Part 6: Design of Experiments

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Our focus for the first five publications in this series has been on introducing you to Statistical Process Control (SPC)—what it is, how and why it works, and how to determine where to focus initial efforts to use SPC in your company.

Experience has shown that SPC is most effective when focused on a few key areas as opposed to measuring anything and everything. With that in mind, we described how tools such as Pareto analysis and check sheets (Part 3) help with project selection by revealing the most frequent and costly problems. Then we emphasized how constructing flowcharts (Part 4) helps build consensus on the actual steps involved in a process, which in turn helps define where quality problems might be occurring. We also showed how cause-and-effect diagrams (Part 5) help quality improvement teams identify the root cause of problems.

In Part 6, we continue the discussion of root cause analysis with a brief introduction to design of experiments (DOE). We have yet to cover the most common tool of SPC: control charts.

It is important, however, to not lose sight of the primary goal: Improve quality, and in so doing, improve customer satisfaction and the company's profitability.

We've identified potential causes, but what's the *true cause*?

In an example that continues throughout this series, a quality improvement team from XYZ Forest Products Inc. (a fictional company) identified an important quality problem, identified the process steps where problems may occur, and brainstormed potential causes. They now need to know how specific process variables (e.g., feed speed, wood moisture, wood species, or tooling) influence the problem. In short, they need to filter the list to see which potential causes have a significant impact on the problem.

They determined that *size out of specification* for wooden handles (hereafter called out-of-spec handles) was the most frequent and costly quality problem (Part 3). A flowchart (Part 4) showed that part size and shape were inspected with a go/no-go (i.e., acceptable/unacceptable) gauge at the infeed to a machine that tapers the handles. Despite this inspection step, customers still indicated that handle sizes were not meeting their specifications. The team constructed a cause-and-effect diagram (Part 5) to brainstorm a list of potential causes for the problem, but they don't yet know which potential cause is the true, or root, cause.

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Figure 1 shows the cause-and-effect diagram from Part 5. Issues related to moisture appear in several places on the diagram. Given that wood shrinks and swells with changes in moisture content, it's likely that moisture variation is at least one of the primary causes. But the team has no assurance that moisture content is the dominant cause rather than machine setup, knife grinding, or any other cause listed on the diagram.

At this point, the team could simply assume that all causes are relevant. They would then develop standard operating procedures related to each and monitor the process to ensure procedures are followed. However, it is costly and inefficient to monitor aspects of the process that have little impact on the problem. Further, equipment operators often become frustrated when they are expected to spend time making measurements, analyzing, and charting results, particularly when no one follows up on the results.

The team needs to identify and focus on the *root cause*. Other causes may be important and need to be addressed in sequence, but for now, the focus is on critical rather than trivial information. To determine the primary cause or causes, the team needs to conduct an experiment.

Even in a relatively simple experiment, it can be challenging to set up the experiment, create samples, and analyze results. In an industrial setting, experiments often are more complex, time consuming, and expensive (e.g., if samples are tested destructively), and it is difficult to control the wide range of variables that may affect the results. And even when everything goes well, making sense of the data is no small task. Using statistically designed, conducted, and analyzed experiments can help ensure you get the most value for your investment.
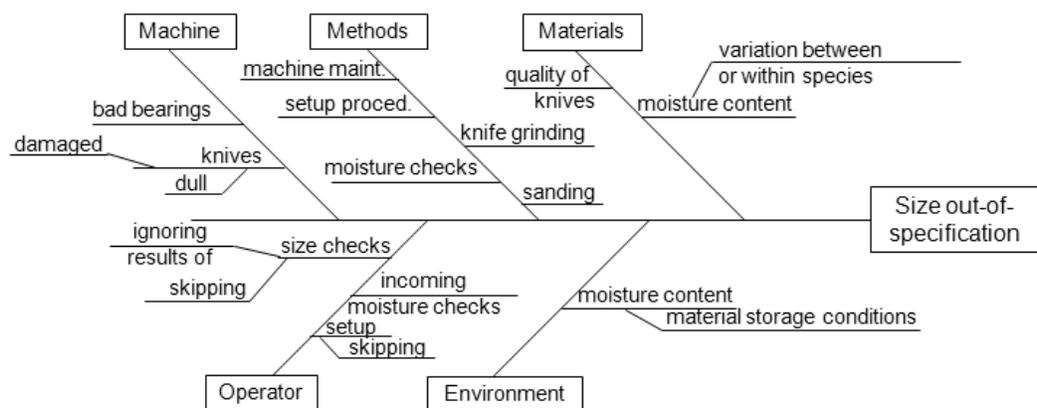

Figure 1. Cause-and-effect diagram (reproduced from Part 5 in this series).

Design of experiments

There is a difference between *designing an experiment* and *design of experiments* (DOE). Designing an experiment is the step in experimentation during which the experimenter determines objectives for the experiment, variables that will be tested, outcomes to observe, and how outcomes will be measured. Conversely, DOE is a term used for a set of statistical methods and tools that ensure effective and efficient conduct of experiments. Designing an experiment is just one of the steps (although a very important one) in DOE. Other steps include the actual conduct of the experiment, data analysis, and of course, interpretation of the results.

An in-depth description of the statistics required to become proficient in DOE is beyond the scope of this publication. Some industrial engineers and statisticians devote their entire careers to this topic. We provide a brief introduction so you will gain some understanding of the power and benefits of DOE. As a result, we hope you will invest in the necessary training or personnel (e.g., hiring an industrial engineer or statistician) to be able to reap the benefits of DOE. We also want to make you aware of the consequences (e.g., wasted money and time) of not conducting experiments properly.

Why not simply tweak the process and see what happens? In fact, companies do this all the time. In an effort to save time and money, manufacturers often test numerous variables at the same time and observe a limited number of results. Without DOE (and statistics), interpreting the results is often challenging, particularly when several variables have been tested. For example, if moisture content, tooling, species, and feed speed were all varied, how could you tell which variable or combination of variables affected the results? If the factors were varied one at a time in several individual experiments, how would you know if certain factors interacted (e.g., one set of tooling works well with one species but not with another)?

Also, without an adequate sample size, it's hard to have any confidence in the results. If the results come out as you hope, how confident can you be that results will be the same when the change (e.g., new moisture content, process speed, or adhesive) is made permanent?

DOE and the statistics involved help answer these important questions:

- Which variable or combination of variables affected the results?

- Are the results significant (i.e., likely to be the same if the experiment were conducted again)?

DOE: Step-by-step

DOE involves the following steps:

1. Objectives
2. Response variables
3. Process variables (factors)
4. Number of replicates
5. Detailed experimental plan
6. Factors to be held constant
7. Post-experiment plans

Step 1. Objectives

Why are you conducting the experiment? What does your company hope to learn?

Step 2. Response variables

What is the outcome of interest? How will you measure it? This step is often more complex than it first appears.

In our ongoing example, it would be easy to say that *handle size* is the response variable of interest. But is this really the case? The response variable needs to match the problem. In this case, what the team is really interested in knowing is which combination of process factors lead to the *fewest number of out-of-spec handles*. Therefore, the number of out-of-spec handles, rather than simply handle size, is the response variable of interest.[1] Once the team identifies the response variable of interest, they need to determine how it will be measured (e.g., with a go/no-go gauge, caliper, or tape measure), where measurements will be taken (both on the part itself as well as where in the factory), the number of measurements per handle, and when measurements will be taken (e.g., immediately after machining or after the wood has had time to equilibrate to ambient conditions).

Step 3. Process variables (factors)

What process variables (often called factors in DOE) will you intentionally vary in the experiment? Which can you really control? Do you need control over some that you currently don't control?

A cause-and-effect diagram is helpful for deciding which factors to control and which to explore, but what if you run an experiment and neglect to explore the major factor causing the problem? For example, what if you study moisture

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[1] In fact, we are also interested in studying the variability in handle dimensions because (assuming the process is on target) lower variability means less material beyond the specification limits. However, studying variation rather than a tally of defects or average size adds more complexity to the analysis than intended for this introduction to the subject.

content and tooling but later discover that species is the more significant factor? Unfortunately, you can't know with certainty which factors to study in a first run. Continuous improvement is a journey, not a destination. Additional experiments will likely be required. Often, the best approach is to rely on employees to guide selection of the factors on the basis of their experiences.

a. **Factor levels:** Determine how many and what specific settings (levels) of the factors you will test. In our continuing example, the team could test two, three, or more moisture contents at several levels (e.g., 5% and 15% or 8%, 10%, and 12%). Again, experience should be the guide. Existing data might show that moisture content of products usually varies from 4% to 16% throughout the year. Levels should be realistic but with enough range such that, if the factor is indeed important, real differences are likely to occur. For example, it would be better to choose 4% and 8% moisture content rather than 4% and 5%, particularly given the challenges of measuring moisture content accurately to within ±1%.

b. **Factor measurement:** For discrete factors (i.e., variables that have a finite number of values) such as tooling, you may simply be able to label them (e.g., brand A vs. brand B). For continuous factors (i.e., variables that can, at least theoretically, have any numerical value) such as moisture content, you must decide how to measure them (e.g., handheld meter, in-line meter, or oven-dry test).

Step 4. Number of replicates

What sample size will you use? For example, will you produce and test one product or 100 products for each test combination? Producing and measuring more replicates takes more time and costs more. However, the ability to detect significant[2] results (known as statistical power) increases as the number of replicates increases.

There are statistical formulas that give guidance on the number of replicates needed depending on the variability of the measure of interest, what level of difference you want to be able to detect (e.g., ±1% or ±15%), and your desired certainty in the outcome (e.g., 99.99% or 95% certain). If experience has shown that the response variable is consistent (i.e., low variability), fewer samples may be needed to detect actual differences. If experience suggests high variability in the results, a larger sample will be needed to detect significant differences. And if variability is extensive, it might make more sense to improve the stability of the process before conducting an experiment.

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[2] In common usage, the term *significant* often simply means *important* and doesn't qualify the degree of importance. In statistics, *significant* refers to a mathematical relationship for which there is a level of significance. For example, results of an experiment may indicate that two treatments are different at the "0.05 level of significance." This means there is only a 5% chance of observing such a difference purely by chance.

Step 5. Detailed experimental plan

This plan details, step by step, who will do what as well as when and where they will do it. Specify, *in detail*, the materials (include suppliers, species, etc.), procedures for each relevant process, equipment operators involved, measurement tools, testing dates and times, and other relevant information.

It's also critical to consider how you will analyze the data and interpret and use the results. Be certain you can analyze the data in such a way to be able to answer the critical questions. In some cases, companies have invested enormous resources in conducting an experiment only to later discover that they can't analyze the data. Statisticians brought in to consult after an experiment often say they really can't analyze the data because the experiment wasn't designed in such a way that statistical methods can be used effectively.

a. **Dry run:** At this point in the planning, it can be helpful to do a dry run to identify what might go wrong. For example, you might need to move material off the production line for measurement or create special fixtures for taking the measurements. A dry run can help identify when Murphy's Law (i.e., anything that can go wrong will) might occur. For example, is it possible that samples at high moisture content (i.e., swollen) will become jammed in the machinery? You can also analyze preliminary data to see if the statistics will work.

b. **Budget and deadline:** During this step, you should develop a budget for the experiment and set deadlines. Experienced experimenters recommend spending no more than about one fourth of the full budget for the experiment on the first trial. Many times, a first trial will reveal more questions and provide suggestions for what to study next.

Step 6. Factors to be held constant

In Step 3, you identified which factors to *intentionally* vary. Other factors that are held constant still need to be taken into account.

Companies naturally want to minimize the hassle and disruption inherent in industrial experimentation by answering all possible questions in a single experiment. This approach results in huge experiments[3] that take an extremely long time to design and conduct, data that are challenging to analyze, and results that are difficult to interpret.

The preferred approach is to attempt to hold constant other potential causes revealed in the cause-and-effect diagram. In our continuing example, the number of out-of-spec handles is the response variable, and factors that might be held constant include operator, measurement devices, time of day, and machine. In

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[3] For example, an experiment with five moisture contents, eight wood species, four types of tooling, 10 machines, six operators, and three shifts—even with only one replicate for each combination—would require producing 28,800 samples.

short, the goal in this step is to eliminate, to the greatest possible extent, all other potential causes of variability. This provides greater assurance that any differences in results are due to the selected experimental factors.

Step 7. Post-experiment plans

How will you use the results? If the results suggest a potential solution, how, by whom, and when will it be implemented? Will you conduct confirmation trials (i.e., run a few trials at the new settings to confirm that the new settings lead to the desired improvement)? How will you monitor the process to be sure these changes remain in place and continue to effectively reduce the problem?

If the tests are not successful (i.e., did not reveal a potential solution) or regardless of success, you may need to conduct follow-up experiments to explore other factors. For example, you might explore some of the factors that were held constant in the initial experiment.

Using DOE: An example

We now illustrate these seven DOE steps using our continuing example (i.e., out-of-spec handles).

XYZ Forest Products Inc. produces wooden handles for push brooms. Members of a quality improvement team visited a customer's facility and examined the contents of the scrap and rework bins. Using a check sheet and Pareto chart (Part 3), they were able to identify out-of-spec handles as the most frequent and costly quality problem. A flowchart (Part 4) helped build team consensus on the actual (vs. ideal) steps involved in the manufacturing process and enabled the team to identify where in the process problems might occur as well as where measurements were already being taken. A cause-and-effect diagram (figure 1 and Part 5) indicated several possible causes of the problem.

The team now needs to determine the root cause, or combination of causes, of the undesired effect. Once they know which variables have the greatest impact, they will know which are most critical to control. They can then establish standard operating procedures to more closely control these variables and a monitoring system to ensure the process remains stable in day-to-day operations.

Following the DOE steps described previously, the team develops the following (abbreviated) plan.

Steps 1 and 2. Objectives and response variables

On the basis of company experience and discussions during development of the cause-and-effect diagram, the team establishes the objective of exploring the influence of moisture content, species, and tooling on the number of out-of-spec handles. Hence, the number of out-of-spec handles is the response variable. Because the handles are circular rather than oval, the team decides to measure

each handle in a single location 1 inch from the tip by using a go/no-go gauge. They also decide to measure the handles after 1 week of storage because this product usually sits in the warehouse for at least that long before it is delivered to customers' facilities.

Step 3. Process variables (factors)

The team decides to test two levels of moisture content (6% and 12%), tooling (existing and a new brand), and wood species (birch and poplar, the company's top two species used by volume). Moisture content will be measured with a hand-held moisture meter calibrated in accordance with the manufacturer's guidelines. Table 1 shows the eight combinations that will be tested.

Table 1. Factor combinations to be tested

Factor combination	Tooling	Species	Moisture content
1	existing	birch	6%
2	existing	birch	12%
3	existing	poplar	6%
4	existing	poplar	12%
5	new	birch	6%
6	new	birch	12%
7	new	poplar	6%
8	new	poplar	12%

Step 4. Number of replicates

The team spends a fair amount of time debating the number of replicates. They realize the response variable (number of out-of-spec handles) is a tally or count (i.e., a discrete factor) rather than a measurement for an individual item (i.e., a continuous factor). In other words, they will tally out-of-spec handles in *batches* of products.

The team decides to use their standard batch size of 50 handles and five replicates (batches) per combination. For example, they will make a batch of 50 handles at 6% moisture content using existing tooling on birch and then count and record the number of out-of-spec handles in this batch. This will be the first replicate for this combination. They will repeat the process four more times for this combination of moisture content, tooling, and species and then repeat the process for the other seven factor combinations (table 1). The experiment will require the team to make and measure 2,000 handles (eight factor combinations × five replicates × 50 handles per replicate).

Step 5. Detailed experimental plan

The quality manager develops a detailed plan for the experiment that outlines all steps involved. The team conducts a dry run with sample pieces at the high and low end of the moisture content range, with the new tooling, and with both species. They process and measure several pieces to ensure all will go smoothly during the actual experiment. The dry run helps them recognize that accurately using the go/no-go gauge is difficult. As a result, they develop a fixture that holds the handle steady and enables measurement of each handle at the same location on the handle. The team also realizes that simple statistical methods available in software such as Microsoft Excel won't work with this experimental design. They will have to use specialized statistical software, or perhaps work with a consulting statistician.

Step 6. Factors to be held constant

To minimize variation due to factors that are not part of the experiment, the team decides to hold several factors constant. There will be only one operator using a single machine, the same operator will take the handle measurements and use a single go/no-go gauge, and the number of samples required is small enough that all pieces can be produced during one shift.

There are risks of variation related to the passage of time. For example, products in the first batch may be different from products in the last batch because of operator experience or fatigue, changes in ambient conditions, or tool wear. Therefore, the team plans to randomize the order of batches. They list the eight factor combinations (table 1) and then randomly assign a number from 1 to 40 (the total number of batches) to determine which batch will be produced first, second, and so on.

Step 7. Post-experiment plans

Assuming the results suggest specific factors (or factor combinations) that lead to a reduction in the number of out-of-spec handles, the team discusses how they will implement the findings. For example, they talk about other areas that may be affected, such as moisture checks, knife grinding, preventive maintenance, and machine set up. They also discuss running a confirmation trial as well as follow-up experiments with other variables (e.g., other species and machines).

Results

Table 2 shows data collected during the example experiment. Simply looking at the table probably won't reveal which combination is best for minimizing the number of out-of-spec handles. It is often impossible to develop conclusions from raw data. That's why statistics are integral to DOE.

Table 2. Experimental results—raw data

Batch	MC (%)[1]	Tooling	Species	Out-of-spec (no.)	Batch	MC (%)[1]	Tooling	Species	Out-of-spec (no.)
1	6	existing	birch	5	21	12	existing	birch	8
2	6	existing	birch	6	22	12	existing	birch	7
3	6	existing	birch	5	23	12	existing	birch	6
4	6	existing	birch	4	24	12	existing	birch	7
5	6	existing	birch	5	25	12	existing	birch	9
6	6	existing	poplar	4	26	12	existing	poplar	6
7	6	existing	poplar	6	27	12	existing	poplar	5
8	6	existing	poplar	3	28	12	existing	poplar	6
9	6	existing	poplar	2	29	12	existing	poplar	7
10	6	existing	poplar	4	30	12	existing	poplar	8
11	6	new	birch	4	31	12	new	birch	8
12	6	new	birch	6	32	12	new	birch	7
13	6	new	birch	6	33	12	new	birch	9
14	6	new	birch	7	34	12	new	birch	8
15	6	new	birch	5	35	12	new	birch	9
16	6	new	poplar	4	36	12	new	poplar	5
17	6	new	poplar	3	37	12	new	poplar	4
18	6	new	poplar	2	38	12	new	poplar	4
19	6	new	poplar	2	39	12	new	poplar	3
20	6	new	poplar	4	40	12	new	poplar	3

[1] Moisture content.

And although averaging the results for each of the eight factor combinations simplifies things somewhat, the team can't draw any conclusions with certainty (table 3). They might be able to determine that 6% moisture content is better than 12% moisture content. But remember, these are averages. At 6% moisture content, there were as few as two and as many as seven out-of-spec handles in a batch. At 12% moisture content, there were as few as three and as many as nine out-of-spec handles in a batch. Given this amount of variability, the team can't

say with confidence that 6% moisture content is better than 12% moisture content. The team must also consider tooling, species, and factor combinations (known as interactions). For example, maybe the new tooling works better for poplar than for birch (a tooling–species interaction). Being able to identify interactions is a major benefit of DOE and the use of statistics.

Table 3. Experimental results—summarized

Combination (MC%[1]–tooling–species)	Out-of-spec handles (avg. no.)
6–existing–birch	5
6–existing–poplar	3.8
6–new–birch	5.6
6–new–poplar	3
12–existing–birch	7.4
12–existing–poplar	6.4
12–new–birch	8.2
12–new–poplar	3.8

[1] Moisture content.

DOE and statistics

The primary benefit of DOE and the use of statistical methods for analysis is the ability to determine if results are statistically significant. In other words, statistical analysis can indicate how likely it is that a repeated experiment will yield the same or similar results. For example, results might show that "species is significant at $p \leq 0.05$." This means there is a 5% chance of observing such a difference purely by chance and that results would likely be similar in a repeated experiment. Such results can justify making changes (e.g., using different tooling).

Conversely, when results are *not* significant, there is no assurance that a repeated experiment will yield similar results. For example, results may indicate that the average number of out-of-spec handles is higher for the existing tooling than for the new tooling. But if tooling is not statistically significant, results might be different in repeated experiments. Therefore, if the team switches to using the new tooling, they shouldn't be surprised if results are not consistent.

It isn't necessarily a bad thing if experimental results show that a factor is not significant. Knowing which factors are and are not significant helps determine which factors are important to monitor (i.e., the significant ones) and which are not as critical.

And although it is good to know the results of an experiment, what is really important is what the results will be over the long term if changes are made. In the case of our continuing example, assume that species is significant and,

specifically, that there are fewer out-of-spec handles for poplar than for birch. If the company stops using birch, is it guaranteed that there will be fewer out-of-spec handles? No. The statistical analysis simply provides confidence that species has an impact on the results. Running a confirmation trial can increase confidence in the findings. However, many factors were held constant (e.g., operator, shift, environmental conditions, and machine), and other factors were not explored. DOE helps companies make informed decisions to solve problems and improve processes, but the complex nature of manufacturing processes generally prevents guaranteed results.

Again, it's beyond the scope of this publication to train you in DOE. Our primary objective is to demonstrate the power and benefits of DOE with an example. We hope this information and example will encourage you to invest in the necessary training or personnel to be able to effectively use the power of DOE in your company. Rather than walk through all steps involved in data analysis, we will simply present the results of the analysis and explain what they mean.

Statistical analysis example

In our ongoing example, the team uses Stat-Ease Inc.'s Design-Expert software to analyze the data. This software helps users select factors (e.g., moisture content, tooling, and species) and levels (e.g., 6% and 12%, existing and new tooling, and birch and poplar), number of replicates (e.g., 5 batches with 50 handles each), and response variables (e.g., number of out-of-spec handles). It then randomizes the order of the experimental runs (to minimize risks of variation related to the passage of time) and provides a spreadsheet-style table into which users enter results.

The ANOVA (analysis of variance) table for this experiment shows a value of $p < 0.0001$ for the model as a whole. This means that at least one of the factors studied is significant. If this were not the case, there wouldn't be any point in looking at the results any further; the team would conclude that the differences were due to factors that were not researched or the normal variability in the process. The ANOVA table also indicates that moisture content, species, and a tooling–species interaction are all significant. However, neither tooling as a standalone factor nor the interaction between moisture content and tooling is significant.

This is a good start, but the team needs more information before they can make any decisions about what to change. Specifically, they need to know what level of moisture content is best and the nature of the tooling–species interaction. Figures 2 and 3 help answer these questions.

Figure 2 shows the number of out-of-spec handles for each species, type of tooling, and moisture content. There are fewer out-of-spec handles at 6% moisture content than at 12% moisture content regardless of species and tooling.
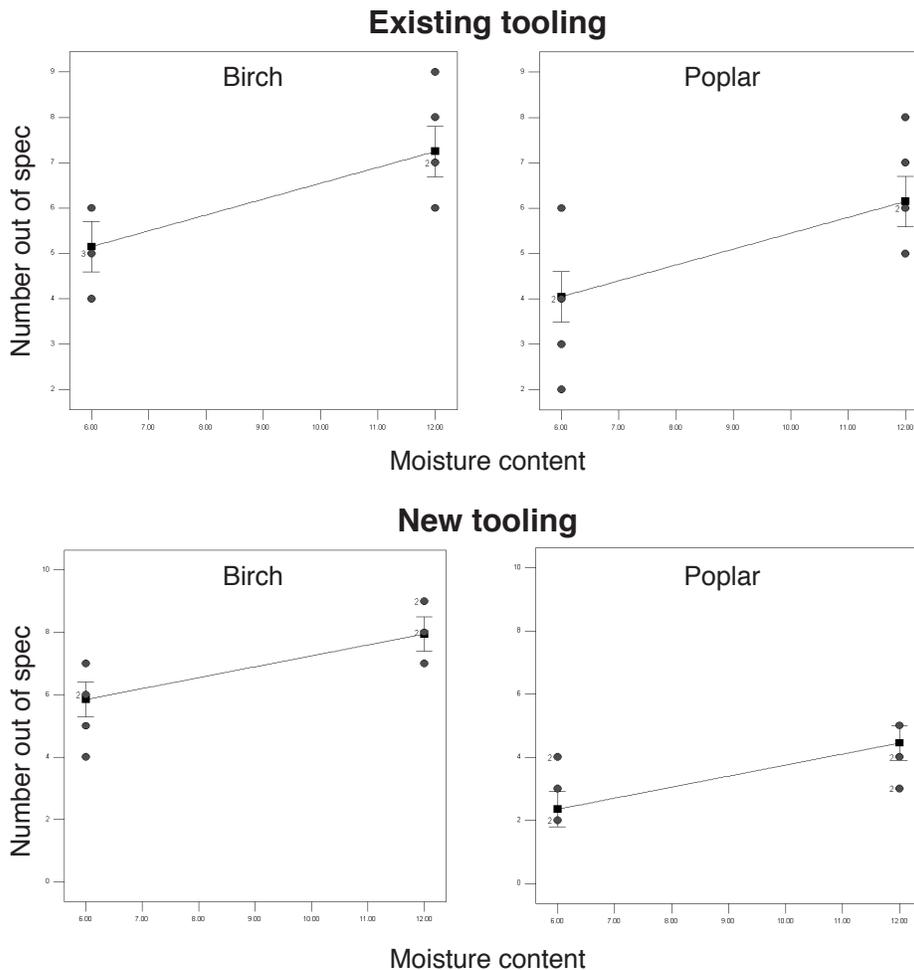
Figure 2. Experimental results for moisture content.
Charts created using Design-Expert software.

Rectangles indicate the average number of out-of-spec handles at each moisture content, and circles show the individual data points from the experiment. The team can't make decisions on the basis of the averages alone; they must also take into account the variability within each group (i.e., the vertical spread between the circles). Because the ANOVA table indicates that moisture content is significant, the team can state with some certainty that machining the wood at a lower moisture content will result in fewer out-of-spec handles.

Knowing there is a tooling–species interaction, the team can't draw any conclusions about species from figure 2. It appears there are more out-of-spec handles for birch than for poplar, but the team has to suspend judgment until they look at charts showing the nature of the interaction between species and tooling. These charts (figure 3) are a bit more complicated to interpret.
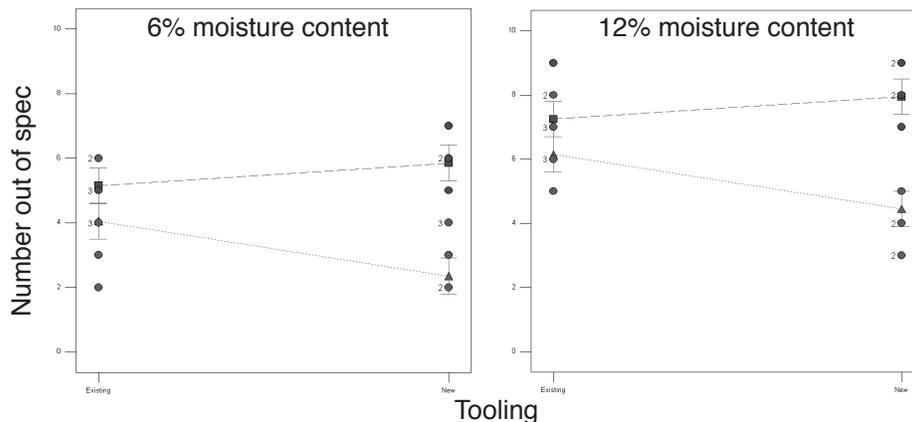
Figure 3. Experimental results for tooling–species interaction.
Charts created using Design-Expert software.

The chart on the left in figure 3 shows the results at 6% moisture content. Existing tooling is on the left side of the chart, and new tooling is on the right. Birch is the upper line, and poplar is the lower line. As in figure 2, rectangles indicate the average number of out-of-spec handles for each combination of tooling and species, and circles show the individual data points from the experiment. The chart on the right in figure 3 is structured the same but shows the results at 12% moisture content.

When interpreting the results for one factor in a significant interaction, the answer is always, "It depends." For example, the simple answer to the question, "Which tooling is best?" is, "It depends on species." As mentioned previously, figure 2 shows there are fewer out-of-spec handles at 6% moisture content than at 12% moisture content regardless of species and tooling. However, figure 3 shows that the situation is more complex. At 6% moisture content (chart on left), it appears that tooling makes little difference for birch (upper line). The average number of out-of-spec handles is similar for existing and new tooling—between about five and six in a batch of 50. And even at 12% moisture content (chart on right), the difference between existing and new tooling for birch is small. But regardless of moisture content, the new tooling seems to result in slightly more out-of-spec handles for birch. The situation is quite different for poplar; the new tooling results in fewer out-of-spec handles regardless of moisture content.

Recommendations

The team has conducted an experiment and analyzed and interpreted (to some extent) the results, but they still haven't made any recommendations for what the company should do.

Because customers require handles made from both species, the team is limited to changing moisture content, tooling, or both. Because the experiment revealed a significant interaction between factors, the team has to conclude that "it depends." Their recommendations to the company depend on a few assumptions:

1. If the company can tightly control and monitor moisture content and prefers not to change tooling each time they switch between birch and poplar, the team recommends machining poplar and birch at 6% moisture content using the new tooling. However, this involves a trade-off. Figure 3 indicates that using the new tooling will result in fewer out-of-spec handles with poplar but slightly more out-of-spec handles with birch. Hence, the decision should also depend on how frequently each species is used. If birch is the dominant species used in production, the company might want to continue using the existing tooling.

2. If the company can't tightly control moisture content and changing tooling between species is feasible, the team recommends using the existing tooling for birch (regardless of moisture content) and the new tooling for poplar (regardless of moisture content).

Now that the experiment is complete and the recommendations are made, the hard work begins. First, the company may want to run a few confirmation trials (i.e., produce several more batches at the new settings). If the actual results are consistent with the experimental results, the company can change their standard operating procedures accordingly. If not, they have more experimenting to do.

In fact, the company will likely conduct more experiments regardless of the results because they strive for continuous process improvement. In this example, the best result was two out-of-spec handles per batch of 50. The long-term goal is zero out-of-spec handles, but the team has yet to discover the optimum combination of process factors that will result in zero defects. These factors could include a moisture content lower than 6%, different tooling or storage conditions, or something else.

Next steps

The steps taken to this point to identify and solve the most critical quality problem at XYZ Forest Products Inc. *should* result in improvements in product quality and customer satisfaction. Assuming that customers return reject handles for a refund (or worse, switch suppliers), these steps will undoubtedly also improve the company's bottom line.

But even if the company implements the changes, there's still one major hurdle that stands in their way of reaping the benefits. They must monitor the process over time to ensure the changes are consistently implemented. For example, if they decide to use wood at 6% moisture content, how can they ensure the wood is at 6% from day to day? It's one thing to write a standard operating procedure; it's another thing to ensure it is followed.

In summary, rather than making random changes to your process and hoping for the best, you can use the tools we're presenting in this series of publications to make well-informed decisions. In business, well-informed decisions save money.

The next publication in this series will describe process monitoring and control, which is accomplished with the primary tool of SPC: control charts.

For more information

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PERFORMANCE EXCELLENCE IN THE WOOD PRODUCTS INDUSTRY

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