

Using Taguchi methods to improve a control scheme by adjustment of changeable settings: A case study

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ABSTRACT *It is demonstrated, through a case study, how statistically designed experiments can help in improving online process control schemes remarkably. The study was conducted in the packing plant of a company manufacturing urea. The packing machine had an in-built computerized control mechanism that was supposed to control the variation in packed bag weights by automatic measurement and adjustment. However, despite following the instruction manual rigorously, the machine was unable to deliver a satisfactory performance from the point of view of variation. An orthogonal array experiment conducted with some of the machine parameters could bring about a dramatic improvement in the effectiveness of the control scheme.*

Introduction

In this age of automation, there are many processes that boast of an in-built online control mechanism. 'The process takes care of itself' is the common belief in such situations. Essentially, what these processes do is to check the output at predetermined time intervals, measure the deviation from the targeted values and make adjustments with the objective of minimizing the variation around the target. There are certain parameters associated with the control system which can be pre-set by the user on the basis of his/her requirements, e.g. the sampling frequency, amount of correction to be given, etc. Usually owners of such processes tend to follow blindly the instructions of either their collaborators or the manufacturers and installers of the machines regarding set values of the parameters. In very few cases is there an endeavour to find the optimum combination of these parameters that can enhance the effectiveness of the control scheme. This reluctance often arises from: (i) acceptance of the current quality status as 'fate'; (ii) fear of taking risk; or (iii) ignorance of modern concepts of experimentation.

In this article we demonstrate, through a case study, that modern concepts of design of experiments can be applied very successfully to enhance the effectiveness of a control scheme in complicated situations where a large number of parameters are expected to affect the efficiency of the control scheme. Each step taken during the course of experimentation is discussed briefly. At the end we discuss the aspects which can make such experiments successful and point out how each such aspect was taken into consideration in this study.

Background

A reputable fertilizer manufacturing company had been using a sophisticated computerized packing machine to pack urea into bags. The specification for weight of a packed bag was 50 ± 0.150 kg. The packing machine was supposed to control the weight of the packed bags within specified tolerances by measuring the weight of sampled bags and providing corrections for discrepancies. The *modus operandi* of the machine was dependent on the values of several machine parameters that could be set by the user. The manufacturer of the machine had suggested some set values for the machine parameters which the organization had been following blindly. The packing performance was, however, far from satisfactory and highly inconsistent. With the existing level of machine parameters the extent of variation in weight of packed bags was found to be very high, leading to a high percentage of non-conformities. At the instance of company management, this study was taken up with the objective of studying the effects of the controllable machine parameters on the weight of the packed bags and optimizing their levels to get a robust packing performance.

The packing process and automatic adjustment mechanism

The packing process is represented in Fig. 1. The manufactured urea used to be fed continuously to the bagging plant through an overhead conveyor. A hopper with a fixed storage capacity of 40-50 tons received the material. Just below the hopper was a sub-hopper from which the material would flow into the packing machine through a Y-piece (used for cleaning purposes and to ensure ease of flow). The material was fed in two stages: main feed and dribble feed (fine adjustment). At the bottom of the device was a weighpan.

The machine had a large number of control parameters, which could be set according to the user's requirement in order to get the desired packing performance. These parameters were broadly divided into two categories, viz. adjustable parameters that determine the characteristics of the weighing system and weight programme parameters or the material-dependent parameters. In a nutshell, this computerized packing machine made use of an online control scheme that was somewhat similar to Taguchi's β -correction technique (Taguchi, 1981). It weighed sampled bags (the sampling proportion was to be determined

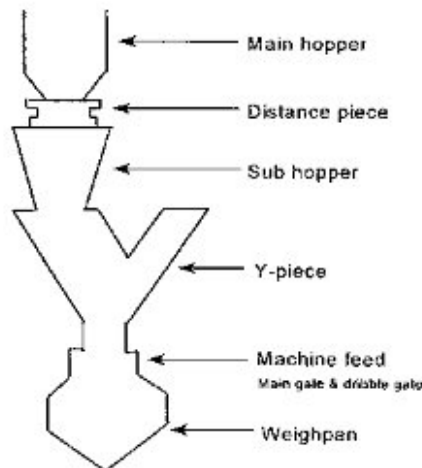


Figure 1. The packing process.

by the user), compared them with the set target and gave corrections (the extent of correction to be given was also to be decided by the user). A brief description of the overall functioning of the system with respect to the important parameters is given in the Appendix.

The existing level of performance and need for experimentation

As already mentioned, the set values for the machine parameters were selected as per the recommendations of the user's manual and the manufacturer of the machine. This, however, led to a rather unsatisfactory packing performance from the point of view of variation. Sample data on weights of packed urea bags collected over a period of 1 week were analysed to give the following summary:

Number of observations (n)	= 280
Average weight (kg)	= 50.05
Standard deviation	= 0.1205
Process capability index (C_p)	= 0.4149
Process performance index (C_{pk})	= 0.3873
Percentage of observations below lower spec (49.85 kg)	= 3
Percentage of observations above upper spec (50.15 kg)	= 14
Overall percentage of non-conformities (actual)	= 17

Figure 2 shows the histogram constructed with the data.

A run chart of 100 consecutive bags is shown in Fig. 3. The run chart shows that the control scheme of the machine was able to remove drifts quite effectively; but still the inherent variation is quite high, resulting in about 16% non-conformities, mostly above the USL.

The following points emerged from the preliminary analysis:

- (1) The process was more or less stable—shifts and drifts were almost absent.
- (2) The setting was always on the higher side, about 50 grams more than the nominal value. This was done deliberately in order to avoid non-conformities below LSL and thereby reduce customer dissatisfaction. However, this could be taken care of easily by selecting the target weight as 50.0 kg.
- (3) The inherent variation was very high, resulting in a high percentage of non-conformances.

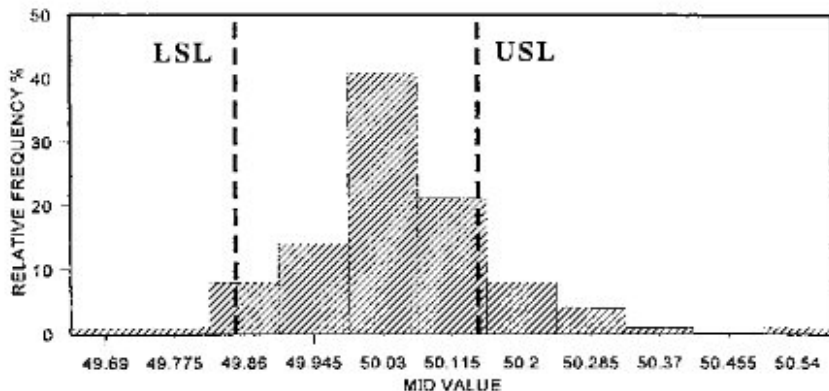


Figure 2. Histogram of bag weights.

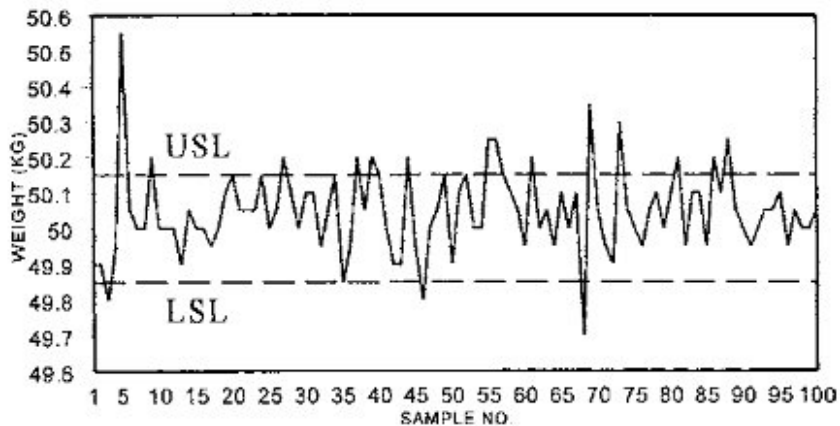


Figure 3. Run chart of bag weight.

It was thus evident that improvement of packing performance meant reduction of inherent variation; which in turn calls for reduction of the impact of noise factors on the process. The noise factors, which were believed to affect strongly the packing process, were the density and flowability of the material. The only option available was to conduct a designed experiment with the vast multitude of parameters in order to identify an optimum combination of parameters that would enhance the effectiveness of the control scheme.

Selection of factors and levels

After detailed brainstorming sessions and discussions with maintenance engineers, 16 factors (both from adjustable parameters and weight programmes) were selected for experimentation; while selection factors like 'nominal value', 'overfill', etc. which were meant only to set the target were ignored. All factors that were thought to affect the process variation were chosen.

Three of these 16 factors were kept at three levels and the remaining 13 were kept at two levels. The nature of impact of each factor on the process variation was studied through a few small one-factor-at-a-time pilot studies conducted at the plant level for about a week to obtain the proper direction. Too much flexibility could not be allowed during selection of levels since this was a plant-level experiment. Further, there were certain parameters that along with reduction of variation could adversely affect the production speed. For example, corresponding to a sample frequency of 20, if the sample number were changed from three to five, it would mean that the machine would have to check five instead of three bags among every 20 bags filled. This would definitely slow down production and thereby reduce the 'bagging rate'. Such aspects had also to be taken into consideration. Table 1 shows the identified factors and their levels.

It was decided that along with the main effects, five interactions would be estimated. These interactions were $A \times B$, $B \times D$, $G \times J$, $G \times M$ and $H \times L$.

The experimental layout

The total degrees of freedom associated with the experiment (to estimate 16 main effects and five interactions) were 27. It was decided to use the L_{32} orthogonal array with an idle column to design the experiment. The idle column method is a method of allocating three-

Table 1. Factors and levels

Sl No.	Name of the factor	Factor code	Levels		
			1	2	3
1	Sample frequency	A	20*	10	—
2	Sample number	B	3*	5	—
3	Sample frequency timer (s)	C	300*	240	—
4	Auto compensation proportional constant	D	0.3*	0.2	0.4
5	Main feed blanking timer (s)	E	0.9*	0.5	—
6	Dribble feed blanking timer (s)	F	0.9*	0.5	—
7	Discharge timer (s)	G	0.3*	0.6	0.9
8	Dribble feed time correction constant (s)	H	0.1	0.8*	—
9	Gate allowance timer (s)	I	2.0*	0.4	—
10	Feed delay timer (s)	J	0.3*	0.7	—
11	In-flight material compensation (start)	K	2.0	3.0*	—
12	Dribble feed quantity (start) (kg)	L	12*	8	—
13	Discharge cut-off value (kg)	M	30*	20	—
14	Overweight tolerance (kg)	N	0.15*	0.20	—
15	Underweight tolerance (kg)	P	0.15*	0.10	—
16	Dribble feed time (s)	Q	1.2*	1.4	1.6

*Denotes the existing levels.

level factors in two-level orthogonal arrays and is discussed in detail by Taguchi (1987) and Ross (1988).

The linear graph constructed to assign columns of the orthogonal array to different main effects and interactions is shown in Fig. 4. Column 1 is treated as the idle column and the three three-level factors D, G and Q are allocated to columns (16, 17), (2, 3) and (20, 21), respectively.

The orthogonal array lay out of the experiment is shown in Table 2.

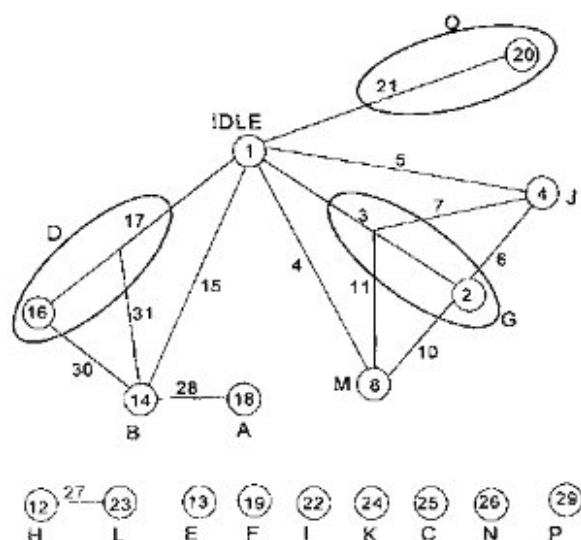


Figure 4. Linear graph.

Table 2. The orthogonal array layout

Expt No.	Idle 1	A 18	B 14	C 25	D 16,17	E 13	F 19	G 2,3	H 12	I 22	J 4	K 24	L 23	M 8	N 26	P 29	Q 20,21
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	2	1	2	2	1	2	1	1	2	1	2	2	1	2	2	2
3	1	1	2	2	1	2	1	1	2	1	1	2	1	2	2	2	1
4	1	2	2	1	2	2	2	1	2	2	1	1	2	2	1	1	2
5	1	1	2	1	1	2	1	1	2	2	2	1	2	1	1	2	2
6	1	2	2	2	2	2	2	1	2	1	2	2	1	1	2	1	1
7	1	1	1	2	1	1	1	1	1	2	2	2	2	2	2	1	2
8	1	2	1	1	2	1	2	1	1	1	2	1	1	2	1	2	1
9	1	2	2	1	1	1	2	3	1	2	1	1	2	1	2	1	1
10	1	1	2	2	2	1	1	3	1	1	1	2	1	1	1	2	2
11	1	2	1	2	1	2	2	3	2	2	1	2	2	2	1	2	1
12	1	1	1	1	2	2	1	3	2	1	1	1	1	2	2	1	2
13	1	2	1	1	1	2	2	3	2	1	2	1	1	1	2	2	2
14	1	1	1	2	2	2	1	3	2	2	2	2	2	1	1	1	1
5	1	2	2	2	1	1	2	3	1	1	2	2	1	2	1	1	2
5	1	1	2	1	2	1	1	3	1	2	2	1	2	2	2	2	1
7	2	1	1	2	1	2	2	2	1	1	1	1	2	1	1	2	1
3	2	2	1	1	3	2	1	2	1	2	1	2	1	1	2	1	3
9	2	1	2	1	1	1	2	2	2	1	1	2	2	2	2	1	1
0	2	2	2	2	3	1	1	2	2	2	1	1	1	2	1	2	3
1	2	1	2	2	1	1	2	2	2	2	2	1	1	1	1	1	3
2	2	2	2	1	3	1	1	2	2	1	2	2	2	1	2	2	1
23	2	1	1	1	1	2	2	2	1	2	2	2	1	2	2	2	3
24	2	2	1	2	3	2	1	2	1	1	2	1	2	2	1	1	1
25	2	2	2	2	1	2	1	3	1	2	1	1	1	1	2	2	1
26	2	1	2	1	3	2	2	3	1	1	1	2	2	1	1	1	3
27	2	2	1	1	1	1	1	3	2	2	1	2	1	2	1	1	1
28	2	1	1	2	3	1	2	3	2	1	1	1	2	2	2	2	3
29	2	2	1	2	1	1	1	3	2	1	2	1	2	1	2	1	3
30	2	1	1	1	3	1	2	3	2	2	2	2	1	1	1	2	1
31	2	2	2	1	1	2	1	3	1	1	2	2	2	2	2	2	3
32	2	1	2	2	3	2	2	3	1	2	2	1	1	2	1	1	1

Conducting the experiment

Replication and randomization

It was decided that the basic experiment would be replicated thrice, i.e. 96 trials would be conducted in all. The trials were randomized as a safeguard against systematic bias. Although in many situations randomization is likely to increase the duration of the experiment, there was no such fear in this particular experiment. The time required to change the parameter settings between two successive trials was very small irrespective of whether a single factor was changed or multiple factors were changed, as it was a question of changing some computerized settings only. In fact the time required to clean the chute and packer scale between two successive trials was much more compared to the time required to change the settings.

Duration

In all, 96 trials were to be conducted. It was decided that 60 observations on weight would be recorded corresponding to each trial. The duration of a particular trial would depend on

the sampling frequency and sampling number for that experimental combination. An experimental combination having sample frequency 20 and sample number 3 would require 400 bags to be filled before collection of 60 weight observations, whereas that with a (12, 5) combination would require only 144 bags to be filled to obtain the required data. Considering the fact that around 6000 bags could be filled in a shift under normal conditions, it was decided to conduct seven trials per shift, which would require a maximum production of 2800 bags and allow sufficient time for process setting and cleaning after every trial. Since controlled conditions (as described in the following sub-section) could be guaranteed only in the general shift, it took 14 general shifts, i.e. 2 weeks, to complete the 96 trials at the rate of seven trials per shift (day).

Controlled conditions for the experiment

During each trial, the following aspects were ensured:

- The inlet chute was clean.
- The packer scale was washed and dried (by blowing air).
- The packer scale was properly calibrated.
- The material flow rate was more or less constant.
- Any disturbance or abnormality was recorded.
- The parameters that were not considered as control factors in the experiment were kept constant at specified levels.

Data generation

The data generated during the experiment were available in the form of computer printouts. The following information was made available for each experimental combination:

- (1) The values of all the control factors for that combination (to cross check whether the proper combination has been run).
- (2) The 60 individual bag weights.
- (3) Statistical information like average weight and standard deviation.

Analysis of experimental data

Selection and computation of signal-to-noise ratio

As described in the previous section, 60 observations were obtained against each experimental combination in a single replicate.

Denoting these weights as y_1, y_2, \dots, y_{60} , the signal-to-noise (S/N) ratio given by $-10 \log V_c$ was chosen for analysis, where $V_c = \sum (y_i - \bar{y})^2 / 59$ is the sample variance computed from these 60 observations. $-10 \log V_c$ was chosen since the current experiment did not involve a two-step optimization and was solely intended for reduction of variation. The parameter used to adjust the nominal weight was known; and was not used as a control factor in the experiment.

The log transformation of the sample variance was originally recommended by Bartlett (1937). In the context of Taguchi methods, the S/N ratio given by $-10 \log V_c$ is also recommended by Hunter (1987), although for nominally the best characteristics the more popular and widely used expression for S/N ratio is

$$10 \log [(S_m - V_c) / nV_c]$$

Table 3. S/N ratios for the 32 trials

Expt No.	S/N ratio for			Expt No.	S/N ratio for		
	Rep I	Rep II	Rep III		Rep I	Rep II	Rep III
1	22.110	31.3727	28.4043	17	15.2894	35.9176	26.0206
2	18.2019	19.1721	25.3521	18	19.1721	28.1787	19.3449
3	17.6546	17.5230	16.1934	19	24.4249	18.3443	10.2290
4	41.9382	25.1927	33.1515	20	40.9151	35.9176	39.1721
5	29.8910	32.0412	33.5556	21	35.9176	33.5556	35.9176
6	37.0774	26.5580	37.0774	22	20.9151	37.0774	41.9382
7	21.5144	17.6546	16.0269	23	16.5948	16.0269	16.7726
8	29.1186	33.5556	20.4570	24	33.5556	32.3958	32.0412
9	32.0412	33.1515	39.1721	25	29.1186	39.1721	19.8424
10	22.9748	17.5230	16.9542	26	16.8328	14.0229	27.0774
11	19.4939	19.4123	18.6363	27	18.4164	18.5624	19.2515
12	27.0133	28.1787	37.7211	28	34.4249	32.0412	39.1721
13	31.0568	35.3910	39.1721	29	34.4249	35.3910	39.1721
14	16.7726	16.5948	16.5948	30	16.4205	16.4205	17.6546
15	39.1721	16.8328	37.0774	31	37.7211	27.5230	37.0774
16	33.1515	34.4249	29.6297	32	33.5556	37.0774	33.1515

where $S_m = (\Sigma y)^2/m$ and n is the total number of observations.

Table 3 shows the summarized experimental data.

Analysis of variance and identification of significant factors

The results obtained from the analysis of variance (ANOVA) carried out with the S/N ratio are presented in the ANOVA table (Table 4).

Six main effects A, B, I, J, K, Q and two interactions $A \times B$ and $G \times M$ were found to be statistically significant from the analysis. The fact that $Q_1 Q_3$ was significant but $Q_1 Q_2$ was not indicated some differences in average S/N ratios from condition Q_1 to Q_3 , but no detectable difference in average S/N ratios from Q_1 to Q_2 .

Selecting the optimum combination

Response graphs (Fig. 5(a-f)) for the significant main effects and interactions helped to identify the following levels of these factors giving higher S/N ratios:

$$A = A_2, B = B_2, I = I_1, J = J_2, K = K_1, G = G_2, M = M_1, Q = Q_3$$

Thus, the optimum combination of significant factors was $A_2 B_2 G_2 I_1 J_2 K_1 M_1 Q_3$.

Prediction of performance at the optimum combination

The predicted S/N ratio at the optimum combination was obtained as

$$\hat{\eta}_{opt} = \overline{A_2 B_2} + \overline{G_2 M_1} + \bar{I}_1 + \bar{J}_2 + \bar{K}_1 + \bar{Q}_3 - 5\bar{T}$$

where \bar{X}_j denotes the average S/N ratio corresponding to level j of factor X, $\overline{X_j Y_k}$ denotes

Table 4. ANOVA table for S/N ratio

Source	df	SS	MS	F	S'	$\rho\%$
Idle	1	26.265	26.265	1.050	1.240	0.02
A	1	701.001	701.001	28.012*	675.976	9.55
B	1	526.501	526.501	21.039*	501.476	7.09
C	1	12.259	12.259	—	—	—
D ₁ D ₂	1	0.0006	0.0006	—	—	—
D ₁ D ₃	1	69.580	69.580	2.780	44.555	0.63
E	1	11.581	11.581	—	—	—
F	1	0.579	0.579	—	—	—
G ₁ G ₂	1	15.574	15.574	—	—	—
G ₂ G ₃	1	1.297	1.297	—	—	—
H	1	52.577	52.577	2.101	27.552	0.39
I	1	126.725	126.725	5.064*	101.700	1.44
J	1	298.574	298.574	11.931*	273.549	3.86
K	1	2604.326	2604.326	104.068*	2579.301	36.44
L	1	5.754	5.754	—	—	—
M	1	0.045	0.045	—	—	—
N	1	41.661	41.661	1.665	16.635	0.24
P	1	8.595	8.595	—	—	—
Q ₁ Q ₂	1	27.887	27.887	1.114	2.861	0.04
Q ₁ Q ₃	1	152.560	152.560	6.096*	127.535	1.80
A × B	1	119.240	119.240	4.765*	94.215	1.33
B × D	2	10.882	5.441	—	—	—
G × J	2	7.109	3.555	—	—	—
G × M	2	303.783	151.891	6.070*	253.732	3.58
H × L	1	16.095	16.095	—	—	—
e ₁	3	40.816	13.605	—	—	—
e ₂	64	1896.464	29.632	—	—	—
e (pooled)	81	2027.051	25.025	—	2377.406	33.59
Total:	95	7077.731	74.502	—	—	—

the average S/N ratio corresponding to level j of factor X and level k of factor Y and \bar{T} denotes the average of all the $32 \times 3 = 96$ S/N ratios. Thus

$$\begin{aligned}\hat{\eta}_{\text{opt}} &= 33.535 + 29.371 + 28.525 + 29.140 + 32.585 + 29.669 - 5 \times 27.376 \\ &= 45.945 \text{ (dB)}\end{aligned}$$

The predicted S/N ratio at the existing combination $[A_1 B_1 G_1 I_1 J_1 K_2 M_1 Q_1]$ was obtained as

$$\begin{aligned}\hat{\eta}_{\text{existing}} &= \overline{A_1 B_1} + \overline{G_1 M_1} + \bar{I}_1 + \bar{J}_1 + \bar{K}_2 + \bar{Q}_1 - 5\bar{T} \\ &= 23.446 + 27.426 + 28.525 + 25.613 + 22.168 + 26.104 - 5 \times 27.376 \\ &= 16.402 \text{ (dB)}\end{aligned}$$

Thus

$$\text{Expected gain} = 45.945 - 16.402 = 29.543 \text{ (dB)}$$

It may be noted that $\hat{\eta}_{\text{opt}} = 45.945$ gives $s_{\text{opt}} = 0.005$ whereas $\hat{\eta}_{\text{existing}} = 16.402$ gives $s_{\text{existing}} = 0.1517$.

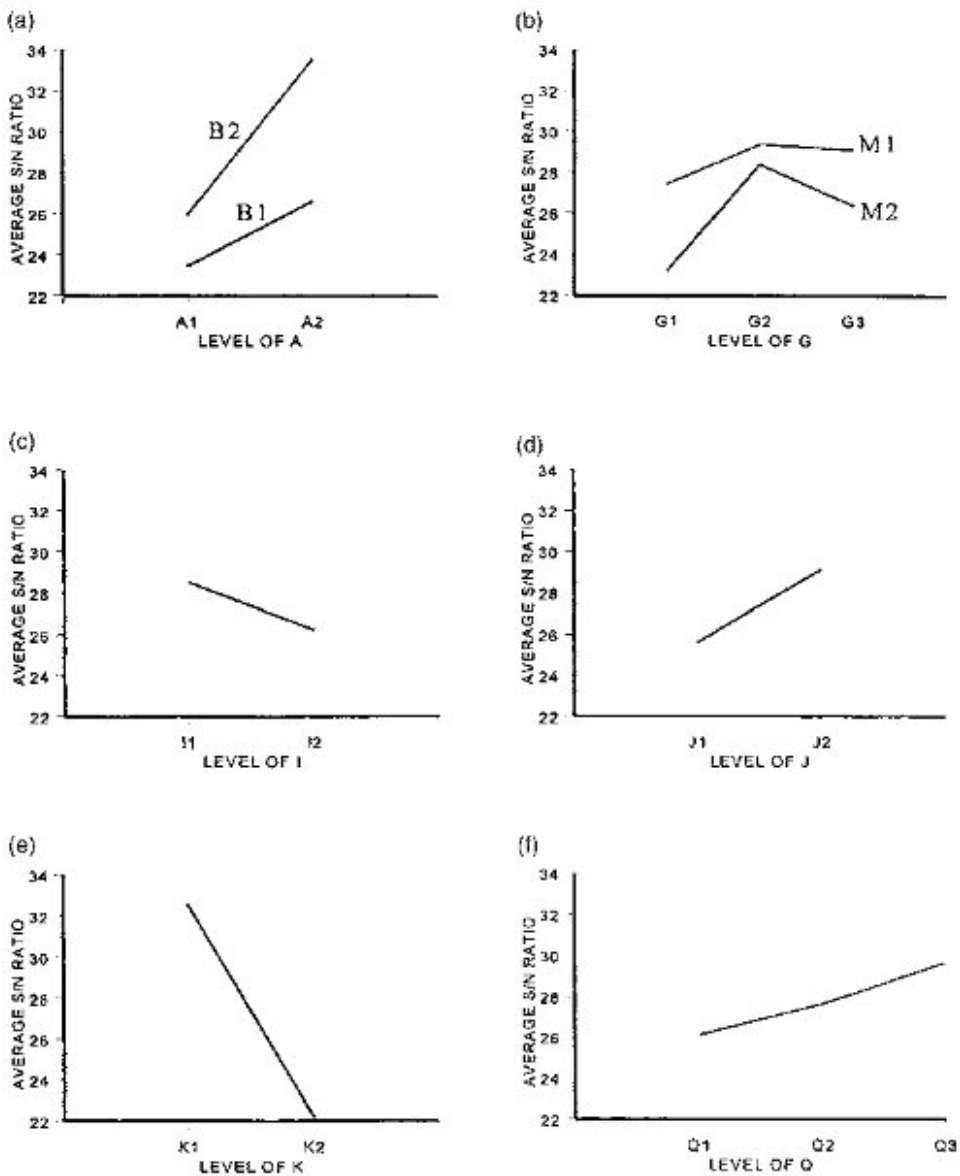


Figure 5. (a) Average response graph for $A \times B$. (b) Average response graph for $G \times M$. (c) Average response graph for I . (d) Average response graph for J . (e) Average response graph for K . (f) Average response graph for Q .

Results of trial runs and the improvement

Trial runs were conducted with the optimum combination derived in the previous section. The eight other insignificant factors were kept at the more practicable and economical levels as follows:

$$C = C_2 = 240, \quad D = D_1 = 0.3, \quad E = E_1 = 0.9, \quad F = F_2 = 0.5,$$

$$H = H_1 = 0.1, \quad L = L_2 = 8, \quad N = N_1 = 0.15, \quad P = P_1 = 0.15$$

Table 5. Result of trial runs

Time point	A			B			C		
	\bar{x}	s	% off spec	\bar{x}	s	% off spec	\bar{x}	s	% off spec
1	50.01	0.015	Nil	50.03	0.023	Nil	50.02	0.013	Nil
2	50.00	0.022	Nil	50.01	0.014	Nil	50.01	0.026	Nil
3	50.00	0.014	Nil	50.00	0.014	Nil	50.01	0.008	Nil
4	50.02	0.013	Nil	50.01	0.085	1	50.00	0.010	Nil

This combination was run for three shifts and weight measurements of 50 bags were collected at an interval of 2 hours in each shift. The target weight was set at 50.0 kg. Table 5 presents the summary of the results.

It can be seen clearly from Table 5 that the maximum and minimum standard deviations among the 12 sets of observations were 0.085 and 0.008, respectively, and only one non-conformance was observed out of the 600 sampled bags. This was a remarkable improvement over the existing situation.

One more important aspect, of course, had to be seen. Logically, it was clear that the recommended levels of some of the factors, parallel to reducing variation, would reduce the production speed. For example, in the optimum combination, the values of the sample frequency and sample number were 10 and 5, respectively, as compared to the existing levels of 20 and 3. This meant that to improve accuracy significantly, the machine would have to check five out of 10 bags, whereas earlier three out of 20 were checked. Although all this checking was automatic, the impact of this change on bagging rate had to be seen and agreed upon by the management.

It was found that the new combination resulted in an average bagging rate of 11.7 bags per minute as compared to 12.5 obtained with the existing combination. This was equivalent to the reduction of production rate by 1152 bags per day, which was considered to be acceptable by the management from the point of view of the large volume of production (nearly 20 000 bags per day) and the massive reduction of variation in packed bag weights.

The recommended levels of the significant control factors were implemented promptly in the organization.

Concluding remarks

This study is an example of designing and conducting complex plant-level experiments involving several factors with the objective of improving upon a control scheme. The remarkable improvements achieved can be seen in Table 6, which shows the comparative quality status before and after the study. Some of the factors that contributed to the success

Table 6. Comparison of results before and after study

Sample size/statistic	Before study	After study
Number of observations (n)	280	600
Average weight	50.05	50.01
Standard deviation	0.1205	0.031
Below lower spec	14%	Nil
Above upper spec	17%	0.17%

of this experiment and are also likely to help others to conduct similar successful experiments are discussed below.

The support and involvement of the top management

Since the current study was taken up on the basis of the top management's concern regarding weight variation, there was no dearth of support, thereby ensuring adequate resources and smooth execution at every stage.

Unambiguous and well-defined objective

The sole objective of the experiment was to increase the efficiency of the existing control system by selecting an optimum combination of control parameters which would reduce the variation in packed bag weights.

Proper selection of factors and levels

It is evident that lack of adequate knowledge about the control scheme is likely to result in improper selection of factors and levels and consequently result in all the efforts ending in smoke. In this study, several days were spent in plain discussion with the process engineers, operators and supervisors regarding the functioning of the machine. The manual describing each and every aspect of the operation was read thoroughly. The supplier was even contacted whenever some points were not satisfactorily understood. A few small pilot studies were also conducted prior to selection of factors and levels.

Proper selection of response

The considerations from which the S/N ratio $-10 \log V_c$ was chosen as the response has already been discussed.

Adequate time for each trial and replication of the basic experiment

Here, as discussed earlier, each experimental combination was conducted until 60 bags were sampled and weighed. Normally it is extremely difficult to conduct three replications of an L_{32} experiment, i.e. 96 experimental runs in any kind of industry. This was possible here for two reasons: (a) very high production speed; and (b) availability of response data in the form of computer printouts. No physical measurement was involved in the experiment.

Conducting the experiment in controlled conditions

The same set of conditions was maintained during each trial so that the comparisons between factor levels were proper and not distorted by any unforeseen disturbances.

Generation of reliable data

The reliability of data was easy to check as all the data were available in the form of computer printouts coming out from the machine directly. In addition to the 60 individual bag weights, the printout for each trial also contained the values of all the control factors for that trial so

that it was possible to cross check whether the proper combination had been run. In fact, a few trials had to be repeated on the basis of this scrutiny.

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Appendix: The overall functioning of the packing machine and the weight adjustment mechanism—a brief description

The two parameters that determine the target weight are nominal weight and overfill value. The target weight is the sum of the set nominal weight and the overfill value.

The material flows into the bags in two stages—the first stage is the main feed when the material flows in a thick stream and fills the bag fast, the second stage is the dribble feed during which the urea trickles down to ensure fine adjustment of weight. The dribble feed quantity and the dribble feed time both can be pre-set. The period of dribble feed must be long enough to ensure settling of the weighpan after the main feed is cut off, but must not be so long as to slow down the overall machine cycle time.

The main feed cut-off point is determined by three things—the target weight, the dribble feed quantity and a parameter called the in-flight material compensation. In fact, main feed cut off point = target weight - (dribble feed quantity + in-flight material compensation). The in-flight material compensation is a very important parameter, and although pre-set, can be automatically corrected by the machine depending on the weight error.

The control mechanism of the machine depends on three important parameters—the sample frequency, sample number and the auto compensation proportional constant. The sample frequency and the sample number decide at what interval the sample weight checking will be done and how many bags will be checked in a cycle. On the basis of the checked weights, the average weight error is calculated by subtracting the target weight from the average actual weight. This average weight error is multiplied by the auto compensation proportional constant to determine how much correction should be given. This correction is given to the in-flight material compensation value.

Underweight and overweight tolerances are also parameters that can be specified. Whenever the weight of a sampled bag falls beyond either of these two limits, a warning signal is given and the bag has to be removed manually. In case the actual weights of all the sampled bags in a cycle are beyond these limits, then after giving the correction the next filled bag will be sampled. If this falls within the tolerance then from the next bag onwards the machine enters in unsample mode; otherwise auto zeroing takes place and again the same number of bags (as specified by the sample number) is taken for further corrections.

It is understood that the less the checking of filled bag weights, the more the weigher throughput. The user may select any proportion of sampling, from every bag being checked to one bag checked out of 50. The latter achieves the highest throughput, but relies on excellent product consistency.

There is a large number of timers which determine the time of various activities. For example, the sample frequency timer determines up to how much stoppage time of the

packer scale (due to power failure or any other reason) will be allowed before weight samples will restart. This is necessary because if the machine remains stopped for a long period, weight variation may be large due to higher hopper level or vacuum created or any other reason.

The weight adjustment mechanism of the machine is illustrated here with an example with some arbitrary values of the related parameters.

Suppose,

Nominal weight = 50 kg, overfill = 0.05 kg and hence target weight = 50.05 kg

Sample frequency = 20, Sample number = 4, Auto proportional correction constant = 0.5

Dribble feed quantity = 12 kg, In-flight material compensation = 3.5 kg

Overweight tolerance = 0.1 kg, Underweight tolerance = 0.1 kg

Thus, the main feed will be cut off at $50.05 - (12 + 3.5) = 34.45$ kg.

The first four out of 20 filled bags will be sampled. Let the weights of the sampled bags be 50.10, 50.05, 50.10, 50.10 (all in kilograms). Then the average weight error = $50.0875 - 50.05 = 0.0375$ kg.

Thus the amount of correction to be given to the in-flight material compensation = $0.0375 \times 0.5 = 0.01875$ kg. Consequently, the new value of in-flight material compensation becomes $3.5 + 0.01875 = 3.520$ kg (approximately), i.e. a correction of + 20 grams is given.