# Decomposition to Components with a Unit Degree of Freedom

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## 31.1. Introduction

In previous chapters, the total sum of the squares was decomposed into the sum of the variations of a correction factor, the main effect of a factor, and the error. This decomposition can be extended by looking at what the researcher feels could be causing the variations; or the total sum of the squares can be decomposed into the sum of the variations of causes with a unit degree of freedom. The latter method is described in this chapter. This chapter is based on Genichi Taguchi et al., *Design of Experiments*. Tokyo: Japanese Standards Association, 1973.

#### 31.2. Comparison and Its Variation

The analysis of variance for the example in Section 30.2 showed that A is significant. This meant that the roundness differed by the order of the various processes used in making the pinholes. Sometimes we would like to know whether the difference was caused by the difference between  $A_1$  and  $A_2$ , or between  $A_2$  and the mean of  $A_1$  and  $A_2$ .

Everyone knows to compare  $A_1$  and  $A_2$  by

$$L_1 = \frac{A_1}{10} - \frac{A_2}{10} \tag{31.1}$$

However,  $A_3$  and the mean of  $A_1$  and  $A_1$  would be compared by using the following linear equation:

$$L_2 = \frac{A_1 + A_2}{20} - \frac{A_3}{10} \tag{31.2}$$

#### 31.2. Comparison and Its Variation

 $L_1$  and  $L_2$  are linear equations; their sum of the coefficients for  $A_1$ ,  $A_2$ , and  $A_3$  is equal to zero either in  $L_1$  or in  $L_2$ .

$$L_1: \quad \frac{1}{10} - \frac{1}{10} = 0 \tag{31.3}$$

$$L_2: \quad \frac{1}{20} + \frac{1}{20} - \frac{1}{10} = 0 \tag{31.4}$$

Assume that the sums  $A_1, A_2, ..., A_a$  each has the same number of data (b) making up their respective total.

In a linear equation with constant coefficients  $A_1, A_2, \dots, A_{\omega}$ 

$$L = c_1 A_1 + c_2 A_2 + \dots + c_a A_a \tag{31.5}$$

when the sum of the coefficients is equal to zero,

$$c_1 + c_2 + \dots + c_a = 0 \tag{31.6}$$

then L is called either contrast or comparison.

As described previously, in a linear equation with constant coefficients,

$$L = c_1 A_1 + c_2 A_2 + \dots + c_a A_a \tag{31.7}$$

the variation of L, or  $S_L$ , is given by

$$S_L \frac{(c_1 A_1 + \dots + c_a A_a)^2}{(c_1^2 + c_1^2 + \dots + c_a^2)b}$$
(31.8)

where  $S_L$  has one degree of freedom. Calculation and estimation of a contrast are made in exactly the same way.

In two contrasts,

$$L_1 = c_1 A_1 + \dots + c_a A_a \tag{31.9}$$

$$L_{21} = c_1' A_1 + \dots + c_a' A_a \tag{31.10}$$

when their sum of products is equal to zero,

$$c_1c_1' + c_2c_2' + \dots + c_ac_a' = 0 \tag{31.11}$$

 $L_1$  and  $L_2$  are orthogonal. When  $L_1$  and  $L_2$  are orthogonal, each of

$$S_{L_1} = \frac{L_1^2}{(c_1^2 + \dots + c_a^2)b}$$
(31.12)

$$S_{L_2} = \frac{L_2^2}{(c_1'2 + \dots + c_a'^2)b}$$
(31.13)

is variation having one degree of freedom; each variation consists of one of the components in  $S_A$ . Therefore, when (a - 1) comparisons,  $L_1$ ,  $L_2$ , ...,  $L_{(a-1)}$ , are orthogonal to each other, the following equation is used:

$$S_A = S_{L_1} + S_{L_2} + \dots + S_{L(a-1)}$$
(31.14)

## □ Example 1

In an example of pinhole processing,

$$L_1 = \frac{A_1}{10} - \frac{A_2}{10} \tag{31.15}$$

$$L_2 = \frac{A_1 + A_2}{20} - \frac{A_3}{10} \tag{31.16}$$

The orthogonality between  $L_1$  and  $L_2$  is proven by

$$\left(\frac{1}{10}\right)\left(\frac{1}{20}\right) + \left(-\frac{1}{10}\right)\left(\frac{1}{20}\right) + 0\left(-\frac{1}{10}\right) = 0$$
 (31.17)

Therefore, the following relation can be made:

$$S_A = S_L + S_{L_2}$$
 (31.18)

where  $S_{{\scriptscriptstyle L}1}$  and  $S_{{\scriptscriptstyle L}2}$  are calculated from equation (31.8) as

$$S_{L_1} = \frac{(A_1/10 - A_2/10)^2}{[(1/10)^2 + (-1/10)^2](10)} = \frac{(1/10)^2 (A_1 - A_2)^2}{(1/10)^2 [1^2 + (-1)^2](10)}$$
  

$$= \frac{(A_1 - A_2)^2}{20}$$
  

$$= \frac{(87 - 85)^2}{20}$$
  

$$= 0.2 \qquad (31.19)$$
  

$$S_{L_2} = \frac{[(A_1 + A_2)/20 - A_3/10)]^2}{[(1/20)^2 + (1/20)^2 + (-1/10)^2](10)}$$
  

$$= \frac{(1/20)^2 (A_1 + A_2 - 2A_3)^2}{(1/20)^2 (6)(10)}$$
  

$$= 173.4 \qquad (31.20)$$

Thus, the magnitude of the variation in roundness, which is caused by  $A_1$ ,  $A_2$ , and  $A_3$ , namely,  $S_A$ , is decomposed into the variation caused by the difference between  $A_1$  and  $A_2$ , namely,  $S_{L_1}$ , and that variation caused by the difference between  $A_3$  and the mean of  $A_1$  and  $A_2$ , namely,  $S_{L_2}$ :

$$S_{L_1} + S_{L_2} = 0.2 + 173.4 = 174 = S_A$$
 (31.21)

## □ Example 2

We have the following four types of products:

$A_1$ :	foreign	products
/11.	loicign	products

- A<sub>2</sub>: our company's products
- $A_3$ : domestic:  $\alpha$  company's products
- $A_4$ : domestic:  $\beta$  company's products

Two, ten, six, and six products were sampled from each type, respectively, and a 300-hour continuous deterioration test was made. The percent of deterioration (Table 31.1) was determined as follows:

$$y = \frac{\text{(value after the test)} - \text{(initial value)}}{\text{initial value}}$$
(31.22)

$$S_m = \frac{T^2}{n} = \frac{488^2}{24}$$
  
= 9923 (31.23)

$$S_{A} = \frac{A_{1}^{2}}{2} + \frac{A_{2}^{2}}{10} + \frac{A_{3}^{2}}{6} + \frac{A_{4}^{2}}{6} - S_{m}$$
$$= \frac{26^{2}}{2} + \frac{175^{2}}{10} + \frac{147^{2} + 140^{2}}{6} - 9923$$
$$= 346 \qquad (31.24)$$

$$S_{\tau} = 12^2 + 14^2 + 20^2 + \dots + 24^2$$
  
= 10,426 (31.25)

$$S_e = S_T - S_m - S_A$$
  
= 10,426 - 9923 - 346  
= 157 (31.26)

The analysis of variance is shown in Table 31.2.

Instead of making an overall comparison among the four products, we usually want to make a more detailed comparison, such as:

- *L*<sub>1</sub>: difference between foreign and domestic products
- $L_2$ : difference between our company and the other domestic products
- $L_3$ : difference between the other domestic companies' products

Table 31.1Percent of deterioration

Level	Data	Total
A <sub>1</sub>	12, 14	26
A <sub>2</sub>	20, 18, 19, 17, 15, 16, 13, 18, 22, 17	175
A <sub>3</sub>	26, 19, 26, 28, 23, 25	147
A <sub>4</sub>	24, 25, 18, 22, 27, 24	140
Total		488

The comparison above can be made by using the following linear equations:

$L_1 = \frac{A_1}{2} - \frac{A_2 + A_3 + A_4}{22}$	
$=\frac{26}{2}-\frac{462}{22}$	
= -8.0	(31.27)
$L_2 = \frac{A_2}{10} - \frac{A_3 + A_4}{12}$	
$=\frac{175}{10}-\frac{287}{12}$	
= -6.4	(31.28)
$L_3 = \frac{A_3 - A_4}{6}$	
$=\frac{147-140}{6}$	
= 1.2	(31.29)

Table 3	1.2
ANOVA	table

Source	f	S	V	S'	<b>ρ (%)</b>
т	1	9,923	9,923	9,915	95.1
А	3	346	115.3	322	3.0
е	20	157	7.85	189	1.8
Total	24	10,426		10,426	100.0

These equations are orthogonal to each other, and also orthogonal with the general mean,

$$L_m = \frac{A_1 + A_2 + A_3 + A_4}{24} \tag{31.30}$$

For example, the orthogonality between  $L_m$  and  $L_1$  is proven by

$$\left(\frac{1}{2}\right)\left(\frac{1}{24}\right)(2) + \left(-\frac{1}{22}\right)\left(\frac{1}{24}\right)(22) = 0$$
 (31.31)

where the sum of product of the coefficients is zero. The orthogonality between  $L_1$  and  $L_2$  is proven by

$$\left(\frac{1}{2}\right)(0)(2) + \left(-\frac{1}{22}\right)\left(\frac{1}{10}\right)(10) + \left(-\frac{1}{22}\right)\left(-\frac{1}{12}\right)(12) = 0$$
(31.32)

After calculating the variations of  $L_1$ ,  $L_2$ , and  $L_3$ , we obtain the following decomposition:

$$\begin{split} S_{A} &= S_{L_{1}} + S_{L_{2}} + S_{L_{3}} \quad (31.33) \\ S_{L_{1}} &= \frac{L_{1}^{2}}{\text{sum of the coefficients squared}} \\ &= \frac{[A_{1}/2 - (A_{2} + A_{3} + A_{4})/22]^{2}}{(1/2)^{2}(2) + (-1/22)^{2}(22)} \\ &= \frac{[11A_{1} - (A_{2} + A_{3} + A_{4})]^{2}}{(11^{2})(2) + (-1)^{2}(22)} \\ &= \frac{(286 - 462)^{2}}{264} \\ &= 117 \quad (31.34) \\ S_{L_{2}} &= \frac{[A_{2}/10 - (A_{3} + A_{4})/12]^{2}}{(1/10)^{2}(10) + (-1/12)^{2}(12)} \\ &= \frac{[6A_{2} - 5(A_{3} + A_{4})]^{2}}{(6^{2})(10) + (-5)^{2}(12)} \\ &= \frac{(1050 - 1435)^{2}}{660} = 225 \quad (31.35) \\ S_{L_{2}} &= \frac{(A_{3}/6 - A_{4}/6)^{2}}{12} \\ &= 4 \quad (31.36) \end{split}$$

An ANOVA table with the decomposition of *A* into three components with a unit degree of freedom is shown in Table 31.3.

From the analysis of variance, it has been determined that there is a significant difference between  $L_1$  and  $L_2$ , but none between the other domestic companies.

When there is no significance, as in this case, it is better to pool the effect with the error to show the miscellaneous effect. Pooling the effect of  $L_3$  with the error, the degrees of contribution would then be 1.9%.

Where the error variance,  $V_{e}$ , is calculated from the pooled error variation,

$$V_e = \frac{157 + 4}{21}$$
  
= 7.67 (31.37)

number of units = sum of coefficients squared

$$= \left(\frac{1}{2}\right)^{2}(2) + \left(-\frac{1}{22}\right)^{2}(22)$$

$$= \frac{1}{2} + \frac{1}{22}$$

$$= \frac{12}{22}$$

$$= \frac{6}{11}$$
(31.38)

The other confidence intervals were calculated in the same way. Since  $L_3$  of equation (31.29) is not significant, it is generally not estimated.

## 31.3. Linear Regression Equation

The tensile strength of a product was measured at different temperatures,  $x_1$ ,  $x_2$ , ...,  $x_n$ , to get  $y_1$ ,  $y_2$ , ...,  $y_n$ .

# Table 31.3

ANOVA table

Source	f	S	V	S'	<b>ρ (%)</b>
т	1	9,923	9,923	9,915	95.1
А					
$L_1$	1	117	117	109	1.0
$L_2$ $L_3$	1	225 4	225 4	217	2.0
e	20	157	7.85	185	1.8
Total	24	10,426		10,426	100.0

#### 31.3. Linear Regression Equation

The relationship of the tensile strength, y, to temperature, x, is usually expressed by a linear function:

$$a + bx = y \tag{31.39}$$

Then *n* observational values  $(x_1, y_1)$ ,  $(x_2, y_2)$ , ...,  $(x_n, y_n)$ , are put in equation (31.39):

$$a + bx_i = y_i$$
  $(i = 1, 2, ..., n)$  (31.40)

Equation (31.40) is called an *observational equation*. When the *n* pairs of observational values are put in the equation, there are *n* simultaneous equations with two unknowns, *a* and *b*.

When the number of equations exceeds the number of unknowns, a solution that perfectly satisfies both of these equations does not exist; however, a solution that minimizes the differences between both sides of the equations can be obtained. That is, to find a and b would minimize the residual sum of the squares or the differences between the two sides:

$$S_e = (y_1 - a - bx_1)^2 + (y_2 - a - bx_2)^2 + \dots + (y_n - a - bx_n)^2 \quad (31.41)$$

This solution was named by K. F. Gauss and is known as the *least squares method*. It is obtained by solving the following normal equations:

$$na + \left(\sum x_i\right)b = \sum y_i \tag{31.42}$$

$$\left(\sum x_i\right)a + \left(\sum x_i^2\right)b = \sum x_i y_i \tag{31.43}$$

where

1

 $\mathbf{X}$ 

n = sum of coefficients squared of a in (31.40); the coefficients

are equal to 1

$$= 1^2 + 1^2 + \dots + 1^2 \tag{31.44}$$

$$\left(\sum x_i\right) = \text{sum of products of the coefficients of } a \text{ and } b \text{ in (31.40)}$$
$$= 1x_1 + 1x_2 + \dots + 1x_n \tag{31.45}$$

$$\left(\sum y_i\right) = \text{sum of products of the coefficients of } a \text{ and observational} \\ \text{values of } y \text{ in } (31.40) \\ = 1y_1 + 1y_2 + \dots + 1y_n$$
(31.46)

$$\left(\sum x_i^2\right) = \text{sum of the coefficients squared of } b \text{ in } (31.40)$$
$$= x_1^2 + x_2^2 + \dots + x_n^2$$
(31.47)

$$\sum x_i y_i = \text{sum of products of the coefficients of } b \text{ and}$$
  
observational values of y in (31.40)  

$$= x_1 y_1 + x_2 y_2 + \dots + x_n y_n$$
(31.48)

It is highly desirable that the reader be able to write equations (39.42) and (31.43) at any time. Their memorization should not be difficult.

To solve the simultaneous equations (31.42) and (31.43),  $x_i$  is multiplied by both sides of (31.42). Also, *n* has to be multiplied by both sides of (31.43). After subtracting the same sides of the two equations from each other, term *a* disappears and term *b* is left.

$$\left[\left(\sum x_i\right)^2 - n\sum x_i\right)^2\right]b = \left(\sum x_i\right)\left(\sum y_i\right) - n\sum x_iy_i \qquad (31.49)$$

From this,

$$b = \frac{n \sum x_i y_i - \left(\sum x_i\right) \left(\sum y_i\right)}{n \left(\sum x_i^2\right) - \left(\sum x_i\right)^2}$$
(31.50)

and then dividing the denominator and the numerator by n, respectively,

$$b = \frac{x_1 y_1 + \dots + x_n y_n - [(x_1 + \dots + x_n)(y_1 + \dots + y_n)/n]}{x_1^2 + \dots + x_n^2 - \frac{(x_1 + \dots + x_n)^2}{n}}$$
$$= \frac{S_T(xy)}{S_T(xx)}$$
(31.51)

where  $S_T(xx)$  is the total variation of the temperature, x:

$$S_T(xx) = x_1^2 + x_2^2 + \dots + x_n^2 - \frac{(x_1 + x_2 + \dots + x_n)^2}{n}$$
(31.52)

 $S_T(xy)$  is called the *covariance* of x and y and is determined by

$$S_{T}(xy) = x_{1}y_{1} + x_{2}y_{2} + \dots + x_{n}y_{n} - \frac{(x_{1} + x_{2} + \dots + x_{n})(y_{1} + y_{2} + \dots + y_{n})}{n}$$
(31.53)

In the equation of covariance, the square term in the equation of variation is substituted for by the product of x and y.

Putting b of (31.50) into (31.42), a is obtained:

$$a = \frac{1}{n} \left[ \sum y_i - \frac{S_T(xy)}{S_T(xx)} \left( \sum x_i \right) \right]$$
(31.54)

It is known from (31.54) that when

$$\sum x_i = 0 \tag{31.55}$$

then

$$a = \frac{y_1 + \dots + y_n}{n} = \overline{y} \tag{31.56}$$

Thus, the estimation of the unknowns a and b becomes very simple. For this purpose, equation (31.39) may be expanded as follows:

$$m + b(x - \bar{x}) = y \tag{31.57}$$

where  $\overline{x}$  is the mean of  $x_1, x_2, \dots, x_n$ . Such an expansion is called an *orthogonal* expansion.

The orthogonal expansion has the following meaning: Either the general mean, m, or the linear coefficient, b, is estimated from the linear equation of y. Using equation (31.57), the two linear equations are orthogonal; therefore, the magnitudes of their influences are easily evaluated.

In the observational equation

$$m + b(x_i - \overline{x}) = y_i$$
 (*i* = 1, 2, ..., *n*) (31.58)

the sum of the products of the unknowns m and b,

$$\sum (x_i - \overline{x}) = 0$$

becomes zero. Accordingly, the normal equations become

$$nm + 0b = \sum y_i$$
$$0m + \left[\sum (x_i - \overline{x})^2\right]b = \sum (x_i - \overline{x})y_i \qquad (31.59)$$

Letting the estimates of *m* and *b* be  $\hat{m}$  and  $\hat{b}$ ,

$$\hat{m} = \frac{y_1 + y_2 + \dots + y_n}{n}$$
(31.60)  
$$\hat{b} = \frac{\sum (x_i - \bar{x})y_i}{\sum (x_i - \bar{x})^2}$$
$$= \frac{S_T(xy)}{S_T(xx)}$$
(31.61)

Not only  $\hat{m}$ , but also  $\hat{b}$ , is a linear equation of  $y_1, y_2, ..., y_n$ .

$$c_{1} = \frac{x_{1} - \overline{x}}{S_{T}(xx)}$$

$$c_{2} = \frac{x_{2} - \overline{x}}{S_{T}(xx)}$$

$$\vdots$$

$$c_{n} = \frac{x_{n} - \overline{x}}{S_{T}(xx)}$$
(31.62)

#### 31. Decomposition to Components with a Unit Degree of Freedom

The number of units of the sum of the coefficients squared is

$$c_{1}^{2} + c_{2}^{2} + \dots + c_{n}^{2} = \left[\frac{x_{1} - \overline{x}}{S_{T}(xx)}\right]^{2} + \left[\frac{x_{2} - \overline{x}}{S_{T}(xx)}\right]^{2} + \dots + \left[\frac{x_{n} - \overline{x}}{S_{T}(xx)}\right]^{2}$$
$$= \frac{1}{[S_{T}(xx)]^{2}} [(x_{1} - \overline{x})^{2} + (x_{2} - \overline{x})^{2} + \dots + (x_{n} - \overline{x})^{2}]$$
$$= \frac{S_{T}(xx)}{[S_{T}(xx)]^{2}}$$
$$= \frac{1}{S_{T}(xx)}$$
(31.63)

The variations of *m*, *b*, and error are

$$S_{m} = CF = \frac{(y_{1} + \dots + y_{n})^{2}}{n}$$

$$S_{b} = \frac{(b)^{2}}{\text{no. of units}}$$

$$= \frac{[S_{T}(xy)/S_{T}(xx]^{2}]}{1/S_{T}(xx)}$$

$$= \frac{S_{T}(xy)^{2}}{S_{T}(xx)}$$
(31.64)
$$S_{e} = y_{1}^{2} + y_{2}^{2} + \dots + y_{n}^{2} - S_{m} - S_{b}$$
(31.65)

The number of degrees of freedom is 1 for  $S_m$  or  $S_b$ , and n - 2 for  $S_e$ .

## □ Example

To observe the change of tensile strength of a product, given a change in temperature, the tensile strength of two test pieces was measured at four different temperatures, with the following results (kg/mm<sup>2</sup>):

A <sub>1</sub> (0°C):	84.0,	85.2
A <sub>2</sub> (20°C):	77.2,	76.8
<i>A</i> <sub>3</sub> (40°C):	67.4,	68.6
A <sub>4</sub> (60°C):	58.2,	60.4

If there is no objective value, such as a given specification, the degrees of freedom of the total variation is 7, where the degree of freedom for the correction factor is not included.

Subtracting a working mean, 70.0, the data in Table 31.4 are obtained.

$$CF = \frac{17.8^2}{8} = 39.60$$
(31.66)  
$$S_7 = 14.0^2 + 15.2 + \dots + (9.6)^2 - CF = 765.24 - 39.60$$
$$= 725.64$$
(31.67)

Assuming that tensile strength changes in the same way as the linear function of temperature, *A*, the observational equations will become

$$y = m + b(A - \overline{A}) \tag{31.68}$$

where A signifies temperature and  $\overline{A}$  represents the mean value of the various temperature changes:

$$\overline{A} = \frac{1}{8}[(2)(0) + (2)(20) + (2)(40) + (2)(60)] = 30^{\circ}C \quad (31.69)$$

In the linear equation, m is a constant and b is a coefficient indicating how much the tensile strength decreases with a 1°C temperature change. The actual observational values are put into equation (31.68), as follows:

$$m + b(0 - 30) = 84.0$$
  

$$m + b(0 - 30) = 85.2$$
  

$$m + b(20 - 30) = 77.2$$
  

$$m + b(20 - 30) = 76.8$$
 (31.70)  

$$m + b(40 - 30) = 67.4$$
  

$$m + b(40 - 30) = 68.6$$
  

$$m + b(60 - 30) = 58.2$$
  

$$m + b(60 - 30) = 60.4$$

Data	after	sub	tracting	а	wor	king	mean
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Level	Data	Total
<i>A</i> <sub>1</sub>	14.0, 15.2	29.2
A <sub>2</sub>	7.2, 6.8	14.0
A <sub>3</sub>	-2.6, -1.4	-4.0
A <sub>4</sub>	-11.8, -9.6	-21.4
Total		17.8

The unknowns are m and b, and there are eight equations. Therefore, the least squares method is used to find m and b.

$$n = \text{ sum of the coefficients squared of } m \qquad (31.71)$$

$$= 8$$

$$\left(\sum x_{i}\right) = \text{ sum of the coefficients of } b$$

$$= (-30) + (-30) + (-10) + (-10) + 10 + 10 + 30 + 30$$

$$= 0 \qquad (31.72)$$

$$\left(\sum y_{i}\right) = \text{ sum of products of } y \text{ and the coefficients of } m$$

$$= 84.0 + 85.2 + \dots + 60.4$$

$$= (70.0)(8) + 17.8$$

$$= 577.8 \qquad (31.73)$$

$$\left(\sum x_{i}^{2}\right) = \text{ sum of the coefficients squared of } b$$

$$= (-30)^{2} + (-30)^{2} + (-10)^{2} + (-10)^{2} + 10^{2} + 30^{2} + 30^{2}$$

$$= 4000 \qquad (31.74)$$

$$\left(\sum x_{i}y_{i}\right) = \text{ sum of products of } y \text{ and the coefficients of } b$$

$$= (-30)(84.0) + (-30)(85.2) + \dots + (30)(58.2) + (30)(60.4)$$

$$= (-30)(169.2) + (-10)(154.0) + (10)(136.0) + (30)(118.6)$$

$$= -1698.0 \qquad (31.75)$$

The following simultaneous equations are then obtained:

$$8m + 0b = 577.8$$
  
 $0m + 4000b = -1698.0$  (31.76)

Solving these yields

$$\hat{m} = \frac{577.8}{8} = 72.22 \tag{31.77}$$

$$\hat{b} = \frac{-1698.0}{4000} = -0.4245 \tag{31.78}$$

The orthogonality of these equations is proved as follows: Let the eight observational data be  $y_1, y_2, \ldots, y_8$ .

$$\hat{m} = \frac{y_1 + y_2 + \dots + y_8}{8}$$
(31.79)  
$$\hat{b} = \frac{-30(y_1 + y_2) - 10(y_3 + y_4) + 10(y_5 + y_6) + 30(y_7 + y_8)}{4000}$$
$$= \frac{-3(y_1 + y_2) - (y_3 + y_4) + (y_5 + y_6) + 3(y_7 + y_8)}{400}$$
(31.80)

The sum of products of the corresponding coefficients of  $\hat{m}$  and  $\hat{b}$  is

$$2\left[\left(\frac{1}{8}\right)\left(\frac{-3}{400}\right) + \left(\frac{1}{8}\right)\left(\frac{-1}{400}\right) + \left(\frac{1}{8}\right)\left(\frac{3}{400}\right)\right] = 0$$
(31.81)

The variation of m,  $S_m$ , is identical to the correction factor.

$$S_{m} = CF = \frac{577.8^{2}}{8}$$

$$= 41,731.60 \qquad (31.82)$$

$$S_{b} = \frac{S_{7}(xy)^{2}}{S_{7}(xx)}$$

$$= \frac{(-1698.0)^{2}}{4000}$$

$$= 720.80 \qquad (31.83)$$

The total sum of the observational values squared,  $S_{\scriptscriptstyle T}$ , is

$$S_{\tau} = 84.0^2 + 85.2^2 + \dots + 60.4^2$$
  
= 42.457.24 (31.84)

The error variation,  $S_e$ , is then

$$S_e = S_T - S_m - S_b$$
  
= 42,457.24 - 41,731.60 - 720.80  
= 4.84 (31.85)

The error variance, with 6 degrees of freedom, is

$$V_{e} = \frac{S_{e}}{6}$$
$$= \frac{4.84}{6}$$
$$= 0.807$$
(31.86)

The pure variations of the general mean and the linear coefficient, b, are

$$S'_{m} = S_{m} - V_{e}$$

$$= 41,731.60 - 0.807$$

$$= 41,730.793$$

$$S'_{b} = S_{b} - V_{e}$$

$$= 720.80 - 0.807$$

$$= 719.993$$
(31.88)

Degrees of contributions are calculated as follows:

$$\rho_m = \frac{41,730.793}{42,457.24}$$
  
= 98.289% (31.89)

$$\rho_b = \frac{719.993}{42,457.24}$$

$$= 1.696\%$$
 (31.90)

$$\rho_e = \frac{4.84 + (2)(0.807)}{42,457.24}$$

The analysis of variance is shown in Table 31.5. The tensile strength y at temperature x is estimated as

$$y = \hat{m} + \hat{b}(x - \bar{x})$$
  
= 72.22 - 0.4245(x - 30) (31.92)

# 31.4. Application of Orthogonal Polynomials

The type of contrast, or comparison, to cite is up to a researcher. The appropriate selection is crucial if the results achieved are to be based on practical and justifiable

Table 31.5 ANOVA table

Source	f	S	V	S'	<b>ρ (%)</b>
т	1	41,731.60	41,731.60	41,730.793	98.289
b	1	720.80	720.80	719.993	1.696
е	6	4.84	0.807	6.545	0.015
Total	8	42,457.24		42,457.240	100.000

comparisons rather than simply on the theoretical methodologies. Only a researcher or an engineer who is thoroughly knowledgeable of the products or conditions being investigated can know what comparison would be practical. However, the contrasts of orthogonal polynomials in linear, quadratic, ..., are often used. Let  $A_1, A_2, \ldots, A_a$  denote the values of first, second, ..., a level, respectively.

Assuming that the levels of A are of equal intervals, the levels are expressed as

$$A_{1} = A_{1}$$

$$A_{2} = A_{1} + h$$

$$A_{3} = A_{1} + 2h$$

$$\vdots$$

$$A_{a} = A_{1} + (a - 1)h$$
(31.93)

From each level of  $A_1, A_2, ..., A_a$ , *r* data are taken. The sum of each level is denoted by  $y_1, y_2, ..., y_a$ , respectively. When *A* has levels with the same interval, an orthogonal polynomial, which is called the *orthogonal function* of P. L. Chebyshev, is generally used.

The expanded equation is

$$y = b_0 + b_1(A - \overline{A}) + b_2 \left[ (A - \overline{A})^2 - \frac{a^2 - 1}{12} h^2 \right] + \cdots$$
 (31.94)

where  $\overline{A}$  is the mean of the levels of A:

$$\overline{A} = A_1 + \frac{a-1}{2}h$$
 (31.95)

The characteristics of the expansion above are that it attaches importance to the terms of the lower orders, such as a constant, a linear function, or even a quadratic function. First, the constant term  $b_0$  is tried. If it does not fit well, a linear term is tried. If it still does not show linear tendency, the quadratic term is tried, and so on. When sums  $y_1, y_2, \ldots, y_a$  were obtained from r data of the levels  $A_1, A_2, \ldots, A_a$ , respectively, the values are  $b_0, b_1, \ldots$ . Equation (31.94) will be obtained by solving the following observational equation with order a using the least squares method:

31. Decomposition to Components with a Unit Degree of Freedom

$$b_{0} + b_{1}(A_{1} - \overline{A}) + b_{2} \left[ (A_{1} - \overline{A})^{2} - \frac{a^{2} - 1}{12} h^{2} \right] + \dots = \frac{y_{1}}{r}$$

$$\vdots \qquad (31.96)$$

$$b_{0} = b_{1}(A_{a} - A) + b_{2} \left[ (A_{a} - \overline{A})^{2} - \frac{a^{2} - 1}{12} h^{2} \right] + \dots = \frac{y_{a}}{r}$$

The estimates of  $b_0$ ,  $b_1$ , ... are denoted by  $b'_0$ ,  $b'_0$ ,  $b'_0$ , ... :

$$b'_0 = \frac{y_1 + \dots + y_a}{ar}$$
(31.97)

$$b_{1}' = \frac{(A_{1} - \overline{A})y_{1} + \dots + (A_{a} - \overline{A})y_{a}}{[(A_{1} - \overline{A})^{2} + \dots + (A_{a} - \overline{A})^{2}]r}$$
(31.98)

It is easy to calculate  $b'_0$ , since it is the mean of the total data. But it seems to be troublesome to obtain  $b'_1$ ,  $b'_2$ , ... Actually, it is easy to estimate them by using Table 31.6, which shows the coefficients of orthogonal polynomials when a = 3(three levels).  $b_1$  and  $b_2$  are linear and quadratic coefficients, respectively. These are given by

$$b_1' = \frac{W_1 A_1 + W_2 A_2 + W_3 A_3}{r(\lambda S) h}$$
(31.99)

$$b_2' = \frac{W_1 A_1 + W_2 A_2 + W_3 A_3}{r(\lambda S) h^2}$$
(31.100)

In the equations above,  $A_1$ ,  $A_2$ , and  $A_3$  are used instead of  $y_1$ ,  $y_2$ , and  $y_3$ . For  $b_1$ , the values of  $W_1$ ,  $W_2$ , and  $W_3$  are -1, 0, and 1. Also, *S* is 2.  $b'_1$  is then

$$b_1' = \frac{-A_1 + A_3}{2rh} \tag{31.101}$$

Similarly,

$$b_2' = \frac{A_1 - 2A_2 + A_3}{2rh^2} \tag{31.102}$$

#### Table 31.6

Coefficients of orthogonal polynomial for three levels

Coefficients	<b>b</b> 1	<b>b</b> <sub>2</sub>
$W_1$	-1	1
W <sub>2</sub>	0	-2
W <sub>3</sub>	1	1
$\lambda^2 S$	2	6
λS	2	2
S	2	<u>2</u> 3

#### 31.4. Application of Orthogonal Polynomials

The variations of  $b'_1$  and  $b'_2$  are denoted by  $S_{A1}$  and  $S_{Aq}$ , respectively. These are given by the squares of equations (31.101) and (31.102) divided by their numbers of units, respectively.

$$S_{A_l} = \frac{(-A_1 + A_3)^2}{2r}$$
(31.103)

$$S_{A_q} = \frac{(A_1 - 2A_2 + A_3)^2}{6r}$$
(31.104)

The denominator of equations (31.103) and (31.104) is  $r(\lambda^2 S)$  ( $\lambda^2 S$  is the sum of squares of the coefficients of W). The effective number of replication,  $n_{\phi}$  is given by

$$b_1': n_e = rSh^2$$
 (31.105)

$$b_2': n_e = rSh^4$$
 (31.106)

In general, the *i*th coefficient  $b_i$  and its variation on  $S_{A_i}$  are

$$b_1' = \frac{W_1 A_1 + \dots + W_a A_a}{r(\lambda S) h^i}$$
(31.107)

$$S_{A_i} = \frac{(W_1 A_1 + \dots + W_a A_a)^2}{(W_1^2 + \dots + W_a^2)r}$$
(31.108)

### □ Example

To observe the change of the tensile strength of a synthetic resin due to changes in temperature, the tensile strength of five test pieces was measured at  $A_1 = 5^{\circ}$ C,  $A_2 = 20^{\circ}$ C, and  $A_3 = 35^{\circ}$ C, respectively, to get the results in Table 31.7. The main effect *A* is decomposed into linear, quadratic, and cubic components to find the correct order of polynomial to be used. From Table 31.8, find the coefficients at the number of levels k = 4.

# Table 31.7

Tensil	e stre	ength	(kg/	′mm²)	
--------	--------	-------	------	-------	--

Level	Data	Total
A <sub>1</sub> (5°C)	43, 47, 45, 43, 45	233
A <sub>2</sub> (20°C)	43, 41, 45, 41, 39	209
A <sub>3</sub> (35°C)	37, 36, 39, 40, 38	190
A <sub>4</sub> (50°C)	34, 32, 36, 35, 35	172

Table 31.8Orthogonal polynomials with equal intervals

	$b_{5}$	-4	11	-4	6	0	6	4	-11	4	468	3,120	20,800	3/20		$b_{5}$	က ၂	9	1	-4	-4	0	4	4	-1	9-
= 9	$oldsymbol{b}_4$	14	-21	-11	6	18	6	-11	-21	14	2,002	3,432	41,184/7	7/12	11	$oldsymbol{b}_4$	9	-9	-9	-1	4	9	4	-1	-9	-9
<i>k</i> =	$b_3$	-14	7	13	6	0	6-	-13	-7	14	066	1,188	7,128/5	5/6	k =	$b_3$	-30	9	22	23	14	0	-14	-23	-22	9-
	$b_2$	28	7	<b>00</b> 	-17	-20	-17	<b>00</b> 	7	28	2772	924	308	m		$\boldsymbol{b}_2$	15	9	-1	9–	6 	-10	6 	9-	-1	9
	$\boldsymbol{b}_1$	-4	ი ს	-2	-1	0	1	2	n	4	60	60	60	-		$\boldsymbol{b}_1$	<u>9</u> –	-4	ကို	-2	$^{-1}$	0	1	2	ω	4
	$b_5$	-7	23	-17	-15	15	17	-23	7		2184	3,102	31,200/7	10/7		$b_{5}$	9-	14	-1	-11	9-	9	11	1	-14	9
	$m{b}_4$	7	-13	ကို	6	6	ကို	-13	7		616	1,056	12,672/7	12/7		$\boldsymbol{b}_4$	18	-22	-17	ς	18	18	ς	-17	-22	18
<i>k</i> = 8	$b_3$	-7	2	7	ς	က 	-7	<u>9</u> –	7		264	396	594	2/3	k = 10	$b_{3}$	-42	14	35	31	12	-12	-31	-35	-14	42
	$b_2$	7	1	ლ 	<u>9</u> –	<u>9</u> –	ლ 	1	7		168	168	168	1		$b_2$	9	2	-1	ლ 	-4	-4	ლ 	-1	2	9
	$b_1$	-7	<u>ا</u>	ကို	-1	1	n	വ	7		168	84	42	N		$b_1$	6–	-7	- D	ကျ	$^{-1}$	1	m	Ð	7	6
	Coeff.	$W_{1}$	$W_2$	W <sub>3</sub>	$W_4$	$W_5$	$W_6$	$W_{7}$	$W_{\rm s}$	$W_9$	λ'S	УV	S	Y		Coeff.	$W_{1}$	$W_2$	W <sub>3</sub>	$W_4$	$W_5$	$W_6$	$W_{7}$	$W_{\rm s}$	$W_9$	$W_{10}$

			S	1	5	9	9	2	4	0	2	4	6	9	0	0	1	4	0
	1	$b_4$ $b_5$	9	286			3,432				41,184						1/12		
	k = 11	$b_3$	30	4,290			5,148				30,886/5						5/6		
		$\boldsymbol{b}_2$	15	858			858				858						1		
		$b_1$	Ð	110			110				110						1		
		$b_{5}$		780			7,800				78,000						1/10		
( nonunned )		$oldsymbol{b}_4$		2,860			6,864				82,368/5						5/12		
Utiliogoliai polyliolillais witil equal illervais (contrinueu)	k = 10	<b>b</b> <sub>3</sub> 8,580					5,148				15,444/5						5/3		
als will e		$b_2$		132			264				528						1/2		
iai pulyilulii		$\boldsymbol{b}_1$		330			165				165/2						2		
Ortinugui		Coeff.	$W_{_{11}}$	λ'S			λS				S						~		

 Table 31.8
 Orthogonal polynomials with equal intervals (Continued)

	$\boldsymbol{b}_{\mathrm{5}}$	-22	33	18	-11	-26	-20	0	20	26	11	-18	-33	22	6,188	106,080	12,729,600/7	7/120
= 13	$b_4$	66	-66	-96	-54	11	64	84	64	11	-54	-96	-66	66	68,068	116,688	1,400,256/7	7/12
<i>k</i> =	$b_3$	-11	0	9	∞	7	4	0	-4	-7	<b>00</b> 	9-	0	11	572	3,432	20,592	1/6
	$b_2$	22	11	2	<u>9</u> 	-10	-13	-14	-13	-10	<u>ا</u> 1	2	11	22	2,002	2,002	2,002	1
	$b_1$	9–	<u>ں</u> ا	-4	ლ 	-2	-1	0	1	2	m	4	Ð	9	182	182	182	1
	$b_{5}$	-33	57	21	-29	-44	-20	20	44	29	-21	57	33		15,912	106,080	707,200	3/20
	$\boldsymbol{b}_4$	33	-27	-33	-13	12	28	28	12	-13	-33	-27	33		8,008	27,456	658,944/7	7/24
<i>k</i> = 12	$b_3$	-33	ε	21	25	19	7	-7	-19	-25	-21	ლ 	33		5,148	7,722	11,583	2/3
	$b_2$				-17										12,012	4,004	4,004/3	ε
	$\boldsymbol{b}_1$	-11	6–	-7	-2	ကို	-1	1	m	2	7	6	11		572	286	143	N
	Coeff.	$M_{_{\rm I}}$	$W_2$	W <sub>3</sub>	$W_4$	$W_5$	$W_{_6}$	$W_{\gamma}$	$W_{_{ m B}}$	$W_9$	$W_{10}$	$W_{11}$	$W_{12}$	$W_{13}$	λ'S	УV	S	$\checkmark$

$$S_{A_{l}} = \frac{(W_{1}A_{1} + W_{2}A_{2} + W_{2}A_{2} + W_{3}A_{3} + W_{4}A_{4})^{2}}{r(\lambda^{2}S)}$$
$$= \frac{[-3(223) - 209 + 190 + 3(172)]^{2}}{(5)(20)}$$
$$= \frac{(-172)^{2}}{100} = 296$$
(31.109)

$$S_{A_q} = \frac{(223 - 209 - 190 + 172)^2}{(5)(4)} = \frac{(-4)^2}{20} = 1$$
 (31.110)

$$S_{A_c} = \frac{[-223 + 3(209) - 3(190) + 172]^2}{(5)(20)} = \frac{6^2}{100} = 0 \quad (31.111)$$

$$S_T = 43^2 + 47^2 + \dots + 35^2 - CF = 348$$

$$S_e = S_T - S_{A_l} - S_{A_q} - S_{A_c}$$

$$= 51 \quad (31.112)$$

It is known from Table 31.9 that only the linear term of A is significant; hence, the relationship between temperature, A, and tensile strength, y, can be deemed to be linear within the range of our experimental temperature changes. The estimate of the linear coefficient of temperature, b, is

$$b'_{1} = \frac{-3(223) - 209 + 190 + 3(172)}{r(\lambda S)h}$$
$$= \frac{-172}{(5)(10)(15)} = -0.23$$
(31.113)

# Table 31.9

ANOVA table

Source	f	S	V	<b>ρ (%)</b>
A Linear Quadratic Cubic	1 1 1	296 1 0	296 1 0	84.2
е	16	51	3.2	
Total	19	348		100.0
(e)	(18)	(52)	(2.9)	(15.8)

# 31.4. Application of Orthogonal Polynomials

The relationship between temperature and tensile strength is then

$$y = b'_{0} + b'_{1} (A - A)$$

$$= \frac{794}{20} - 0.23(A - 27.5)$$

$$= 39.70 - 0.23(A - 27.5) \qquad (31.114)$$

$$b_{1}: 1 \text{ linear}$$

$$b_{2}: 2 \text{ quadratic}$$

$$\hat{b} = \frac{W_{1}A_{1} + \dots + W_{a}A_{a}}{r(\lambda S)h^{i}} \qquad (31.115)$$

$$Var(\hat{b}_{i}) = \frac{\sigma^{2}}{rSh^{2i}}$$

$$S_{b_{i}} = \frac{(W_{1}A_{1} + \dots + W_{a}A_{a})^{2}}{r(\lambda^{2}S)}$$