	-1.0429

Table E.12. (cont'd) Location and Dispersion Pseudo-observations for Each Set of Parameter Settings for Duplicator Example

10	1	0	1	0	1	0	1	0	1	0	1	0	-3.5849	1.3138
11	1	0	1	1	0	1	0	1	1	0	1	0	-2.2107	-1.0429
12	1	0	1	1	0	1	1	0	0	1	0	1	-0.8365	-3.3996
13	1	1	0	0	1	1	0	1	0	1	1	0	3.7343	0.9624
14	1	1	0	0	1	1	1	0	1	0	0	1	5.9749	3.9483
15	1	1	0	1	0	0	0	1	1	0	0	1	2.5692	0.2744
16	1	1	0	1	0	0	1	0	0	1	1	0	-1.0456	-0.3548

Table E.13. Averages of Location and Dispersion Pseudo-observations for each Actual Factor for Duplicator Example

Level	**B**	**F**	**K**	**L**
Location				
0	**2.2107**	**0.7506**	-0.5788	**0.4967**
1	-2.2107	-0.7506	**0.5788**	-0.4967
Level	**B**			
Dispersion				
0	1.0429			
1	**-1.0429**			

E.5 Results of Weighted Probability Scoring Scheme Method for Duplicator Example

Table E.14. Proportions of observation p_{ij} for each category i and set j of parameter settings for Duplicator Example

Exp. No	**CATEGORIES**			
	I	**II**	**III**	**IV**
1	0.2500	0.7500	0.0000	0.0000
2	0.2500	0.7500	0.0000	0.0000
3	0.2500	0.7500	0.0000	0.0000

Table E.14. (cont'd) Proportions of observation p_{ij} for each category i and set j of parameter settings for Duplicator Example

4	0.2500	0.7500	0.0000	0.0000
5	0.0000	0.7500	0.0000	0.2500
6	0.2500	0.0000	0.0000	0.7500
7	0.2500	0.2500	0.2500	0.2500
8	0.0000	0.5000	0.2500	0.2500
9	0.2500	0.7500	0.0000	0.0000
10	0.5000	0.5000	0.0000	0.0000
11	0.2500	0.7500	0.0000	0.0000
12	0.0000	1.0000	0.0000	0.0000
13	0.0000	0.2500	0.2500	0.5000
14	0.0000	0.0000	0.0000	1.0000
15	0.0000	0.5000	0.0000	0.5000
16	0.2500	0.5000	0.2500	0.0000

Table E.15. Location, Dispersion and Mean Squared Deviation Scores for each set of parameter settings for Duplicator Example

Exp. No	A	B	C	D	E	F	G	H	I	J	K	L	L_i	d_i^2	MSD
1	0	0	0	0	0	0	0	0	0	0	0	0	1.7500	18.3125	6.1841
2	0	0	0	0	0	0	1	1	1	1	1	1	1.7500	18.3125	6.1841
3	0	0	0	1	1	1	0	0	1	1	1	1	1.7500	18.3125	6.1841
4	0	0	0	1	1	1	1	1	0	0	0	0	1.7500	18.3125	6.1841
5	0	1	1	0	0	1	0	0	0	0	1	1	2.5000	11.2500	1.0240
6	0	1	1	0	0	1	1	1	1	1	0	0	3.2500	1.0625	0.1232
7	0	1	1	1	1	0	0	0	1	1	0	0	2.5000	9.8750	0.9184
8	0	1	1	1	1	0	1	1	0	0	1	1	2.7500	10.5625	0.6863
9	1	0	1	0	1	0	0	1	0	1	0	1	1.7500	18.3125	6.1841
10	1	0	1	0	1	0	1	0	1	0	1	0	1.5000	17.2500	10.6667

Table E.15. (cont'd) Location, Dispersion and Mean Squared Deviation Scores for each set of parameter settings for Duplicator Example

11	1	0	1	1	0	1	0	1	1	0	1	0	1.7500	18.3125	6.1841
12	1	0	1	1	0	1	1	0	0	1	0	1	2.0000	20.0000	4.0000
13	1	1	0	0	1	1	0	1	0	1	1	0	3.2500	4.8125	0.2241
14	1	1	0	0	1	1	1	0	1	0	0	1	4.0000	0.0000	0.0625
15	1	1	0	1	0	0	0	1	1	0	0	1	3.0000	5.0000	0.2963
16	1	1	0	1	0	0	1	0	0	1	1	0	2.0000	17.6250	3.5547

Table E.16. Averages of Mean Square Deviation for each Factor for Duplicator Example

Levels	**Factors**			
	B	**F**	**K**	**L**
0	6.4714	4.3343	**2.9941**	4.2549
1	**0.8612**	**2.9983**	4.3385	**3.0777**