Minitab

EXCHANGE

Build Better with the Connected Factory

2 June 2026
Manufacturing Technology Centre

£1 generated by UK manufacturing supports an additional **£1.80** across the wider UK economy

Oxford Economics

Cost is manufacturers' biggest challenge

$253M

lost in average large plant from unplanned downtime

Siemens

$8T

lost annually due to process inefficiencies & defects

Forbes

Today's Agenda

Registration	08:30 - 09:30
Morning Introduction	09:30 - 09:40
AI in Manufacturing: Behind Smoke and Mirrors	09:40 - 10:25
The Hidden Factory	10:25 - 10:50
Networking Break	10:50 - 11:15
The Silent Profit Killer	11:15 - 11:45
From Monitoring to Mastery	11:45 - 12:15
Designing Better Processes	12:15 - 12:50
Morning Conclusion	12:50 - 12:55
Networking Lunch	12:55 - 13:55
Afternoon Introduction	13:55 - 14:00
Keynote by Chris Powley and Kush Patel, The Manufacturing Technology Centre	14:00 - 14:25
Networking Break	14:25 - 14:40
Deeper Dive Live: Solving Manufacturing Challenges with Data-Driven Experimentation	14:40 - 16:05
Takeaways & Conclusion	16:05 - 16:10
Networking	16:10 - 16:30

Chris

Technical Specialist - Electronics Manufacturing

Component Manufacturing Technology

The Manufacturing Technology Centre

Kush

Senior Research Engineer

Modelling and Simulation / Digital Engineering

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Consultant

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AI in Manufacturing: Behind Smoke and Mirrors

Mikhail Golovnya
Senior Advisory Data Scientist

In this session, we'll talk about…

- Digital Transformation
- Data Universe
- Data Analytics
- Machine Learning
- Generative AI
- Agentic AI and AGI

Digital Transformation

- **Digital Transformation** integrating digital technologies to **fundamentally change how a company operates**, delivers value to customers, and responds to market dynamics
- **Digital Transformation** is about rethinking everything you do —internally and externally.

What is Digital Transformation?

Key Aspects

- Technology integration (**data analytics**, cloud computing, AI, automation, IT infrastructure, etc.)
- Data-Driven Decision Making (**predictive analytics** to inform strategic and day-to-day choices)
- Cultural and Organizational Change (innovation, agility, embracing new technologies)
- Business Process Optimization (automating manual tasks, workflows, efficiency, productivity)
- Enhanced Customer Experience (aps, social media, chat bots, support, personalized services)

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Data Universe: Half a Century of Growth

- **1970s–1980s: Megabytes**
  Thousands to hundreds of thousands of records, Apollo
- **1990s: Gigabytes Become Common**
  Internet, transactions, server logs, Human Genome
- **2000s: Terabyte Era**
  Digital and social media, Google, Facebook, CERN
- **2010s: Petabyte and Exabyte Scale**
  Big data revolution, YouTube, Climate Modeling
- **2020s: Zettabyte Era and Beyond**
  IoT, social media, video, sensor data

- Exponential Growth for the past 50 years!
  150 dB Growth

Data Universe: YouTube Growth

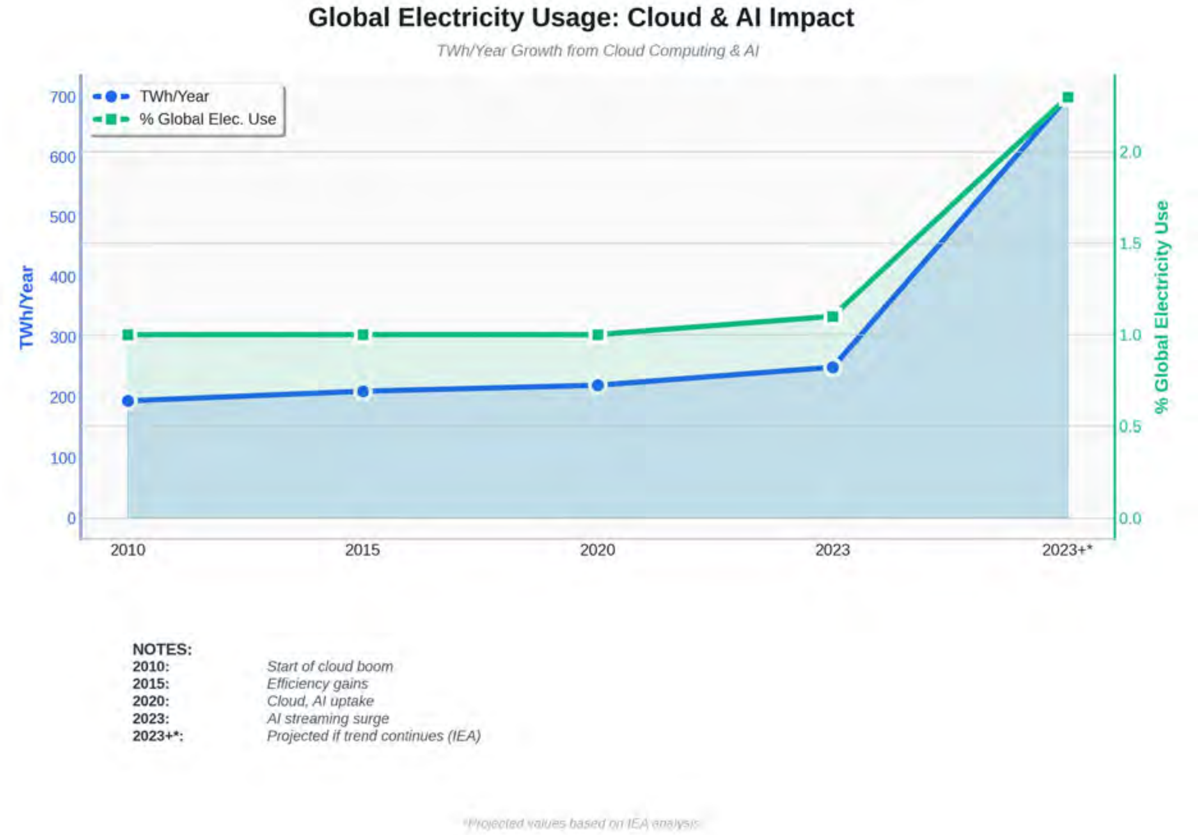
Key Milestones

Hours of videos uploaded per minute

YEAR	HRS/MIN	HRS/DAY	NOTES
2007	~6	8,640	Early rapid growth
2010	24	34,560	Social and smartphone era begins
2012	72	103,680	YouTube mainstream, HD videos rise
2014	300	432,000	Explosion in global smartphone use
2017	400	576,000	Live streaming, 4K, mobile creators
2019	500	720,000	Global user base, monetization
2022	500+	720,000+	Number stayed stable but content length increases
2024	600 - 700	864,000–1M+	Continued grown (unofficial estimates)

Global Data Center Power Consumption

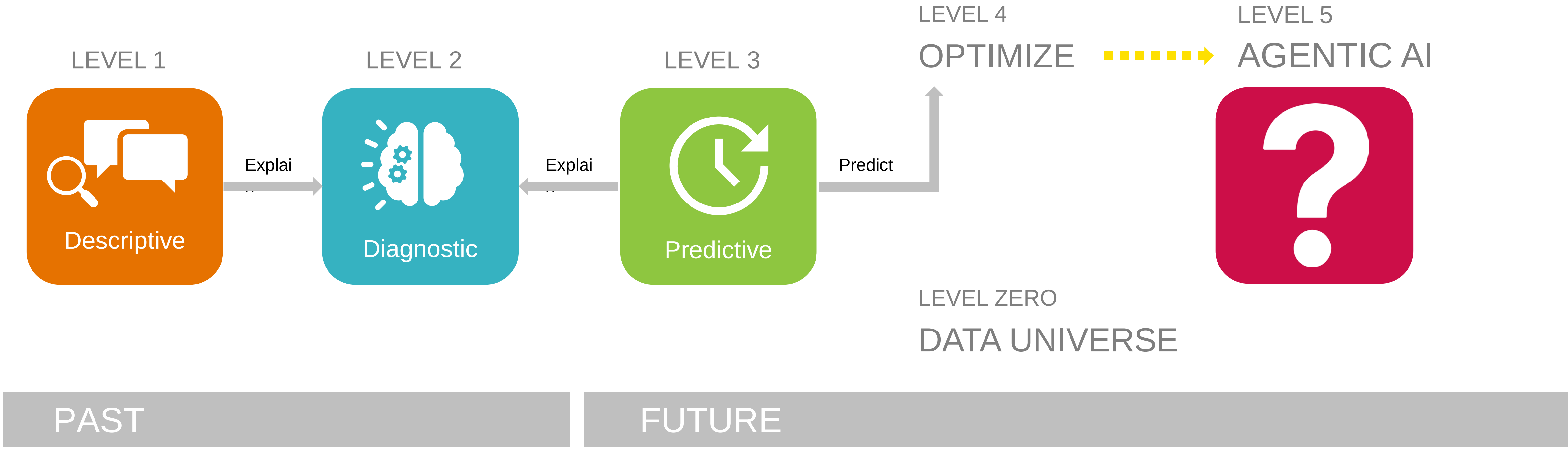
Estimated Global Data Center Power Consumption by Year



Key Takeaways

- **Current**: Data centers use ~250 TWH/year (2023-24), about 1% of all global electricity.
- **Trend**: After years of efficiency, demand is rising rapidly due to AI and digitization.
- **Future**: Could triple by 2030 unless efficiency and renewable adoption keep up.

Data Analytics – The Quest for AI



AI Developments: 20th Century 1st Track

- **Reactive Machines:**
  - These are basic rule-based systems that operate based on predefined rules.
- **Expert Systems:**
  - These are computer systems that mimic the decision-making ability of a human expert in a specific domain.

KNOWING

AI Developments: 20th Century 2nd Track

Machine Learning (ML) Systems:

- ML is a subset of AI that focuses on developing algorithms and models that enable computers to learn from data.
- Types of ML systems include **supervised learning (PA)**, unsupervised learning, and reinforcement learning.

LEARNING

AI Developments: Modern Landscape

Machine Learning (ML) Systems:

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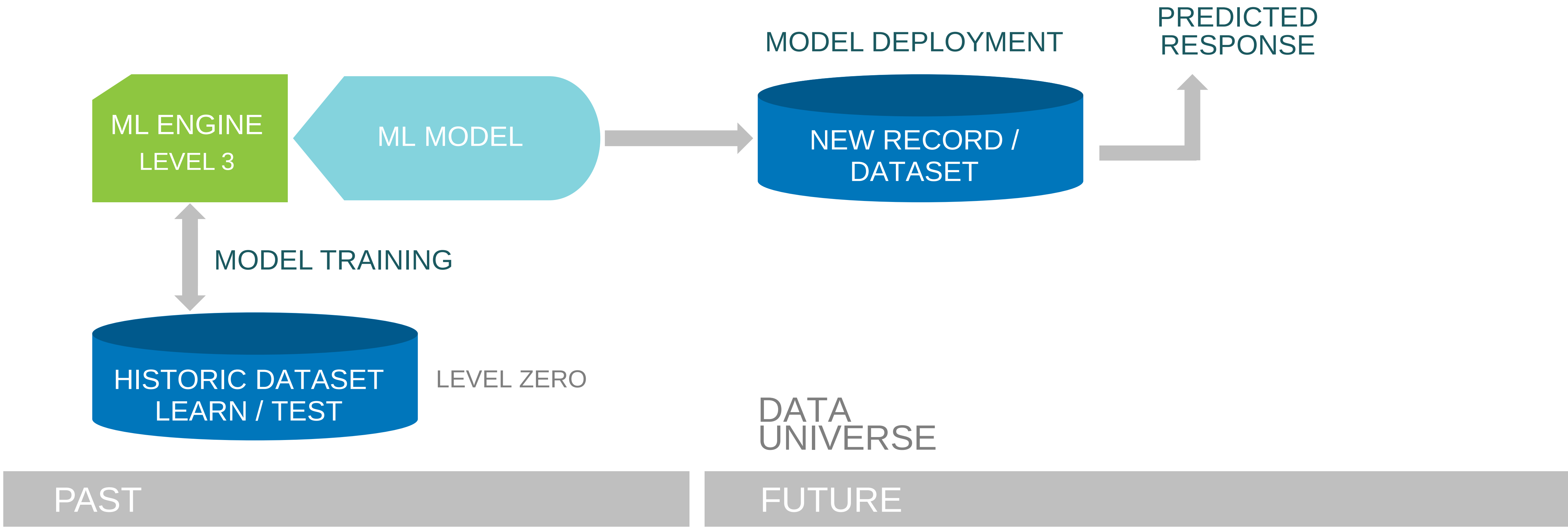
Neural Networks:

- Inspired by the human brain, neural networks are a key component of many AI systems.

NUMBERS

Machine Learning Process



Machine Learning in Manufacturing

- Quality Control and Defect Detection
- Fault Diagnosis
- Predictive Maintenance
- Process Optimization
- Demand Forecasting
- Supply Chain Risk Prediction
- Yield Prediction
- Energy Consumption Prediction

Example: Predicting Equipment Failure

- Problem

  Predict the probability of a machine failure based on the current operating conditions (real-time sensor data)

Impact

Capture the problem before things blow up!

Example: Steel Plate Fault Detection

- Problem

    Automatic detection of surface defects during steel manufacturing process using real time sensor and process-derived measurements

Impact

Reduce waste of material and resources

OEE – Overall Equipment Effectiveness

- A key metric that measures how efficiently and effectively manufacturing equipment is utilized
- Percentage of planned production time that is truly productive
- Components:
  - Availability
  - Performance/Speed
  - Quality

Major Hurdles to Digital Transformation

- Reluctance (fear) to adopt innovation
- Not understanding the actual business need
- Accommodating technology for the sake of technology
- New Features/Capability over Reliability
- Gathering the data we don't need
- Don't gathering the data we do need
- Fundamental limitations of machine learning
- Moore's law yielding to the 80/20 rule
- Regulatory constraints (emissions, etc.)

GPT: Generative Pretrained Transformer

- Genuine **revolution in Data Analytics** ability to communicate with the machines using natural human language (**conversational retrieval**)
- Transformer technology introduced by Google to convert words to word vectors
- Pretrained on humongous volume of various on-line text sources
- Generative – sequential generation of words to produce large blocks of text
- Made computationally feasible by the advent of **GPUs** and large parallel processing arrays

TEXT

Training Corpora in Perspective

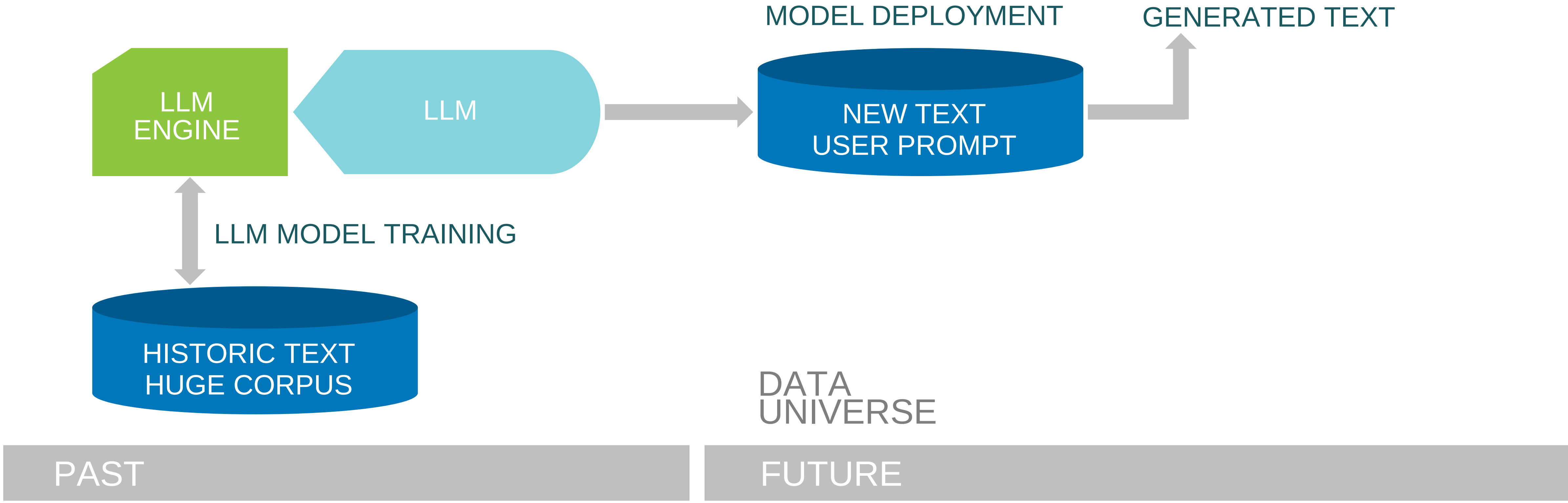
ALL GPT models are trained on a human-supplied source text!

- The Complete Works of William Shakespeare (or the Bible)
    - 0.006G (3 months of reading)
- Babylonian Talmud
    - 0.040G (1.5 years of reading)
- Complete works of Vladimir Lenin
    - 0.100G (4 years of reading)
- Encyclopedia Britannica
    - 0.250G (10 years of reading)

- GPT-1 (2018)
    - 5G (180 years of reading)
- GPT-2 (2019)
    - 40G (1,500 years of reading)
- GPT-3 (2020)
    - 570G (20,000 years of reading)
- GPT-4 (2023)
    - 5,000G
- GPT-5 (2025)
    - 20,000G

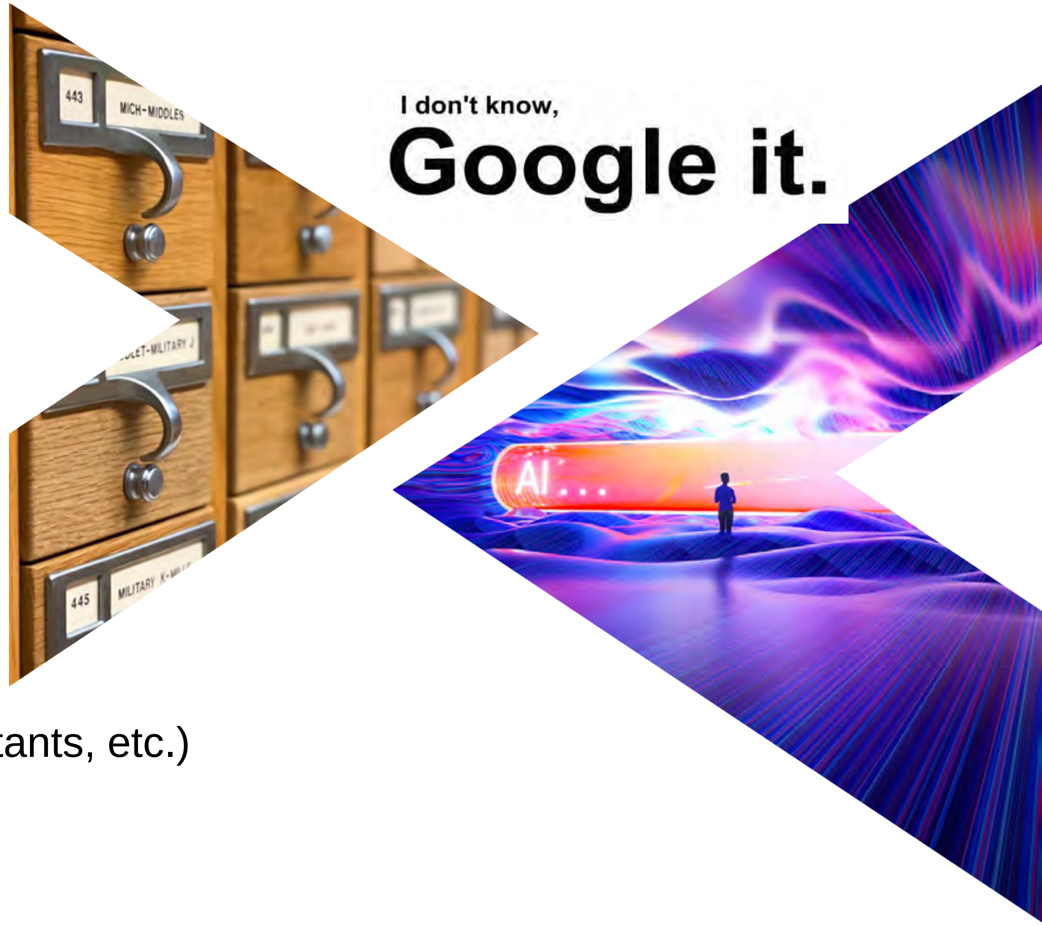
- Wikipedia
    - 500G (Comparable to GPT-3)
- US Library of Congress
    - 100,000G
- Public crawlable web
    - 5,000,000G

Large Language Model Process



GenAI as Information Retrieval System

- **Libraries**
  - As old as ancient Greece and Egypt
  - Culminated in the Library of Congress Classification
- **Pre-digital Mechanization**
  (19th-20th centuries: index cards, punch cards, etc.)
- **Early Computerized IR**
  (1940s-1960s: Boolean searches, etc.)
- **Search Databases**
  (1970s-1980s: electronic abstracts, indices, etc.)
- **Web-search era**
  (1990s-2000s: Web Crawler, Alta Vista, Yahoo, Google, etc.)
- **Big Data and ML**
  (2010s: collaborative filtering, recommender systems, personal assistants, etc.)
- Generative AI and Conversational Retrieval
  (2020s: ChatGPT and its likes)



How Should We Handle Generative AI?

DIVINATION

INTERROGATION

GenAI in Manufacturing

- Generative Design
  (Product Development)
- Synthetic Data Generation
  for Training Models
- Process Optimization and Simulation
- Scenario Generation
- Automated Documentation
- Digital Twins

GenAI Fundamental Flaws

- The abrupt end of scalability with the release of GPT 5.0
  (Moore's law yielding to the 80/20 rule)
- Creation vs Regurgitation
- Unacceptable Liability (Code Generation vs Medical Advice)
- Hacking and code/prompt injection attacks
- Emotional attachments
- Ethical considerations
- Inherently prone to hallucinations
- Flooding the Data Universe with the superfluous content
  - Amazon book mills
  - Science paper mills
  - Web-bot comments and reviews

What About AGI?

Self-aware AI:

- This refers to hypothetical AI systems with self-awareness and consciousness.

Theory of Mind:

- This is a more advanced form of AI that can understand human emotions, beliefs, intentions, and thoughts.

General AI (Strong AI):

- General AI systems can understand, learn, and apply knowledge across diverse domains.
- They can perform any intellectual task that a human being can do.

Superintelligent AI:

- This is a theoretical AI that surpasses human intelligence in every aspect.

AGI

SCI FI

RELIGION

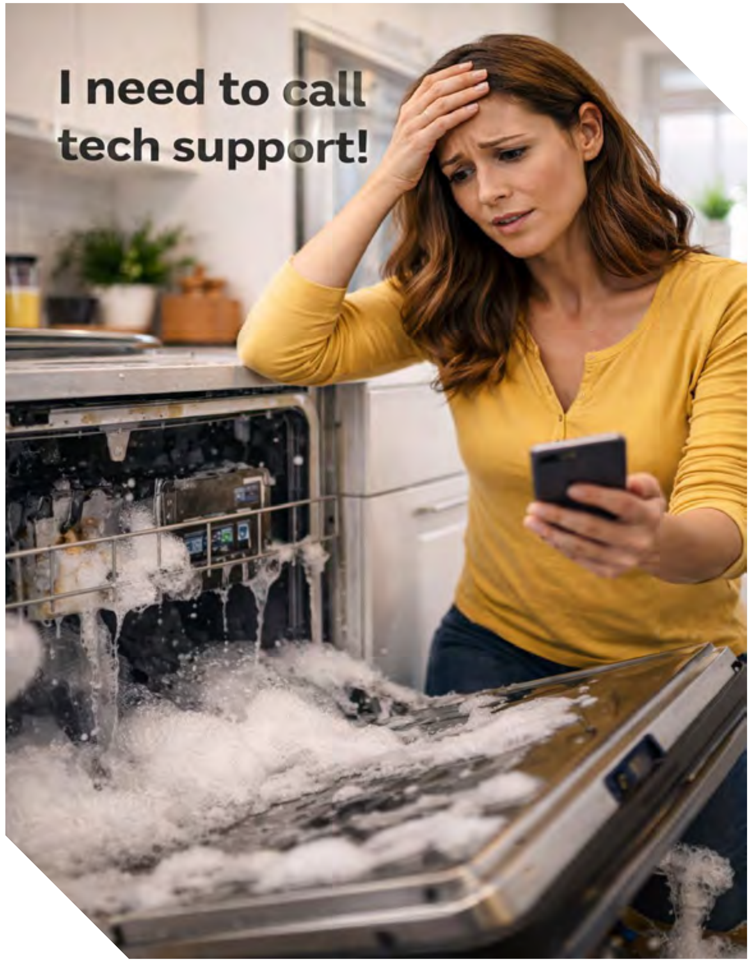
Obstacles to Reaching AGI

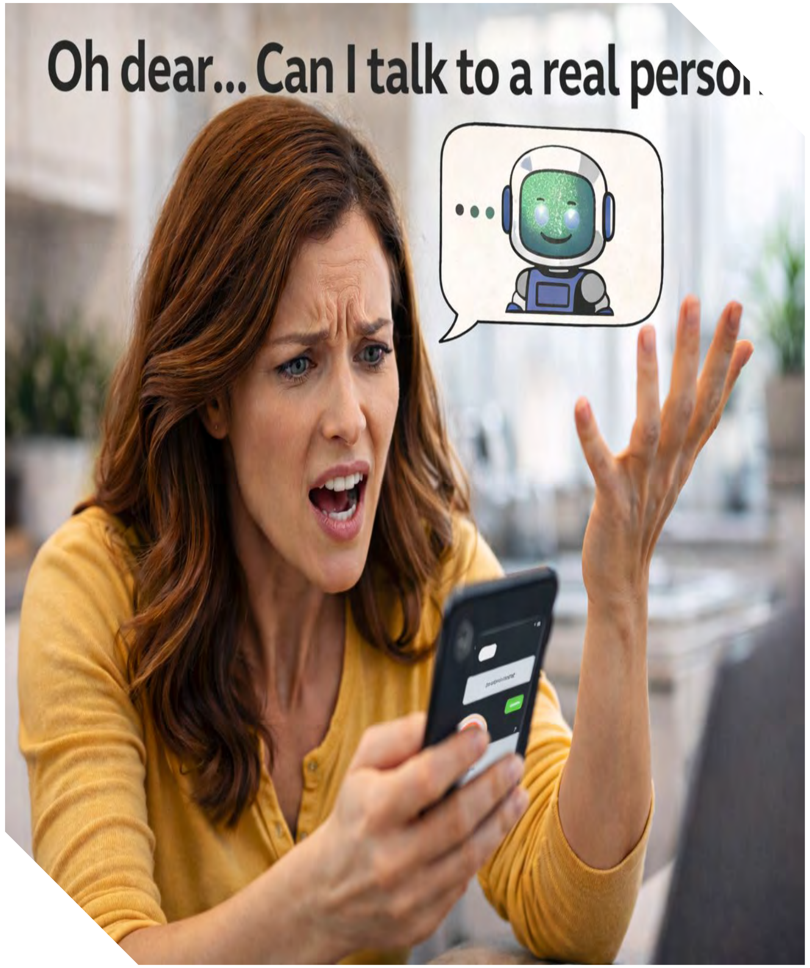
- Narrow AI (Gen AI) alone is not enough!
- The world is **open-ended** – the modern AI systems are **closed**
- Five Areas Where Human Intelligence Remains Superior
  - Understanding **language**
  - Understanding the **world**
  - **Adapting** to new circumstances
  - Learning **new things** quickly bypassing data
  - **Reasoning** in the face of incomplete and inconsistent information
- Presence of non-verbal inferred context/information in most human interactions
- The elusive idea of common sense
- Issues of trust and accountability

Agentic AI: Dangerous Crossroads

- Agentic AI (inductive): systems that can **act autonomously** to pursue goals, **make decisions and** take multi-step actions **with limited or no human intervention.**
  - Very challenging to develop, maintain, and monitor
  - Rewards speed for scrutiny
  - Trades short term operational gains for long-term lack of resilience
  - Dissolution of trust and accountability
  - May trigger **costly avalanche-like failures**
  - Ignores qualified minority views
  - Maximizes efficiency and minimizes exploration
  - May unintentionally lead to technocratic tyranny

And What About Customer Experience?





Agentic AI: Dangerous Crossroads

- **Hybrid Cognition** as a viable alternative
  - Human intelligence at the center of decision making
  - AI serves as memory assist and cognitive amplifier
  - Interpretation is separated from authority
  - Preserves vigilance and accountability

A car moves faster than me …

… but it will never fly!

An excavator lifts more than me …

… but it will never build a sandcastle!

A calculator adds faster than me …

… but it will never have an eureka moment!

The Deep Blue computer plays chess better than me …

… but it will never play hockey like my son!

ChatGPT creates an illusion of a relationship …

… but it will never have a soul!

“The only thing more dangerous than ignorance is arrogance.

Imagination is more important than knowledge.”

– Albert Einstein

THE ULTIMATE DANGER

We Become Like AI

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OEE: Insights, Blind Spots and Better Decisions

Nick Jones and Tony Smith

Solutions Architects

Quiz
What OEE Actually Measures

How it works:

1. We give an example that affects the OEE in a negative way
   “Unplanned machine breakdown”
2. You choose „loss category“: **Availability, Performance** or **Quality**
3. You have 10 seconds to answer: don’t overthink it!

The winner will be awarded!

Availability x Performance x Quality

What OEE Actually Measures

Availability x **Performance** x **Quality**

Availability

Unplanned breakdowns
Mechanical/Electrical failures
Planned maintenance
Tool/die/product changeovers
Product changeovers/setups
Material shortages
Waiting for personnel
Safety stops or utility outages

Performance

Reduced machine speed
Repeated stops/interruptions
Material feed issues
Operator speed reduction
Increased cycle time
Equipment bottlenecks
Frequent adjustments
Suboptimal settings

Quality

Out-of-spec parts
Surface defects
Assembly errors
Packaging/labeling errors
Material contamination
Weld defects
Paint/coating defects
Rework or scrap

Recent Acquisitions around OEE

Availability
Performance
Quality

SCYTEC DATAXCHANGE

Real-time OEE

Downtime and runtime tracking

Machine + operator data

Quality

Prolink
DATA COLLECTION/ANALYSIS SOFTWARE

CMM, gage, PLC data collection

SPC reporting

Automated and real-time

Process
Simulation

SIMUL8

Process simulation

Digital twins

Process mining + simulation

Drive Performance with Real-Time Data

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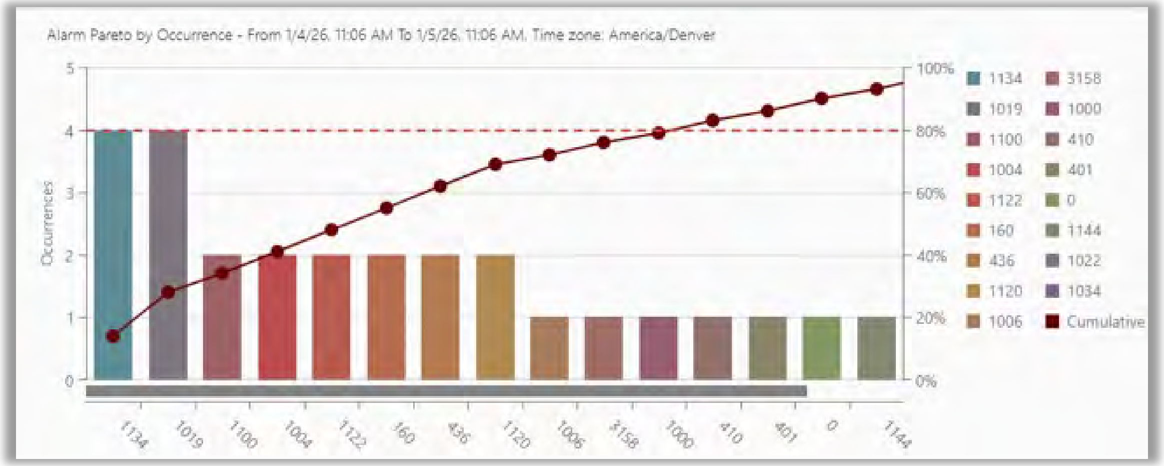
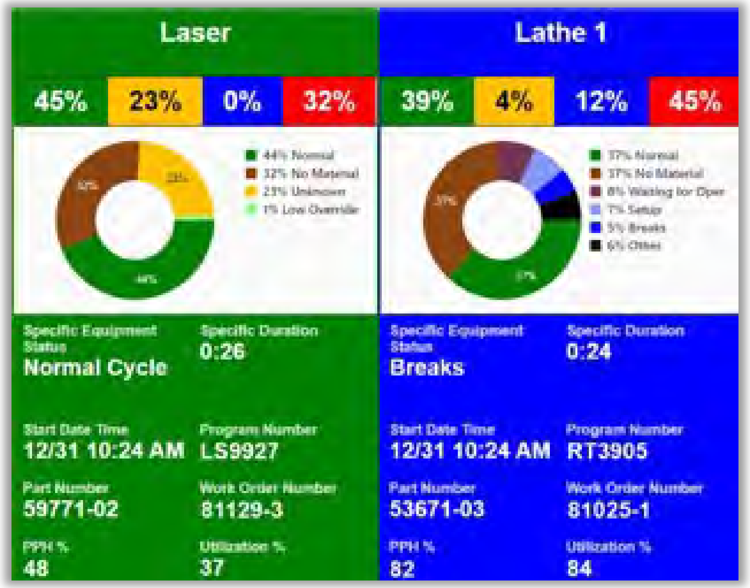
DATA XCHANGE

- Replace manual tracking with real-time data
- Identify downtime root causes
- Improve utilization and throughput
- Standardize OEE across operations





Problem #1
85% OEE, why?

Machine breakdowns

Reduced speed

Scrap/Rework

How To Collect Data?

Automatic collection

Operator Input

Integration

Automatic Data Collection

Standard protocols

Proprietary machine protocols

Hardware based options and sensors

Custom integrations

Case Study

Utilization Increase and Improved Processes with Machine Monitoring

Business Outcomes at AMT senior Aerospace

- 15–20% higher utilization
- Greater visibility into downtime causes
- Increased production capacity
- Better process insights from tool & probe data

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Process Variation: The Silent Profit Killer

Nick Jones and Tony Smith
Solutions Architects

Where Do You Lose Profit?

Missed deliveries

High scrape rates

Product recalls

Lost Profit

Customer Returns

Work on scrapped parts

Process variation can be the driving force behind all these factors!

Contributing Factors in Process Variation

- Inconsistent Data Collection
- Operators rely on guesswork
- Variability in raw material properties
- Untracked tool wear
- Environmental Factors
- Setup Variations
- Lack of data

Manufacturers often struggle to address these problems because they do not have a strong data strategy

Not collecting the right data

Data quality is inconsistent

Data exists in siloes

Digital Thread is incomplete

Data Strategy

Data analytics and AI are NOT intelligent.
They are only able to work with the data that is provided.

Rubbish In → ML model → Rubbish Out

Incomplete Data → AI model → Hallucinations

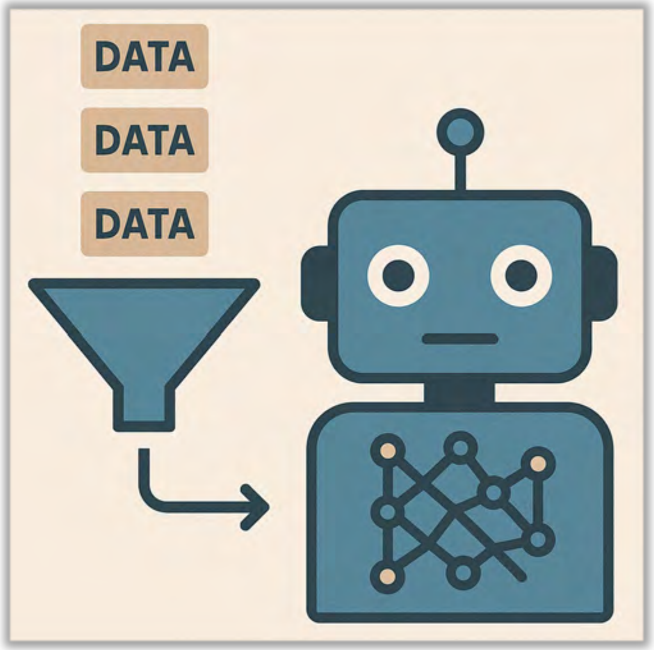
For analytics to deliver real value to an organisation, data needs to be holistic, accurate and reliable.

1 Data Capture

2 Data Validation

3 Data Centralisation & Preparation

Objective Driven



1 Data Capture

How Minitab can help to capture data across a plant:

- Incoming Inspection
- Moulding Operations
- Machining Operations
- Final Inspection

Real-time insights and better decisions

Reduces waste and errors in manual data collection

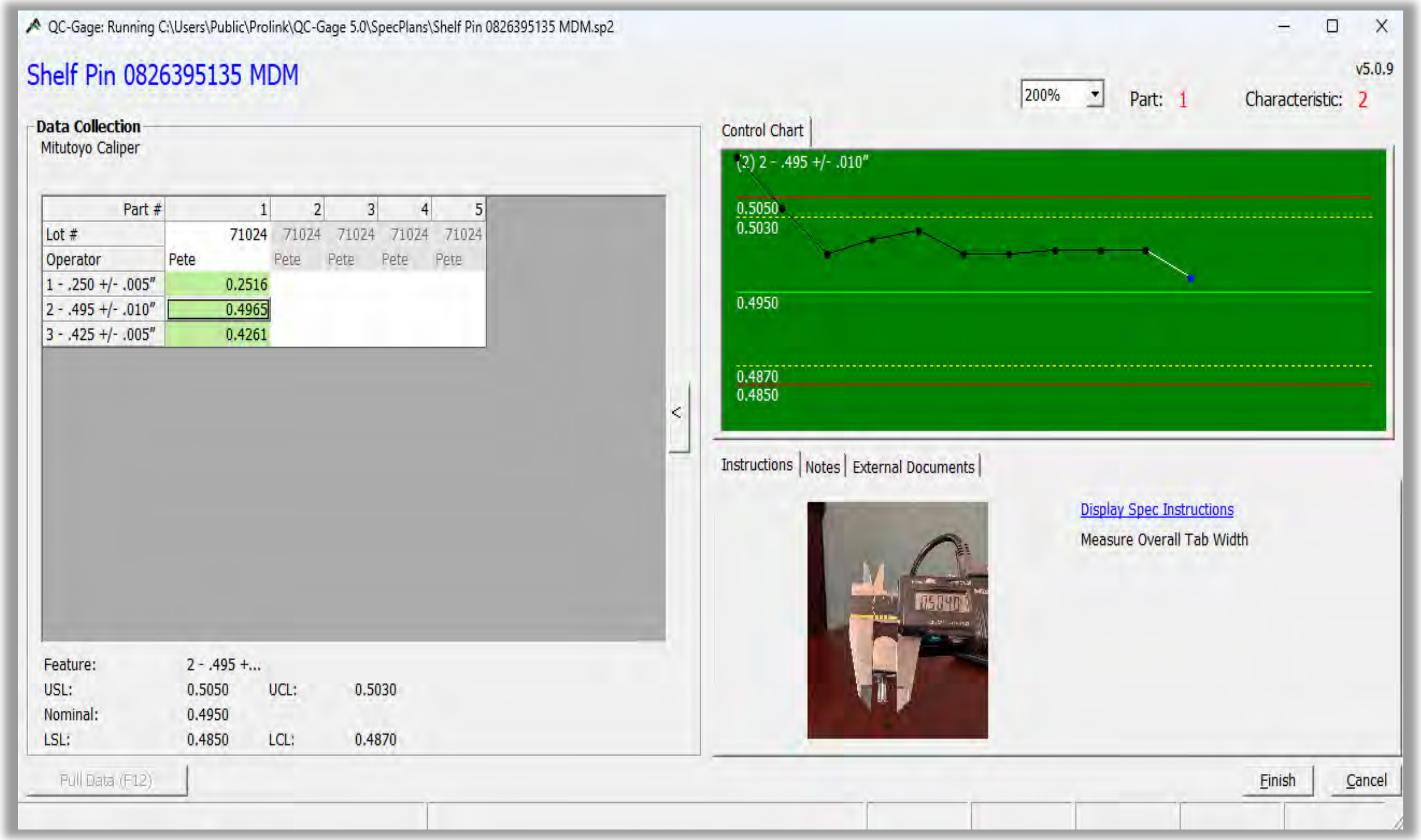
Incoming Inspection Common Challenges

- Measurements recorded on paper
- Results results disconnected from downstream production data
- Limited visibility of supplier performance over time

Without connected data, incoming inspection becomes a pass/fail activity rather than a source of insight into process variation.

Incoming Inspection - Solutions

By automatically capturing inspection data and linking it to supplier and material information, manufacturers gain visibility into variation before it enters production.



Moulding Department Common Challenges

- Moulding processes are highly sensitive to process conditions
- Small changes in temperature, pressure or time can introduce lots of variation
- Process data is often available but trapped in PLCs
- This limits the ability for root-cause analysis and process optimisation

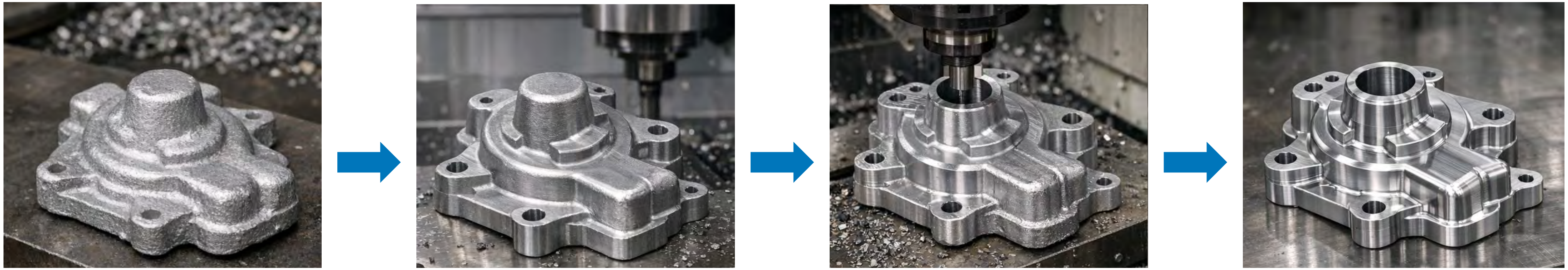
Moulding Department Solutions

- Minitab can integrate directly with every mainstream PLC
- Critical process data is captured and connected to material, production and quality data

Manufacturers gain the ability to correlate process conditions with quality outcomes

Machining Department

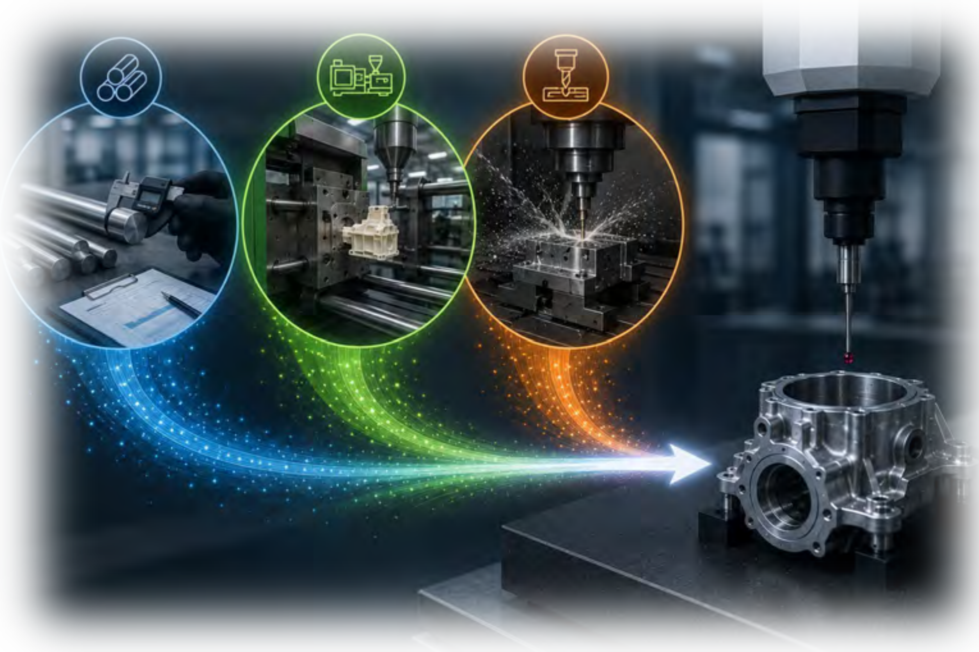
Measure parts after each operation to ensure additional cost is not added to a part that should have been scrapped or recycled.



Why keep machining if there was an out of specification condition in an earlier operation that scrapped the part?

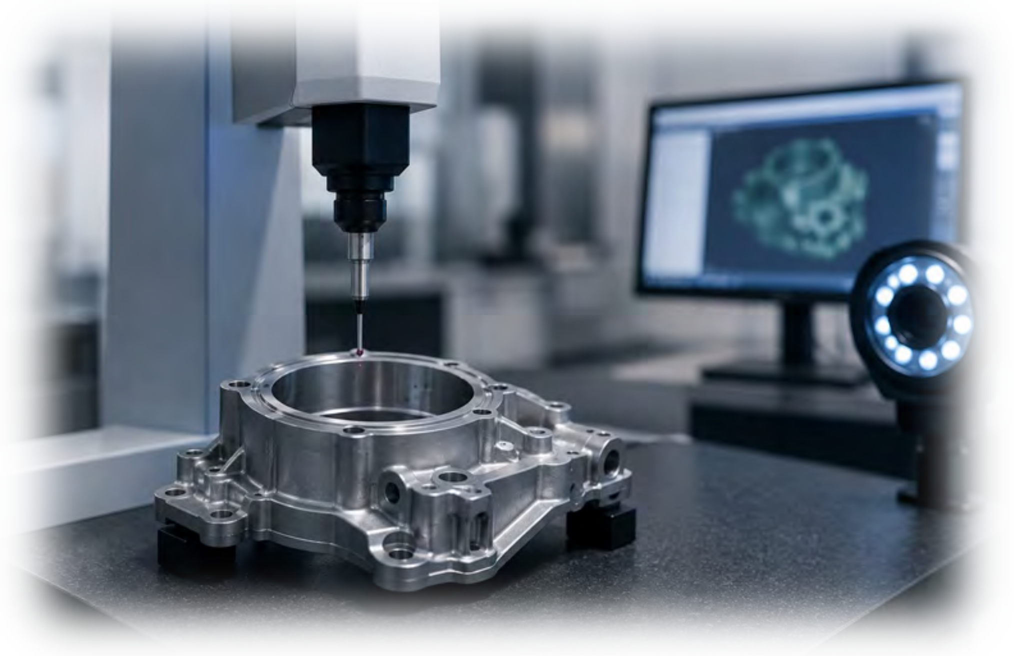
Final Inspection Challenges

- Final inspection is where the impact of variation introduced throughout the manufacturing process becomes visible.
- However, when quality data remains disconnected from the product's history, defects can be identified but their root causes often remain unclear.



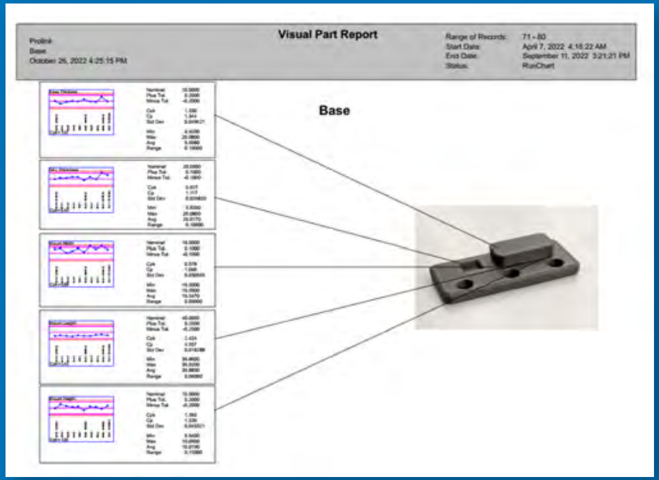
Final Inspection Challenges

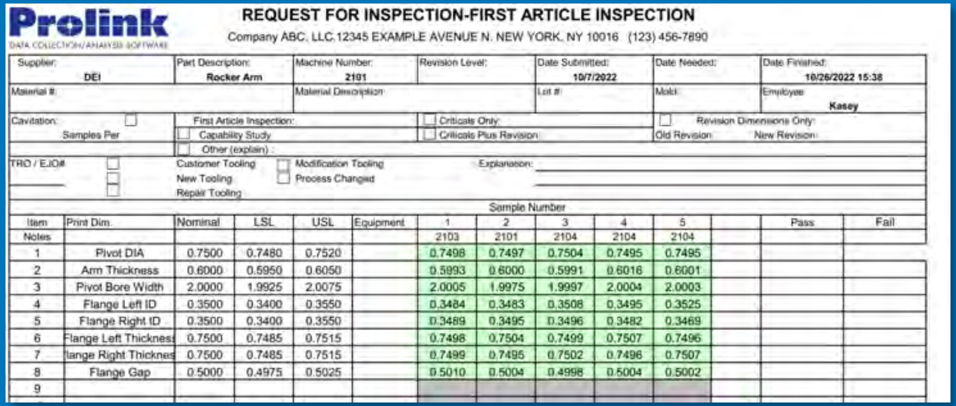
- Measurement data isolated within CMM and vision systems
- Manual reporting and customer documentation
- Limited visibility into the sources of variation
- Difficult root cause investigations



Final Inspection Solutions

- Real-time integration with CMMs to unlock data
- Save time with automated report generation
- Export data to Minitab for root-cause investigations





Prolink
DATA COLLECTION/ANALYSIS SOFTWARE

REQUEST FOR INSPECTION-FIRST ARTICLE INSPECTION

Company ABC, LLC 12345 EXAMPLE AVENUE N. NEW YORK, NY 10016 (123) 456-7890

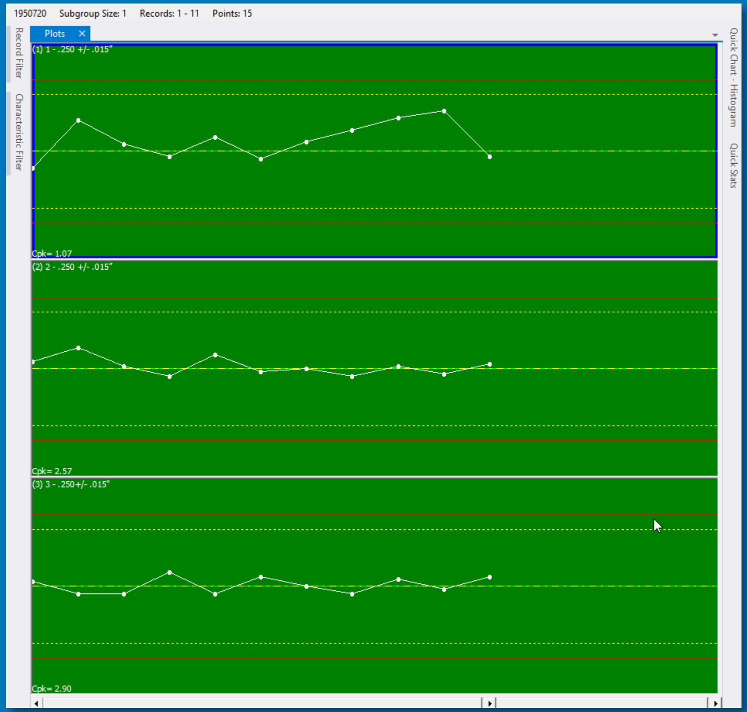
Supplier:	Part Description:	Machine Number:	Revision Level:	Date Submitted:	Date Needed:	Date Finished:
DEI	Rocker Arm	2101		10/7/2022		10/26/2022 15:38

Material #:
Material Description:
Lot #:
Mold:
Employee: Kasey

Cavitation: ☐
Samples Per
First Article Inspection:
☐ Capability Study
☐ Other (explain) :
☐ Criticals Only
☐ Criticals Plus Revision
☐ Revision Dimensions Only:
Old Revision:
New Revision:

TRO / EJO# ☐ ☐ ☐
Customer Tooling
New Tooling
Repair Tooling
☐ Modification Tooling
☐ Process Changed
Explanation:

Item	Print Dim.	Nominal	LSL	USL	Equipment	Sample Number 1	2	3	4	5		Pass	Fail
Notes						2103	2101	2104	2104	2104			
1	Pivot DIA	0.7500	0.7480	0.7520		0.7498	0.7497	0.7504	0.7495	0.7495			
2	Arm Thickness	0.6000	0.5950	0.6050		0.5993	0.6000	0.5991	0.6016	0.6001			
3	Pivot Bore Width	2.0000	1.9925	2.0075		2.0005	1.9975	1.9997	2.0004	2.0003			
4	Flange Left ID	0.3500	0.3400	0.3550		0.3484	0.3483	0.3508	0.3495	0.3525			
5	Flange Right ID	0.3500	0.3400	0.3550		0.3489	0.3495	0.3496	0.3482	0.3469			
6	Flange Left Thicknes	0.7500	0.7485	0.7515		0.7498	0.7504	0.7499	0.7507	0.7496			
7	lange Right Thicknes	0.7500	0.7485	0.7515		0.7499	0.7495	0.7502	0.7496	0.7507			
8	Flange Gap	0.5000	0.4975	0.5025		0.5010	0.5004	0.4998	0.5004	0.5002			
9													



Data Strategy

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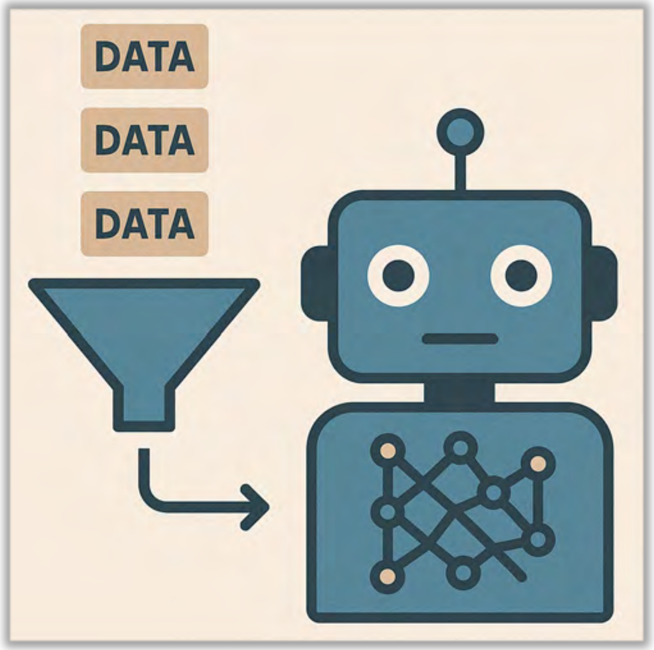


1 Data Capture

2 Data Validation

3 Data Centralisation & Preparation

Objective Driven

2 Data Validation
Measurement System Analysis (MSA)

📌 What is it?

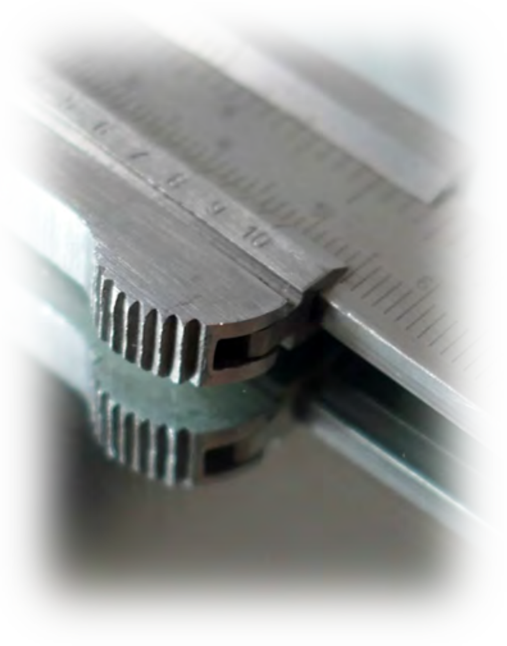
Structured tests to reveal if a measuring system is reliable & consistent

⚠️ Why is it important?

Poor systems lead to false rejects, missed defects, wrong decisions

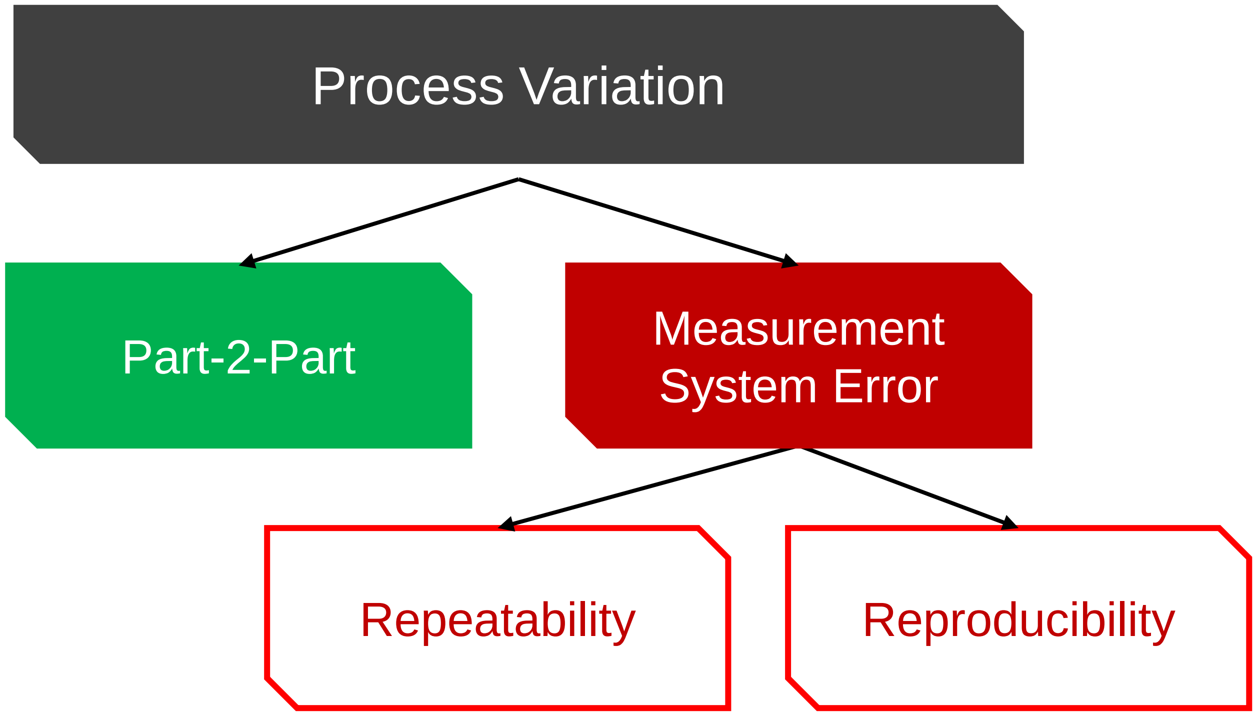
⏰ When to use?

New systems / Equipment changes / Disputes / Routine checks



Confidence in data → Reduced risks → Stronger decisions → Compliance

Partitioning of Process Variation

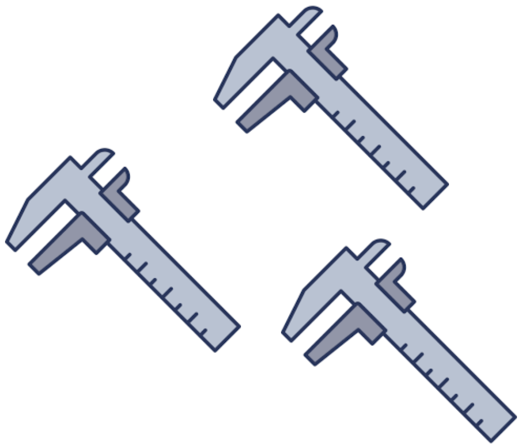


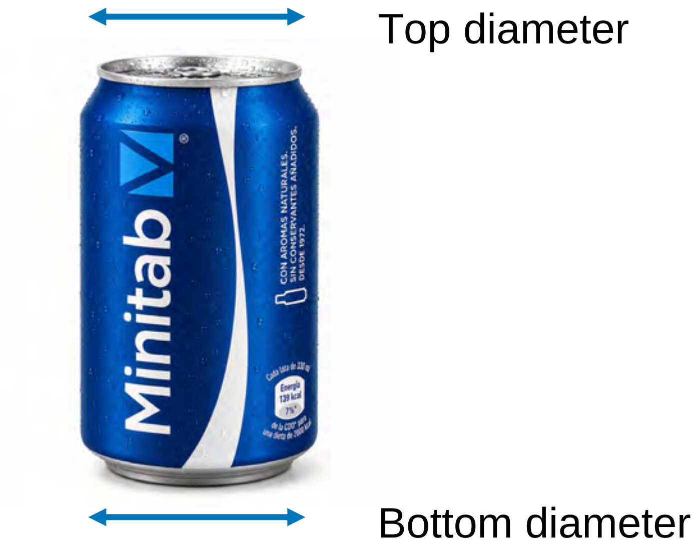
→ variation caused by **measurement system**

→ variation caused by **the operator**
→ ???

0 - 10% = ✅ acceptable
10 - 30% = ⚠️ marginal
> 30% = ❌ unacceptable

But How to Handle Additional Factors?





Include more than one measurement system within a study

Measure a dimension in multiple locations

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Incomplete Data → AI model → Hallucinations

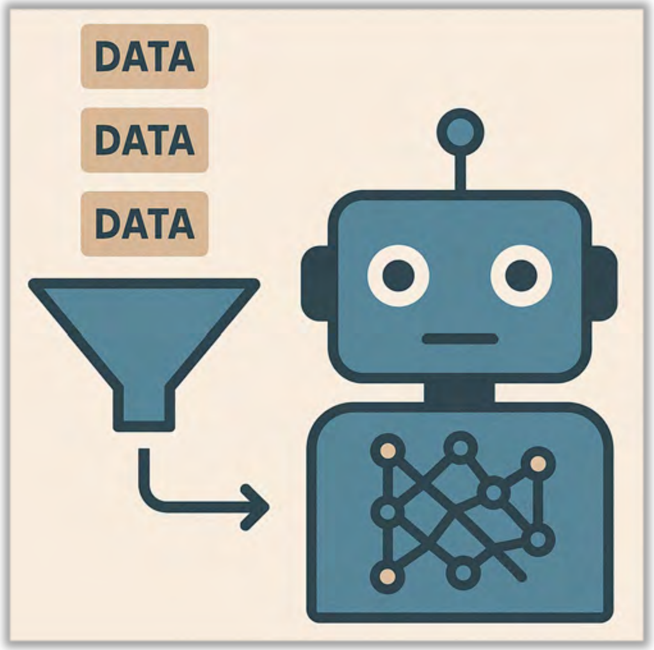
For analytics to deliver real value to an organisation, data needs to be holistic, accurate and reliable.

1 Data Capture

2 Data Validation

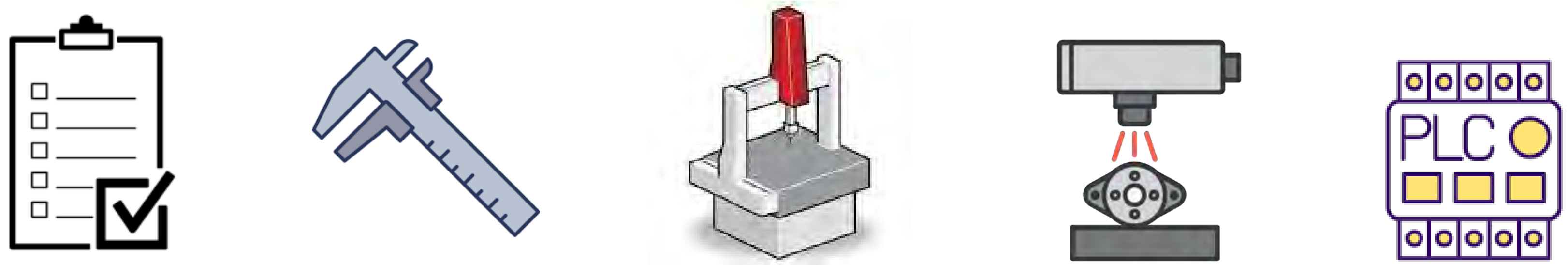
3 Data Centralisation & Preparation

Objective Driven



Capture

No consistent capture of data across devices



'Centralisation'

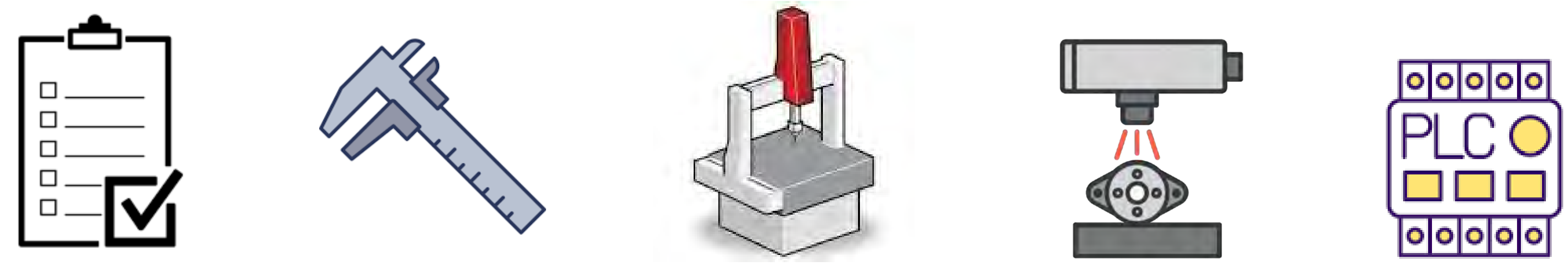
Data fragmented in silos
Hard to access

Preparation

Impossible to combine

Capture

All data sources connected



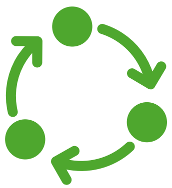
Centralisation

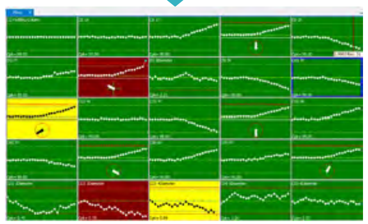
Single source of truth for analytics

Minitab®

Preparation

Automated preparation and contextualisation





Dashboards

+

Alerts

+

Root cause analysis

Summary

Creating a strong data strategy and a digital thread transforms production data into actionable information:

Identify, understand, and reduce process variation

See the Health of the Plant:

- Factory floor view
- Red / Amber / Green status indicators
- Immediate visibility of problem areas

Monitor Process Stability

- Real-time SPC
- Trends
- Alerts
- Capability metrics

Drill Down into Issues

- Production line
- Machine
- Product
- Characteristic

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EXCHANGE

From Monitoring to Mastery: Root Cause Analysis

Nick Jones and Tony Smith
Solutions Architects

Root Symptom Analysis (RSA)

"Everyone doing the wrong thing together, enthusiastically, accelerating short-term solutions with long-term consequences"

Root Symptom Analysis (RSA)

Reactive symptom analysis keeps the factory busy but the root cause alive

Trial-and-error is not a root-cause method

Root Symptom Analysis RSA

Symptom
an alarm, defect, or low-yield batch appears

Containment
a quick change is made to stop the pain

Temporary relief
performance improves for a shift or a run

Recurrence
the issue returns because the mechanism was never isolated

Root Cause Analysis RCA

Collect the Data
machines, sensors, lab systems

Find key drivers
rank what actually drives the response

Validate & Quantify
prove change was real

Scale learning
repeat the learning line to line

Monitoring shows what changed, not why

Monitoring tells you when & how much something changed but it does not automatically tell you why it changed and what changed

Monitoring Detects

- ➢ Yield loss
- ➢ Process shifts
- ➢ Increased scrap
- ➢ Out-of-control conditions
- ➢ Declining capability

Beyond Detection: Critical Decisions

- ✓ Identify the driver
- ✓ Prioritize the inputs
- ✓ Verify process capability
- ✓ Confirm effectiveness
- ✓ Prevent recurrence

The signal is the beginning of the conversation not the end. It starts the investigation, it doesn't close it!

From Y to X

Monitoring shows the Y, root cause analytics helps identify the Xs that matter

Ys: Process outcomes

- ✓ Scrap
- ✓ Defect rate
- ✓ Diameter deviation
- ✓ Downtime
- ✓ Customer quality

Y = f(X)

Xs: Process drivers

- ✓ Tool age
- ✓ Vibration
- ✓ Speed
- ✓ Pressure
- ✓ Temperature

The improvement question: which Xs are meaningful, measurable and actionable

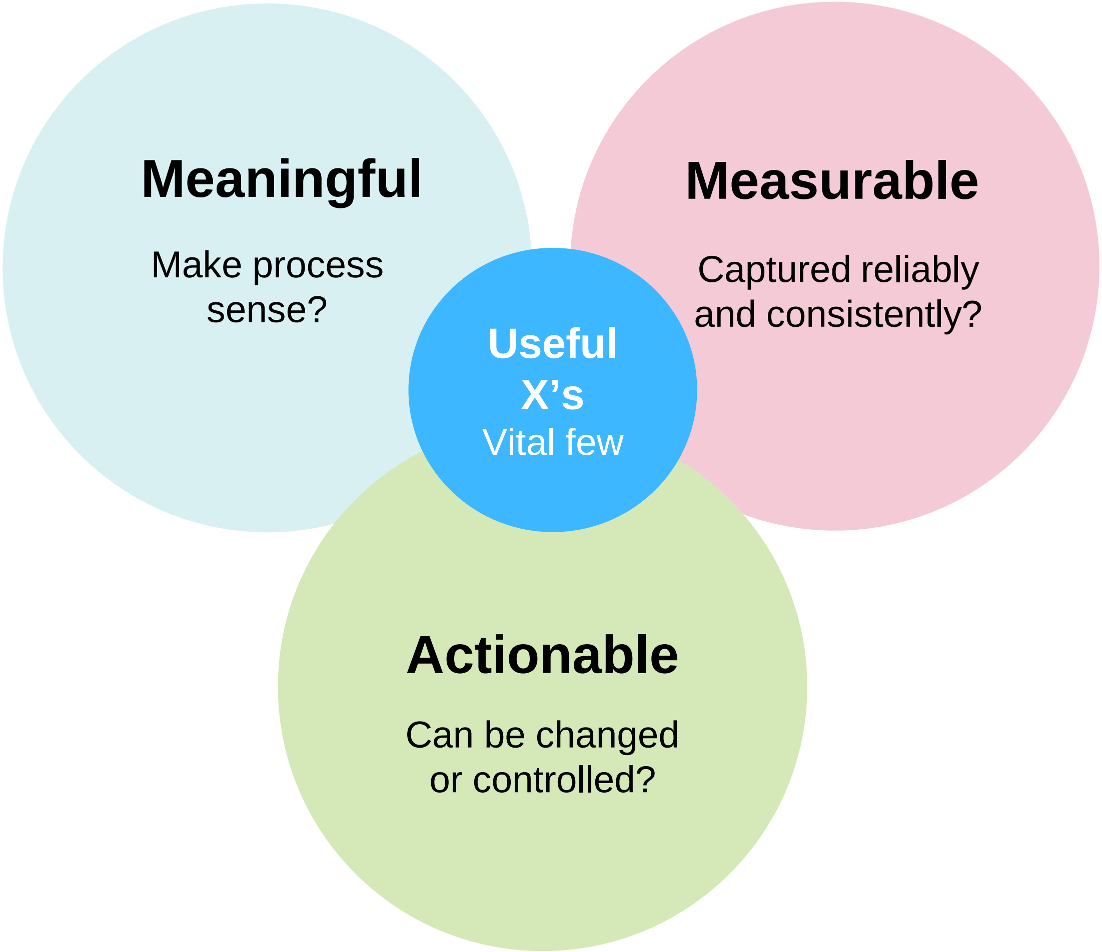
Root Cause Starts Before the Model

Manufacturers have more data than ever, but more data is not the same as better process knowledge

Ask better questions, but don't filter too early

Questions to ask:

1. Meaningful
   Does this variable make process sense?
2. Measurable
   Can we capture it reliably and consistently?
3. Actionable
   Can the team actually change or control it?



Example

A manufacturer is producing precision-machined pump housings. The engineering team tracks real-time process variables during machining and inspection data from the finished part.

First-pass yield ≈ 94%

Finished Pump Housing

Quality Metric (Target)
Bore Diameter Deviation
Target = 0 µm
Spec = ± 10 µm

Potential Drivers of Variation

Field	Type	Description
Timestamp	Datetime	Production timestamp at roughly 8-minute intervals
Part ID	Text	Unique finished part identifier.
Machine ID	Categorical	CNC machine producing the part
Material Lot	Categorical	Incoming material lot
Material Hardness Rc	Numeric	Rockwell hardness
Spindle_Speed_RPM	Numeric	Machining speed
Tool_Age_parts	Numeric	Parts since tool change
Coolant Temp C	Numeric	Coolant temperature
Vibration RMS mm s	Numeric	Measured vibration
Ambient_Temp_C	Numeric	Ambient shop temperature
Clamp Pressure bar	Numeric	Fixturing pressure
Bore Diameter Deviation microns	Numeric target	Finished-part dimensional quality metric
Surface Roughness Ra um	Numeric target	Secondary finished-part quality metric.
Pass/Fail	Categorical target	Classification target: Fail when dimensional or roughness specification is missed.

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EXCHANGE

Design Better Processes

Nick Jones and Tony Smith

Solutions Architects

Design Better Processes

Proactive quality with DOE. Digital validation with simulation

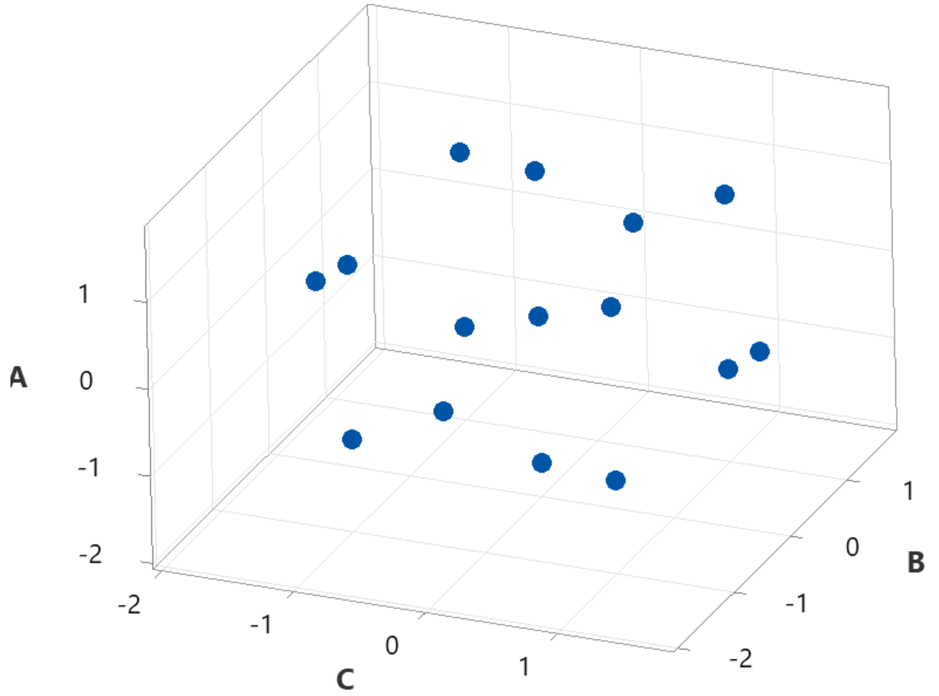
Experiment → Optimize → Simulate → Decide

Design of experiments and simulation reduce the number of physical trial loops needed to reach a stable operating window in both discrete and process manufacturing.

Design Better Processes

DOE systematically changes multiple inputs simultaneously to determine:

- ✓ Which factors matter most
- ✓ How factors interact
- ✓ Where the optimal operating region exists
- ✓ How robust the process is to variation



DOE
Why One-Factor-at-a-Time Improvement Falls Short

Traditional Approach

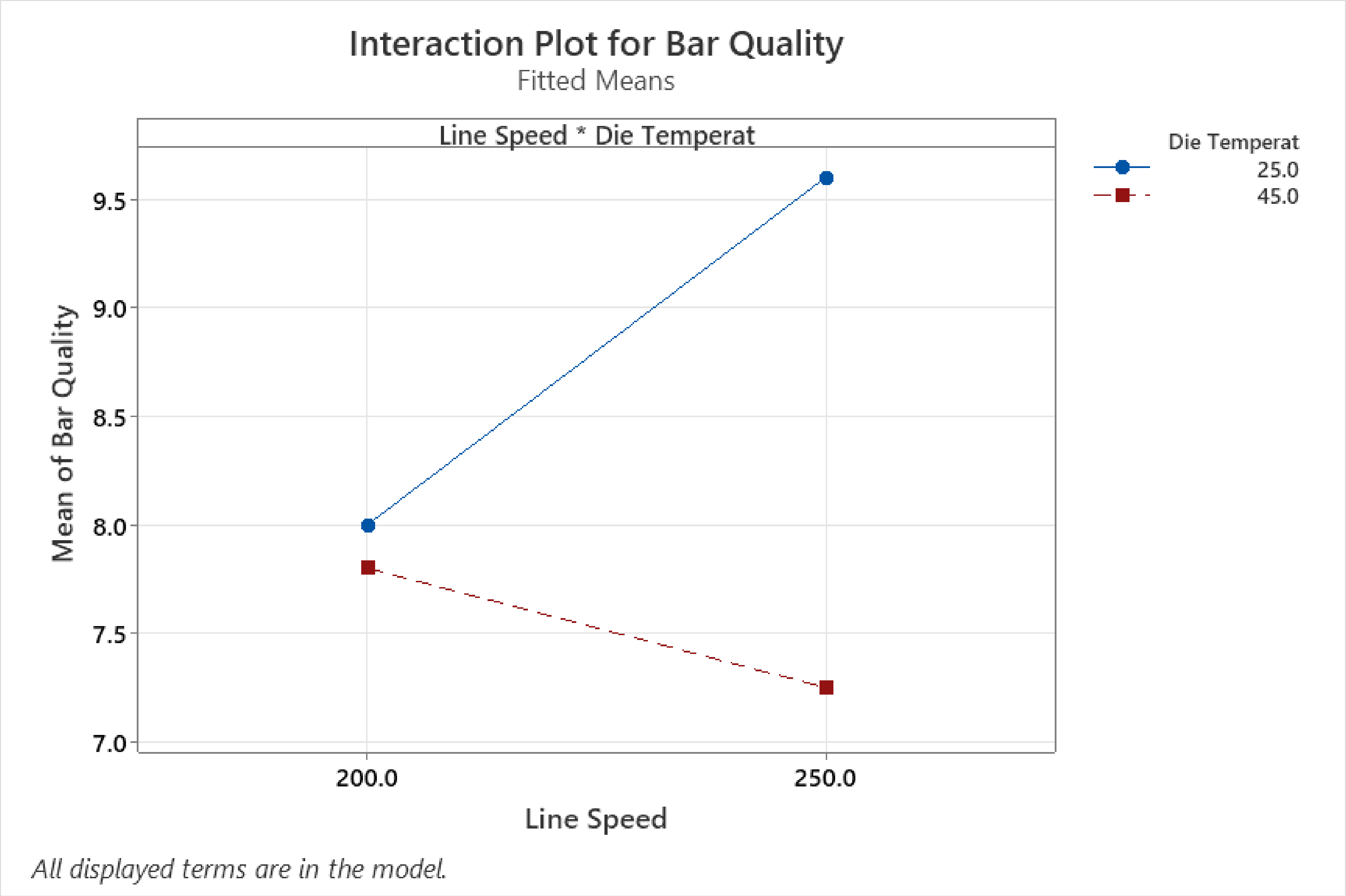
- Change one variable
- Observe the outcome
- Repeat until performance improves

The Problem

Interactions between variables are missed

Optimization becomes slow and expensive

Engineering conclusions are often incomplete


Interaction Plot for Bar Quality
Fitted Means
Line Speed * Die Temperat
Die Temperat
25.0
45.0
Mean of Bar Quality
9.5
9.0
8.5
8.0
7.5
7.0
200.0
250.0
Line Speed
All displayed terms are in the model.

The Evolution of Experimental Designs
Minitab DOE by Effex

Why Modern DOE Matters

Manufacturing systems are becoming:

- ➢ More complex
- ➢ More constrained
- ➢ More expensive to test
- ➢ More multi-objective

Minitab DOE by Effex adds

- ✓ Advanced optimal designs
- ✓ OMARS® experimental designs
- ✓ AI-assisted design selection
- ✓ Reduced experimental runs
- ✓ Integrated optimization workflows
- ✓ Better performance for high-factor systems

DOE Use Case: Pressure-Differential Drying

Minitab EXCHANGE

Persimmon Chips

Factors

- Pressure differential
- Drying temperature
- Drying time

Responses

- Moisture
- Crispness
- Sensory quality

Minitab turns experimental data into candidate process recipes

Published DOE Dataset

Hezhou University
Guilin University of Technology

Batched Drying Process

Taking raw persimmons, preparing, baking, and packing

Quality Responses

Pressure effects puffiness,
Higher temperatures increases browning
Drying time impacts crispness

Scrap

Prepare › Batch › Dry › Cool › Inspect › Pack › Ship

Minitab DOE by Effex Demo

Data

Optimal Design

Candidate Recipes

A Process Can Be Optimized…
…and still fail operationally

Bottlenecks and Shifts Downstream

Buffers Overflow

Labor Becomes Constrained

Changeovers Disrupt Schedules

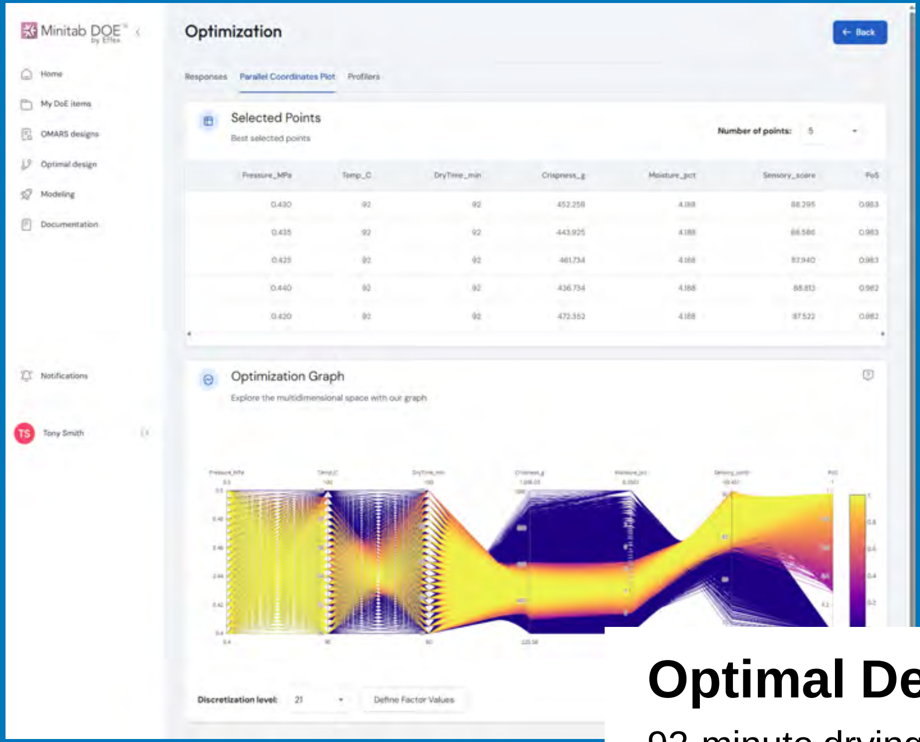
WIP Inventory Grows

Throughput Stalls

Optimization must balance the system

Current Design

90-minute drying time, Estimated Pass Rate: 93%

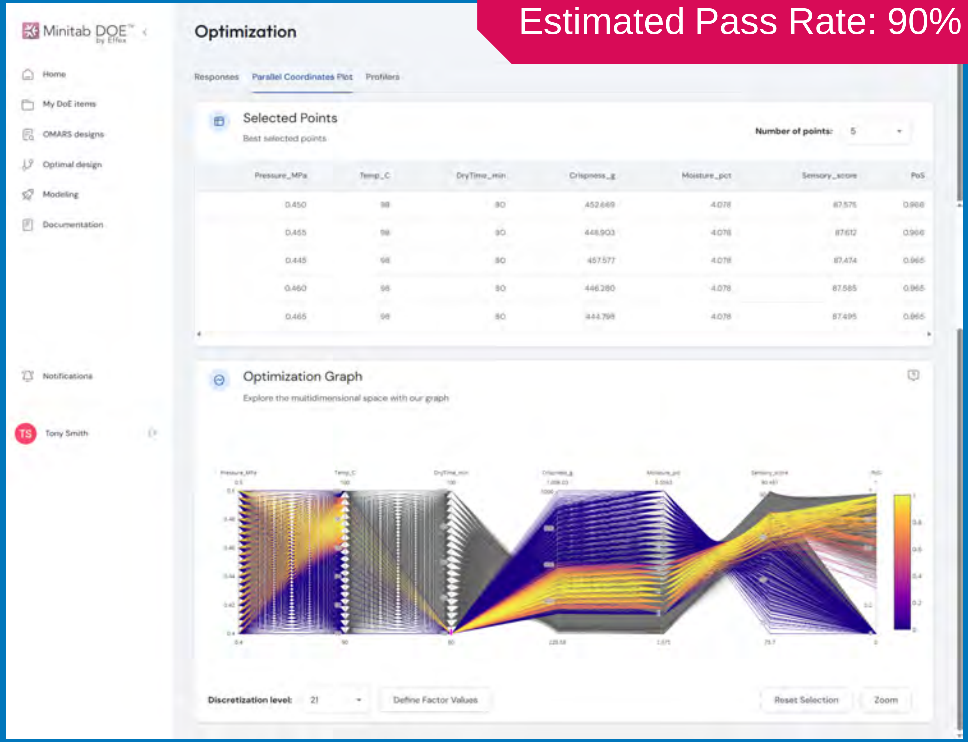


Optimal Design

92-minute drying time
Estimated Pass Rate: 97%

Fast Design

80-minute drying time
Estimated Pass Rate: 90%



What is Discrete Event Simulation?

A digital representation of a manufacturing system that models:

- Machines
- Operators
- Queues
- Material flow
- Downtime
- Shift schedules
- Variability

Current Design

90-minute drying time
Estimated Pass Rate: 93%

Optimal Design

92-minute drying time
Estimated Pass Rate: 97%

Fast Design

80-minute drying time
Estimated Pass Rate: 90%

DOE Informed Simulation

Simulation allows us to see the impact of candidate process designs on the wider system.

Map your process › **Simulate the DOE recipes** › **Compare scenarios** › **Move forward with evidence**

A model or simulation does not replace engineering judgment. It helps the team spend physical trials only where the odds of success are meaningfully higher.

Virtual experiments reduce the cost of being wrong.

Same

Demand, process and resources

Scenarios

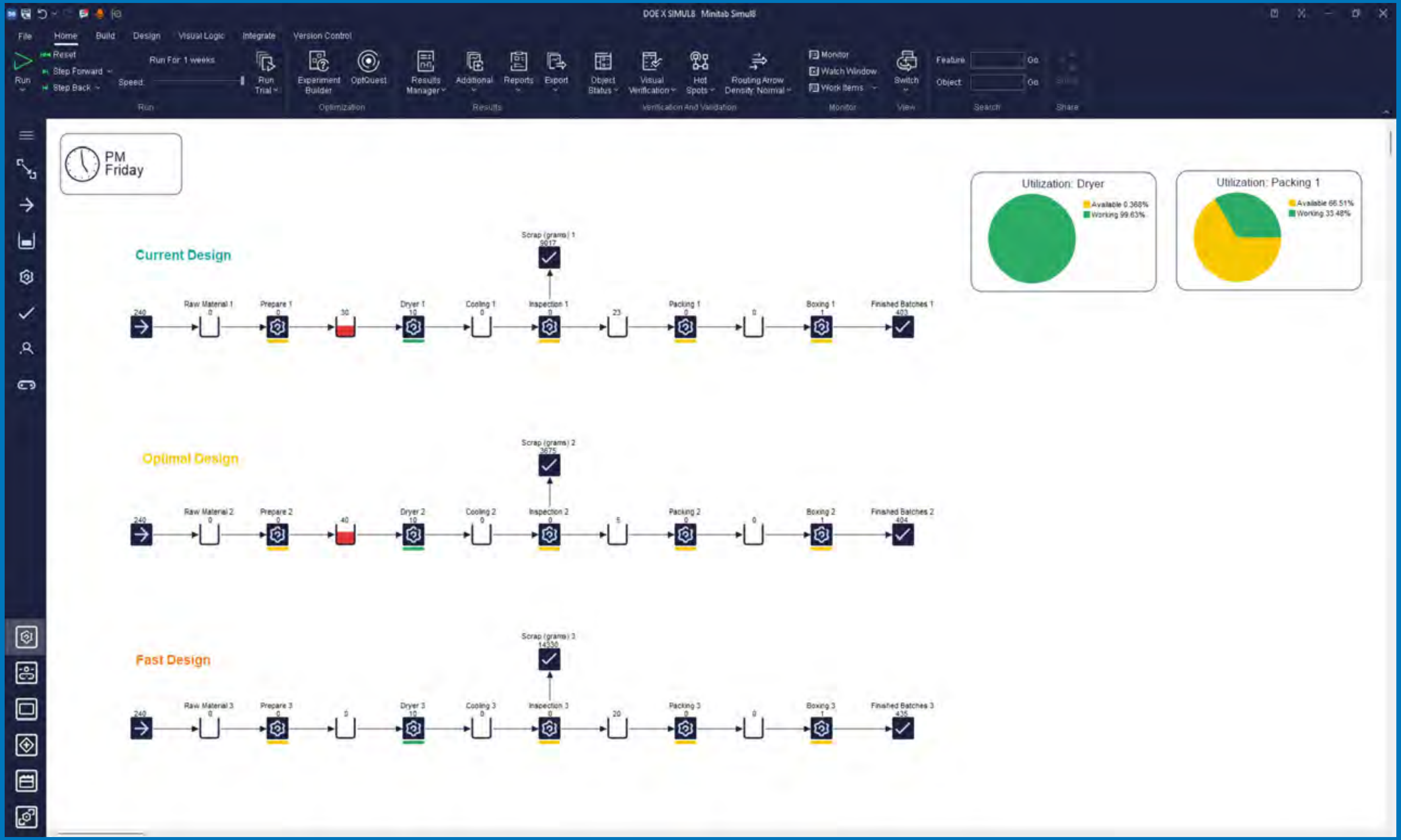
Drying time: Excepted pass rate (impact of temp.)

Results

Output, scrap, WIP & utilization

Insights from the Simulation

Which recipe gives the best operating balance?



Current Design

Finished Cases Shipped: **403**
Scrap Volume: **9090g**
WIP: 30 **Batches**
Dryer Utilization: **99.6%**

Optimal Design

Finished Cases Shipped: **404**
Scrap Volume: **3748g**
WIP: **40 Batches**
Dryer Utilization: **99.6%**

Fast Design

Finished Cases Shipped: **435**
Scrap Volume: **14481g**
WIP: **0 Batches**
Dryer Utilization: **99.5%**

Takeaways

One-factor-at-a-time optimization leaves performance undiscovered

DOE accelerates learning and identifies true process relationships

Combining experimentation and simulation creates smarter manufacturing decisions

Minitab DOE by Effex expands DOE capability for complex systems

Simul8 allows manufacturers to predict operational behavior before implementation

Chris Powley is a Technical Specialist in Electronics Manufacturing within the Component Manufacturing Technology team at the Manufacturing Technology Centre.

Over 25 years' experience in high-reliability electronics design, manufacturing, and industrial R&D, has worked on semiconductor components for aerospace, space, and defence applications.

Specializes in microelectronics, electronics manufacturing, process engineering, and manufacturing readiness.

At the MTC, he supports industrial and collaborative R&D projects focused on advancing process capability and novel electronics manufacturing technologies.

Kush Patel (CEng) is a Senior Research Engineer within the Digital Engineering, Modelling and Simulation group at the Manufacturing Technology Centre.

Chartered Engineer with an MSc in Mechanical Engineering and 16+ years' experience in turbomachinery across power, aerospace, and oil & gas.

Specializes in developing industrial technologies from concept to deployment, with expertise in CFD, aerodynamics, structural analysis, and process modelling.

At the MTC, he has led research in additive manufacturing fatigue, topology optimisation, and advanced heat transfer applications.

Design of Experiments in Practice

Chris Powley & Kush Patel

02/06/2026

Rev 1.0

About us

Our purpose

To harness the power of our **pioneering mindset** and **engineering excellence** to positively impact society

- Independent Research Technology Organisation (RTO)
- Opened in 2011
- Opened training facility in 2015
- £120 million+ in turnover
- 1000+ staff members
  over 600 engineers & 100 apprentices

Market sectors

Our broad experience across a range of sectors means we can transfer valuable knowledge and insights, giving us the expertise to help with your next challenge.

Energy & Utilities

Civil nuclear, Hydrogen, Electrification, Renewables & Water

Defence & Security

Air, Land, Sea, Platform systems, Sub systems & Government security

Built Environment

Construction, Rail & Road

Future Mobility

Automotive, Aerospace & Space

Further Focus

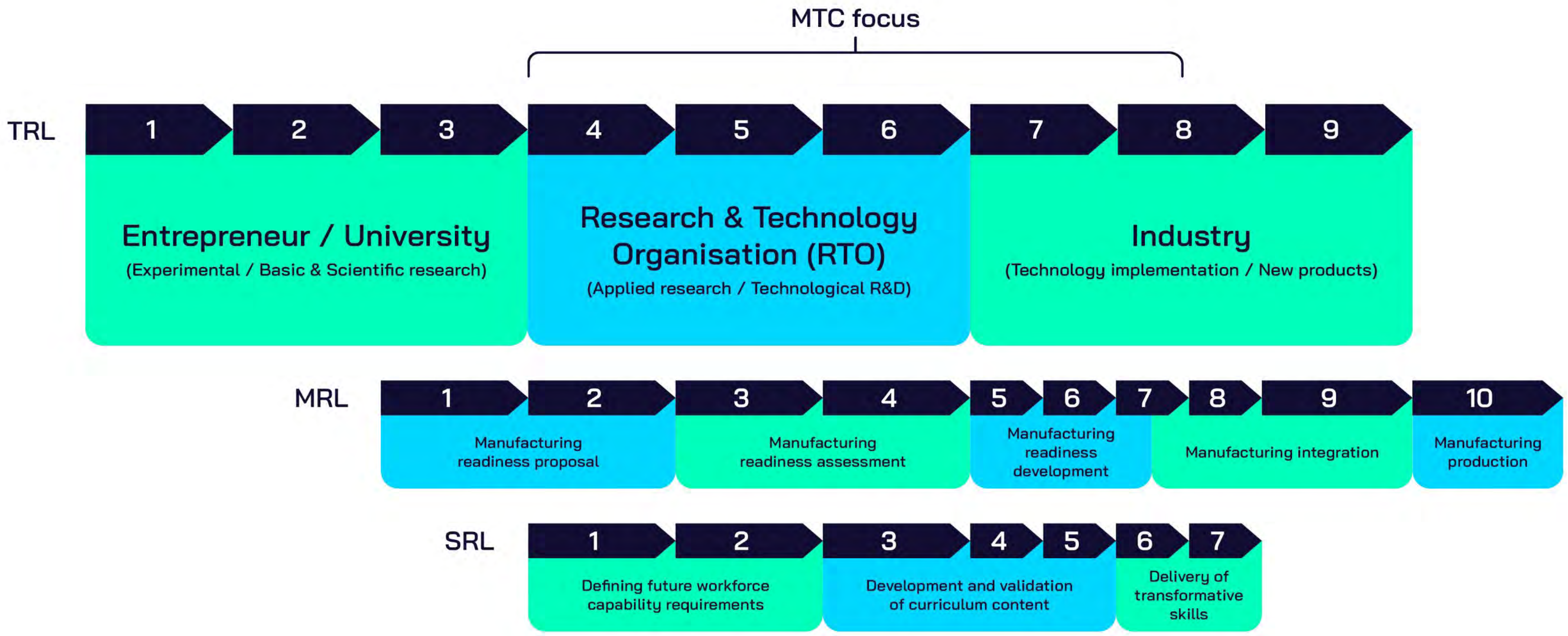
Agri-food, FMCG, Circular economy & Life sciences

Business challenges

We work with businesses of all sizes, from SMEs, start-ups, and entrepreneurs to large and multinational organisations, helping solve challenges and achieve goals.

- Product innovation & development
- Process innovation & development
- Digital transformation & servitisation
- Industrialisation & scale-up
- Supply chain transformation
- Sustainable manufacturing & net zero
- Skills & training

Bridging the valley of death



TRL = Technology readiness level MRL = Manufacturing readiness level SRL = Skills readiness level

Our impact in numbers

9000+
Projects delivered

600+
Multi-disciplinary engineers

90+
Collaborative members

1200+
Apprentices trained

200+
Upskilling courses available

3500+
SMEs worked with

mtc

Our members

ABB · ABICOR BINZEL · ADDIGURU · AEGIS SOFTWARE · AIRBUS · ALTUS GROUP · Amey · Ansys · ASM · Atlas Copco · ATS · AWE Nuclear Security Technologies

BAE SYSTEMS · BECKHOFF · BT · BOC A Member of The Linde Group · BROWN & HOLMES (Tamworth) LTD Precision Workholding and Machining · CAPVIDIA · CCAD · CONTROL 2K everything in control · Cummins · element · eos · EPICOR

ERICSSON · esi get it right · ETEK europe · eyelit TECHNOLOGIES · fairfield · ferrovial construction · FICO · FLOW-3D · GE VERNOVA · GKN PLC · GÜDEL · HAL robotics

Haskoning Enhancing Society Together · HEXAGON Manufacturing Intelligence · hp · hs2 · iBase-t · INNEO That's IT. · IPG Photonics · KaizenPLM · KATRICK TECHNOLOGIES · KIER · KOTEM · LOCKHEED MARTIN

London Underground · 18p · LUMENTUM · MAHER · makita · MBDA · Minitab · MTA The Manufacturing Technologies Association · materialise innovators you can count on · national highways · NetworkRail · NANODIMENSION Electrifying Additive Manufacturing

Origin International Inc. · Parker Aerospace · PRIME · Prodtex Production / Technology / Excellence · ptc · RENISHAW apply innovation · rexroth A Bosch Company · RHEA Space Activity · Rolls Royce · SANDVIK Coromant · SENSOFAR · SIEMENS

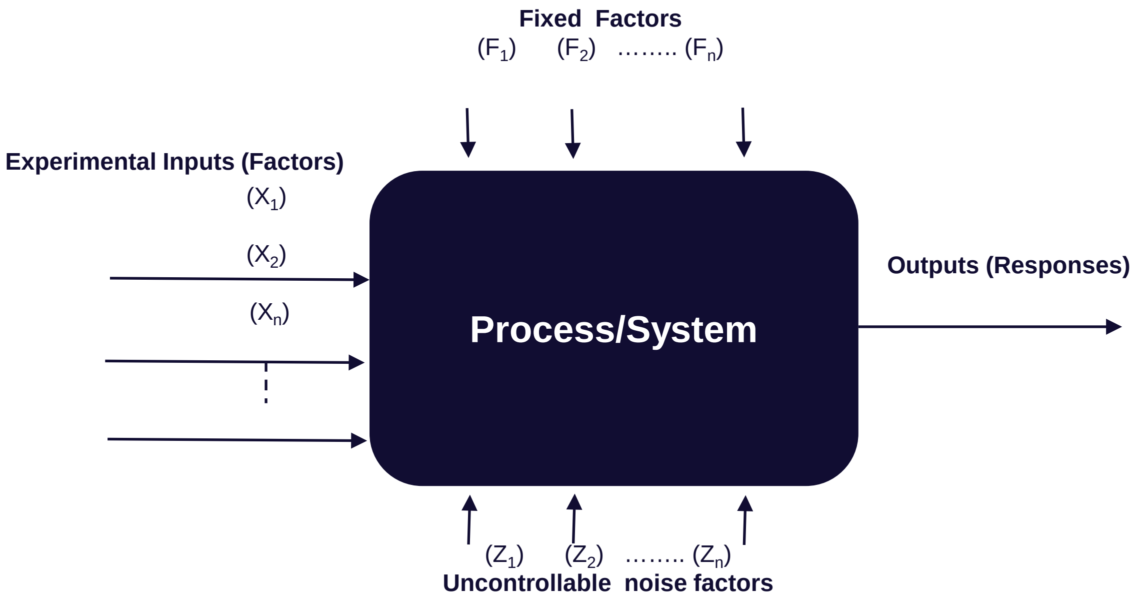
Simportal · SMC · smiths · STIRLINGX A Gallos Company · SYNOVA · THALES · Trafnidiaeth Cymru Transport for Wales · TRUMPF · Ubisense · Unilever · UNITED MACHINING · valuechain

Vericut · vero Software · werth · ZESTRON High Precision Cleaning · 3dscannersuk · 3DGBIRE Additive Manufacturing for Industry · 3M

Introduction to DoE

What is Design of Experiments?

Design of experiments (DOE) is a systematic, statistical approach for determining cause and effect relationships between process inputs (Factors) and key process /system outputs (Responses).



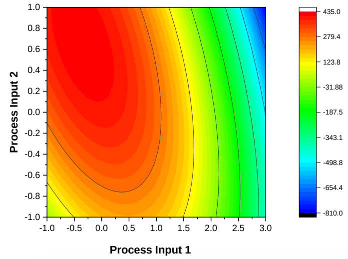
General model of a process or system

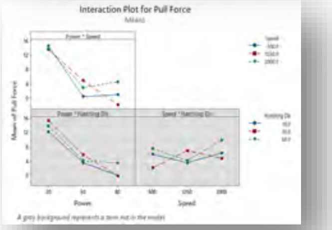
Use-cases for DOE

- **Process optimisation** – process is working but isn't optimal
  - Multiple variables could be changed
  - Changes currently made by intuition or trial-and-error

- **Product/System Process development**
  - Many potential options/ choices/factors to tune
  - Limited time, budget or materials
  - Don't know where to start on understanding a process

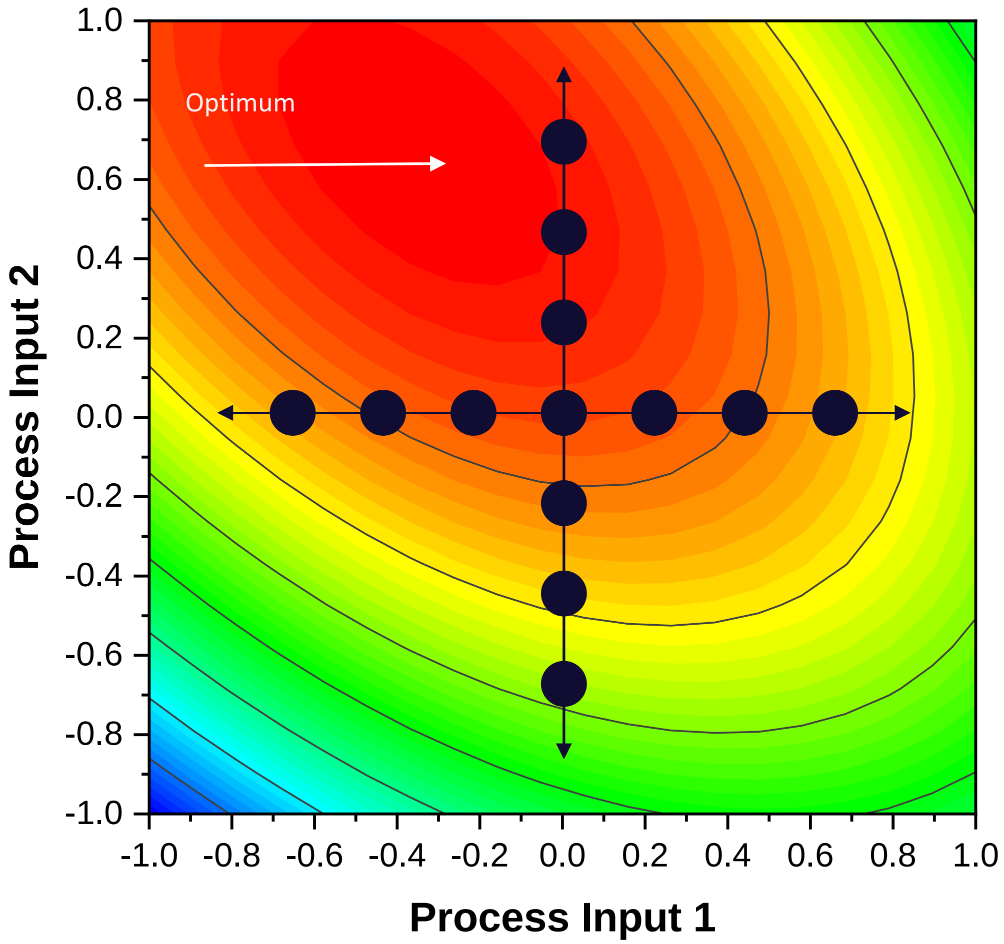
- **Root-cause analysis**
  - DOE identifies which process inputs significantly influence the output(s).





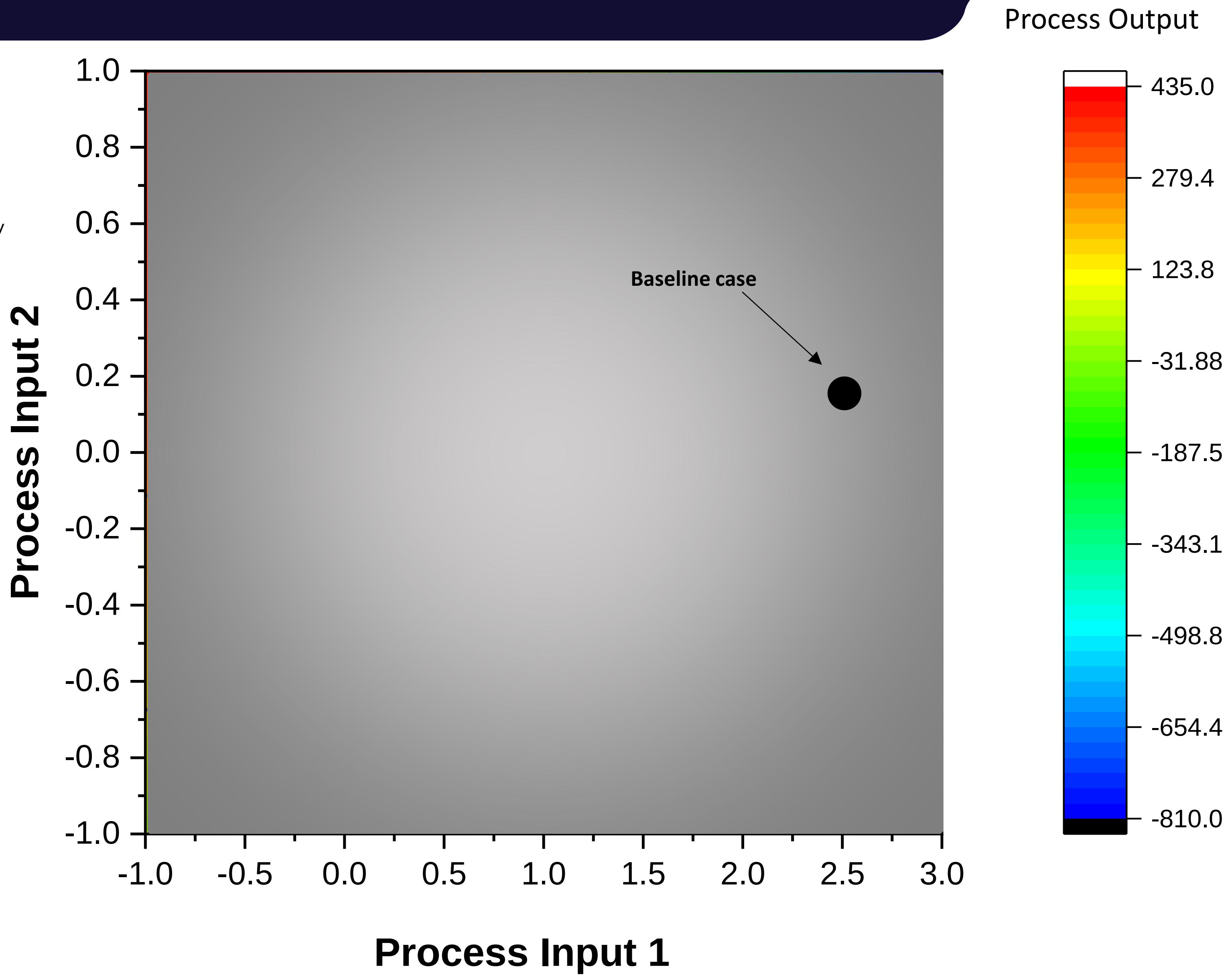
One-Factor-At-A-Time or Trial and Error Experiments

- Experiment with one factor at a time and fix all others
- High risk that the true optimum is not found.
- Large number of treatments
- Inefficient/Unstructured
- No Information on interactions
- May draw incorrect conclusions
- Order and starting point of test order important!



One-Factor-At-A-Time or Trial and Error Experiments

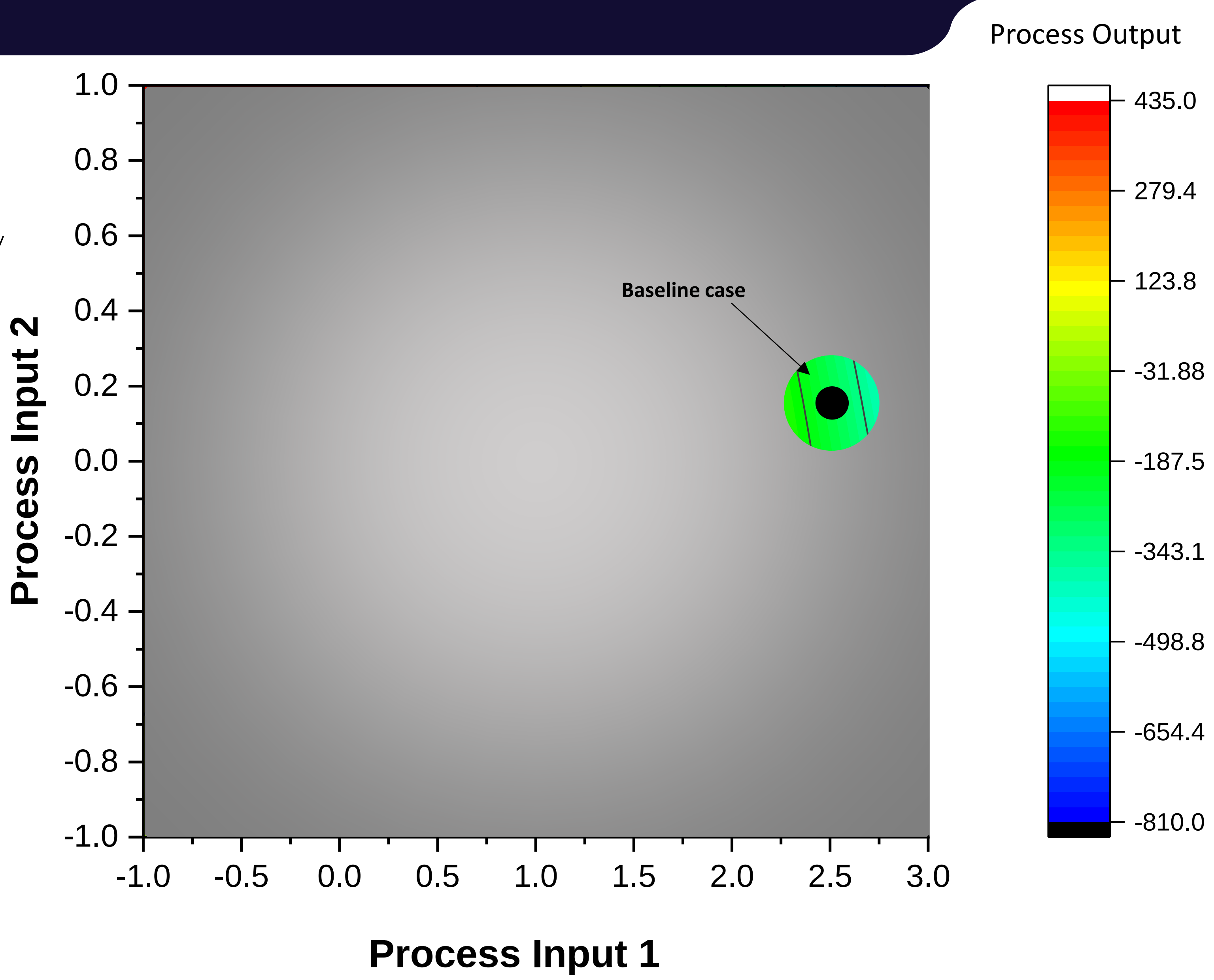
- Project can afford limited trials
- 2 process inputs to optimise only



One-Factor-At-A-Time or Trial and Error Experiments

- Project can afford limited trials
- 2 process inputs to optimise only

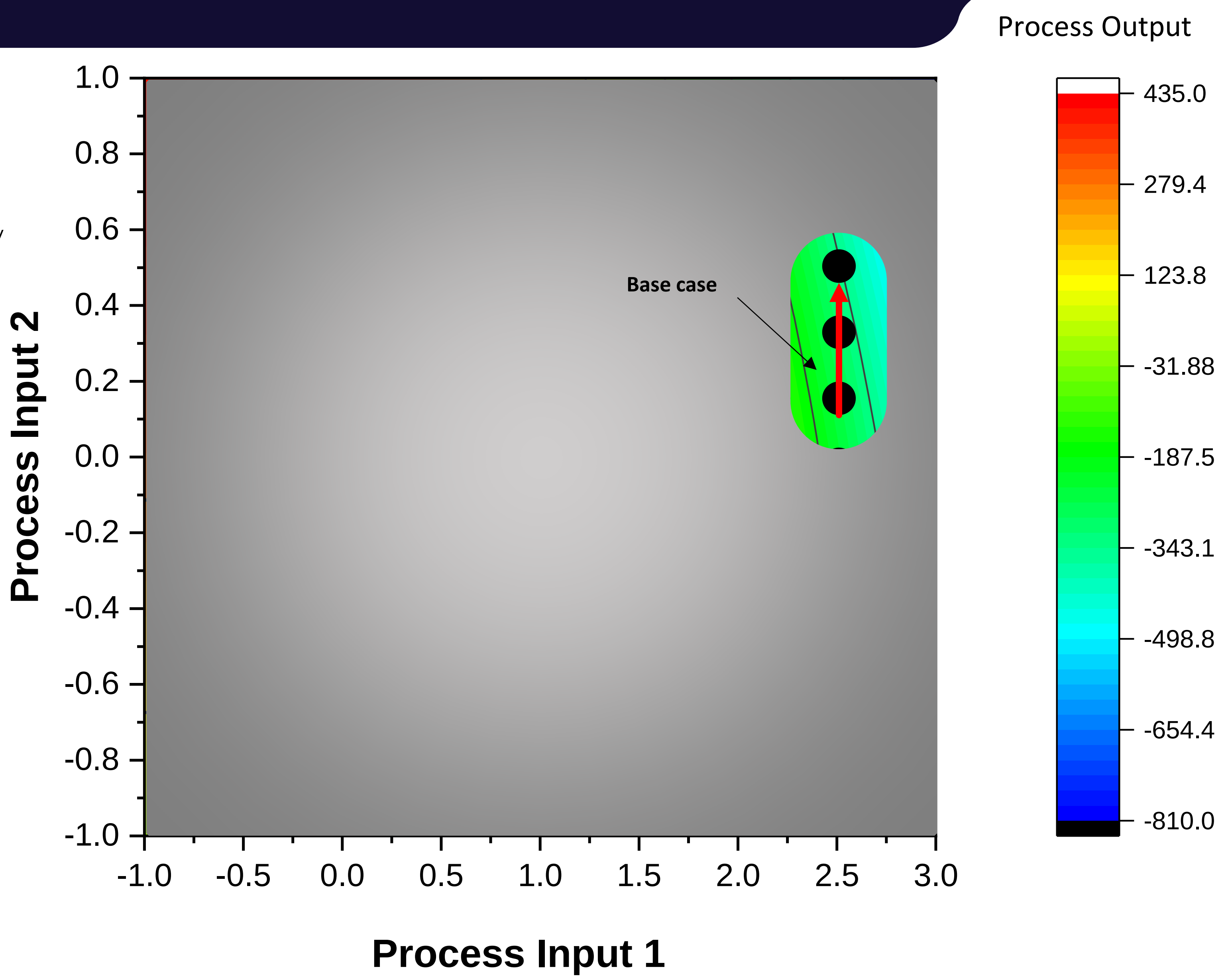
Runs: 1



One-Factor-At-A-Time or Trial and Error Experiments

- Project can afford limited trials
- 2 process inputs to optimise only

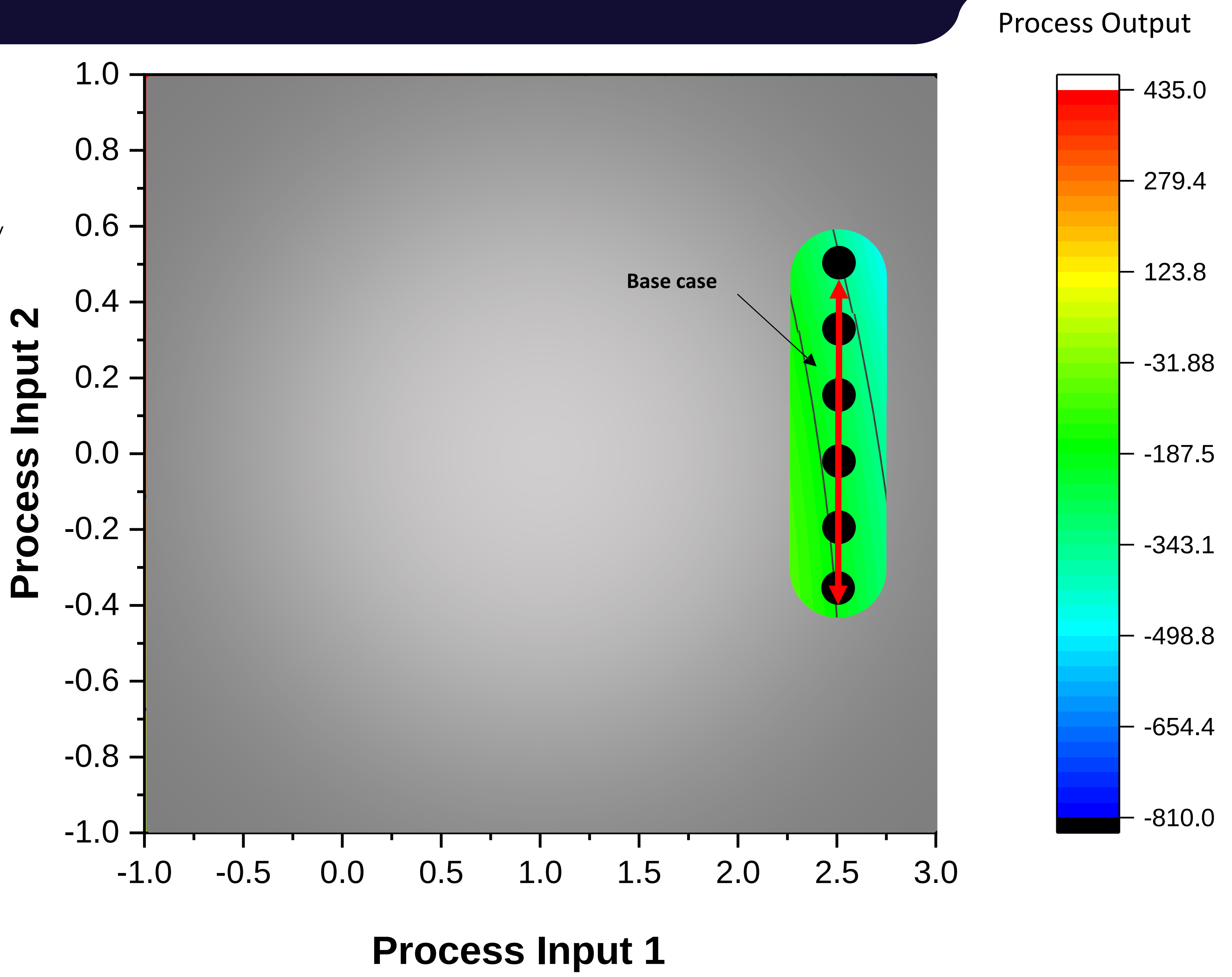
Runs: 3



One-Factor-At-A-Time or Trial and Error Experiments

- Project can afford limited trials
- 2 process inputs to optimise only

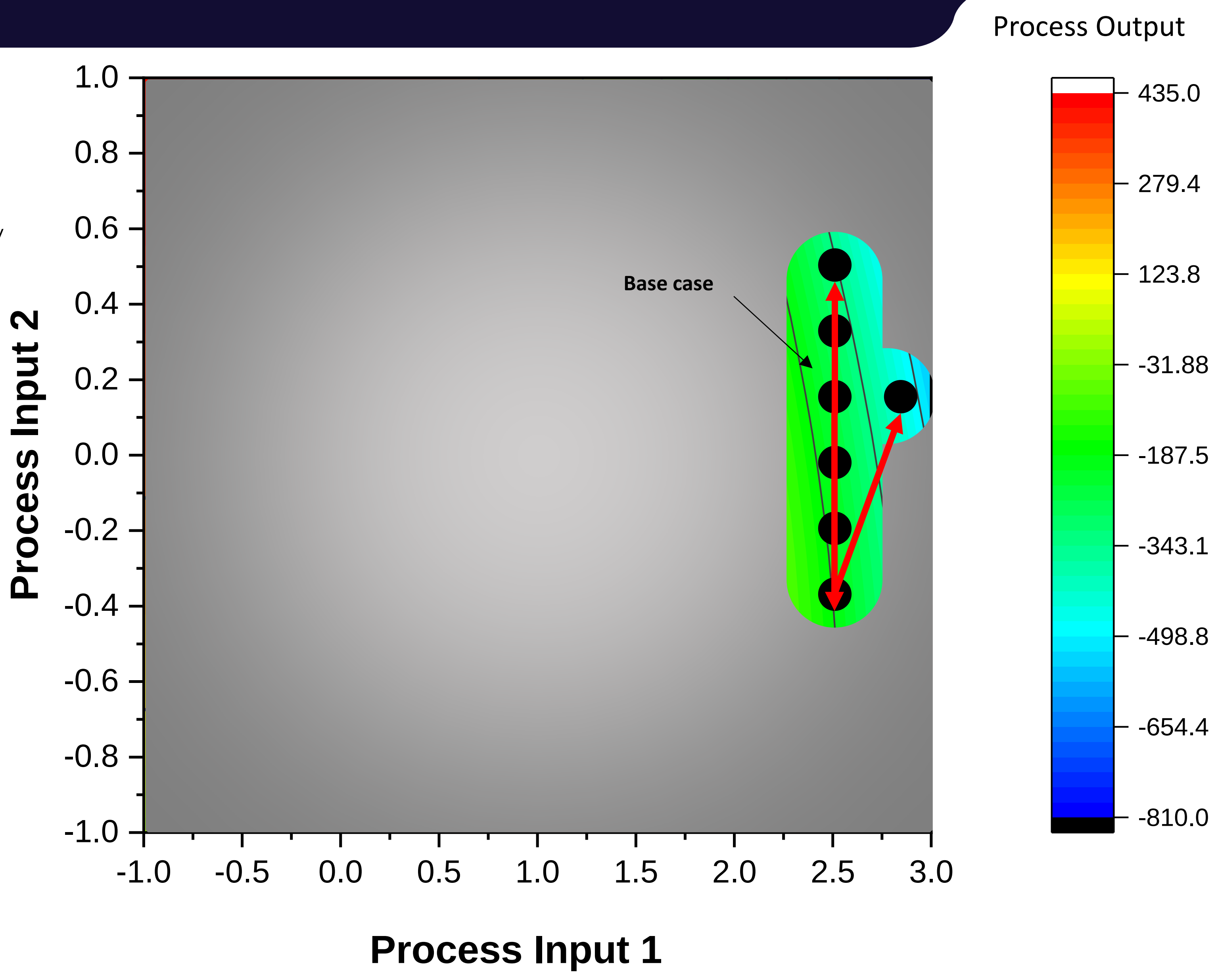
Runs: 6



One-Factor-At-A-Time or Trial and Error Experiments

- Project can afford limited trials
- 2 process inputs to optimise only

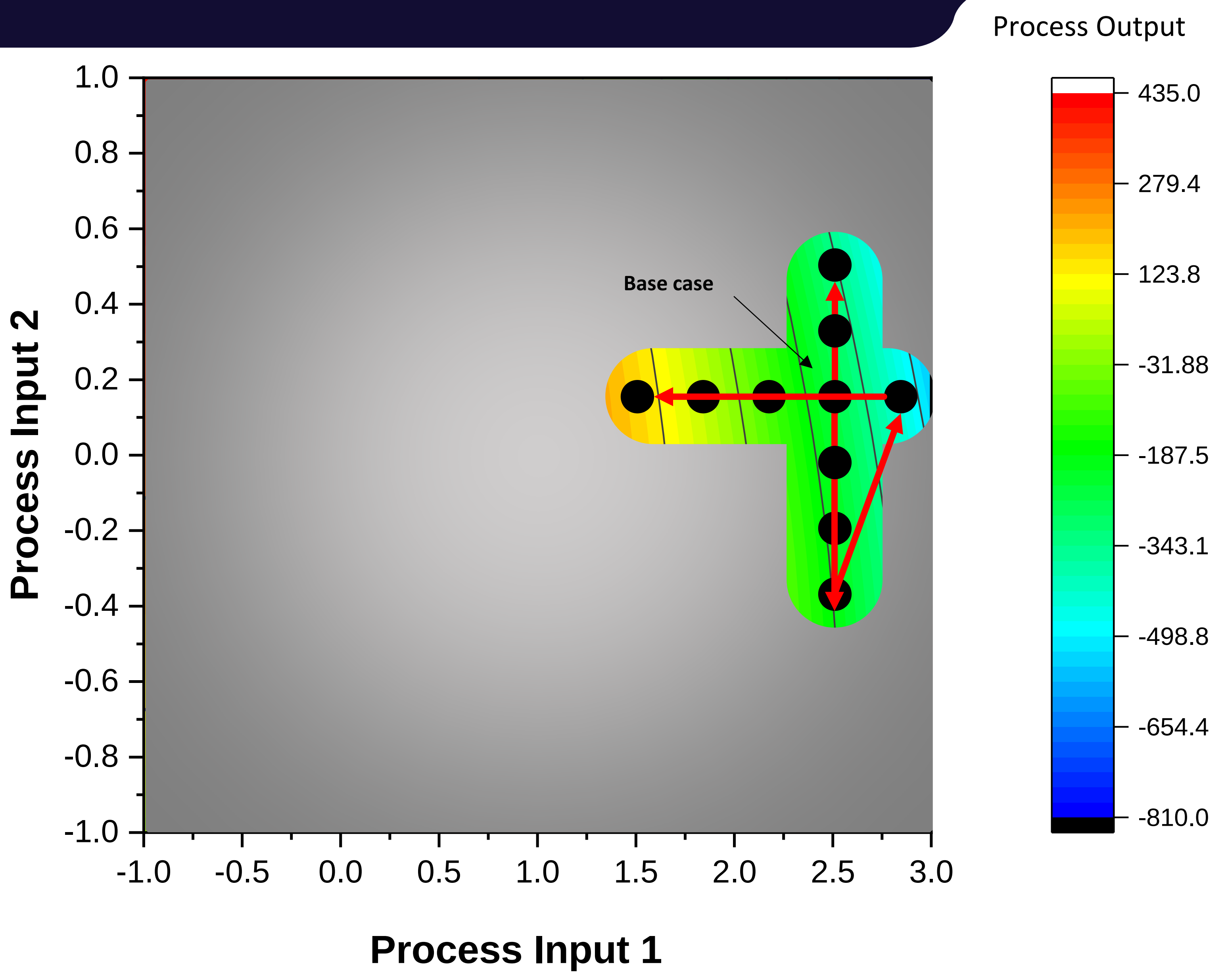
Runs: 7



One-Factor-At-A-Time or Trial and Error Experiments

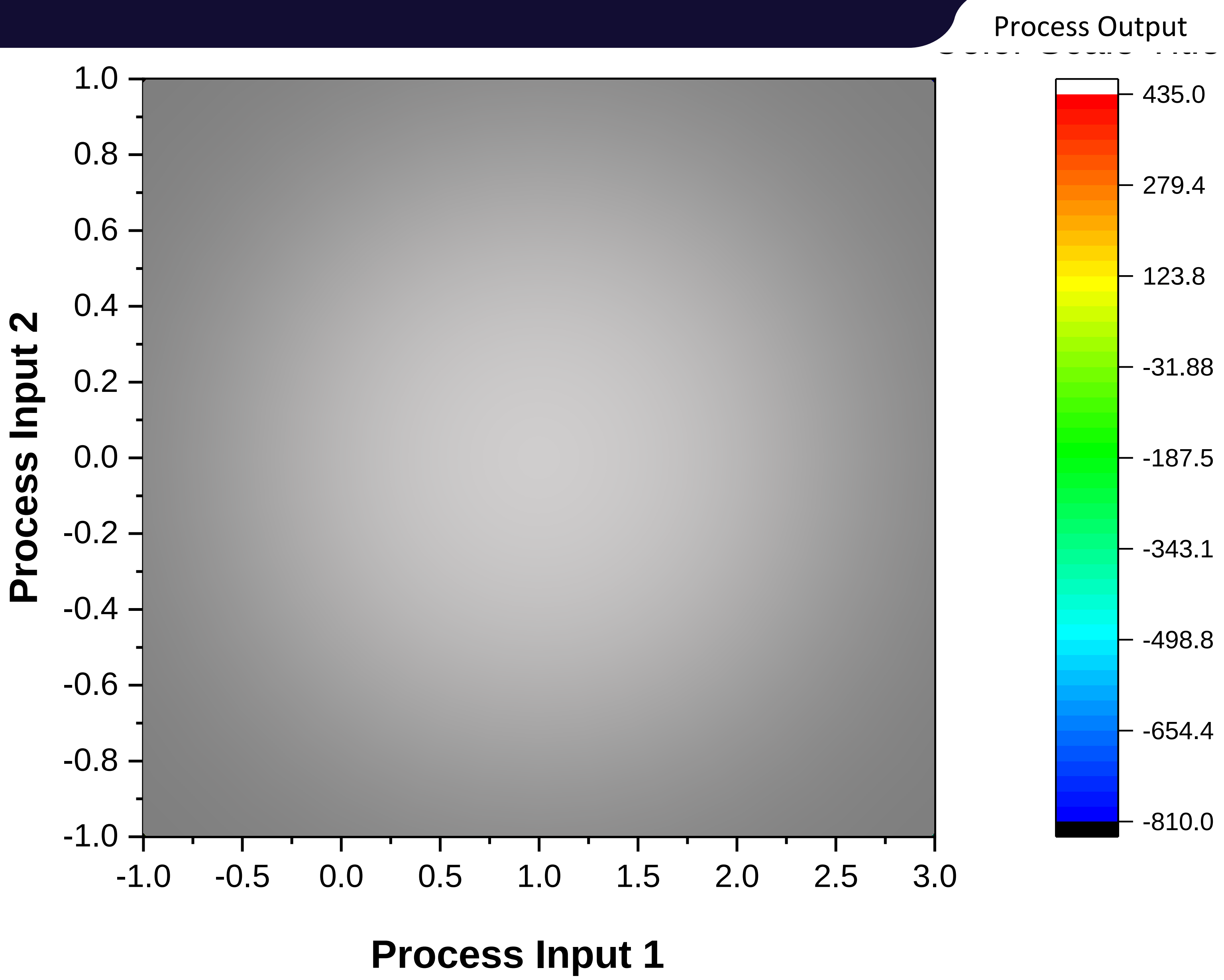
- After 10 runs, we still have limited understanding of process
- Running out of resources
  - Time
  - Materials
  - Budget
  - Access to machine time

Runs: 10



One-Factor-At-A-Time or Trial and Error Experiments

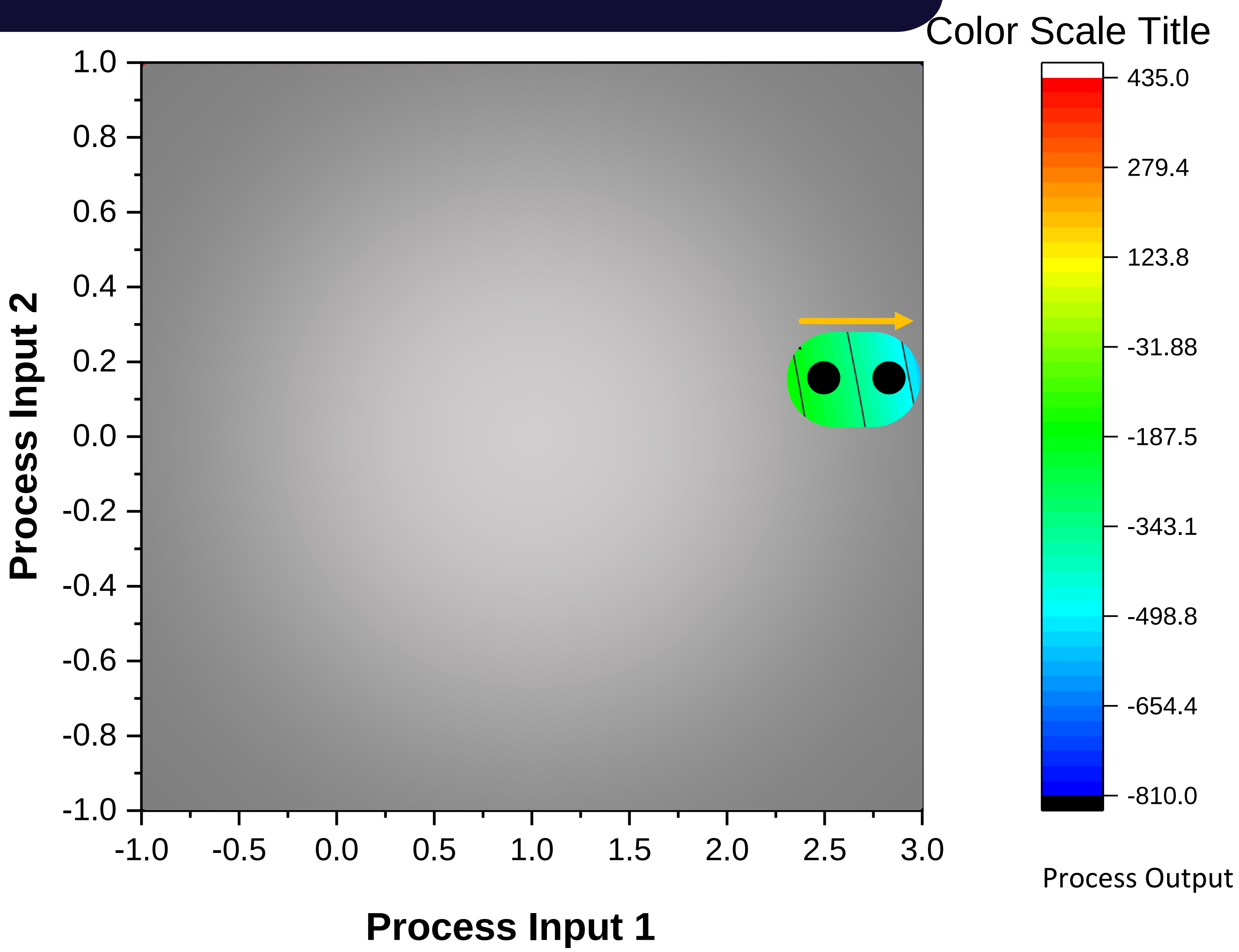
A different engineer may experiment using a different approach and achieve dramatically different results



One-Factor-At-A-Time or Trial and Error Experiments

A different engineer may experiment using a different approach and achieve dramatically different results

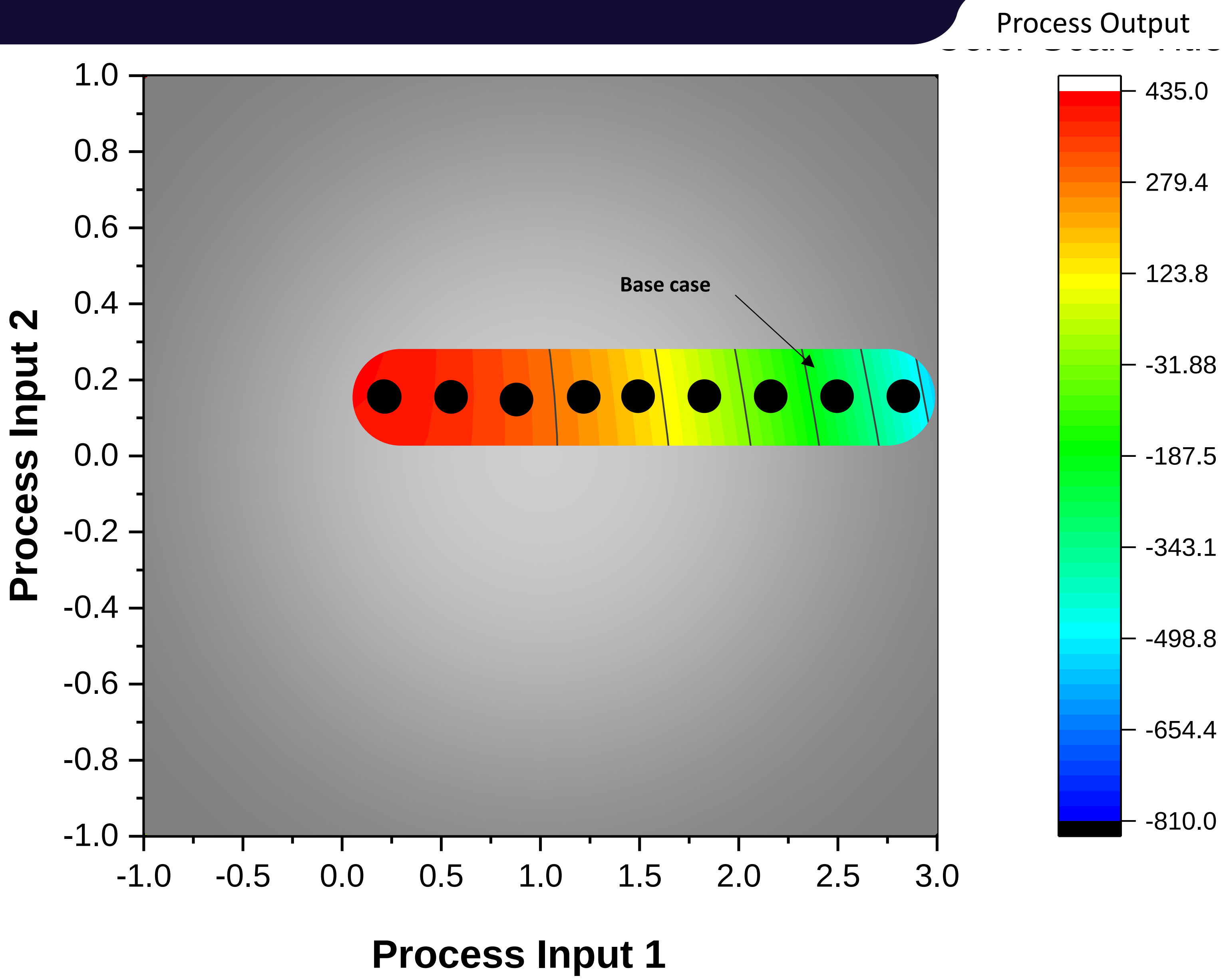
Runs: 2



One-Factor-At-A-Time or Trial and Error Experiments

A different test operator may experiment using a different approach and achieve dramatically different results with same number of trials

Runs: 9



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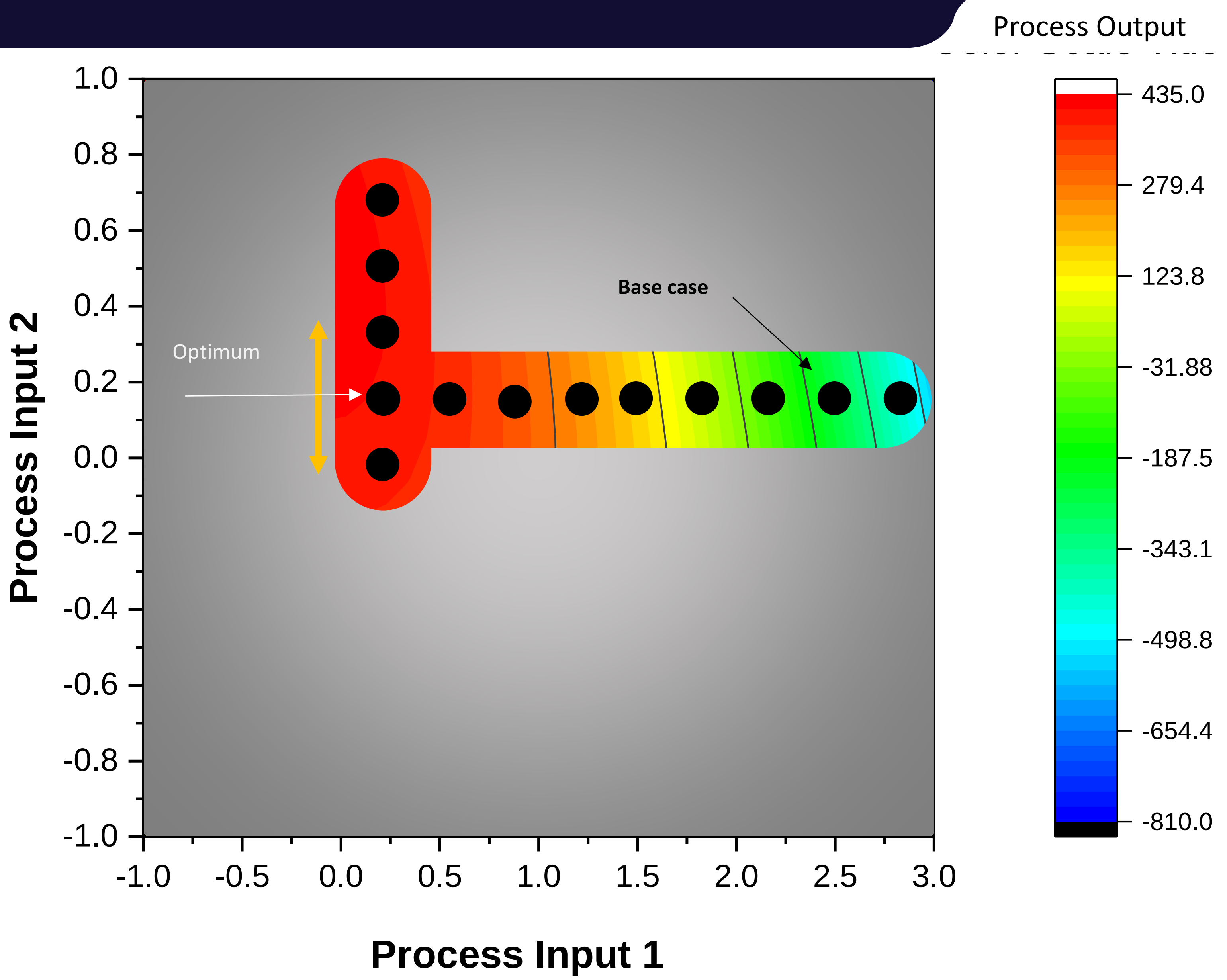

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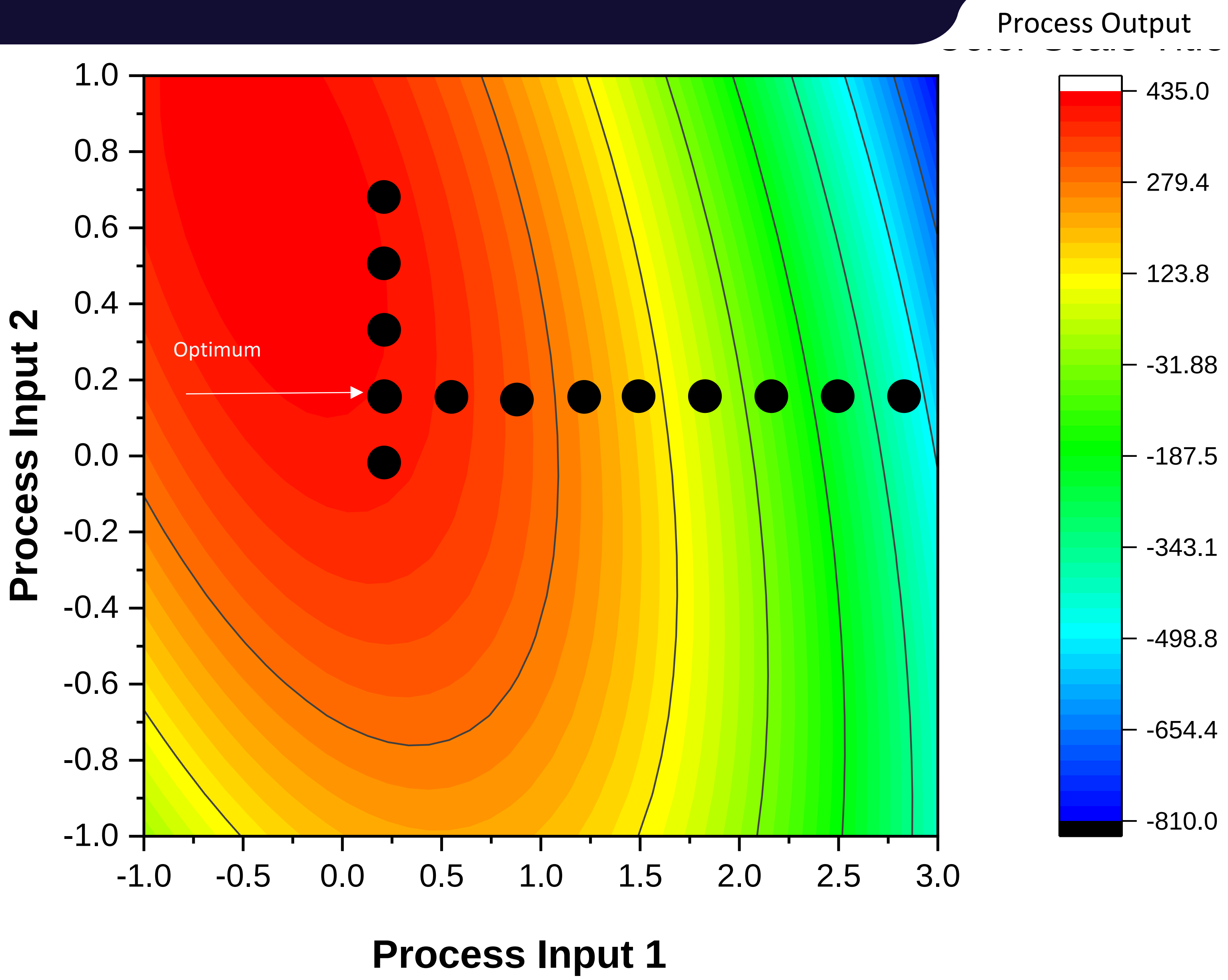
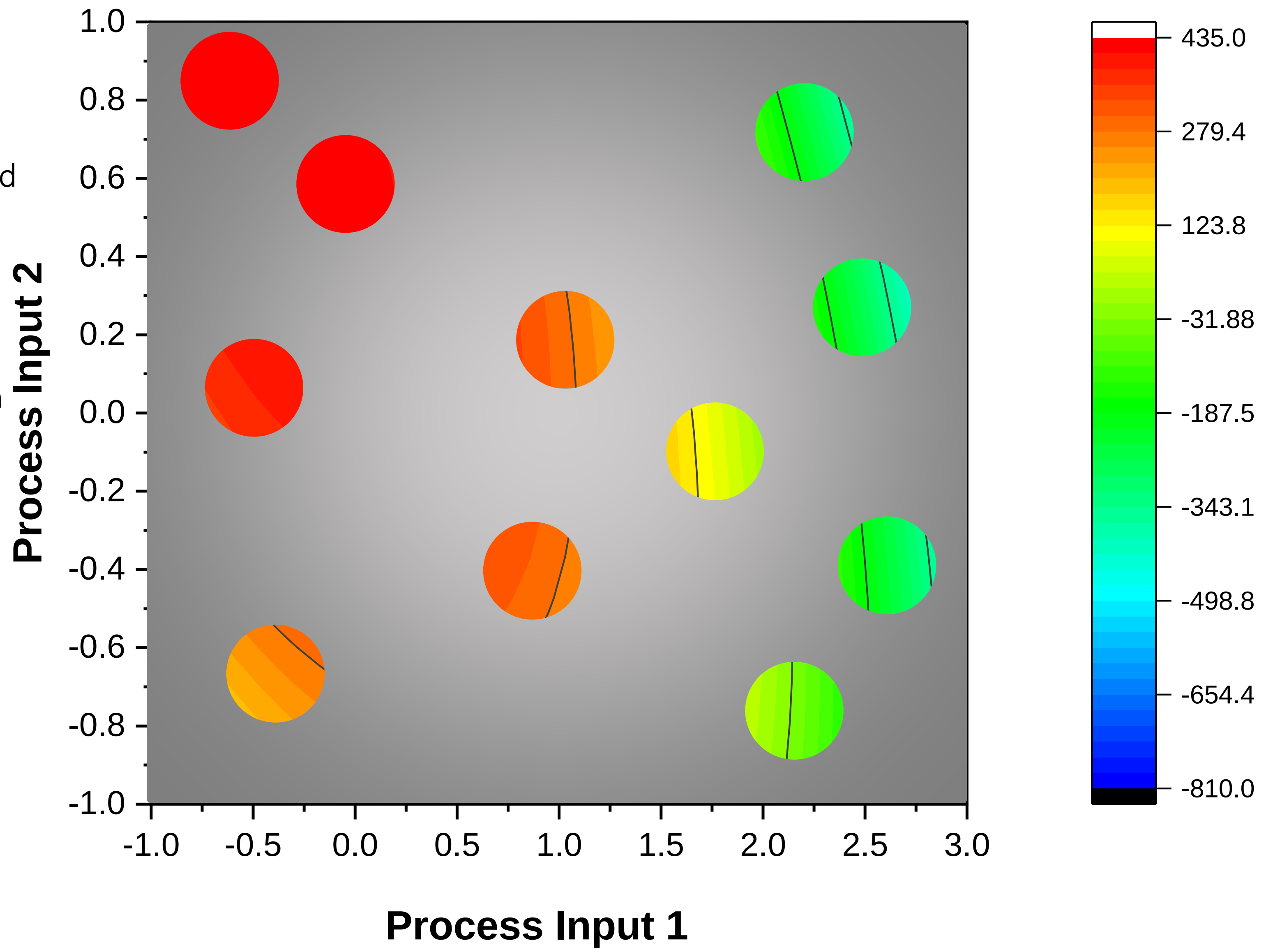


Trial-and-Error – (Shotgun Approach!)

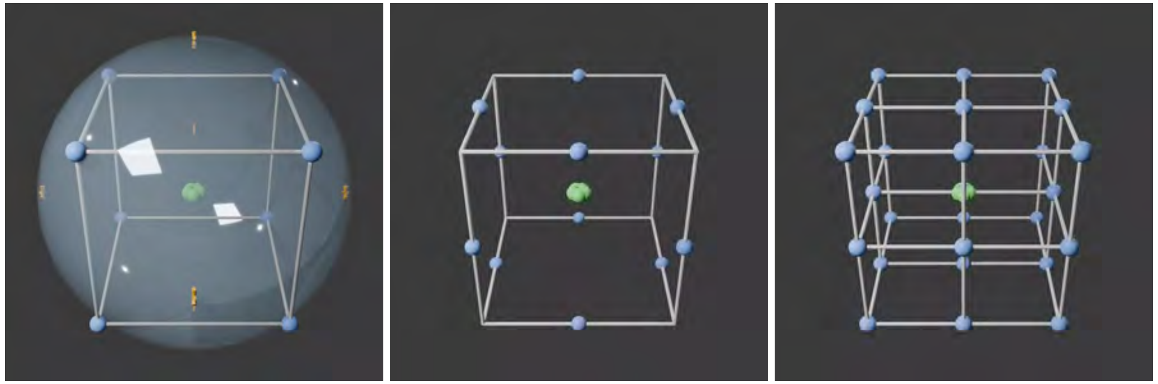
- Different people would have different levels of success (Gambling)
- Involvement of subject matter expert and their experience becomes increasingly important
- The simple example with just 2 factors
- Probability of optimisation low with high factor count

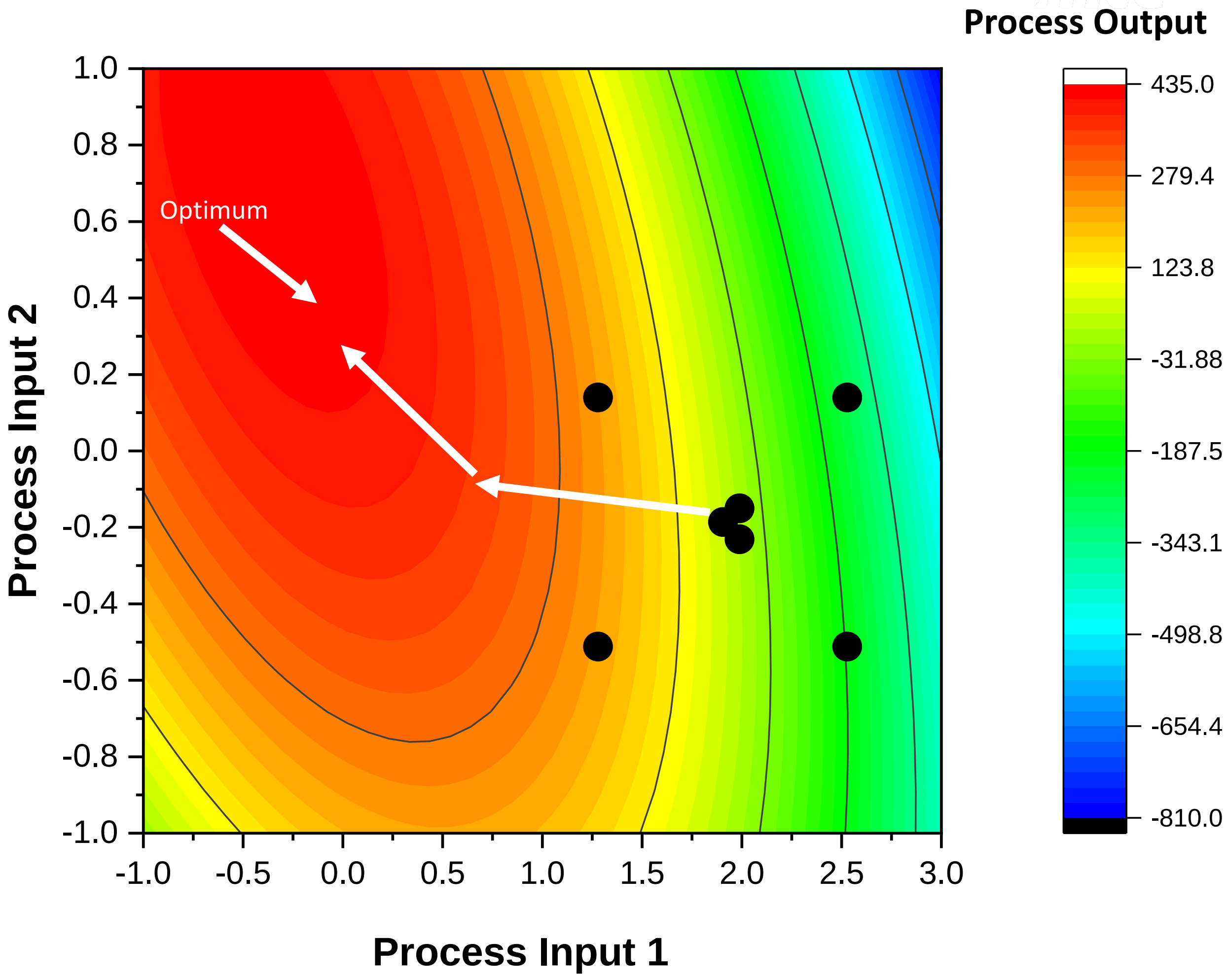


Design of Experiments

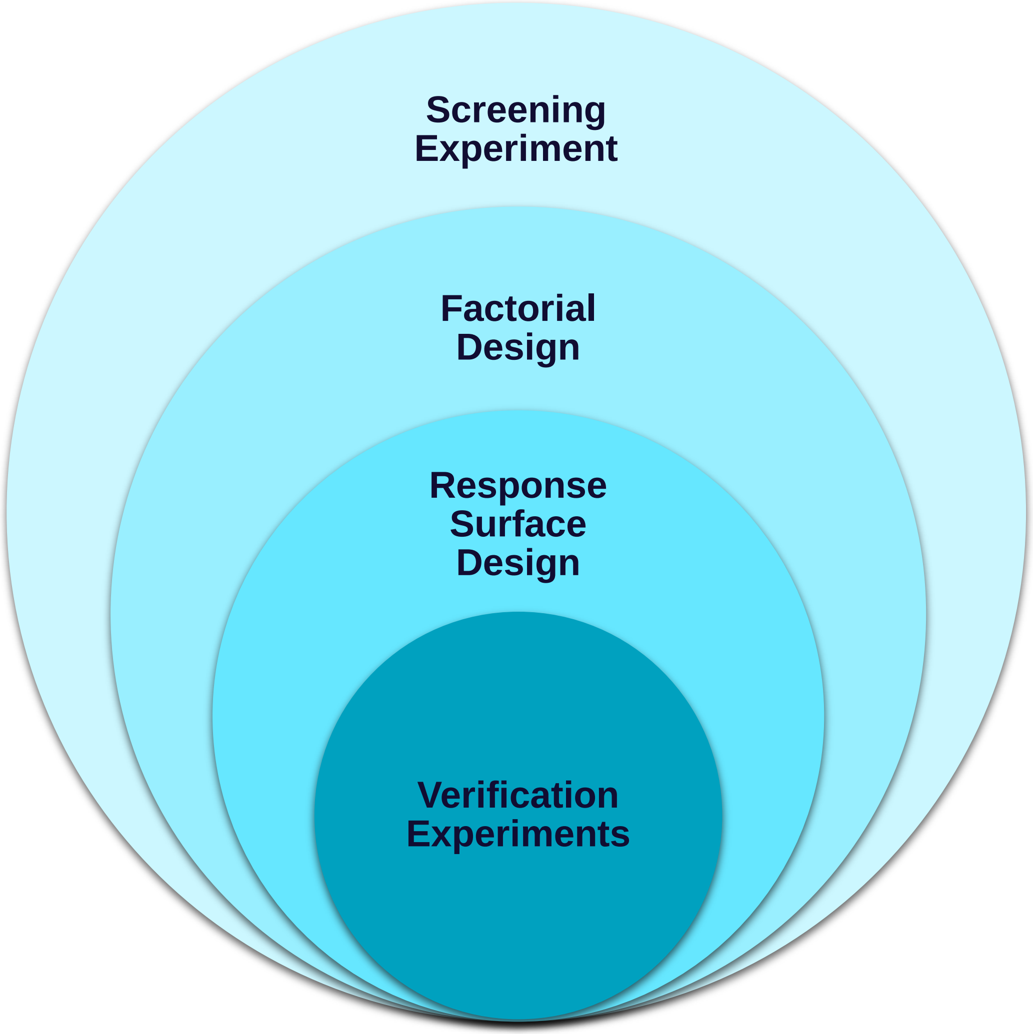
DOE systematically varies multiple input factors across predefined combinations to quantify their individual and interaction effects on the response.

- Collect more information with less trials
- Factors can vary simultaneously
- Complex interaction effects quantified
- Cost effective
- Various DOE types to address different problems
- Creates a model (equation) to predict process behavior
- Methodical iterative experimentation
- Guides you in direction of improvement





DoE Sequencing



6+ Factor Screening:

Identifies the most influential factors while minimising the number of experiments required

2-5 Factorial Modelling:

Quantifies effects and interactions, defining influence and direction on the response

2-5 Response Surface Modelling:

Models non-linear relationships to refine and optimise factor settings.

Verification experiments:

Confirm performance and repeatability

Factorial Design

DoE Case Studies

Application of Minitab for the development of future aerospace PCBs

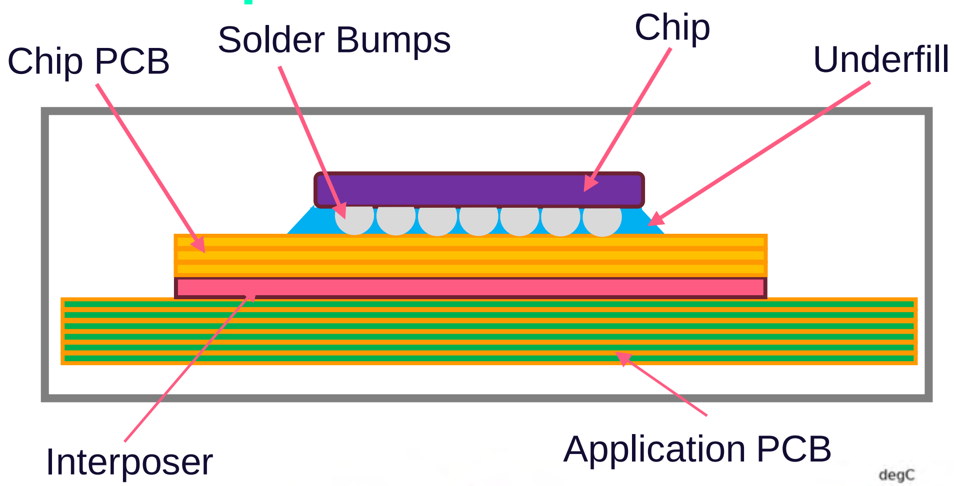
Aero-engine control systems need more computing power, but advanced semiconductor technologies remain costly and difficult to access at low volumes.

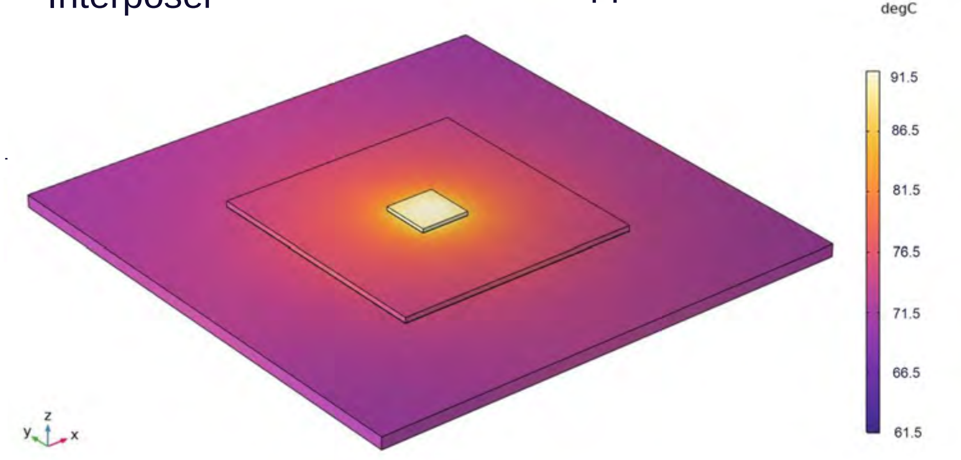
This study explores the thermal impact of future concepts of PCB assembly design for these control systems.

The physics was modelled in COMSOL 6.4.

A sensitivity evaluation of various material and geometric variables was carried → 54 variants of the concept(s).

- Data from the analysis was later analysed within **Minitab** to quantify the effect of key design factors.
- Key learnings from Minitab evaluations were used to steer later concept developments.





Proposed concept of flip chip assembly stack up

An insight into a simulation application of Minitab

What were the results

Main effects plots were leveraged to evaluate sensitivity of chip temperature based on variations of:

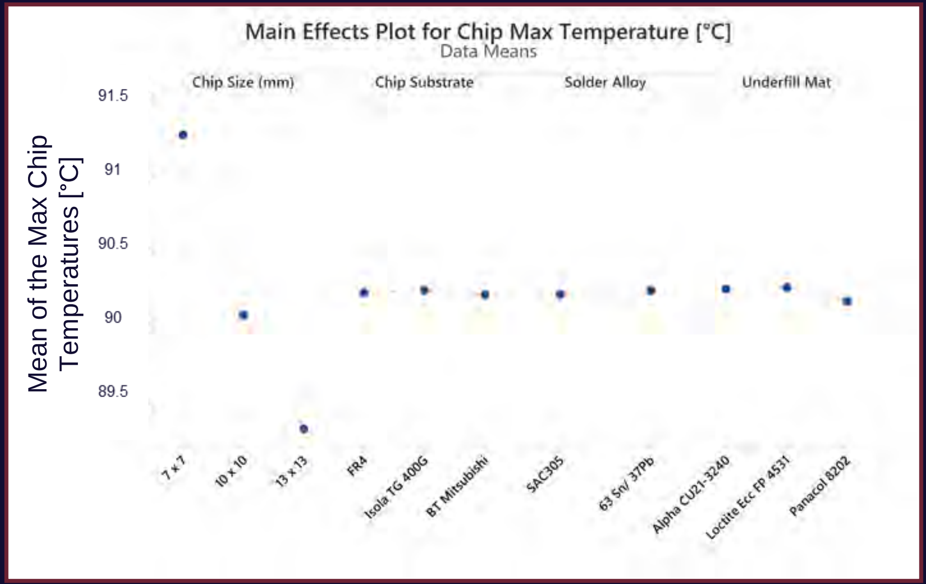
- chip size
- board material
- solder material
- underfill material and others

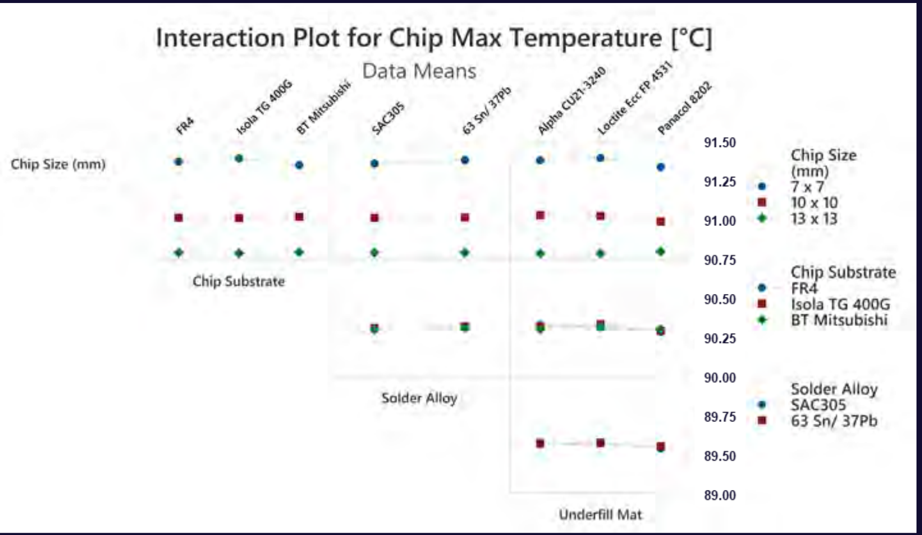
Interaction plots were used to evaluate key drivers of chip temperature.

Results showed:

1. Chip size directly impacted chip temperature.
2. Whereas assembly material combinations yielded negligible impact to chip temperature.

Minitab enables engineers to quickly visualise the sensitivity of physical parameters, against key requirements (i.e. chip temperature) .





An insight into a simulation application of Minitab

What were the results

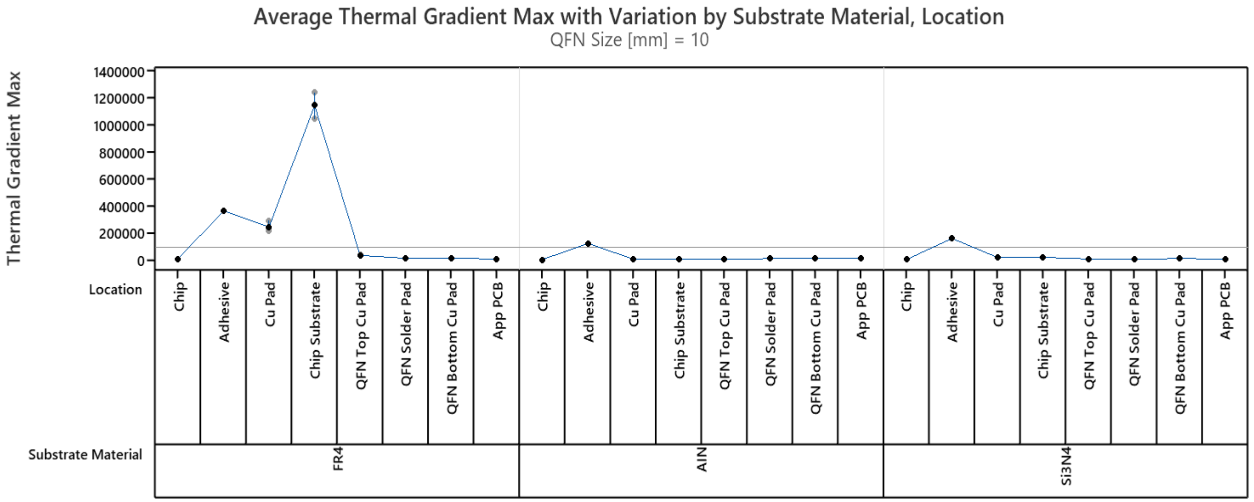
As part of the thermal study, examination of thermal gradients across the assembly are shown here.

The thermal gradient identifies the rate at which a component goes from hot to cold.

A large thermal gradient in a specific component usually indicates:

- Heat is being “forced” through a material that does not conduct well.
- So, temperature drops rapidly → high gradient.

The Minitab evaluation clearly identified the chip substrate material plays a key role as a bottleneck to heat transfer through the assembly.



Comparison of the maximum thermal gradient per component within the 10 x 10 mm PCB assembly, for the three substrate materials

An insight into a simulation application of Minitab

What does a Design of Experiments (DoE) provide (the value)

DoE with Minitab enabled rapid, data-driven insight:

- Clearly identifying which parameters most strongly influence chip temperature.

Sensitivity analysis pinpointed the true bottleneck:

- Chip size and the thermal conduction path through the solder bump architecture.

Structured Sensitivity studies replaced trial-and-error:

- Efficient exploration of parametric variations and interactions, which can be used as a precursor to a larger DoE.

Targeted concept development and expanding exploration to the link between thermal performance to stress:

Future development and assessment iterations focus on maximising conductive heat paths to the housing, where convection is not feasible.

- Enabling simultaneous optimisation of heat transfer and mechanical reliability.
- Faster development, reduced iteration cycles, and design decisions driven by quantified sensitivity and evidence.

PROLASE Project

Prolase – Next Generation IC Probe Card Manufacturing via Precision Laser Processing

Application: Next Generation IC Probe Card Manufacturing using Precision Laser Processing

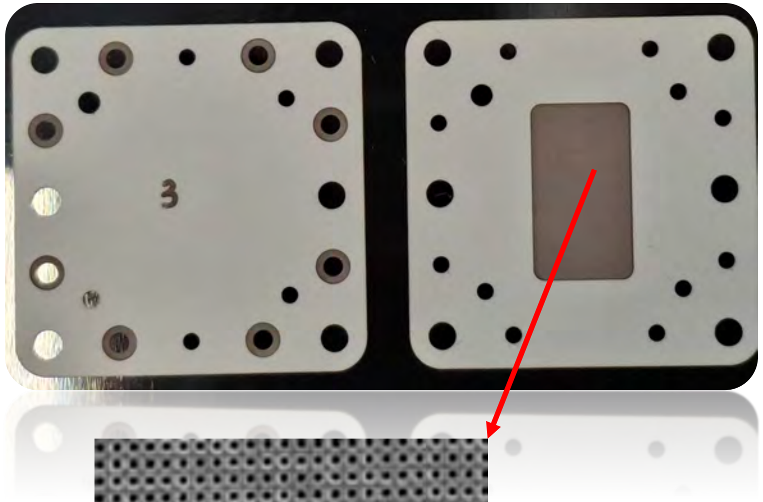
Funding Body: Innovate UK
UK–Taiwan Collaborative R&D (CRD) 2024 competition

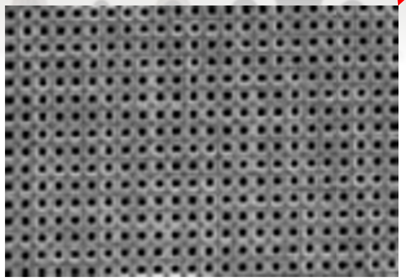
Project Duration: 2 years

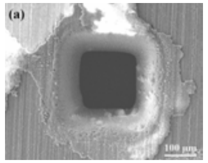
Project aim: System and Process development for macro and micro drilling in technical advanced ceramics for advanced guide plate fabrication.

Project partners: **UK** (MTC and msolv Uk Ltd) and **Taiwan** (ITRI, HAT, and RTM)

“Quantify the effect of key laser process parameters on aluminium nitride cutting performance - optimising for cut quality and throughput.







25 x 25 µm holes
Pitch = 50 µm
1000 – 2000 holes

DoE Framework – Planning, conducting & Analysing and Experiments

Define Objective & Problem Statement

- Recognition and statement of the problem in non-statistical language
- Objective should be unbiased, specific, measurable, and of practical consequence

Choice of factors, levels and ranges

- Brainstorming to identify process independent inputs
- Categorising input type - experimental/Fixed/noise or hard to change factors)
- Define the range and levels for each input (i.e minimum and maximum values and number of points in between)

Define response parameters

- Define the process output to be measured (may be more than one)
- Ensure you don’t forget any

Design Experiment

- Develop the experimental design, e.g type of design, resolution, centre point number of replicates, randomisation and blocking.
- Consider how we control, monitoring and management of nuisance factors and process inputs to be held constant
- Document/agree experimental procedure (e.g how to set input and measure outputs
- Validate measurements systems

Perform experiments

- Conduct experiment
- Record deviation from plan

Analysis

- Statistical analysis, data visualisation – To determine the statistical and practical significance of results
- Create and analyse model

Draw conclusion & verification trials

- Drawing conclusions, recommendations
- Verification trials to validate model
- Plan or identify further experiments as needed

Prolase – Process Inputs Categorising

Define Objective & Problem Statement

Choice of factors, levels and ranges

Define response parameters

Design Experiment

Perform experiments

Analysis

Draw conclusion & verification trials

“Quantify the effect of key laser process parameters on aluminium nitride cutting performance - optimising for cut quality and throughput.”

Prolase – Process Inputs Categorising

Define Objective & Problem Statement

Choice of factors, levels and ranges

Define response parameters

Design Experiment

Perform experiments

Analysis

Draw conclusion & verification trials

Experimental Factors

Parameters	Levels		
	1	2	3
Average Power (W)	60	120	180
Scanning speed (mm/s)	2000	4000	6000
Frequency (kHz)	400	1000	2000
Passes	50	100	200

Held Constant

- Laser wavelength
- Energy Distribution (1 Pulse)
- Spot size (30um)
- Material Thickness (0.635mm)
- Environment (Air)

Noise/Nuisance Factors

- Air Extraction
- Silicon nitride Material lot number variation
- Initial surface roughness
- Laser Focus – Compensation Strategy
- Contamination
- Equipment movements…..etc.

Fix//Monitor/ Manage/Randomise/Block

Prolase – Process Outputs

- Define Objective & Problem Statement
- Choice of factors, levels and ranges
- **Define response parameters**
- Design Experiment
- Perform experiments
- Analysis
- Draw conclusion & verification trials

"Quantify the effect of key laser process parameters on aluminium nitride cutting performance - optimising for cut quality and throughput.

Cut Quality

- Presence of Macro or Micro Cracking
- Minimising heat effected zone
- Minimise tapering
- Dimensional Accuracy

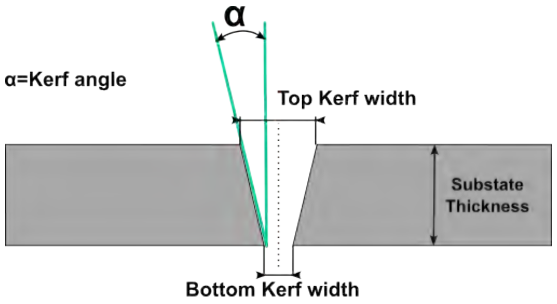
Throughput

$$\text{Cutting speed (mm/min)} = \left(\frac{Length\ of\ Cut}{Time}\right)$$

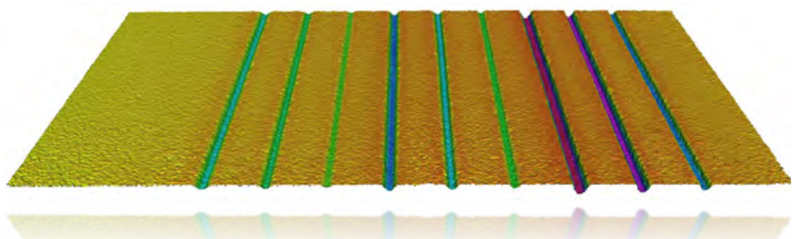
$$\text{Efficiency (mm/min. W)} = \left(\frac{Cutting\ speed}{Average\ power}\right)$$

Measurement Techniques Used:

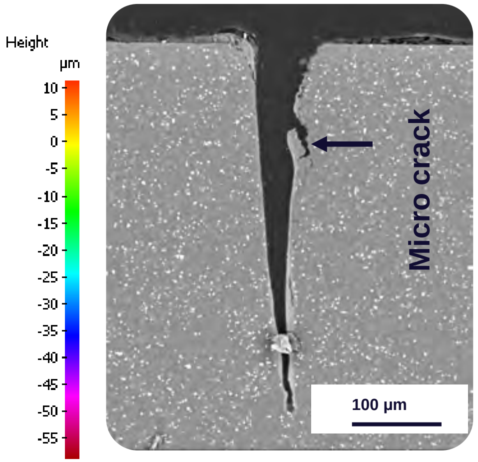
- Optical microscopy
  - Assessed cut quality and kerf geometry
- 3D surface profilometry
  - Measured kerf width, depth, and surface topography
- Cross-sectioning and polishing
  - Evaluated internal cut profile, integrity, and taper
- SEM with EDX
  - Identified defects and analysed composition



Hole Tapering



Cutting Speed Measurement



Cut Quality

Prolase –Designing and Running Experiments

Define Objective & Problem Statement

Choice of factors, levels and ranges

Define response parameters

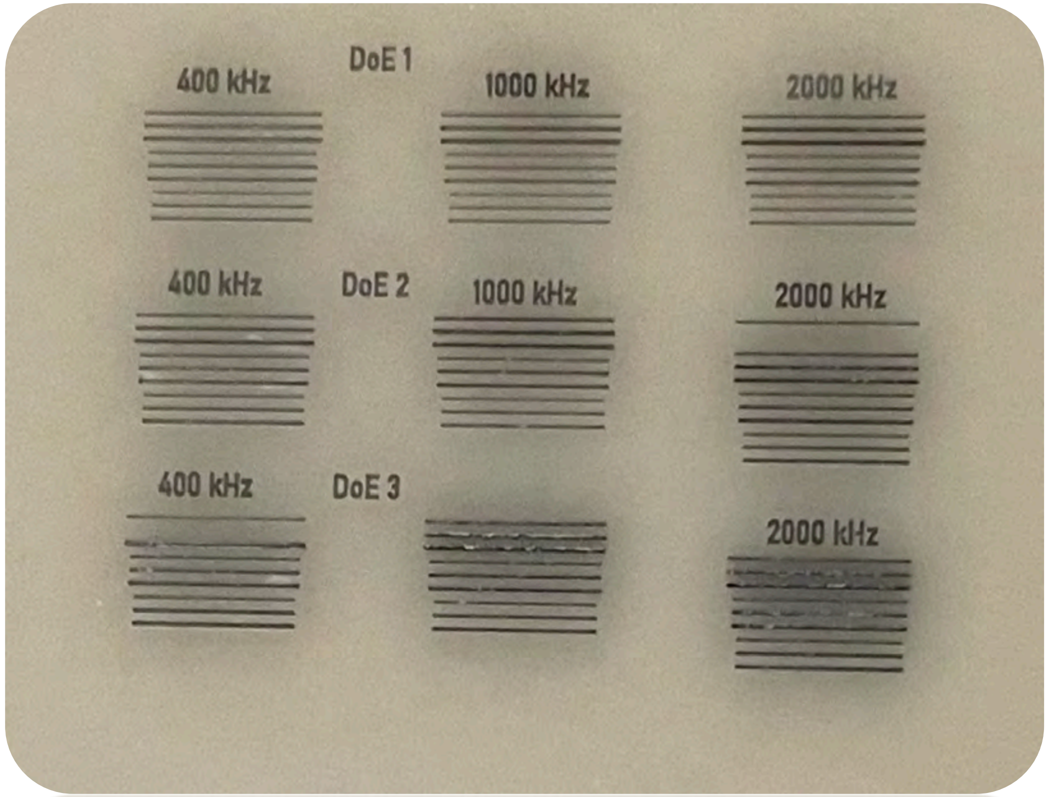
Design Experiment

Perform experiments

Analysis

Draw conclusion & verification trials

Carried out a series of experiments and captured cutting quality and throughput metrics

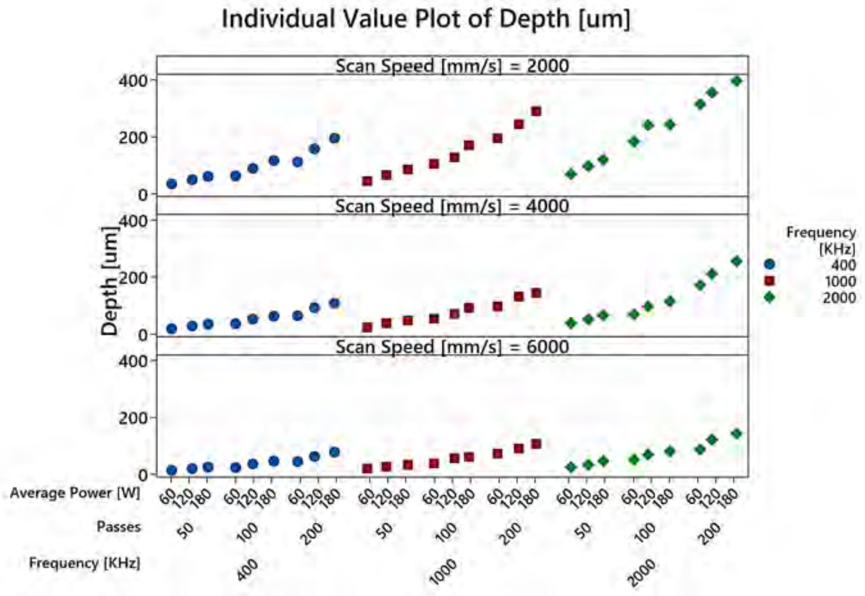


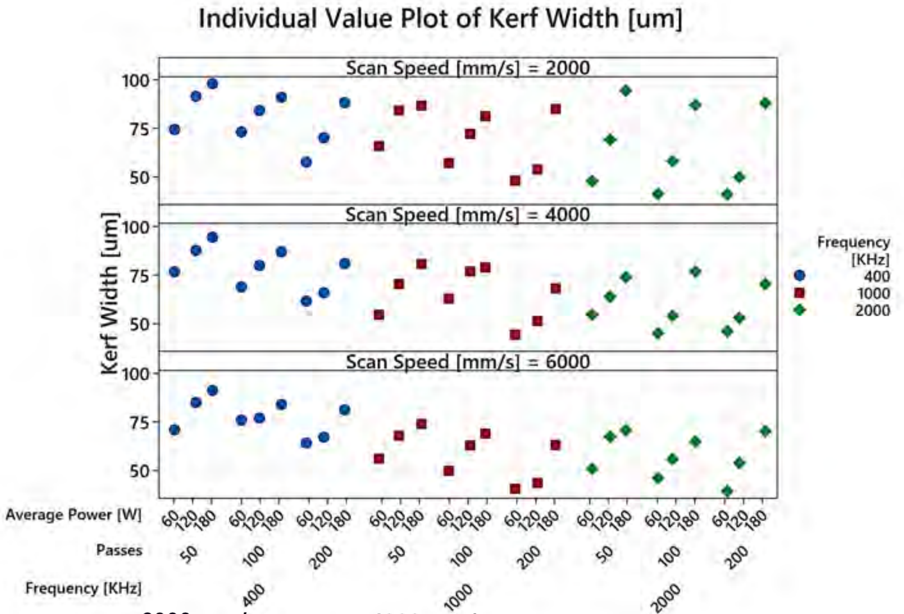
Example Silicon Process Test Tile

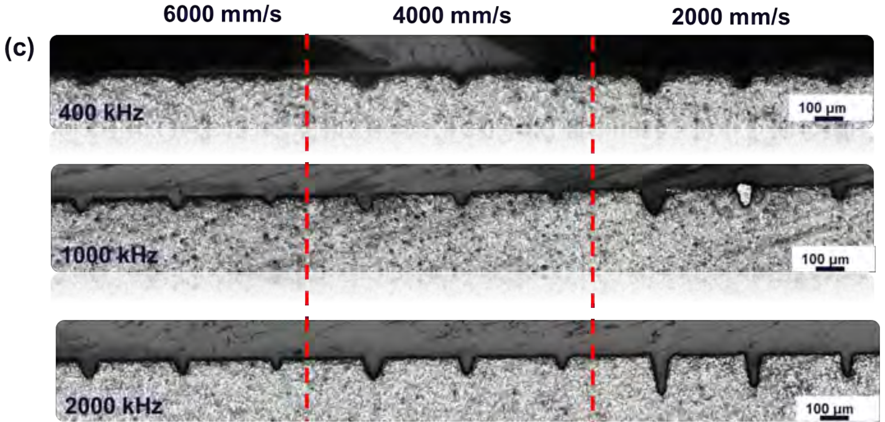
Prolase – Plot Results

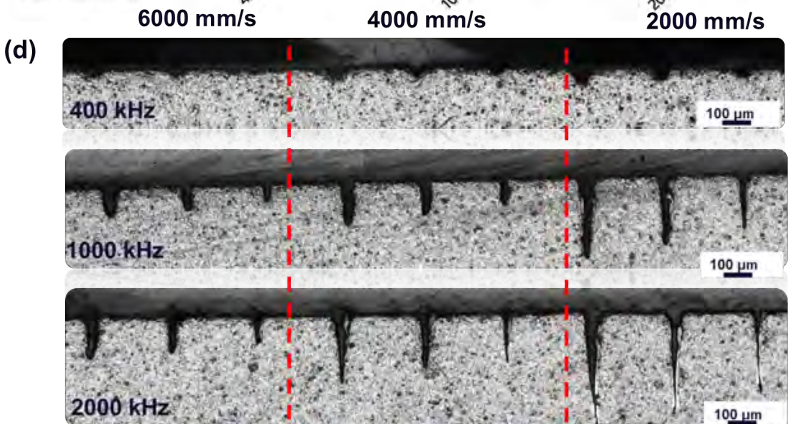
- Define Objective & Problem Statement
- Choice of factors, levels and ranges
- Define response parameters
- Design Experiment
- Perform experiments
- **Analysis**
- Draw conclusion & verification trials

Visualise Process Output Data – Looking for outliers and trends





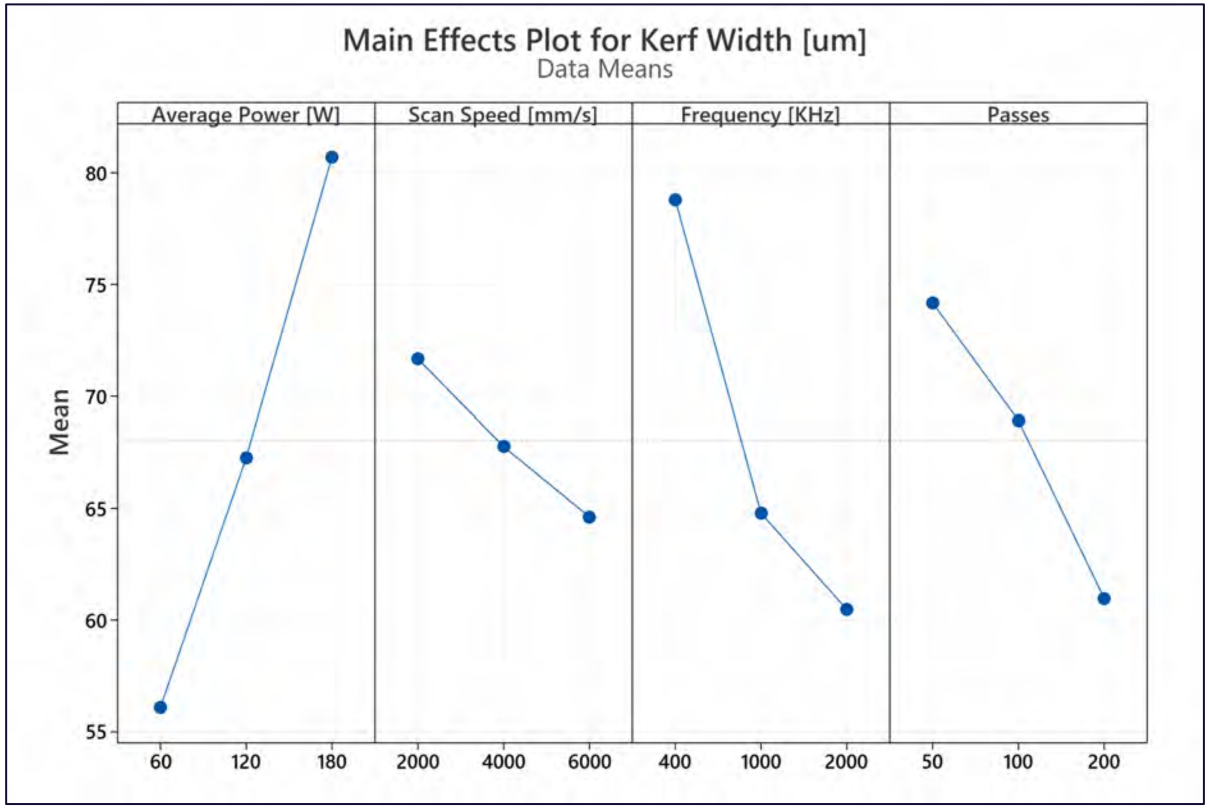


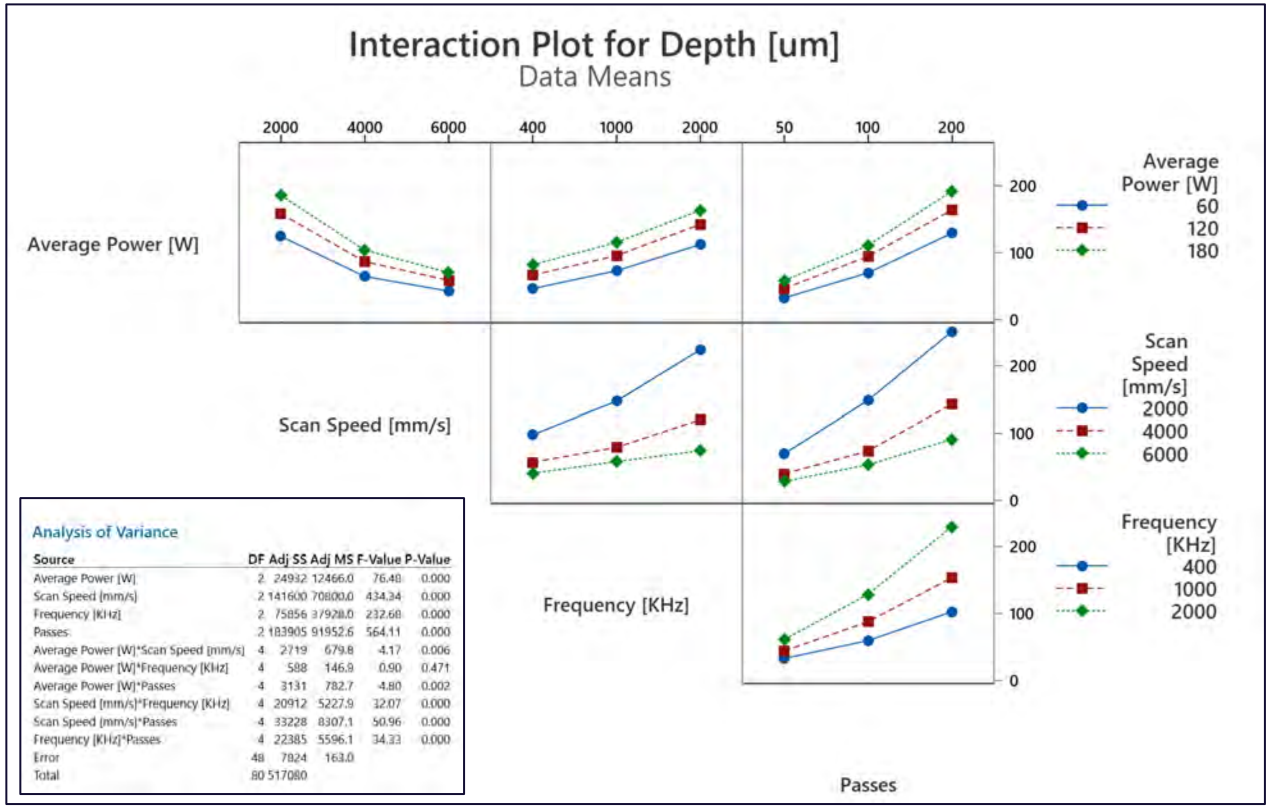


Minitab DoE Analysis of Results

Using Minitab we Analysed Outputs Producing visual and statistical analysis

- Quantified main effects and interactions of all laser processing inputs
- Validated the relative influence of input parameters on response variables
- Developed model to predict cutting rate
- Defined next experimental steps to optimisation





Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Average Power [W]	2	24932	12466.0	76.48	0.000
Scan Speed [mm/s]	2	141600	70800.0	434.34	0.000
Frequency [KHz]	2	75856	37928.0	232.68	0.000
Passes	2	183905	91952.6	564.11	0.000
Average Power [W]*Scan Speed [mm/s]	4	2719	679.8	4.17	0.006
Average Power [W]*Frequency [KHz]	4	588	146.9	0.90	0.471
Average Power [W]*Passes	4	3131	782.7	4.80	0.002
Scan Speed [mm/s]*Frequency [KHz]	4	20912	5227.9	32.07	0.000
Scan Speed [mm/s]*Passes	4	33228	8307.1	50.96	0.000
Frequency [KHz]*Passes	4	22385	5596.1	34.33	0.000
Error	48	7824	163.0		
Total	80	517080			

Key Findings from Phase 1 of Experimentation

Define Objective & Problem Statement

Choice of factors, levels and ranges

Define response parameters

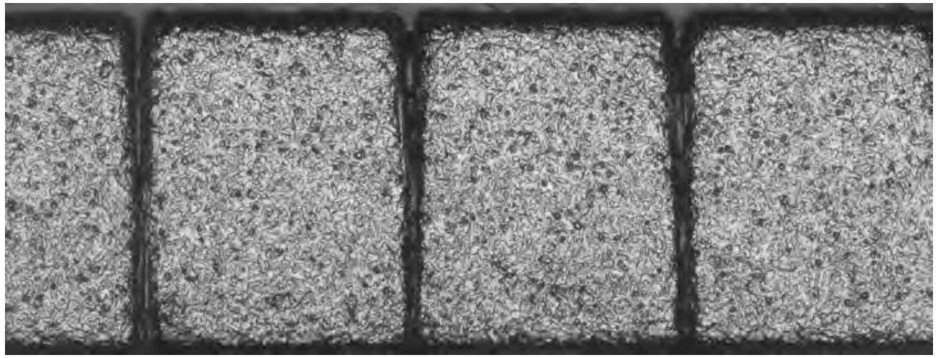
Design Experiment

Perform experiments

Analysis

Draw conclusion & verification trials

- Depth is primarily driven by passes, scan speed, and frequency, with all main effects significant; key interactions include power × scan speed and frequency × passes
- Kerf width is influenced by all input parameters, with average power and frequency as the dominant contributors.
- **Follow-on trials enabled further optimisation**, introducing:
  - **Focal compensation mitigates taper during multi-pass cutting** by dynamically adjusting the focal position as groove depth increases
  - **Burst mode enhances performance**, delivering up to ~4× increase in depth at 400 kHz and reduced kerf width
- **Optimised process conditions achieved high cutting performance**, demonstrating improved efficiency and process control



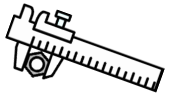
DoE Challenges & ~~Failures~~

Experimentation in Practice: – Where It Goes Wrong

Define Objective & Problem Statement

Choice of factors, levels and ranges

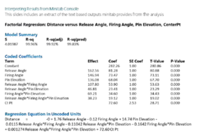
Define response parameters

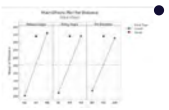


Design Experiment

Perform experiments

Statistical Analysis





Draw conclusion & verification trials

- Design of Experiments is a well-established and powerful tool (100 years old!).
- However, it's effectiveness hinges on how it is applied in practice.
- Risks exist at every stage of this flow
- Early decisions can influence final conclusions.

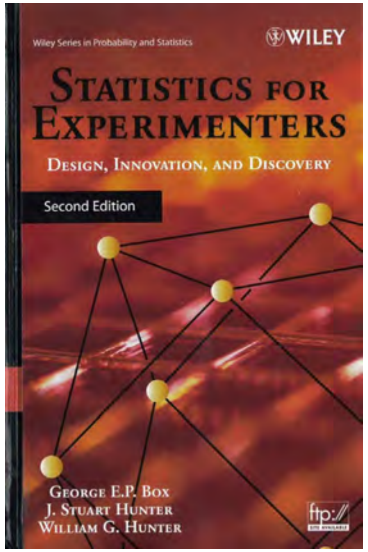
"Just give us the spreadsheet and we'll run with it"

I've heard this and similar statements before

- Reducing what might be complex experimentation to a table
- View DoE as a data-collection exercise rather than a structured investigation

+	C1	C2	C3	C4	C5	C6	C7	C8-T
	StdOrder	RunOrder	CenterPt	Blocks	Time [mins]	Power[%]	Speed [mm/s]	Material
1	13	1	1	1	100	25	100	Copper
2	10	2	1	1	200	25	50	Copper
3	4	3	1	1	200	75	50	Aluminium
4	14	4	1	1	200	25	100	Copper
5	15	5	1	1	100	75	100	Copper
6	9	6	1	1	100	25	50	Copper
7	11	7	1	1	100	75	50	Copper
8	1	8	1	1	100	25	50	Aluminium
9	6	9	1	1	200	25	100	Aluminium
10	12	10	1	1	200	75	50	Copper
11	5	11	1	1	100	25	100	Aluminium
12	16	12	1	1	200	75	100	Copper
13	2	13	1	1	200	25	50	Aluminium
14	7	14	1	1	100	75	100	Aluminium
15	3	15	1	1	100	75	50	Aluminium
16	8	16	1	1	200	75	100	Aluminium

Experimentation in Practice: – Where It Goes Wrong

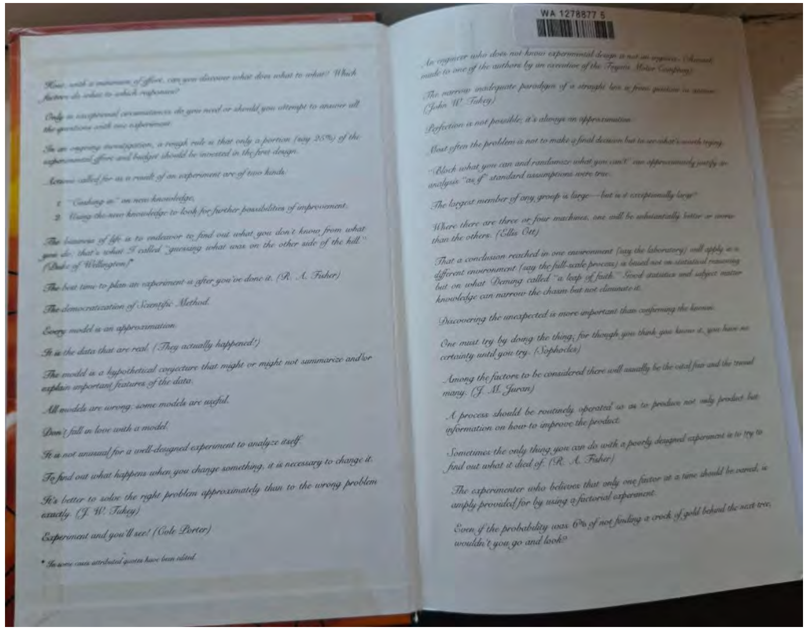


Statistics for Experimenters:
Design, Innovation, and Discovery (First Edition Published in 1974)

- **George E. P. Box**
- **J. Stuart Hunter**
- **William G. Hunter**

Inside the covers of this old DoE text are four pages of insightful observation grounded practical experience.

The following slides reflect on the continued relevance of some of these observations today where common causes of experimental error don't change.



How, with a minimum of effort, can you discover what does what to what? Which factors do what to which responses?

Only in exceptional circumstances do you need or should you attempt to answer all the questions with one experiment.

In an ongoing investigation, a rough rule is that only a portion (say 25%) of the experimental effort and budget should be invested in the first design.

Actions called for as a result of an experiment are of two kinds:

1. *"Cashing in" on new knowledge.*
2. *Using the new knowledge to look for further possibilities of improvement.*

*The business of life is to endeavor to find out what you don't know from what you do; that's what I called "guessing what was on the other side of the hill." (Duke of Wellington)**

The best time to plan an experiment is after you've done it. (R. A. Fisher)

The democratization of Scientific Method.

Every model is an approximation.

It is the data that are real. (They actually happened!)

The model is a hypothetical conjecture that might or might not summarize and/or explain important features of the data.

All models are wrong; some models are useful.

Don't fall in love with a model.

It is not unusual for a well-designed experiment to analyze itself.

To find out what happens when you change something, it is necessary to change it.

It's better to solve the right problem approximately than to the wrong problem exactly. (J. W. Tukey)

Experiment and you'll see! (Cole Porter)

* *In some cases attributed quotes have been edited.*

WA 1278877 5

An engineer who does not know experimental design is not an engineer. [illegible] made to one of the authors by an executive of the [illegible] Motor Company)

The narrow inadequate paradigm of a straight line [illegible] (John W. Tukey)

Perfection is not possible; it's always an approximation.

Most often the problem is not to make a final decision but to see what's worth trying.

"Block what you can and randomize what you can't" can approximately justify an analysis "as if" standard assumptions were true.

The largest member of any group is large—but is it exceptionally large?

Where there are three or four machines, one will be substantially better or worse than the others. (Ellis Ott)

That a conclusion reached in one environment (say the laboratory) will apply in a different environment (say the full-scale process) is based not on statistical reasoning but on what Deming called "a leap of faith." Good statistics and subject matter knowledge can narrow the chasm but not eliminate it.

Discovering the unexpected is more important than confirming the known.

One must try by doing the thing; for though you think you know it, you have no certainty until you try. (Sophocles)

Among the factors to be considered there will usually be the vital few and the trivial many. (J. M. Juran)

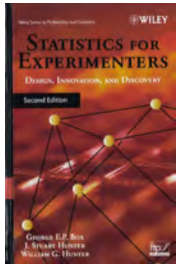
A process should be routinely operated so as to produce not only product but information on how to improve the product.

Sometimes the only thing you can do with a poorly designed experiment is to try to find out what it died of. (R. A. Fisher)

The experimenter who believes that only one factor at a time should be varied, is amply provided for by using a factorial experiment.

Even if the probability was 6% of not finding a crock of gold behind the next tree, wouldn't you go and look?

Experimentation in Practice: – Where It Goes Wrong



- *"The best time to plan an experiment is after you have done it" (R. A. Fisher)"*
- *In an ongoing investigation, a rough rule is that only a portion (say 25%) of the experimental effort and budget should be invested in the first design."*
- *"Sometimes the only thing you can do with a poorly designed experiment is to try to find out what it died off(R. A. Fisher)"*
- *"You can see a lot by just looking"*
- *"It is better to solve the right problem approximately than the wrong problem exactly (J. W. Tukey)"*

Other valid consideration from: Design and Analysis of Experiments by Douglas C. Montgomery

- *"All experiments are designed experiments; some of them are designed well, and some of them are designed really badly. The badly designed ones often tell you nothing."*
- *"Never let one person design and conduct an experiment alone….."*

Experimentation in Practice: – Where It Goes Wrong

- Define Objective & Problem Statement
- Choice of factors, levels and ranges
- Define response parameters
- **Design Experiment**
- Perform experiments
- Statistical Analysis
- Draw conclusion & verification trials

- *"All experiments are designed experiments; some of them are designed well, and some of them are designed really badly. The badly designed ones often tell you nothing."*
- *"Sometimes the only thing you can do with a poorly designed experiment is to try to find out what it died off" (R. A. Fisher)*
- *"You can see a lot by just looking"*

Key message

- Good design and execution determine value of experiment - Analysis cannot fix failure.
- Clearly define experiment method from start to finish
- Visualise the results before analysis – (Unexpected results /trends)

If key aspects are missing, such as:

- Clear definition on experimental method
- Overlooked a significant source of output variation!
- Insufficient replication of experiments
- No randomisation
- Poor factor selection

Then: The data cannot support robust conclusions

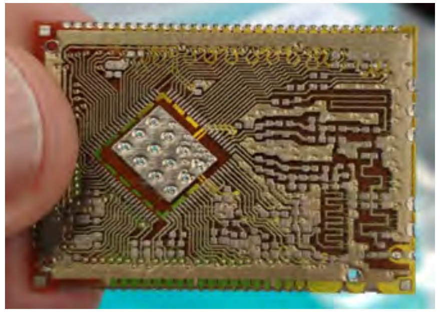
Unplanned Benefit: Reduced Sensitivity to Noise Factors

Key message
- *Good design and execution determine value - Analysis cannot fix failure.*
- *Look at the system and the data first - Analysis comes after.*

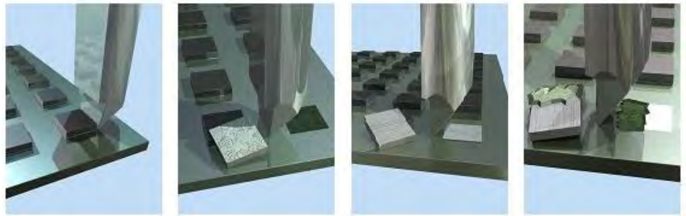
***Case Study** – Assessing the Impact of Laser Surface Texturing of Stainless Steel for Improving Adhesion of 3D Printed Electronics*

***Challenge**: Evaluate effect of 6 different surface treatments on shear strength performance*

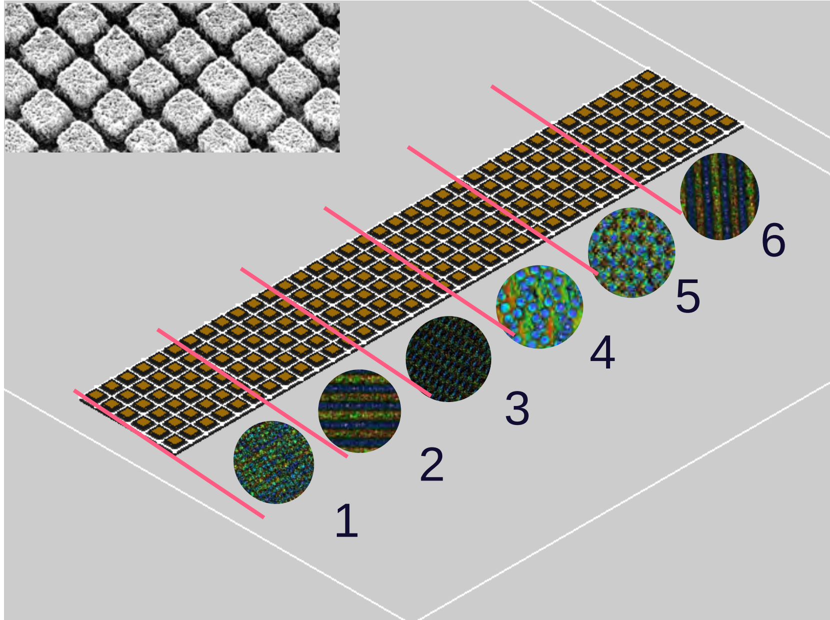
Nanodimension 3D Printer



Example Multilayer
3D Printed Electronics



Destructive Shear Testing

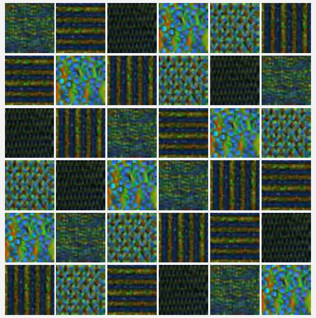


Original Proposed arrangement of 6 Surface treatments along metal coupon length

Sensitivity to Noise Factors

Recommendation: Introduce either randomisation or a Latin Square for treatment locations as a mitigation to a noise factor (such as localised contamination)

1	2	3	4	5	6
2	4	6	5	3	1
3	6	1	2	4	5
5	3	4	1	6	2
4	1	5	6	2	3
6	5	2	3	1	4

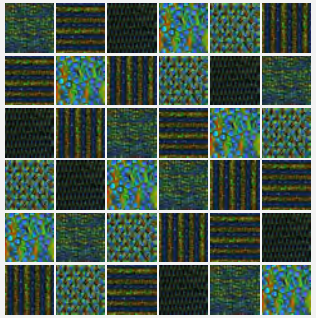


6 x 6 Latin Square

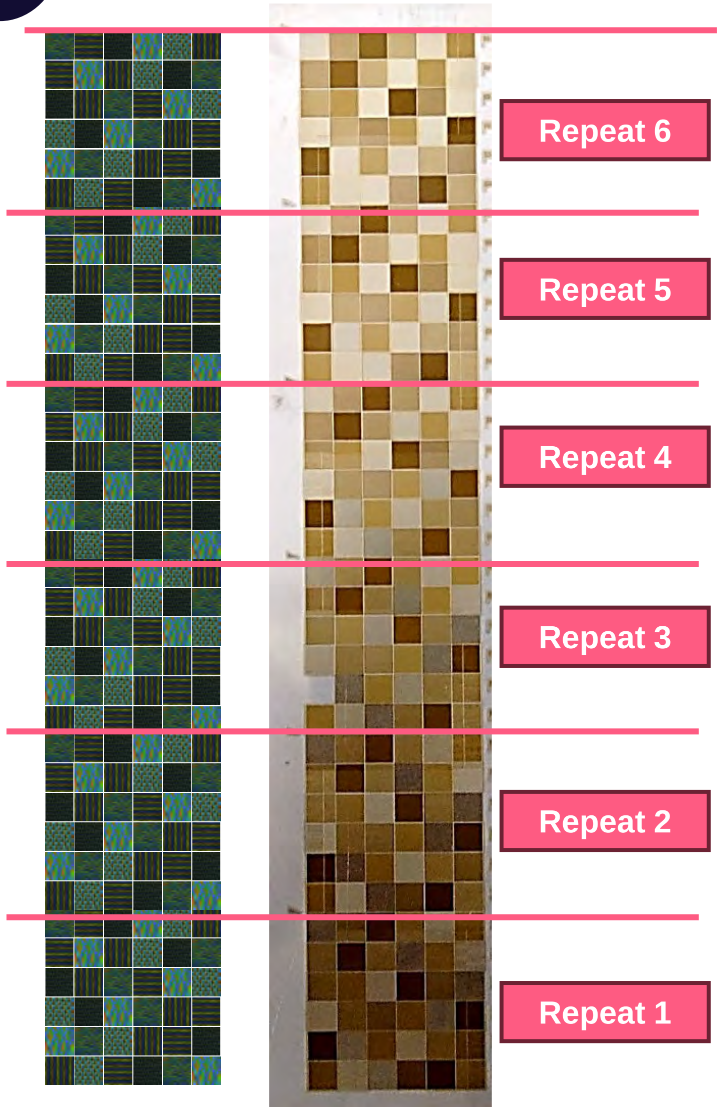
Sensitivity to Noise Factors

Recommendation: Introduce either randomisation or a Latin Square for treatment locations as a mitigation to a noise factor (such as localised contamination)

1	2	3	4	5	6
2	4	6	5	3	1
3	6	1	2	4	5
5	3	4	1	6	2
4	1	5	6	2	3
6	5	2	3	1	4

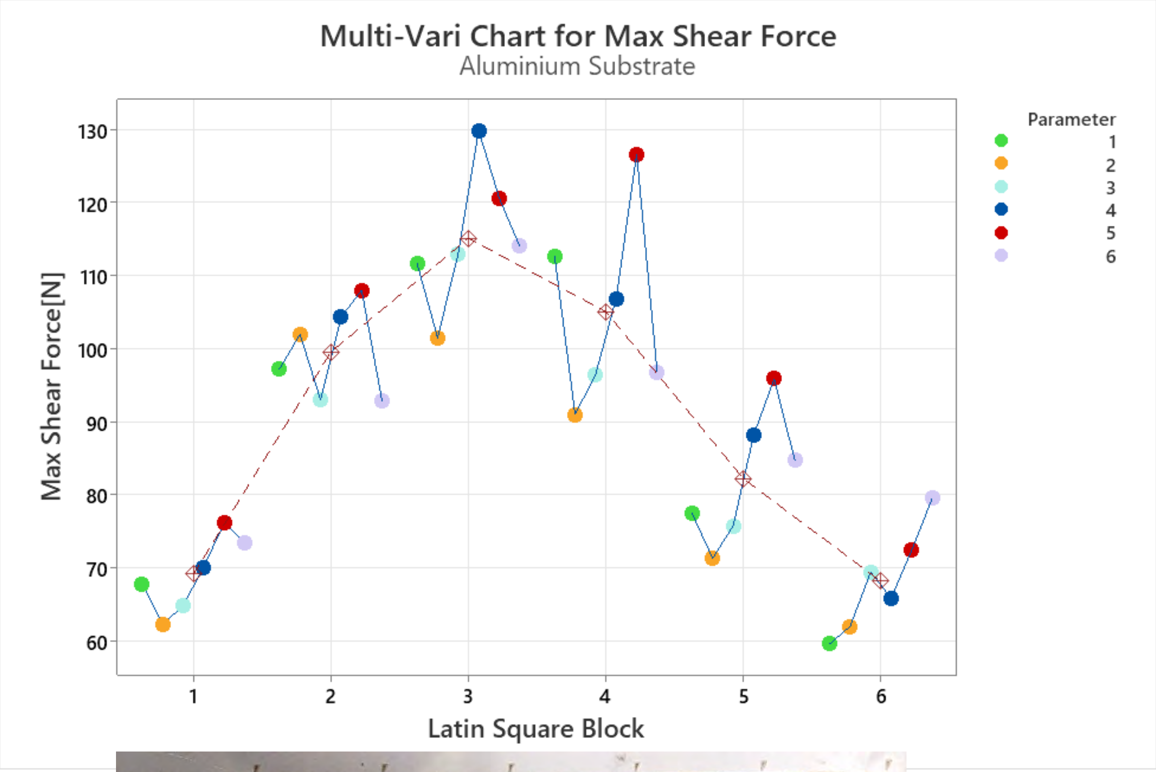


6 x 6 Latin Square



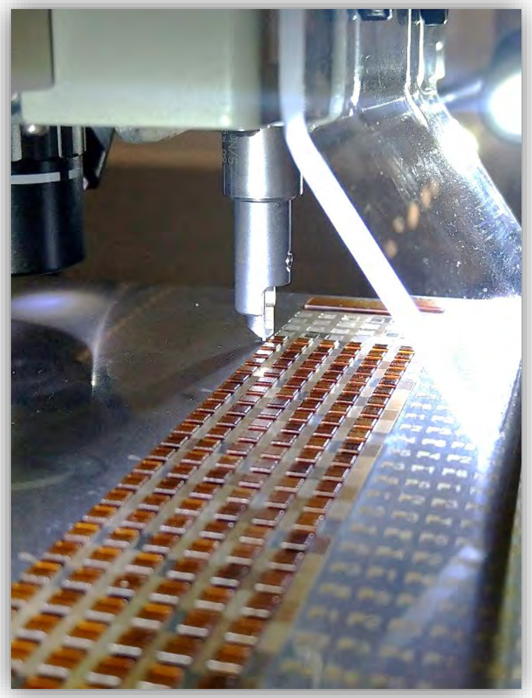
Sensitivity to Noise Factors

Unexpected Results: A plot of the data before further analysis highlighted that along the length of the coupon, the highest shear strength were only found at the centre of the metal coupon with results dropping off towards both ends.



Inconsistent shear test results

Treatment Type

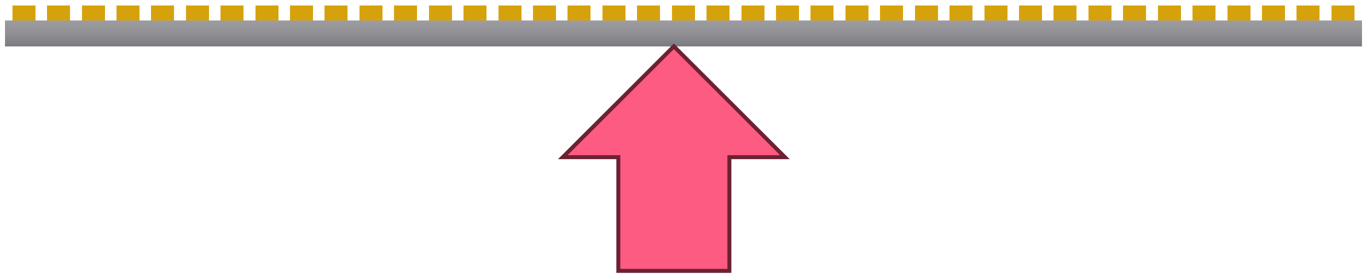


Destructive Shear Testing

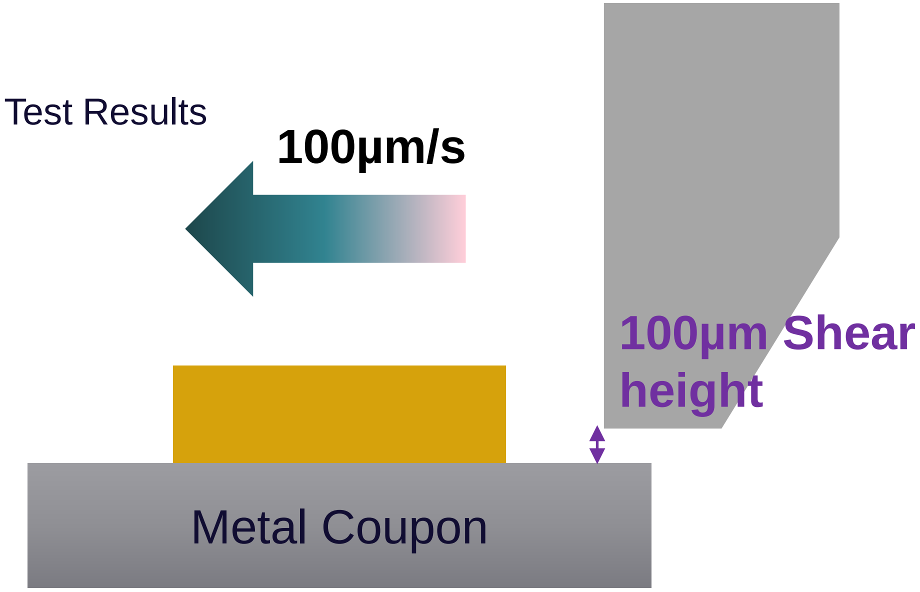
Sensitivity to Noise Factors

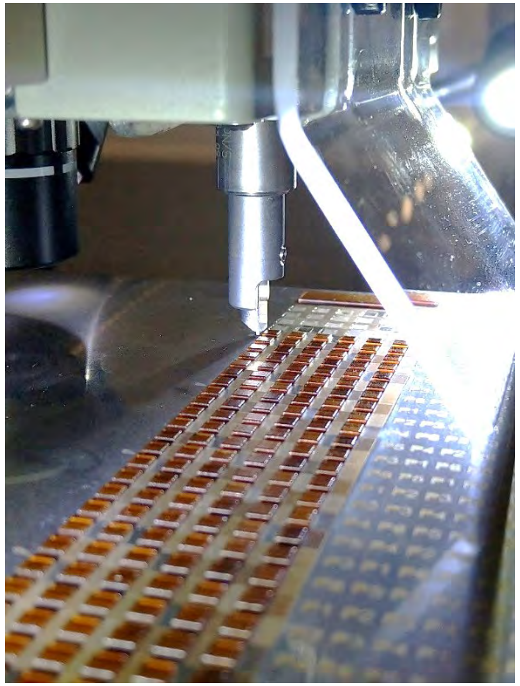
Root Cause: During shear testing the test coupon was clamped in the centre only testing cause causing repeatability to be poor due to flexing of substrate

This produce inconsistent shear height and resulting in a peeling forces and a change in failure mode in some cases.



Clamped centrally shear Test Results

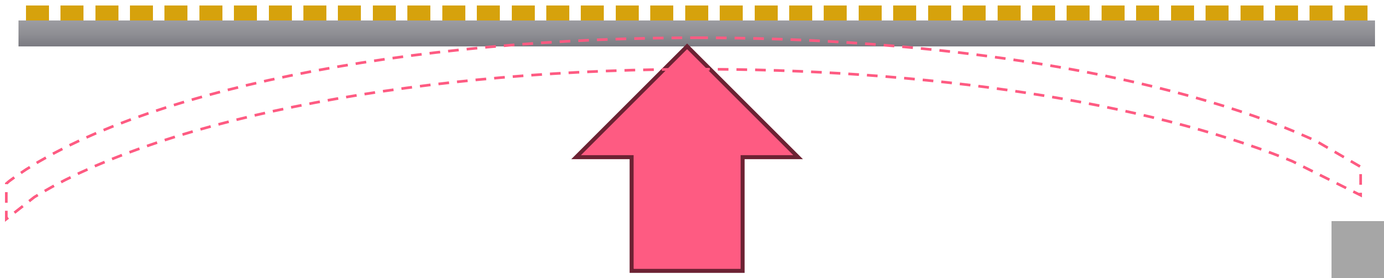




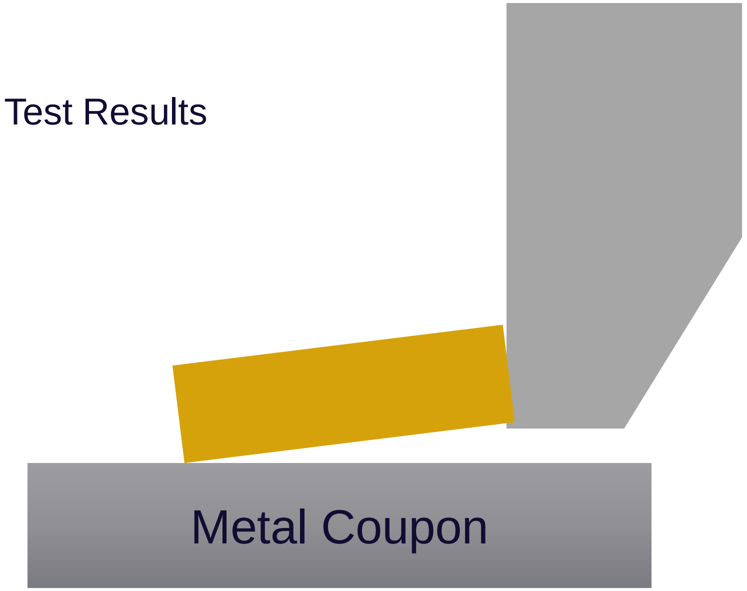
Destructive Shear Testing

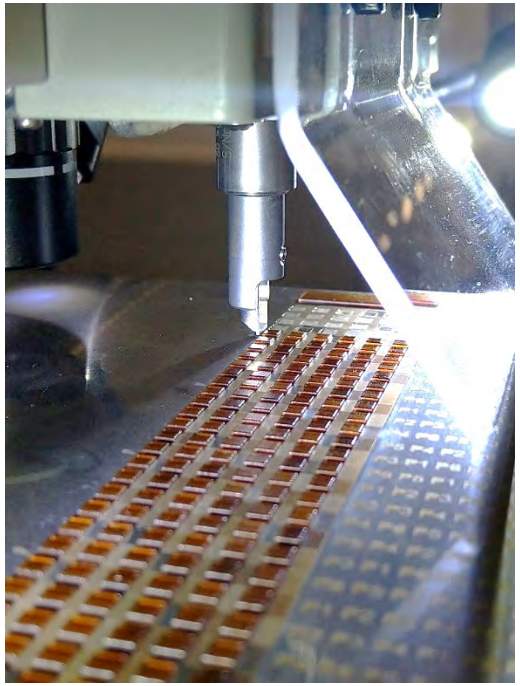
Sensitivity to Noise Factors

Root Cause Analysis: During shear testing the coupon was clamped in central region only, not move withing vice jaw to constrain movement during testing.
This caused poor repeatability due to bending of substrate, inconsistent shear height and resulting in a a change in failure mode



Clamped centrally shear Test Results

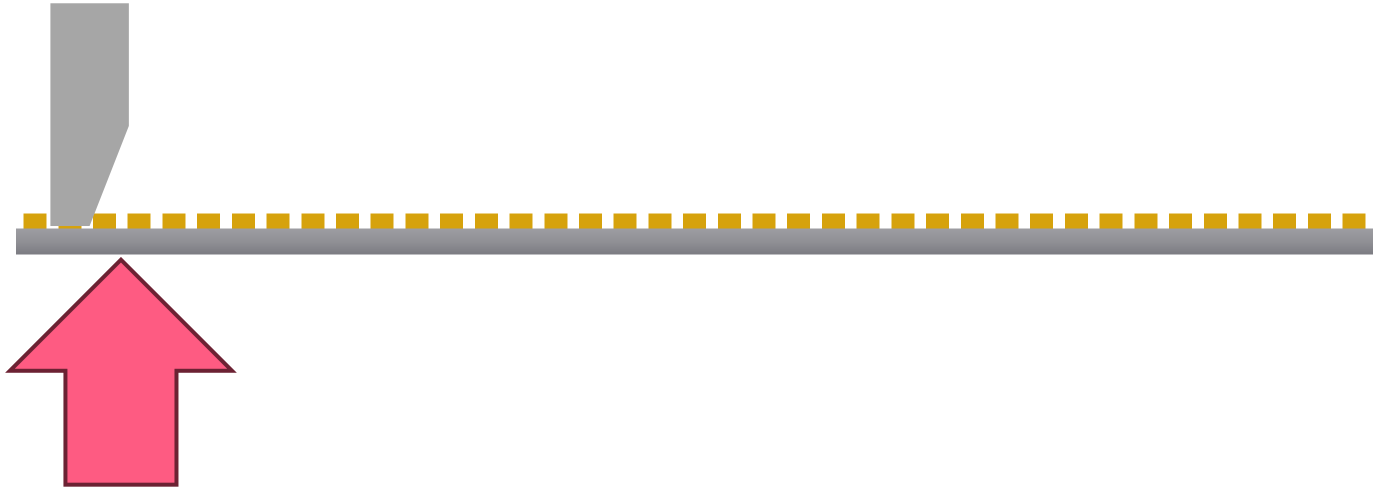




Destructive Shear Testing

Sensitivity to Noise Factors

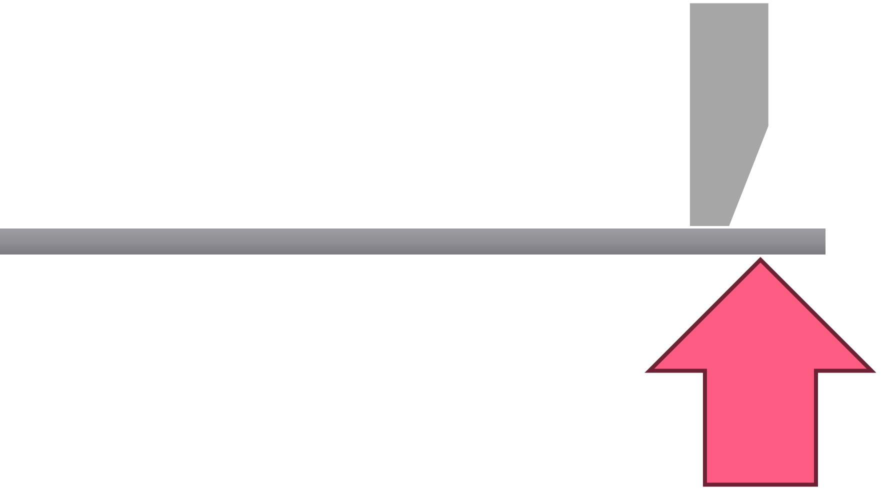
This highlights the importance of measurement system analysis and documenting **exactly** how a response should be measured. e.g. Clamping locally around each block would improve repeatability



Moving of coupon within clamping for each 36 x 36 array.

Sensitivity to Noise Factors

This highlights the importance of **measurement system analysis**, **Blocking** and **randomisation** and defining **exactly** how a process output should be measured. e.g.



Key take-away:
This Highlights the importance of managing experimental noise factors through randomisation or blocking.

Not all results were invalidated, with only the outer blocks affected, sufficient data remained to enable comparison with the control experiment

Moving of coupon within clamping for each 36 x 36 array.

Experimentation in Practice: – Where It Goes wrong

- Define Objective & Problem Statement
- Choice of factors, levels and ranges
- Define response parameters
- Design Experiment
- Perform experiments
- Statistical Analysis
- Draw conclusion & verification trials

- *"It is better to solve the right problem approximately than the wrong problem exactly"*
- *"The best time to plan an experiment is after you have done it" (R. A. Fisher)"* ***again!***

Key message
A clear and complete problem definition drives meaningful analysis

Its Important that an objective defines:

- It must define what knowledge/relationship(s) you want to understand from the data, and help inform factor selection, responses, and design choice.
- Avoid focusing on a single process output when multiple are critical
- State Trade-offs and between responses

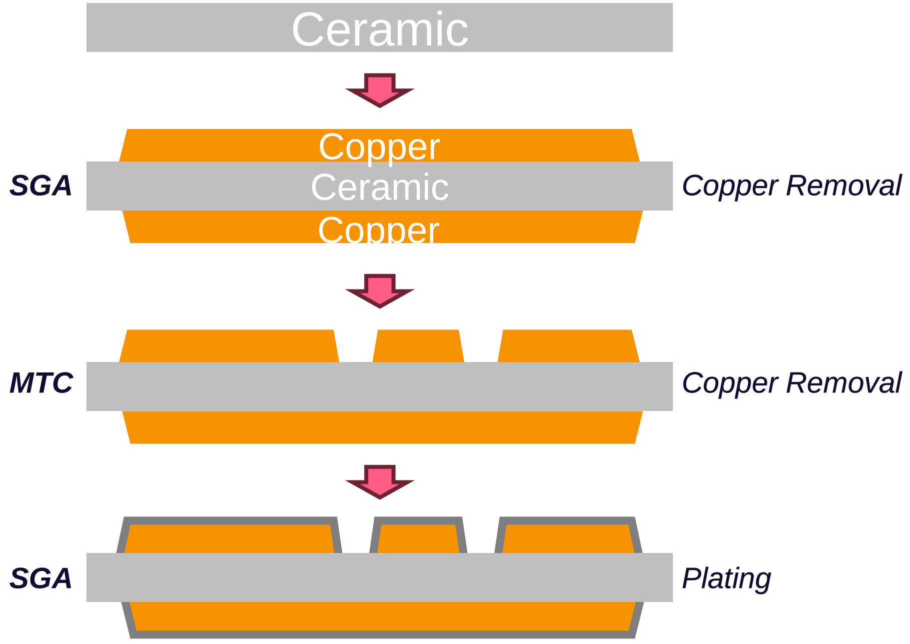
Consequence

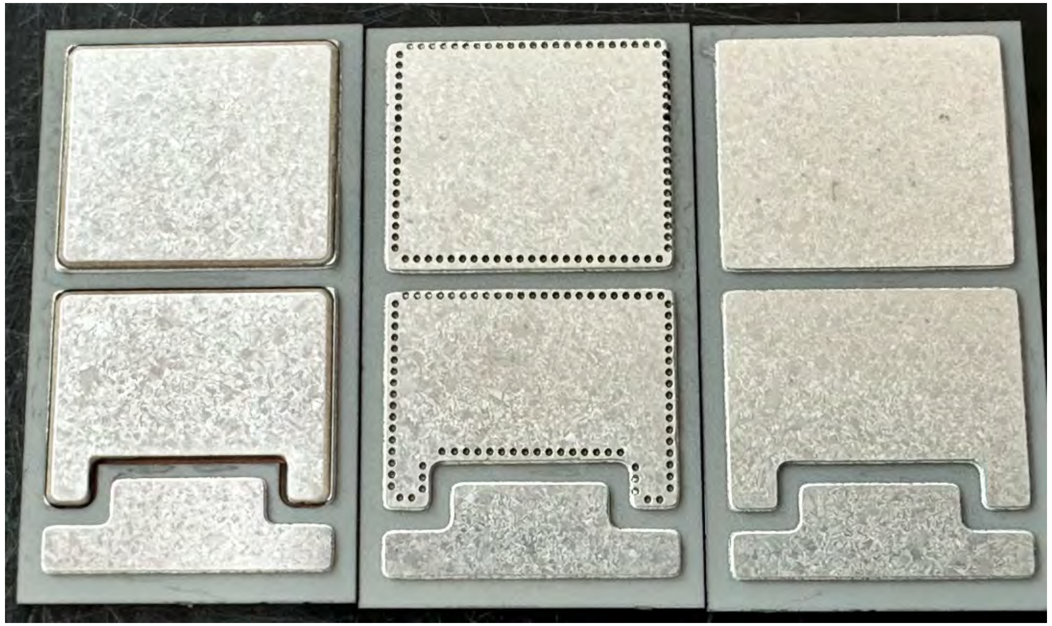
- DoE might give you a statistically "correct" answer
- But only to the question you asked
- Misleading "successful" outcomes that fail in application
- Repeating experimentation to address new process outputs (additional cost/time/analysis).

Importance of Well-defined Objectives

Key message
A clear and complete problem definition drives meaningful analysis

***Case Study** - SGA Technologies – Selective Copper removal and feature refinement on Active Metal Braze (AMB) Power Electronics Substrates*
***Challenge**: Process development of selective laser ablation of copper to produce fine feature definition (tracks, chip pads, and stress-relief features).*

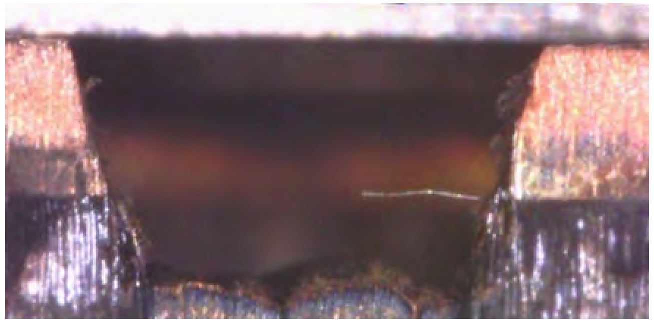




[3] Example Active Metal Braze Substrate

[3] Circuit Board Micro-Features Using Laser Ablation | MTC

Importance of Well-defined Objectives



[3] Example Microsection -Showing excessive ceramic removal

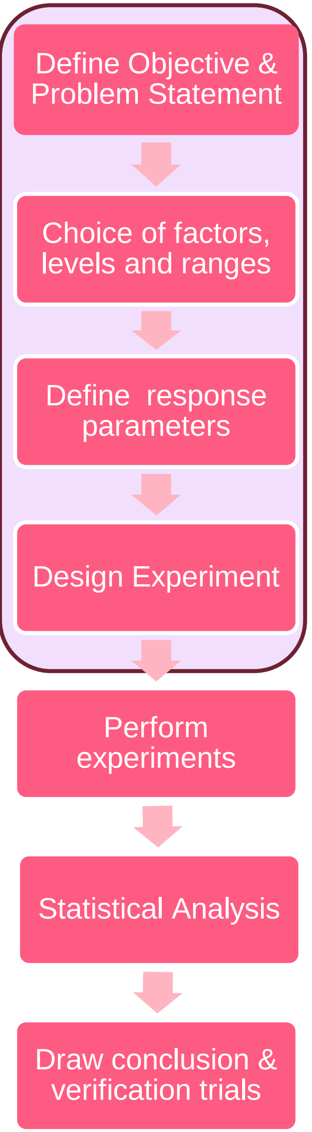
Observation: The initial experimental objective focused primarily on copper removal rate, with insufficient consideration of other critical outputs relevant to the end application, including:

- Unintended removal of the ceramic material once copper was cleared
- Surface roughness of the exposed ceramic (not defined as a DoE response)

Outcome

- Development of a staged process approach to provide greater control as the copper–ceramic interface was approached (re-ising knowledge gained from first phase)
- Additional trials conducted to characterise and optimise ceramic surface roughness

Experimentation in Practice: – Where It Goes Wrong



- *"The best time to plan an experiment is after you have done it"*
- *"In an ongoing investigation, a rough rule is that only a portion (say 25%) of the experimental effort and budget should be invested in the first design."*

Key message
Where possible experiments should be designed as part of an iterative learning process, not as a one-off attempt to reach a final answer."

Do not attempt to:

- Include too many factors, levels and responses in one study
- Overcommit too much budget to an initial "perfect" design

Consequence

- Over-complex designs
- Limited ability to adapt when assumptions are incorrect or experiments fail to tell us anything

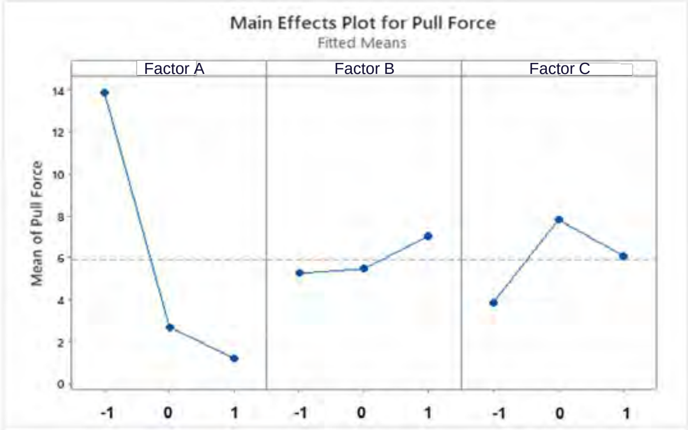
Iterative Experimentation and Learning

Key message
Where possible experiments should be designed as part of an iterative learning process, not as a one-off attempt to reach a final answer..”

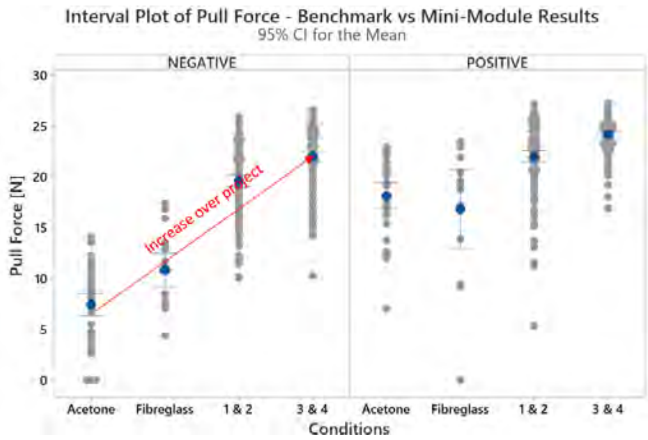
***Case Study** - Electroflight – Battery Laser Cleaning For Wirebond Interconnect*

***Challenge**: Evaluate Feasibility of laser clearing of cells to improve destructive wirebond pull strength*

Over 6000 cells [1] ~100,000 Interconnects! [1]



DOE Highlighted Sensitivity to a factors



[2] Plots show all results combined for each phase (not individual results)

Across 3 short DoE Phases

This output resulted in a 130% increase in mean bond strength and improved variability in follow trials.

[1] https://www.batterydesign.net/spirit-of-innovation/
[2] MTC Electroflight Case Study

Takeaways: DoE in Practice

Well-designed Experiments can still fail through poor execution
Do not underestimate the complexity of what appears to be a simple experiment.

Recommendations to Prevent this:

- Develop or use a **DOE Planning Template** [5]
- Use a Pre-experimental activity checklist to prepare
  - Minitab provide good guidance.-(Checklist of pre-experiment activities – Minitab)

Planning

- Define a clear experimental objective to drive the design
- Negotiate: Experiment resource – (Time/Budget/Material/Machine access)
- Brainstorm sources of variation (Decide what to experiment/held constant and how to manage nuisance factors)
- Start simple, then build complexity: screen → model → optimise → validate

Executing Experiments

- Ensure all procedures are clearly defined, documented and followed
- Run trial experiments before committing to full studies
- Visualise Data before Analysing

[5] v3501001 A Systematic Approach to Planning for a Designed Industrial Experiment

Minitab

EXCHANGE

Deeper Dive:
Turning Process Data into Operational Confidence

Nick Jones & Tony Smith
Solutions Architects

José Nunez Ares
Consultant

Meet Your Speakers

Nick

Solutions Engineer

Minitab

José

Consultant

Minitab

What We'll Explore Today

A Manufacturing Challenge

Identify and reduce process variability in a real-world polymer production case

From Data to Decisions

Centralize data, automate workflows and enable trusted, scalable decision-making

Design, Optimize, Innovate

Enable faster innovation and more robust process development with advanced experimental designs

Key Take Aways

Build a foundation for proactive operational excellence

When Consistency Becomes a Challenge

Minitab EXCHANGE

Rising Variability

Despite unchanged process settings

Operational Impact

Scrap increased, specifications became harder to meet, and supplier variability grew

Engineering Challenge

More troubleshooting, less time for optimization

The Root Problem Emerges

After reviewing historical production data, a major source of variability was identified:

1 critical raw material was being supplied by 3 different vendors, each introducing subtle but significant differences into the process.

The challenge was no longer just technical, it became operational and organizational.

Scrap Increased

More material wasted per batch as variability grew

Specs Harder to Hold

Customer requirements increasingly difficult to maintain

Engineers Stretched

The benefit of using our solution

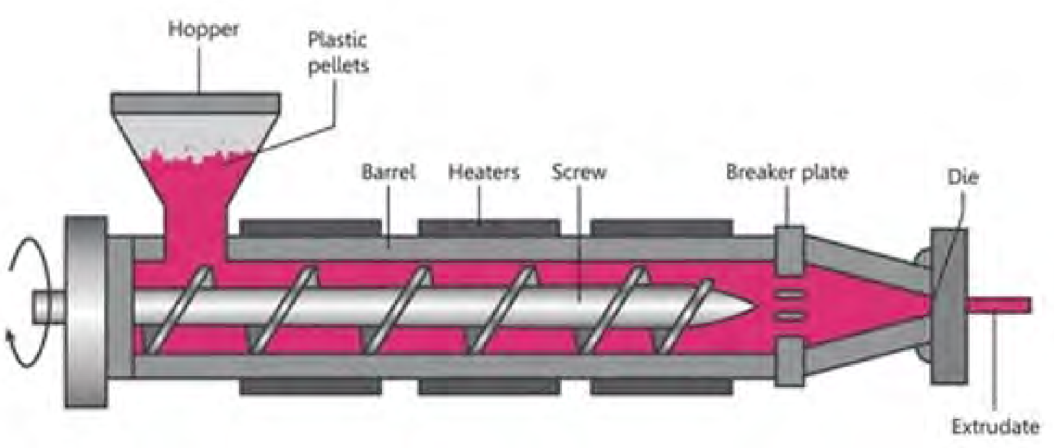
Data Ingestion → Preparation Workflows → Automation → Dashboard-Ready Datasets

Reduced Manual Effort → Faster Reporting Cycles → Consistent KPIs → Better Collaboration

Once visibility is established, the next step is optimization

The experimental challenge

- ✓ Product variability increasing
- ✓ Raw material differences identified as the root cause
- ✓ Robust process settings required
- ✓ Experiments are expensive



Polymer extrusion

5-Step DOE Process

1. Prepare

Define your experiment goals and desired outputs

2. Setup

Choose the combinations of input values to be tested, which is your experimental design.

3. Experiment

Conduct tests according to the selected experimental design

4. Analyze

Discover the influence of the inputs on the outputs through interactive graphs

5. Optimize

Find the best inputs for the desired outputs

Data Collection

Data Analytics

Setting up the experiment

Critical material attributes

Critical process parameters

→

Polymer extrusion

→

Critical quality attributes that characterize the product/process

Limited to 24 tests due to high cost and time

Experimental factors and responses

Factor type	Factor name	Factor range
CMA	Supplier (categorical)	A, B, C
CPP	Temperature oven (°C)	[180,200]
	Time in the oven (h)	[7,9]
	Pressure (MPa)	[75,84]

1 Critical Material Attribute:

- ✓ One categorical with three levels

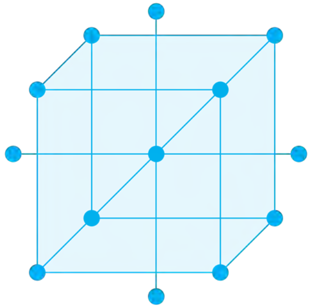
3 Critical Process Parameters

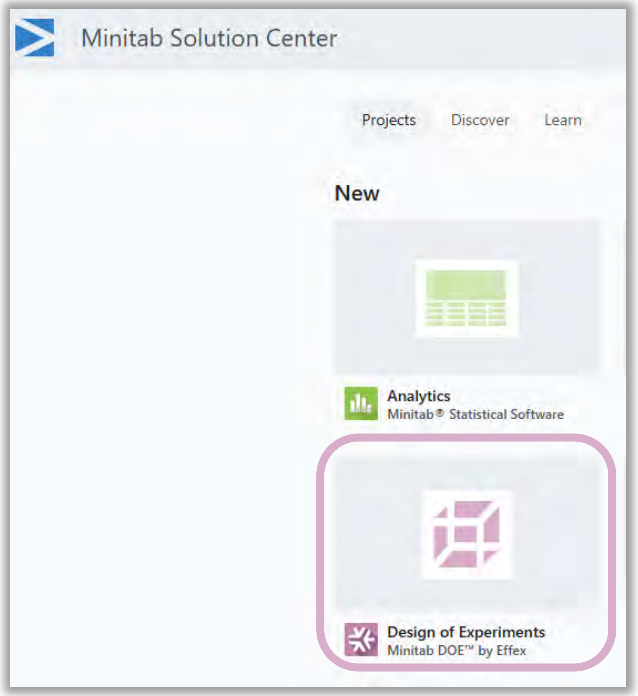
- ✓ All controllable
- ✓ All numerical
- ✓ Crucial to determine the factor ranges

CQA	Optimization sense	Value	Target value
Residual (ppm)	Minimization	<50	25
Density (g/cm3)	On target	[0.89, 0.93]	0.91
Melting temperature (°C)	Maximization	>168	170

3 Critical Quality Attributes with specs

Minitab DOE by Effex Demo





- Obtain an experimental design for the polymer extrusion robustness challenge
- Analyze the experimental data
- Optimize the models

Demo Key Take Aways

Minitab DOE™ by Effex

Minitab EXCHANGE

What we've done:

Selected the optimal experimental design balancing tests and information

Modeled multiple responses with significant linear and nonlinear effects

Identified robust operating conditions across three raw material suppliers

Benefits:

Fewer tests, better designs

Guided design & model selection

Interactive, intuitive and visual multi-response optimization

Unlocking Operational Intelligence From Data to Decisions

The combined value of data management and decision optimization

Business Impact

- Faster operational decisions
- Proactive management
- Reduced variability
- Better resource allocation

Transformation Journey

- Integration of fragmented data
- End-to-end operational intelligence
- Confident decision-making

Potential Areas

- Time savings
- Faster decisions
- Improved KPI consistency
- Operational agility
- Scalability

Data visibility & trust → Real-time optimization of decisions & actions → Measurable business impact → One integrated journey

What Now?

Scale

Expand adoption across functions, sites, and global operations

Predict

Leverage advanced analytical models to anticipate outcomes and risks

Expand optimization use cases

Drive more value by solving new operational and business challenges.

Stronger decisions → **Smarter operations** → **Lasting impact**

Next: Let Minitab Visit You!

- **See and advise** on your challenges firsthand
- **Involve your team on-site** at your workplace
- **Identify quick wins** and strategic moves

Thank You