RPM Virtual Process Labs™

Instructor Guide

Injection Molding – Design of Experiments (DOE) Edition

Turning Knowledge into Capability

Interactive learning experiences that transform Lean Six Sigma concepts into hands-on practice.

Learn. Experiment. Improve.

RPM-Academy Virtual Process Labs™

Table of Contents

1. Welcome to the Virtual Process Lab

RPM Virtual Process Labs™ are designed to bridge the gap between learning statistical methods and applying them.

The Injection Molding – Design of Experiments (DOE) Lab places learners in a simulated process environment where they must make experimental decisions, collect data, analyze results, challenge assumptions, and determine what to do next.

Unlike a worked example in which the data and analytical pathway are already known, the Virtual Process Lab asks learners to discover the process through experimentation. Decisions have consequences. Models may need refinement. Initial conclusions may change as new evidence becomes available.

That uncertainty is intentional.

The Instructor's Role

The instructor's role is not simply to demonstrate the mechanics of DOE or guide learners toward a predetermined answer. It is to create an environment in which learners can:

- Ask meaningful questions about the process.
- Make and defend experimental decisions.
- Interpret statistical evidence in operational terms.
- Recognize when the evidence is insufficient.
- Learn from imperfect models and unexpected results.
- Decide what they need to learn next.

Whenever possible, resist the temptation to immediately correct an analytical mistake or reveal what the simulation contains. A well-placed question can create a more powerful learning experience than providing the answer.

GUIDING PRINCIPLE
The goal is not to complete the experiment… the goal is to learn from it.

This Instructor Guide provides the structure, teaching points, discussion questions, expected discoveries, and facilitation guidance needed to help make that learning happen.

2. Purpose of this Guide

This Instructor Guide is designed to help instructors, facilitators, and coaches use the RPM Virtual Process Lab™ as an experiential learning environment, rather than simply as a software exercise.

It complements the Quick Start Guide, which explains how to navigate and operate the Lab. This guide focuses instead on how to facilitate the learning experience – what learners should discover, what questions to ask, where they may struggle, and when to allow the experiment itself to become the teacher.

How to Use This Guide

The guide provides:

- Learning objectives that define the capabilities learners should develop.
- Instructor preparation guidance for becoming familiar with the Lab before facilitating it.
- A recommended learning journey that moves from initial experimentation through analysis, optimization, capability assessment, and further experimentation.
- Facilitation questions designed to encourage learners to explain and defend their reasoning.
- Instructor insights identifying opportunities for discussion and deeper learning.
- Common learner pitfalls and suggestions for turning them into teachable moments.
- Instructor reference information describing the relationships intentionally embedded within the simulated process.
- Debrief and assessment guidance for evaluating experimental thinking rather than simply obtaining the "right" numerical result.

A Guide, Not a Script

The recommended learning journey presented here is intentionally flexible.

Instructors may adapt the Lab to suit different audiences, available time, statistical software, and levels of DOE experience. Learners may also take different analytical paths and reach somewhat different numerical results.

That is part of the experience.

The objective is not to reproduce a predetermined analysis. It is to help learners develop the ability to design experiments thoughtfully, interpret evidence critically, and make better decisions about what to do next.

> ***INSTRUCTOR TIP***
>
> *Use this guide as a roadmap, not a script. Allow learners enough freedom to make decisions, encounter uncertainty, and learn from the consequences.*

3. Learning Objectives

The Injection Molding – Design of Experiments (DOE) Virtual Process Lab™ is designed to move learners beyond the mechanics of creating and analyzing an experimental design toward the development of experimental thinking and data-informed decision-making.

By completing the Lab and participating in the associated analysis and debrief, learners should be able to:

Design and Conduct an Experiment

- Translate a process problem into an experimental objective.
- Identify controllable factors, factor levels, response measures, targets, and specification limits.
- Select an experimental design appropriate to the learning objective and available experimental resources.
- Explain the implications of using a fractional factorial design, including resolution and potential aliasing.
- Conduct experimental runs systematically and capture the resulting data for analysis.

Analyze and Interpret the Evidence

- Identify and interpret important main effects and interactions.
- Distinguish statistical significance from practical or operational significance.
- Evaluate model adequacy using R^2, adjusted R^2, predicted R^2, residual analysis, and other relevant diagnostic evidence.
- Apply thoughtful model reduction while respecting model hierarchy.
- Recognize evidence that a first-order model may not adequately describe the process.

Optimize and Evaluate the Process

- Use response optimization and graphical methods such as contour plots to explore promising operating conditions.
- Interpret a predicted optimum as a hypothesis to be validated rather than a guaranteed result.
- Evaluate process capability at proposed operating conditions.
- Connect statistical findings to practical process decisions.

Extend the Learning

- Identify limitations in an initial experimental design.
- Determine when additional experimentation is warranted.
- Explain how sequential experimentation can build upon knowledge already gained.
- Use design augmentation to investigate curvature and refine understanding of the process.
- Compare conclusions before and after additional experimental evidence becomes available.

Think Like an Experimenter

Most importantly, learners should develop the ability to ask:

- What do we know?
- How do we know it?
- What are we still uncertain about?
- What should we learn next?

INSTRUCTOR INSIGHT

Success in the Virtual Process Lab™ is not defined by obtaining a particular R^2 value, identifying a predetermined optimum, or reproducing an instructor's analysis. Success is demonstrated when learners can use experimental evidence to explain what they believe about the process—and defend what they would do next.

4. Before You Facilitate the Lab

A successful Virtual Process Lab™ experience requires relatively little instructor preparation, but instructors should be familiar with both the simulated process and the intended learning journey before facilitating the exercise.

Whenever possible, experience the Lab first as a learner. Run an experiment, analyze the resulting data, explore the model, and consider what you would do next before reviewing the instructor-only information later in this guide.

Instructor Preparation Checklist

Before facilitating the Lab:

- Review the RPM Virtual Process Lab™ Quick Start Guide.
- Open the Virtual Process Lab and confirm that it is functioning correctly.
- Familiarize yourself with the five experimental factors, their allowable settings, and the response being measured.
- Review the process target and specification limits.
- Conduct at least one experimental design using the Lab.
- Transfer the experimental results into your preferred statistical analysis software and complete an analysis.
- Explore the response optimizer and appropriate graphical tools, including contour plots.
- Review the concepts of factorial design, fractional factorial design, resolution, aliasing, interactions, model hierarchy, and curvature.
- Review the Instructor Reference section of this guide so you understand the relationships intentionally embedded within the simulated process.
- Decide how much information learners will receive before beginning the exercise—and what you want them to discover for themselves.

Statistical Software

The Virtual Process Lab™ generates experimental data; it does not require learners to use a specific statistical analysis package.

Instructors may use SigmaXL, Minitab, JMP, Design-Expert, R, Python, or another suitable analytical tool, depending on the learning environment and available resources.

Where software-specific instructions are provided separately, they should support the learning experience rather than define it. The central questions remain the same regardless of the analytical platform:

- What is the experiment telling us?
- How much confidence should we place in the model?
- What should we do next?
- Decide What You Will Reveal

One of the most important instructor decisions occurs before the experiment begins.

Learners need sufficient information to understand the process challenge, factors, response, target, specifications, and available experimental resources. They do not need to know which factors or interactions are important, whether curvature exists, or where the optimum is likely to occur.

Those are discoveries.

Revealing them prematurely turns an experiment into a demonstration.

INSTRUCTOR TIP — EXPERIENCE BEFORE EXPLANATION

When learners ask, "Is this factor important?" or "Is there curvature?", consider answering with another question: "How could you use the experiment to find out?"

Prepare the Learning Environment

Before beginning, confirm that learners have access to:

- The Virtual Process Lab™ workbook.
- The participant Quick Start Guide.
- Appropriate statistical analysis software.
- A method for recording experimental decisions and observations.
- Sufficient time to analyze and discuss results—not merely generate data.

If learners are working in teams, consider assigning roles such as experiment lead, process operator, analyst, and recorder. Roles can be rotated as the exercise progresses so that everyone participates in both experimentation and interpretation.

WATCH FOR

The Lab can become a race to generate data. Encourage learners to pause between experimentation and analysis. The value of DOE comes not from how quickly experimental runs are completed, but from how much is learned from each experimental sequence.

5. The Learning Scenario

The Injection Molding – Design of Experiments (DOE) Virtual Process Lab™ places learners in the role of a process improvement team responsible for improving the dimensional performance of a simulated injection-molding process.

The process produces a critical molded component with a target dimension of 12.50 mm and specification limits of 12.35 mm to 12.65 mm.

The challenge is not simply to produce a part within specification. Learners must develop an understanding of how the process behaves, identify the factors and relationships that influence dimensional performance, and determine operating conditions capable of producing consistent results.

The Experimental Factors

Five controllable factors are available for investigation:

Factor	Low Level	High Level
Mold Temperature	180°C	220°C
Injection Pressure	70 MPa	110 MPa
Cooling Time	10 sec	20 sec
Resin Supplier	Supplier A	Supplier B
Vent Design	Standard	Modified

The first three factors are continuous variables, while Material Supplier and Vent Configuration are categorical variables.

This combination allows learners to explore not only individual factor effects, but also the possibility that factors may behave differently depending upon the settings of other factors.

The Response

The primary response is the measured dimension of the molded component.

- Target: 12.50 mm
- Lower Specification Limit (LSL): 12.35 mm
- Upper Specification Limit (USL): 12.65 mm

Experimental results include natural process variation. Repeating the same operating conditions therefore should not be expected to produce an identical response every time.

This is intentional.

Learners must distinguish between the underlying process relationships and the variation that accompanies any real process.

The Challenge

Learners are asked to use Design of Experiments to investigate the process and ultimately recommend operating conditions that provide strong and predictable dimensional performance. Their challenge is to determine:

- Which factors meaningfully influence the response?
- Are important interactions present?
- How well does the experimental model describe the process?
- How well is the model likely to predict future results?
- Where should the process be operated?
- Is the process capable at the proposed operating conditions?
- What uncertainty remains after the initial experiment?
- Is additional experimentation justified?

There is intentionally no experimental recipe provided for answering all of these questions.

The learners' job is to use evidence to progressively build an understanding of the process.

> ***INSTRUCTOR INSIGHT — DON'T GIVE AWAY THE PROCESS***
>
> *Learners should know the factors, available ranges, response, target, and specifications. They should not be told which factors are significant, which interactions exist, whether curvature is present, or where the optimum lies. Those relationships are intentionally embedded within the Virtual Process Engine™ for learners to discover.*

The Experimental Budget

An important part of DOE is deciding how much experimentation is justified to answer the question at hand.

Encourage learners to consider experimental efficiency rather than automatically selecting the largest available design. Be sure to ask:

"What do we need to learn—and what is the smallest experiment that can reliably help us learn it?"

This question sets the stage for the sequential experimental strategy used later in the Lab.

ASK THE LEARNERS

Before anyone opens the statistical software, ask each team to explain what they want their first experiment to teach them.

A good experimental design begins with a learning objective—not with a software dialogue box.

6. Recommended Learning Journey

Round 1 — Explore the Process

Round 1 is designed to give learners a strong first look at the process while preserving the uncertainty that makes DOE valuable.

The recommended starting point is a ½ Fraction Resolution V factorial design using the five available factors:

- Mold Temperature
- Injection Pressure
- Cooling Time
- Resin Supplier
- Vent Design

This design provides an efficient way to investigate the process while allowing learners to estimate main effects and selected interactions without immediately committing to a full factorial experiment.

The Learning Objective

The objective of Round 1 is not to find the final answer.

It is to develop an initial model of the process, determine what appears important, and identify what remains uncertain.

Learners should be encouraged to approach the first experiment with a clear question:

"What can we learn efficiently about this process before deciding whether more experimentation is necessary?"

Recommended Learner Tasks

Ask learners to:

- Create a ½ Fraction Resolution V factorial design for the five factors.

- Conduct the required experimental runs using the Virtual Process Lab™.
- Transfer the resulting data into their statistical analysis software.
- Fit and evaluate an appropriate model.
- Identify important main effects and interactions.
- Review model statistics and diagnostic evidence.
- Apply model reduction where appropriate while respecting model hierarchy.
- Use response optimization to identify promising operating conditions.
- Generate appropriate contour plots to explore the response surface.
- Use the proposed operating conditions to generate additional process observations.
- Conduct a capability analysis against the specification limits of 12.35 mm to 12.65 mm.
- Prepare a short summary of what they believe they have learned about the process.

Suggested Round 1 Deliverables

Before moving on, learners should be able to present:

- Their experimental design and rationale.
- Their final fitted model.
- Key model statistics, including R^2, adjusted R^2, and predicted R^2.
- Significant or practically important main effects and interactions.
- Relevant residual or diagnostic plots.
- A response optimizer result.
- At least one useful contour plot.
- Their proposed operating conditions.
- A capability analysis at those conditions.
- A brief statement describing what they believe they know—and what they are still uncertain about.

The final item is particularly important. A strong Round 1 analysis should not simply conclude: "We found the optimum." It should also ask: "What evidence supports that conclusion, and what evidence might still be missing?"

Why Start with a Resolution V Half-Fraction?

The design is intentionally efficient.

With five factors, a full two-level factorial design would require considerably more experimental runs. A Resolution V half-fraction allows learners to investigate the process using fewer runs while maintaining useful separation between main effects and lower-order interactions.

This creates an important teaching opportunity.

DOE is not about collecting the maximum amount of data possible. It is about collecting the right data efficiently enough to make better decisions about what to do next.

INSTRUCTOR INSIGHT — EFFICIENCY IS PART OF THE DESIGN

Ask learners why they selected the design they did. If the answer is simply, "Because that is what the exercise said to use," push further. What information does the design give us? What information does it sacrifice?

Model Reduction: Let the Learners Struggle Productively

Depending on how learners initially specify the model, they may create an unnecessarily complex model.

This may produce a very high R^2 while generating a weak or even unusable predicted R^2.

Do not immediately correct this. Instead, ask learners to compare:

- R^2
- Adjusted R^2
- Predicted R^2
- Residual behaviour
- Number of model terms
- Model hierarchy

Then ask: "Is the model explaining the data—or learning the data?" This distinction is one of the most valuable lessons in Round 1.

WATCH FOR

Learners may assume that the model with the highest R^2 is automatically the best model. Use this as an opportunity to introduce the risk of overfitting and the importance of predictive performance.

Optimization Is Not the Finish Line

Once learners have developed a reasonable model, allow them to use the response optimizer and contour plots to identify promising process settings.

Encourage them to interpret the optimizer as a model-based recommendation, not as proof that the predicted result will occur. Ask: "What would you need to do before you were willing to run the real process at these settings?"

This naturally leads to confirmation and capability assessment.

Capability as a Reality Check

After selecting proposed operating conditions, learners should generate additional observations from the Virtual Process Lab™ and evaluate process capability.

This reinforces an important distinction: A statistically useful model does not automatically guarantee a capable process.

The ultimate question is whether the knowledge gained through experimentation can be translated into operating conditions that consistently meet customer requirements.

The Critical Pause

Once Round 1 is complete, stop the exercise.

Do not immediately introduce design augmentation or curvature.

Instead, ask learners to review the evidence they already have. Suggested questions include:

- How confident are you in your model?
- How well does it predict?
- What does the contour plot suggest?
- Are there regions of the factor space that remain poorly understood?
- Does the model appear entirely linear?
- What assumptions are you making about the shape of the response surface?
- What would you investigate next if additional experimental runs were available?

Allow learners to identify the limitations themselves.

> ***INSTRUCTOR TIP — DO NOT REVEAL ROUND 2 TOO EARLY***
>
> *The transition to augmentation is most powerful when learners first recognize that their initial experiment may not answer every important question.*
>
> *Let the need for additional experimentation emerge from the evidence.*

Round 1 is complete when learners can explain not only what they believe about the process, but also what they still need to learn.

7. Round 1 Instructor Debrief

The Round 1 debrief is an opportunity to move learners from statistical output to experimental understanding.

Rather than reviewing every table or graph produced during the analysis, focus the discussion on what the evidence means, how confident learners are in their conclusions, and what questions remain unanswered.

Whenever possible, ask learners to explain their reasoning before offering instructor interpretation.

1. What Did the Experiment Tell You?

ASK THE LEARNERS: Which factors appear to have the greatest influence on dimensional performance?

LISTEN FOR: Learners should distinguish between important main effects and interactions and should be able to describe their findings in process terms—not simply report coefficients or p-values.

TEACHING POINT

Statistical significance identifies evidence of an effect. Experimental understanding requires learners to explain what that effect means for the process.

2. Are Any Factors Working Together?

ASK THE LEARNERS: Did you identify important interactions? What do they mean operationally?

LISTEN FOR: Learners should recognize that the effect of one factor may depend upon the setting of another factor.

TEACHING POINT

When an interaction is important, statements such as "higher pressure is better" may be misleading. The effect of Injection Pressure, for example, may depend upon another process condition.

Encourage learners to use interaction plots or other graphical evidence to explain the relationship.

3. How Good Is Your Model?

ASK THE LEARNERS: What evidence tells you that this is a useful model?

LISTEN FOR: Learners should look beyond R^2 and consider:

- Adjusted R^2
- Predicted R^2
- Residual behaviour
- Model significance
- Individual model terms
- Model hierarchy
- Practical usefulness

TEACHING POINT

A model can describe the experimental observations extremely well while still performing poorly when asked to predict new observations.

INSTRUCTOR INSIGHT — THE R^2 TRAP

If learners proudly report a very high R^2, respond with: "Excellent. Now convince me that the model can predict."

4. What Happened During Model Reduction?

ASK THE LEARNERS: Did your model change as you removed unnecessary terms? What happened to adjusted and predicted R^2?

LISTEN FOR: Learners may observe that removing unnecessary terms improves predicted performance even though ordinary R^2 changes very little or decreases slightly.

TEACHING POINT

More model terms do not necessarily produce a better predictive model.

Model reduction should be thoughtful rather than mechanical. Learners should consider statistical evidence, model hierarchy, process knowledge, and the purpose for which the model will be used.

WATCH FOR

Learners may remove a lower-order term while retaining an interaction or higher-order term involving that factor. Use this opportunity to reinforce model hierarchy.

5. What Do the Residuals Tell You?

ASK THE LEARNERS: Do the residuals support the assumptions behind your model?

LISTEN FOR: Learners should examine residual plots for unusual patterns, non-random structure, changing variation, extreme observations, or other evidence suggesting that the fitted model may be incomplete.

TEACHING POINT

Residuals represent what the model has not explained.

Encourage learners to treat residual analysis as part of model development rather than as a statistical formality performed after the "real" analysis is finished.

6. What Does the Optimizer Really Tell You?

ASK THE LEARNERS: The optimizer has recommended settings. Why should we believe them?

LISTEN FOR: Learners should recognize that optimization is based upon the fitted model and is therefore only as trustworthy as the model itself.

TEACHING POINT

The optimizer does not discover truth. It searches the mathematical model for settings predicted to satisfy the objective.

The recommended optimum should therefore be treated as a testable prediction.

7. What Do the Contour Plots Add?

ASK THE LEARNERS: What can you see in the contour plots that is harder to recognize from the regression equation alone?

LISTEN FOR: Learners may identify regions of better performance, interaction behaviour, gradients across the experimental space, or patterns that raise questions about whether a simple linear relationship adequately describes the process.

TEACHING POINT

Graphical analysis helps translate statistical models into process understanding.

Encourage learners to explore more than one pair of continuous factors rather than producing a contour plot merely because the exercise requests one.

8. Is the Process Capable?

ASK THE LEARNERS: At your proposed settings, would you be comfortable releasing this process to production?

LISTEN FOR: Learners should consider:

- Process centering
- Process variation
- Capability indices
- Sample size
- Stability assumptions
- Whether the operating conditions have been adequately confirmed

TEACHING POINT

Capability analysis is not simply another statistic to report. It connects the experimental model to the customer's requirements.

A good model is useful only if it helps us make better process decisions.

9. What Doesn't the Experiment Tell Us?

ASK THE LEARNERS: What assumptions are we making that our experiment has not actually tested? Allow some silence here.

LISTEN FOR: Learners may recognize that a two-level factorial experiment primarily describes relationships between the low and high settings and may not fully characterize what happens between them.

Some may begin questioning whether the response behaves linearly throughout the experimental region.

TEACHING POINT

This is the pivotal discovery in Round 1. Do not introduce augmentation yet. Instead ask: "How could we find out?"

10. What Would You Do Next?

ASK THE LEARNERS: If I gave you a limited number of additional experimental runs, where would you spend them—and why?

LISTEN FOR: There is no requirement that learners immediately propose the intended augmentation strategy.

The important outcome is that they begin thinking sequentially: Experiment → Learn → Identify uncertainty → Experiment again

TEACHING POINT

DOE is not necessarily a single event. Effective experimentation often progresses through a sequence of increasingly focused questions.

INSTRUCTOR TIP — RESIST THE RESCUE

If learners recognize uncertainty but do not know what experiment should come next, do not immediately provide the design. Help them first articulate what they need to learn.

Once the learning question is clear, the appropriate experimental strategy becomes much easier to discuss.

Closing Round 1

Conclude the debrief by asking each team to complete two statements:

- Based on our experiment, we believe...
- We are still uncertain about...

Capture both...

The first statement summarizes what the experiment has taught them.

The second provides the reason for conducting the next experiment.

8. Round 2 — Extend the Experiment

Round 1 gave learners an initial understanding of the injection-molding process.

Round 2 asks a different question: "What do we still need to learn?"

Rather than abandoning the original experiment and beginning again, learners will build upon the information already collected. This introduces one of the most powerful ideas in Design of Experiments:

1. Experimentation can—and often should—be sequential.
2. From Screening to Deeper Understanding

The Resolution V half-fraction used in Round 1 provides valuable information about main effects and interactions. However, the continuous factors were investigated primarily at two levels:

- Mold Temperature: 180°C and 220°C
- Injection Pressure: 70 MPa and 110 MPa
- Cooling Time: 10 sec and 20 sec

A two-level design can describe how the response changes between these settings, but it provides limited information about the shape of the response between them.

If learners suspect that the process may contain curvature, additional experimental evidence is required.

The question becomes: "How can we extend what we already know without throwing away the experiment we have already conducted?"

Introduce Design Augmentation

At this point, introduce the concept of design augmentation.

Explain that an existing experimental design can sometimes be expanded strategically by adding new experimental points that provide information the original design could not estimate adequately.

For this Lab, learners will augment their original design by **adding face-centered axial points** for the continuous factors.

These additional runs allow learners to investigate intermediate settings and estimate curvature while retaining the information obtained during Round 1.

INSTRUCTOR INSIGHT — BUILD, DON'T RESTART

The important lesson is not simply how to add axial points.

It is that experimentation can evolve as understanding improves:

Design → Experiment → Learn → Refine the Question → Experiment Again

Face-Centered Axial Points

For the three continuous factors, the center settings are:

Factor	Low	Centre	High
Mold Temperature	180°C	200°C	220°C
Injection Pressure	70 MPa	90 MPa	110 MPa
Cooling Time	10 sec	15 sec	20 sec

The face-centered axial points introduce experimental observations at intermediate settings while remaining within the original factor ranges.

Resin Supplier and Vent Design remain categorical factors and therefore do not receive axial settings.

Recommended Round 2 Learner Tasks

Ask learners to:

- Retain the experimental data collected during Round 1.
- Augment the existing design using face-centered axial points for Mold Temperature, Injection Pressure, and Cooling Time.
- Do not add additional replicates or center points unless the instructor intentionally modifies the exercise.
- Conduct the additional experimental runs using the Virtual Process Lab™.
- Combine the new observations with the original Round 1 data.
- Reanalyze the expanded experimental dataset.
- Investigate appropriate quadratic terms for the continuous factors.
- Apply thoughtful model reduction while maintaining model hierarchy.
- Compare model quality with the Round 1 model.
- Revisit response optimization using the refined model.
- Generate new contour plots and compare them with the Round 1 graphical analysis.
- Select revised operating conditions where appropriate.
- Generate confirmation observations at the proposed settings.
- Reassess process capability.
- Compare the conclusions from Round 1 and Round 2.

Compare, Don't Simply Replace

Learners should not treat the Round 2 model as though Round 1 never occurred.

Ask them to compare the two stages of experimentation.

Consider:

- Which conclusions remained unchanged?
- Which effects became clearer?
- Did previously important effects remain important?
- Did evidence of curvature emerge?
- Did model quality improve?
- Did predicted R^2 change?
- Did the predicted optimum move?
- Did the shape of the contour plots change?
- Did expected process capability improve?
- Which uncertainties were resolved?
- What uncertainties remain?

This comparison is central to understanding why the additional experimental runs were valuable.

Curvature Changes the Story

Once intermediate experimental settings become available, learners may discover that a relationship previously represented as approximately linear is better described by curvature.

This is an important learning moment. A Round 1 model was not necessarily "wrong." It represented what could reasonably be learned from the experimental evidence available at that time. Round 2 provides new evidence.

Good experimental thinking means being willing to update the model when the evidence changes.

ASK THE LEARNERS: "If your conclusion changed after collecting better data, does that mean your first experiment failed?"

LISTEN FOR: No. The first experiment taught us what we needed to investigate next.

Revisit the Optimum

After developing the augmented model, learners should again use response optimization and contour plots to identify promising operating conditions.

Ask them to compare these settings with those recommended following Round 1. If the optimum changes, ask: "Why?"

The answer should not simply be: "Because the optimizer gave us different numbers."

Encourage learners to connect the change to the additional process knowledge captured by the augmented model.

Confirmation Before Capability

Before conducting the final capability assessment, learners should generate additional observations at their proposed operating conditions.

This reinforces the sequence:

1. Model → Predict → Confirm → Assess Capability
2. The optimizer predicts.
3. The confirmation runs test the prediction.
4. The capability analysis evaluates whether the resulting process performance is likely to satisfy customer requirements consistently.

These are related—but different—questions.

The Round 2 Deliverable

At the end of Round 2, learners should be prepared to explain:

- What additional question they were trying to answer.
- Why augmentation was an appropriate strategy.
- What the additional experimental runs revealed.
- How the model changed.
- Whether curvature was detected.
- How their recommended operating conditions changed, if at all.
- Whether the confirmation observations supported the model prediction.
- Whether the proposed process appears capable.
- What they would recommend doing next.

> ***INSTRUCTOR TIP — THE REAL OUTPUT IS LEARNING***
>
> *Do not evaluate Round 2 solely by whether learners identify the expected quadratic effect or achieve a particular capability index. Ask instead: "Did the additional experiment reduce an important uncertainty?" If the answer is yes, the experiment created value.*

The Bigger Lesson

Round 2 demonstrates a principle that extends far beyond this Virtual Process Lab™: A good experiment does not have to answer every question. It should answer enough of the right questions to help us decide what to do—or what to learn—next.

9. Round 2 Instructor Debrief

The Round 2 debrief should focus less on whether learners produced a more sophisticated statistical model and more on what the additional experiment taught them.

Learners should compare their conclusions before and after augmentation and explain how the new evidence affected their understanding of the process.

The central question is: “What do we understand now that we did not understand after Round 1?”

1. Why Did We Conduct Another Experiment?

ASK THE LEARNERS: What uncertainty from Round 1 were we trying to reduce?

LISTEN FOR: Learners should connect the second experiment to a specific limitation or unanswered question identified during the Round 1 analysis.

They may mention:

- Uncertainty about linearity.
- Evidence suggesting curvature.
- Limitations of a two-level design.
- Uncertainty about the predicted optimum.
- A need to better understand the response between the original low and high settings.

TEACHING POINT

Additional experimentation should have a purpose. The reason for Round 2 was not simply that more experimental runs were available. The additional runs were selected because they could provide new information that the original design could not provide adequately.

2. What Did Augmentation Buy Us?

ASK THE LEARNERS: What information did the additional experimental points provide that we did not have before?

LISTEN FOR: Learners should recognize that the face-centered axial points introduced information about intermediate settings of the continuous factors and provided the ability to investigate curvature.

TEACHING POINT

The value of augmentation should be measured in additional knowledge, not simply additional data. Ask: “Did every new experimental run have a reason for being there?” This reinforces experimental economy.

3. What Changed in the Model?

ASK THE LEARNERS: Compare your Round 1 and Round 2 models. What changed?

LISTEN FOR: Learners may identify:

- Changes in model terms.
- Improved estimates of existing effects.
- Evidence of quadratic behaviour.
- Changes in model statistics.

- Improved predictive performance.
- Changes in residual behaviour.
- A different interpretation of the process.

TEACHING POINT

Models should evolve when new evidence justifies changing them.

Do not frame differences between the Round 1 and Round 2 models as evidence that the first model "failed."

The first model represented what could reasonably be learned from the available evidence. The augmented experiment provided additional evidence and therefore allowed a richer model.

4. Did We Find Curvature?

ASK THE LEARNERS: What evidence supports the conclusion that curvature is—or is not—present?

LISTEN FOR: Learners should refer to statistical and graphical evidence rather than simply stating that a quadratic term was significant.

They may consider:

- Quadratic model terms.
- Changes in residual patterns.
- Response-surface behaviour.
- Contour plots.
- Differences between observed and first-order predicted responses.
- Improvements in model adequacy after introducing appropriate quadratic terms.

TEACHING POINT

Curvature means that the effect of changing a continuous factor is not adequately described by a constant straight-line relationship throughout the experimental region.

The practical implication is more important than the terminology. Ask: "What would we get wrong about the process if we ignored the curvature?"

5. What Happened to Predictive Performance?

ASK THE LEARNERS: How did R^2, adjusted R^2, and predicted R^2 change between the two models?

LISTEN FOR: Learners should evaluate the measures together rather than celebrating whichever statistic has the largest value.

TEACHING POINT

The objective is not to maximize R^2. A useful model should balance explanatory power, predictive usefulness, model simplicity, hierarchy, and process understanding.

INSTRUCTOR INSIGHT — BETTER IS NOT ALWAYS BIGGER

A larger model is not automatically a better model. Ask: "Would you trust this model to predict a result we haven't observed yet? Why?"

6. Did the Optimum Move?

ASK THE LEARNERS: Compare the operating conditions recommended after Round 1 with those recommended after Round 2. Did they change?

LISTEN FOR: If the settings changed, learners should connect the difference to the improved representation of the process rather than simply attributing it to the optimizer.

TEACHING POINT

An optimum is conditional upon the model used to predict it. When the model changes because better information becomes available, the predicted optimum may also change. Ask: "Which recommendation would you be more willing to defend to a process owner—and why?"

7. What Did the Contour Plots Reveal?

ASK THE LEARNERS: How do your Round 2 contour plots differ from those generated in Round 1?

LISTEN FOR: Learners may observe:

- Curved rather than approximately straight contours.
- Changes in the location of desirable operating regions.
- Different sensitivity to factor settings.
- Regions where small changes in settings produce larger changes in response.
- Broader or narrower operating windows.

TEACHING POINT

A contour plot is more than a presentation graphic.

It provides a visual representation of the response surface and can help learners understand where the process may be robust and where it may be sensitive.

8. Did the Confirmation Runs Agree?

ASK THE LEARNERS: How closely did the confirmation observations agree with what the model predicted?

LISTEN FOR: Learners should recognize that exact agreement is neither necessary nor expected because natural process variation is built into the simulation.

They should instead assess whether the confirmation results are reasonably consistent with the model prediction.

> ***TEACHING POINT***
>
> *Confirmation is where a statistical prediction meets experimental reality. If confirmation results differ materially from the prediction, the appropriate response is not to ignore them. Ask: "What might this discrepancy be telling us?"*

9. Is the Process Capable Now?

ASK THE LEARNERS: Based on your confirmation data and capability analysis, would you recommend these operating conditions for the process?

LISTEN FOR: Learners should integrate:

- Process centering.
- Process variation.
- Capability indices.
- Model confidence.
- Confirmation evidence.
- Practical operating considerations.

> ***TEACHING POINT***
>
> *Capability is the bridge between experimental knowledge and customer requirements.*
>
> *The purpose of DOE is not merely to develop an elegant statistical model. It is to enable better process decisions.*

10. Was Augmentation Better Than Starting Over?

ASK THE LEARNERS: Why did we add to the original experiment instead of discarding it and conducting an entirely new DOE?

LISTEN FOR: Learners should recognize that the Round 1 observations still contained valuable information.

Augmentation allowed them to preserve that investment while strategically adding the information needed to answer the next question.

TEACHING POINT

Sequential experimentation can be both statistically powerful and economically efficient.

In a real organization, experimental runs may consume material, machine time, labour, energy, capacity, or product. Good experimental design respects those resources.

11. What Are We Still Uncertain About?

ASK THE LEARNERS: Has Round 2 answered everything we could possibly want to know about this process? the answer should be: “No.”

LISTEN FOR: Learners may identify questions involving:

- Wider operating ranges.
- Additional factors.
- Long-term process stability.
- Environmental or noise variables.
- Different materials or equipment.
- Confirmation under production conditions.
- Robustness to uncontrollable variation.

TEACHING POINT

No experiment eliminates all uncertainty. The goal is to reduce the important uncertainty sufficiently to support the next decision.

12. What Would You Do Next?

ASK THE LEARNERS: If this were a real manufacturing process and you owned the next decision, what would you recommend? Require learners to choose and defend an action. Possible recommendations might include:

- Implement the proposed operating conditions.
- Conduct additional confirmation runs.
- Investigate robustness.
- Expand the experimental region.
- Study another response.
- Introduce additional factors.
- Conduct a further sequential experiment.

There is not necessarily one correct answer.

TEACHING POINT

The strongest recommendation is the one that connects: Evidence → Uncertainty → Risk → Decision

INSTRUCTOR TIP — ASK FOR THE DECISION

Do not allow the final presentation to end with statistical results. Ask: “So what should we do?” The purpose of analysis is to support a decision.

Closing the Experimental Journey

Return to the two statements used at the end of Round 1:

- After Round 1, we believed...
- After Round 2, we now believe...

Then add a third:

- If this were our process, our next action would be...

This creates a simple record of how experimental evidence changed the team's understanding and ultimately influenced its recommendation. The progression captures the essence of sequential experimentation:

We formed an understanding.

We challenged it with new evidence.

We improved it.

We made a better decision.

FINAL DEBRIEF QUESTION

“What did this Lab teach you about experimentation that you could not have learned simply by reading about DOE?”

10. Understanding Model Quality

One of the most important teaching opportunities in the Virtual Process Lab™ occurs when learners begin evaluating the quality of their fitted model.

It is tempting to reduce model evaluation to a single statistic—particularly R^2.

A strong experimental model, however, should be evaluated using multiple pieces of evidence.

The instructor's role is to help learners move from asking, “How high is our R^2?”, to asking, “How much confidence should we place in this model—and for what purpose?”

R^2 — How Well Did We Explain What We Observed?

R^2 describes the proportion of observed variation in the response explained by the fitted model. A high R^2 can be useful evidence that the model describes the experimental data well.

However, R^2 has an important limitation:

Adding model terms will generally cause R^2 to increase or remain unchanged—even when those additional terms contribute little useful predictive information.

For this reason, R^2 should never be used alone to determine model quality.

ASK THE LEARNERS: "If adding more terms always tends to improve R^2, could we make a model look better simply by making it more complicated?"

Adjusted R^2 — Did the Additional Terms Earn Their Place?

Adjusted R^2 considers both model fit and model complexity. Unlike ordinary R^2, it can decrease when additional terms fail to improve the model sufficiently to justify their inclusion.

This makes adjusted R^2 useful when learners are comparing models containing different numbers of terms.

A substantial difference between R^2 and adjusted R^2 may be a signal that the model contains terms contributing relatively little useful information.

The question becomes: "Are we gaining understanding—or merely gaining terms?"

Predicted R^2 — Can the Model Predict What It Hasn't Seen?

Predicted R^2 addresses a different and particularly important question: How well is the model likely to predict observations that were not used to fit it?

A model can have an impressive R^2 while having a surprisingly poor predicted R^2.

This is a powerful teaching moment.

The model may be fitting the existing experimental observations extremely well while capturing noise or unnecessary complexity that does not generalize to new observations.

This is commonly associated with overfitting.

INSTRUCTOR INSIGHT — THE PREDICTION TEST

When learners present a model with high R^2 but weak predicted R^2, resist the temptation to tell them immediately which terms to remove. Ask instead: "Why does a model that explains our existing data so well struggle to predict new data?"

When Predicted R^2 Collapses

Learners may occasionally produce a model with:

- Very high R^2.
- Reasonable or high adjusted R^2.
- Very low—or even effectively zero—predicted R^2.

This does not necessarily mean the experiment failed. It may indicate that the fitted model is too complex for the amount of experimental information available.

Encourage learners to investigate whether:

- Unnecessary terms have been included.
- The model is approaching saturation.
- Individual terms are supported by the evidence.
- Model hierarchy has been maintained.
- Influential observations are affecting the fit.
- Residual patterns suggest model inadequacy.
- Additional experimental information is needed.

After thoughtful model reduction, learners may find that predicted R^2 improves dramatically even though ordinary R^2 decreases slightly.

That is not a step backward. A simpler model that predicts reliably may be considerably more useful than a complex model that perfectly describes the observations already collected.

Model Hierarchy

Model reduction should never become a mechanical exercise of repeatedly deleting the term with the largest p-value.

When higher-order terms such as interactions or quadratic effects are retained, the corresponding lower-order terms should generally remain in the model to preserve model hierarchy.

For example, if an interaction between Mold Temperature and Injection Pressure is retained, the associated Mold Temperature and Injection Pressure main effects should ordinarily remain in the model—even if one of those individual main-effect p-values appears relatively weak.

WATCH FOR: Learners may treat the p-value column as an instruction list:

$p > 0.05$ → delete.

Encourage them to consider model hierarchy, experimental purpose, process knowledge, graphical evidence, and predictive performance before removing a term.

Residuals — What Has the Model Failed to Explain?

Residuals are the differences between observed responses and the values predicted by the fitted model. They represent the portion of the experimental behaviour the model has not explained. Residual analysis can help identify:

- Non-random patterns.
- Changing variation.
- Unusual observations.
- Possible model misspecification.
- Evidence of unmodelled curvature.
- Violations of assumptions underlying the analysis.

Encourage learners to view residual analysis as part of building the model, not simply as a final checkbox after the model has been selected. Ask: "What are the residuals trying to tell us?"

Statistical Significance Is Not Model Quality

A model containing statistically significant terms is not automatically a useful model.

Likewise, a term with a small p-value is not automatically operationally important.

Learners should consider: Statistical evidence + Predictive performance + Process knowledge + Practical significance

A statistically detectable change that has negligible operational importance may not deserve the same attention as an effect that materially changes process performance.

Avoid Chasing Statistics

There is no universal R^2, adjusted R^2, or predicted R^2 value that automatically defines a "good" model. The appropriate standard depends upon the:

- Process.
- Amount of natural variation.
- Experimental objective.
- Consequences of prediction error.
- Decision the model is intended to support.

The objective is not to maximize a statistic. The objective is to develop a model that is useful for the decision being made.

A Practical Instructor Framework

When learners present a model, ask them to defend it using five questions:

1. FIT

Does the model adequately describe the experimental observations?

2. PREDICTION

Does it appear capable of predicting observations it has not already seen?

3. ASSUMPTIONS

Do the residuals and diagnostic evidence support the model assumptions?

4. INTERPRETATION

Does the model make practical sense in the context of the process?

5. PURPOSE

Is the model good enough to support the decision we need to make?

INSTRUCTOR TIP — DON'T ASK "IS THIS A GOOD MODEL?"

Ask instead: "Is this model good enough for what you intend to do with it?" A model is a decision-making tool—not the final destination.

11. Common Learner Pitfalls

The Virtual Process Lab™ is intentionally designed to allow learners to make decisions, encounter uncertainty, and occasionally take an analytical path that requires reconsideration.

These moments are not failures.

They are often the most valuable learning opportunities in the Lab.

Rather than immediately correcting an analysis, use questions to help learners identify the problem, examine the evidence, and determine what they should do differently.

Instructor Quick Reference

What You May See	What's Really Happening	Coaching Question
"Our R^2 is 98%, so the model is excellent."	Learners are equating model fit with model quality.	"How well does it predict?"
Every possible model term is retained.	The model may be overfitted or unnecessarily complex.	"Does every term earn its place?"
Predicted R^2 is very poor despite high R^2.	The model may describe existing observations well but generalize poorly.	"Why can we explain the data but not predict it?"
Terms are removed solely because $p > 0.05$.	Model reduction has become mechanical rather than thoughtful.	"What else should influence whether that term stays?"
A main effect is removed while its interaction remains.	Model hierarchy may have been violated.	"What terms are required to support that interaction?"
Learners focus only on p-values.	Statistical significance is being confused with practical importance.	"What does this effect actually mean for the process?"
Residual plots are ignored.	Learners are treating diagnostics as optional.	"What has your model failed to explain?"
The optimizer result is accepted immediately.	A model prediction is being treated as an observed result.	"How would you verify that recommendation?"
Only one contour plot is generated.	The plot is being treated as a required deliverable rather than an exploratory tool.	"What other factor combinations might help you understand the process?"
Capability is assessed before operating conditions are justified.	Learners are moving to performance evaluation before establishing where the process should operate.	"Capability at which settings—and why those settings?"
A good Cpk is treated as proof of a good DOE model.	Process capability and model adequacy are being confused.	"What question does Cpk answer, and what question does it not answer?"
Round 1 is treated as the final answer.	Learners may not recognize the limitations of a two-level design.	"What assumptions are we making about what happens between the low and high settings?"
Evidence of curvature is overlooked.	Learners may be forcing a first-order explanation onto a nonlinear process.	"What evidence would tell you that a straight-line relationship isn't enough?"
Learners want to discard Round 1 and start over.	They have not yet recognized the value of sequential experimentation.	"What information have we already paid to learn?"

Go to next page for more quick references...

What You May See	What's Really Happening	Coaching Question
The Round 2 model differs from Round 1, so learners conclude Round 1 was wrong.	Improved evidence is being confused with failure of the earlier experiment.	"What could Round 1 reasonably tell us with the data available then?"
Confirmation results do not exactly match the optimizer prediction.	Natural process variation is being overlooked.	"Should we expect an observation to equal a prediction exactly?"
Teams chase the highest possible capability index.	Statistical optimization may be replacing practical decision-making.	"How much capability do we need, and what trade-offs come with these settings?"
Teams race through experimental runs.	Data collection has become the objective instead of learning.	"What did the last set of runs teach you before you collect more?"
Teams ask the instructor, "Are we doing this right?"	Learners are seeking validation instead of defending their reasoning.	"What does your evidence tell you?"

Productive Struggle

In traditional instruction, an incorrect analytical choice may be something to prevent.

In experiential learning, an imperfect choice can become the starting point for deeper understanding. If learners:

- Overfit a model,
- Misinterpret an interaction,
- Trust an optimizer too quickly,
- Ignore residual evidence,
- Select questionable operating conditions, or
- Reach a conclusion that later changes,

...Consider whether allowing them to encounter the consequence will create more learning than correcting them immediately.

The Virtual Process Lab™ provides a safe environment in which learners can make these mistakes without risking production equipment, customer requirements, material, or real-world process performance.

INSTRUCTOR INSIGHT — DON'T STEAL THE DISCOVERY

Before correcting a learner, ask yourself: "Can the data teach this lesson better than I can?" If the answer is yes, ask a question and allow the learner to investigate.

When to Intervene

Productive struggle should not become unproductive frustration. Instructor intervention may be appropriate when:

- Learners misunderstand the fundamental experimental objective.
- A software or data-entry error prevents meaningful analysis.
- Learners are applying a statistical method incorrectly in a way they cannot reasonably diagnose.
- A misconception prevents the team from progressing.
- Available time requires the instructor to redirect the exercise.

Even then, provide the minimum intervention necessary to restart the learning process.

Rather than saying, “Here's what you need to do.”, consider asking: “What would you need to know before deciding what to do?”

The Instructor's Coaching Cycle

When a learner encounters difficulty, use a simple sequence:

OBSERVE: What is the learner doing or concluding?

QUESTION: What question might help them examine their reasoning?

EVIDENCE: What experimental evidence could help answer that question?

REFLECT: What did the learner discover?

DECIDE: What will they do differently as a result?

This creates a coaching cycle that mirrors the experimental process itself.

INSTRUCTOR TIP

The best facilitation often feels slower than simply providing the answer. But the objective of the Virtual Process Lab™ is not to help learners finish faster. It is to help them become less dependent on the instructor.

12. Instructor Reference — What's Hidden in the Process?

For Instructor Use

The Virtual Process Engine™ underlying the Injection Molding Lab contains intentionally embedded process relationships designed to create realistic opportunities for experimental discovery. This section provides instructors with a reference to those relationships.

It should not be shared with learners before or during the experimental exercise. Knowing which effects have been intentionally embedded would remove much of the uncertainty that makes the Lab an experiential learning environment.

The Important Distinction

The relationships described in the following section represent the underlying simulated process. They are not a list of terms that learners must necessarily identify as statistically significant in every analysis.

Experimental results include random process variation. In addition, the conclusions learners reach may be influenced by:

- The experimental design selected.
- The observations generated during their experiment.
- The model initially specified.
- Model-reduction decisions.
- The treatment of hierarchy.
- The analytical software used.
- The amount of experimental information available.

Evaluate whether learners have developed a reasonable, defensible understanding of the process, rather than whether their output reproduces a predetermined list of p-values.

Relationships Embedded in the Virtual Process Engine™

The simulated process includes effects associated with the five experimental factors:

- Mold Temperature
- Injection Pressure
- Cooling Time
- Resin Supplier
- Vent Design

The engine also contains selected interaction effects involving:

- Mold Temperature × Injection Pressure
- Mold Temperature × Cooling Time
- Injection Pressure × Resin Supplier
- Injection Pressure × Vent Design

In addition, the process contains a quadratic Mold Temperature effect, **creating curvature** that cannot be fully characterized using only the original two-level factorial design. This curvature provides the primary learning signal supporting the transition from Round 1 to Round 2.

What Learners Should Discover in Round 1

The Resolution V half-fraction should provide learners with sufficient evidence to begin developing a useful first-order understanding of the process.

Depending upon the experimental observations generated and the model fitted, learners should generally be able to identify several meaningful main effects and interactions. More importantly, they should be able to develop a model that:

- Explains a substantial proportion of the observed response variation.
- Provides useful insight into factor behaviour.
- Identifies important interactions.
- Supports preliminary optimization.

- Allows proposed operating conditions to be explored.
- Raises questions about what the initial design may not adequately describe.

Round 1 should create useful knowledge without creating complete knowledge.

INSTRUCTOR INSIGHT — DON'T GRADE AGAINST THE ENGINE

The Virtual Process Engine™ represents the underlying truth of the simulation. Learners do not have access to that truth. Their task is to infer process behaviour from limited experimental evidence—just as they would with a real process.

The Hidden Curvature

The quadratic effect associated with Mold Temperature is particularly important to the intended learning journey.

During Round 1, Mold Temperature is investigated at its low and high settings: 180°C and 220°C

A two-level design provides information about the change in response between these settings, but it cannot fully describe a curved relationship within that range.

When the design is augmented in Round 2, the additional intermediate information—including the 200°C center setting—allows learners to investigate whether a first-order representation of Mold Temperature is sufficient.

The intended discovery is not simply: "Temperature squared is significant."

The deeper learning is: "Our original experimental design did not contain enough information to fully describe this relationship."

That realization is the reason for augmentation.

Interactions Matter Operationally

The embedded interactions are designed to reinforce the idea that process factors should not always be interpreted independently.

For example, the effect associated with Injection Pressure may depend upon another process condition such as Mold Temperature, Resin Supplier, or Vent Design.

When learners identify an interaction, encourage them to move beyond its statistical significance.

Ask: "What would this interaction mean to someone operating the process?"

A useful DOE model should help people understand how to operate the process, not merely identify statistically significant coefficients.

Expected Model Behaviour

Learners may initially fit models that are unnecessarily complex. When too many terms are included relative to the experimental information available, instructors may observe:

- Very high R^2.
- Lower adjusted R^2.
- Poor or unstable predicted R^2.
- Terms with weak statistical support.
- Difficulty distinguishing useful signal from model complexity.

Thoughtful model reduction can substantially improve predictive usefulness while retaining the important process relationships.

This behaviour is intentional from a learning perspective. It creates an opportunity to demonstrate that the model that best fits the observations is not necessarily the model that best predicts the process.

What Should Change in Round 2?

After augmentation, learners gain additional information about the continuous factor space. A successful Round 2 analysis should generally provide:

- Better information about curvature.
- An opportunity to estimate an appropriate quadratic Mold Temperature term.
- A richer representation of the response surface.
- Improved understanding of the location and shape of desirable operating regions.
- Greater confidence in optimization decisions.
- A stronger basis for confirmation and capability assessment.

The exact numerical results will vary. The direction of learning is more important than reproduction of a particular model.

Expected Capability Behaviour

When learners develop a reasonable model, identify promising operating conditions, and generate confirmation observations, the simulated process is capable of producing strong dimensional performance relative to the specification limits.

However, capability results will vary because the Virtual Process Engine™ includes random process variation. Instructors should therefore avoid specifying a single expected Cp, Cpk, Pp, or Ppk value as the “correct” answer. Instead, ask learners to determine whether:

- The process is reasonably centered.
- Variation is small relative to the specification width.
- Capability results support the proposed operating conditions.
- The amount of confirmation data is sufficient to justify the confidence being claimed.

When Learner Results Differ From Expectations

If a team's analysis differs materially from the expected process relationships, do not immediately assume that the learner—or the Lab—is wrong.

Investigate the experimental journey. Ask:

- Was the experimental design created correctly?
- Were the factor settings entered correctly?
- Were the generated responses transferred correctly?
- What model was initially fitted?
- How was model reduction performed?
- Was hierarchy preserved?
- What do the residuals indicate?
- Does the graphical evidence support the team's interpretation?
- Would additional experimental evidence resolve the disagreement?

A surprising result is often an excellent opportunity to demonstrate how experimentalists respond when the data do not behave exactly as expected.

WATCH FOR — THE ANSWER-KEY EFFECT

Once instructors know what is embedded in the Virtual Process Engine™, it can become tempting to steer learners toward those answers. Avoid doing so. If learners reach a different but statistically and operationally defensible conclusion, ask them to defend it with evidence. The objective is experimental reasoning—not reverse-engineering the simulation.

The Instructor's Reference Standard

When evaluating learner performance, consider three levels of understanding:

DISCOVERY: Did the learner identify meaningful process relationships from the available evidence?

INTERPRETATION: Can the learner explain what those relationships mean operationally?

DECISION: Can the learner use that understanding to recommend and defend an appropriate next action?

The strongest learner is not necessarily the one whose fitted model most closely resembles the Virtual Process Engine™. It is the learner who can make the strongest evidence-based argument about what the process is doing and what should happen next.

13. Expected Results — Without One “Right Answer”

The Virtual Process Lab™ is designed to simulate experimentation, not reproduce a predetermined set of statistical outputs.

Because the Virtual Process Engine™ includes natural process variation, different learners or teams may obtain somewhat different results even when conducting the same experimental design. Differences may also arise from:

- Model specification.
- Model-reduction decisions.
- Treatment of hierarchy.
- Analytical software.
- Interpretation of statistical and graphical evidence.
- Selection of operating conditions.
- Confirmation data generated by the Lab.

For this reason, instructors should avoid evaluating learner performance against a single set of expected numerical results.

Evaluate the Reasoning

A strong analysis is one that learners can explain and defend with evidence. Rather than asking, "Did they get the right answer?", consider asking, "Did they make a reasonable decision based upon the evidence available to them?" Look for evidence that learners can:

- Explain why they selected their experimental design.
- Identify and interpret meaningful process relationships.
- Evaluate model quality using more than R^2 alone.
- Maintain model hierarchy during model refinement.
- Use residual and graphical evidence appropriately.
- Recognize limitations in the available experimental information.
- Explain why additional experimentation may be warranted.
- Use optimization as a prediction rather than an answer.
- Confirm proposed operating conditions experimentally.
- Connect experimental results to process capability.
- Recommend and defend an appropriate next action.
- Different Numbers Can Support the Same Learning

Two teams may produce slightly different:

- Regression coefficients.
- P-values.
- Model statistics.
- Optimized settings.
- Confirmation results.
- Capability indices.

Both analyses may still demonstrate strong experimental reasoning. The instructor should focus on whether each team's conclusions are consistent with its evidence and whether the proposed decision is reasonable given the uncertainty that remains.

INSTRUCTOR INSIGHT — ASK FOR THE EVIDENCE

When two teams reach different conclusions, resist the temptation to immediately identify which one is "correct." Ask each team, "What evidence led you to that conclusion?" The comparison itself may become one of the most valuable discussions in the Lab.

When Results Are Materially Different

Not every difference should be attributed to random variation. If a learner's results differ substantially from what would reasonably be expected, investigate:

- Experimental design.
- Factor settings.
- Data entry.
- Model specification.
- Model reduction.
- Hierarchy.
- Residual behaviour.
- Interpretation of the output.

The objective is not to force the analysis toward an expected answer. It is to determine whether the conclusion is supported by a sound experimental and analytical process.

The Standard for Success

Success in the Virtual Process Lab™ is demonstrated when learners can complete three statements:

- Based on the evidence, we believe...
- We remain uncertain about...
- Therefore, we recommend...

Those three statements connect experimental evidence to uncertainty and uncertainty to action. That is the capability the Lab is designed to develop.

REMEMBER: Good experimentation does not eliminate uncertainty. It reduces uncertainty enough to make a better decision.

14. Capability as the Final Reality Check

A successful DOE does more than identify statistically significant factors or produce an impressive predictive model. Ultimately, the experimental learning must translate into process performance that satisfies customer requirements.

For the Injection Molding Virtual Process Lab™, the dimensional requirement is:

- Target: 12.50 mm
- LSL: 12.35 mm
- USL: 12.65 mm

Once learners have developed an appropriate model and identified promising operating conditions, capability analysis provides an important reality check. The question changes from, “Can we model the process?” to, “Can we operate the process so that it consistently meets requirements?”

The Recommended Sequence

Encourage learners to follow the complete decision-making sequence: MODEL → PREDICT → CONFIRM → ASSESS CAPABILITY → DECIDE

MODEL: Develop an evidence-based representation of process behaviour.

PREDICT: Use the model to identify operating conditions expected to achieve the desired response.

CONFIRM: Generate new observations at those settings and determine whether actual performance reasonably agrees with the prediction.

ASSESS CAPABILITY: Evaluate whether the resulting process is sufficiently centered and has sufficiently low variation relative to the specification limits.

DECIDE: Determine whether the evidence is strong enough to recommend the proposed operating conditions.

Capability Does Not Validate the Model

Learners may be tempted to treat a strong capability index as proof that their DOE model is correct. **It is not.** Model adequacy and process capability answer different questions.

Model adequacy asks: How well do we understand and predict process behaviour?

Capability asks: At these operating conditions, how well does process performance fit within the specification limits?

Both matter.

ASK THE LEARNERS: “Could we have a capable process and still have an inadequate understanding of how it works?”

The response should be “Yes.”

That distinction is important when deciding whether a process is merely performing well today or is sufficiently understood to be managed confidently.

Avoid the Capability Number Chase

The objective is not to maximize Cp, Cpk, Pp, or Ppk simply because a larger number appears better. Encourage learners to consider:

- Is the process centered appropriately?
- Is the observed variation acceptable?
- Are the confirmation data sufficient to support the conclusion?
- Are the operating settings practical and sustainable?

- Is the process likely to remain robust to normal variation?
- Does the demonstrated capability satisfy the organization's requirements?

A statistically optimized setting may not always be the most practical operating setting.

Bring It Back to the Customer

The final purpose of the experiment is not the model, optimizer, contour plot, or capability report. Those are tools. The purpose is to make a better process decision.

INSTRUCTOR INSIGHT — THE CUSTOMER DOESN'T SEE THE MODEL

A customer never receives an R^2 value with the product. They experience the result of the process. DOE creates value when experimental knowledge helps that process deliver what the customer requires—consistently.

15. Suggested Assessment

Assessment of the Virtual Process Lab™ should focus on the learner's ability to think experimentally, interpret evidence, and make defensible process decisions.

Statistical accuracy is important, but successful completion should not depend upon reproducing a predetermined model, optimum, or capability index.

A simple assessment framework can be organized around five dimensions.

1. Experimental Strategy

Developing: Conducts the experiment but provides limited rationale for the design or experimental approach.

Competent: Selects and executes an appropriate design and explains what information the experiment is intended to provide.

Strong: Connects the experimental design to a clear learning objective, recognizes design limitations, and identifies an appropriate strategy for additional experimentation.

2. Analysis and Model Development

Developing: Relies heavily on individual statistics or software output with limited evaluation of model adequacy.

Competent: Evaluates model fit, predictive performance, residual evidence, statistical significance, and model hierarchy appropriately.

Strong: Develops a parsimonious and defensible model, integrates multiple sources of statistical evidence, and clearly explains both the strengths and limitations of the model.

3. Process Understanding

Developing: Identifies statistical effects but has difficulty explaining their operational meaning.

Competent: Interprets important main effects, interactions, and curvature in the context of process behaviour.

Strong: Translates statistical relationships into a coherent explanation of how the process behaves and identifies meaningful remaining uncertainties.

4. Decision-Making

Developing: Accepts optimizer or capability results with limited validation or consideration of uncertainty.

Competent: Uses model predictions, confirmation observations, graphical evidence, and capability analysis to support a reasonable recommendation.

Strong: Integrates evidence, uncertainty, practical considerations, and risk into a clearly defended process decision and identifies an appropriate next action.

5. Communication

Developing: Reports statistical output with limited explanation of what it means.

Competent: Communicates the experimental approach, findings, limitations, and recommendation clearly.

Strong: Builds a concise evidence-based story connecting the process problem, experimental learning, uncertainty, and recommended action.

A Simple Final Assessment

Regardless of the scoring or grading approach used, ask learners to complete three statements:

- Based on the evidence, we believe…
- We remain uncertain about…
- Therefore, we recommend…

If learners can complete those statements clearly and defend each one using experimental evidence, they have demonstrated much more than the ability to operate statistical software. They have demonstrated experimental thinking.

INSTRUCTOR INSIGHT — ASSESS THE THINKING

Do not ask only, “Did they perform the analysis correctly?” Also ask, “Could I trust this person to use experimental evidence to make a real process decision?”

16. Facilitation Options

The Virtual Process Lab™ can be adapted to different learning environments, available time, group sizes, and levels of DOE experience.

The recommended two-round learning journey provides the foundation, but instructors are encouraged to adapt the delivery approach while preserving the central principle:

Learners should make decisions, examine evidence, and determine what to do next.

Independent Learning

Learners complete the Lab individually using the Quick Start Guide and an assigned experimental challenge.

They conduct the experiment, analyze the results, document their reasoning, and submit a short recommendation.

A subsequent instructor debrief can focus on:

- Experimental strategy.
- Model development.
- Remaining uncertainty.
- Recommended next actions.

Best suited for: Self-directed learning, asynchronous programs, or individual assignments.

Facilitated Workshop

The instructor guides learners through the Lab while deliberately pausing at key decision points. A recommended sequence is:

Round 1 → Analysis → Debrief → Round 2 → Analysis → Final Debrief

Avoid demonstrating the complete analytical pathway before learners begin. Allow teams to make decisions and compare approaches before introducing additional concepts or experimental strategies.

Best suited for: Instructor-led Lean Six Sigma training, DOE workshops, and applied statistical learning.

Team Challenge

Small teams independently investigate the same process challenge.

Each team develops its experimental strategy, conducts its analysis, and presents its conclusions.

Differences between team models, optimized settings, and recommendations become part of the learning experience.

Ask teams to challenge one another: “What evidence supports your recommendation?”

Best suited for: Black Belt programs, corporate workshops, and collaborative learning.

Experimental Competition

The Lab can also be delivered as a friendly competition in which teams are given a limited experimental budget.

The objective should not simply be to achieve the highest capability index. Instead, teams might be challenged to develop the strongest process recommendation while using experimental resources efficiently.

Possible evaluation criteria include:

- Experimental efficiency.
- Model quality.
- Process understanding.
- Confirmation evidence.
- Capability.
- Quality of the final recommendation.

This format reinforces an important real-world constraint... Experiments consume resources. Material, machine time, labour, capacity, and time all have value. Effective experimentalists seek the greatest useful learning from the resources available.

Best suited for: Advanced workshops, team-based learning, and experiential Lean Six Sigma events.

INSTRUCTOR TIP — PRESERVE THE DISCOVERY

Regardless of the delivery format, avoid turning the Lab into a sequence of prescribed software steps. Change the timing. Change the teams. Change the challenge. But preserve the opportunity for learners to discover, question, and decide.

Adapt Without Losing the Purpose

Instructors may shorten, extend, or modify the exercise depending upon the learning objective. Whatever format is selected, learners should leave the Lab having experienced the fundamental experimental cycle:

QUESTION → EXPERIMENT → EVIDENCE → LEARNING → NEXT DECISION

The format can change. The learning process should not.

17. Closing the Lab

The Injection Molding – Design of Experiments Virtual Process Lab™ begins with a process problem. But the real subject of the Lab is learning.

Learners begin with limited knowledge of the process. They design an experiment, collect evidence, build a model, make predictions, test assumptions, encounter uncertainty, and decide what they need to learn next. Then they experiment again.

That journey reflects how meaningful process improvement happens in the real world.

End With Reflection

Before concluding the Lab, ask learners to step away from the statistical output and reflect on the experience. Ask:

- What did you initially believe about the process?
- What evidence changed your understanding?
- What did the first experiment fail to tell you?
- How did the second experiment reduce that uncertainty?
- What would you do next if this were a real process?

Then ask one final question: “What did this Lab teach you about experimentation that you could not have learned simply by reading about DOE?”

Allow learners to answer in their own words.

From Knowledge to Capability

Knowing the terminology of Design of Experiments is valuable. Knowing how to create a factorial design is valuable. Knowing how to interpret statistical output is valuable. But capability requires something more.

It requires knowing when to experiment, what question to ask, how much confidence to place in the evidence, when to challenge a conclusion, and what to do next.

That is the capability this Virtual Process Lab™ is designed to develop.

FINAL INSTRUCTOR THOUGHT

Resist the temptation to measure the success of the Lab by how quickly learners reach the answer. Measure it by the quality of the questions they are asking when they finish.

The Experimental Mindset

A good experiment does not always provide the final answer. Sometimes it reveals that the question needs to change. Sometimes it challenges what we thought we knew. Sometimes it gives us enough confidence to act.

And sometimes… its greatest contribution is showing us what we need to learn next. That is not a limitation of experimentation. That is its power.

QUESTION → EXPERIMENT → EVIDENCE → LEARNING → DECISION

Then ask the next question.

Need Additional Help?

Additional Virtual Process Lab resources are available through RPM-Academy, including:

- Instructor Guides
- Video demonstrations
- Lean Six Sigma Knowledge Hub articles
- Additional Virtual Process Labs
- Lean Six Sigma certification programs

Visit Our Website: https://www.rpm-academy.com/

About RPM Virtual Process Labs™

RPM Virtual Process Labs™ transform traditional training into immersive learning experiences. Rather than simply reading about Lean Six Sigma tools, learners actively apply them within realistic process simulations that reinforce critical thinking, structured problem solving, and data-driven decision making.

Each Virtual Process Lab is designed to help learners move beyond knowledge acquisition toward practical capability.

Remember… Knowledge tells us what to do. Practice teaches us how to do it. Capability comes from doing it repeatedly.

Continue Your Learning Journey

The RPM Virtual Process Lab™ is just one part of the RPM-Academy learning ecosystem. Create your free RPM-Academy Learning Portal account to access additional learning resources, stay informed about new Virtual Process Labs, and explore hundreds of professional development opportunities. A free account gives you access to:

- Featured courses and learning resources
- The Lean Six Sigma Knowledge Hub
- Updates on new Virtual Process Labs™
- Learning Bytes™ micro-learning modules
- Course previews and certification information
- Exclusive announcements and educational content

Creating an account is quick, completely free, and no credit card is required. Start your learning journey today: https://platinum-rpmacademy.talentlms.com/. Already have an RPM-Academy account? Simply sign in and continue learning.

Thank you for choosing RPM Virtual Process Labs™.