A Procedure for Robust Evolutionary Operations

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Abstract

Evolutionary operation (EVOP) is a continuous improvement system which explores a region of process operating conditions by deliberately creating some systematic changes to the process variable levels without jeopardizing the product. It is aimed at securing a satisfactory operating condition in full-scale manufacturing processes, which is generally different from that obtained in laboratory or pilot plant experiments. Information on how to improve the process is generated from a simple experimental design. Traditional EVOP procedures are established on the assumption that the variance of the response variable should be small and stable in the region of the process operation. However, it is often the case that process noises have an influence on the stability of the process. This process instability is due to many factors such as raw materials, ambient temperature, and equipment wear. Therefore, process variables should be optimized continuously not only to meet the target value but also to keep the variance of the response variables as low as possible. We propose a scheme to achieve robust process improvement. As a process performance measure, we adopted the mean square error (MSE) of the replicate response values on a specific operating condition, and used the Kruskal-Wallis test to identify significant differences between the process operating conditions.

1. Introduction

Response surface methodology is often used by engineers and scientists to determine the values of the input variables for optimizing response variables. Response surface methodology can be used normally in laboratory or pilot plant experiments [Myers and Montgomery, 1995].

When the objective is to optimize a full-scale production process, evolutionary operation (EVOP) can be an alternative to response surface methodology.

EVOP is a step-by-step approach to optimize on-line full-scale production processes by making small changes to the levels of process variables without jeopardizing the quality of the items produced. Although the changes may be very small, EVOP is able to find statistically significant differences in the response variable by taking advantage of large-scale production quantities. EVOP is applicable to continuous or large batch processes such as steel making, polymer production, continuous casting, paper making, and many others. EVOP is a part of routine plant operation, carried out by manufacturing or operating personnel with minimum involvement of the engineering or development staff.

Traditional EVOP procedures have been established on the assumption that the variance of the response variable should be small and stable in the region of process operation. However, the stability of the process is often disrupted by noise factors. Typical noise factors are raw materials, ambient temperature, and equipment wear. As time passes, the optimum conditions in a production process can drift due to such noise factors. Therefore, process variables should be optimized continuously not only to achieve the target mean value, but to maintain the variance of the response variable to as low a level as possible. In this paper we propose an EVOP scheme to achieve robust process improvement. As a process performance measure, we adopt the MSE (mean square error) of the replicate response values for a specific operating condition. This measure is adopted for dual response surface optimization [Lin and Tu, 1995]. This approach is a general method for examining both the mean and variance of the response variable. To determine whether there were significant differences among the process operating conditions, the non-parametric Kruskal-Wallis test was used.

2. Review of Traditional EVOP

Traditional EVOP systematically introduces small changes in the levels of the process variables under consideration, using 2^2 or 2^3 factorial design points and a center point.

Figure 1 shows a 2^2 factorial design with a center point as used for the traditional EVOP. Center point represents the current operating condition of the production process.

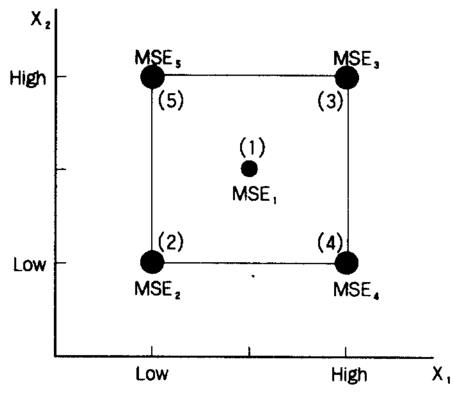


Fig. 1 Design points for 2^2 factorial experiments

When one observation has been taken at each operating condition, one cycle is completed. Then the main effects and interactions of the process variables are computed. Since one cycle is not sufficient to detect any significant effect, more cycles are taken until a significant effect on the response emerges. At this point, one may decide to move the operating conditions in the direction of the improved response. When an improved operating condition is detected, one phase is said to have been completed.

An illustrative EVOP procedure is shown in Figure 2.

3. Procedure for Achieving Process Robustness

Since production processes are affected by uncontrollable noise factors, there is a need to find more stable operating conditions. In this paper, we propose a scheme to achieve on-line process robustness. There are two

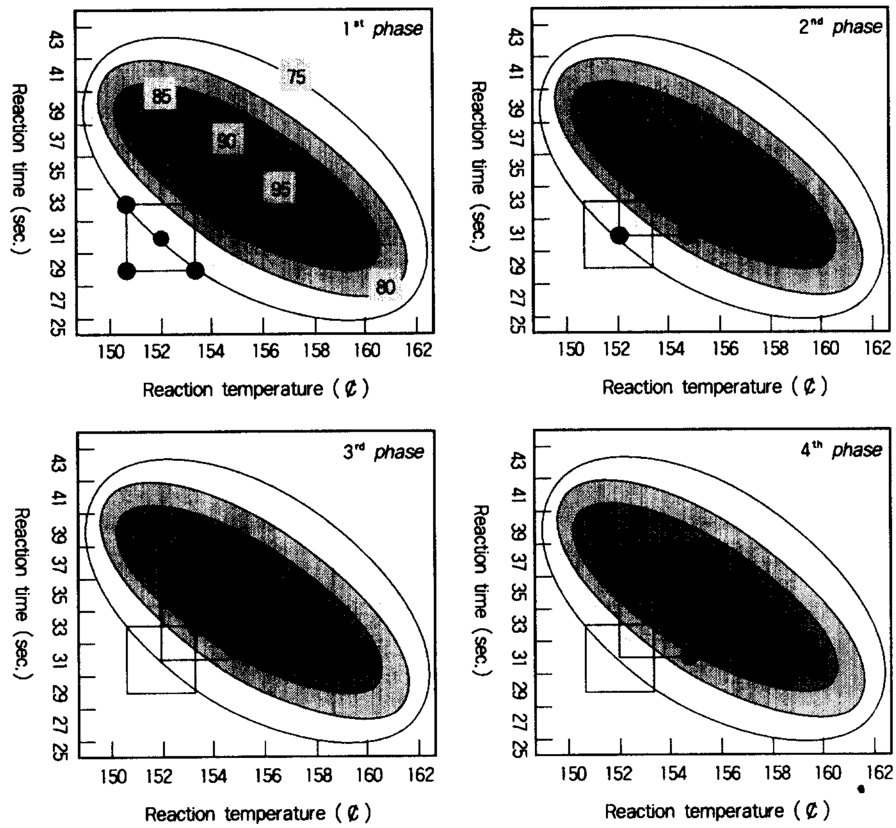


Fig. 2 Summary of EVOP procedure using 2^2 factorial designs major differences between our approach and the traditional one. Firstly, we adopted the mean square error (MSE) as the process performance criterion to achieve process robustness, which can be easily implemented.

Since the MSE is an aggregate measure of mean and variance of the response values, the MSE value can be used as a measure of process robustness. Secondly, since MSE values are not normally distributed, we used the distribution-free Kruskal-Wallis test to determine whether there was a significant difference among operating conditions in terms of the MSE values. Since we need to have replicates on the response variable to obtain an MSE value at each operating condition, we defined a cycle to be complete when a set of replicate MSE values were obtained at each operating condition. Since one cycle is not always sufficient to detect significant differences among different operating conditions, more cycles may be needed to achieve the necessary level of statistical significance. When an improved operating condition is identified, one phase is said to have been completed.

We focus on target-the-best case to illustrate the basic idea and discuss other cases later in this section. To demonstrate the procedure adopted, we consider a standard form of two process variables with 2^2 factorial points and a center point as shown in Figure 1. We will run experiments on these five operating conditions. The run order is randomly chosen. Let the target value of the quality characteristic be t. After running each cycle,

① We calculate both the response mean $\overline{y}_{ij}$ and the response variance s^2_{ij} for the i^{th} operating condition of the j^{th} cycle.

② MSE_{ij} values are obtained from

$$MSE_{ij} = (\overline{y}_{ij} - t)^2 + s^2_{ij} \quad (1)$$

③ The Kruskal-Wallis test is performed to determine whether there is a significant difference between the operating conditions. If an improved condition is detected, one phase is said to have been completed.

The process is then moved in the direction of the improvement by setting the improved condition as the center point for the next phase. This procedure is iterated until a phase is reached where the center point is superior or equal to the other operating conditions in terms of the MSE. When this phase is reached, the exploring is concluded and the process is accepted to be at an optimum at the current center point condition. When the optimum is unsatisfactory, we can drop some of the current process variable(s) and introduce new variable(s) and start a new robust EVOP procedure.

During exploration, if two or more conditions are found to be better than others, decisions upon the direction of exploration can be made by taking into consideration the economic aspects and the ease of operation, after consultation with the people concerned.

The aforementioned approach can be easily applied to the smaller-the-better (STB) and the larger-the-better (LTB) cases. We can let $t = 0$ in equation (1), for the STB case. For the LTB case we can let $z_{ij} = 1 / y_{ij}$ as the substituted response variable value, leading to the STB case for the z response.

4. An Example

We illustrate the approach developed in this paper with an example [Box and Draper, 1987]. The experiment was conducted to optimize a certain quality characteristic of a printing process which is related to the ability to apply coloring inks, with respect to three process variables, x_1(speed), x_2(pressure), and x_3(distance).

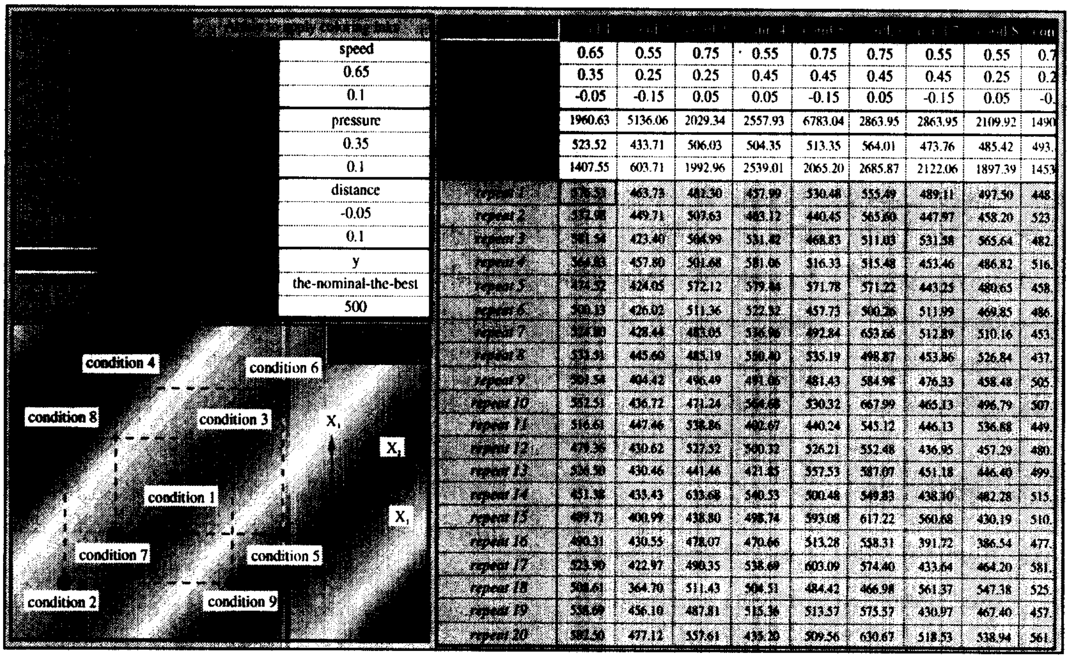
The target value of the quality characteristic is 500. The experiment is a 3^3 factorial design with 3 replicates at each operating condition. Response surfaces for the mean and for the standard deviation are based on the models fitted by 'Vining and Myers (1990)':

$$\hat{\omega}_\mu = 327.6 + 177.0x_1 + 109.4x_2 + 131.5x_3 + 32.0x_1^2 - 22.4x_2^2 - 29.1x_3^2 \quad (2)$$

$$\hat{\omega}_\sigma = 34.9 + 11.5x_1 + 15.3x_2 + 29.2x_3 + 4.2x_1^2 - 1.3x_2^2 - 16.8x_3^2 + 7.7x_1x_2 + 5.1x_1x_3 + 14.1x_2x_3 \quad (3)$$

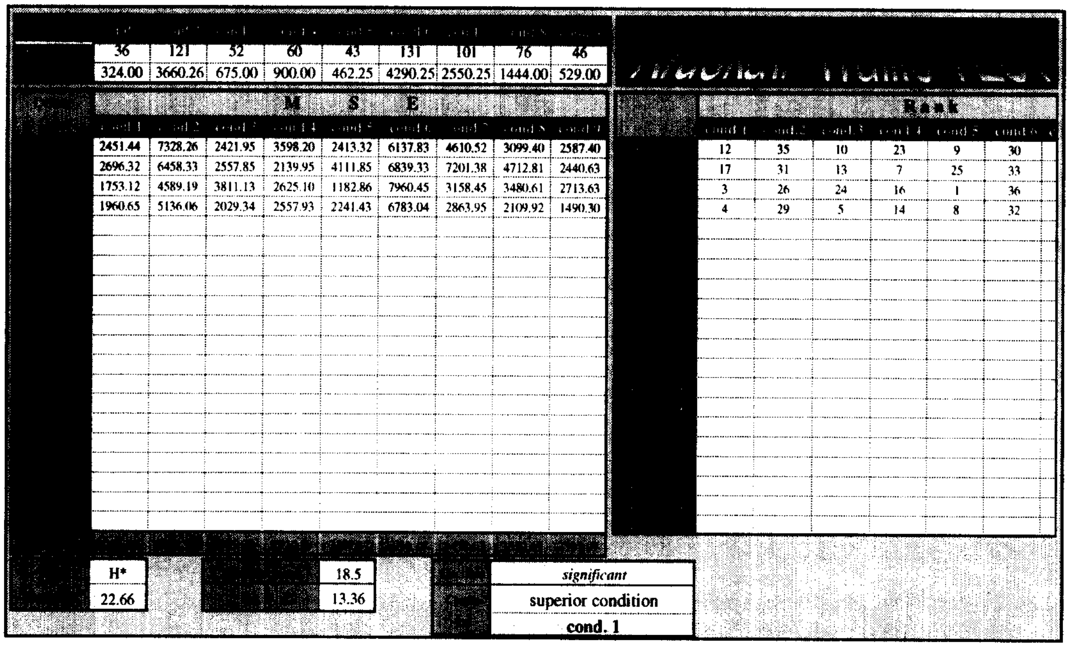
At each cycle, 20 data simulations are created at each operating condition based on models (2) and (3). From this simulation data, the mean $\overline{y}_{ij}$, the variance s_{ij}^2 and the MSE_{ij} are calculated at each operating condition. Figure 3 shows the operating conditions using a 2^3 factorial design, 20 simulated data sets, mean, variance, and the MSE value, at the 4^{th} cycle in the 10^{th} phase.

Figure 4 shows the tables for the Kruskal-Wallis test in the 10^{th} phase. Since a single cycle was insufficient to find significant differences between the operating conditions in a certain phase, we simulated four cycles at each operating condition and represented the average MSE values by $\overline{MSE}$ at each operating condition. In Figure 5 it can be seen that the best condition in the first phase was $(x_1, x_2, x_3) = (0.10, 0.10, 0.10)$, which produces an average MSE value 17956.40. Next (0.10, 0.10, 0.10) is made the center point for the second phase. This procedure was then iterated until no further improvement in $\overline{MSE}$ was obtained, meaning that we have minimum $\overline{MSE}$ value at the center point. As shown in Figure 5, the optimal operating condition is $(x_1, x_2, x_3)=(0.65, 0.35, -0.05)$ which was the center point in the 10^{th} phase and has a smaller $\overline{MSE}$ value than any other peripheral operating condition.



	0.65	0.55	0.75	0.55	0.75	0.75	0.55	0.55	0.7
	0.35	0.25	0.25	0.45	0.45	0.45	0.45	0.25	0.2
	-0.05	-0.15	0.05	0.05	-0.15	0.05	-0.15	0.05	-0.
	1960.63	5136.06	2029.34	2557.93	6783.04	2863.95	2863.95	2109.92	1490
	523.52	433.71	506.03	504.35	513.35	564.01	473.76	485.42	493.
	1407.55	603.71	1992.96	2539.01	2065.20	2685.87	2122.06	1897.39	1453
repeat 1	576.53	463.73	481.30	457.99	530.48	555.49	489.11	497.50	448.
repeat 2	532.98	449.71	507.63	483.12	440.45	565.60	447.97	458.20	523.
repeat 3	581.54	423.40	504.99	531.82	468.83	511.03	531.38	565.64	482.
repeat 4	564.83	457.80	501.68	581.06	516.33	515.48	453.46	486.82	516.
repeat 5	474.52	424.05	572.12	579.84	571.78	571.22	443.25	480.65	458.
repeat 6	500.13	426.02	511.36	522.82	457.73	500.26	511.99	469.85	486.
repeat 7	524.80	428.44	483.05	536.96	492.84	653.66	512.89	510.16	453.
repeat 8	533.91	445.60	485.19	580.40	535.19	498.87	453.86	526.84	437.
repeat 9	501.54	404.42	496.49	491.06	481.43	584.98	476.33	458.48	505.
repeat 10	552.51	436.72	471.24	564.68	530.32	667.99	465.13	496.79	507.
repeat 11	516.61	447.46	538.86	402.67	440.24	545.12	446.13	536.88	449.
repeat 12	479.36	430.62	527.52	500.32	526.21	552.48	436.95	457.29	480.
repeat 13	534.30	430.46	441.46	421.85	557.53	587.07	451.18	446.40	499.
repeat 14	451.38	433.43	633.68	540.53	500.48	549.83	438.10	482.28	515.
repeat 15	499.71	400.99	438.80	498.74	593.08	617.22	560.68	430.19	510.
repeat 16	490.31	430.55	478.07	470.66	513.28	558.31	391.72	386.54	477.
repeat 17	523.90	422.97	490.35	538.69	603.09	574.40	433.64	464.20	581.
repeat 18	508.61	364.70	511.43	504.51	484.42	466.98	561.37	547.38	525.
repeat 19	538.69	456.10	487.81	515.36	513.57	575.37	430.97	467.40	457.
repeat 20	582.50	477.12	557.61	435.20	509.56	630.67	518.53	538.94	561.

Fig. 3 Operating conditions and simulation data for 2^{-3} factorial experiments



36	121	52	60	43	131	101	76	46
324.00	3660.26	675.00	900.00	462.25	4290.25	2550.25	1444.00	529.00

M S E								
2451.44	7328.26	2421.95	3598.20	2413.32	6137.83	4610.52	3099.40	2587.40
2696.32	6458.33	2557.85	2139.95	4111.85	6839.33	7201.38	4712.81	2440.63
1753.12	4589.19	3811.13	2625.10	1182.86	7960.45	3158.45	3480.61	2713.63
1960.65	5136.06	2029.34	2557.93	2241.43	6783.04	2863.95	2109.92	1490.30

Rank					
12	35	10	23	9	30
17	31	13	7	25	33
3	26	24	16	1	36
4	29	5	14	8	32

H*		
22.66	18.5	*significant*
	13.36	superior condition
		cond. 1

Fig. 4 Kruskal - Wallis test in the 10^{th} phase

1 phase	cond.1	cond.2	cond.3	cond.4	cond.5	cond.6	cond.7	cond.8	cond.9
speed	0	-0.1	0.1	-0.1	0.1	0.1	-0.1	-0.1	0.1
pressure	0	-0.1	-0.1	0.1	0.1	0.1	0.1	-0.1	-0.1
distance	0	-0.1	0.1	0.1	-0.1	0.1	-0.1	0.1	-0.1
2 phase	cond.1	cond.2	cond.3	cond.4	cond.5	cond.6	cond.7	cond.8	cond.9
speed	0.1	0	0.2	0	0.2	0.2	0	0	0.2
pressure	0.1	0	0	0.2	0.2	0.2	0.2	0	0
distance	0.1	0	0.2	0.2	0	0.2	0	0.2	0
3 phase	cond.1	cond.2	cond.3	cond.4	cond.5	cond.6	cond.7	cond.8	cond.9
speed	0.2	0.1	0.3	0.1	0.3	0.3	0.1	0.1	0.3
pressure	0.2	0.1	0.1	0.3	0.3	0.3	0.3	0.1	0.1
distance	0.2	0.1	0.3	0.3	0.1	0.3	0.1	0.3	0.1
4 phase	cond.1	cond.2	cond.3	cond.4	cond.5	cond.6	cond.7	cond.8	cond.9
speed	0.3	0.2	0.4	0.2	0.4	0.4	0.2	0.2	0.4
pressure	0.3	0.2	0.2	0.4	0.4	0.4	0.4	0.2	0.2
distance	0.3	0.2	0.4	0.2	0..2	0.4	0.2	0.4	0.2
5 phase	cond.1	cond.2	cond.3	cond.4	cond.5	cond.6	cond.7	cond.8	cond.9
speed	0.4	0.3	0.5	0.3	0.5	0.5	0.5	0.3	0.5
pressure	0.4	0.3	0.3	0.5	0.5	0.5	0.5	0.3	0.3
distance	0.2	0.1	0.5	0.3	0.1	0.3	0.1	0.3	0.1
6 phase	cond.1	cond.2	cond.3	cond.4	cond.5	cond.6	cond.7	cond.8	cond.9
speed	0.45	0.35	0.35	0.35	0.55	0.55	0.35	0.35	0.55
pressure	0.35	0.25	0.25	0.45	0.45	0.45	0.45	0.25	0.25
distance	0.15	0.05	0.25	0.25	0.05	0.25	0.05	0.25	0.05
7 phase	cond.1	cond.2	cond.3	cond.4	cond.5	cond.6	cond.7	cond.8	cond.9
speed	0.55	0.45	0.65	0.45	0.65	0.65	0.45	0.45	0.65
pressure	0.25	0.15	0.15	0.35	0.35	0.35	0.35	0.15	0.15
distance	0.25	0.15	0.35	0.35	0.15	0.35	0.15	0.35	0.15
8 phase	cond.1	cond.2	cond.3	cond.4	cond.5	cond.6	cond.7	cond.8	cond.9
speed	0.65	0.55	0.75	0.55	0.75	0.75	0.55	0.55	0.75
pressure	0.15	0.05	0.05	0.25	0.25	0.25	0.25	0.05	0.05
distance	0.15	0.05	0.25	0.25	0.05	0.25	0.05	0.25	0.05
9 phase	cond.1	cond.2	cond.3	cond.4	cond.5	cond.6	cond.7	cond.8	cond.9
speed	0.55	0.45	0.65	0.45	0.65	0.65	0.45	0.45	0.65
pressure	0.25	0.15	0.15	0.35	0.35	0.35	0.35	0.15	0.15
distance	0.05	-0.05	0.15	0.15	-0.05	0.15	-0.05	0.15	-0.05
10 phase	cond.1	cond.2	cond.3	cond.4	cond.5	cond.6	cond.7	cond.8	cond.9
speed	0.65	0.55	0.75	0.55	0.75	0.75	0.55	0.55	0.75
pressure	0.35	0.25	0.25	0.45	0.45	0.45	0.45	0.25	0.25
distance	-0.05	-0.15	0.05	0.05	-0.15	0.05	-0.15	0.05	-0.15

Fig. 5 summary of 10 phases with the average *MSE* values

5. Concluding Remarks

To successfully implement the robust EVOP procedure developed in this paper, we suggest three considerations. Firstly, in a certain phase, when sufficient cycles have been run (say 4 to 8) and no improved conditions emerge, try to replace one or two process variables with new variables, and then iterate the procedure. Secondly, when the result of a cycle is significantly different from the previous one at the same operating condition, stop the exploration and investigate whether there is time effect. Finally, we should reemphasize that the experimentation plan should be carefully worked out to avoid jeopardizing the product or the production schedule.

Acknowledgment

This study was supported by the Development Fund Foundation of Gyeongsang National University, KOREA.

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