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Standard Least Squares Method for Identifying Problem Tools in a Manufacturing Environment
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ABSTRACT

We describe an analytical method to identify problem tools in a manufacturing environment. Using JMP® software, we visualized a yield problem, collected a relevant data set, and created a Standard Least Squares model to identify the tools contributing most to the problem. Once identified, further analysis in JMP® software gave insight into the underlying root cause that allowed us to fix the problem and prevent future occurrences. On numerous occasions, we have found this method to be an effective and efficient method to identify problem tools.

INTRODUCTION

From a sustaining engineering perspective, there are at two types of problems that arise in manufacturing. Discrete, obvious, and high-rate problems can be readily figured out on the manufacturing floor. What does the defect look like? Where is the defect being caught? Answer those questions, apply some process insight, and the source can be quickly found. While these types of investigations must always happen, they can turn up empty when the problem occurs with low frequency and is not obvious to direct means of characterization. In situations such as these, we have found JMP® software to be a highly effective tool for visualizing the problem and identifying its source.

Such was the situation when we were faced with the mysterious "Defect_A" in the summer of 2006. Of course, that is not the real name of the defect. As with other details of our process, I will use aliases to protect the details of our intellectual property, for the knowledge we gained during this problem, investigation, and solution remains relevant to our LED manufacturing process at Cree today. Suffice it to say, Defect _A is a bad defect to have. It is known to cause LED failures; indeed, it may cause losses of several thousand die per wafer. These losses, though, are only evident in downstream characterizations after several subsequent processing steps have been performed. At the point where the defect is initiated, in our department, it cannot be detected except through tedious and destructive means. Adding to the complexity, this defect occurs inconsistently. Typically, if it is present, it is at a very low level. At the nadir of this problem, it was observed at a higher level, but still not on every wafer.

DEFINE THE PROBLEM

The first challenge was to describe the "higher level" at which the defect was observed. Because we had no ready, non-destructive means to detect the defect on wafers in our department, we instead had to examine the downstream characterization data to understand the increase in the defect.   To do this, we imported the downstream processing and characterization data into JMP® software using an ODBC connection to the database used to store this information. Each wafer is characterized at several points for this defect, and because each point is entered into the database as its own entry record, we then used JMP® software to summarize by wafer to generate a sum of Defect_A per wafer. Further summarization by downstream wafer processing date shows a clear increase in the incidence of this problem around July 29, 2006.

Control Chart

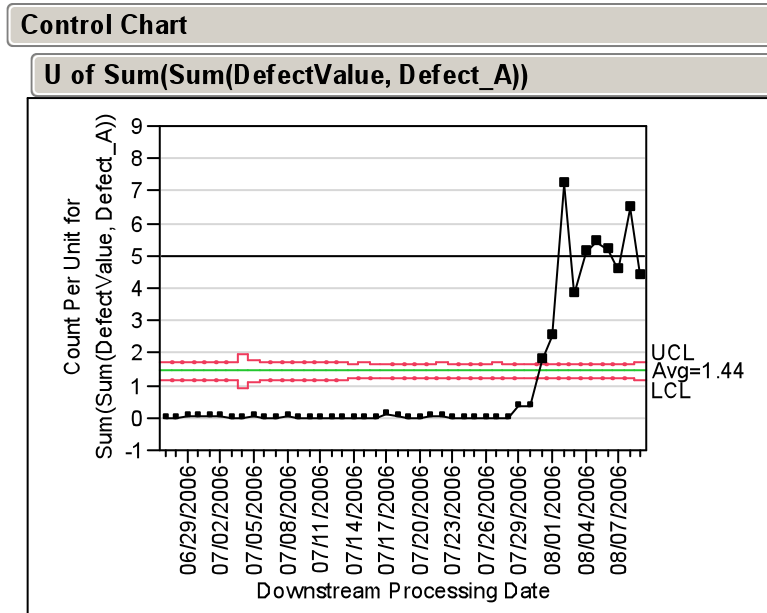**U of Sum(Sum(DefectValue, Defect_A))**

Figure 1: U-chart showing the increase in average Defect_A count per wafer by downstream processing date relative to the upper specification limit for this defect, 5 per wafer. Out-of-control data points used in subsequent analysis are highlighted in bold.

The u-chart showed a clear and significant increase in the incidence of Defect_A, to the point where the average count per wafer was at or above the upper specification limit of 5 per wafer. Was this problem really generating a 50% failure rate? Using the lasso tool to select the out-of-control data points, we created a subset of data from which we plotted the distribution of the sum of Defect_A per wafer.
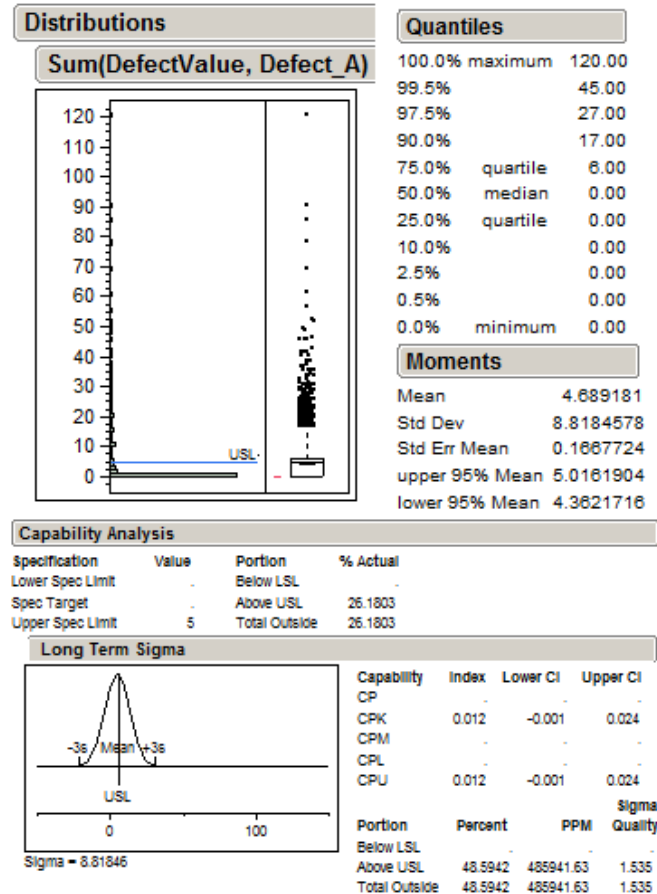
Figure 2: Distribution and statistics describing the sum of Defect_A observed on a sample of wafers taken during the problem period.

Clearly, this distribution is not normal, with few wafers of very high sums of Defect_A shifting the average well above the median sum of Defect_A. Applying a transformation to this data set would make it more normal. While that would be useful for comparative statistics, and, as I will describe later, in modeling the data, the added complication of explaining the transformation makes it less suitable for conveying the nature of the problem. The capability analysis does a better job of this, showing that over this period of time, 26% of the wafers exceeded the specification for this value. This is a quantification that has direct relevance to our downstream department and to management, so we began plotting this problem as a fraction of wafers that fail the specification.

We created a formula in JMP® software to compare the sum of Defect_A per wafer to the specification and assign a pass (0) or fail (1) value to each wafer. Then, summarizing by downstream processing date, we generated a p-chart that accurately showed the fraction of wafers that failed the specification per day. Given that we process a large number of wafers per day, we found that a oneway analysis of the average pass-fail value versus processing date was an accurate method to depict the same trend as the p-chart but easier to produce.
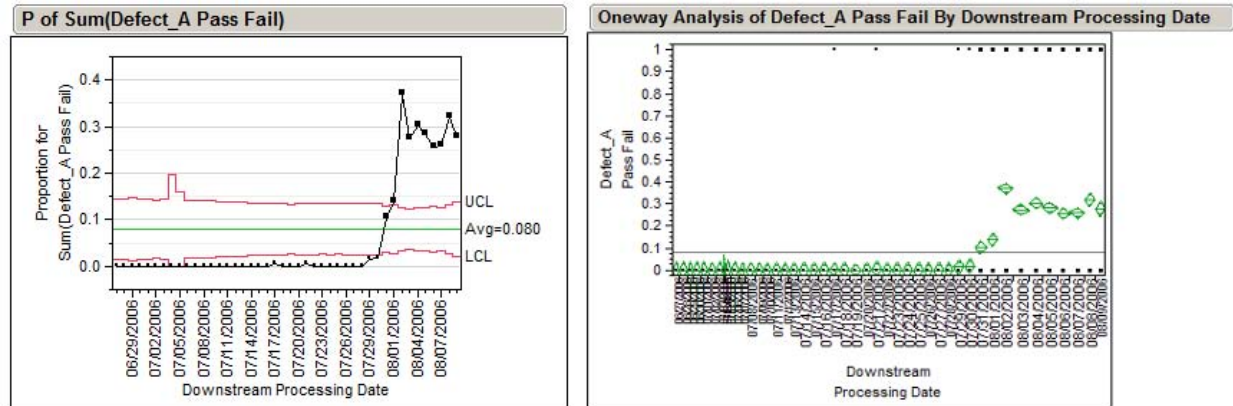
Figure 3: The failure rate of Defect_A versus processing date, depicted both as a p-chart and as a oneway analysis of the average failure rate per day (0 = pass, 1 = fail).

COMPILE THE DATA SET

After defining the scale of the problem, our next step was to figure out what caused the increase. One of our first observations was that Defect_A was at a zero level for a long period of time prior to the onset of the crisis. For a problem that would eventually affect such a large fraction of wafers, it seemed odd that Defect_A was hardly seen before. Suspecting a gauge issue, we talked to the inspectors in the downstream department about Defect_A, how they characterize it, and how long they had been seeing it. These conversations turned up an important detail. Inspectors were re-trained to look for this defect in late July, after the first few wafers with high levels of Defect_A were found. With renewed focus, more wafers with Defect_A were found in subsequent days. However, production wafers from previous days had already moved on, so it was not possible to retroactively apply this same inspection rigor to them. Thus, we could not be sure if the sharp onset of the problem was due to a specific production event or to the more rigorous inspection protocol.

 Since this uncertainty would cloud any analysis that included data from older wafers, we decided instead to focus the investigation on data collected with the tightened inspection protocol. These wafers were all inspected to the same standard, so comparisons between them would be relevant. For each of these wafers, we retrieved into JMP® software via ODBC their full processing history through our department. This included such details as which production tool each wafer went through at each processing step, the time stamp for that processing, and parametric data for the conditions under which the wafer was processed. Wafers that were processed through low-capacity or infrequently-used sister tools were excluded, both because such small wafer volumes could not explain the scale of the problem and because we did not want the error inherent to small sample sizes distorting the result of the analysis.

IDENTIFY THE SIGNIFICANT FACTORS

Our experience was that problems like this typically don't occur across sister tools at the same processing step as long as those sister tools are truly unique; for instance, not sharing any common supplies of chemicals. It would be a tedious affair, though, to examine the large number of oneway analyses and p-charts to look for differences between the sister tools and find the one tool that changed: for each step, for each sister tool, by each processing date and condition would easily be hundreds of charts. This method could also lead to inaccurate or incomplete conclusions, as it would not capture the effect of the interactions between tools at different production steps. A better method is to analyze this data as a model in JMP® software. Each production step can be treated as a factor, with the sister tools used at each step acting as the values for that factor.

We fit a Standard Least Squares model to the sample of Defect_A observed during the problem period with the improved inspection protocol, with the emphasis on Effect Screening.   The RSq of this model is poor, only 0.31, largely because of the substantial non-normality of the data set. To improve this, we calculated a Box-Cox Transformation, with the best λ chosen by JMP® software, and then modeled the transformed data. (Note that we had to add a constant, 1, to our observed levels of Defect_A to apply this transformation since many wafers had zero

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observed Defect_A.) The model fit to the transformed data has a higher RSq value, but it is still relatively low because of the large number of wafers that are free of Defect_A. Nevertheless, the model is sufficient to identify the factors that are not significant to the result.
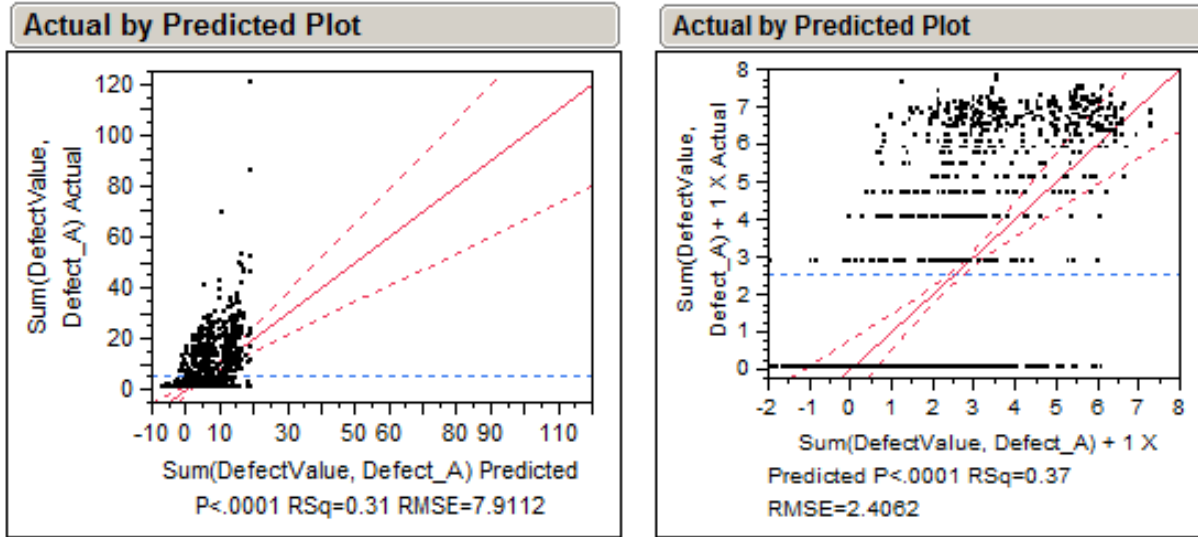

Figure 1: Models fit to the original (left) and transformed (right) Defect_A data. These first models include all factors (all processing steps) and all levels (sister tools) within each factor.

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Tool - Step 01	2	2	34.5839	2.9867	0.0508
Tool - Step 02	3	3	37.7489	2.1733	0.0894
Tool - Step 03	4	4	74.5402	3.2187	0.0122*
Tool - Step 04	2	2	33.7398	2.9138	0.0546
Tool - Step 05	1	1	37.4135	6.4621	0.0111*
Tool - Step 06	5	5	144.2595	4.9833	0.0002*
Tool - Step 07	3	3	98.5552	5.6742	0.0007*
Tool - Step 08	1	1	17.0000	2.9362	0.0868
Tool - Step 09	2	2	2055.8088	177.5398	<.0001*
Tool - Step 10	1	1	6.6355	1.1461	0.2846
Tool - Step 11	31	31	1892.4269	10.5439	<.0001*

Figure 2: The Effect Screening emphasis of the Standard Least Squares model tabulates the significance of each factor in the model.

The processing tools of Steps 01, 02, 03, 04, 05, 08, and 10 have high P-values, so they are excluded and the model ran again. Doing so reduces the RSq value slightly but improves the resolution to the remaining factors.

Effect Tests

Source	Nparm	DF	Sum of Squares	F Ratio	Prob > F
Tool - Step 06	5	5	68.3810	2.2657	0.0456*
Tool - Step 07	3	3	67.7213	3.7397	0.0107*
Tool - Step 09	2	2	3633.1806	300.9492	<.0001*
Tool - Step 11	31	31	2571.7463	13.7437	<.0001*

Figure 6: After excluding insignificant factors from the model, resolution to the remaining factors is improved.

The remaining factors all have statistical significance to the model, but they differ by the magnitude of the effect they have on the result. Tools in process steps that contribute in large and significant ways are probably where the problem lies, while tools in process steps that contribute in small but significant ways are probably not the cause of the problem. The Prediction Profiler provides a quick way to understand this behavior and identify the tools that have the greatest contribution to the result.
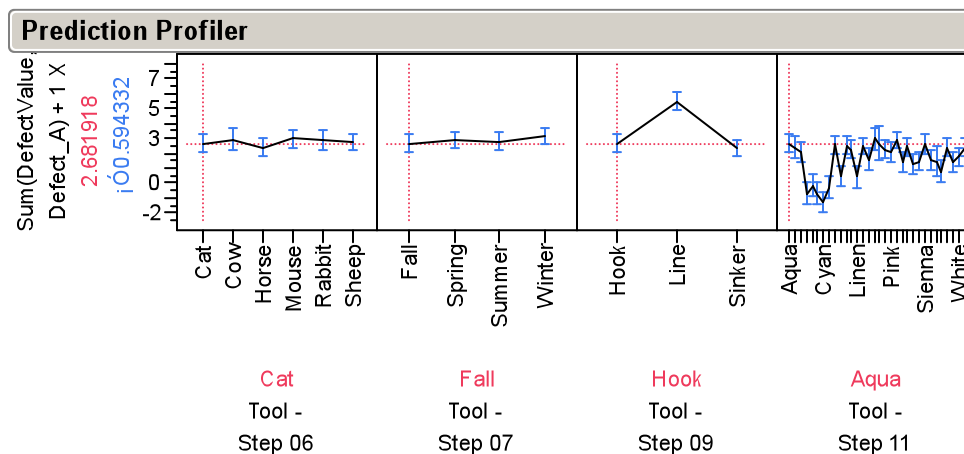

Figure 3: Prediction Profiler for the model that includes only the significant factors, processing steps 06, 07, 09, and 11. For each processing step, the names of the sister tools are given. The profiler makes it clear which tools contribute most to the problem and which tools are affected least by it.

The differences between the sister tools in Steps 09 and 11 are much larger than those between tools in Steps 06 and 07. With little impairment to its ability to identify the source of the problem, then, Steps 06 and 07 can be removed from the model. The benefit of removing these two factors is a large reduction in the number of processing combinations. The fewer the number of combinations there are, the more likely we are to have wafers that satisfy every combination, allowing us to model the interaction between tools at those steps. Doing so improves model beyond the original result, increasing the RSq value from 0.37 to 0.44, and gives us much greater insight to the problem. This is again visualized using the Prediction Profiler. Tool "Line" in Step 09 shows a higher incidence of Defect_A than its sister tools, but it also appears to aggravate the behavior of some of the tools in Step 11. Tools "Brown" through "Fuchsia" and "Teal" are immune to the tool used in Step 09, but the remaining sister tools in Step 11 show a very large increase in Defect_A when they process wafers that went through tool "Line" in Step 09. Something about tool "Line" was bad, and my engineering group was tasked with understanding and fixing what was wrong with it. On the other hand, tools "Brown" through "Fuchsia" and "Teal" in Step 11 were operating in a robust

parameter space that has made them immune to upstream variation. A second engineering group was tasked with identifying these process conditions and propagating them to the other sister tools at this step.
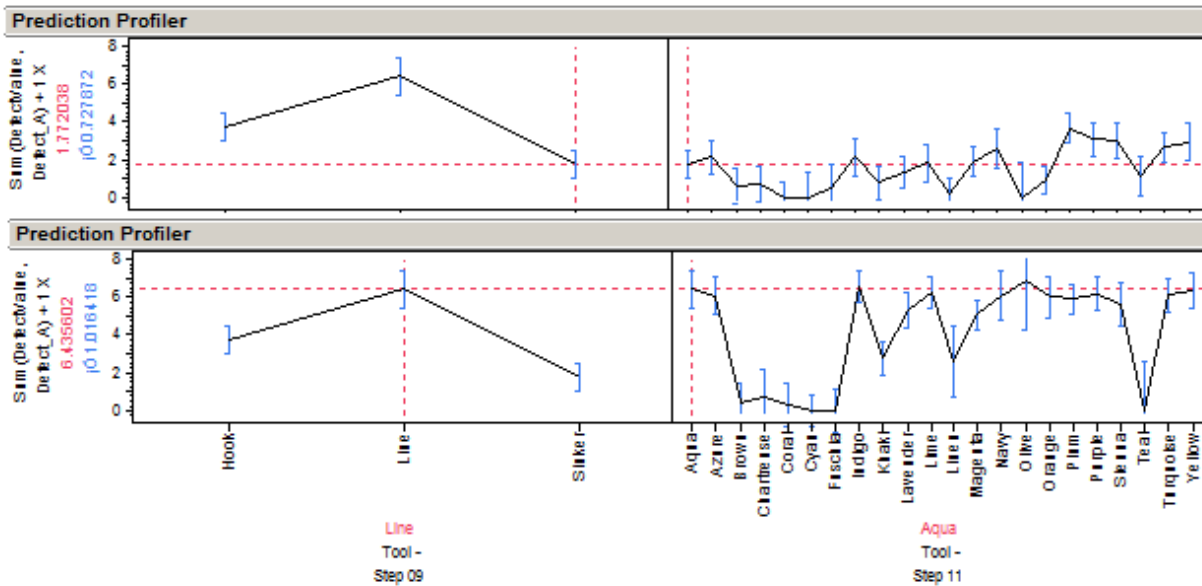

Figure 4: Prediction Profiler for the refined model that includes only the significant factors, the tools in Steps 09 and 11, and the interactions between the tools in those two steps. The top chart shows the predicted incidence of Defect_A on wafers processed through tool "Sinker" in Step 09, while the bottom chart shows the predicted incidence of Defect_A on wafers processed through tool "Line" in Step 09.

INVESTIGATE THE SIGNIFICANT FACTORS

My engineering group began the investigation into the sister tools at Step 09 with an examination of the parametric data collected at this step, specifically the position of the wafer in the tool during the process and its relationship to the observed levels of Defect_A. We found considerable variation, and interestingly, different patterns of variation from one tool to the next. Ideally, our next step would have been to measure the process conditions at each position for each tool, but the nature of the process and the layout of the tool itself made this impossible. Without a direct, *in-situ*, measurement, the best we could do was compare the rates of Defect_A failures to other measureable attributes already known to be correlated to different process conditions. When we found patterns of variation in Attribute_B that matched up with the patterns of Defect_A failures, and combined that with the knowledge that variation in Attribute_B is driven by subtle concentration variations between the positions in the tool, we knew that these same concentration variations were driving the rate of Defect_A failures. Moreover, we could explain not only why tool "Line" was worse than the other sister tools, but why tools "Hook" and "Sinker" showed some Defect_A failures as well.
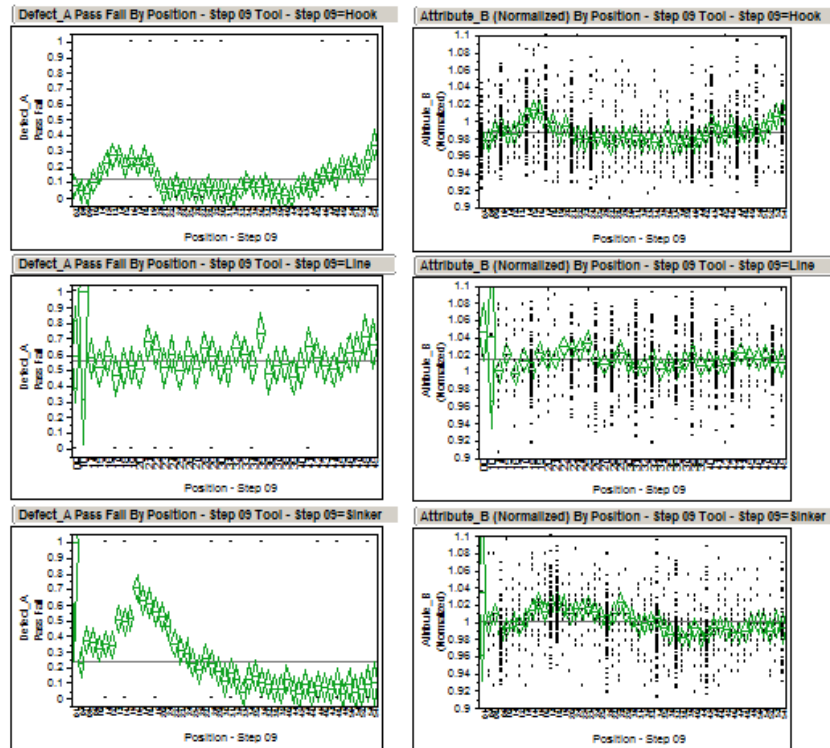
Figure 5: Oneway analyses showing the failure rate of Defect_A (left) and the measured observation of Attribute_B (right) by position within each tool at Step 09. The spatial agreement of these two trends across wafer position in these tools suggested they had the same underlying root cause.

TAKE ACTION

With the insight that concentration variations were driving the rate of Defect_A failures just as they drove the changes in Attribute_B, we began work on improving our concentration uniformity and control in the tools of Step 09. Concurrently, the other engineering group moved the tools of Step 11 to the more robust process conditions. It took time both to understand the problem and make these changes, but by the middle of September, the rate of Defect_A failures had returned to near-zero levels.
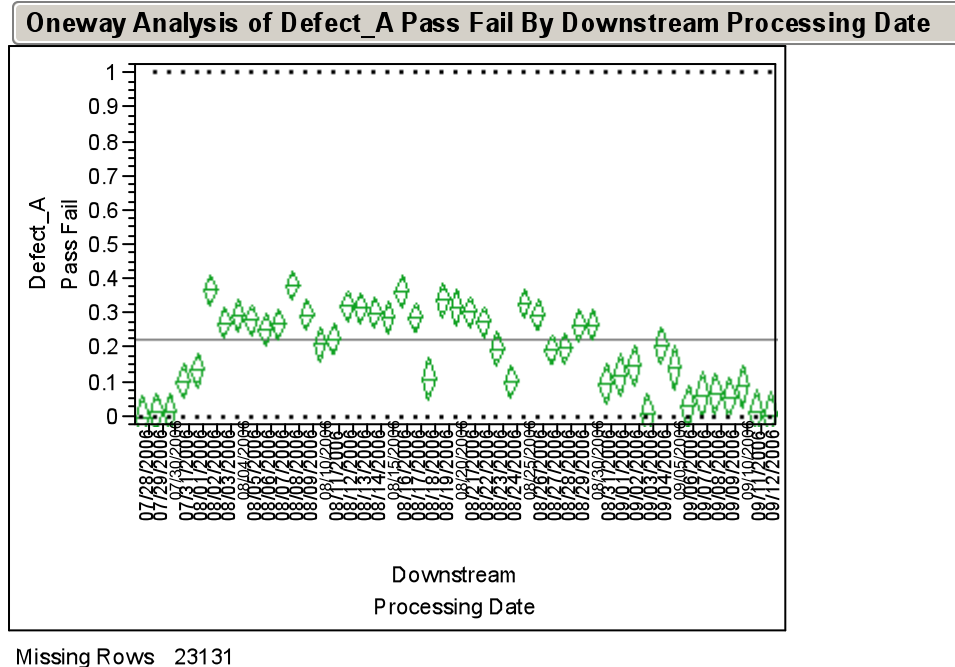
Figure 6: Defect_A failure rate versus downstream processing date. The crisis that began in late July was fully resolved by mid-September.

CONCLUSION

Several years later, it shocks me that this problem took over a month to understand and solve. However, I now take for granted this analytical sequence to identify problem tools and conditions. At the time of the Defect_A crisis in 2006, we had neither this method nor some of the basic data visibility in place. Indeed, it was this crisis that drove us to develop this method and infrastructure. Our previous methods were not working; only when we used JMP® software in this manner did we identify the root cause. We have since been able to control the levels of Defect_A by controlling the concentration uniformity in the tools of Step 09 and the process conditions of the tools of Step 11. Moreover, we have been able to apply this technique to many other different problems. Each time, it has proven to be an effective and efficient method to identify problem tools.

CONTACT INFORMATION

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