JMP Academic Case Study 040

Manufacturing Systems Variation at Saint-Gobain NorPro

Variability Gauge, Component Analysis of Variance, Nested Design

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Key Ideas

This case study requires the use of Nested Variability chart to understand and analyze the different components of variances. It also explores the ways to minimize the variability by applying various rules of operation related to variance.

Background

Saint-Gobain NorPro (subsidiary of Saint-Gobain) is an international company with an undisputed leadership position in providing an impressive collection of engineered ceramic media and shapes using leading edge ceramics technology. The company has been serving the petrochemical, chemical, refining, environmental and gas processing industries for well over 100 years; even more impressive is that parent company Saint-Gobain has served its customers for more than 350 years.

The ceramic pellets manufactured by the company are used for multiple purposes, including:

- Supporting media, literally supporting the bed of catalyst inside a reactor vessel for the chemical and refinery industries.
- Filtering media at the top of the large reactors, cleaning up the feed streams before these streams interact with the catalyst.
- Carrying catalysts to ensure certain reactions take place, then using the ceramic pills to hold the metals in place inside the reactors.

Depending on the customer's application and reactor size, an order of carriers could range from 50,000 kg to 200,000 kg. Since many of the products are custom-made to suit the application and the exact geometry of the reactor, Saint-Gobain NorPro often makes the same pills in varying sizes for a single customer with multiple reactor sizes.

The ceramic pills come in a wide variety of shapes and sizes. Some spheres are as small as 3 mm in diameter and weighing a tenth of a gram. Some rings are 35 mm in diameter and weigh up to 10 grams.

Other cylindrical or multifaceted shapes can range from 8 to 15 mm in diameter with variable lengths and weighing 0.5 to 1.0 gram.

Customer order fulfillment

When a customer buys 100,000 kg of a specific media consisting of 500 pills per kg, that translates to 50 million individual pills. Naturally the customer expects 100% consistency in pills delivered, meaning that all the pills are exactly same. But Saint-Gobain NorPro can't make 50 million pills at one time. It runs a continuous operation making small batches of green ware that are later loaded into large kilns and fired into a finished ceramic called fired ware. It takes several days to make enough green ware to start loading into the kilns and a few more days for all of the product to flow through the kilns. So, for an order this size, it takes many days or even weeks of continuous production to complete. During this period, there will be many variables, from shift changes to new batches of raw materials to replacing the dies, etc.

Quality control

A small sample of the fired ware is collected every minute of every day throughout the production period and placed in a sample reservoir, all of which happens while the main product stream is flowing into a super sack (SS). When the super sack is full (roughly 500 kg), the sample reservoir is dumped into a smaller sealed bag, which becomes the *composite sample* for the super sack. Multiple super sacks are made each day, meaning bags of composite samples for each super sack. Half of the material from every super sack's composite sample is put into a five-gallon bucket as the *daily composite sample*.

The lab then mixes this daily composite sample to achieve homogeneity (a process called riffling) and then analyzes the quality of the product for that day. Next, the lab conducts the Wetted Ionic Deposit Index (WIDI) test to capture the sample's score, which is an excellent predictor of how well the pills behave as catalyst carriers. If a problem is noted, the lab can also riffle and analyze each super sack sample to identify the exact time and day when the process might have drifted off.

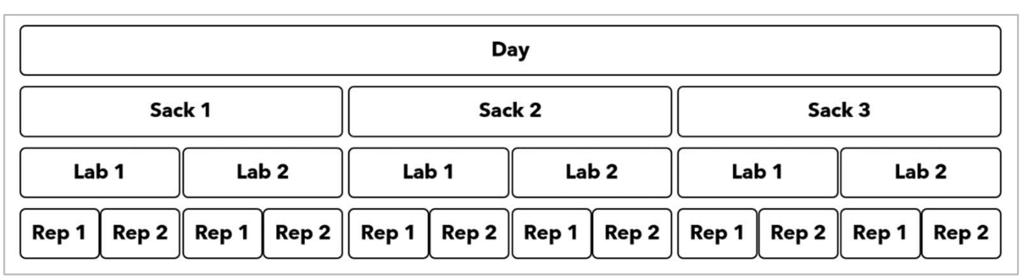
The Task

One of the commercial managers observed a high variability (which is the enemy of quality!) in the products delivered to a customer and wants the plant to fix it. As is all too common in the world of manufacturing, the production department says the problem is in the lab's inability to measure the quality properly. However, the lab says the problem is that production is not controlling the process tightly enough. The R&D team thinks that everybody at the plant is doing everything wrong and everything needs to be fixed. But the plant manager does not have the resources to explore every step in the process. So, there is a need to leverage the available resources to fix the problem to minimize variability. The task is to identify the greatest source of variability so that the team can align their resources to make the greatest improvement.

The Data **widi.jmp**

The sampling plan below uses samples from every super sack for three days; each sample is analyzed at both the production and R&D labs in duplicate. There are four sacks for Day1, six sacks for Day2 and two sacks for Day3. Exhibit 1 shows a representation of the sampling at the different levels.

Exhibit 1 Pictorial Representation of the Sampling Plan



The SS results are "nested" within a day and the lab results are nested within a super sack. The data table contains data on WIDI measurements for each day and multiple sacks. In addition, each sack is tested by two labs and each lab performs two repetitions. The variables in the data set are:

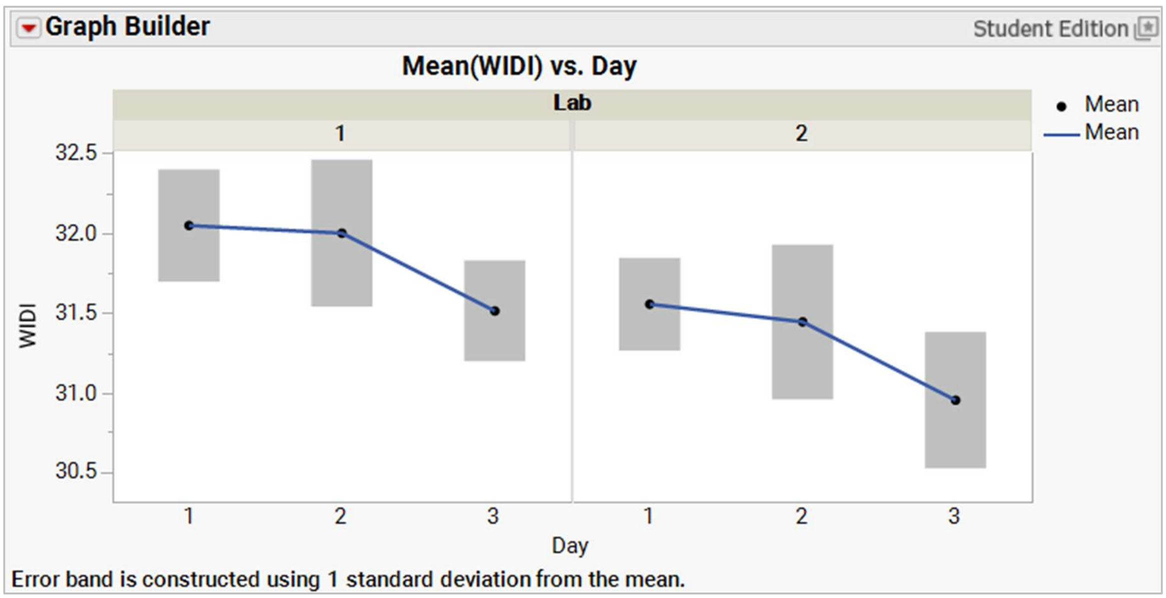
Day	Day on which sample was taken
SS	The serial number of super stack sample for a given day
Lab	The lab where the measurement or test was made (1 for production lab, 2 for R&D lab)
Rep	Test number
WIDI	WIDI test result value for that sample

The WIDI variable contains continuous data. The Day, SS, Lab and Rep variables contain nominal data.

Analysis

To begin, first visualize the data using Graph Builder, JMP's powerful exploratory data analysis platform that enables the researcher or engineer to explore the data.

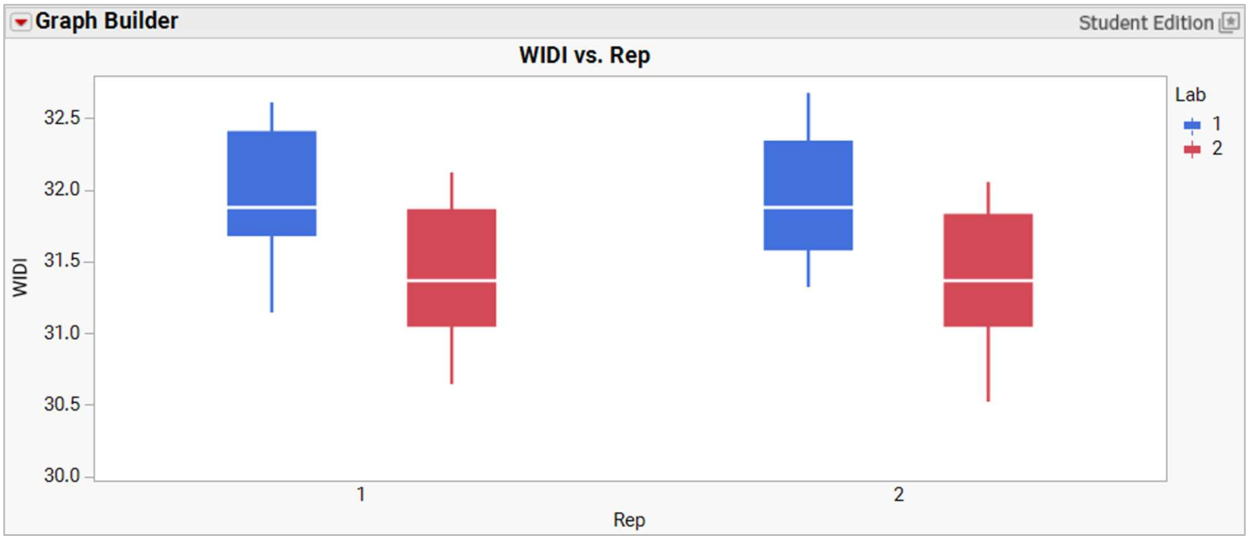
Exhibit 2 Average WIDI Versus Day and Lab



(To create, Graph>Graph Builder>WIDI to Y axis, Day to X axis, Lab to Group X. By default, the scatter plot will be displayed. On the left side of the graph, from the points option, select mean option from summary statistics, standard deviation option from Error Interval, and Band from Interval Style. Add line chart from the top using shift button .)

Exhibit 2 shows that the average WIDI decreases from Day1 to Day3; it also reveals that the overall average for Lab1 is slightly higher than for Lab2. The standard deviation band for each day also shows that the variability differs across the days.

Exhibit 3   Average WIDI Versus Rep



(To create, Graph>Graph Builder>WIDI to Y axis, Rep to X axis, Lab to overlay. Select Box Plot. Choose Solid Box Style.)

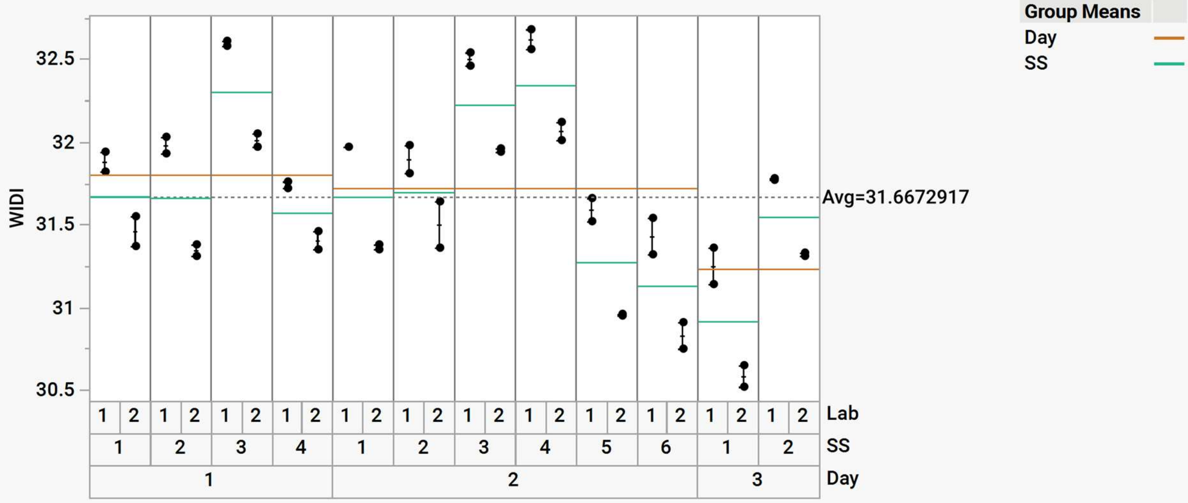
Exhibit 3 reveals that the average WIDI does not change over Rep, but it decreases for Lab2 significantly.

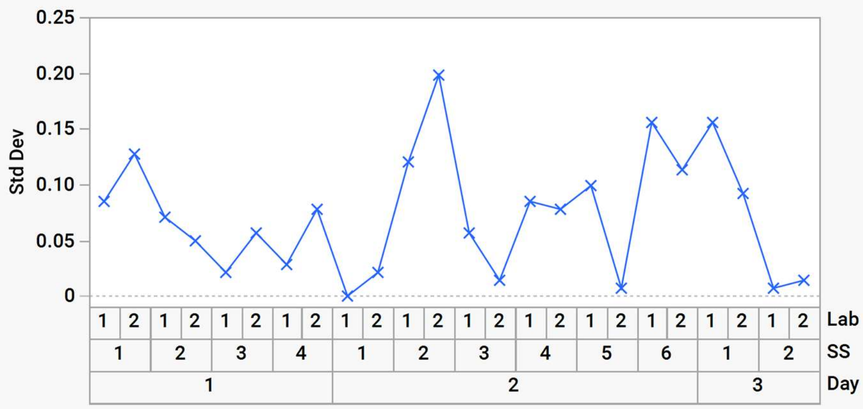
To explore the total variance components, it is important to visualize the data using a variability chart. The variance for total process is shown to be 0.24 (Exhibit 4). Variance for each level of the nested design is also listed.

Exhibit 4 Variability Gauge

Variability Gauge Analysis for WIDI

Variability Chart for WIDI





Switching to Bayesian estimates because of negative REML variance component(s).

Bayesian Variance Component Estimates

Random Effect	Var Component	Pct of Total
Day	0.0302578	12.576
SS[Day]	0.0824757	34.280
Lab[Day,SS]	0.1204811	50.077
Residual	0.0073789	3.067
Total	0.2405935	100.000

Variance Components

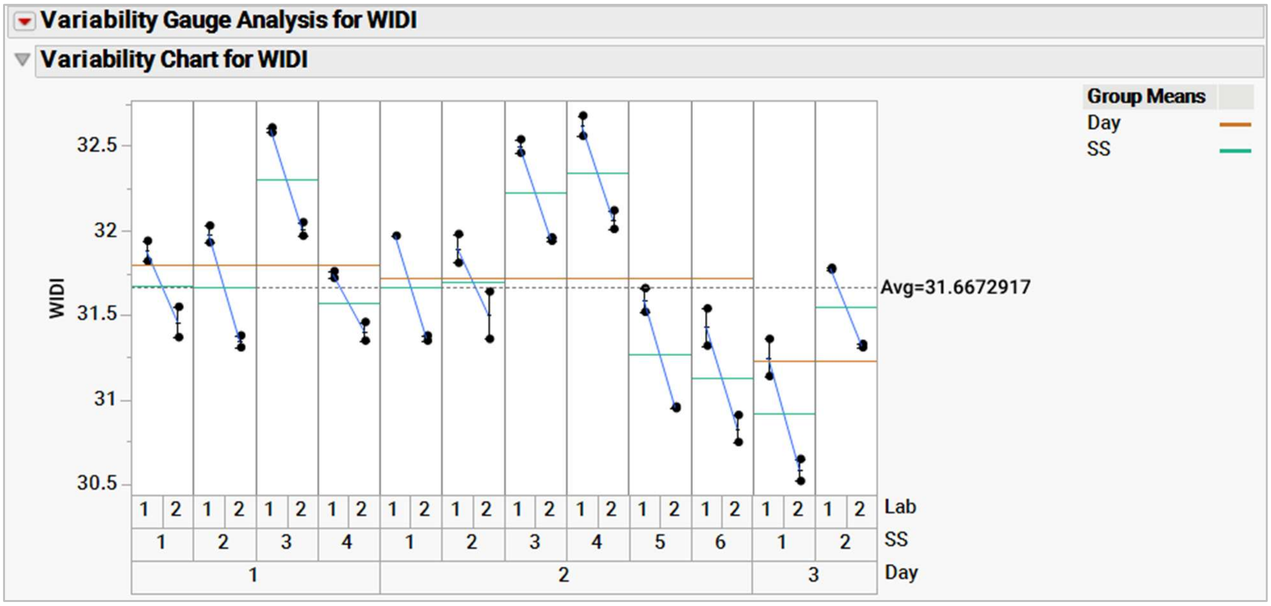
Component	Var Component	% of Total	20 40 60 80	Sqrt(Var Comp)
Day	0.03025780	12.6		0.17395
SS[Day]	0.08247566	34.3		0.28719
Lab[Day,SS]	0.12048113	50.1		0.34710
Within	0.00737894	3.1		0.08590
Total	0.24059353	100.0		0.49050

To create, Analyze>Quality & Process>Variability/Attribute Gauge Chart; Y, Response = WIDI; X, Grouping = Day, SS, Lab. Chart Type = Variability. Model Type = Nested. >OK. Use the red triangle drop down and select Show Group Means, Grand Means and Variance Components)

The output has a variability chart followed by a report on variance component estimates. Please note that Rep level is not included in this design. If Rep is included in the design, the variance component for Rep will be 0.0073789 and residual (or within) will be zero.

The variability chart shows two results for each lab and are the values obtained for the repetition test done by each lab. Since the values are closer (in some cases, almost the same value), it can be concluded that there is lesser variability in analyzing the same sample in the same lab.

Exhibit 5 Variance Components with Connected Cell Means



(Use the red triangle drop down and select Connect Cell Means option to highlight this point.)

Exhibit 5 demonstrates that the pairs (replicates) of data from Lab1 are always a little higher than the results from Lab2. The group means for the SS level (green lines) vary up and down and are sometimes close. The group mean for Day1 (reddish-brown line) is almost equal to the group mean for Day2, but it dropped for Day3. To have a more in-depth understanding of these variations, the variance component table needs to be examined more closely.

Exhibit 6 Variance Components with Connected Cell Means

Variance Components

Component	Var Component	% of Total	20 40 60 80	Sqrt(Var Comp)
Day	0.03025780	12.6		0.17395
SS[Day]	0.08247566	34.3		0.28719
Lab[Day,SS]	0.12048113	50.1		0.34710
Within	0.00737894	3.1		0.08590
Total	0.24059353	100.0		0.49050

Exhibit 6 shows the variance component and its percentage of total for each level of the design, both in a tabular and graphical fashion. The variability chart showed an obvious difference in the Lab-to-Lab variability than Day-to-Day or SS-to-SS variability. The variance component table confirms this finding, as the Lab-to-Lab variability accounts for 50% (% of Total = 50.1) of the total variation measured.

It looks like the production department was right; there is a strong need to measurement systems (the measurement variation also needs to be discussed).

The ability of either lab to replicate their own analytical results is very good. The Within results only represent 3.1% of the total variation. From this, it can be concluded that the analytical test is acceptable but the application of the test at two different laboratories needs a closer look.

The last column on the right, entitled Sqrt (VarComp) is nothing but the square root of the variance component, which is important information as all the process and method capability indices (Cpk, Cp, Cm, and Shewhart control charts) use the standard deviation in their calculations. Control charts typically have upper and lower limits set at ±3 standard deviations. Capability indices are a ratio of the tolerance width (spec width) divided by the process variability, typically expressed as a total of 6 standard deviations. The Method Capability Index (Cm) uses the standard deviation of 0.08590 (within) for its calculation.

Back to the nested design results. Since it was determined that the greatest source of variability in the system was the Lab-to-Lab variation, the organization now needs to focus on this area.

In a perfect world, given all the resources and time, the organization would attempt to make both the labs identical to get similar results by doing a root cause analysis. The reasons could be related to people, process, place, or priorities. But the world is imperfect. Even if the root cause for differences was found easily, the differences may still not be easily addressable. Perhaps the issue is a result of Lab1 using Model-A instrument while Lab2 uses the newer Model-B instrument. Can the organization buy a new one? Maybe, but if so, capital investment decisions take time, as does procuring an additional instrument.

By the way, comparing the results of the newer instrument(s) to the results of the existing instruments is also challenging. What kind of comparative analysis needs to be applied? (We'll save that question for another case study!)

To address this issue of testing variation immediately, some basic rules about the variances need to be understood.

Application of variance rules to minimize variability

Exhibit 7 shows description of the various rules related to the operation of variances. Standard deviation is denoted as s (sigma) and variance is denoted as s².

Exhibit 7 Variance Rules

Rule	Description	Equation
Addition	Variances are additive, but standard deviations are not. The total variance is equal to the sum of the individual (or component) variances. As shown in Exhibit 4, variances can be added to make 100%, which is not the case for standard deviations.	$\sigma_T{}^2 = \sigma_1{}^2 + \sigma_2{}^2 + \ldots$
Average	Like the addition rule, variances can also be averaged. The variance of the average is equal to the variance divided by the number of observations averaged.	$\sigma_{avg}{}^2 = \sigma^2/n$
Combination	This is a combination of addition and averaging rules. The variance of the sum of averages is equal to the sum of the variances of the averages.	$\sigma_T{}^2 = \sigma_1{}^2/n_1 + \sigma_2{}^2/n_2 + \ldots$

Average and combination rules can be applied to minimize variance. If the analytical method variance is too high and there is no way to improve the test quickly, then one way to lower the variance is to test in duplicate and report the average (e.g., lowering the method variance by 2 lowers the standard deviation by the square root of 2, or 1.4). Going one step further, reporting averages of triplicate analyses lowers the standard deviation by the square root of 3, or 1.7, and so on.

With the combination rule, even though multiple samples are taken and run multiple times, a meaningful (and much less variable) result can still be calculated. While this method for achieving a higher Cpk and Cm is perfectly legitimate, it might drive up the analytical costs. On the other hand, this might be the cheapest and quickest pathway to improved capability indices.

As an example of the application of variance rules, let’s say a process runs a single analysis in the lab for every daily sample. Eventually these daily production batches are grouped together into lots, and these lots are sold to customers. A nested design analysis was conducted to see how the total variation is distributed within this system. The results are summarized in Exhibit 8.

Exhibit 8 Variance Components with Single Run Process

Level	**Variance component**	**% or total variance**	**Standard deviation**
Lot	3	12	1.73
Daily	10	40	3.16
Analysis	12	48	3.46
Total	25	100	5.00

The total variance is 25 (total standard deviation is 5) and the largest component of variance is the Analysis level, which accounts for 48% of the total variance. But there are no immediate means to address this analysis issue. It was decided that in short term, each incoming daily sample will be analyzed in triplicate. Exhibit 9 shows the tabulated results.

Exhibit 9 Variance Components with Triplicate Run

Level	**Variance component**	**% or total variance**	**Standard deviation**
Lot	3	18	1.73
Daily	10	59	3.16
Analysis	4	24	2.00
Total	17	100	4.12

With some additional set up and effort, the laboratory ran these tests simultaneously, yet this did not delay the results. The variance rules help to reduce the variance component by a factor of 3 when analyses are run in triplicate, which further reduces the standard deviation of this component by the square root of 3, as shown in Exhibit 8. The single run variance component for the analysis level is 12, but by running the test in triplicate, this is reduced to 4. The total variance is now 17 instead of 25. The standard deviation of the new process is also reduced from 5.0 to 4.12.

Summary

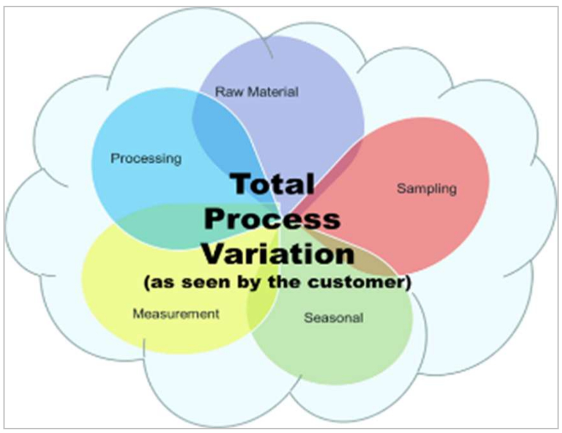
Statistical insights

Nested designs are an excellent way of breaking down the total variation manifested in a process into discreet components to prioritize the allocation of resources for improvements areas. The results from the nested designs provide the details of variability, which can be used to either pursue actual elimination of variability by improving the process or to modify the sampling and analysis processes to reduce the apparent variability. The variance rules can be applied to the processes to make almost instant improvement in the eyes of customers.

Implications

Organizations always strive to minimize the total variation in the process, thus enhancing customer satisfaction for both quality and delivery. Exhibit 10 depicts the various components of the total process variation as seen by a customer.

Exhibit 10 Customer Perspective of Components of Total Process Variation



The above analysis showed that breaking the variance components helped the organization to focus on the improvement areas.

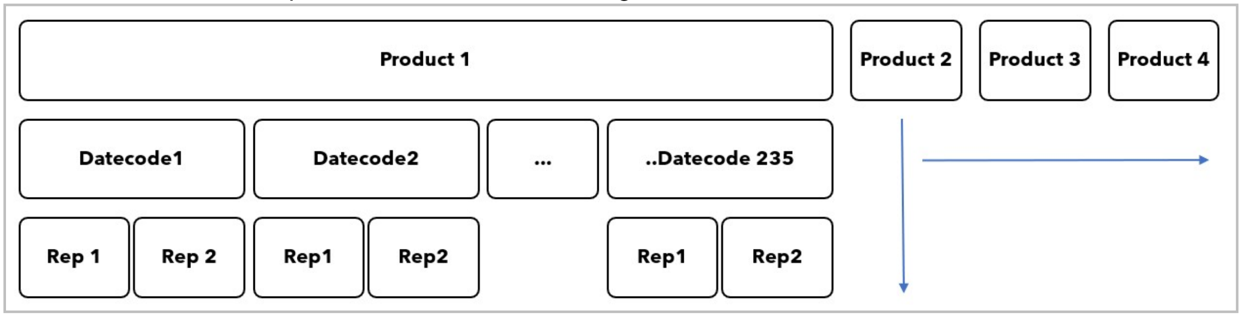
JMP Features and Hints

This study used Graph Builder to visualize the data in the form of mean and error with bar and box plots. It leveraged the variability gauge chart (as part of the Quality and Process platform) to analyze the process variance data.

Exercises

1. The plant decides that all WIDI tests will be run in duplicate to improve the apparent variability of the test, as well as serving as a validation check for lab technicians. If the two results do not agree within 10%, the test is scrapped and rerun. Over the course of several months, WIDI data was collected for four different products. The data is set as a nested design with Product at the top level of design, Datecode in the middle and the Replicate at the lowest level, as shown in Exhibit 11.

Exhibit 11 Pictorial Representation of Nested Design Levels for Exercise 1



Using the data captured in the file widi_Exercise1.jmp, identify the largest variance component to assign resources for improvement.

2. The company recently conducted a nested design study in the laboratory to better understand the sources of variability in the WIDI testing. For 30 days, four technicians made two preparations for each daily sample. After analyzing the final data, the variance components were tabulated in Exhibit 12.

Exhibit 12 Variance Components for Exercise 2

Level	Variance component	% or total variance	Standard deviation
Daily	0.0290	19	0.170
Tech (Daily)	0.0365	24	0.191
Prep (Daily, Tech)	0.0852	56	0.292
Within	0.0008	1	0.029
Total	0.1515	100	0.389

Some of the issues can’t be addressed in the production process, and there are other issues that should be fixed but are outside the scope of what the lab can control.

A. Working within the limitations of the laboratory, what action(s) can be initiated to reduce the variability (improve the quality) of the WIDI testing?
B. Using the different variance rules, how can the test be restructured to minimize the variance? Generate a new results table showing the variance components resulting from the restructured test.