

# Overcoming Process Improvement Obstacles: A JMP / EVOP case study

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**ABSTRACT**

Design of Experiments (DOE) is a proven process improvement technique. However, process improvement teams can encounter insurmountable obstacles to running designed experiments with examples ranging from equipment restrictions, around-the-clock production and financial barriers to fear-of-the-unknown at the management level. In these cases, experimenters need a more subtle approach to process improvement.

One option is Evolutionary Operation or EVOP (pronounced “EVE-OP”), a methodology originally developed by George E. P. Box<sup>1</sup> during his work at Imperial Chemical Industries in the UK. In 1969, Mr. Box co-authored a seminal book on the subject with Norman Draper<sup>2</sup>.

EVOP’s basic philosophy is that:

“...a process should be operated so as to produce not only a product but also *information on how to improve the product*”.<sup>2</sup>

**CASE STUDY PURPOSE**

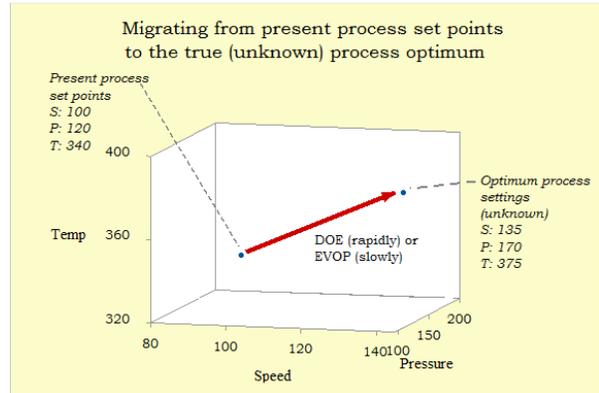
The main intention of this paper is to help others use EVOP to overcome process improvement obstacles. By doing so, the authors hope to positively impact colleagues, acquaintances, Quality Engineers, Process Engineers, Manufacturing Engineers and other process improvement enthusiasts.

**EVOP OVERVIEW**

To attain process improvement information as suggested by Box & Draper, EVOP practitioners plan and make small, simultaneous changes to process settings

during periods of normal production. Some example process settings include temperature, line speed, % additives, tooling and voltage. Product data is accumulated for each combination of process settings and analyzed to gain valuable process insight. This process is then repeated many times either by line workers and supervisors as a normal production routine or, as shown in this case study, by a diverse team working in support of manufacturing operations.

Figure 1 and Table 1 compare the DOE and EVOP approaches to process improvement.



**Figure 1: process migration**

*Table 1, DOE vs EVOP*

DOE	EVOP
Breakthrough	Evolutionary
Off-line	During production
Scrap desired	No scrap allowed
Wide factor ranges	Narrow factor ranges*
Fast data collection	Slow data collection
Iterative by choice	Iterative by design
Collaboration is useful	Collaboration is critical**

*\*EVOP ranges must be small enough to avoid scrap and rework, yet large enough to yield information about process behavior. While experience indicates this balance can be difficult to achieve, engineering and process knowledge often provide useful guidance.*

\*\* Experience indicates that the #1 key to EVOP success is a collaborative approach and advance buy-in from Front Line Workers, Supervisors, Maintenance staff and others. A useful tip for EVOP practitioners - take personal responsibility before the work begins for any process disruptions to assure others don't feel threatened.

### AN ALTERNATIVE TO CONSIDER

Many EVOP practitioners use a factorial approach<sup>3</sup> to inch the process toward its optimum settings and this approach has worked well for many decades. This paper presents the reader with an alternate to consider - *the use of quadratic, I-Optimal designs generated by JMP's Custom Designer*. The advantage of this approach is that quadratic models reveal more process nuances than an interaction model with only a bit more work. The disadvantage is that the quadratic approach takes more patience.

*Nothing valuable is lost by taking time.*  
Abraham Lincoln

One situation where EVOP is often appropriate is where operators routinely adjust process settings to "get good product". In this case, EVOP can give structure to these adjustments and thus draw out the information needed to eliminate process tinkering.

### OTHER APPLICATIONS FOR EVOP

EVOP might prove useful for the following if DOE is not an option.

- ✓ metal die casting
- ✓ metal heat treating
- ✓ food manufacturing
- ✓ plastics extrusion, injection molding and thermoforming
- ✓ non-woven fabric production

### DEATH, TAXES & ENTROPY

This case study is about the improvement of a 40+ year old, well-maintained production line that had been retrofitted with digital controls. Unfortunately, operator turnover and a history of periodic moth-balling meant that much past process knowledge was lost. By decree, process settings had remained constant for

many years but as expected frictional wear, evolving heat transfer behavior, corrosion and other entropic inevitabilities resulted in continuously diminishing process satisfaction. In short, the process was burning money.

Then, the company was sold and the new owners, understandably, wanted better results, higher profits and fewer customer complaints and they wanted it without a single capital request. DOE was considered, but an around-the-clock, 7 day/week production schedule prevented its use. EVOP was deemed to be the best alternative.

### EVOP TEAM

A team of experienced Line Operators, an R&D Engineer and a Quality Engineer jointly managed the EVOP work described in this case study and other people were called in as needed. Hereinafter, this group is referred to collectively as *the team*. Nobody on the team had EVOP experience. However, both engineers had read the Box & Draper book.

### STEP 1 – STOP, LOOK & LISTEN

The best first step to process improvement work (DOE, EVOP or otherwise) is to seek the advice and cooperation of process operators and maintenance staff as they almost always provide vital process insight. Skip this step at your own peril.



Figure 2, Front Line Workers – the key to process improvement<sup>4</sup>

In addition, many process improvement efforts fail because the goals are not carefully defined

in advance. A useful document titled *Checklist for Asking the Right Question*<sup>5</sup> provided a lean, simple solution and a superb forum for group discussion. Despite some pressure to “get going”, the team took time to develop the following goal statement.

*Using a careful evolutionary approach, maximum operator involvement, sound engineering judgement, validated data and the JMP Custom Design generator, the primary goals are:*

- ① maximize learning
- ② move response R1 from 220 to 325
- ③ no additional scrap

The target of 325 was not arbitrarily determined, rather it was based on operator input, engineering judgement and best-in-class benchmarking.

**STEP 2 – CHOOSE A STRATEGY**

The team reviewed the history of the process noting that much knowledge had been lost over time and that the same process settings had been used for many years. They further noted the low output measurement costs.

Within this context, the team decided to execute a series of I-Optimal quadratic designs, rather than take the textbook interaction approach. The rationale was that I-Optimal designs are well known to be efficient in terms of the process knowledge gained for the amount of work done.

**STEP 3 - CREATE A PLAN**

Like DOE, EVOP requires careful planning that starts with an understanding of the process. Based on input from production, maintenance and engineering personnel, five process factors were identified for inclusion as shown in Figure 3.

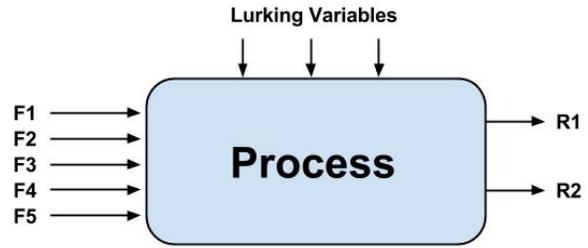


Figure 3: Process Block Diagram

In addition to the 5 factors, the process diagram shows the usual lurking variable and two responses of interest, R1 and R2. Only R1 is covered in this case study.

Table 2 shows available factor ranges, the present setting for each factor and the test range for the first quadratic plan. Note the ranges for F1 to F4 are symmetrical around the present setting. However, engineering knowledge suggested the safest approach to F5 was to test a lower setting, but not a higher setting.

Table 2, process factors

	RANGE	BASELINE SETTINGS	RANGE, EVOP-1
F1	100-200	120	118-122
F2	200-350	325	320-330
F3	1000-2000	1850	1830-1870
F4	10-25	22	21-23
F5	1-7	2	1-2

*EVOP plan design*

The JMP Custom Designer was used throughout the study. Figure 4 shows the screen used to create the work plan. The red rectangle emphasizes the narrow factor ranges.

Critically, the Custom Designer allows the user to determine and then specify the number of replicate runs desired for estimation of response variation. The value of this Custom Designer feature cannot be overstated.

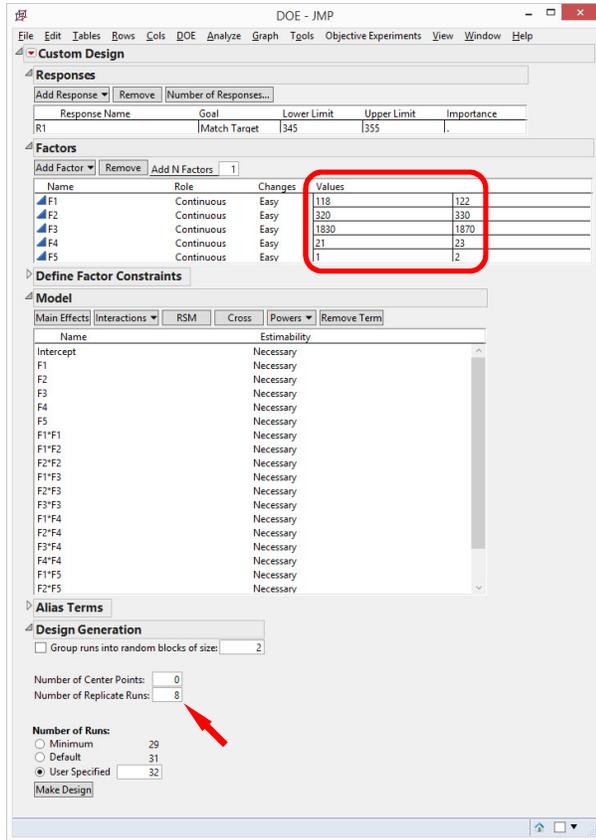


Figure 4: Creating EVOP quadratic plan #1 (EVOP-1)

Figure 5 is the first phase work plan. Note that factor levels change simultaneously from one run to the next. Clearly, EVOP is not one-factor-at-a-time experimentation!

	F1	F2	F3	F4	F5	R1
1	120.2	325	1848	22.9	2	•
2	120	325	1830	22	2	•
3	118	330	1870	23	1	•
4	120.2	324.5	1870	21	1.65	•
5	122	330	1870	21.8	1	•
6	118	330	1866	21.1	2	•
7	121	320.5	1862	23	1	•
8	118	320	1870	21	1	•
9	122	324.5	1850	21	1.4	•
10	122	330	1870	23	2	•
11	122	320	1864	21.8	2	•
12	118	325	1870	22.1	1.5	•
13	120.2	330	1846	22.3	1.5	•
14	118	324.5	1850	22	1.35	•
15	122	328	1830	23	1	•
16	122	324.5	1850	21	1.4	•

Figure 5: part of the EVOP-1 work plan

The team saw real value in the wide variety of settings for each factor. Table 3 provides a factorial-vs-quadratic plan comparison.

Table 3, factor setting granularity

X	FACTORIAL	QUADRATIC
F2	1830, 1870	1830, 1838, 1846, 1848, 1850, 1862, 1864, 1866, 1870
F5	1, 2	1, 1.25, 1.35, 1.4, 1.5, 1.65, 1.9, 2

### STEP 4: VALIDATE MEASUREMENTS

The team knew that measurement noise was a given so they resisted pressure to start the EVOP plan immediately and instead ran a measurement system analysis (MSA). JMP's EMP measurement systems analysis method<sup>6</sup> provides copious graphical and tabular insight as shown in Figures 6 to 10.

### Initial MSA results for Operator A, B and C

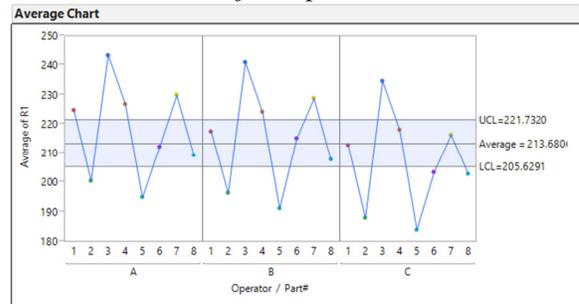


Figure 6: Average chart

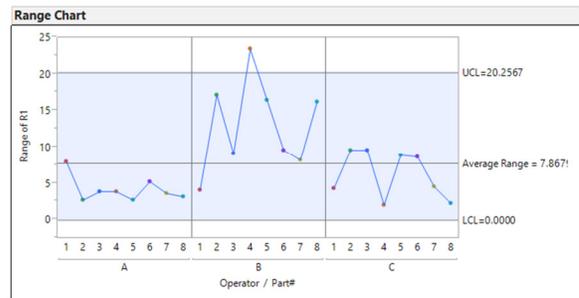


Figure 7: Range chart

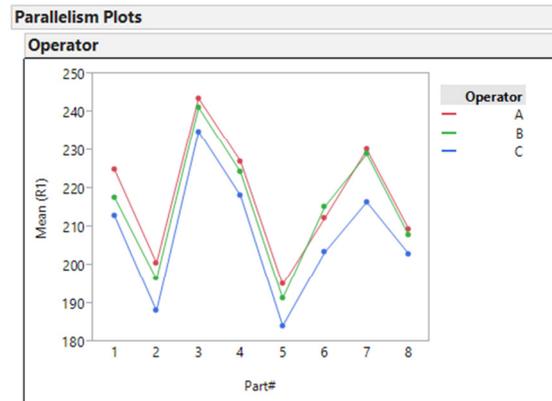


Figure 8: Parallelism plot

EMP Results		
EMP Test	Results	Description
Test-Retest Error	4.6485	Within Error
Degrees of Freedom	43.81	Amount of information used to estimate within error
Probable Error	3.1354	Median error for a single measurement
Intraclass Correlation (no bias)	0.9283	Proportion of variation attributed to part variation without including bias factors
Intraclass Correlation (with bias)	0.85	Proportion of variation attributed to part variation with bias factors
Bias Impact	0.0782	Amount by which the bias factors reduce the intraclass correlation
<b>System Classification</b>		
Current (with bias)	First Class	
Potential (no bias)	First Class	

Figure 9: EMP results

Effective Resolution		
Source	Value	Description
Probable Error	(PE) 3.1354	Median error for a single measurement
Current Measurement Increment	(MI) 0.01	Measurement increment estimated from data (in tenths)
Lower Bound Increment	(0.1*PE) 0.3135	Measurement increment should not be below this value
Smallest Effective Increment	(0.22*PE) 0.6898	Measurement increment is more effective above this value
Largest Effective Increment	(2.2*PE) 6.8978	Measurement increment is more effective below this value
<b>Action: Drop a digit</b>		
Reason: The measurement increment of 0.01 is below the lowest measurement increment bound and should be adjusted to record fewer digits.		

Figure 10: Effective resolution

JMP's highly visual, easy-to-understand MSA output quickly highlighted a few areas of concern. First, the Range Chart clearly indicates that the measurement system has repeatability issue.

Second, the Parallelism Chart highlights a measurement system bias. The 0.08 Bias Impact was deemed significant in light of the small changes expected in R1 during the process improvement work.

Third, the Effective Resolution output indicated that the recorded value of R1 should be reduced by 1 digit.

### First things first

Measurements would be needed at all hours of the day so the measurement system had to accommodate all 3 operators. Resisting building pressure to move forward, the team elected to first work on the measurement system. The Bias Impact was eventually reduced to < 0.02, the Intraclass Correlation Coefficient was improved to 0.96 and the Test-Retest Error was cut by more than half.

## STEP 5 - ESTABLISH BASELINE

Recall that one of the goals was to gain maximum understanding of the process and with that in mind, the team collected baseline data and used JMP's Control Chart Builder to

evaluate the results. See Figure 11 and note that all data presented in this case study are heavily obscured for confidentiality purposes.

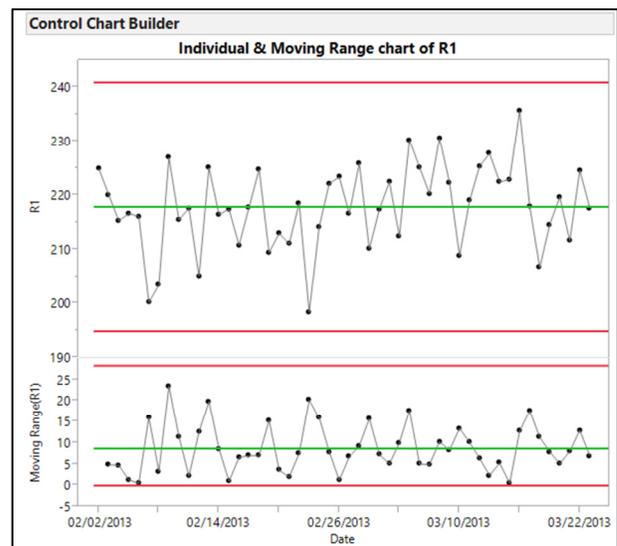


Figure 11: a look at the existing process

Donald Wheeler recommends evaluation of an IR chart within the context of the process and without automatic detection rules<sup>7</sup>. This evaluation was easy with JMP's IR chart in hand and the team concluded that the process was in a steady state of statistical control. When the team invoked the standard Western Electric detection rules as a double-check, they drew the same conclusion.

### Between an experimental rock and a financial hard place

At this point, considerable resources had been consumed, but no "hard results" had been delivered to the new owners. The team was challenged and at one point it was uncertain if the work would continue. However, using JMP's array of crystal-clear graphics, the engineers and operators jointly explained the following gains to the new owners and secured the OK to proceed.

- ✓ 2 significant measurement system problems were addressed before they could do further harm to the company and its customer. Henceforth, less good product would be

rejected and less off-spec product would be improperly shipped to customers

- ✓ a clear process baseline was in hand
- ✓ a carefully crafted, well-balanced strategy and detailed plan were in place
- ✓ operators were involved in the work, building inter-departmental cooperation

### STEP 6 – COLLECT PROCESS DATA

Each run was maintained for a significant period of time. The response was measured at various intervals with the average assigned to R1 for each run.

As a *fail-safe* plan, production line operators were instructed to return the process to its historical setting if they saw unexplained degradation or other sign of trouble.

During the lengthy data collection process, process behavior charts were used to better understand the small run-to-run differences (see Figure 12) and the more significant plan-to-plan differences.

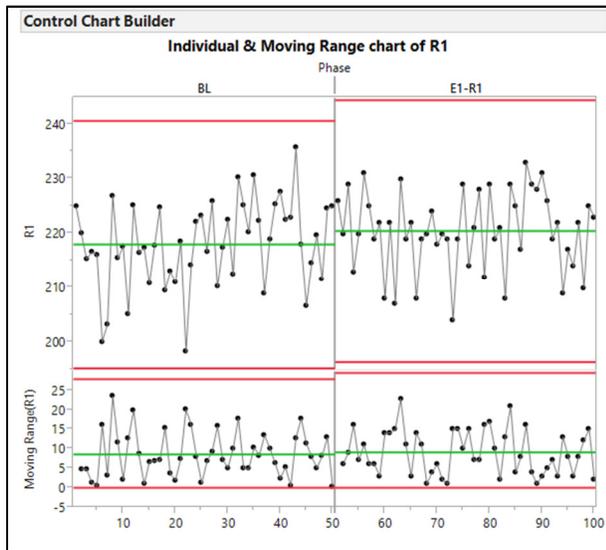


Figure 12, Baseline-vs-EVOP1, Run 1

### STEP 7 – ANALYZE PROCESS DATA

Like DOE, EVOP is best managed by checking important pre-requisites before launching into the review of the process model and before making important process decisions. For example, the team immediately

checked for constant s and then did a visual sanity check of the 8 replicate runs. JMP's Variability Chart provided a powerful way to check repeatability as shown in Figure 13.

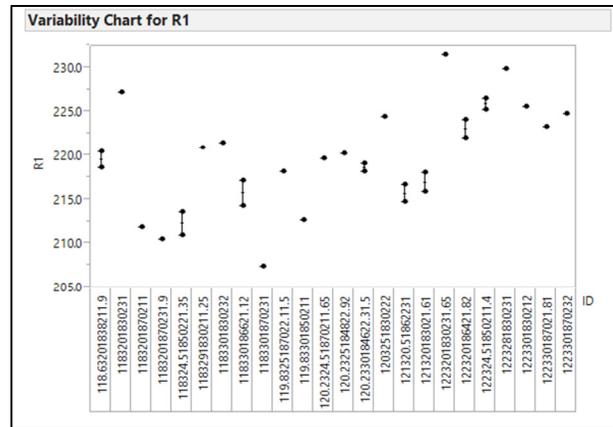


Figure 13: Variability Chart

Had the team discovered significant repeatability problems, they would have to stand down on the work until the cause was found and remediated.

### Fit model

Once the data is fit to the chosen model, JMP provides a number of ways to assess model quality. The Actual by Predicted plot is particularly useful because it's graphical and easy to understand as shown in Figure 14.

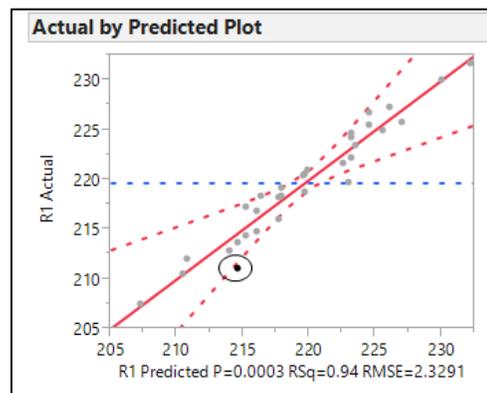


Figure 14: Actual by predicted plot

JMP makes it easy to see that the model predicts well. For example, the indicated point has a predicted value of about 215 and an actual value of about 211.

### Interpret the model

JMP's Sorted Parameter Estimates table and the JMP Prediction Profiler made it easy for the team to separate the vital few model terms from the trivial many. Analysis of the Prediction Profiler (Figure 15) indicated the following significant predictors of R1:

- ✓ main effects F1, F3 and F5
- ✓ the F3\*F4 and F1\*F3 interactions
- ✓ the quadratic term F3\*F3

Term	Estimate	Std Error	t Ratio	Prob>  t
F1(118,122)	4.5137031	0.548169	8.23	<.0001*
F3(1830,1870)	-3.153923	0.564169	-5.59	0.0002*
F3*F4	-2.824689	0.700036	-4.04	0.0020*
F5(1,2)	1.9125213	0.543513	3.52	0.0048*
F1*F3	2.3365705	0.678911	3.44	0.0055*
F3*F3	2.9033009	1.200117	2.42	0.0341*
F1*F1	2.1687161	1.145477	1.89	0.0849
F1*F2	1.1480009	0.640657	1.79	0.1007
F4*F4	1.9626835	1.097238	1.79	0.1012
F5*F5	-1.984994	1.275839	-1.56	0.1480
F4*F5	-0.892104	0.667489	-1.34	0.2084
F2*F3	0.7222766	0.671217	1.08	0.3049
F2*F2	-1.314454	1.224369	-1.07	0.3060
F2*F4	-0.547027	0.660741	-0.83	0.4253
F2*F5	-0.493296	0.620973	-0.79	0.4438
F1*F5	0.4837161	0.676185	0.72	0.4893
F1*F4	0.4242994	0.66456	0.64	0.5362
F2(320,330)	0.3216174	0.528947	0.61	0.5555
F4(21,23)	0.2290704	0.551692	0.42	0.6860
F3*F5	0.1833715	0.679258	0.27	0.7922

Figure 15: Sorted parameter estimates

As another sanity check, the team saw that the confidence interval around the predicted value in the Prediction Profiler contained the SPC chart average of about 218 when F1 to F5 were set to the baseline settings as shown in Figure 16.

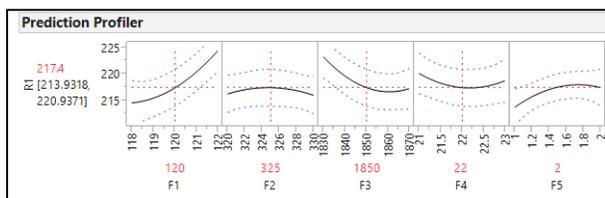


Figure 16: JMP Prediction Profiler, baseline process settings

### Contextual check

The team knew that all predictive models have a measure of uncertainty and for the narrow factor ranges typical of EVOP work, the uncertainty loomed large. The team approached with caution and pondered an important question - *Does the model make sense within the context of the process?*

*Common sense is genius dressed  
in its work clothes*  
Ralph Waldo Emerson

The team used the JMP Prediction Profiler in a group setting as an interactive, graphical representation of the process. For example, moving the red marker along the F3 scale clearly demonstrated to everyone the strong F3\*F4 interaction. See Figure 17.

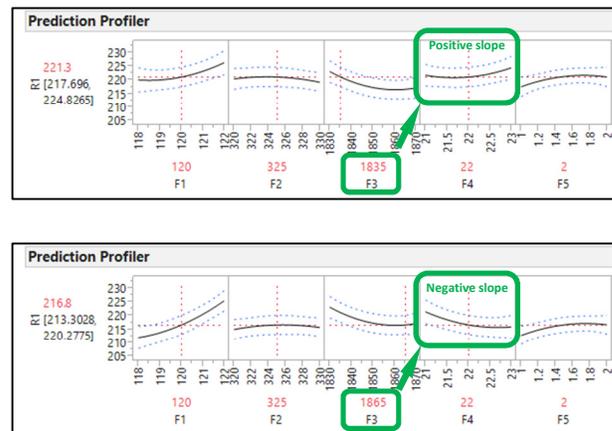


Figure 17: F4\*F3 interaction, graphically demonstrated

The team determined that the strong main effects F1 and F3 were supported by operator, engineering and maintenance knowledge and after lengthy consideration. They further concluded that interactions F1\*F3 and F3\*F4 did not contradict sound engineering judgement and common sense. However, the generally positive main effect F5 did not support their previous assessment.

### STEP 8 – DETERMINE NEW RANGES

Based on new process knowledge gained in EVOP-1, the team developed their EVOP-2 plan (Table 4) and repeated steps 3, 6 & 7.

Table 4, EVOP Plan 2

	RANGE, EVOP-1	RANGE, EVOP-2	RATIONALE
F1	118-122	122-126	Strong positive slope of F1 in Prediction Profiler
F2	320-330	320-330	F2's flat response curve in Prediction Profiler
F3	1830-1870	1810-1830	Strong negative slope of F3 in Prediction Profiler
F4	21-23	23-25	Decrease in F3 causes a more positive slope in F4 due to the strong F3*F4 interaction, see Figure 16
F5	1-2	2-3	Positive slope of F5 in prediction profiler

*Iterate toward the sweet spot*

EVOP-2 data was collected and analyzed leading to the development of EVOP-3. The results of EVOP-3 then lead to the development of EVOP-4 and so forth. An important point is that *every single decision was based on direct observations and data*, not on opinion, hunch, theory, vote, first principles, consensus, edict or flip-of-a-coin. As process knowledge accumulated, factor ranges were gradually widened to generate increasingly useful process insight. In the end, more than 10 iterations were needed to move the process to its new settings.

**STEP 9 – SUSTAIN GEMBA FOCUS**

The team understood the effect of entropy and its inexorable push toward chaos and disaster. They also understood the presence of raw material variation, energy supply fluctuation, tooling wear, gradual equipment misalignment and the accumulating effects of repairs. With all of that in mind, the team developed a plan to address future process degradation. The details of this plan are outside the scope of this paper.

*Acknowledge*

The team acknowledged the vital contributions of front line operators, supervisors and maintenance staff, giving them a sense of ownership in the new process. While this is an

intangible benefit of collaborative work on the factory floor, it is nonetheless vital to long term success.

*Monitor*

As a countermeasure to long-term process degradation, the team put a system in place to track key factors and responses over time. Some team members accepted personal responsibility to monitor the data and look for process shifts.

**GHOSTS IN THE MACHINE**

The industrial process under study was complex and the team made mistakes. Some mistakes lead to the rework of an EVOP plan and on one occasion, the process had to be abruptly returned to the original process settings. Some decisions resulted in lower rather than higher R1. But the team's persistence meant that these mistakes turned into new knowledge and, eventually, a high level of process understanding.

**FINAL RESULTS**

The final process model and simulated set points are shown in Figure 18. While the effort fell short of the original goal of 325, overall improvement proved satisfactory to the new owners after a dramatic drop in both process scrap and customer complaints. EVOP was indeed the right framework for the process improvement work.

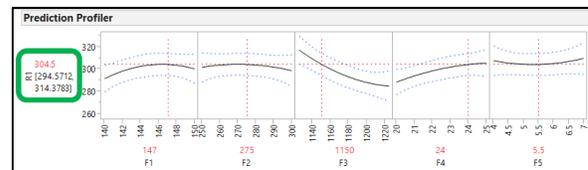


Figure 18: the new process

**KEYS TO SUCCESS**

The primary key to success was the team's collaborative mindset. Interestingly, there was no *Team Leader*. Instead, the work was done by a diverse group of people on the factory floor, interacting with each other, as equals, in a spirit of data-centric continuous

improvement. JMP provided a perfect complement to this approach with its clear, concise graphics and accessible quantitative analysis tools.

Another key to EVOP success is persistence. Like running designed experiments, EVOP rarely goes perfectly according to plan and a strong sense of determination is vital. It is suggested that the faint-of-heart steer well clear of EVOP.

## EPILOGUE

The authors further believe the collaborative mindset and philosophical underpinnings described in this case study yield superior financial and technical results compared to common dictatorial process improvement practices. We specifically caution against the use of:

- ✓ arbitrary improvement targets
- ✓ arbitrary deadlines and *Progress Reports*
- ✓ investigations into operator error
- ✓ spreadsheets for data storage and analysis
- ✓ debate in stuffy conference rooms

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## AUTHOR BIOGRAPHIES

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