Connecticut Center for Advanced Technology, Inc.

HYBRID EVENT

INDUSTRY 4.0 FORUM

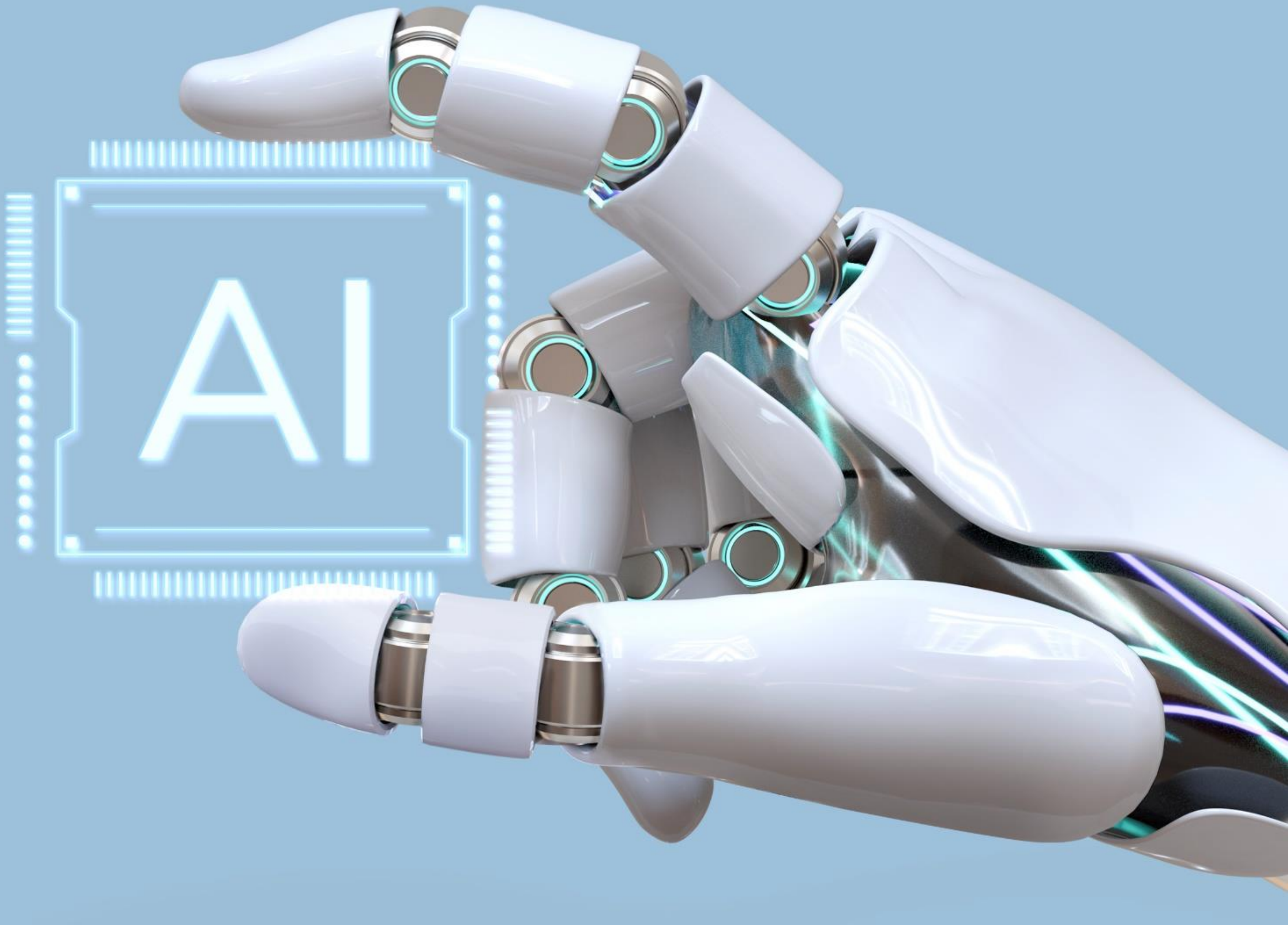
Applications of Artificial Intelligence for Smart Manufacturing

Table of Contents

Applications of Artificial Intelligence for Smart Manufacturing

Nasir Mannan, Principal Engineer, CCAT

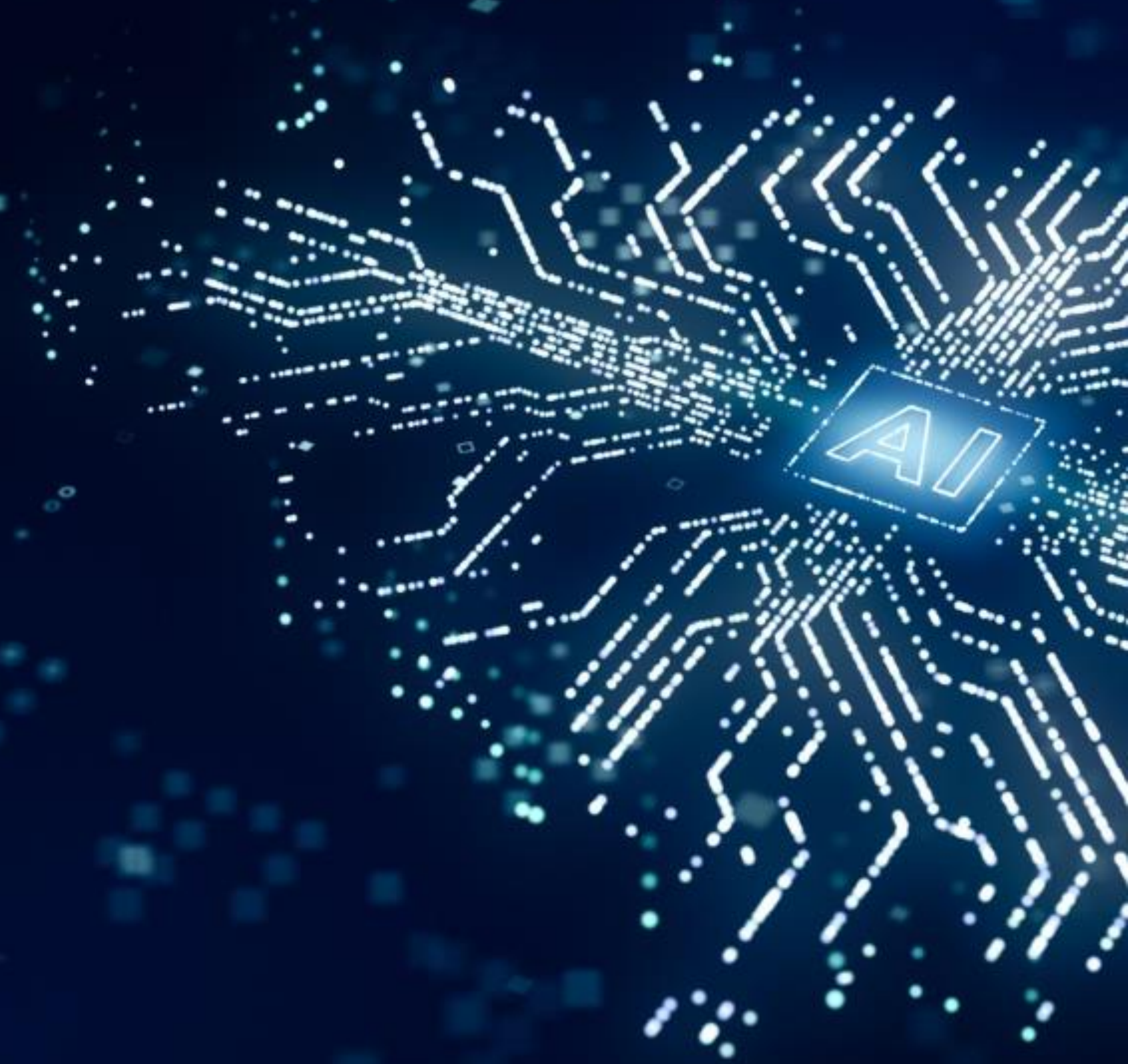
What is

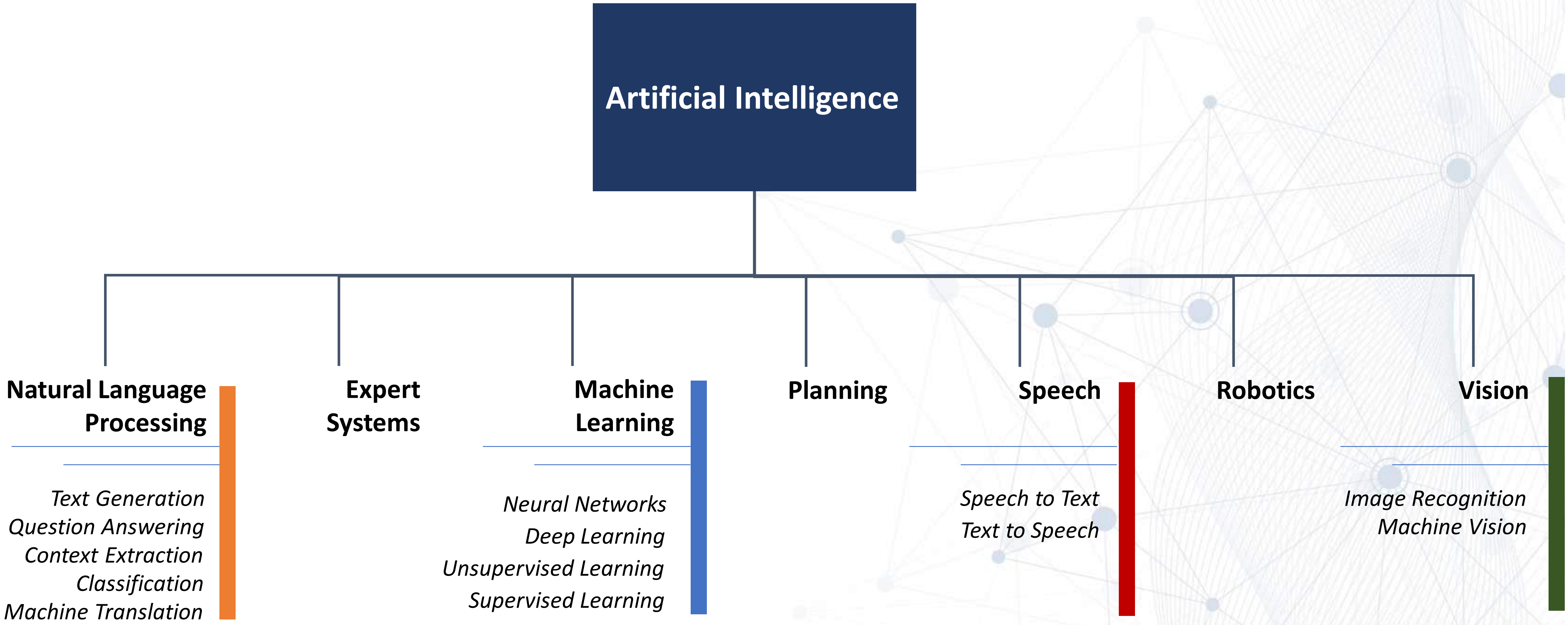


Artificial intelligence (AI) is a field of computer science that aims to create machines and software systems that can perform tasks typically requiring human intelligence. This includes capabilities such as:

- Learning
- Reasoning
- problem-solving
- Perception
- understanding natural language
- adapting to new situations

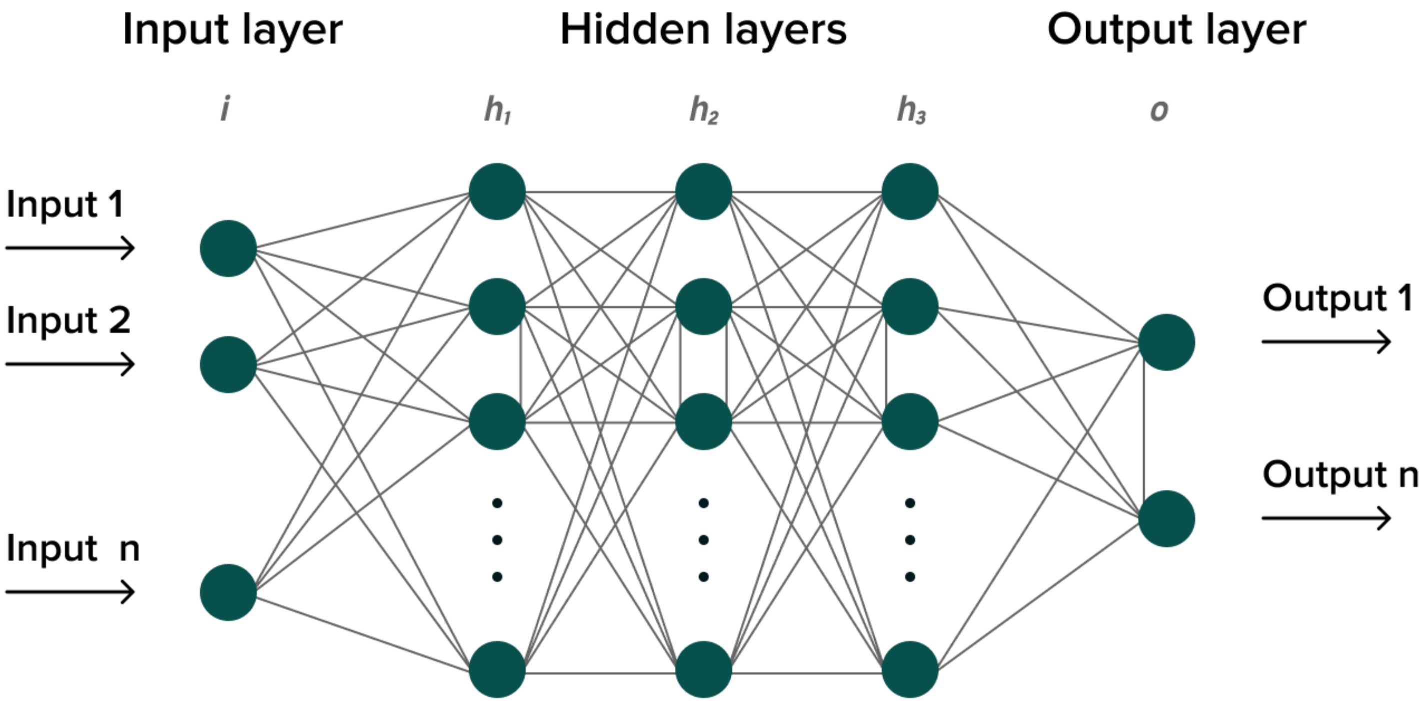
AI systems can be designed to perform a specific task, like recognizing objects in an image, or multiple tasks simultaneously. The ultimate goal of AI research is to develop machines capable of simulating the full range of human intelligence, known as artificial general intelligence (AGI).




Artificial Intelligence
Natural Language Processing
Text Generation
Question Answering
Context Extraction
Classification
Machine Translation
Expert Systems
Machine Learning
Neural Networks
Deep Learning
Unsupervised Learning
Supervised Learning
Planning
Speech
Speech to Text
Text to Speech
Robotics
Vision
Image Recognition
Machine Vision

Human neurons and artificial neural networks are interconnected in the sense that artificial neural networks were inspired by and modeled after the biological neural networks found in the human brain. However, they operate on different principles, and their similarities are more conceptual than direct parallels.

Artificial neural networks (ANNs) in AI are computational models that take inspiration from human neurons but aren't exact replicas of biological neural networks. ANNs consist of artificial neurons, or nodes, organized into layers. These nodes process inputs and transmit information through weighted connections, somewhat analogous to synapses. The weights of the connections are learned or adjusted during the training process to find patterns in data and make predictions or classifications.

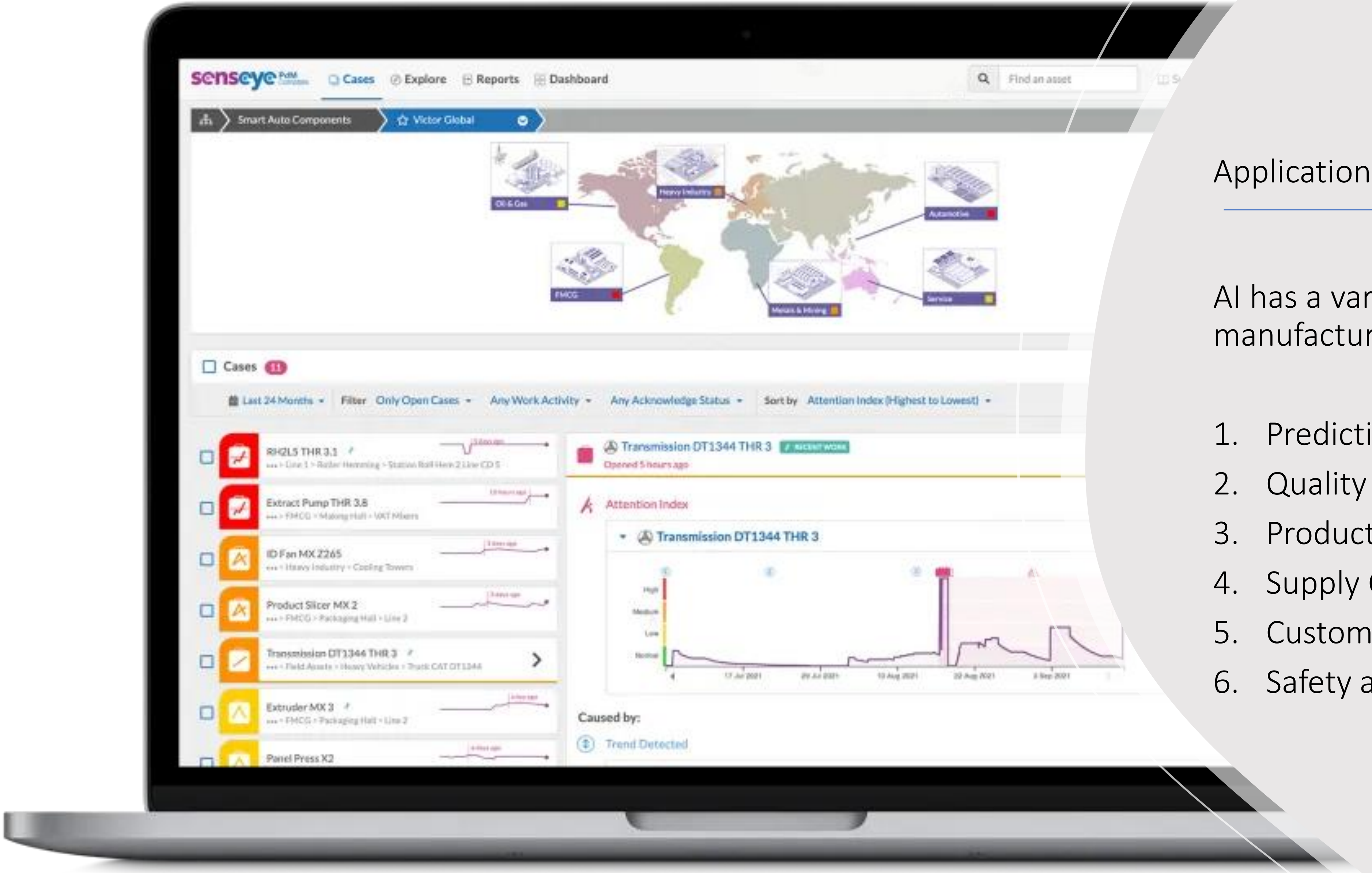


- In summary, the key relation between human neurons and AI neural networks is their shared foundation in the concept of interconnected processing units. AI neural networks are a simplified and abstracted version of biological neural networks with the goal of replicating some aspects of human intelligence in machines. However, they are not direct representations of human neurons, and their operation is fundamentally different on various levels.

- Generally, by augmenting artificial intelligence with human intelligence through the use of AI-embedded technologies, we can benefit from enhanced decision-making, increased efficiency, and an improved ability to solve complex problems while reducing error.

What is Smart Manufacturing?

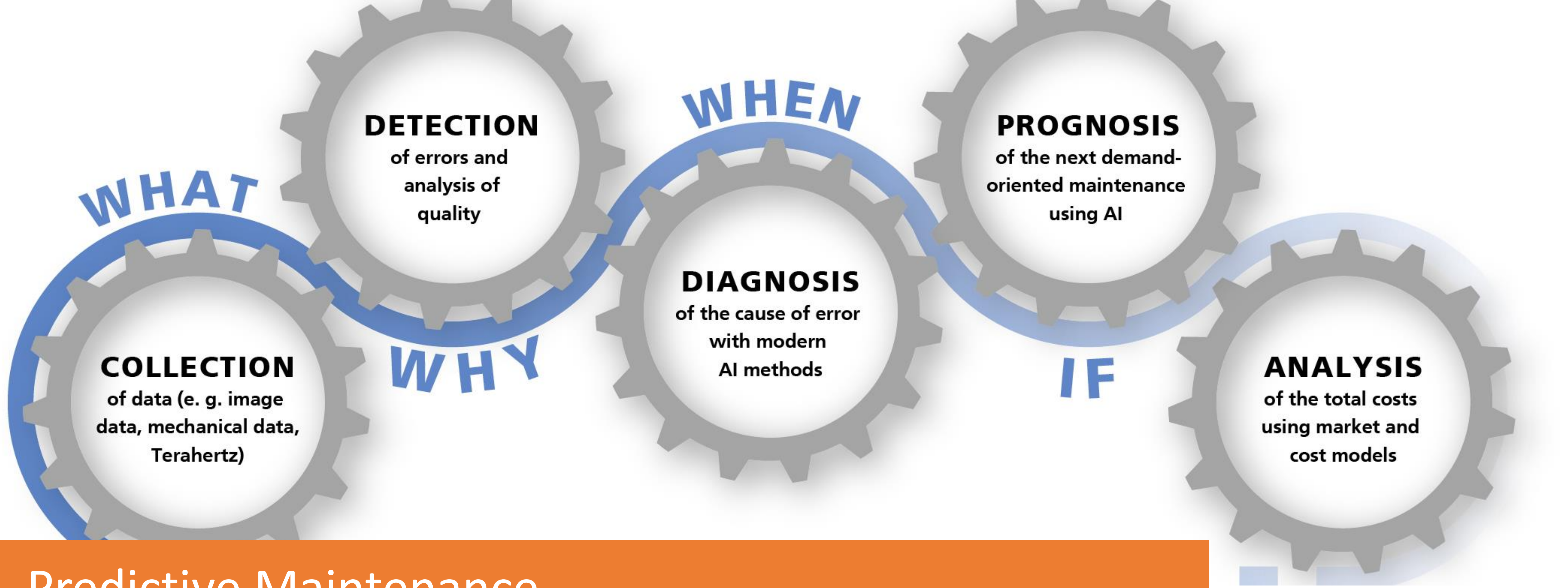
Smart manufacturing is an advanced manufacturing system that utilizes data-driven and intelligent automation to operate more efficiently, accurately, and flexibly. It involves the integration of physical and cyber systems to monitor and optimize the manufacturing process.



Applications of AI for Smart Manufacturing

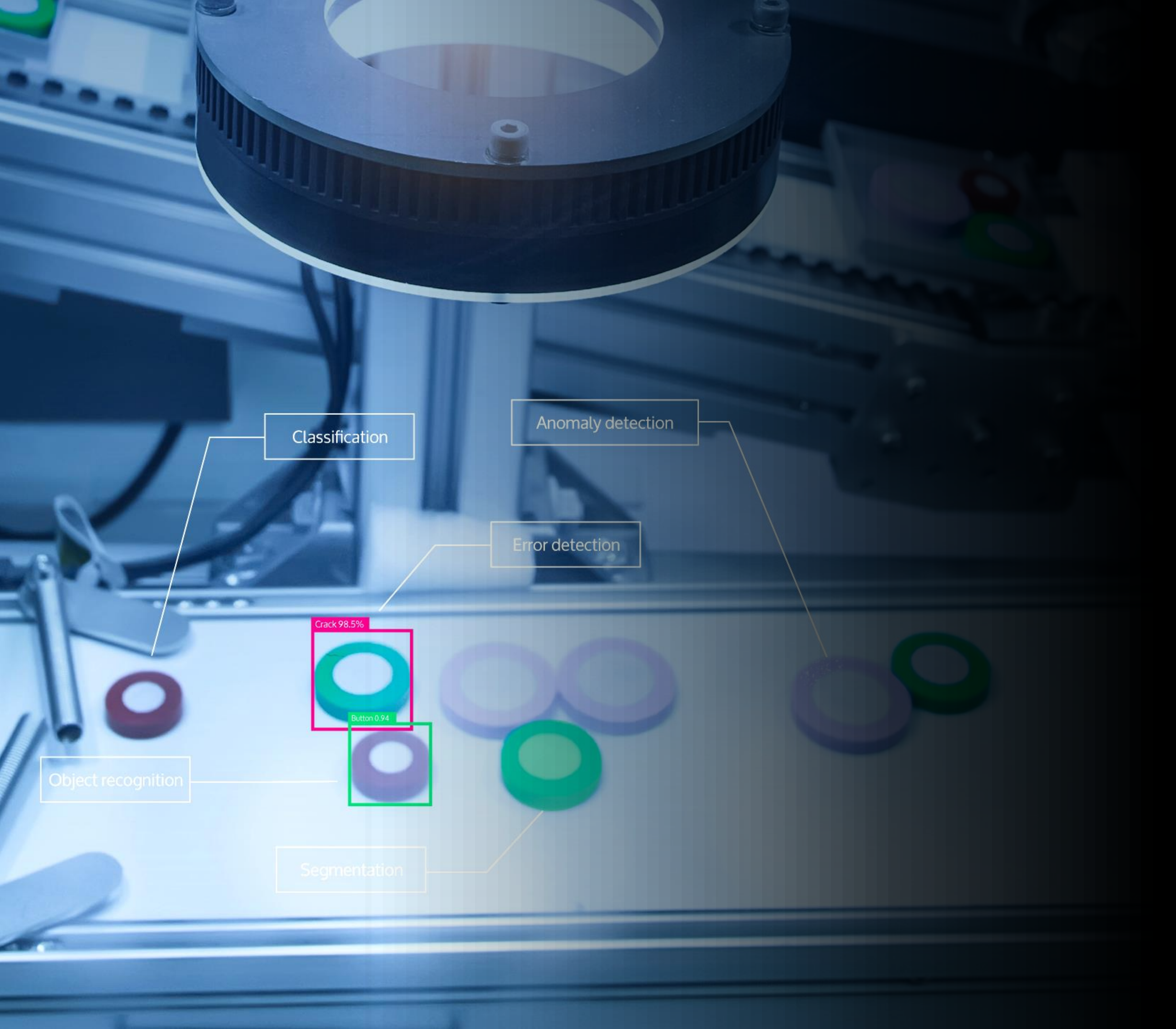
AI has a variety of applications in smart manufacturing, including:

1. Predictive Maintenance
2. Quality Control
3. Production Planning and Scheduling
4. Supply Chain Optimization
5. Customer Service and Support
6. Safety and Compliance



Predictive Maintenance

Predictive maintenance is a data-driven maintenance strategy that uses AI and machine learning algorithms to predict potential equipment failures before they happen. By analyzing data from sensors and other sources, AI can detect patterns that indicate an impending failure. This allows plant managers to schedule maintenance proactively, reducing downtime and repair costs.



Quality Control

AI can be used to improve quality control by analyzing data from sensors and detecting defects in real-time. This allows manufacturers to catch defects early in the production process, reducing waste and improving product quality.

Production Planning and Scheduling

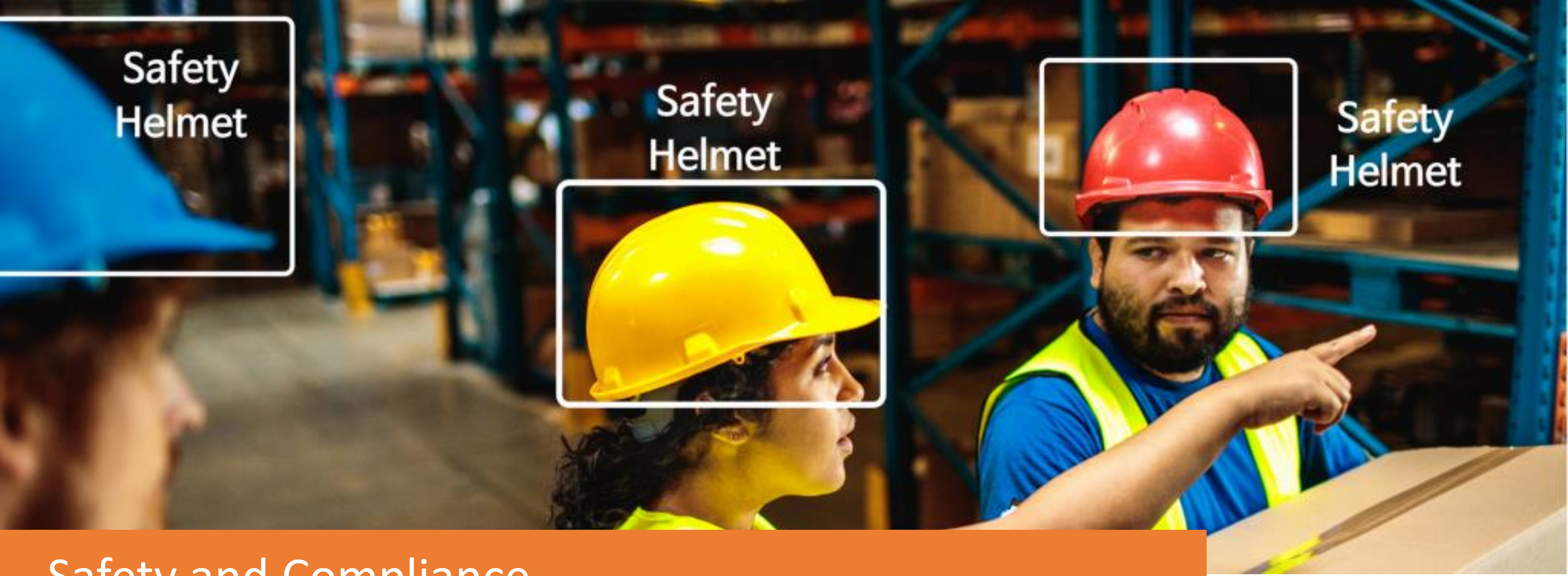
AI can optimize production planning and scheduling by analyzing historical data and predicting future demand. This allows manufacturers to adjust production schedules in real-time, improving efficiency and reducing inventory costs.

Supply Chain Optimization

AI can optimize supply chain operations by analyzing data from multiple sources and identifying bottlenecks in the supply chain. This allows manufacturers to make strategic decisions to reduce lead times, improve delivery times, and reduce transportation costs.

Customer Service and Support

AI can improve customer service and support by automatically answering routine questions and providing personalized recommendations to customers. This improves customer satisfaction and reduces the workload on customer service agents.



Safety and Compliance

AI can improve safety and compliance by analyzing data from sensors and other sources to detect potential hazards. This allows manufacturers to identify safety risks early on and take corrective action before accidents occur. AI can also help manufacturers comply with regulations and standards by automatically monitoring and reporting on compliance.

Conclusion

In conclusion, AI has a variety of applications in smart manufacturing, from predictive maintenance to quality control to supply chain optimization. By leveraging AI technology, manufacturers can improve efficiency, reduce costs, and improve product quality, ultimately driving greater success and growth for their business.

Keynote Speaker

Michael Ambrose

Former Chief Engineer & Vice President of Engineering and Technology
Sikorsky/Lockheed Martin

ROLE OF ARTIFICIAL INTELLIGENCE IN MANUFACTURING AND WHY IT MATTERS TO THE CONNECTICUT SUPPLY CHAIN

MIKE AMBROSE

“The companies that get this right will thrive and differentiate”

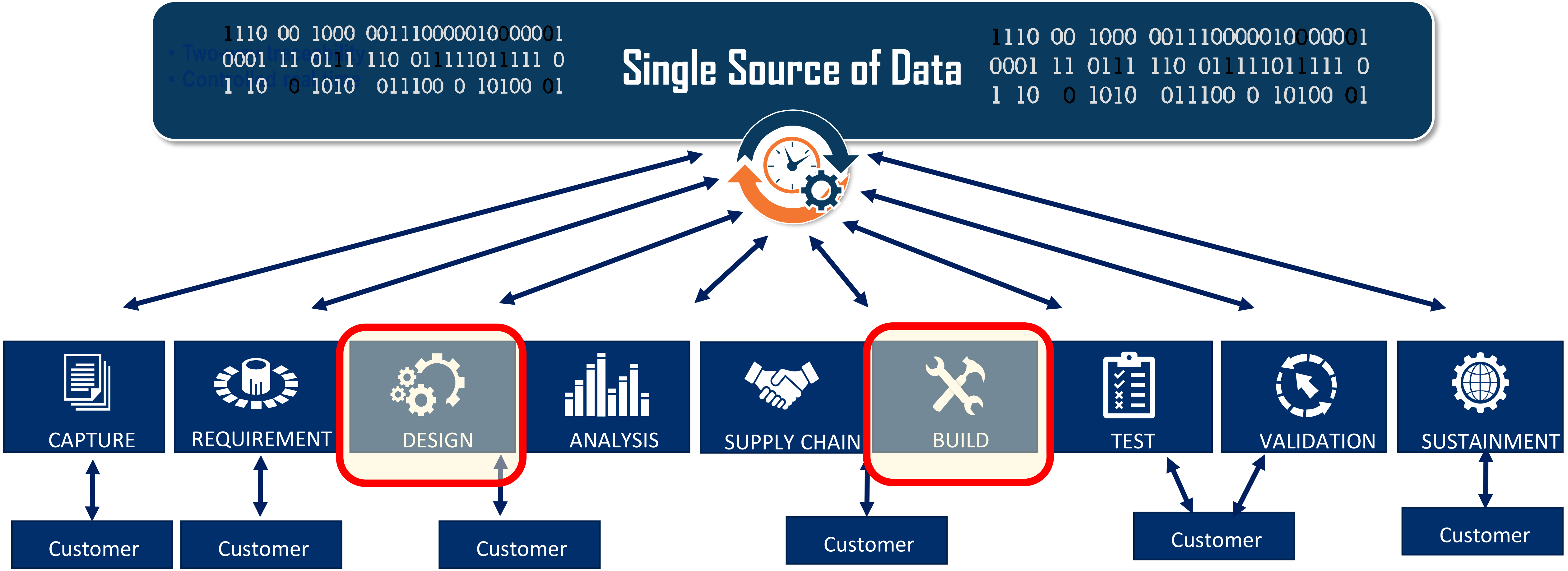
June 7, 2023

miambro404@gmail.com

DIGITAL INTEGRATION OF THE PRODUCT LIFE CYCLE

SIMPLIFIED - SINGLE SOURCE OF TRUTH

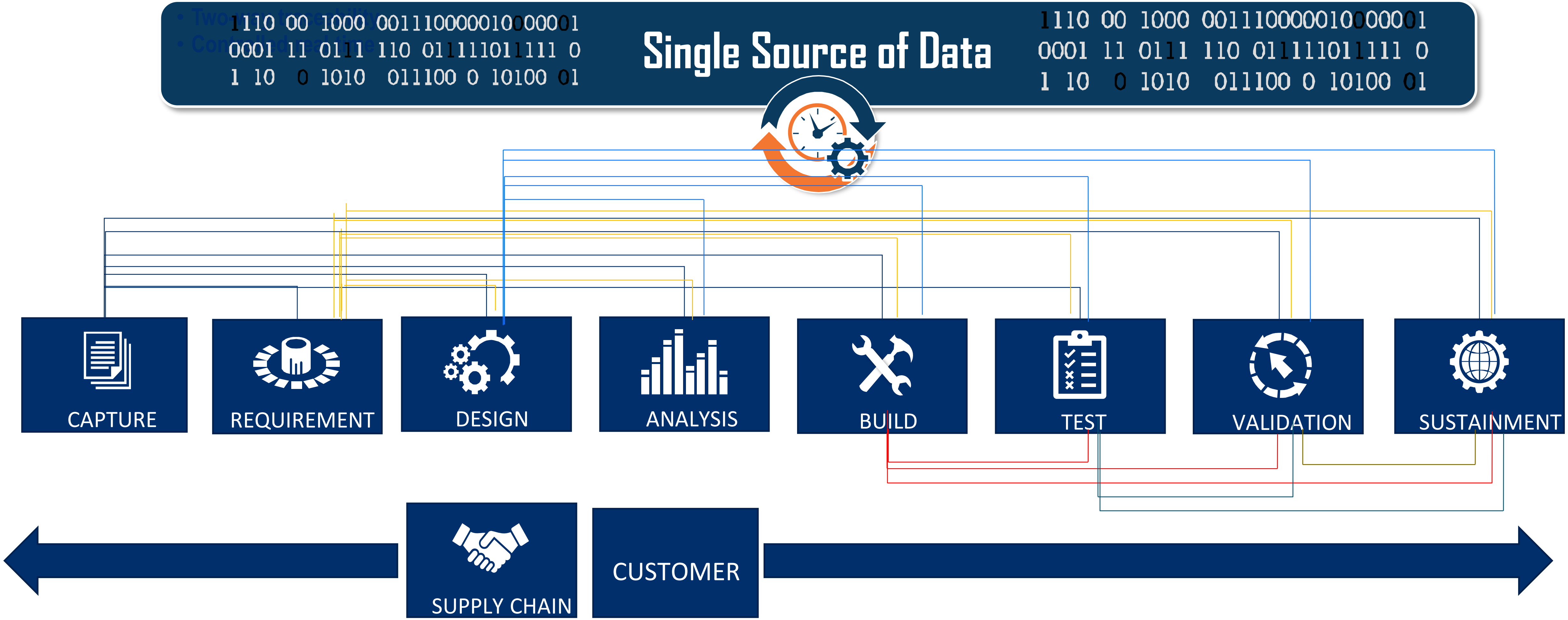
Using a single source of data enables communication & collaboration across the product lifecycle



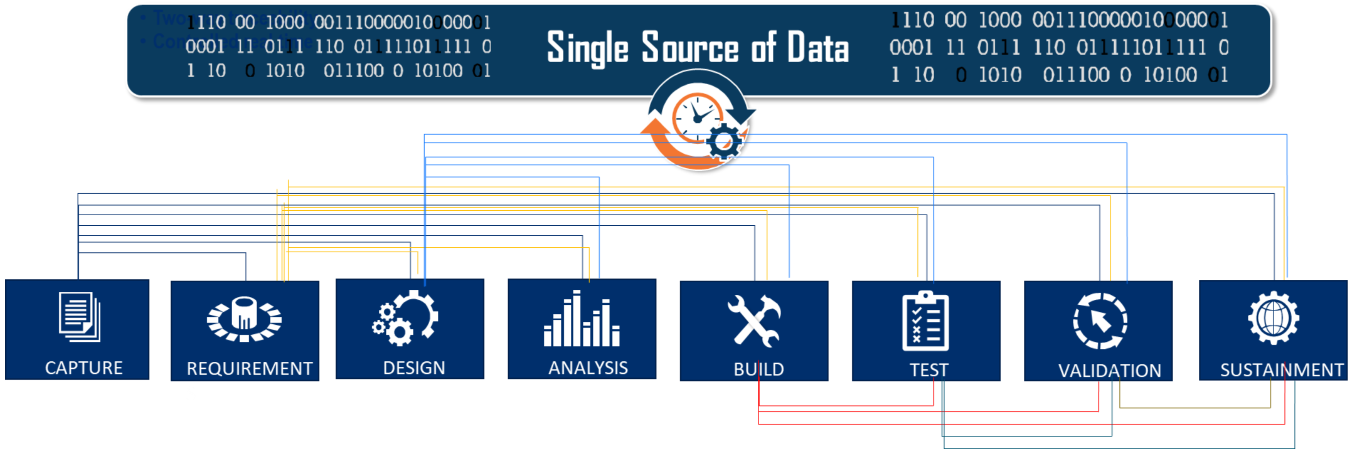
DIGITAL INTEGRATION OF THE PRODUCT LIFE CYCLE

TYPICALLY, 100,000 TO OVER 1,000,000 INTERFACES!

Single source of data connecting every process in the product life cycle



INTEGRATED PRODUCT LIFE CYCLE ENABLES
"SINGLE SOURCE OF TRUTH"



Model Based System Engineering

Digital Twins

"X before you X"

Iterative Simulation

Optimization through Simulation

AI and ML Applications

With integrated product live cycle comes complexity, but customer flexibility

DIGITAL INTEGRATION, DIGITAL TWINS, AI, AND ML

WHY ARE THEY IMPORTANT TO OEMS & SUPPLY CHAIN?

DOD customer requires responsive supply chain

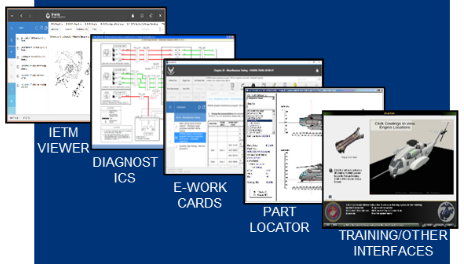
Digital Integration / Digital Twins →
- **Enables faster development, less cost, better quality**

Artificial Intelligence / Machine Learning →
- **Enables Next Gen of automation**
- **Enables simulations of entire product value stream**

ARTIFICIAL INTELLIGENCE / MACHINE LEARNING USE CASE

EMPOWERING THE SUSTAINMENT DIGITAL THREAD

Health Monitoring



+

Predictive Analytics

=

Results

Reduced maintenance
Increased availability

Predictive Maintenance

Prescriptive Analysis

Inventory Optimization

Tailored Part Replacement

Training Simulations

Generative AI - State-of-Art Search Optimization

SUSTAINMENT DIGITAL THREAD

IMPACT ON SUPPLY CHAIN – HOW TO DIFFERENTIATE?

Potential Opportunities, Risks, Things to Think About for Supply Chain

End customers want “data”
Lots of data

How does the supplier value proposition change?

What data is the “right” data?

How to format, manage data interfaces?

How to store data?

What about cyber security?

What is the IP strategy?

ARTIFICIAL INTELLIGENCE / MACHINE LEARNING USE CASE

ENABLING NEXT GEN OF MANUFACTURING AUTOMATION

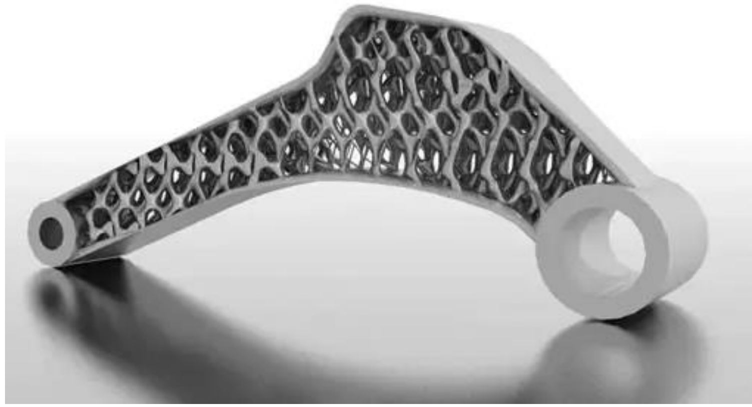
Identify and self-correct process issues

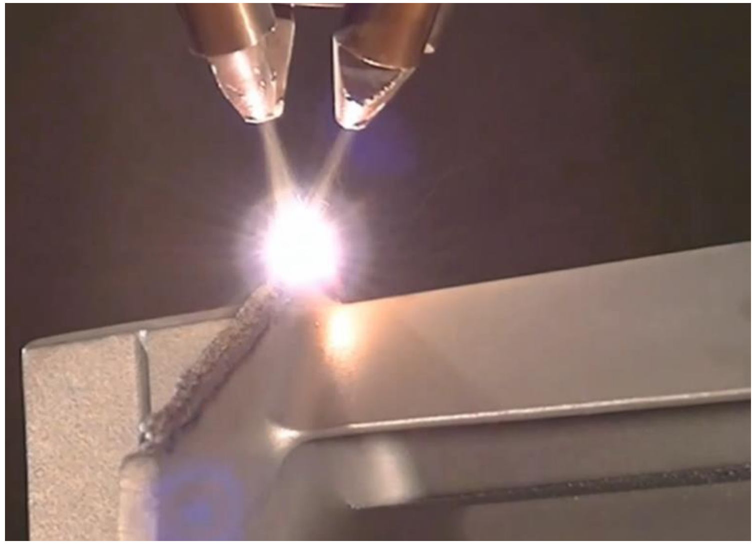
Enables faster product & process optimization

Predictive and prescriptive analytics

ARTIFICIAL INTELLIGENCE / MACHINE LEARNING USE CASE

ENABLING ADDITIVE DESIGN & MANUFACTURING





Iteration & Optimization of Design – Novel Concepts

Integration & Optimization of Physics Based Models

Iteration & Optimization of Build / Tooling / Assembly

AI & ML IN MANUFACTURING

KEY TAKEAWAYS

The product digital thread is enabled by AI and ML

Supply chain integration into the product digital thread is required by DoD

Enables supply chain differentiation in digitally integrated value stream

Next generation of manufacturing automation & productivity enabled by AI

Next generation of additive design & manufacturing enabled by AI

THANK YOU

MIKE AMBROSE CONTACT INFO: **miambro404@gmail.com**

Join us at-the-edge

Easy to use smart cameras for AI and Industry 4.0

James Huston, Sales Engineer

Baumer
Passion for Sensors

Baumer
Passion for Sensors

Join us at-the-edge

Easy to use smart cameras for AI and Industry 4.0

James Huston, Industry 4.0

Image processing is changing – don’t miss it

- Widespread, mainstream use of imaging technology
- Mega trends: Industry 4.0, Edge Processing, Artificial Intelligence
- Higher image quality
- Higher computing power
- Reduction in size, power and bandwidth

Widespread use of imaging technology requires **easy to use, powerful and flexible smart cameras** to simplify system design and provide low total cost of ownership (TCO).

Broad range of applications where AI can be used

Warehouse / Logistics

Detect stock quantities

Food / Beverage

Classify fruits

Transport / Traffic

Analyze traffic

Automobile Manufacturing

Prevent collisions

Retail

Counting, tracking, and profiling people

Automotive / Supplier

Inspect quality

Huge potential versus present day usage

AI ready?

Several industry surveys come to the same conclusion

- **BMWi:** “6% of German businesses using AI, 77% say AI is important or essential”
- **PwC:** “Just 6% of companies using or implementing AI”
- **bitcom:** “Large majority sees AI as a big chance, just 9% are using it”
- **inVISION:** “While 70% of participants say AI systems are ready to use, however just 17% are using the technology”

We can help!

Baumer AX series smart cameras - technical highlights

High-quality industrial camera with standard C-mount

Powerful computing with NVIDIA® Jetson™ modules

Durable robust industrial housing with IP 67 option

Hardware trigger and lighting controller

Flexible connectivity: Ethernet, RS232, USB, HDMI, SD card

Baumer software SDKs and NVIDIA® Linux® / Jetpack™

Wide ranging 3rd party software compatibility

We've made AI easy for you

Simple

The Baumer AX series is an **all-in-one smart camera** based on well known standard technology. Reduces development time for your project.

Powerful

The Baumer AX series provides you with **enough power for 300 fps interference or multiple neural networks** working on the same image data.

Robust

The Baumer AX series is made to be reliable **even in rough industrial environment.**

Open

The Baumer AX series provides a canvas to **project your software ideas on a ready to use hardware platform**

Portfolio overview: AX smart cameras

	Model	Mono | Color	Sensor Type	Sensor	Resolution [px]	Pixel Size [µm]	Full Frames [fps]
NVIDIA® Jetson Nano™	VAX-32.I.NVN	M | C	1/1.8″ CMOS	IMX265	2048 × 1536	3.45 × 3.45	55
NVIDIA® Jetson Xavier™ NX	VAX-50.I.NVX	M | C	2/3″ CMOS	IMX250	2448 × 2048	3.45 × 3.45	77

Application – Smart Ag

The Case:

Identifying and classifying weeds using AI running on the AX Smart Camera.

The AX Smart Camera allows for a more compact inspection solution which is easier to integrate.

Benefits:

- **More compact solution** with easier integration
- IP 67 Rated
- **Realtime inspection** for quick execution

Application – Quality Control of Carbon Fiber

The Case:

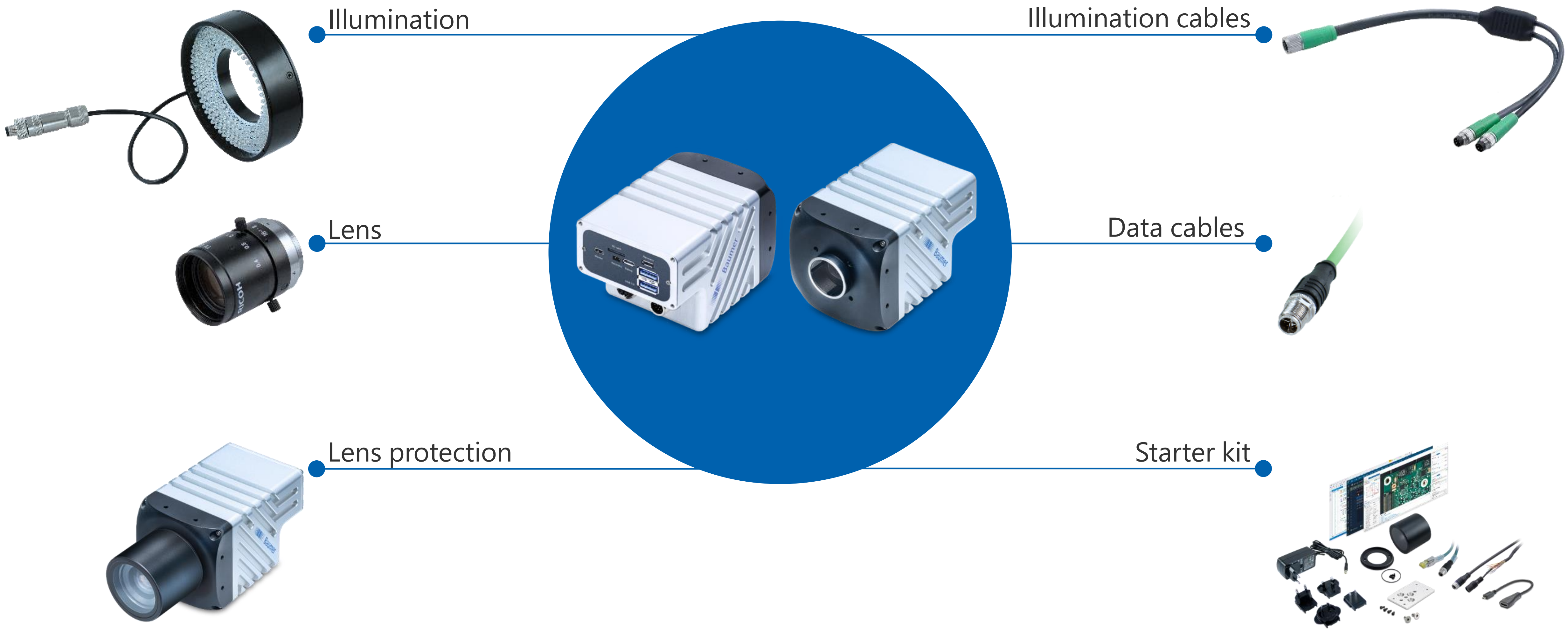
Quality control of carbon fiber for identification and classification of defects as they start to develop with the Baumer AX Smart Camera in connection with a developed AI software.

The freely programmable camera was equipped with an AI software. **Fully embedded system, deep-learning algorithm combined with industrial design.**

Benefits:

- **All in one solution,** no need to wire connections throughout entire plant or need for local compute unit.
- **Realtime quality inspection** including reporting possibilities for quickest reaction time
- **Compact & non-invasive** solution

Easy to work with the Baumer package



Want to dive deeper? Contact us!

We will be happy to support you with our knowledge to **get the best out of your application:**

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Siemens AI Applications for Machine Tools

Visual Machine Awareness & Process Quality Monitoring

August "Gus" Gremillion, Solutions Consultant

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Siemens AI Applications for Machine Tools

Visual Machine Awareness & Process Quality Monitoring

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Automated visual inspections for improved machine protection

- **Use visual analytics for workpiece and environment monitoring**
- **Can be used by every-day users and experts alike**
- **Reduce machine and asset damage costs**

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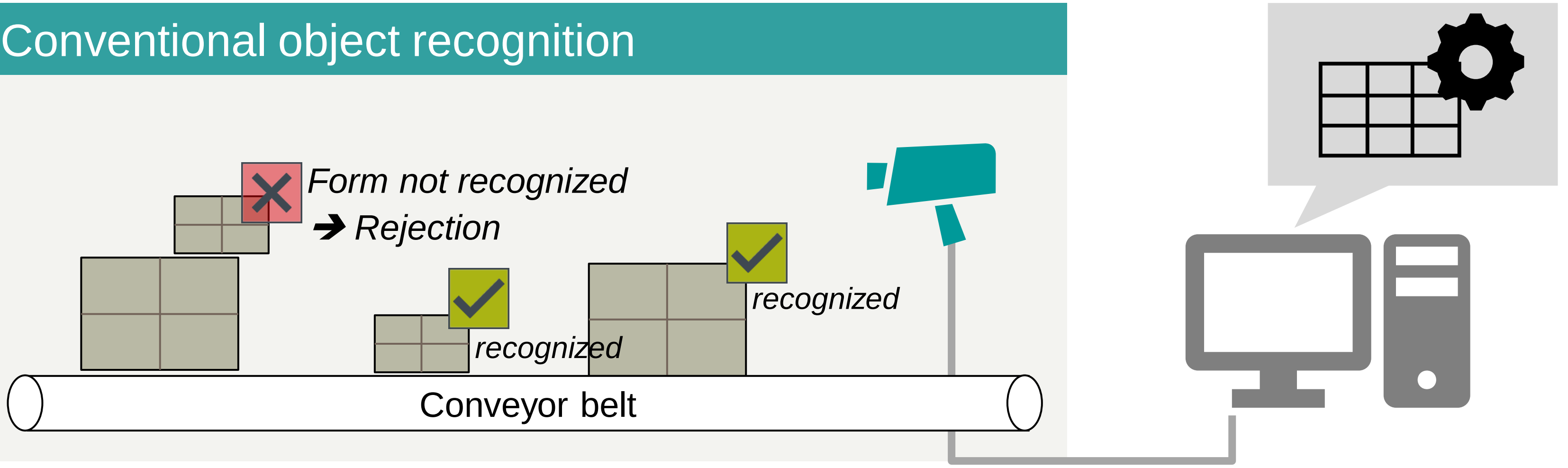
Artificial Intelligence in SIMATIC
Benefits of AI using an example

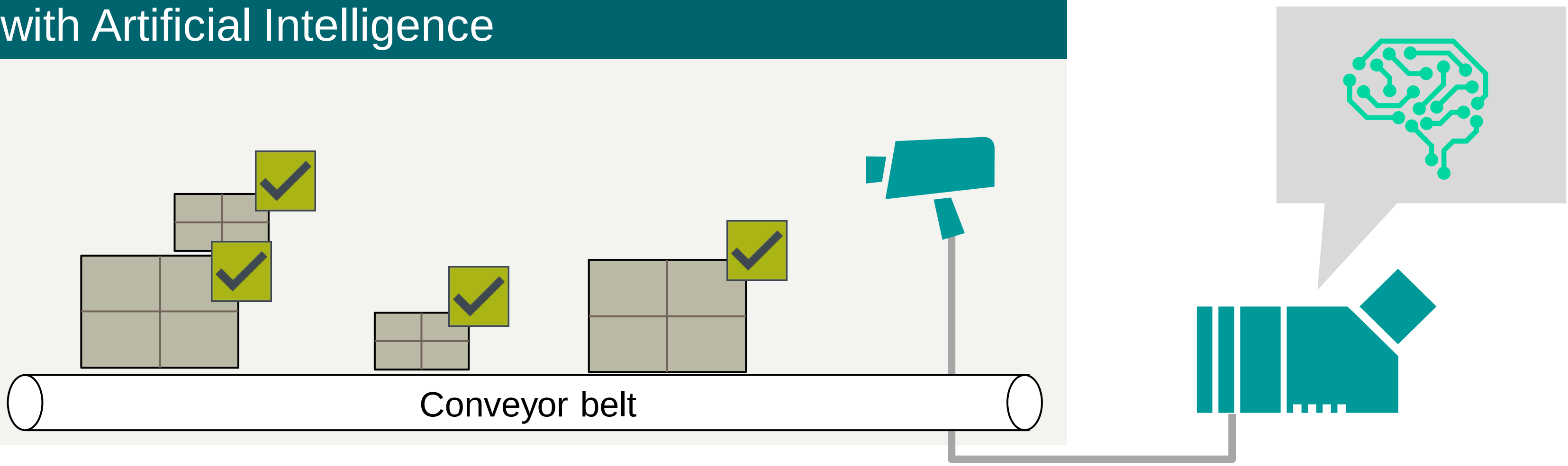
Conventional object recognition



Properties

- Processing of data via programmed image capture system
- Each object to be recognized has to be precisely defined (deviations = rejection)
- Time-consuming programming for new objects

with Artificial Intelligence



Properties

- Processing of input data via neural networks
- Higher availability through detection of **complex patterns**
- Easier handling also of unknown objects

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Customer challenges:
Manual, optical inspections still play a crucial role– amidst increasing automation demands

With manual optical inspection	Without manual optical inspection
Manual monitoring of machine setup, machine cells or shopfloor processes	**Poor machining preparation, unsupervised machine cells or shopfloor processes**
Tie up skilled workers in time-consuming, monotonous tasks	**Limited safety delivery plus higher machine damage risk and production of waste**
missing traceability and integration in automation	**Most alternatives: Setup of visual-based solution is expert-intensive, time-consuming and complex to integrate in automation**

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Visual Machine Awareness:
Automize and support manual, optical inspections in machines, machine cells and shopfloor

Visual Machine Awareness integration

Protect MyMachine /Setup enables workpiece and environment monitoring

Protect MyMachine /Setup support assembly and packaging processes

Skilled workers are freed for "expert tasks"

Manage MyAI enables cutting edge, online AI-model creation for visual analytics

Easy integration in existing automation + traceability and reporting

The applications can be used by every-day users and experts alike

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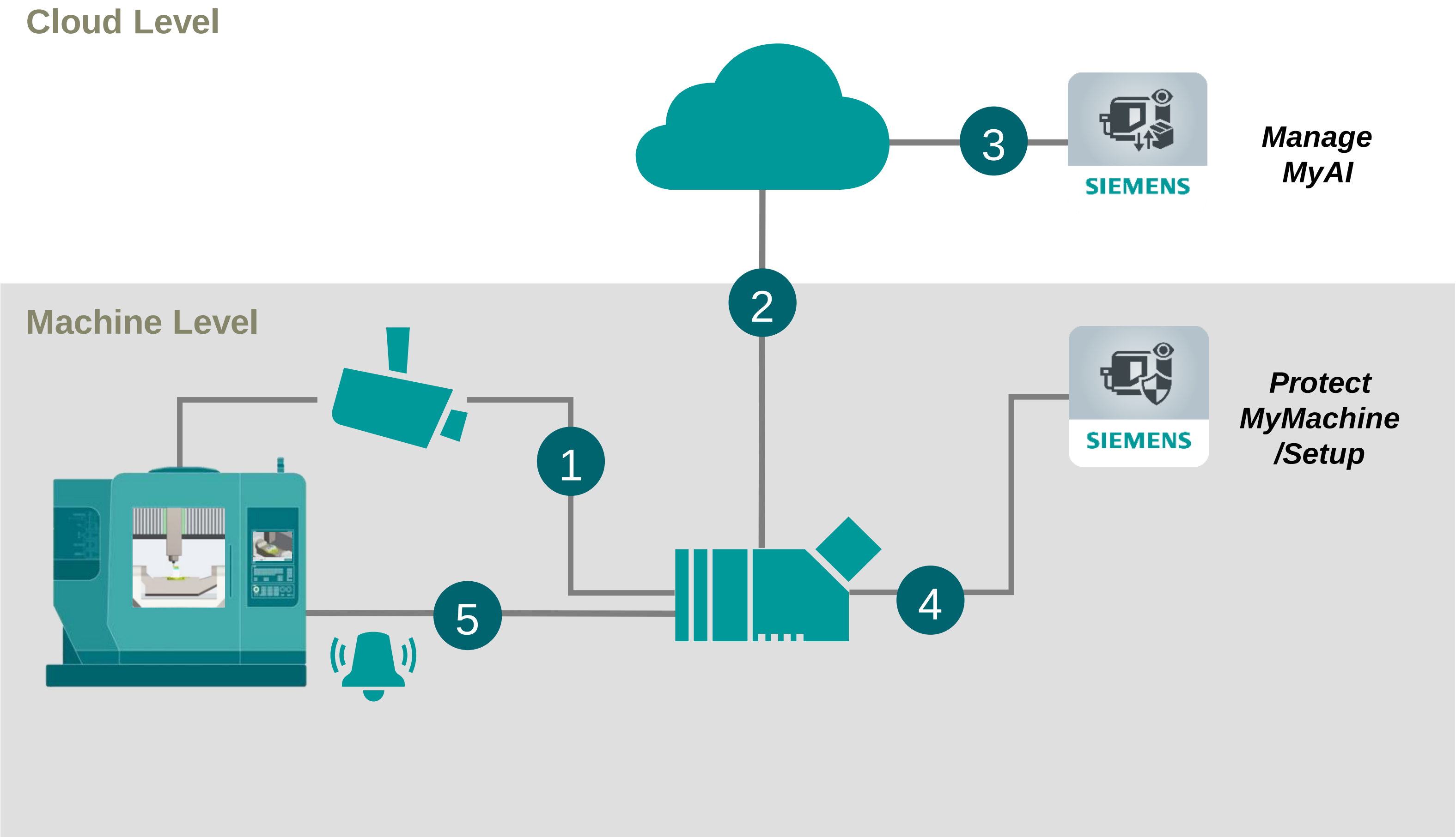
Visual Machine Awareness – Enabling the next generation of automation and machine protection through visual analytics



1. Camera hardware connected directly to Industrial Edge for Machine Tools
2. Training data collected over Industrial Edge for Machine Tools*
3. **Manage MyAI***
   Cloud-based model creation and management
4. **Protect MyMachine /Setup*:**
   Workpiece Monitoring and Object Detection
5. Model results available directly on Industrial Edge for Machine Tools.

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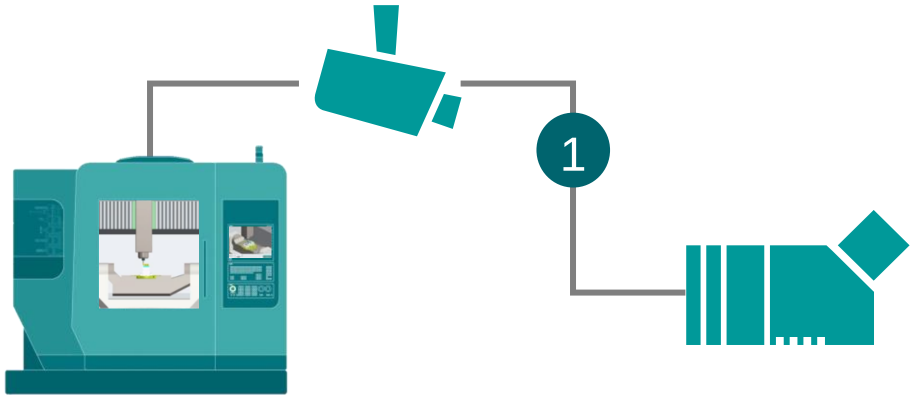
Integrating cameras near or inside the machine tool



1 Camera hardware connected directly to Industrial Edge for Machine Tools

- **Flexible specification enables huge variety of implementation possibilites**
- Camera requirements depend on use case, e.g. microscopic camera for toolwear analysis or special housing for usage in dirty and wet environment
- Simple IP Camera Adapter available from Industrial Edge for Machine Tools platform

Camera Requirements	Features
Connectivity	RTSP (LAN based)
Resolution	Full HD (1920x1080) or HD (1280x960)
IP-Code	IP 65/66/67 recommended
Cabling	PoE (Power over Ethernet)
Video Compression standard (video Codec)	H.264
Frame rate	adjustable

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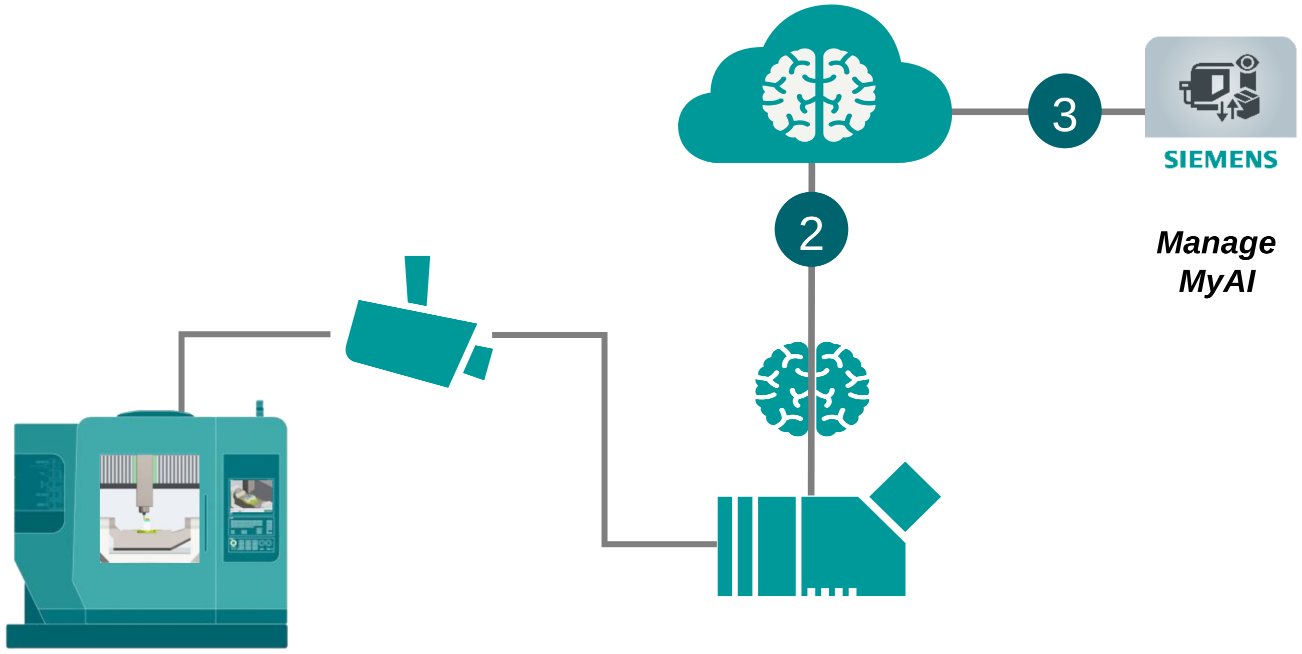
Manage MyAI enables automatic generation of computer vision AI models



2 Training data collected over Industrial Edge for Machine Tools*

3 **Manage MyAI**
Cloud-based model creation and management

- Images collected via Edge application are send automatically to the cloud
  Offline approach without a MindSphere connection also available

- Data labeling, Data Augmentation and CAD-based data generation to reduce required amount of real images and shorten and ease "time to model"

- One-click training of neural network technology
- Model architectures dedicated to many industrial use cases

→ Easy to use tool for everyday users;
no Machine Learning knowledge required

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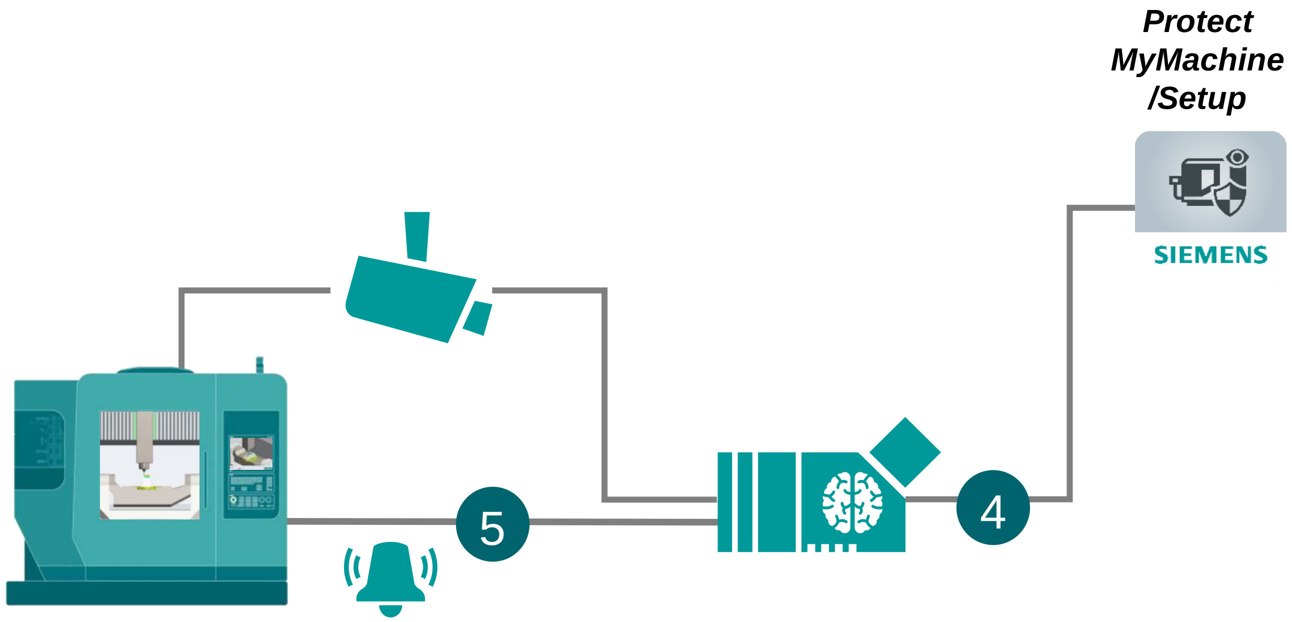
Approach: compliment existing visual processes with advanced analytics – directly at the machine tool



5 Model results available directly on Industrial Edge for Machine Tools.

4 **Protect MyMachine /Setup*:** Workpiece Monitoring and Object Detection

- Enablement of several industrial use cases:
  - Workpiece Identification and Rotation Analysis
  - Anomaly Detection
  - Object Detection
  - Feature based Identification:
  Detection of objects based on predefined features, e.g. motor identification based on plates, screws
  - Series Monitoring:
  Sequential model inference to support processes like packaging or assembly

- Automized model inference and result processing possible, e.g. via SINUMERIK or Rest API
- Documentation of camera images and corresponding results for reporting

→ Benefit from state of the art technology in the machine tool and its surrounding

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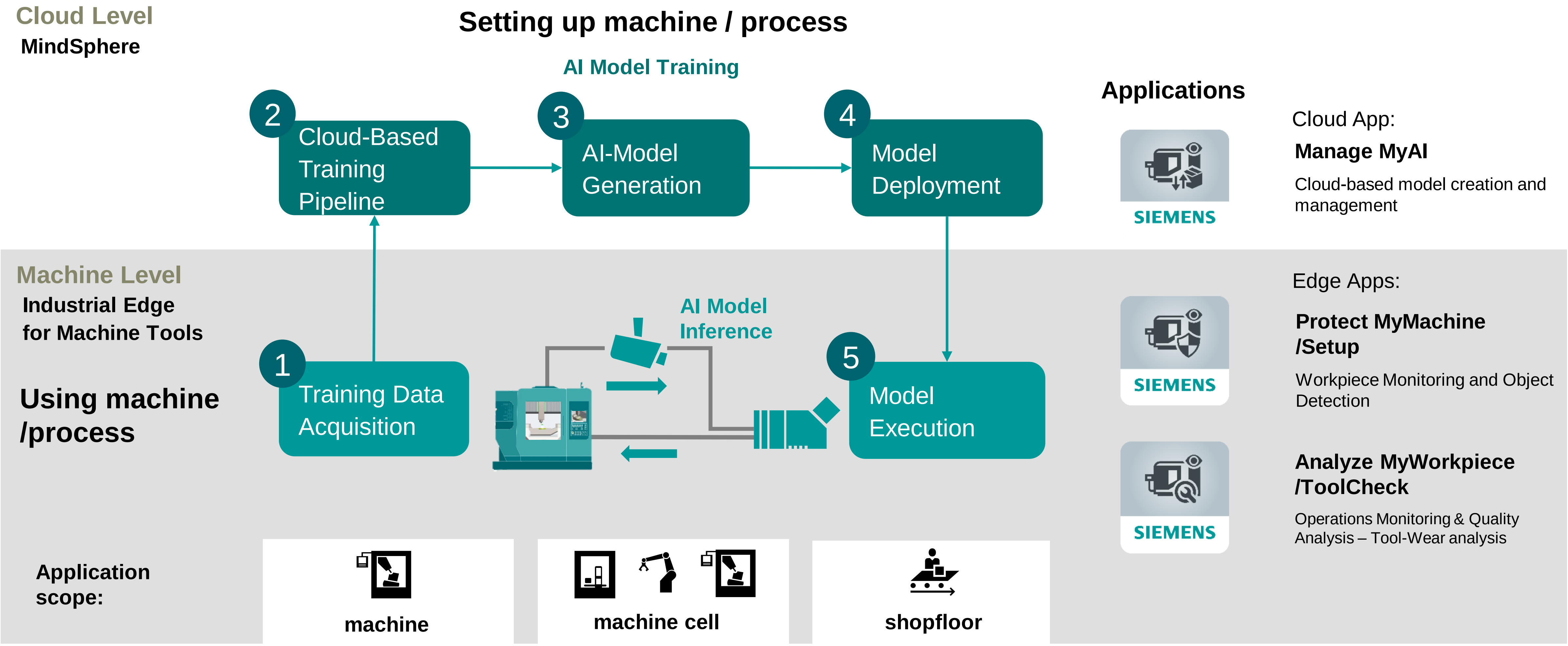
How can a closed loop ecosystem enable AI model training and deployment?



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Machine Protection with Protect MyMachine /Setup

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Use cases

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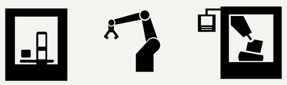
Visual Machine Awareness

Protect MyMachine /Setup - Use Case Overview

- Workpiece Identification
- Workpiece Verification
- Workpiece Rotation Verification
- Workspace Monitoring
- Anomaly Detection in Assembly
- Motor Assembly Support
- Packaging Support

Application scope:



machine cell

machine

shopfloor

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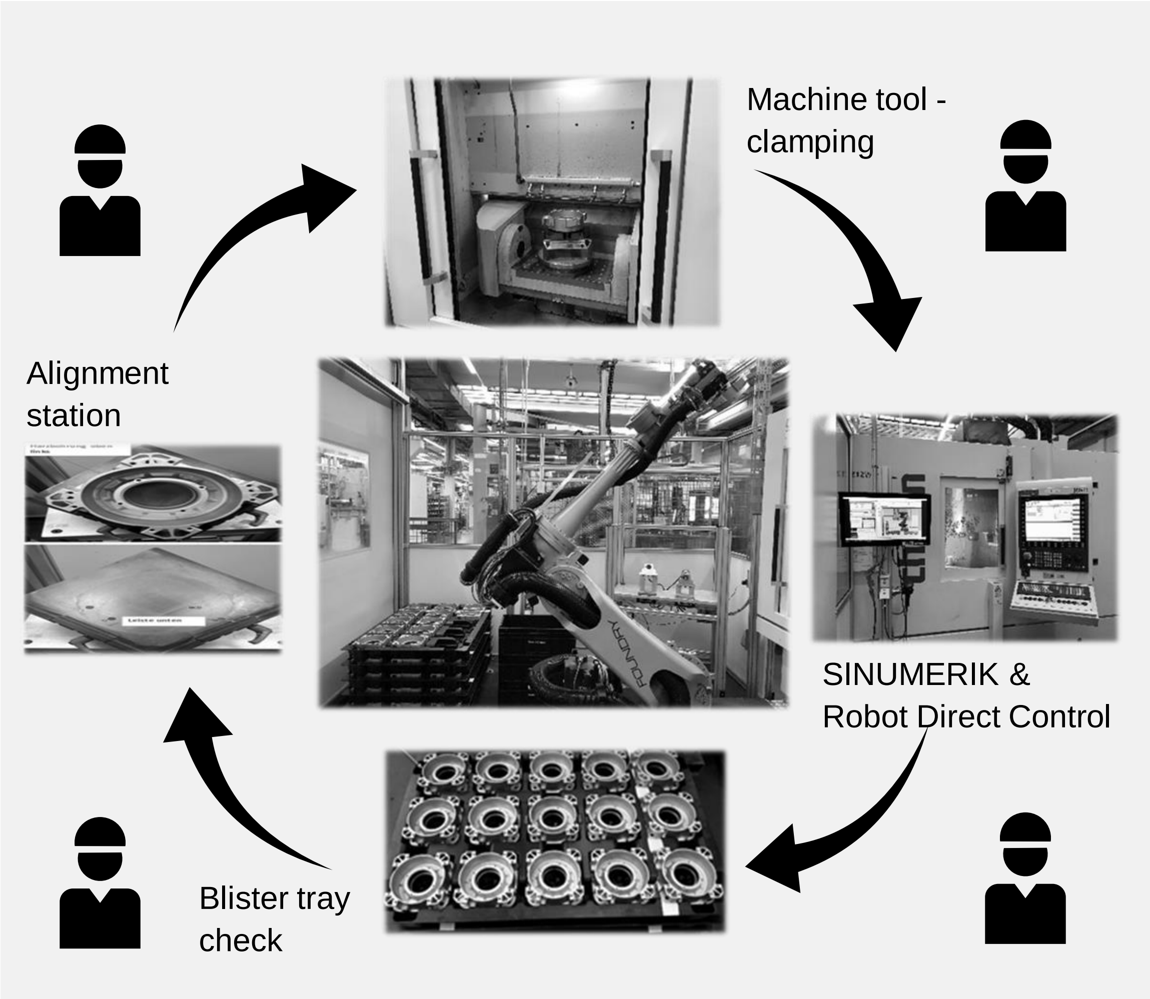
Before: Manual process work causes lag and machine collisions on production machines



Blister Tray Check

Order Scanned

Robot Referenced

Clamping Adjusted

NC-Program called

Workpiece pick and place

Sensor monitoring

CNC Machining

Manually regulated by machine operator.

- **Manual set-up requires approx. 45 min.**
- **Sensor approach is unreliable:**
  - **Long training times and unique features (small holes) can not be detected**
- **Set-up takes ~16% of production time**

Manual process

Automated Process

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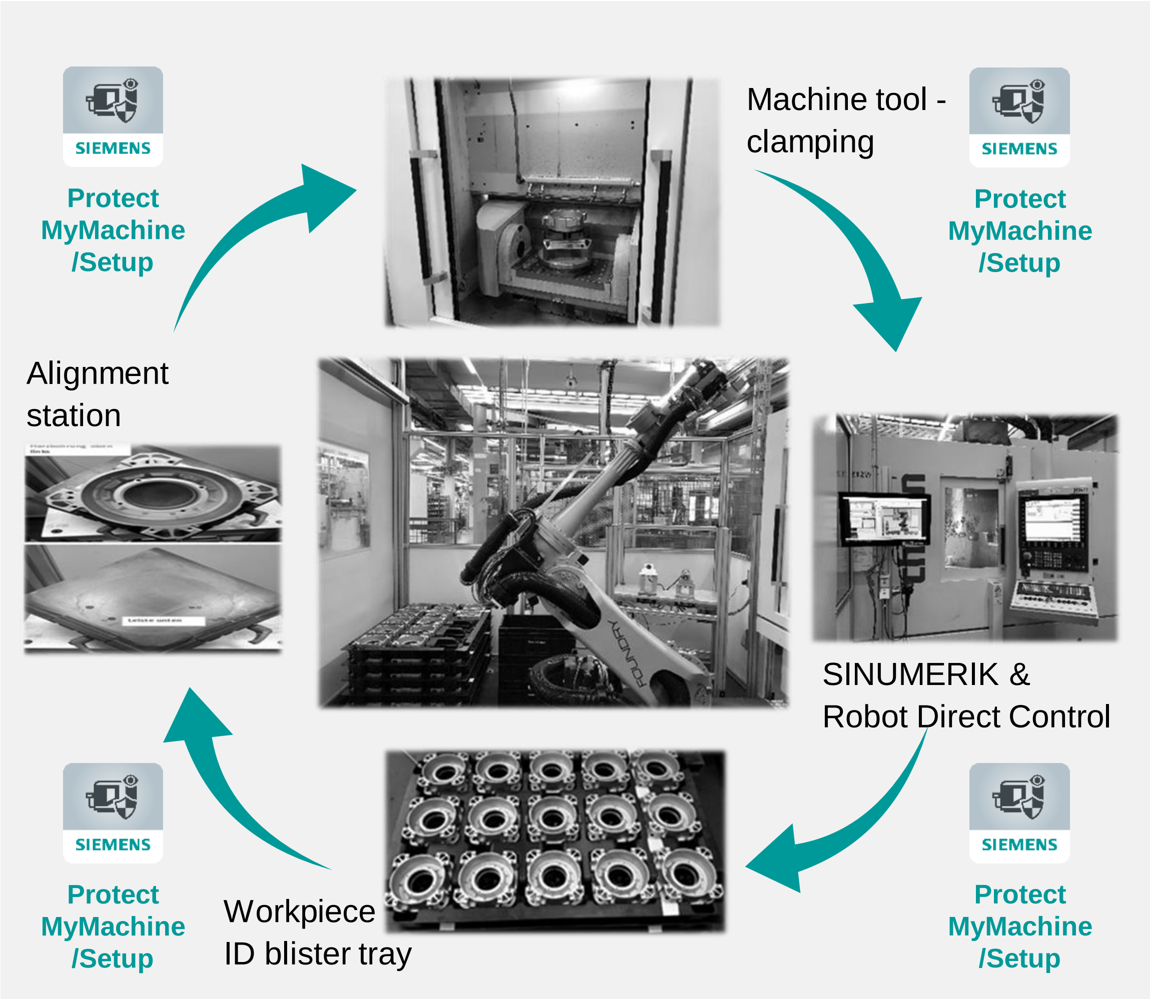
After: Protect MyMachine /Setup enables process automation through secure and reliable visual analytics



- Visual AI Model: Workpiece ID in Blister Tray
- Robot Grip Referenced over MGUD
- Clamping Adjusted by Robot over MGUD
- Visual AI Model: Rotation Check
- Workpiece pick and place
- NC-Program called over MGUD
- CNC Machining

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Protect MyMachine /Setup

Automatically initiated by Protect MyMachine /Setup Supervised by machine operator.

- **Automation can be powered by Protect MyMachine /Setup**
- **Application uses visual analytics AI to train new models**
- **Minimum 16% savings potential + higher process reliability**

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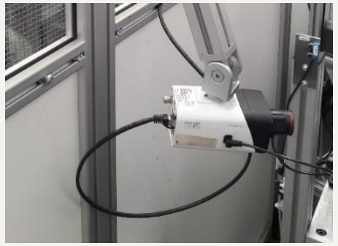
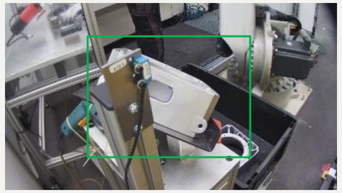
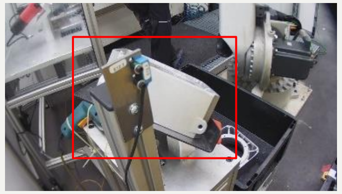
Protect MyMachine /Setup Use Case: Workpiece Identification and Position Verification – robotics automated machine loading

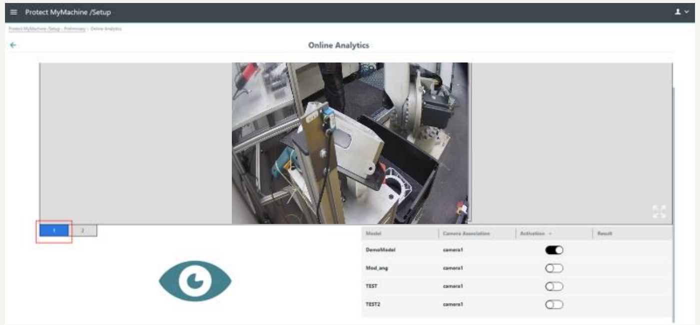
1. Model Training



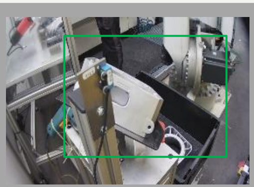




2. Simple Edge-application configuration



3. Environment Deployment



Protect MyMachine /Setup

Workpiece ID / Workpiece Orientation

- Camera live stream in the loading environment
- Detection of workpiece ID and rotation
- Visualization of collected data (process quality, workpiece ID)

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Protect MyMachine /Setup Use Case:
Workpiece Identification – robotics automated machine loading

machine | machine cell | shopfloor

Faster production due to efficient work piece handling

Automatic identification of workpieces to eliminate time consuming manual tasks

CUSTOMER PAIN(S)

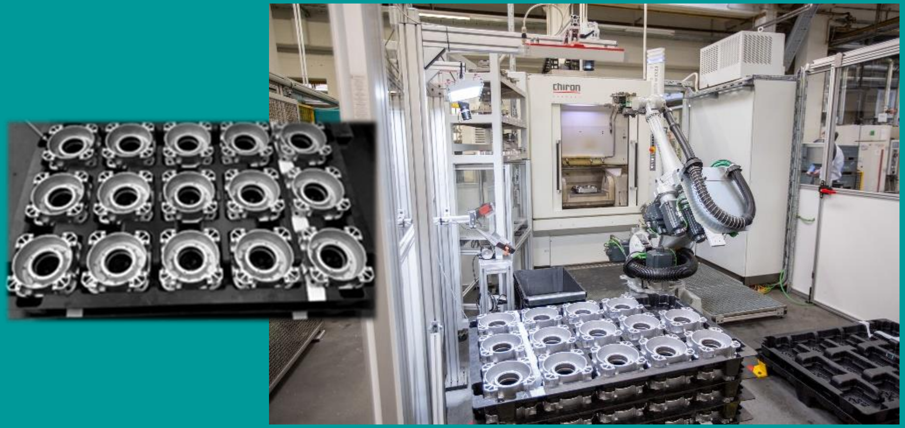
- Several similar looking types of bearing plates are machined
- Manual identification of workpiece type and machine adjustments are time consuming
- The following steps can not be automated because of this manual step
- Total manual handling and process adjustments for new work pieces including positioning and robot referencing take around 45min
- Wrongly identified pieces cause waste or harm the machine

Manage MyAI

Protect MyMachine /Setup

OUR APPROACH

- Using camera based **Protect MyMachine /Setup** Edge App for exact work piece identification
- Newest vision based AI technology trained to the customer use case
- Automized and guided workflow in **Manage MyAI MindApp** for model creation and management



CUSTOMER VALUE

- Automizing the identification and the following handling steps **saves ~16% of production time**
- Approach is directly integrated in handling program
- Freeing time of machinist for more relevant tasks
- Benefits of an AI approach without the need of an AI expert

SIEMENS

Protect MyMachine /Setup Use Case: Assembly Completeness Check

machine cell shopfloor

Ensure proper assembly due to feature based identification

Detection of misassembled pieces

CUSTOMER PAIN(S)

- Several similar looking types of motors are assembled
- Small differences like direction of power supply connection, bearing plate type and mounted screws lead to extremely high numbers of variations
- The motor assembly is challenging and requires precision and expert knowledge
- Sensor or standard vision approach is unreliable because the assembled party vary in size and look

Manage MyAI

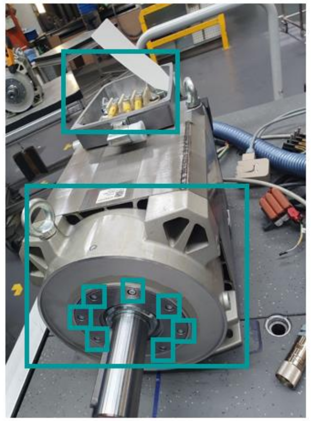
Protect MyMachine /Setup

OUR APPROACH

- Using camera based **Protect MyMachine /Setup** Edge App to teach features and identify objects based on these features
- Newest vision based AI technology trained to the customer use case
- Automized and guided workflow in **Manage MyAI MindApp** for model creation and management

Detected product:
Motor PMMS – 1002-R
MLFB: ABC-12-ABC

Feature details:	
Screw mounted:	7
Gearing plate:	type A
Cover top:	Yes



CUSTOMER VALUE

- Improved quality and reduced scrap rate
- Direct feedback and support to worker via app result visualization
- Easy adaption to new products as feature based approach can differential between similar looking objects
- Benefits of AI without the need to know AI

SIEMENS

Protect MyMachine /Setup Use Case: Sequential Assembly Support

machine cell   shopfloor

Improved quality due to series assembly monitoring

Direct detection of incorrect mounting when it happens

CUSTOMER PAIN(S)

- Incorrect mounting in assembly are often not directly detected
- Missing parts inside the motor can not be detected at EOL quality check
- Malfunction at customer side is expensive, time consuming and damages the reputation
- The motor assembly is challenging and requires precision and expert knowledge
- Sensor or standard vision approach is unreliable because the assembled party vary in size and look

Manage MyAI

Protect MyMachine /Setup

OUR APPROACH

- Using camera based **Protect MyMachine /Setup** Edge App to sequentially monitor the assembly
- Newest vision based AI technology trained to the customer use case
- Automized and guided workflow in **Manage MyAI MindApp** for model creation and management

CUSTOMER VALUE

- Improved quality and reduced later complaints
- 360° inspection of the whole assembly process
- Direct feedback and support to worker via app result visualization
- Easy adaption to new products as feature based approach can differential between similar looking objects
- Benefits of AI without the need to know AI

SIEMENS

Protect MyMachine /Setup Use Case: Workpiece Verification

machine · machine cell · shopfloor

Machine and tool protection due to workpiece identification

Automatic identification of workpieces to ensure proper machining

CUSTOMER PAIN(S)

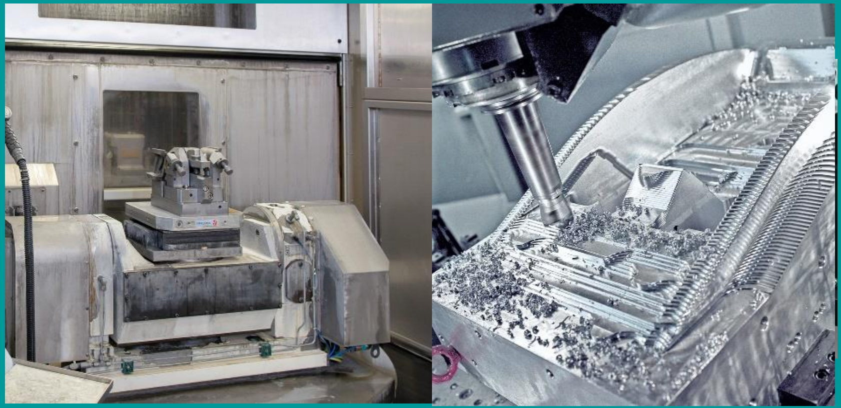
- Different workpieces require different machining with expensive high precision spindle
- Manual selection of CNC program based on workpiece requires expert knowledge and is error-prone
- Wrongly selected CNC program can cause waste and production stop due to machine and tool damage

SIEMENS **Manage MyAI**

SIEMENS **Protect MyMachine /Setup**

OUR APPROACH

- Using camera based **Protect MyMachine /Setup** Edge App to verify workpiece and selected CNC program
- Newest vision based AI technology trained to the customer use case
- Automized and guided workflow in **Manage MyAI MindApp** for model creation and management



CUSTOMER VALUE

- Protection against expensive machine and spindle damages by verifying the machinists work
- Avoidance of downtime und waste
- Seamless integration of verification step in G-code and automation
- Benefits of an AI approach without the need of an AI expert

SIEMENS

Protect MyMachine /Setup Use Case: Workpiece Rotation Verification

machine | machine cell | shopfloor

Avoiding machine downtimes due to workpiece rotation verification

Analysis of workpiece rotation to ensure product quality

CUSTOMER PAIN(S)

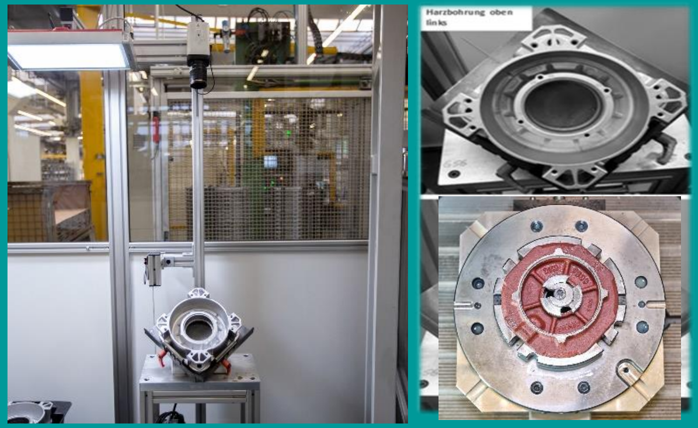
- Workpieces are almost rotational symmetric
- Proper rotation is hard to detect for machinists
- Sensor approach is unreliable: Long training times and unique features (small holes) can not be detected
- Wrongly rotated pieces are waste and must be eliminated by a second manual check after processing

Manage MyAI

Protect MyMachine /Setup

OUR APPROACH

- Using camera based **Protect MyMachine /Setup** Edge App for workpiece rotation verification
- Newest vision based AI technology trained to the customer use case
- Automized and guided workflow in **Manage MyAI MindApp** for model creation and management



CUSTOMER VALUE

- Minimization of production waste
- Freeing time of machinist for more relevant tasks
- Approach is integrated in handling program for optimal automation
- Possibility to integrate several use cases in one step, like a **rotation verification and workpiece identification**

SIEMENS

Customer benefits

SIEMENS

Unique Selling Points
Why select these applications, instead of other computer-vision approaches?

Built-in monitoring integration with controls – direct results transfer to shopfloor

Closed loop workflow directly creating and delivering AI models for multiple use cases

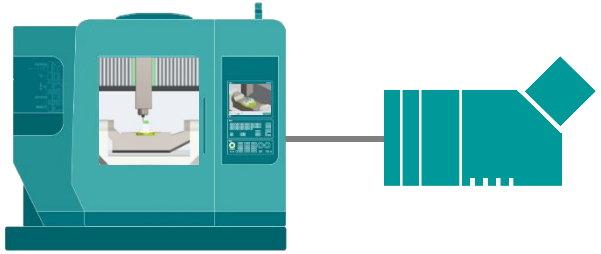
Reduced model training time via synthetic data inputs, integrated within industrial processes

SIEMENS

Process Quality Monitoring

Configure near-realtime process quality monitoring
to enable 100% test coverage

1 Record high frequency data of in-spec process runs

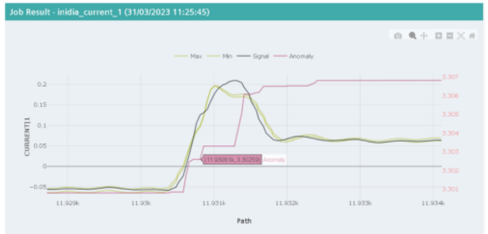


This reference data should reflect the acceptable behavior of the manufacturing process.

2 Specify a signal for which a monitoring model shall be created

The applications automatically generates a monitoring model based on the 6-sigma training concept.

3 Set up a monitoring job for production



Data points outside the model bounds are reported as anomaly. In case of “false positive” results the model can be easily updated without running the training pipeline.

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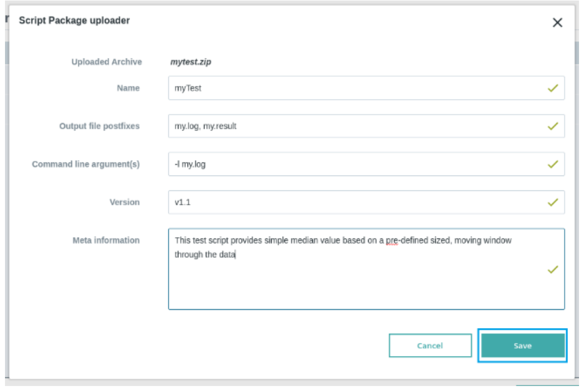
Custom Algorithm Executor (CAE)

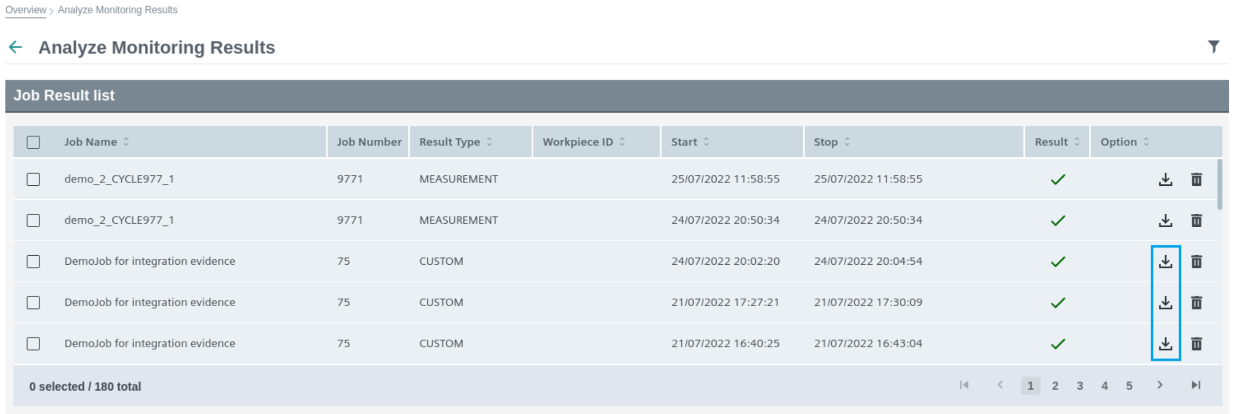
- Secure runtime environment for user-defined data analysis
- Python scripts and Linux executables
- Data provisioning and result reporting managed by host application
- Facilitates rapid implementation of process specific monitoring strategies

1. **Upload algorithm package**



2. **Data processing is triggered according to machining process events.**

3. **Inspect monitoring results**

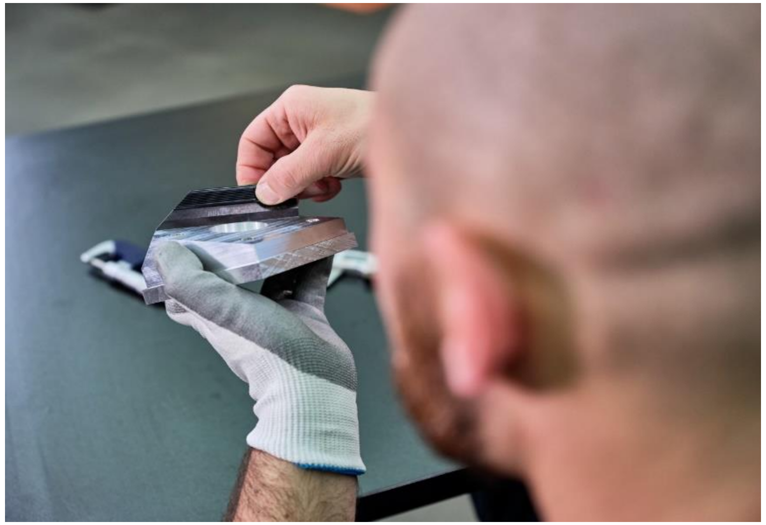


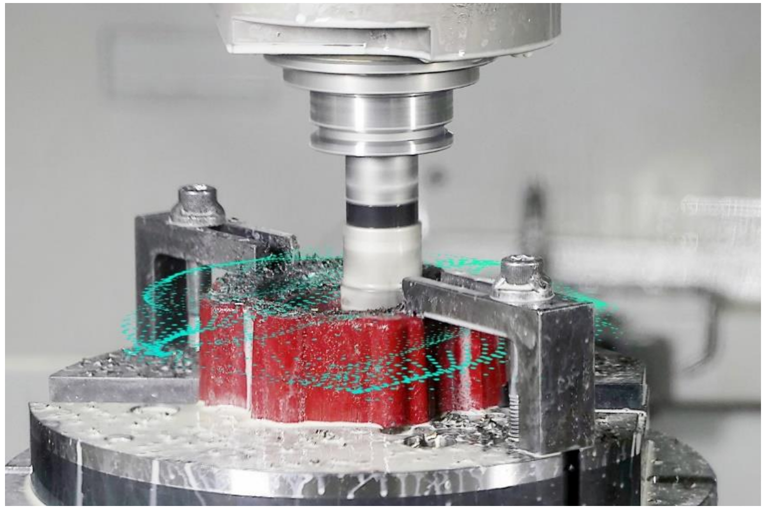
Job Name	Job Number	Result Type	Workpiece ID	Start	Stop	Result	Option
demo_2_CYCLE977_1	9771	MEASUREMENT		25/07/2022 11:58:55	25/07/2022 11:58:55	✓	
demo_2_CYCLE977_1	9771	MEASUREMENT		24/07/2022 20:50:34	24/07/2022 20:50:34	✓	
DemoJob for integration evidence	75	CUSTOM		24/07/2022 20:02:20	24/07/2022 20:04:54	✓	
DemoJob for integration evidence	75	CUSTOM		21/07/2022 17:27:21	21/07/2022 17:30:09	✓	
DemoJob for integration evidence	75	CUSTOM		21/07/2022 16:40:25	21/07/2022 16:43:04	✓	

0 selected / 180 total   1 2 3 4 5

SIEMENS

Use data at the machine to automate processes & ensure in-process quality control





Reduce costs by replacing manual spot checks with a continuous data driven approach.

Early detection of quality problems and saving of follow-up costs through 100% test coverage

Full traceability of production thanks to digital fingerprints of every single workpiece

SIEMENS

Contact

Gus Gremillion
Solutions Consultant – Machine Tool Digitalization
Siemens Industry Software Inc.
+1 (470) 216-3572
august.gremillion@siemens.com

SIEMENS

AI-Enabled Autonomous Optimization for Continuous Manufacturing

Karim Pourak, Co-Founder & CEO
Kamran Paynabar, Ph.D., Co-Founder and CSO

PROCESSMINER™

PROCESSMINER™

Welcome to ProcessMiner™

AI-ENABLED Autonomous optimization for continuous manufacturing

Presenting: Karim Pourak, CEO & Prof. Kamran Paynabar, CSO

PROCESS**MINER** platform

ProcessMiner is an applied AI-driven predictive and prescriptive analytic platform for continuous manufacturing focusing on AUTONOMOUS optimization of:

- **Product Quality**
- **Raw Material Consumption**
- **Downtime Reduction**
- **Sustainability Improvement**

TOP 4 CHALLENGES ALL MANUFACTURERS FACE

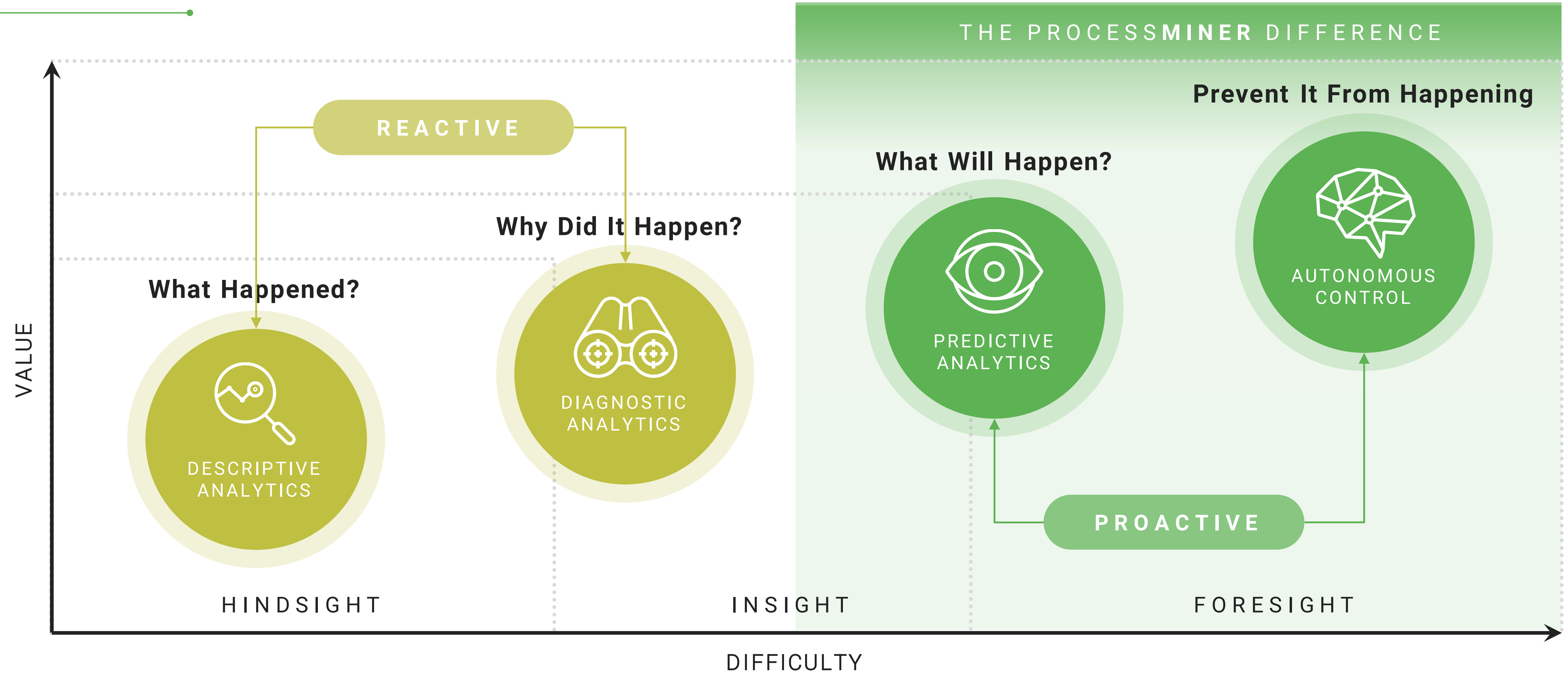
Raw Material Cost

Productivity Gains

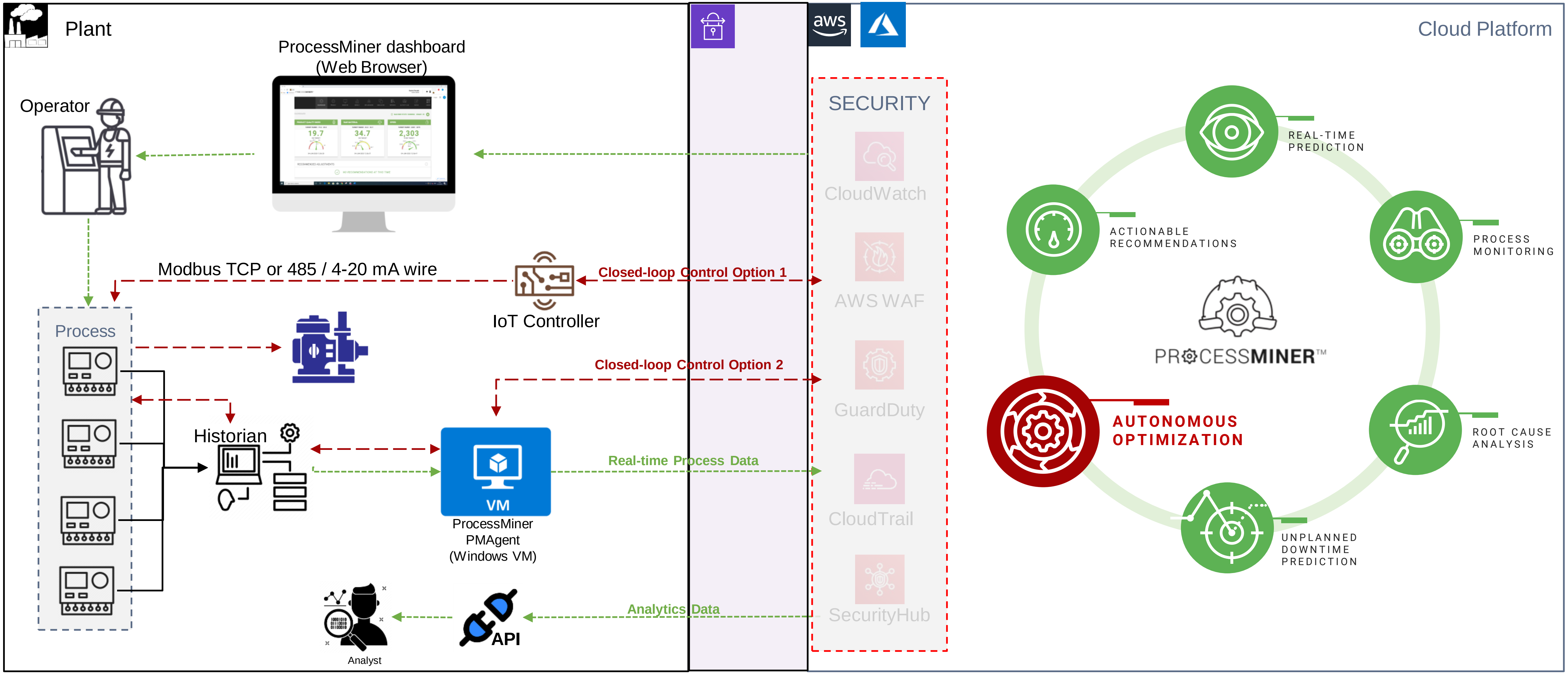
Skilled Labor Gap

Sustainability Goals

PROCESSMINER IS TRANSFORMING THE MANUFACTURING



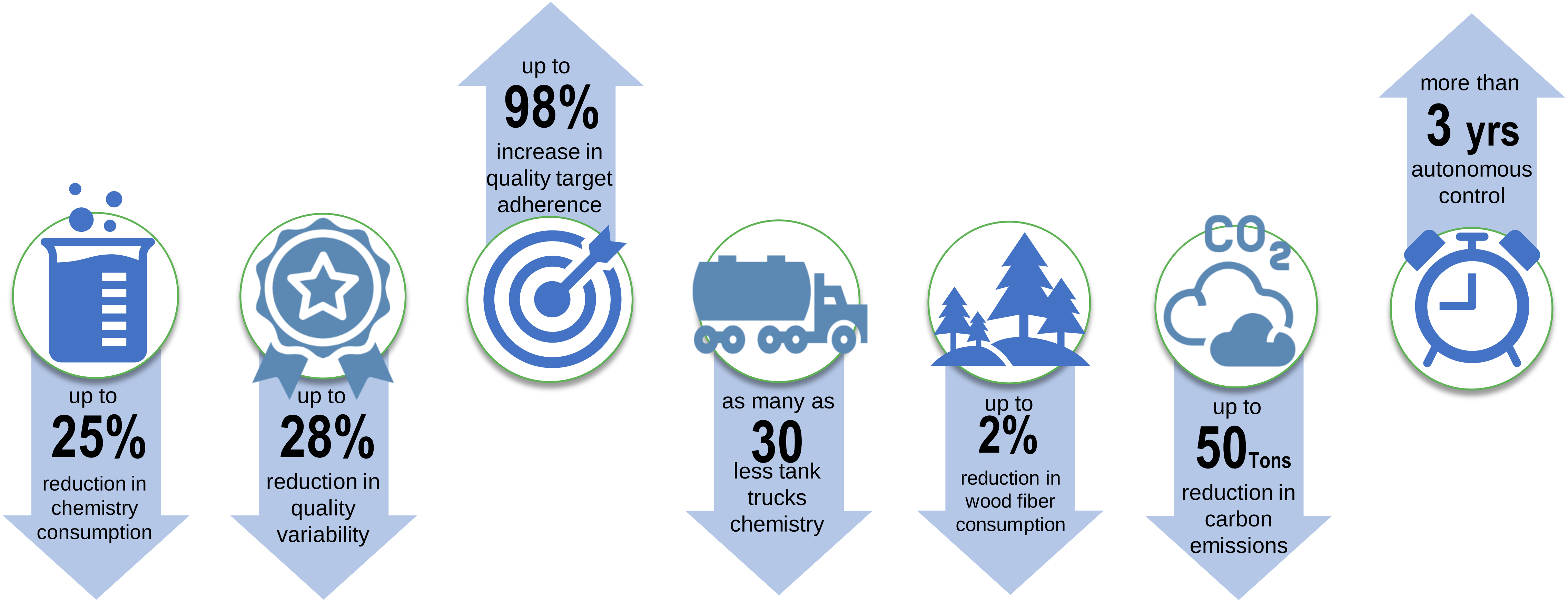
HI-LEVEL ARCHITECTURE ON CLOUD



PROCESSMINER™

DELIVERED BENEFITS OF AUTONOMOUS CONTROL

Several Paper and Tissue mills have been able to achieve one or more of the following (**Annually**):



USE CASE: Paper Mill A

Autonomously Optimized Chemistry Control (Wet Strength)

BACKGROUND

- Goal to reduce raw material consumption
- Maintain target product quality spec limits
- Optimize the dosage of chemistry in the process

CHALLENGE

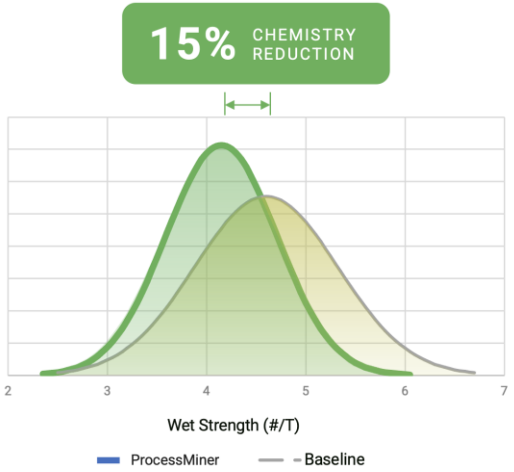
- Reduce raw material consumption while optimizing quality
- Chemistry dosage scheme was inefficient
- Need a real-time autonomous and dynamic solution
- Employee turnover and inexperience impacts consistency

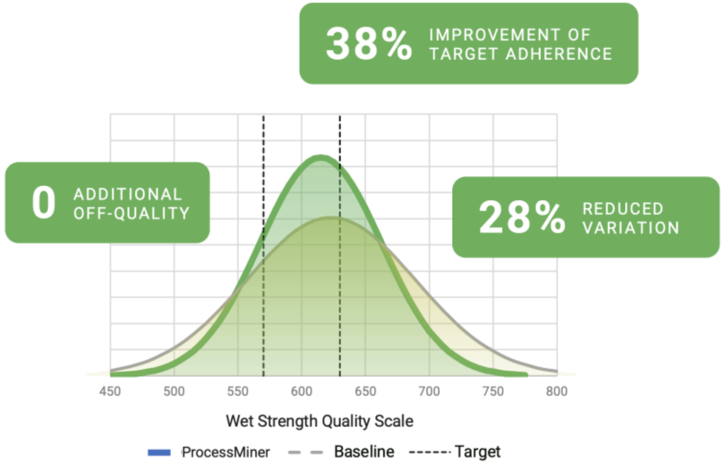
SOLUTION

- Predict and generate closed-loop recommendations to improve quality outcomes
- Use AI to drive optimization of chemistry dosage
- Machine learning ensures the quality measure remains accurate

RESULTS

- 15% Reduction in Chemistry Dosage
- 38% Improvement of Target Adherence
- 28% Reduction in Lab Test Wet Tensile Variation





Value: $500K+ Annual savings per line

PROCESSMINER™

USE CASE: Paper Mill B

Autonomously Optimized Chemistry Control (Wet Strength)

BACKGROUND

- Goal to reduce raw material consumption
- Need to optimize process set points in real-time
- Optimize the dosage of chemistry in the process

CHALLENGE

- Reduce raw material consumption while maintaining quality
- Chemistry dosage scheme was inefficient
- Need a real-time autonomous and dynamic optimization solution

SOLUTION

- Predict and generate closed-loop recommendations to improve quality outcomes
- Use AI to drive optimization of chemistry dosage
- Machine learning ensures the quality predictions remain accurate

RESULTS

25% Reduction in Wet Strength Chemistry Dosage
63% Improvement of Target Adherence
23% Reduction in Wet Tensile Variation

Value: $425K+ Annual savings per line

USE CASE: Plastic Extrusion

Defect and Scrap Reduction:

CHALLENGE

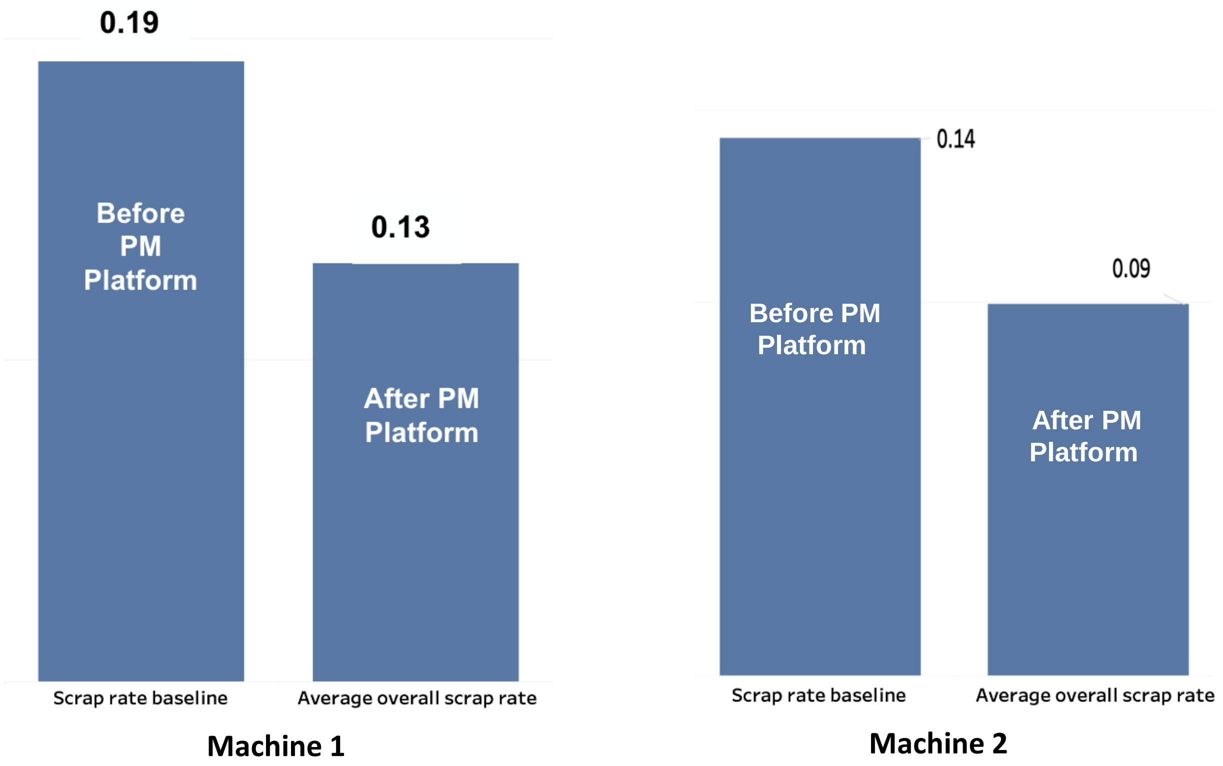
- High Scrap Rates on Medical Viales
- Determining top influencers on scrap as process shifts occur
- Dynamically changing nature of continuous manufacturing presents manual optimization challenges to operators

SOLUTION

- Autonomous Optimization of Plastic SME Knowledge
- Automated Recommendations of dominant parameters
- Providing Operators with the biggest influencers on scrap

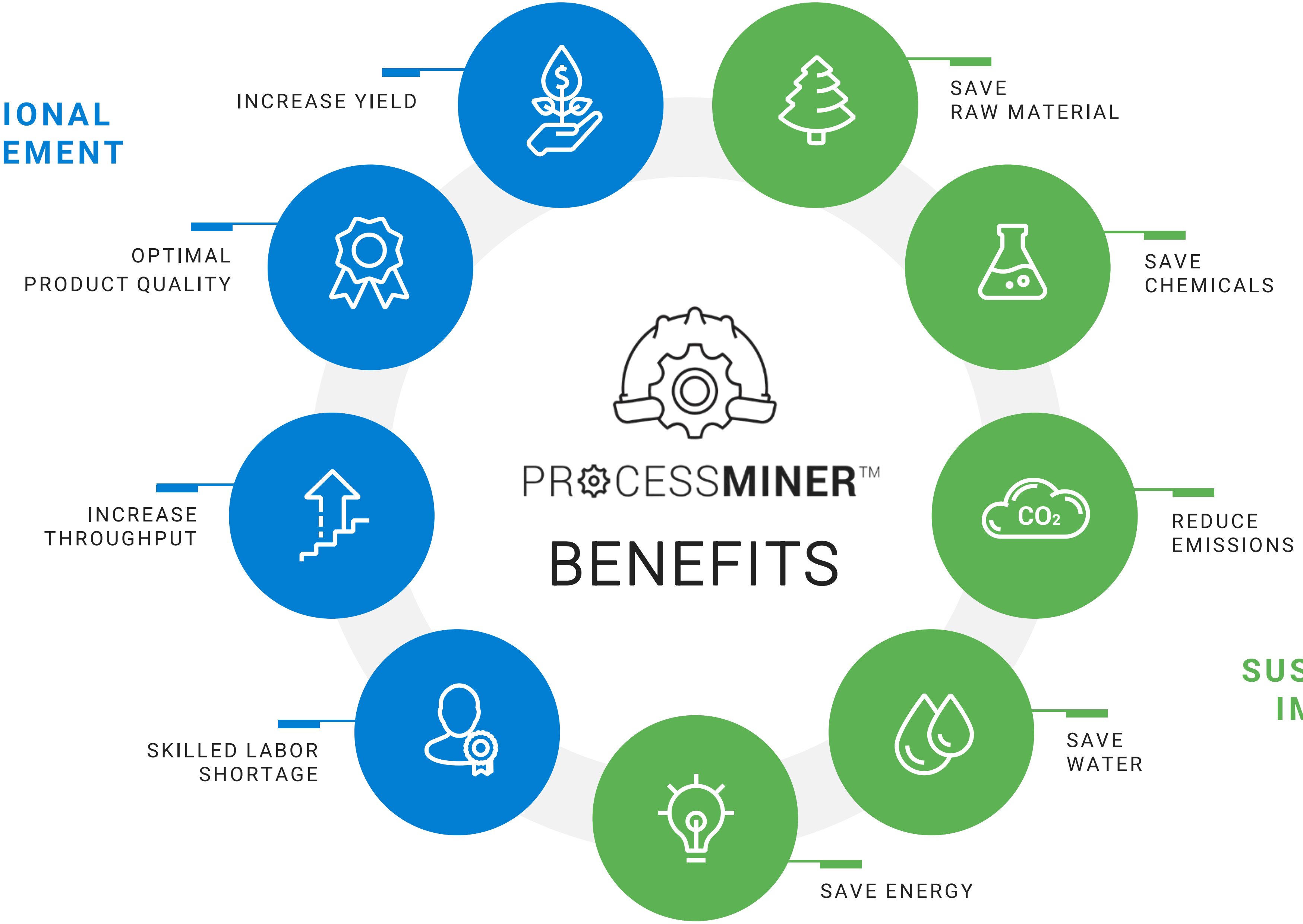
RESULTS

35% reduction in scrapped bottles in 7 months
230K bottles were saved



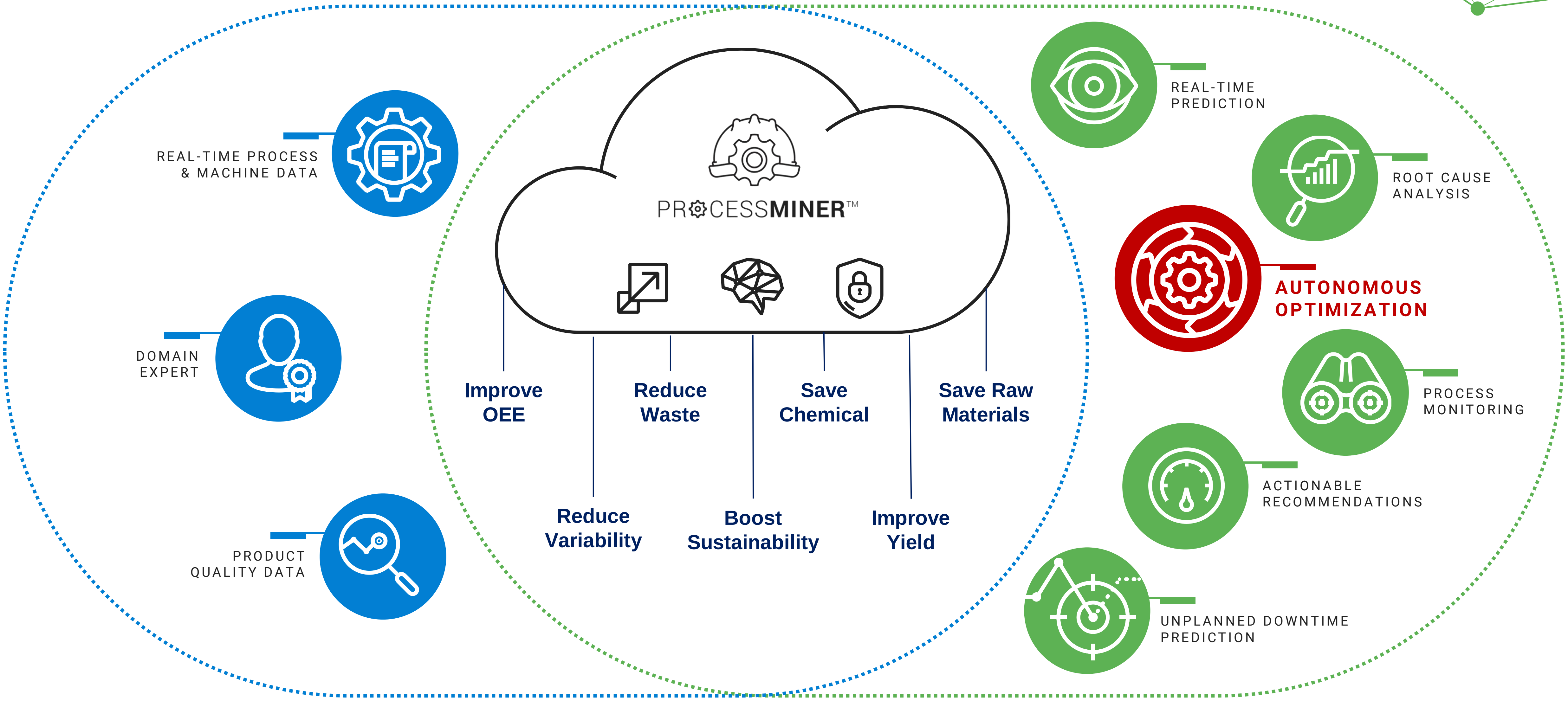
Value: $600k+ annually

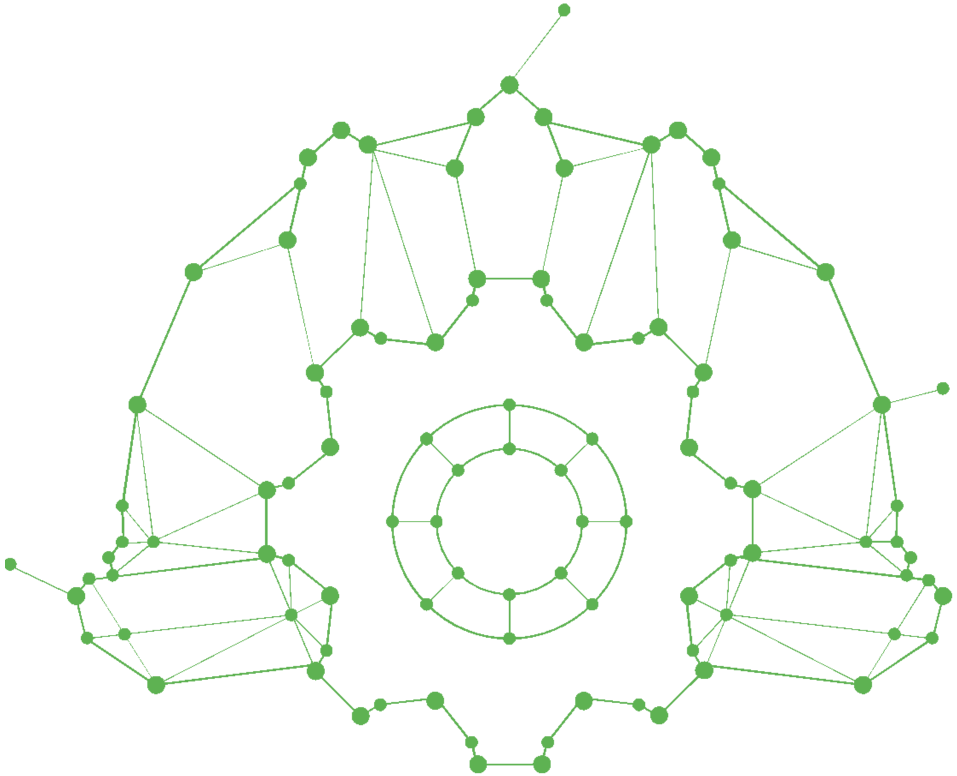
OPERATIONAL IMPROVEMENT



SUSTAINABILITY IMPROVEMENT

PROCESSMINER PLATFORM AT HIGH-LEVEL



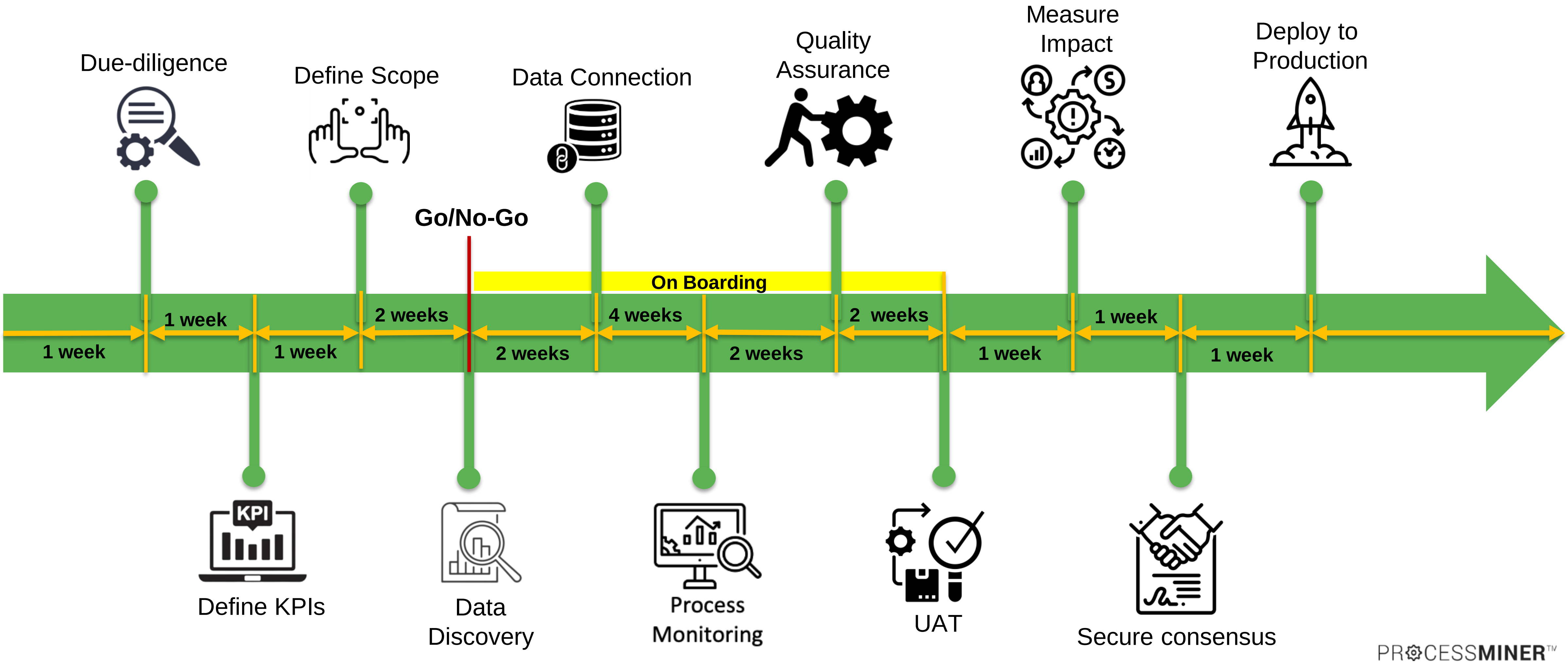


THANK YOU

www.processminer.com

rberman@processminer.com

Proof Of Value Sample Timeline



PROCESSMINER™

Board of advisors with deep domain knowledge

Jeff Fulgham
BUSINESS ADVISOR

Specialty Chemicals

Prof. Kamran Paynabar
CO-FOUNDER AND CSO

AI and Machine Learning

Prof. Chris Luettgen
SCIENCE ADVISOR

Pulp, Paper and Tissue

Prof. Bill Woodall
SCIENCE ADVISOR

Process Monitoring

Dr. Steve Vasconcellos
SCIENCE ADVISOR

Industrial Water

Industry 4.0 AI Forum

Manufacturing Digital Twin Precision Machining Case Study

Professor George Bollas
Director of Pratt & Whitney
Institute for Advanced Systems Engineering

UCONN
SCHOOL OF ENGINEERING

Connecticut Center for Advanced Technology, Inc.

Manufacturing Digital Twin Precision Machining Case Study

Please contact Professor Bollas for questions about his presentation.

George M. Bollas
P&W Endowed Chair Professor – Chemical & Biomolecular Engineering Director
Pratt & Whitney Institute for Advanced Systems Engineering
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utc-iase@uconn.edu
http://www.utc-iase.uconn.edu/

UCONN

Industry 4.0 AI Forum

Hyperdimensional Computing for Near-Sensor Intelligence on Manufacturing Systems

Assistant Professor Farad Imani
Department of Mechanical Engineering

UCONN
SCHOOL OF ENGINEERING

Connecticut Center for Advanced Technology, Inc.

Farhad Imani

Assistant Professor

Department of Mechanical Engineering

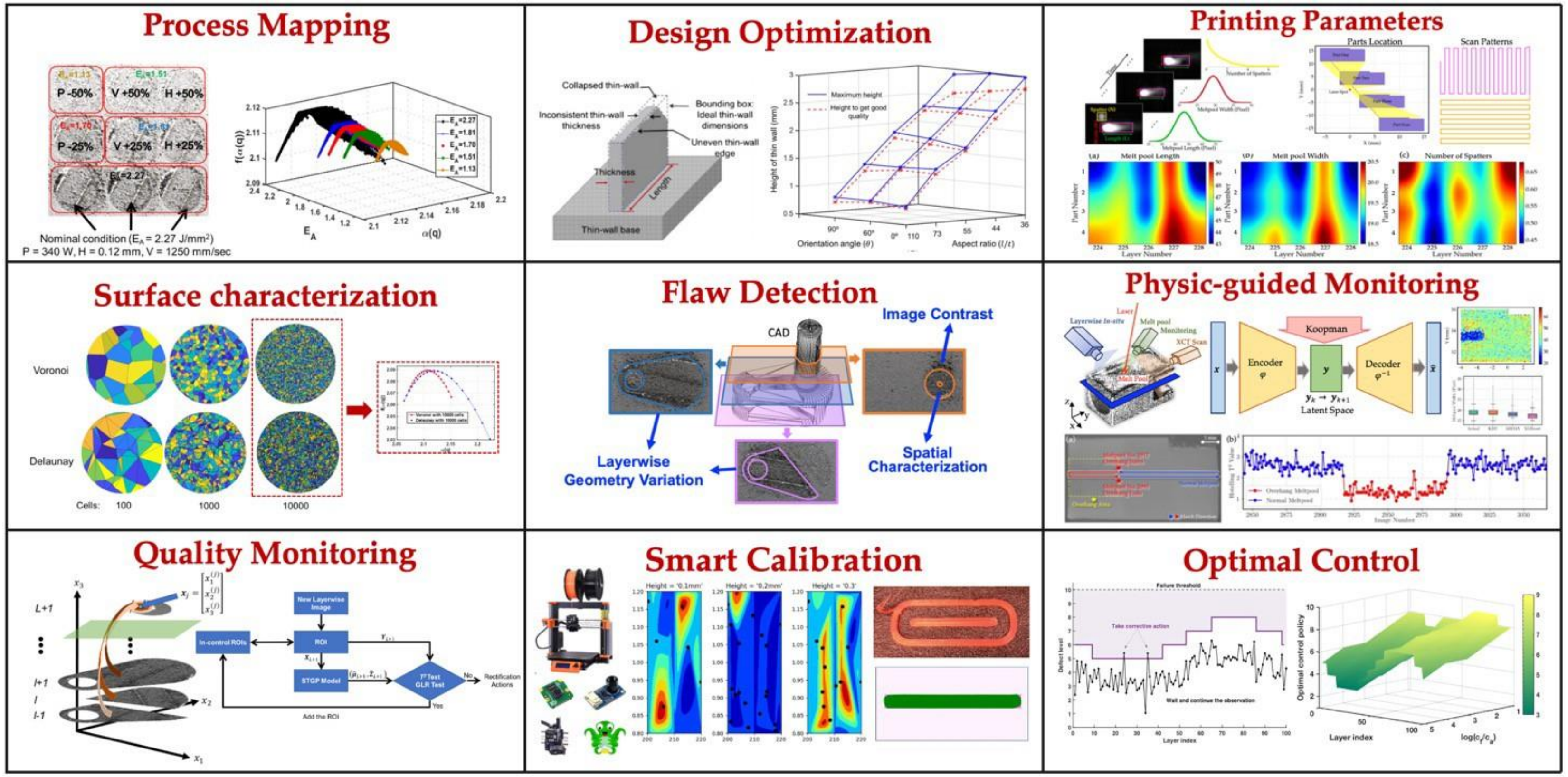
University of Connecticut

June 7, 2023

Intelligent Systems & Control Laboratory (ISCL)

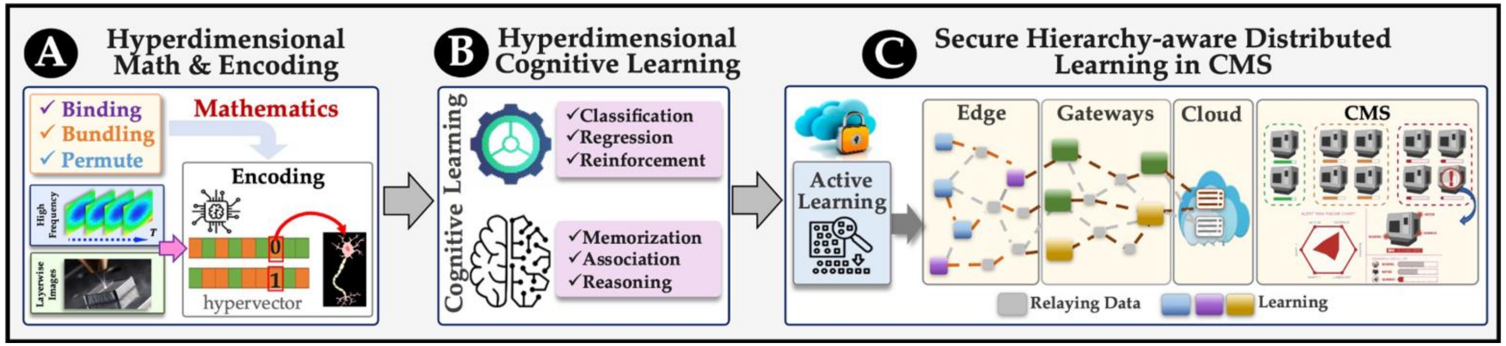
Current Research

- Process Monitoring and Decision Making in Advanced Manufacturing

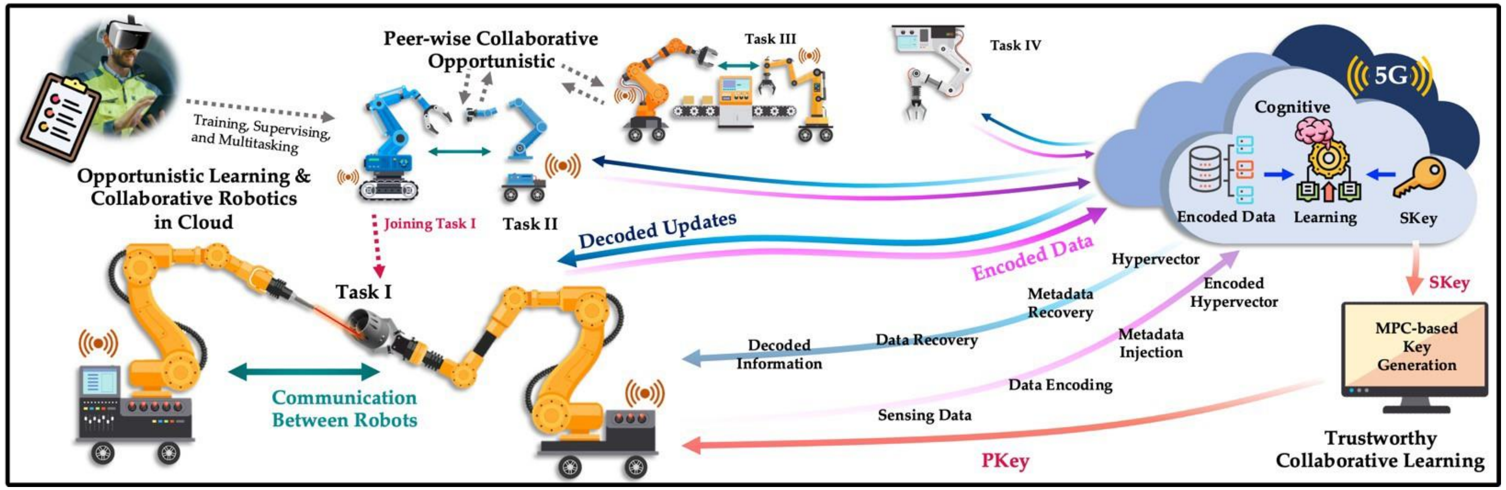


Current Research

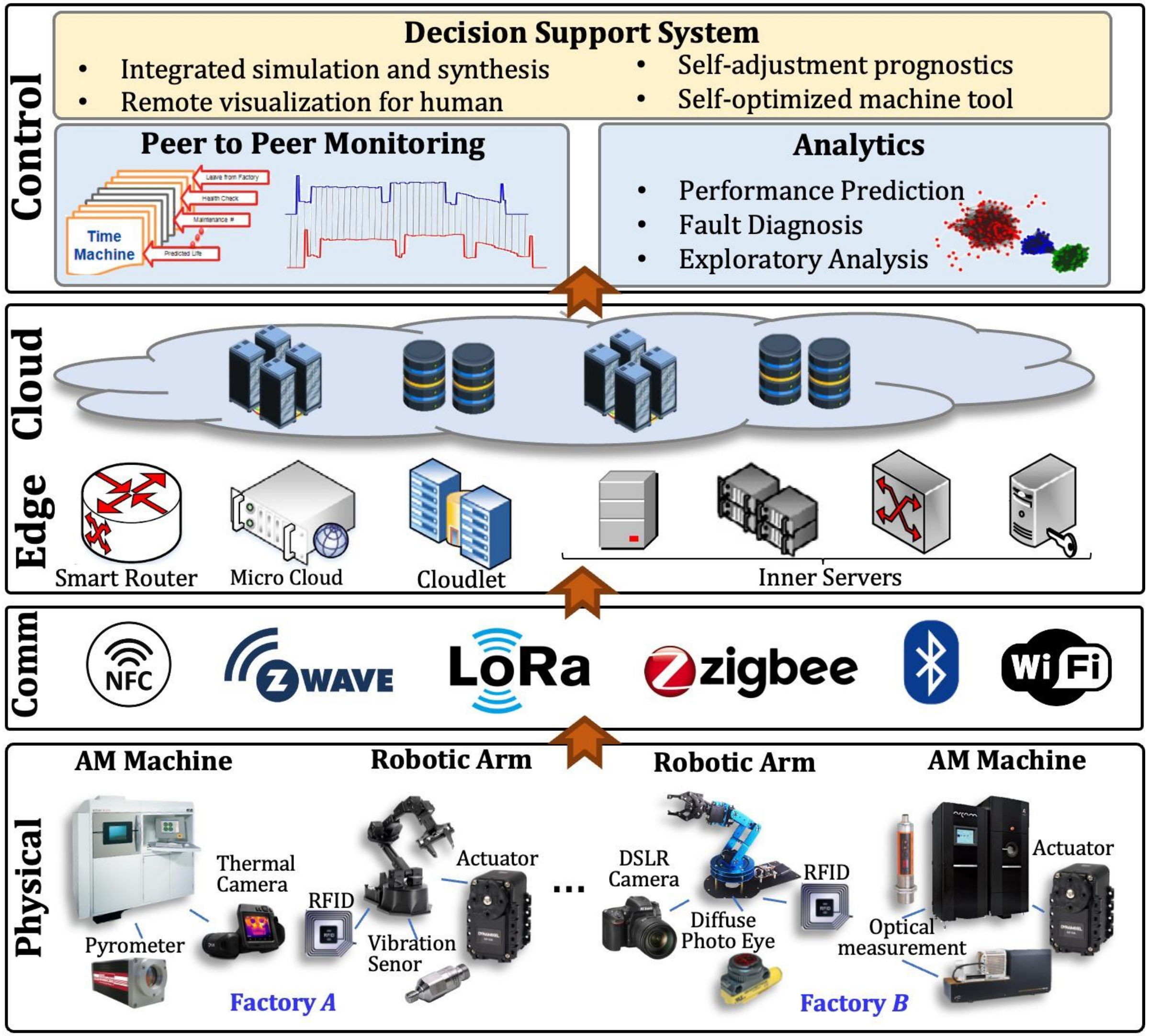
- Cognitive Computing in Cyber Manufacturing



- Collaborative Robotics for Manufacturing

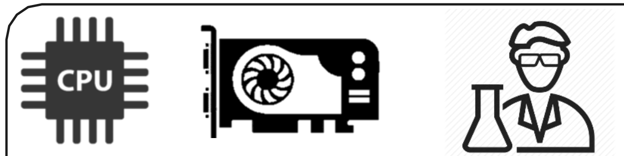


Cyber Manufacturing System



Machine vs Human

AlphaGo



1920X 280X 100X Scientists

1 MWatt, $3000 electric bill/game!

Lee Sedol

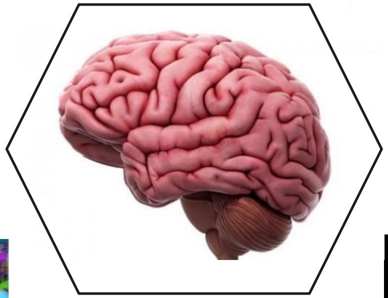
1X 1X 1X

~20W brain or 100W whole body

Google DeepMind

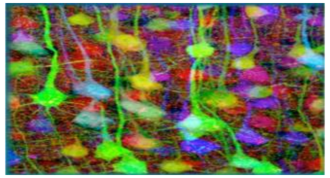
Human Brain Learns Much Better!

Low power
~20 W power consumption



Learning ability
Supervised & unsupervised

Fault tolerance
Noisy input,
Neurons may die



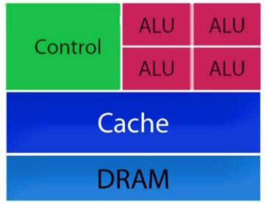
Source: https://steemkr.com

Highly parallel
100 Billion neurons
1000 Trillion synaptic

High power
~KW Power

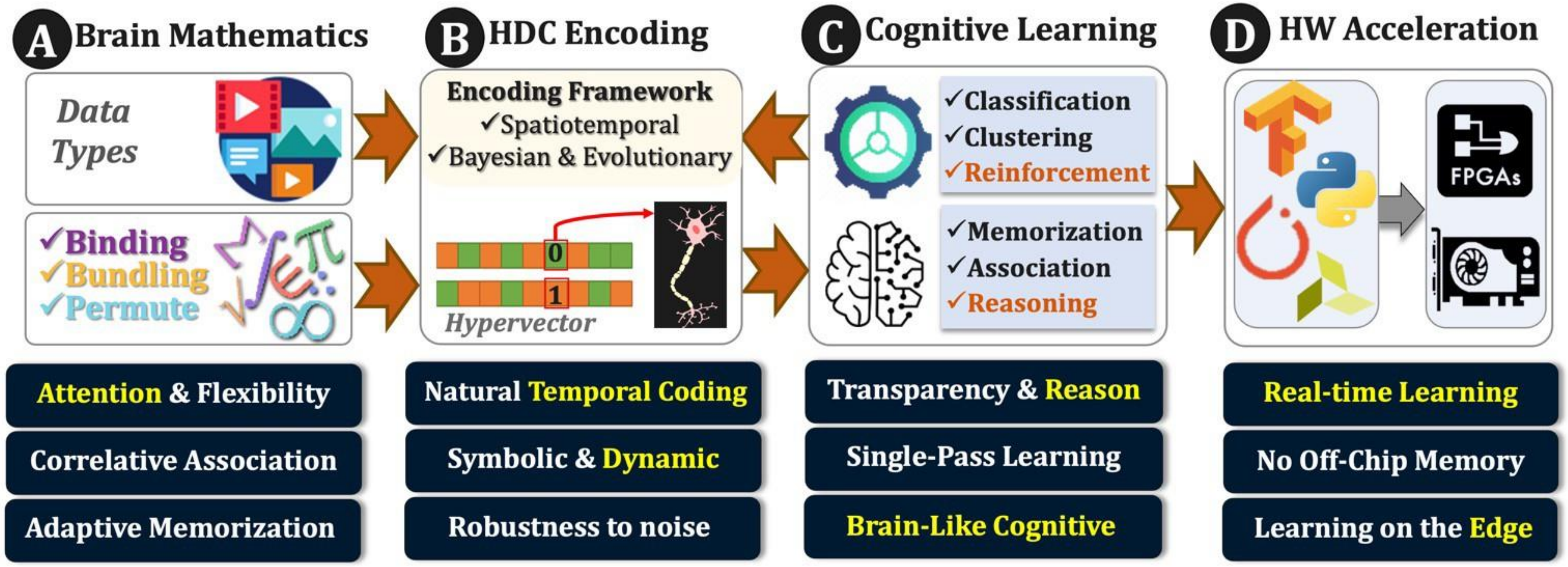
Very slow in learning

Low Robustness
High Variability,
Low SNR



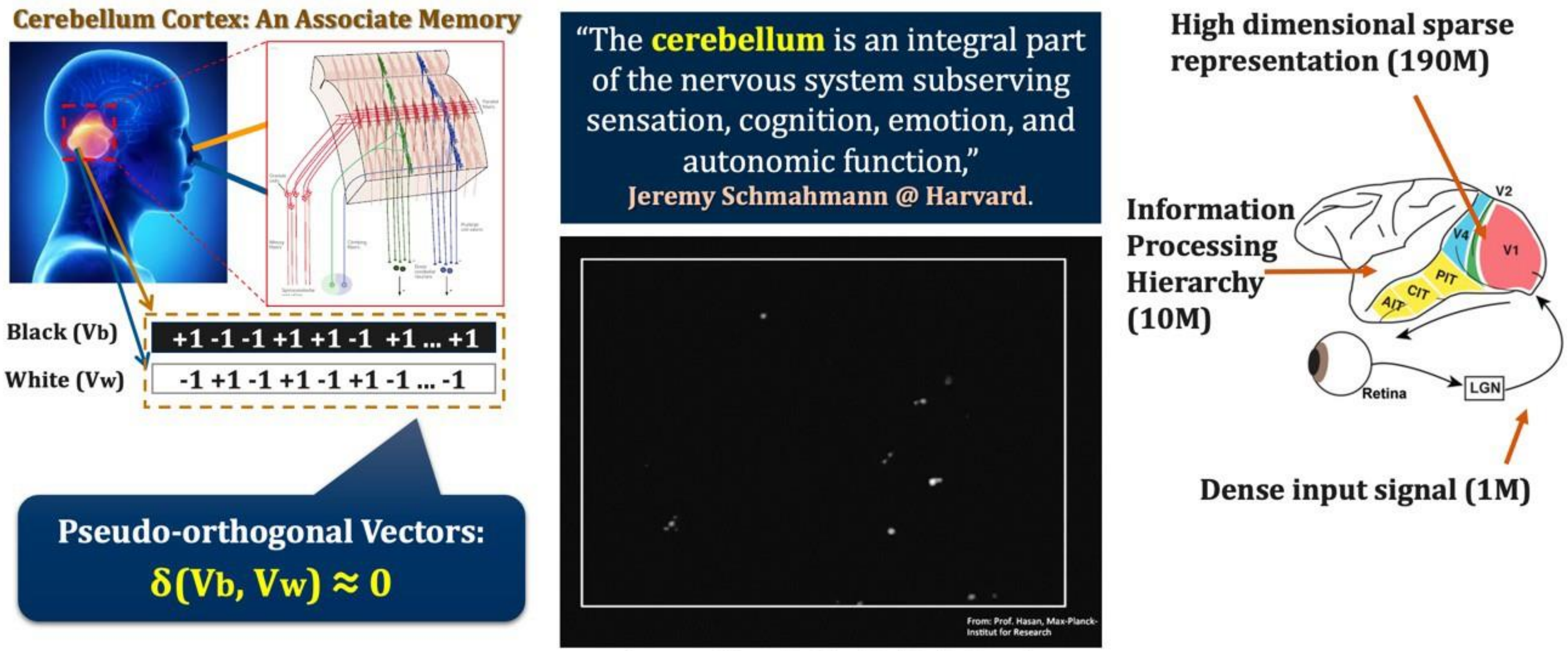
Limited Parallelism
GPU 4000 cores
CPU 100 cores

Brain-like Hyperdimensional (HD) Computing



At least two orders of magnitude higher efficiency, robustness to extreme noise, advanced learnability, and human-like reasoning capability

Brain-inspired Hyperdimensional Computing



Source: prof. Hasan, Max-Planck-Institute for Research

Z. Zou, H. Alimohamadi, A. Zakeri, **F. Imani**, Y. Kim, M. Najafi, and M. Imani, "Memory-inspired spiking hyperdimensional network for robust online learning," Nature Scientific Reports, Vol.3, No. 1, p1-13, 2022.
P. Poduval, A. Zakeri, **F. Imani**, H. Alimohamadi, M. Imani, "Graphd: Graph-based hyperdimensional memorization for brain-like cognitive learning," Frontiers in Neuroscience, Vol. 16, p.5, 2022.

Orthogonality in HD Space

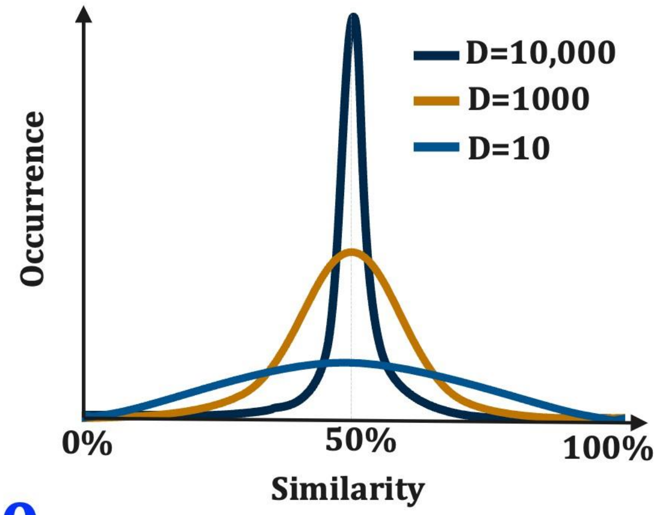
- In High-Dimensions (D»d):
  - Large amount of random vectors are **nearly orthogonal**
  - Orthogonality can be used for **symbolic algebra**

Random Vectors

$$V_1 = [-1\ +1\ -1\ -1\ -1\ -1\ ...]$$
$$V_2 = [+1\ -1\ +1\ +1\ +1\ -1\ ...]$$
$$V_3 = [-1\ -1\ +1\ +1\ -1\ -1\ ...]$$
$$...$$
$$V_p = [-1\ -1\ +1\ -1\ +1\ -1\ ...]$$

$$\xleftrightarrow{\quad D \quad}$$

$$\delta(V_i, V_j) \approx 0$$



R. Chen, M. Imani, and **F. Imani**. "Joint active search and neuromorphic computing for efficient data exploitation and monitoring in additive manufacturing." *Journal of manufacturing processes*, Vol. 71, pp:743-752, 2021.

HD Operations: Bundling

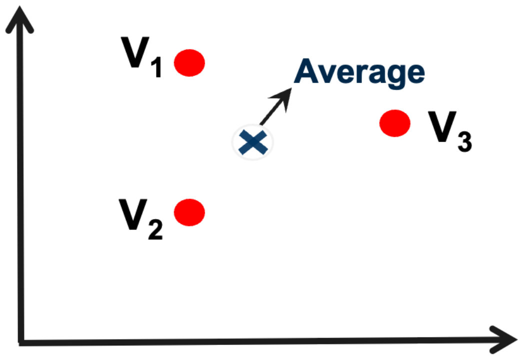
- **Bundling** (+): Represents a set $H = [V_1 + V_2 + V_3]$

D=10,000

V_1 = [−1 +1 −1 −1 −1 −1 −1 ...]
V_2 = [+1 −1 +1 +1 +1 +1 −1 ...]
V_3 = [−1 −1 −1 +1 +1 +1 −1 ...]
V_4 = [+1 +1 −1 −1 −1 +1 +1 ...]

Nearly-orthogonal vectors

$\delta\langle V_i, V_j\rangle \simeq 0$



Bundling is like a memory: remember the input information

$\delta\langle H, V_1\rangle >> 0$

V_1 in H

$\delta\langle H, V_4\rangle \simeq 0$

V_4 in H

HD Operations: Binding

- **Binding** ($*$): Associates two information

$$H = A * R$$

$$A = [-1\ +1\ -1\ +1\ -1\ -1\ -1\ \ldots]$$
$$R = [+1\ -1\ +1\ +1\ +1\ -1\ -1\ \ldots]$$
$$*$$
$$H = [-1\ -1\ -1\ +1\ -1\ +1\ +1\ \ldots]$$

Orthogonal

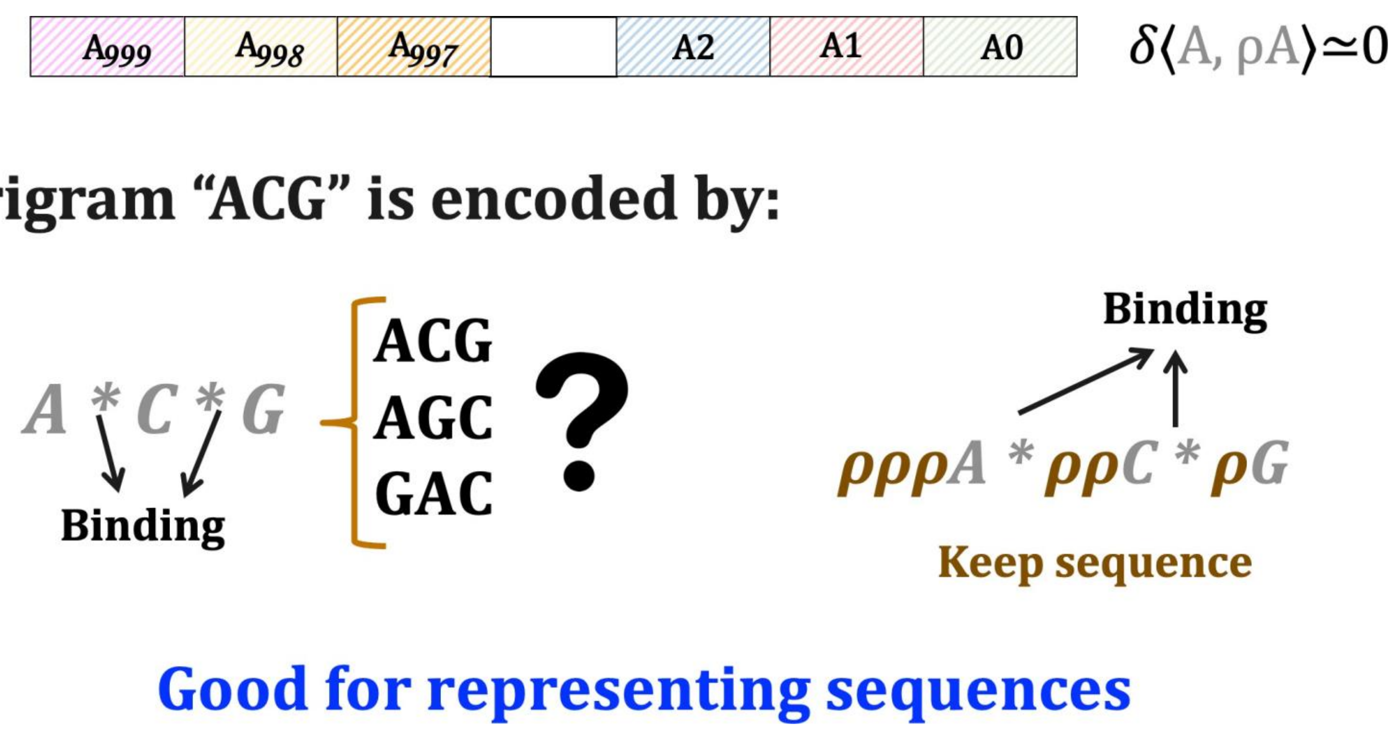
$$\delta\langle H, A\rangle \simeq 0$$
$$\delta\langle H, R\rangle \simeq 0$$

Invertible

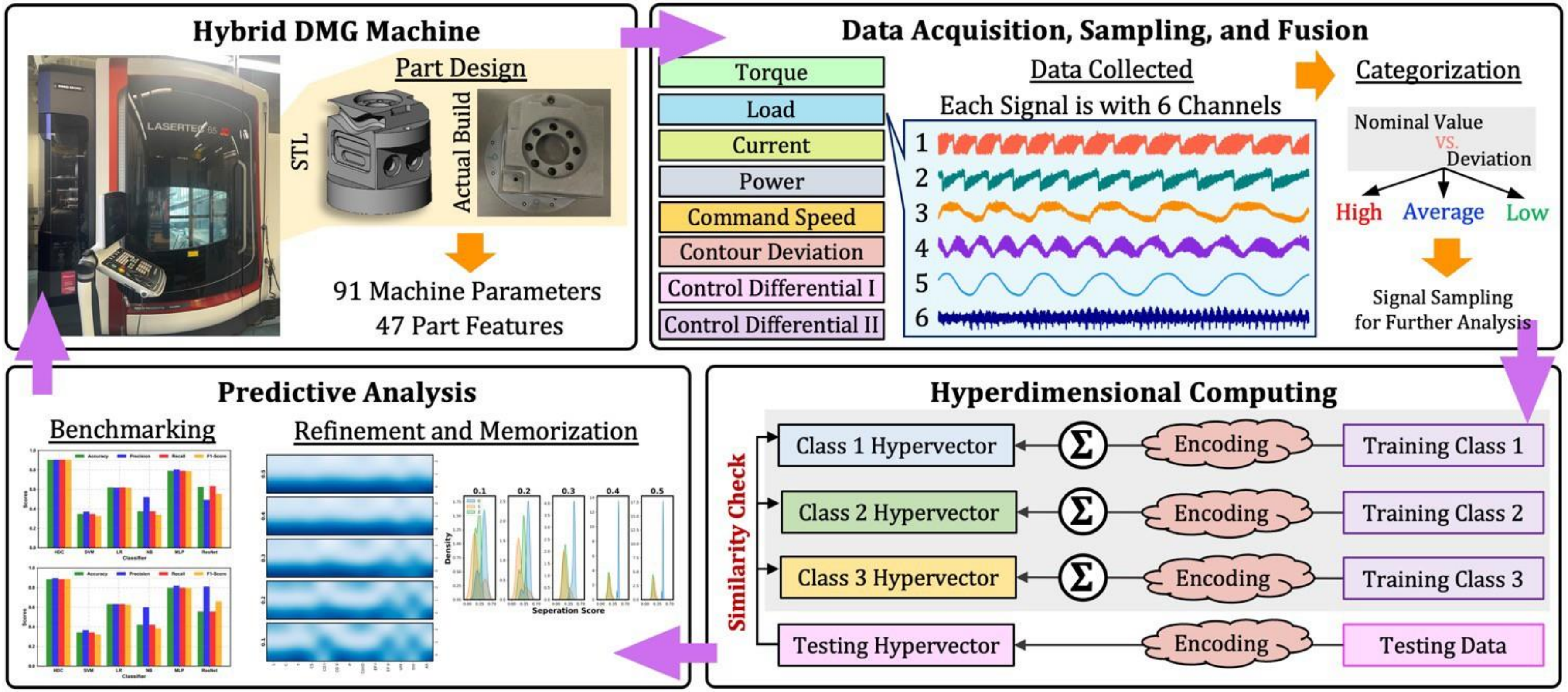
$$H*A=R$$
$$H*R=A$$

HD Operations: Permutation

- **Permutation** (ρ): Makes a dissimilar vector by rotating



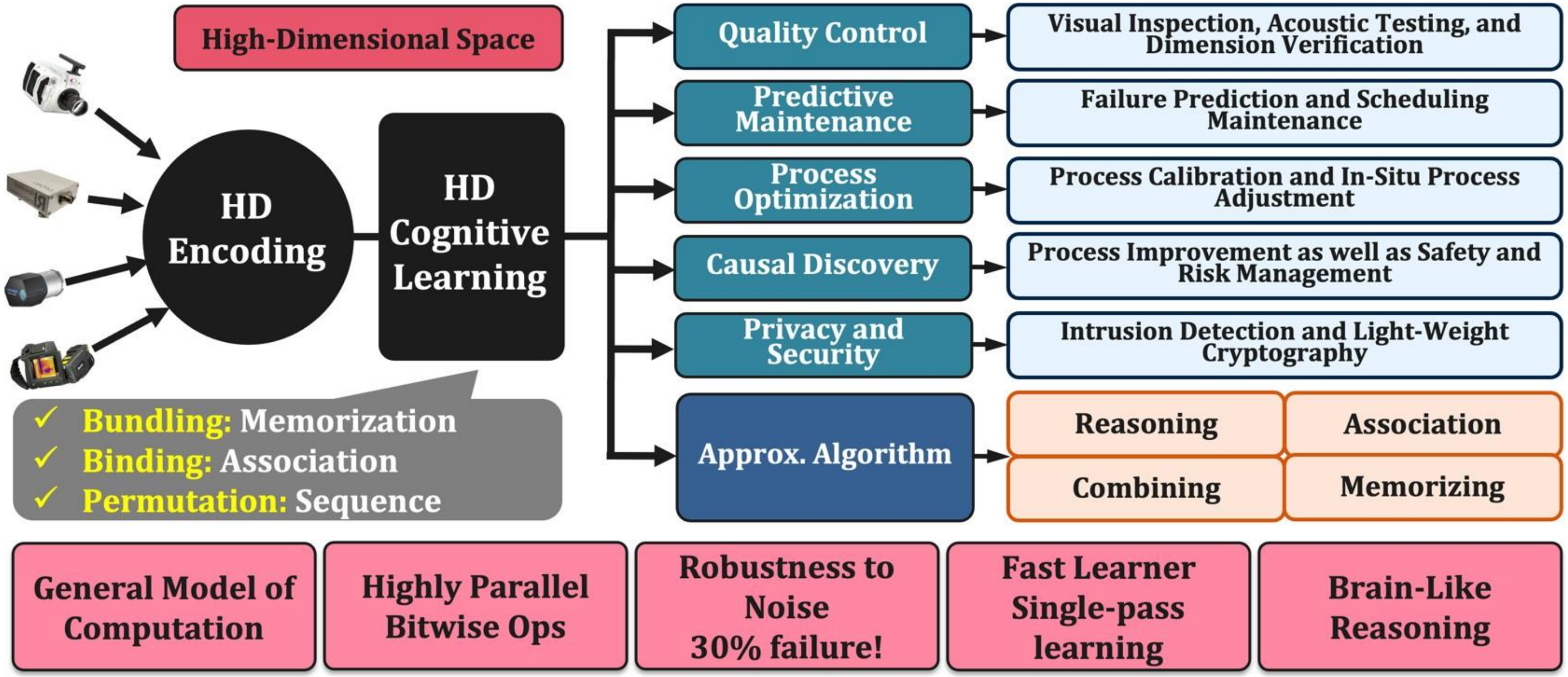
Quality Characterization on Edge



D. Hoang, N. Mannan, R. ElKharboutly, R. Chen, and **F. Imani**, "Edge Cognitive Data Fusion: From In-Situ Sensing to Quality Characterization in Hybrid Manufacturing Process," *ASME Manufacturing Science and Engineering Conference (MSEC)*, 2023. (Accepted)

D. Hoang, N. Mannan, R. ElKharboutly, R. Chen, and **F. Imani**, "Graph-Guided Hyperdimensional Computing for Brain-Like Reasoning in Manufacturing Systems," *Elsevier Journal of Materials Processing Technology*, 2023. (Ready to Submit)

Summary


High-Dimensional Space
HD Encoding
HD Cognitive Learning
Bundling: Memorization
Binding: Association
Permutation: Sequence
Quality Control
Visual Inspection, Acoustic Testing, and Dimension Verification
Predictive Maintenance
Failure Prediction and Scheduling Maintenance
Process Optimization
Process Calibration and In-Situ Process Adjustment
Causal Discovery
Process Improvement as well as Safety and Risk Management
Privacy and Security
Intrusion Detection and Light-Weight Cryptography
Approx. Algorithm
Reasoning
Association
Combining
Memorizing
General Model of Computation
Highly Parallel Bitwise Ops
Robustness to Noise 30% failure!
Fast Learner Single-pass learning
Brain-Like Reasoning

Contact Information

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Software and Physics Based Digital Twin

Zhigang Wang, Senior Principal Engineer,
Raytheon Technologies Research Center




Software and Physics Based Digital Twin

Zhigang Wang

June 7, 2023

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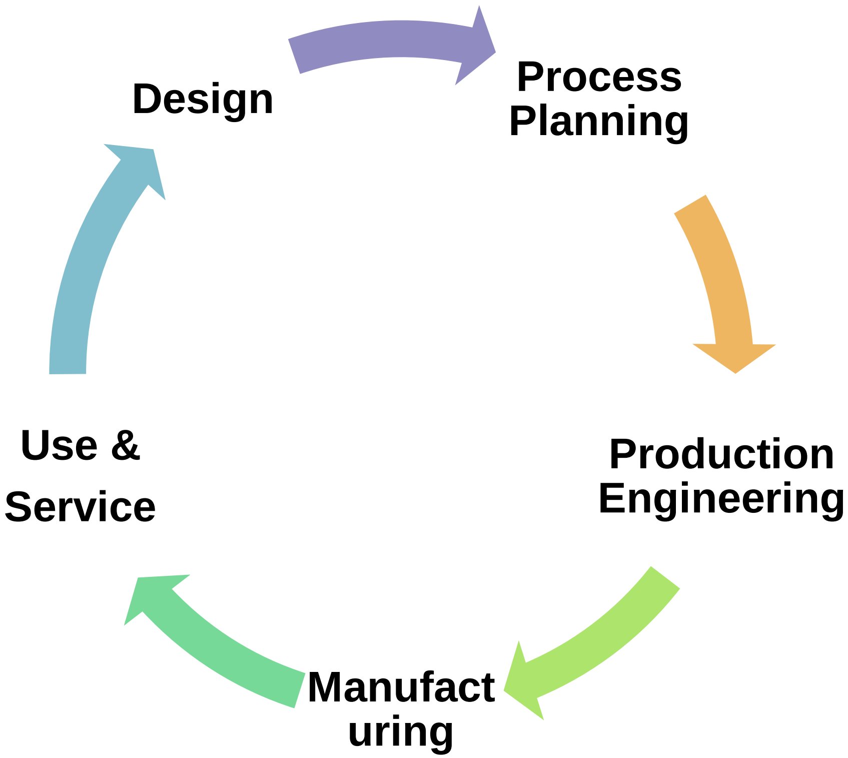
Smart Monitoring and Control of Machining Processes



Product life cycle of traditional manufacturing process (lots of production data), however, limited usage due to no context information to link them.

The most important factor of productivity is reliability.

High cost spent on manufacturing systems maintenance

- **30+% of the operating cost; 60%~75% of the total lifecycle costs (> Initial capital investment)**
- **Unplanned downtime costs an estimated $50 billion each year**
- **Poor maintenance strategies reduce productive capacity ~20%**

Smart Manufacturing: fully digitalized, distributed intelligence, collaborative supply chain, optimal decision making, advanced sensors and big data analytics. -------- NIST

RTX Supplier Health Assessment

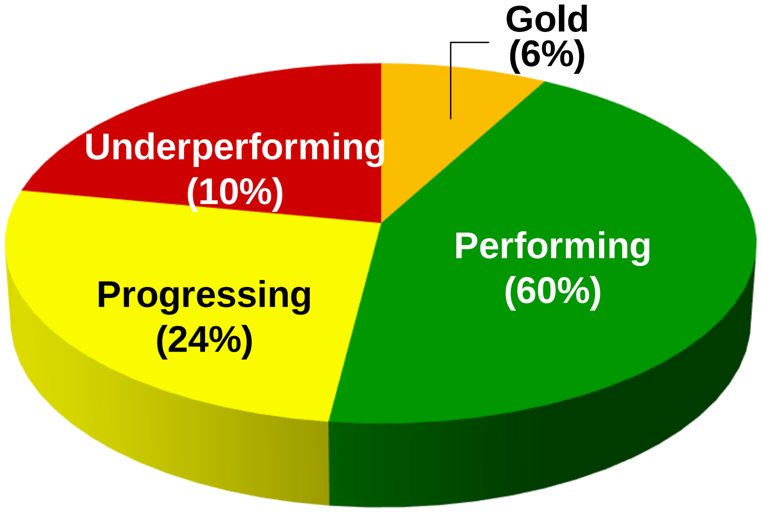
- **Overall equipment effectiveness (OEE) calculation is based on 3 factors: Availability, Performance, and Quality**

A x P x Q = OEE

- **Supply Health Assessment: A structured process to identify risks in the supply base and develop plans to reduce or eliminate them**
  - **Is there a need for change?**
  - **Can the supply base meet expanding demand?**
  - **Do suppliers have the capabilities and capacity?**
  - **Does quality and delivery performance pose a risk to supply?**
  - **Per P&W Middletown control tower metrics in 2017:**
    - **Mean time to respond: 3 hours**
    - **Mean time to repair: 11.4 hours**

  for a typical machine down (unit cost: $500.00 / hour).

2015 UTC Supply Base Performance



Technologies that enables the smart manufacturing

CONNECTED MACHINES	REMOTE MONITORING		PREDICTIVE ANALYSIS	SMART PRODUCTION
Sensors	Network	Integration	Augmented Intelligence	Augmented behavior

Sensors

Built-in sensors
- Existing machine sensors

External sensors
- Temperature
- Vibration
- Amperage

Electrical signals
- All drive axis motor signal
- Encode / scale of each drive axis

Network

Connectivity
- 5G
- Bluetooth
- Wi-Fi
- RFID
- TCP/IP between CNC and PC
- Mobius or High-speed series bus

Integration

Management
- IoT middleware
- Data management

Existing data
- PLC
- CMMS
- ERP
- Data historian
- Industry standards
- Original equipment manufacturer parameters

Augmented Intelligence

Processing
- Event processing

Analytics
- Predictive algorithms
- Failure detection
- Machine learning
- Stream analytics (data in motion)
- Batch analytics (data at rest)

Augmented behavior

Applications / visualizations
- Dashboards / displays
- Integration with legacy software
- Business process management
- Reports

Field service
- Automated maintenance tickets
- Service data log

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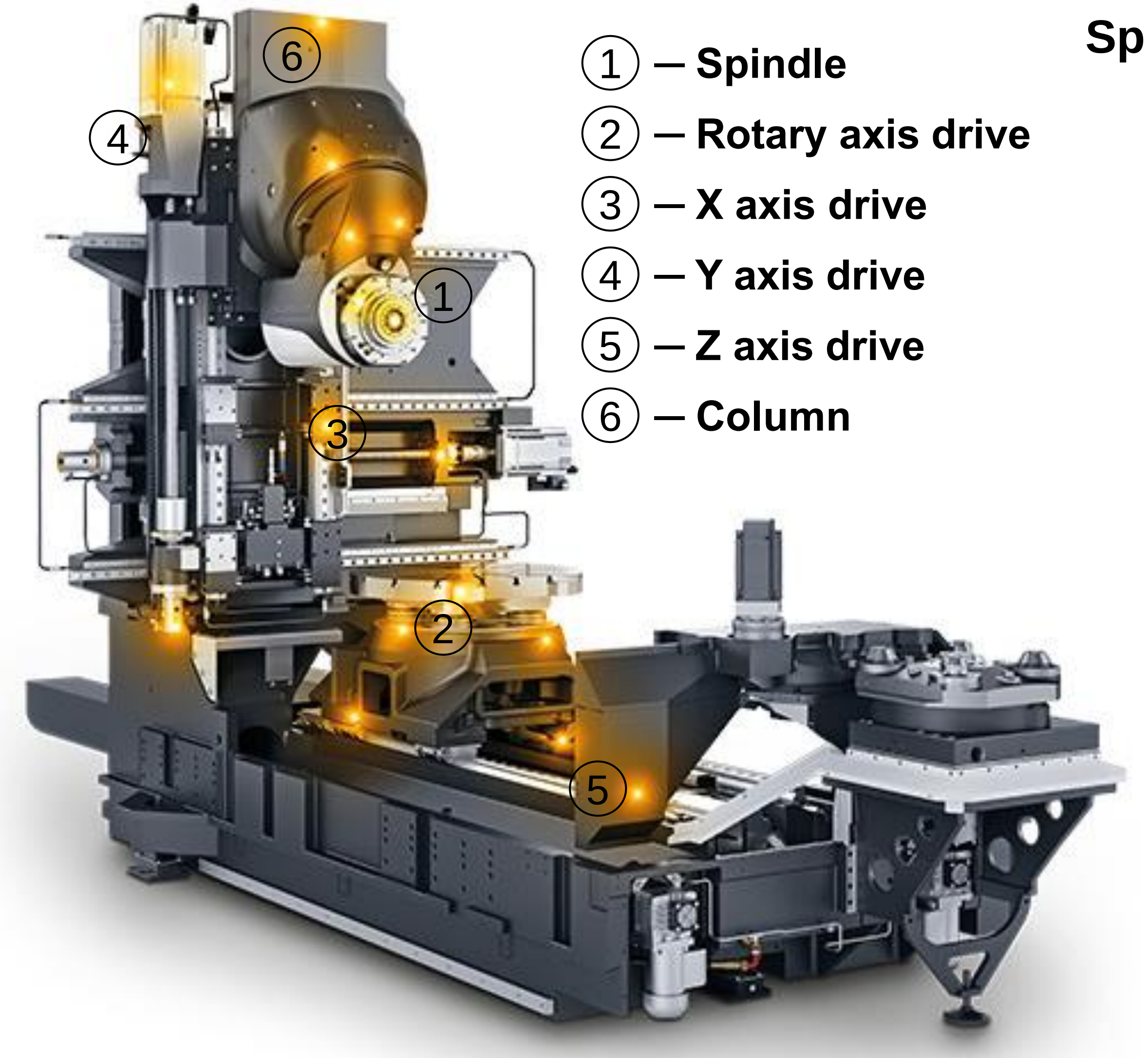
Key components in machine tools to be monitored



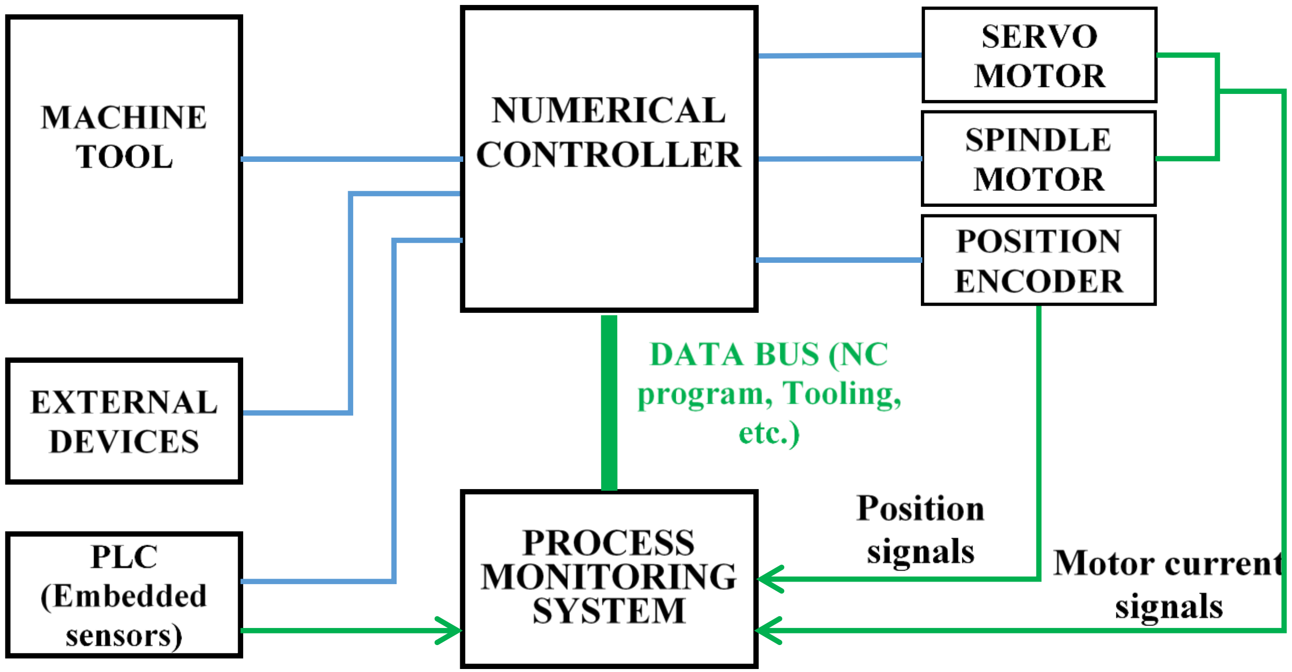
1 – Spindle
2 – Rotary axis drive
3 – X axis drive
4 – Y axis drive
5 – Z axis drive
6 – Column

Spindle and drive axis

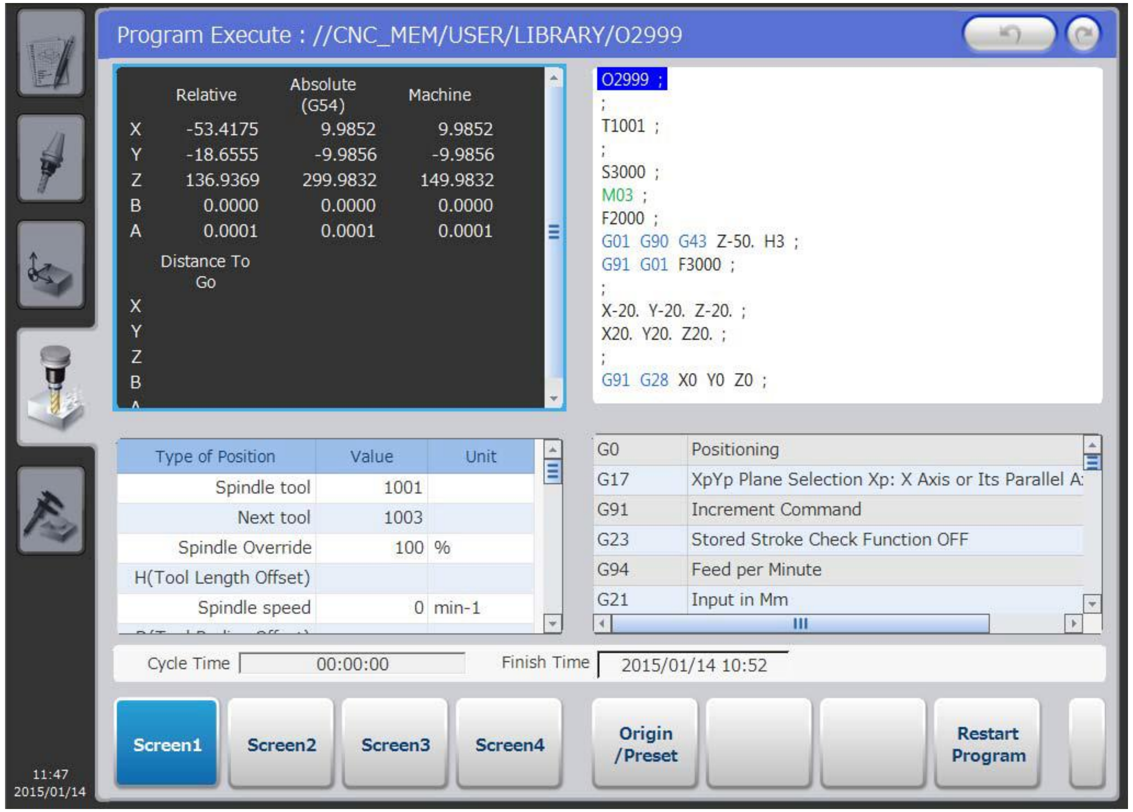
- Preventive protection with vibration sensors on the machine spindle.
- Embedded temperature sensor to determine and compensate for thermal growth.
- Electrical motor and encode signal to detect health condition for each drive axis.
- Tool identification for manual, contact-free reading and writing of tool data
- Internal coolant supply flow monitoring to determine the necessary coolant output

Contextualization of Machining Processes

How to contextualize the machining process based on structured CNC data on the machine tools

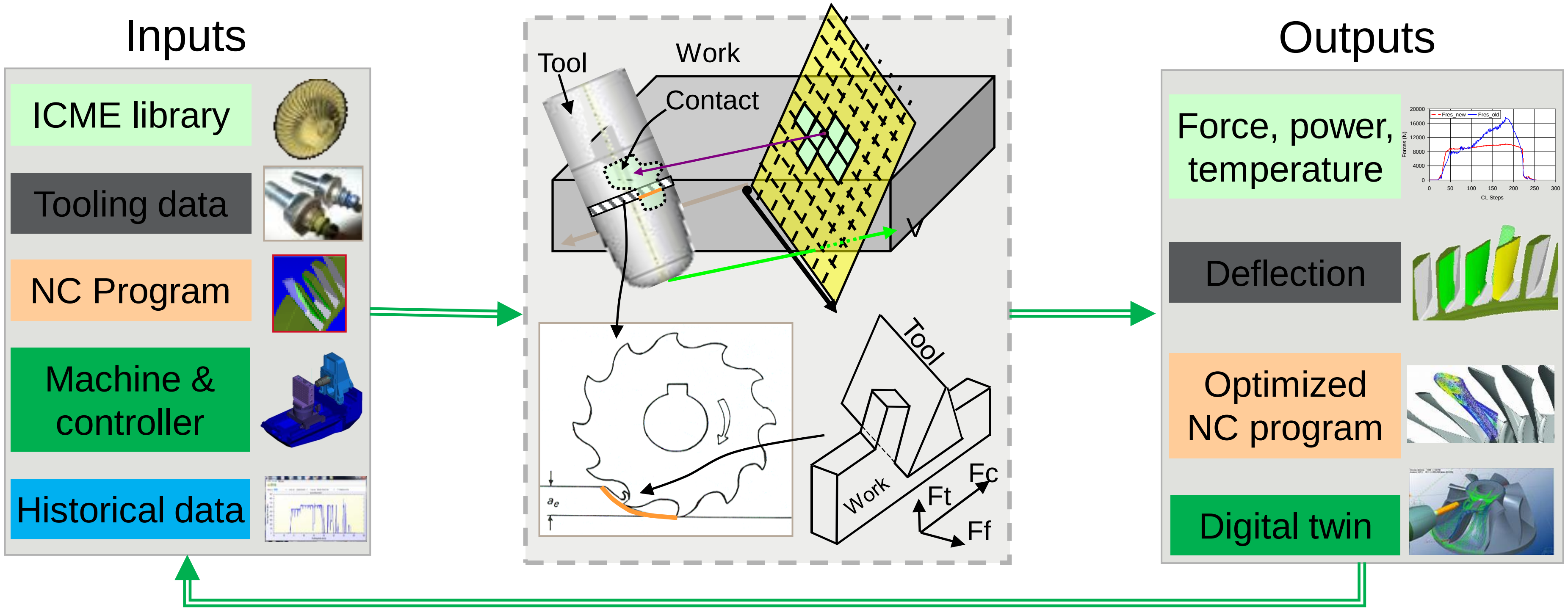


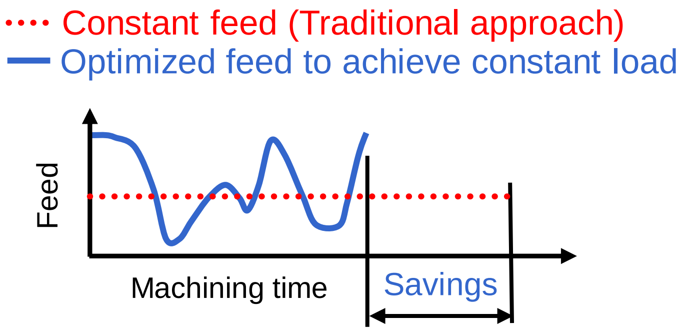
CNC configuration for a typical machine tool



Physics-based process digital twin

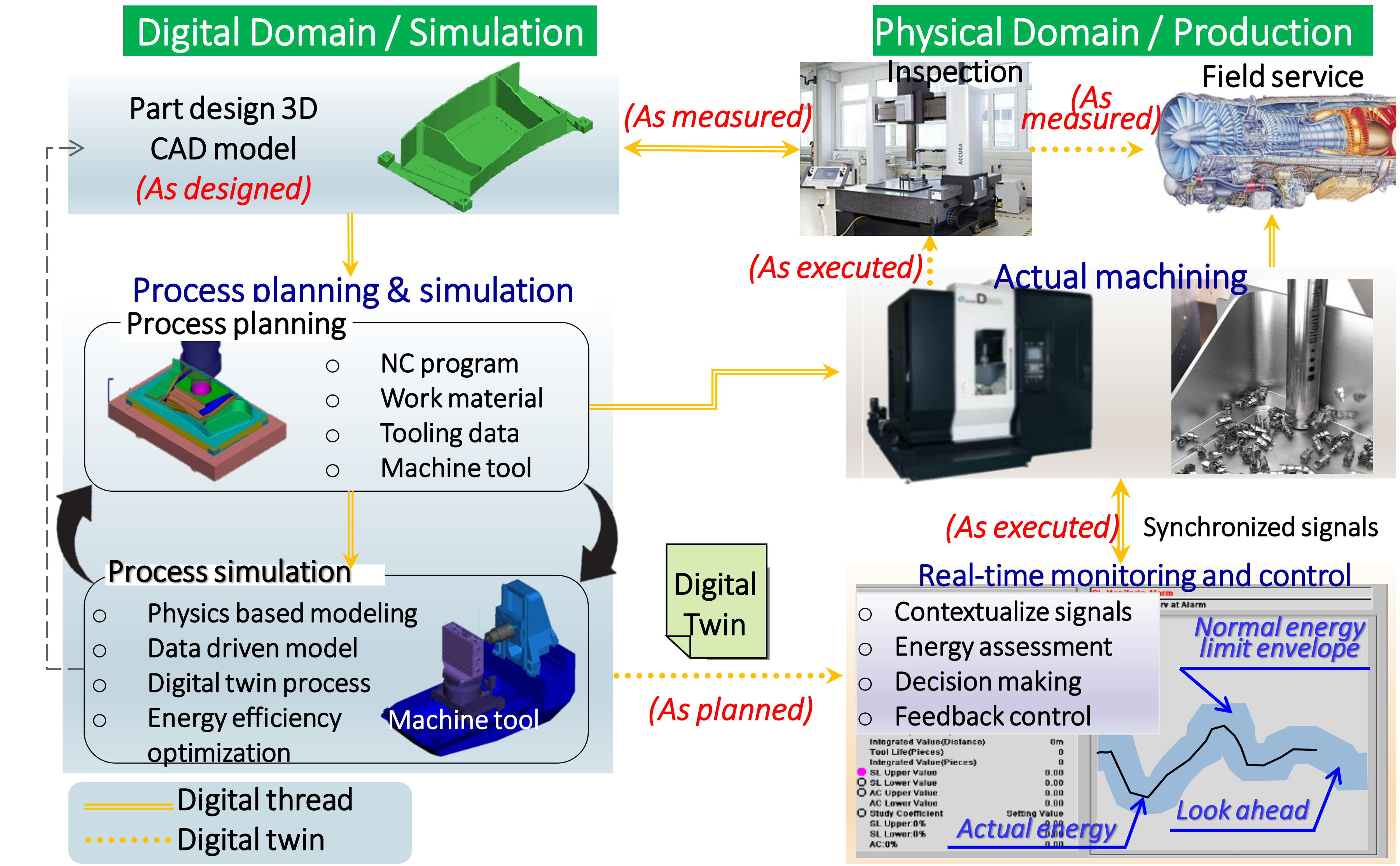
*Use the physics-based model to build the process **digital twin** based on structured CNC data*





- Reduced development time
- More robust process
- Shorter cycle time
- Less process variation
- Improve quality

Smart manufacturing using process digital twin



Use the digital thread to connect process information together and enable smart decision making:

- **As-designed *vs* as-measured.**
- **As-planned *vs* as-executed.**
- **As-executed *vs* as-measured.**

<u>Complete closed-loop smart manufacturing system</u>

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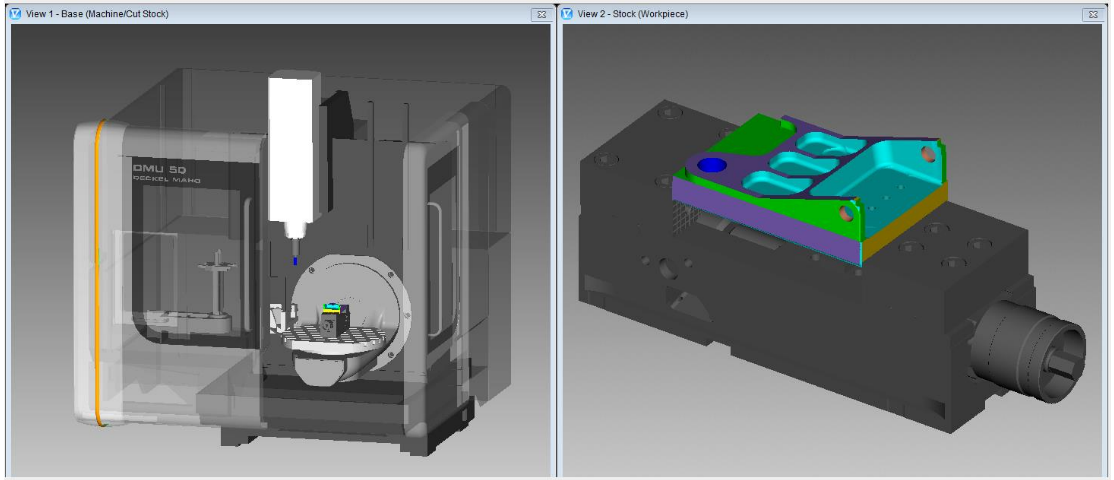
Proposed Use Case

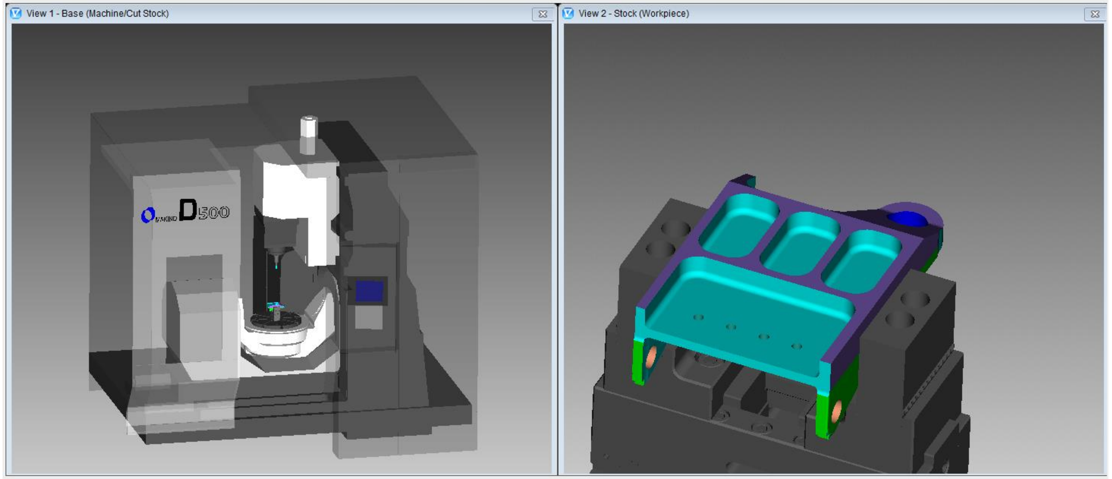
A Ti6Al4V structure part selected for the use case study, which needs two setups on two machines.

Setup 1 on Machine 1		Tool	Cutter	Cutter	Cycle Time	Air Time
Sequence	Record	Description	Height	Stick Out		
1	15: N128 M6	60 (D25 EM)	125	54.95	0:34:17.8	32.28%
2	679: N1456 M6	62 (D63 R6)	12	5.95	0:11:26.4	15.94%
3	768: N1628 M6	58 (D20 R3 EM)	45	45	0:09:56.0	36.09%
4	940: N1972 M6	64 (D12 Drill)	90	40	0:00:37.9	85.63%
5	974: N2040 M6	68 (D5 Drill)	80	33.952	0:00:34.6	73.38%
6	999: N2090 M6	66 (D19.5 Drill)	150	77	0:00:32.2	74.03%
7	1020: N2132 M6	58 (D20 R3 EM)	45	45	0:00:26.1	74.76%
				Total	0:57:51.0	31.40%

Note: Sequence 4 - 6 are drilling process with relatively constant loads, not considered in this study.

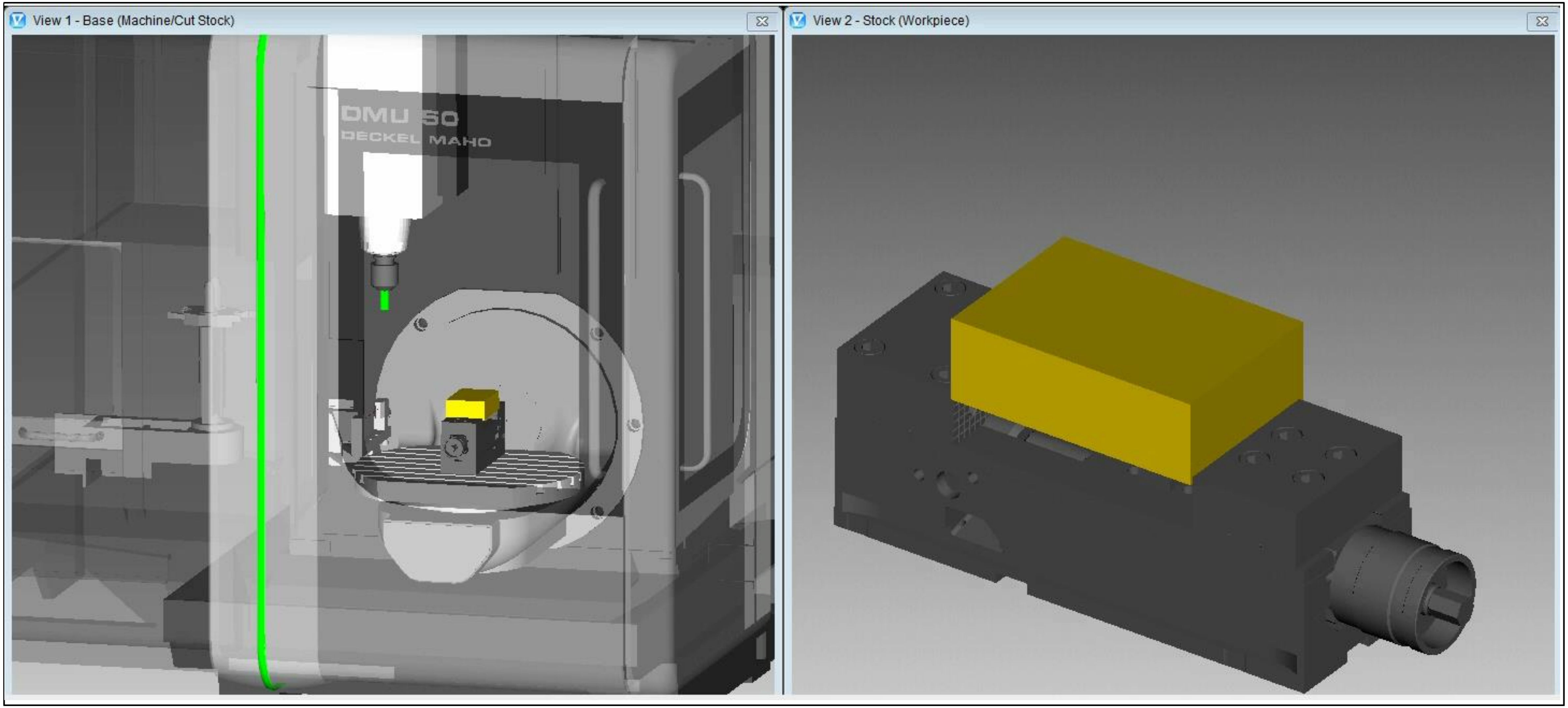


Setup 2 on Machine 2		Tool	Cutter	Cutter	Cycle Time	Air Time
Sequence	Record	Description	Height	Stick Out		
1	N106 T46 M06	46 (D25 EM)	37.5	37.5	0:19:51.9	31.24%
2	N794 T38 M06	38 (D63 R6)	11.875	0.616	0:08:27.0	17.81%
3	N970 T53 M06	53 (D20 R3 EM)	30	30	0:09:25.7	13.78%
				Total	0:37:44.6	23.87%



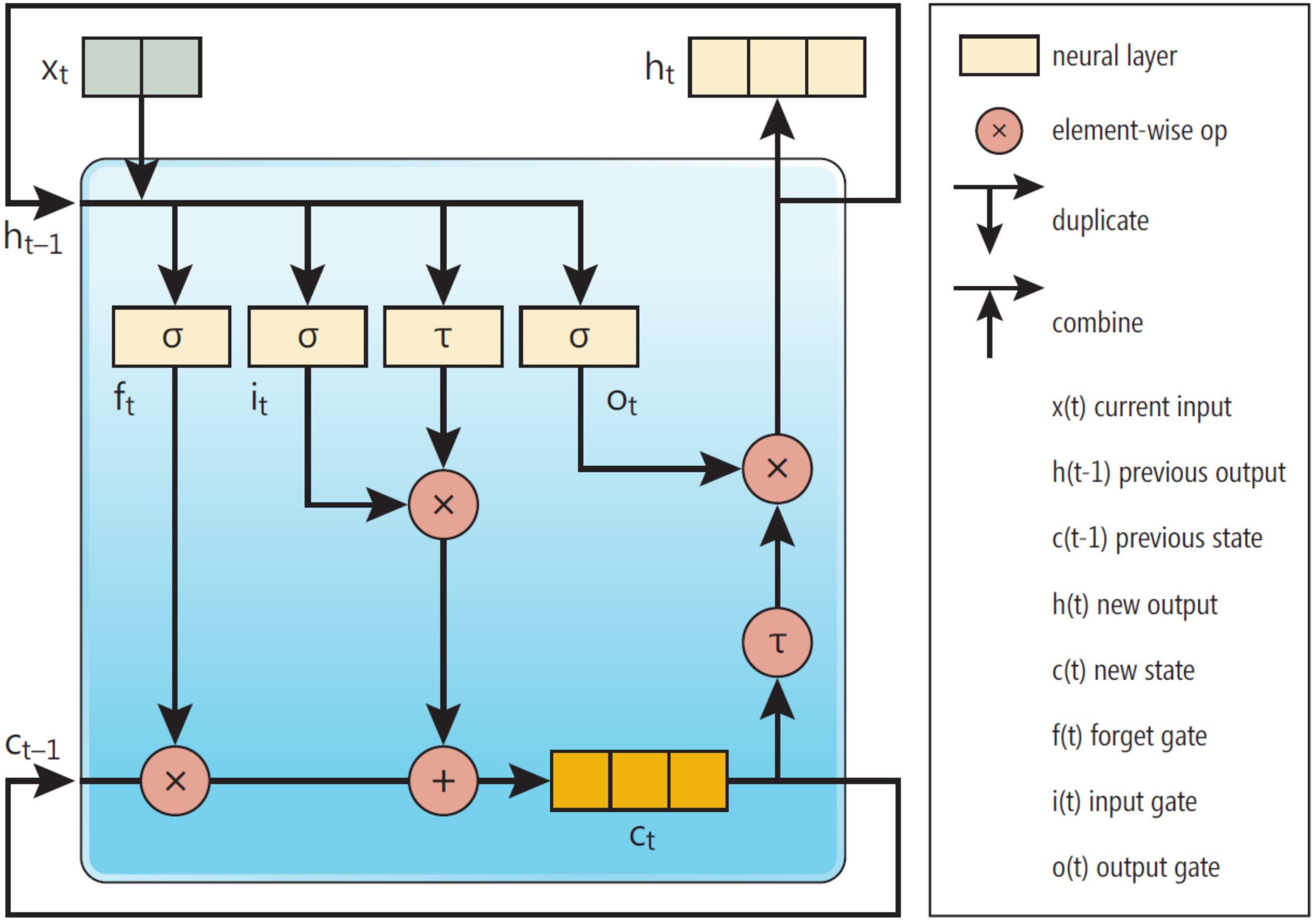
- In-house developed physics-based model was used to generate the process digital twin.
- Preprocess planning to optimize energy-efficiency

Use case demo



Process monitoring using LSTM (Long short-term memory)

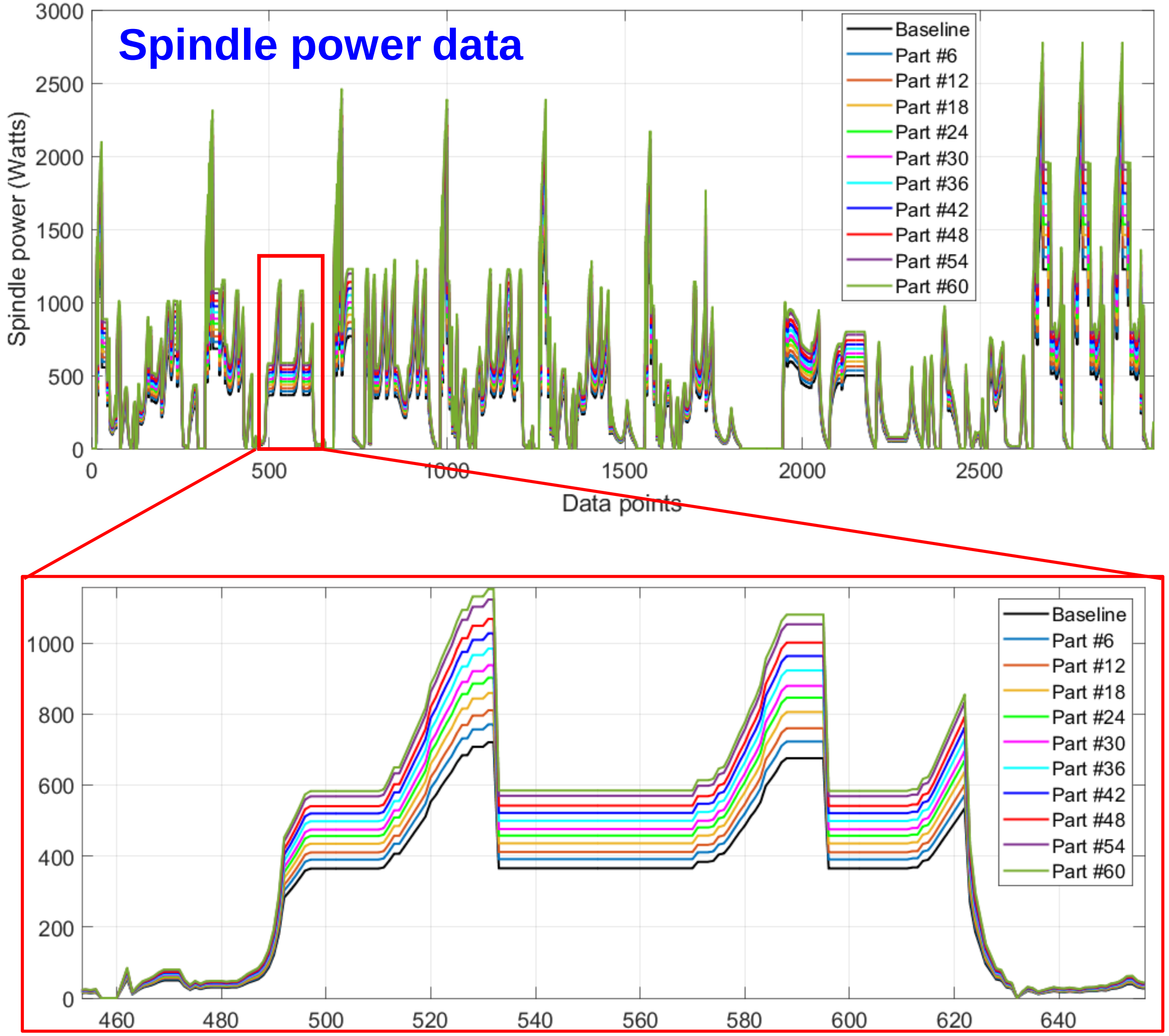
- **Uncertainties in manufacturing causes undesired conditions (scrapped parts and higher power consumption).**
- **Gradual tool wear causes increase of power consumption in the process**
- **Advanced machine learning algorithm (such as LSTM) enables the reliable process monitoring and adaptive control**

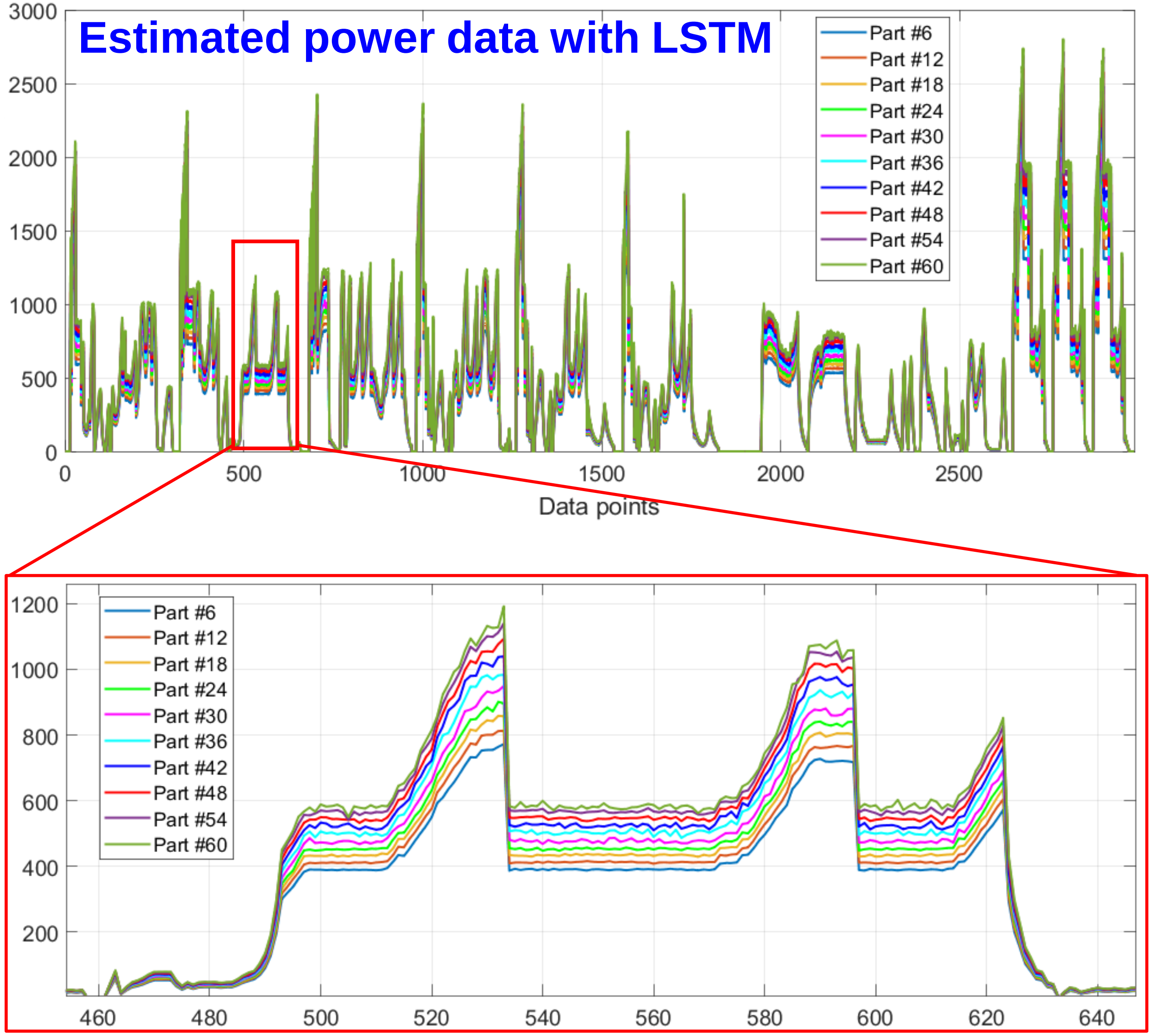


Source: Understanding LSTM cells using C#, MSDN Magazine, Vol. 33 (4), April, 2018.

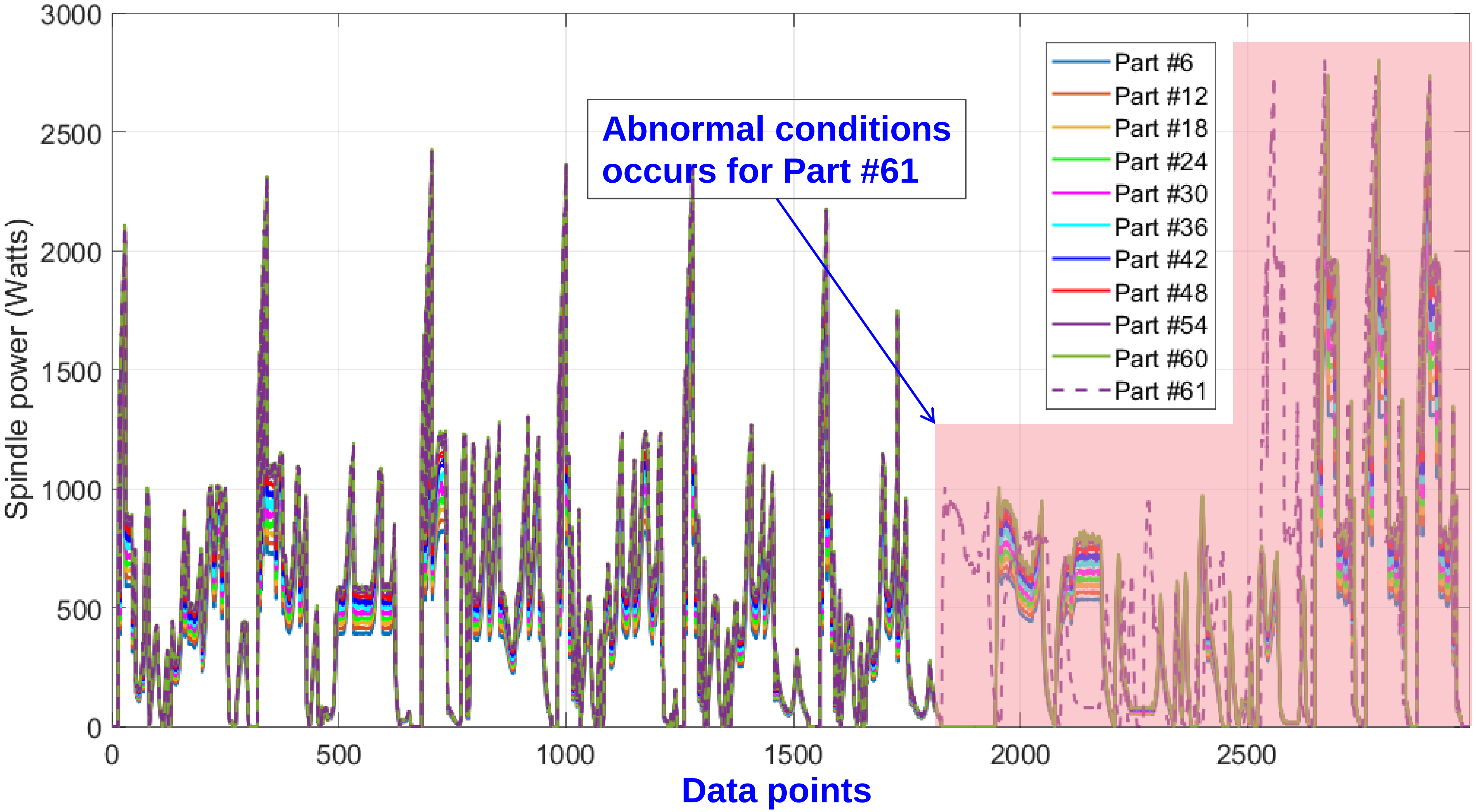
Process digital twin enables increased predictability, real-time monitoring of sensor data and better production control for adjustment of cutting parameters.

Case study of measured power data using LSTM





Case study using LSTM to detect undesired conditions



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Summary

- **Use the simulation results as a process digital twin to monitor the real-time process, then label the process history data.**
- **Employ a machine learning algorithm to extract features of labeled history data of machining loads.**
- **Perform the smart monitoring of machining process based on the feature-based time series data.**
- **It is feasible to perform adaptive process control using process digital twin and contextualized process data, and improve machining process reliability.**

Thank you.

Raytheon Technologies

Industry 4.0 AI Forum

Presentation

Nasir Mannan, Principal Engineer, CCAT

Connecticut Center for Advanced Technology, Inc.

AI Based Digital Twin Accounting for Production Variability

June 7, 2023

Presentation Agenda

- Model Based Definition and Digital Thread To Support AI Based Digital Twin
- Example of Closed Loop Machining for Intermittent Process Control
- Case Study 1: Understanding the Benefits of Model Based Production
- Case Study 2: AI Based Digital Twin for Real-Time Autonomous Control
- Digital Twin Software Development
- Initial Model Training Results
- Work in Progress: Autonomous Manufacturing Cell

Model Based Definition and Digital Thread To Support AI Based Digital Twin

Applicable standards

ASME Y14.41-2012 ‘Digital Product Definition Data Practices’

ISO 16792

The United States Department of Defense released MIL-STD-31000 Revision B in October 2018 to codify the use of MBD as a requirement for technical data packages (TDP)

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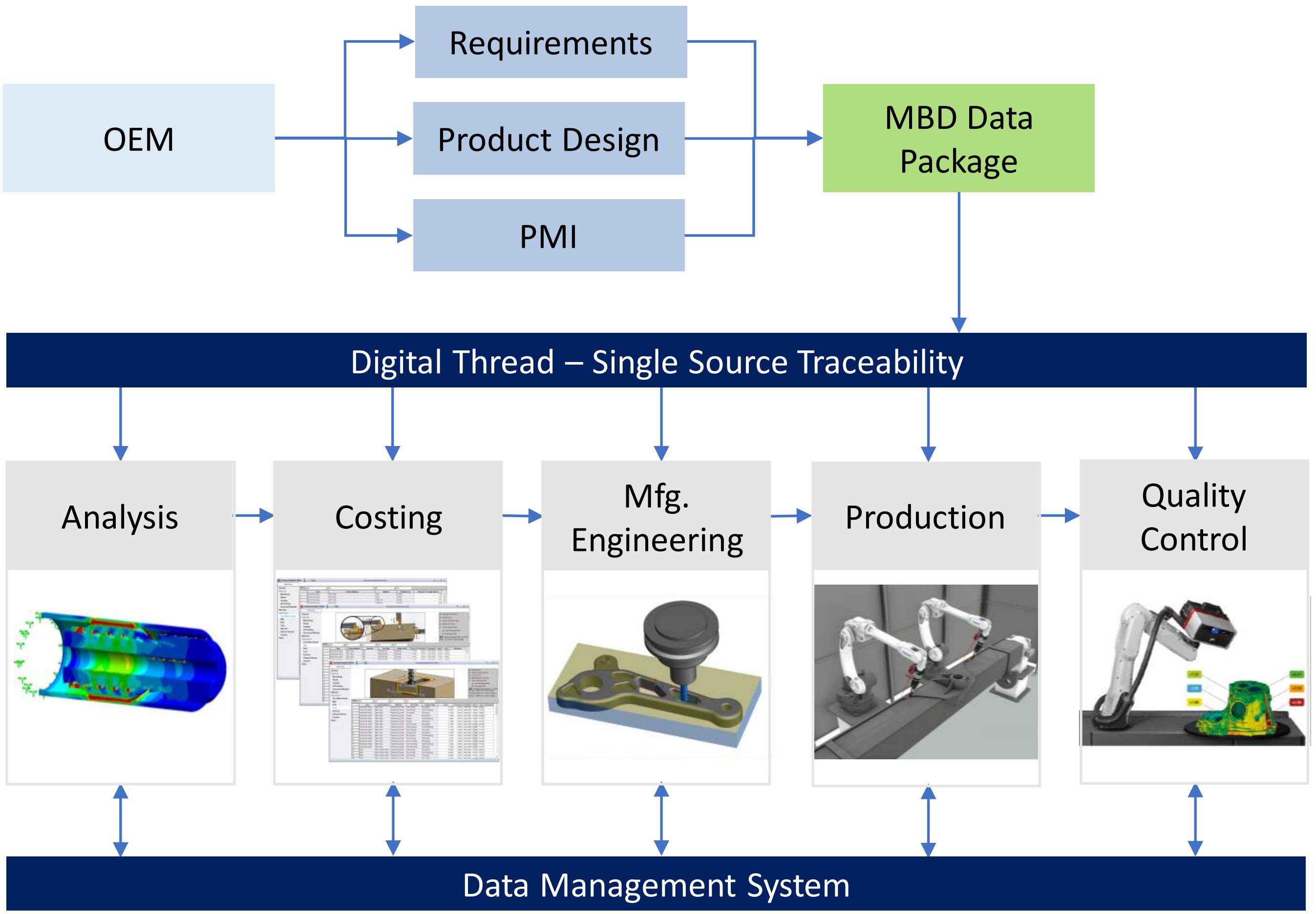
MBD and The Digital Thread



- The 3D model with embedded PMI becomes the single source that defines the part and all manufacturing information.
- The proper consumption of the MBD file increases the speed, accuracy, and efficiency of producing complex parts while also reducing manufacturing costs through the automation of the manufacturing processes.

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Model Based Manufacturing – Costing

aPriori

1. **Use the digital twin**
   - Employ model-based definition (MBD) to establish a single truth CAD file that contains all relevant information for the component being manufactured.
2. **Provide insight for all involved parties**
   - Design Engineers, procurement specialists, cost engineers, and buyers alike receive the same relevant information.
3. **Simulate manufacturing**
   - Apriori provides accurate analysis of real-world manufacturing to provide DFM insights and cost estimates.
4. **Simulate costs using digital factories**
   - Use region-specific digital factories to simulate process costs in various regions

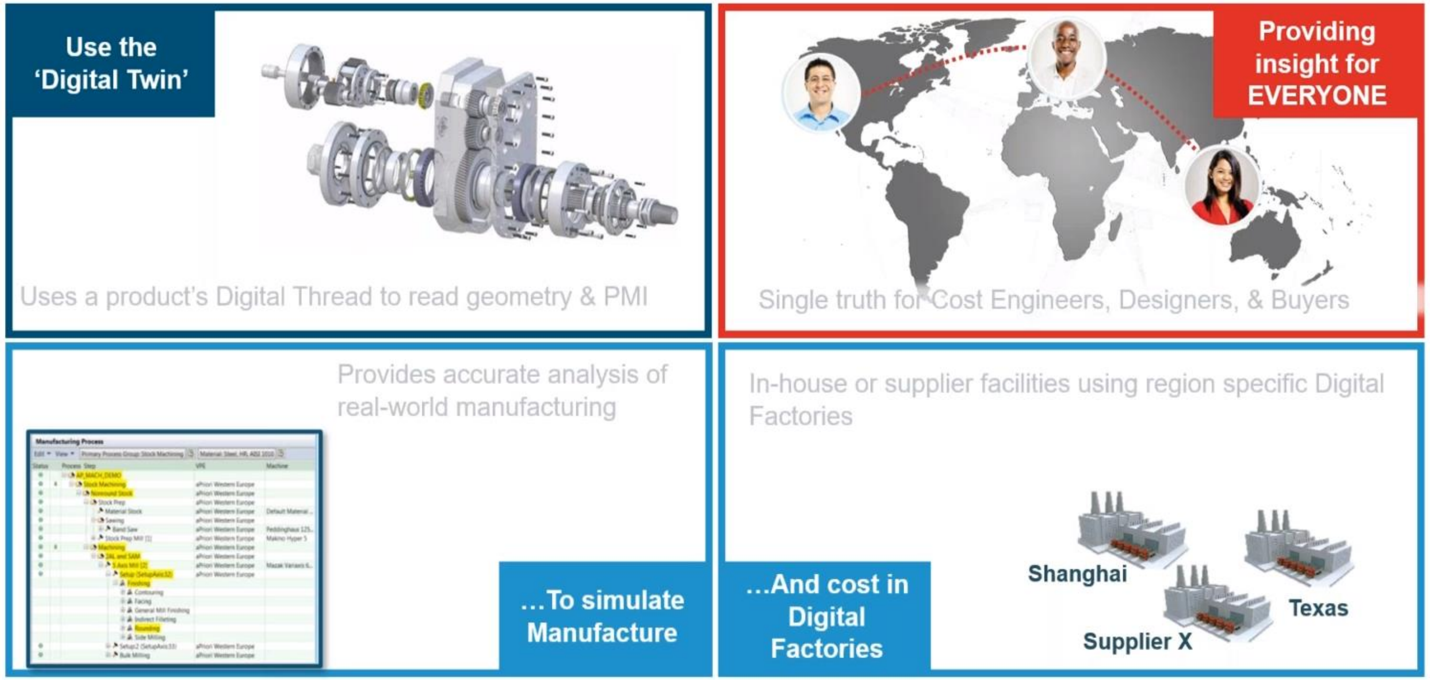
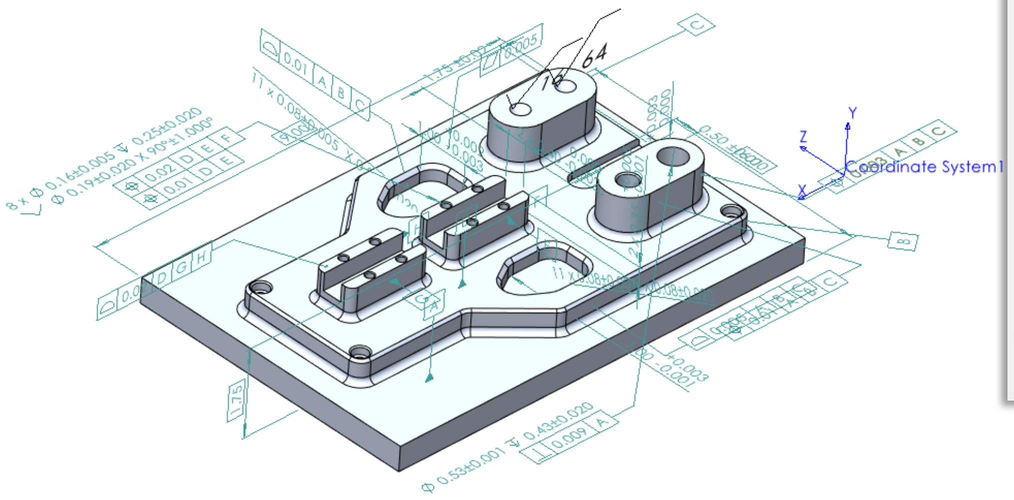
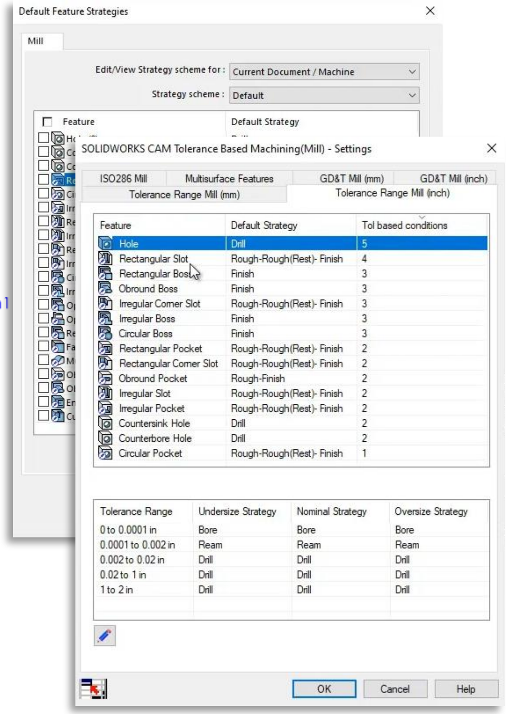
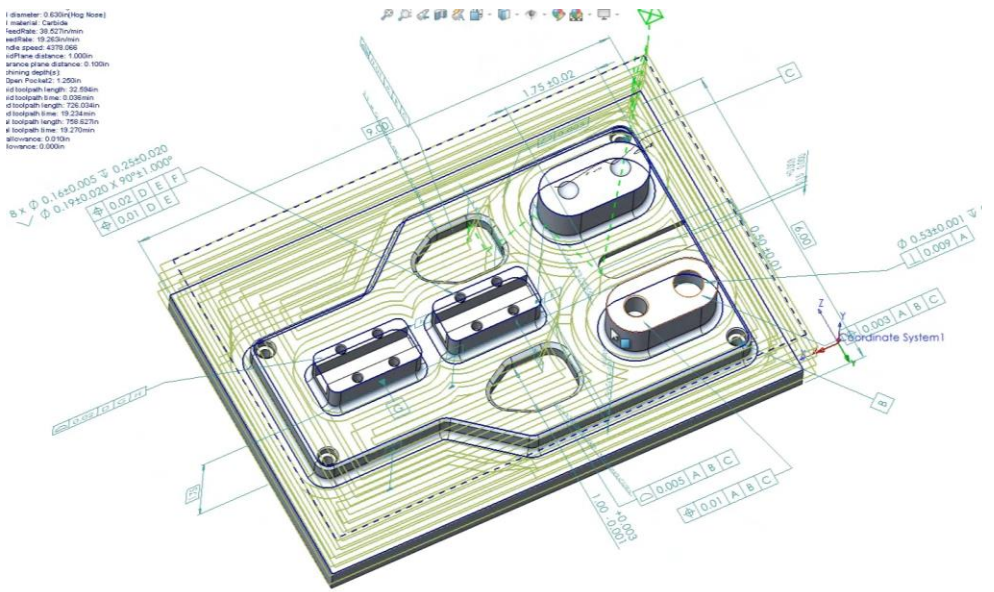


Image from aPriori.com

Model Based Manufacturing – CNC Programming

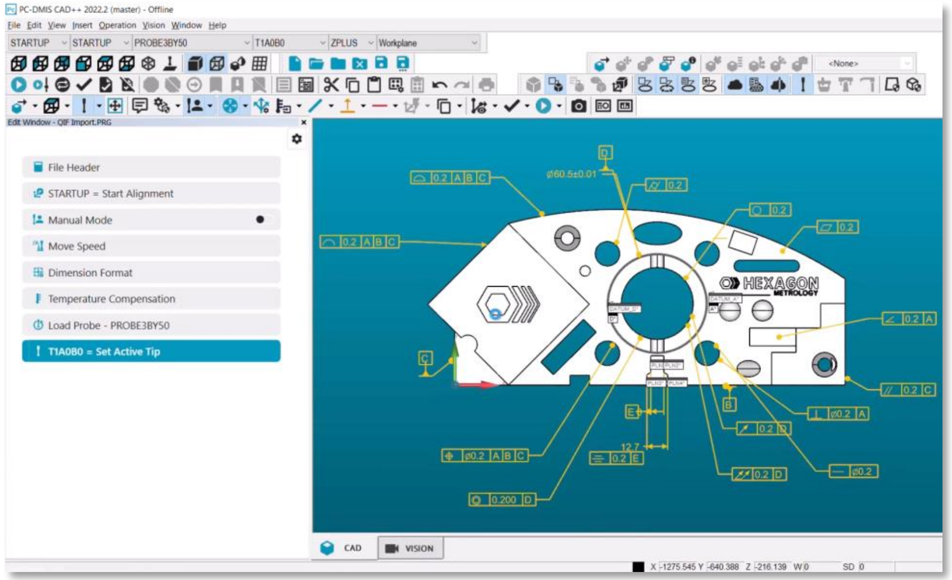


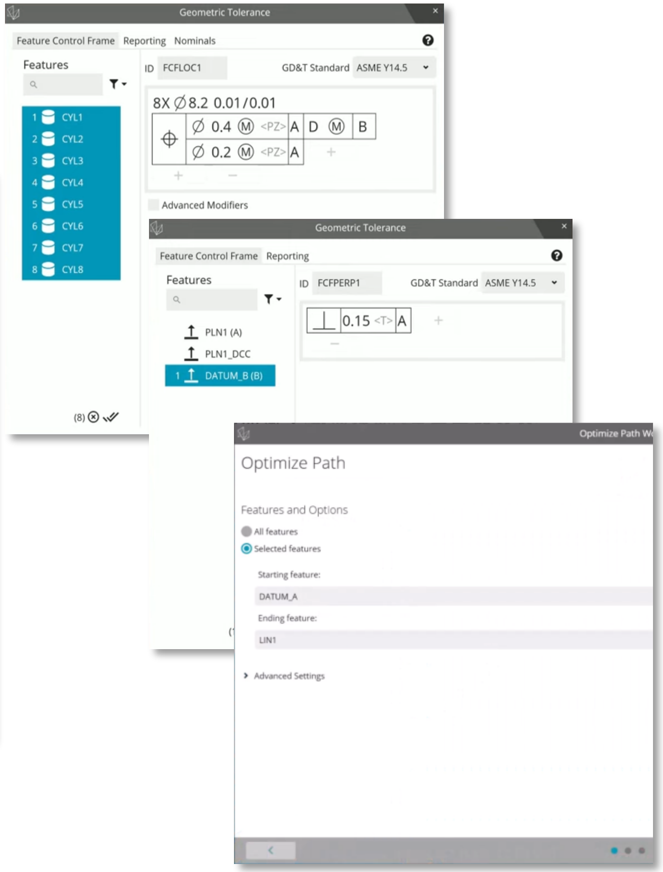


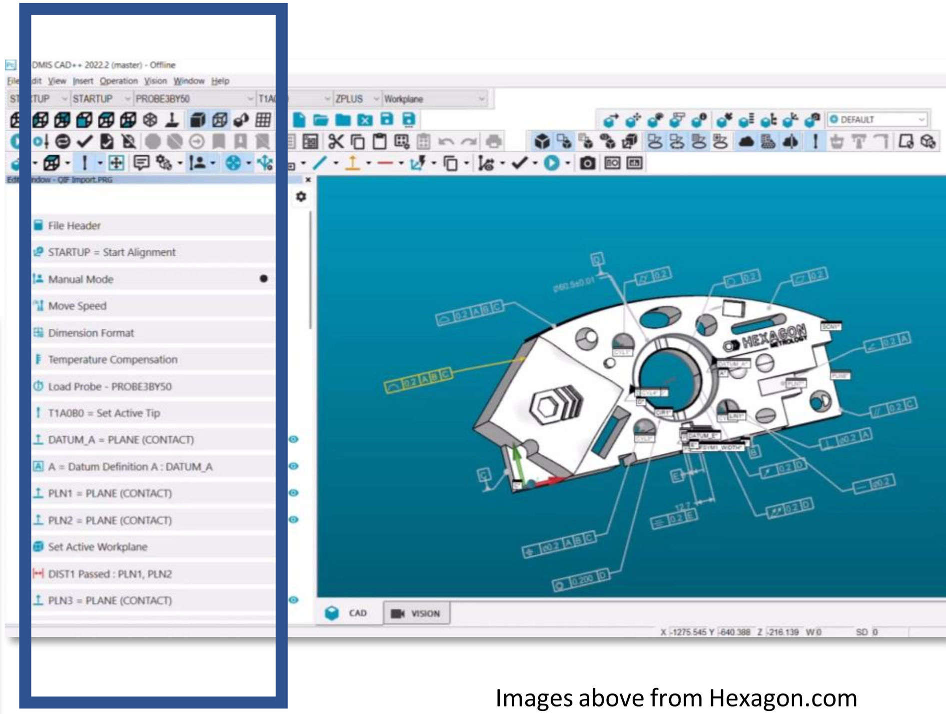


Model based definition → Feature and Tolerance Based Machining Strategies → Automatically selected tools and generated toolpaths

Model Based Manufacturing – CMM Programming







Images above from Hexagon.com

Import QIF Model → Select feature control frames to inspect and optimize path → Automatically generated CMM path

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Example of Closed Loop Machining for Intermittent Process Control

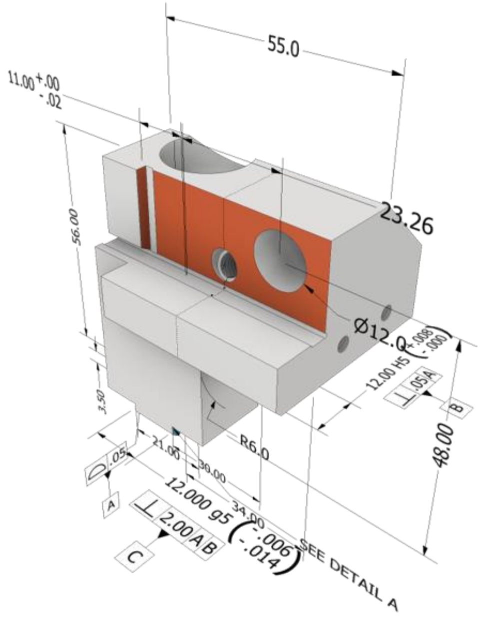
Next Steps

This image from
us.DMGmori.com

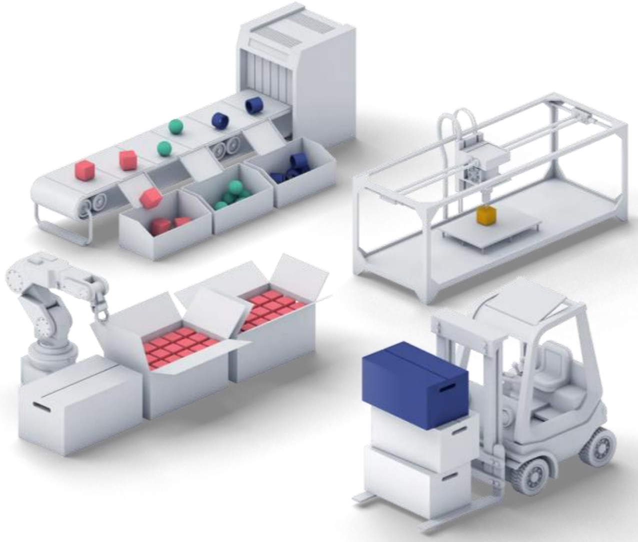
Case Study 1:
Understanding the Benefits of Model Based Production

Production Variation

MBD driven toolpath

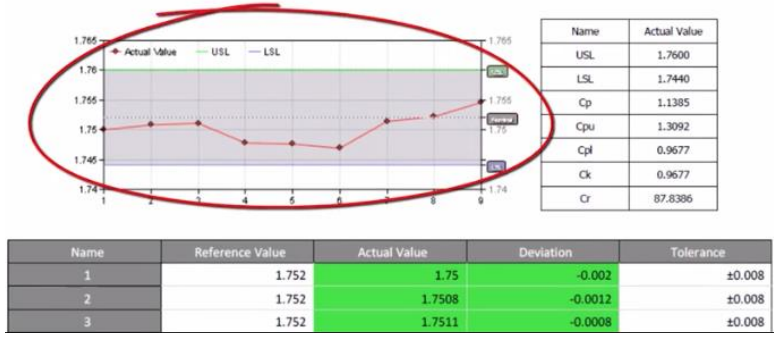


Production



MBD driven measurement trend analysis

The goal of a production model would be to reduce or eliminate production variations autonomously



Name	Actual Value
USL	1.7600
LSL	1.7440
Cp	1.1385
Cpu	1.3092
Cpl	0.9677
Ck	0.9677
Cr	87.8386

Name	Reference Value	Actual Value	Deviation	Tolerance
1	1.752	1.75	-0.002	±0.008
2	1.752	1.7508	-0.0012	±0.008
3	1.752	1.7511	-0.0008	±0.008

Sources of Production Variation

DMG LASERTEC 65 3D Hybrid

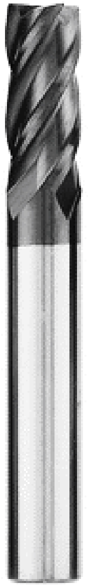
Machine Variations

- Spindle Power

Case Study – Feature 32 – Circular Pocket Machining

Stock Material

Tool path



Flat End Mill

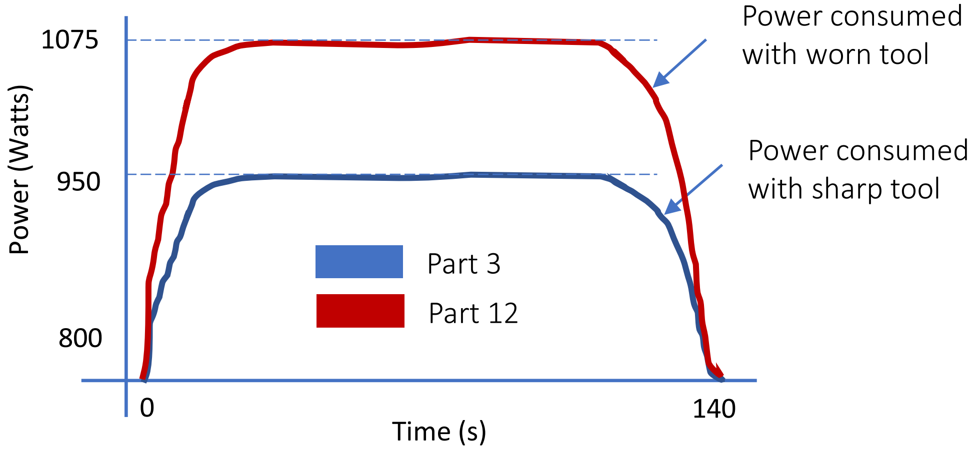
Resulting Part

Feature 32 –Correlation Results

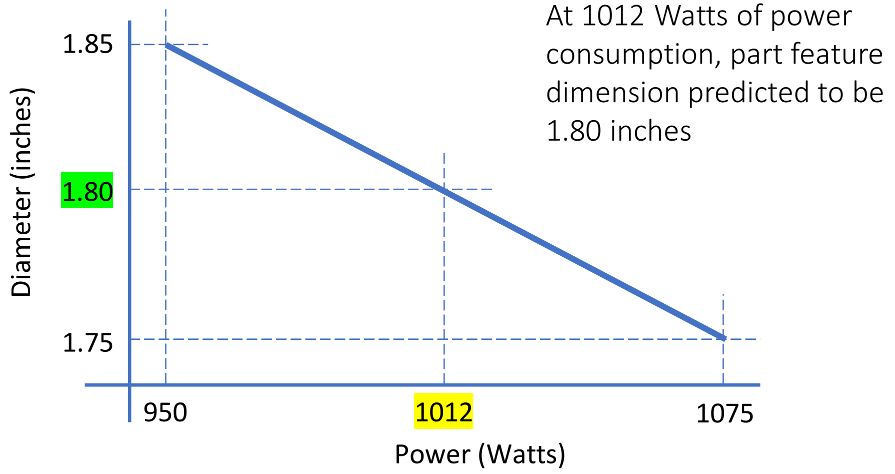
Feature 32 – Post Inspection Diameter

Part #	Diameter (in.)
3	1.8568
12	1.7414

Edge Device Power 6 Data – Feature 32



Power to Diameter Correlation Function



$$Y = -0.0008\,x + 2.6100$$

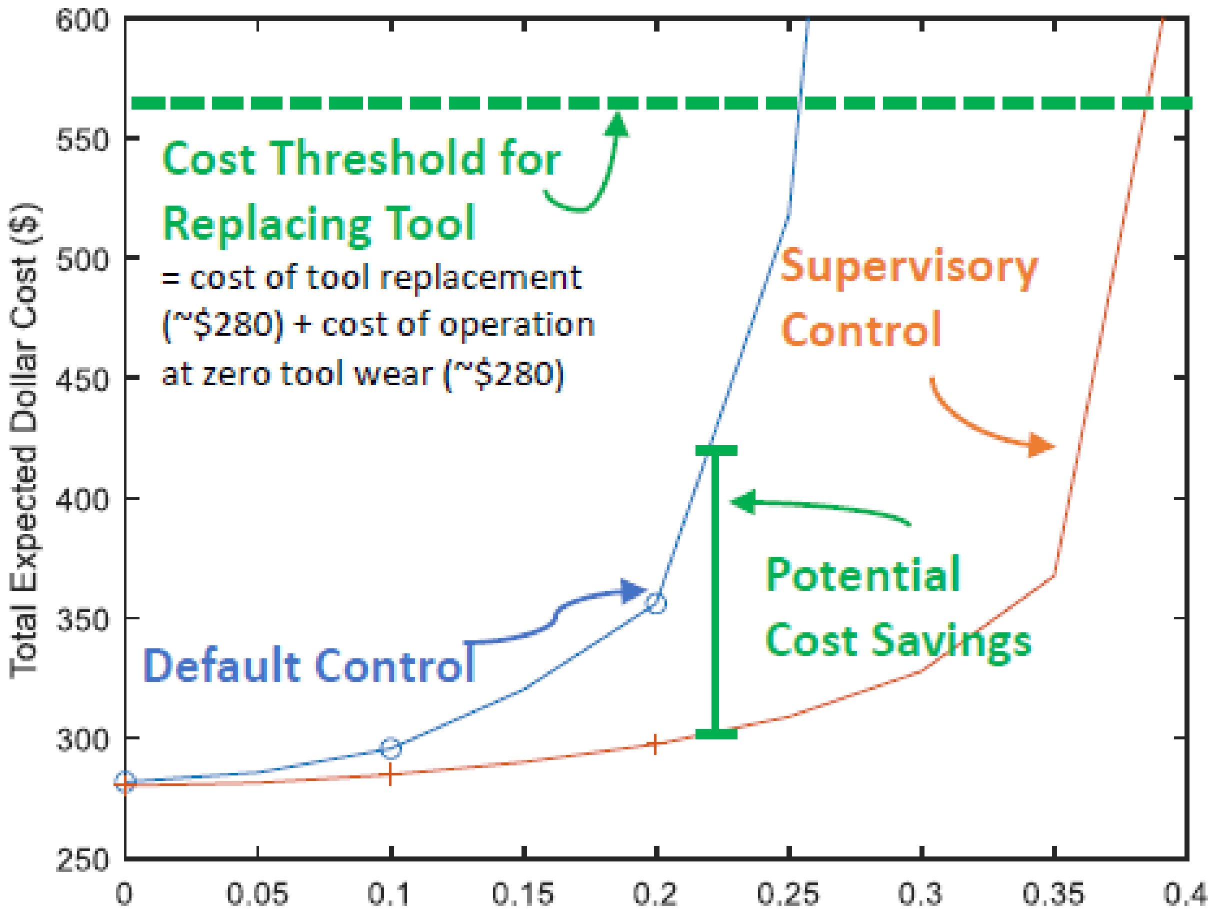
Prediction Value

Power 6 Value

Autonomous Control – Potential Benefits for Manufacturing

- Extended Tool Life
- Reduced Scrap Rate
- Reduced Cost per Part
- Increased Production Rate

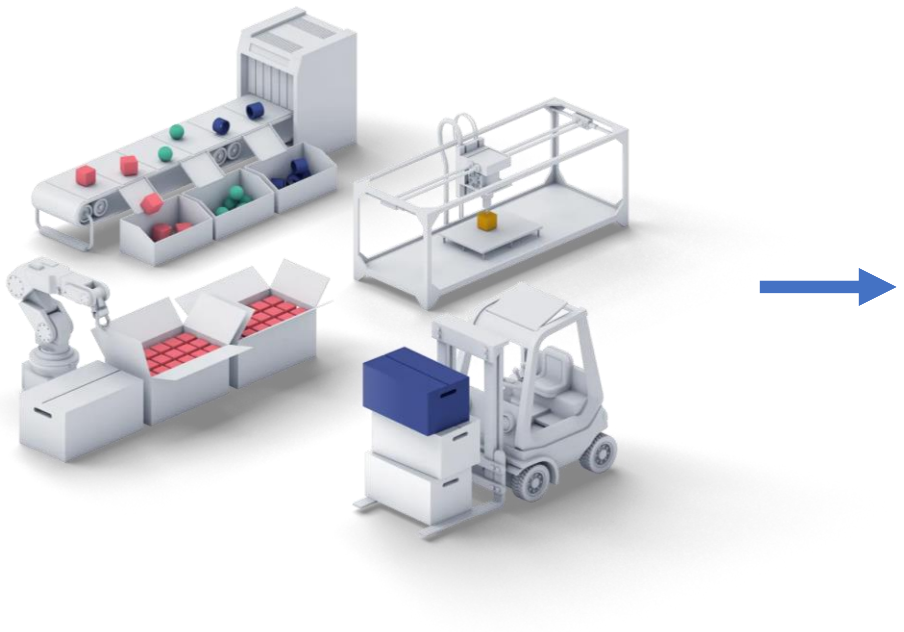
Cost Analysis from CESMII Project Conducted with UCONN and RTX



Case Study 2:
AI Based Digital Twin
for Real-Time Autonomous Control

Many Sources of Production Variability

Production



Production Process Variability

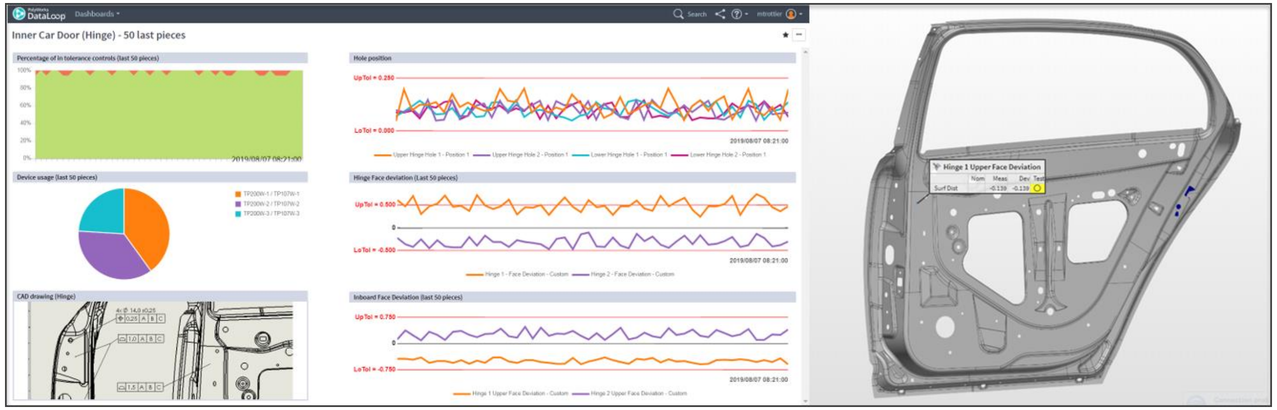


Image from polyworks.com

Sources of Production Variation

Image from us.DMGMori.com

Stock Deviations

- Size
- Hardness
- Grain orientation
- Porosity/inclusion
- Temperature
- Bulk Stress

+

Machine Variations

- Spindle (speed, temperature, load, vibration)
- Axis [x,y,z,a,c] (velocity, position, load, vibration)
- Overrides (federate, rapid)
- Coolant (type, temperature, viscosity)
- Tooling (wear)

+

Technician Distinctions

- Experience
- Training
- Preferences

Process Digitization for Digital Twinning

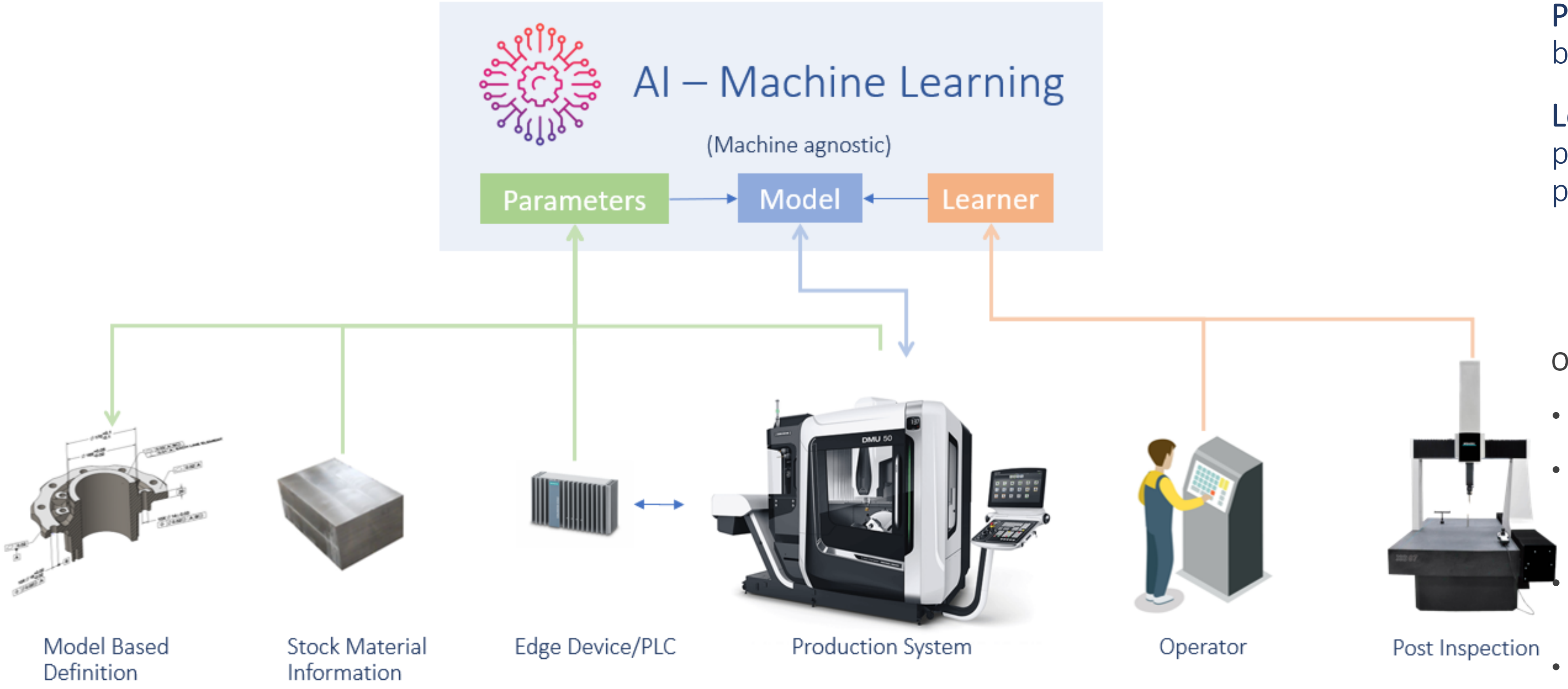


Image from us.DMGMori.com

Major Building Blocks of AI – Machine Learning

Model: The system which makes predictions

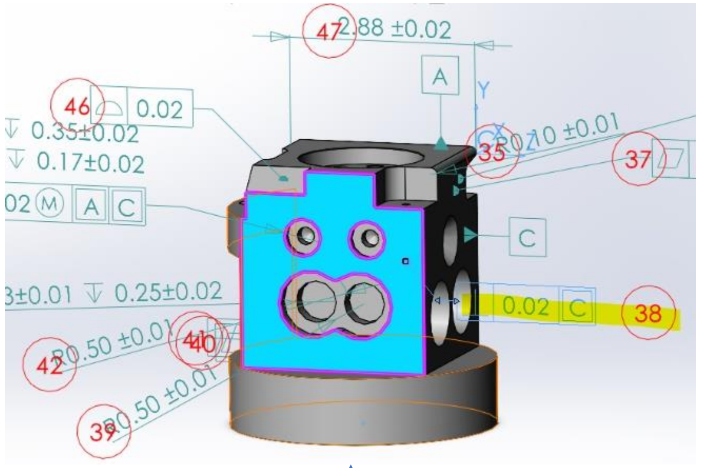
Parameters: the factors which are considered by the model to make predictions

Learner: Makes the adjustments in the parameters and the model to align the predictions to the actual results

Outcomes using an AI-based self-learning production model

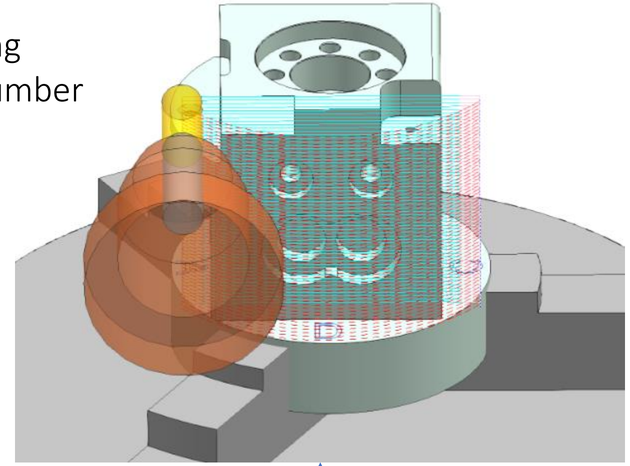
- Status Monitoring: Production statistics
- Predictive Maintenance: Autonomous production parameter trend tracking and suggestions on planned machine maintenance
- Adaptive Control: Real time production anomaly detection and self-directed corrective action decisions
- Intelligent Machine: Self-driven machine parameter optimization for increase production quality
- Anomaly Mapping: Visualize in-process anomalies mapped to 3D space

Case Study - Design of Experiment



Part Feature ID

Manufacturing Operation Number



Mapping in a CSV

Feature IDs

First Article Inspection Report

Form 3: Characteristic Accountability, Verification and Compatibility Evaluation

1. Part Number: 1 | 2. Part Name: MBP-DEMO | 3. | 4. 0

5. Char No.	Reference ...cation	7. Characteristic Designator	8. Requirement	8a. UoM	8b. Upper Limit	8c. Lower Limit	9. Results	10. Design	11. Non-Co	14. Notes	Job #	Description	Name
1		HoleDiameter	Ø .50	in	0.51	0.49					3	Side A .5" hole left	MBP_03_Side_A_500_hole_left
2		HoleDiameter	Ø .50	in	0.51	0.49					4	Side A .5" hole right	MBP_04_Side_A_500_hole_right
3		Concentricity	◎ Ø0.02 E		0.02	0					3	Side A .5" hole left	MBP_03_Side_A_500_hole_left
4		Concentricity	◎ Ø0.02 F		0.02	0					4	Side A .5" hole right	MBP_04_Side_A_500_hole_right
5		Cylindricity	⌭ 0.02		0.02	0					3	Side A .5" hole left	MBP_03_Side_A_500_hole_left
6		Cylindricity	⌭ 0.02		0.02	0					4	Side A .5" hole right	MBP_04_Side_A_500_hole_right
7.1		CounterdrillAngle	.40 X	in	0.41	0.39					11	Side B lower pocket	MBP_11_Side_B_lower_pocket
7.2		CounterboreDiamet	1.40	in	1.42	1.38					11	Side B lower pocket	MBP_11_Side_B_lower_pocket
8.1		CounterdrillAngle	.40 X	in	0.41	0.39					10	Side B top pocket	MBP_10_Side_B_top_pocket
8.2		CounterboreDiamet	2.15	in	2.17	2.13					10	Side B top pocket	MBP_10_Side_B_top_pocket
9		HoleDiameter	Ø .90	in	0.91	0.89					5	Side A 1" counterbore left	MBP_05_Side_A_1000_counterbore_left
10		HoleDiameter	Ø .90	in	0.91	0.89					6	Side A 1" counterbore right	MBP_06_Side_A_1000_counterbore_right
11		Profile	⌓ .007		0.007	0					1	Side A top ledge	MBP_01_Side_A_top_ledge
12		Length	0.13	in	0.15	0.11					10	Side B top pocket	MBP_10_Side_B_top_pocket
13		Length	0.13	in	0.15	0.11					11	Side B lower pocket	MBP_11_Side_B_lower_pocket
14.1		Diameter	.01	in	0.03	-0.01					41	Side E .01" chamfer	MBP_41_Side_E_10_chamfer
14.2		Diameter	.01	in	0.03	-0.01					41	Side E .01" chamfer	MBP_41_Side_E_10_chamfer
14.3		Diameter	.01	in	0.03	-0.01					41	Side E .01" chamfer	MBP_41_Side_E_10_chamfer

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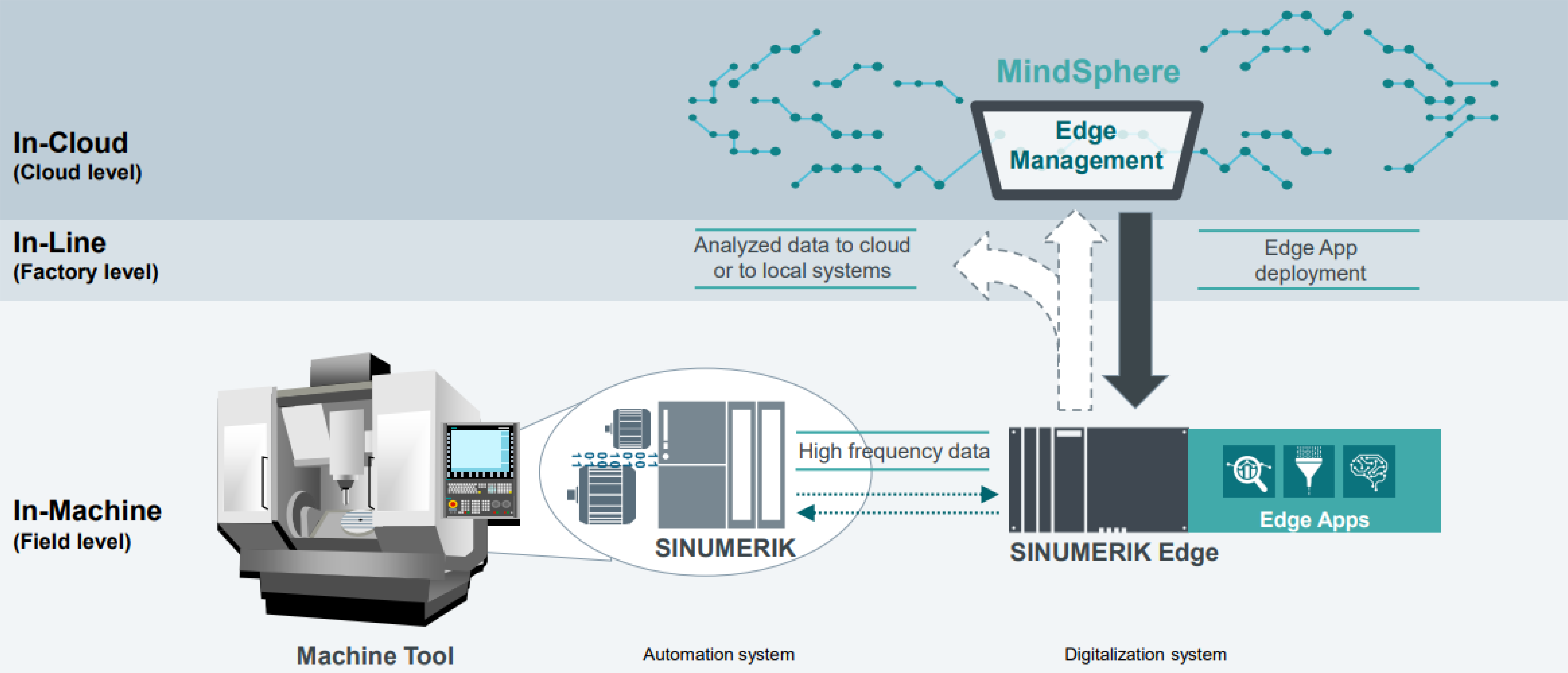
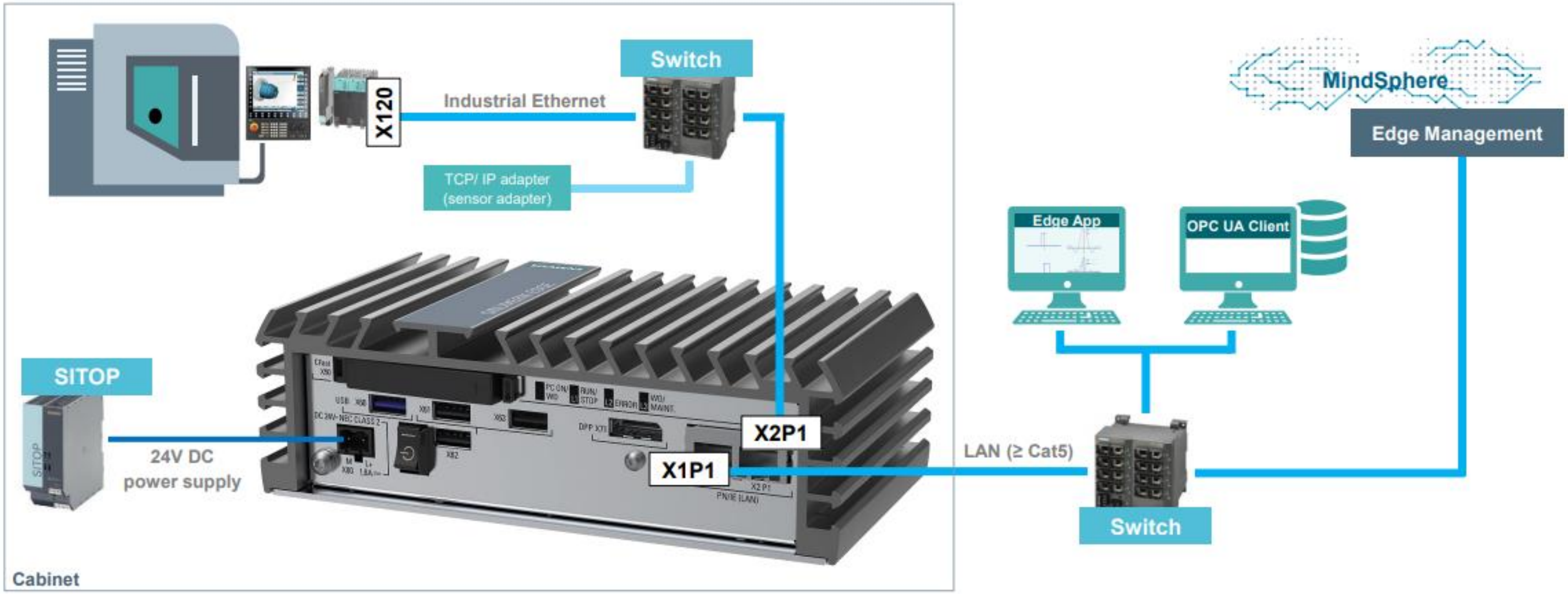
Overview of Machine Connectivity – Sinumerik Edge + Mindsphere



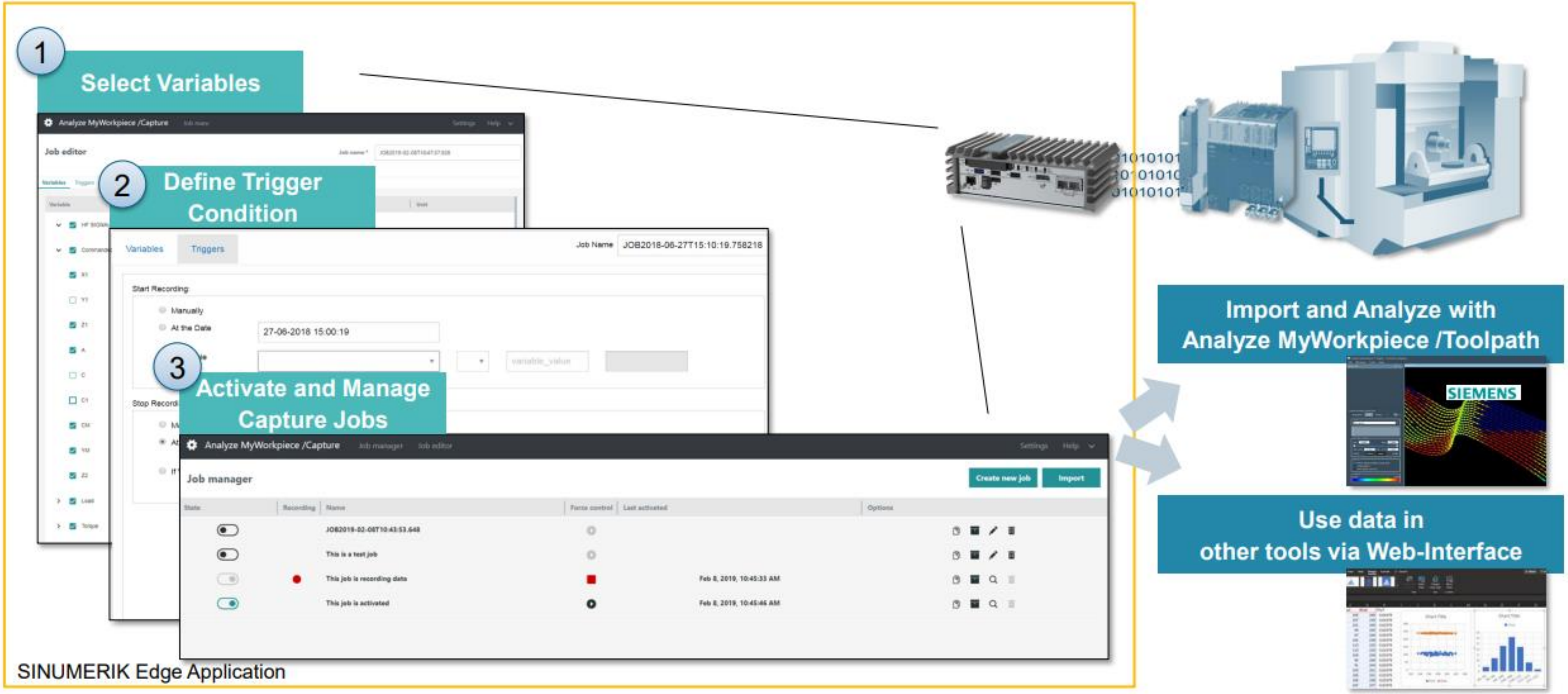
Images from siemens.com

Sinumerik Edge Connection to 840D SL Controller



Images from siemens.com

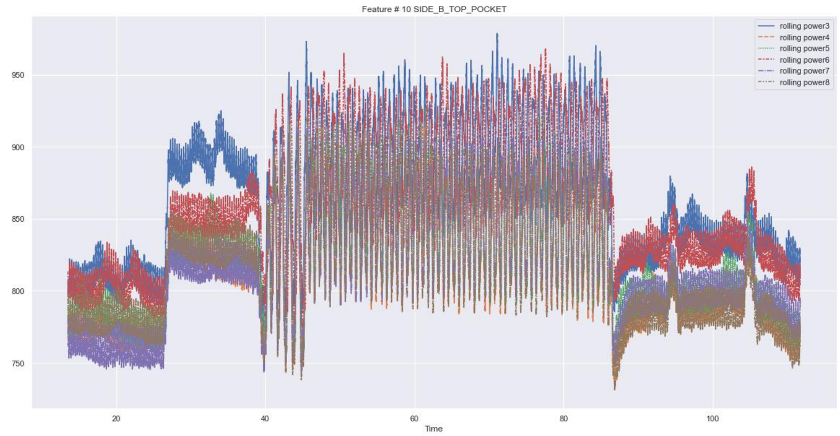
Siemens Edge Software – Analyze MyWorkpiece / Capture4Analysis



Images from siemens.com

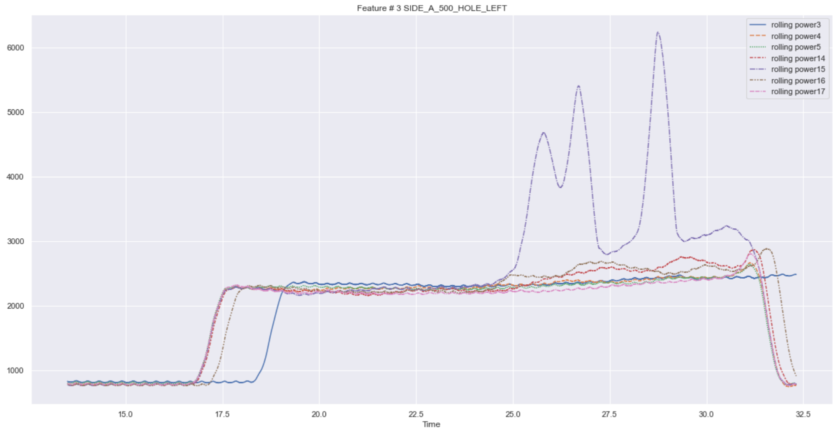
Real Time Machining Data Collection – 92 Parameters / 500 Hz

Feature # 10 SIDE_B_TOP_POCKET



Range: 825-975
Watts = 18%

Feature #3 SIDE_A_500_HOLE_LEFT

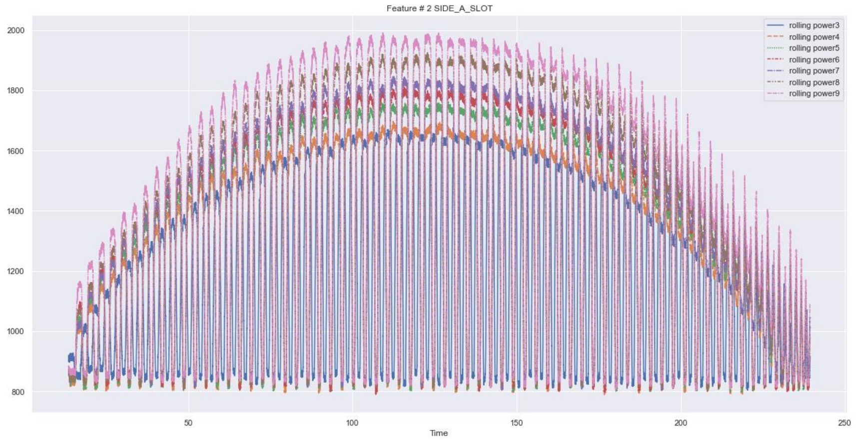


Range: 2.4-6.2
kW = 158%

Feature # 8 SIDE_B_5AXIS_SLOT_FINISHING

Range: 850-1000
Watts = 17.6%

Feature #2 SIDE_A_SLOT 3-9



Range: 1.6-2
kW = 25%

Post-production Inspection

Touch Probe CMM + Comparator

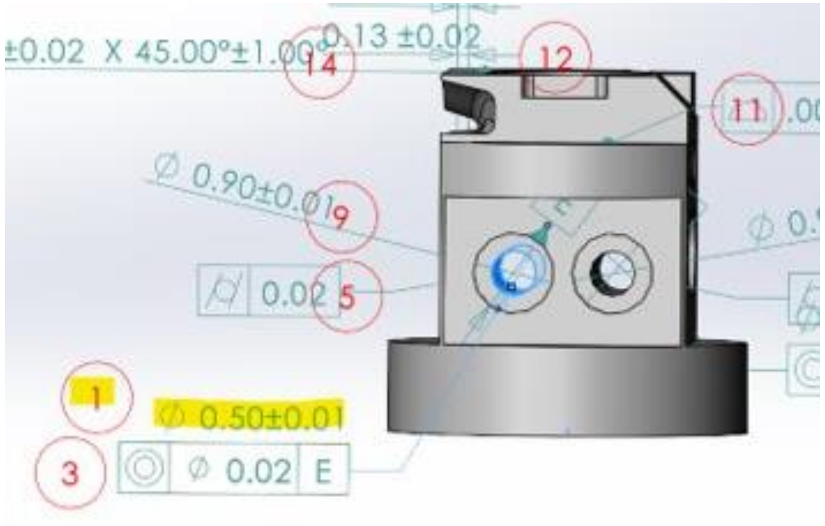
Structured Light 3D Scanning

Structured Light 3D Scanning

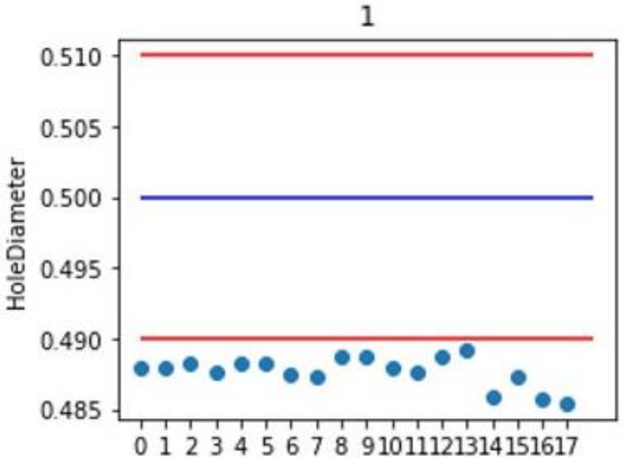
Inspection Results

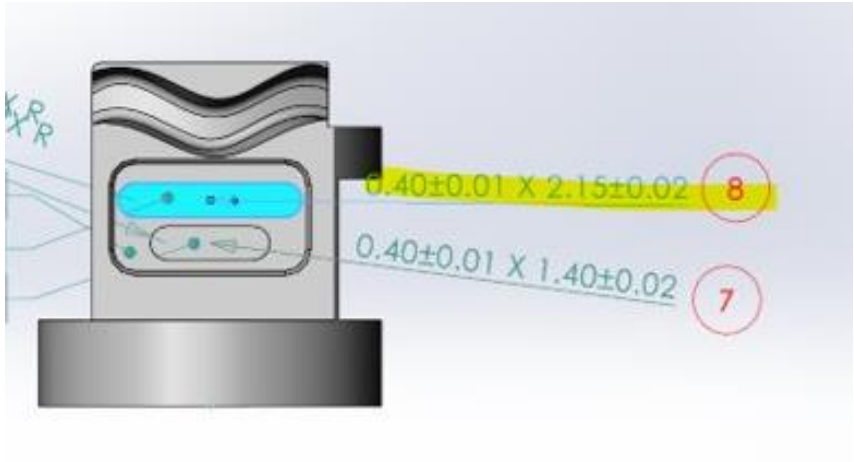
	A	B
1	##Group1	
2	Name	Meas. Value
3	1	0.4881
4	2	0.4884
5	3	0.0712
6	4	0.0768
7	5	0.0048
8	6	0.006
9	7.01	0.394
10	7.02	1.3893
11	8.01	0.3939
12	8.02	2.1393
13	9	0.8931
14	10	0.893
15	11	0.005
16	12	0.1265
17	13	0.1264
18	15	0.002
19	16	0.0053
20	17	0.0045
21	18.01	0.3923
22	19.01	0.9755
23	19.02	0.3023
24	20.01	0.9758
25	20.02	0.3093
26	21	0.001

Post-production Inspection Data

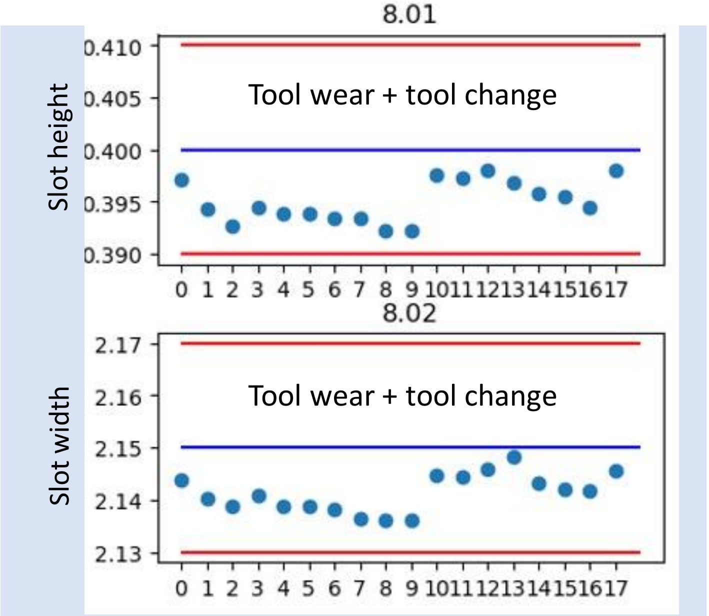


Feature 1: Hole Diameter



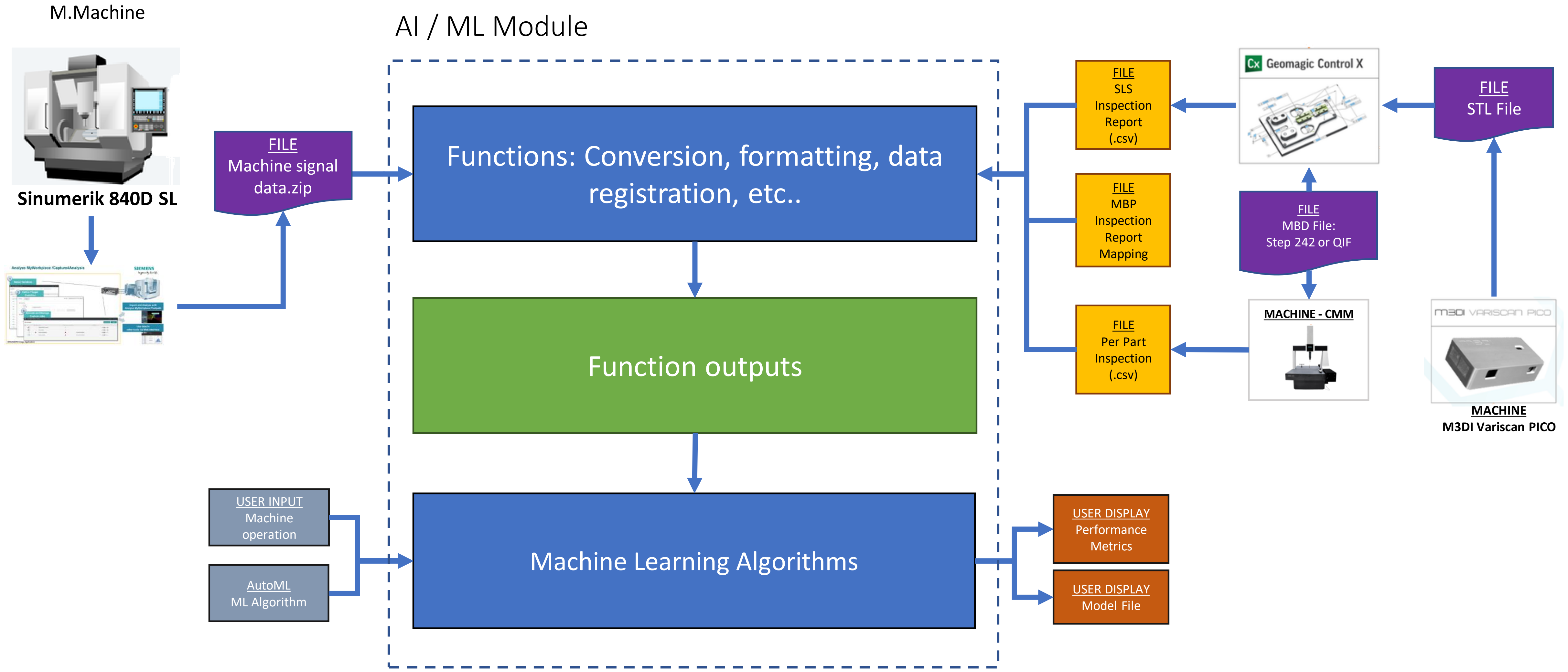


Feature 8: slot height & slot width



Digital Twin Software Development

Digital Twin Software Architecture



Machine Learning Packaging

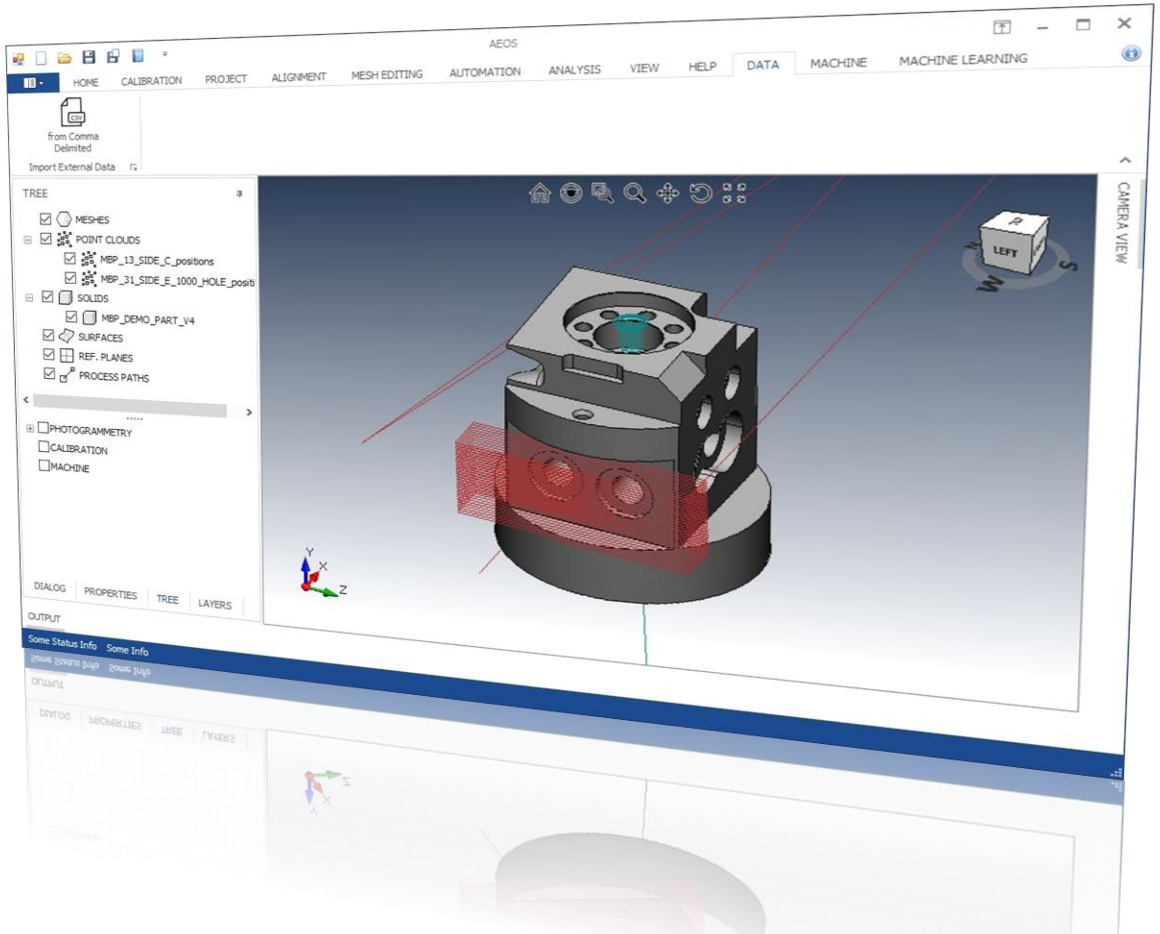
VARISCAN PRO

Based on structured light fringe pattern projection, the Variscan Pro 3D scanner models are our industrial, high accuracy, easy to use solution for those seeking to employ the power of 3D scanning for their applications

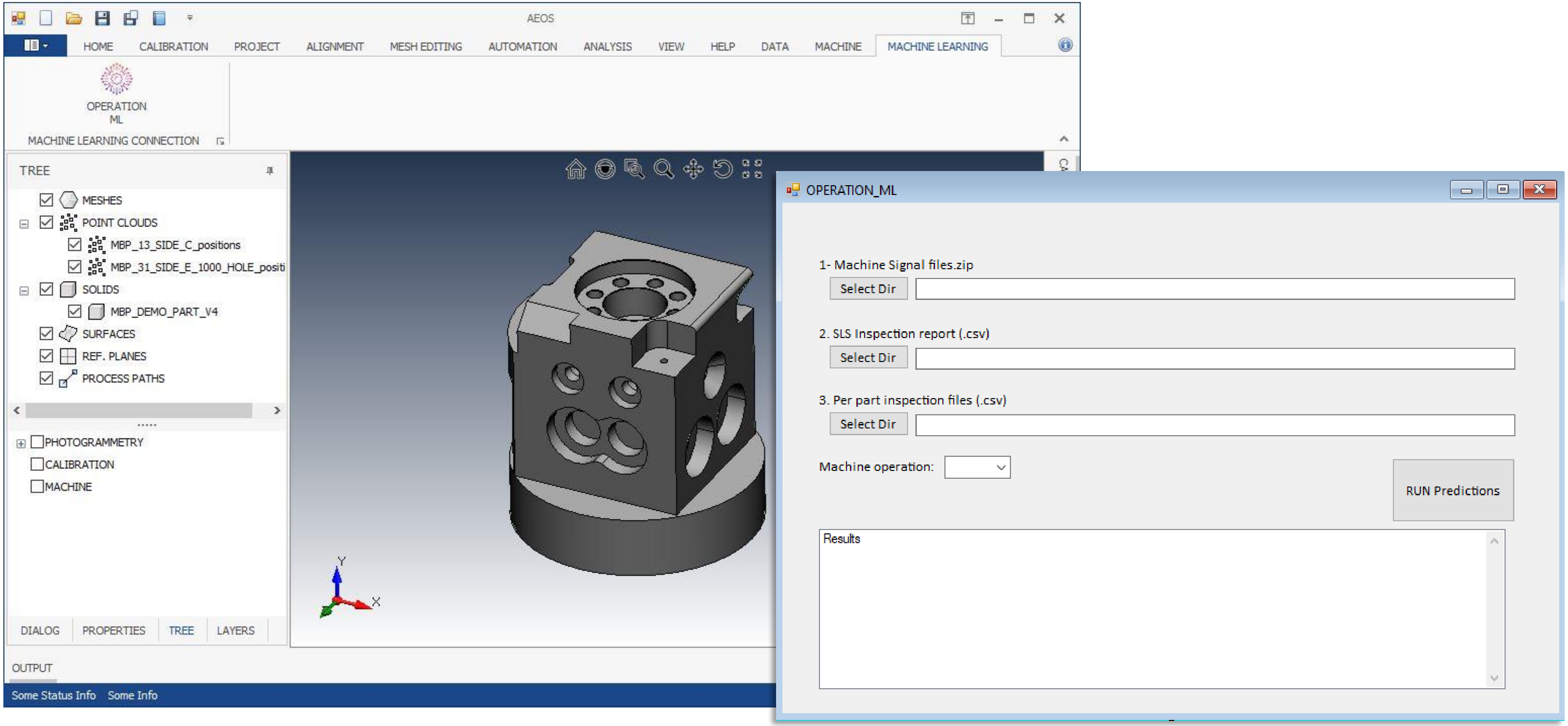
M3DI AEOS

Calibration, 3D Scanning, Post Processing, Analysis, Automation, Machine Learning

Part Digitization + Process Digitization = Digital twin



M3DI AEOS – Machine Learning Plugin

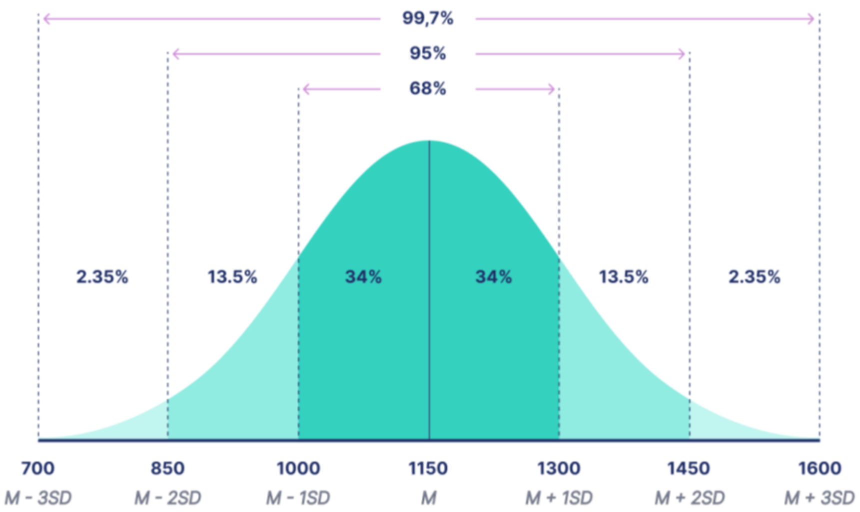


Initial Model Training Results

ML Prediction Algorithms General Setup

- Using the following machine signals
  - Load, Torque, Current, Command, Speed, ControlDiff1, ControlDiff2, Power
- Z-score of part residual is used for classification such that:
  - -1: Low Residual, 0: Average Residual, 1: High Residual

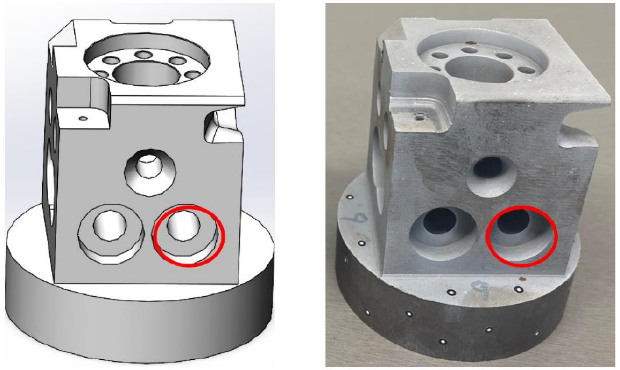
Using the empirical rule in a normal distribution



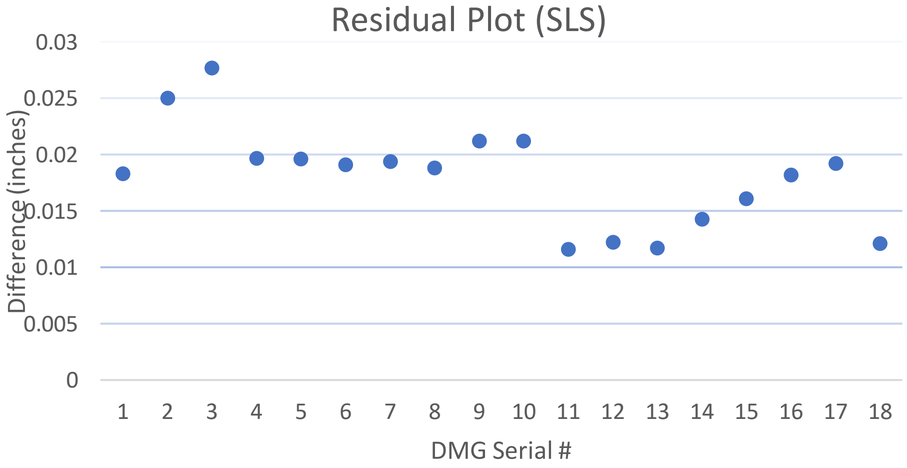
Classification	Even Split	Normal Split
-1 (Low Residual)	Z < -0.44 (33%)	Z < -1 (16%)
0 (Average Residual)	-0.44 < Z < 0.44 (33%)	-1 < Z < 1 (68%)
1 (High Residual)	Z > 0.44 (33%)	Z > 1 (16%)

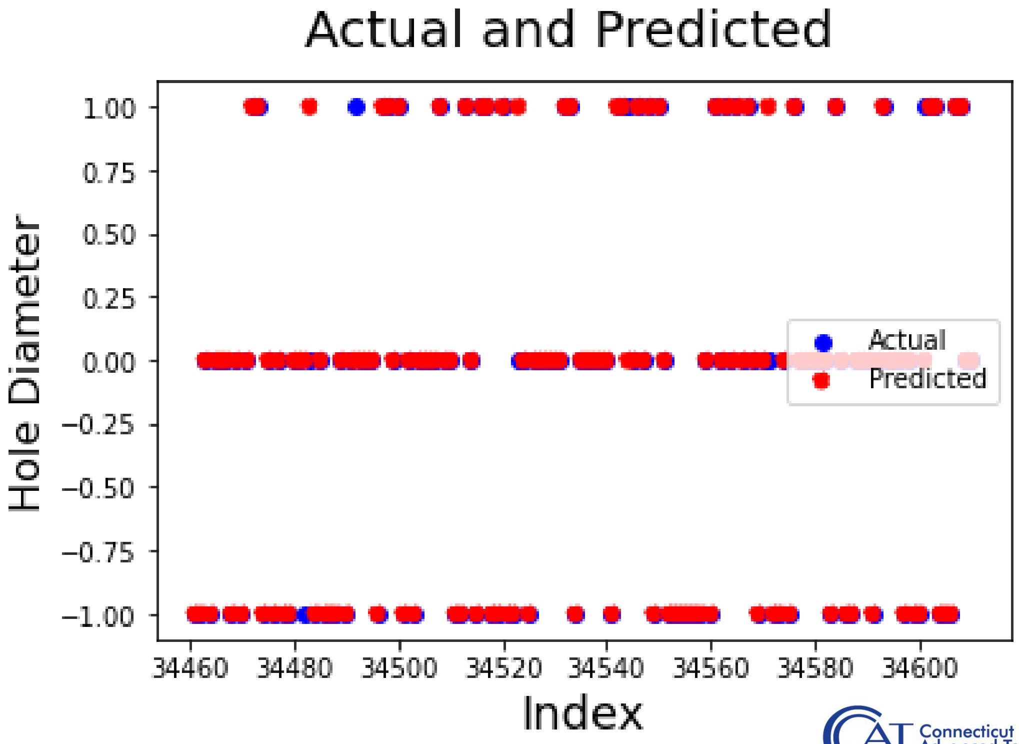
Neural Network Classification – Even Split

- **Accuracy:** 95.3% (scaled data)
- **ControlDif2 6:** 41.40 Weight
- **Hidden layers:** 1, Hidden nodes: 100
- Tanh Activation, 500 max iterations
- **Training time:** ~10 minutes



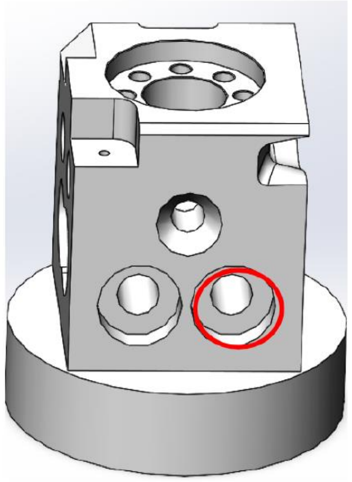
Feature 20.01: Right Counterbore Hole Diameter





Overall Model Comparison Feature 20 Hole Diameter

Classification Algorithm Performance Metrics				
Algorithm	Accuracy	Precision	Recall	F1
RFC (Even)	**0.985**	**0.985**	**0.985**	**0.985**
RFC (Normal)	0.974	0.974	0.974	0.974
MLP NNC (Even)	0.954	0.954	0.954	0.954
MLP NNC (Normal)	0.934	0.934	0.934	0.934
KNN (Even)	0.869	0.869	0.869	0.869
KNN (Normal)	0.854	0.854	0.854	0.854
LogReg (Even)	0.459	0.459	0.459	0.459
LogReg (Normal)	0.703	0.703	0.703	0.703
NBayes (Even)	0.420	0.420	0.420	0.420
NBayes (Normal)	0.295	0.295	0.295	0.295
SVM (Even)	0.692	0.692	0.692	0.692
SVM (Normal)	0.687	0.687	0.687	0.687




Feature 20.01: Right Counterbore Hole Diameter

Regression Performance Metrics	
Algorithm	R^2
RFR	0.970
MLP Reg	0.681
KNN Reg	0.737

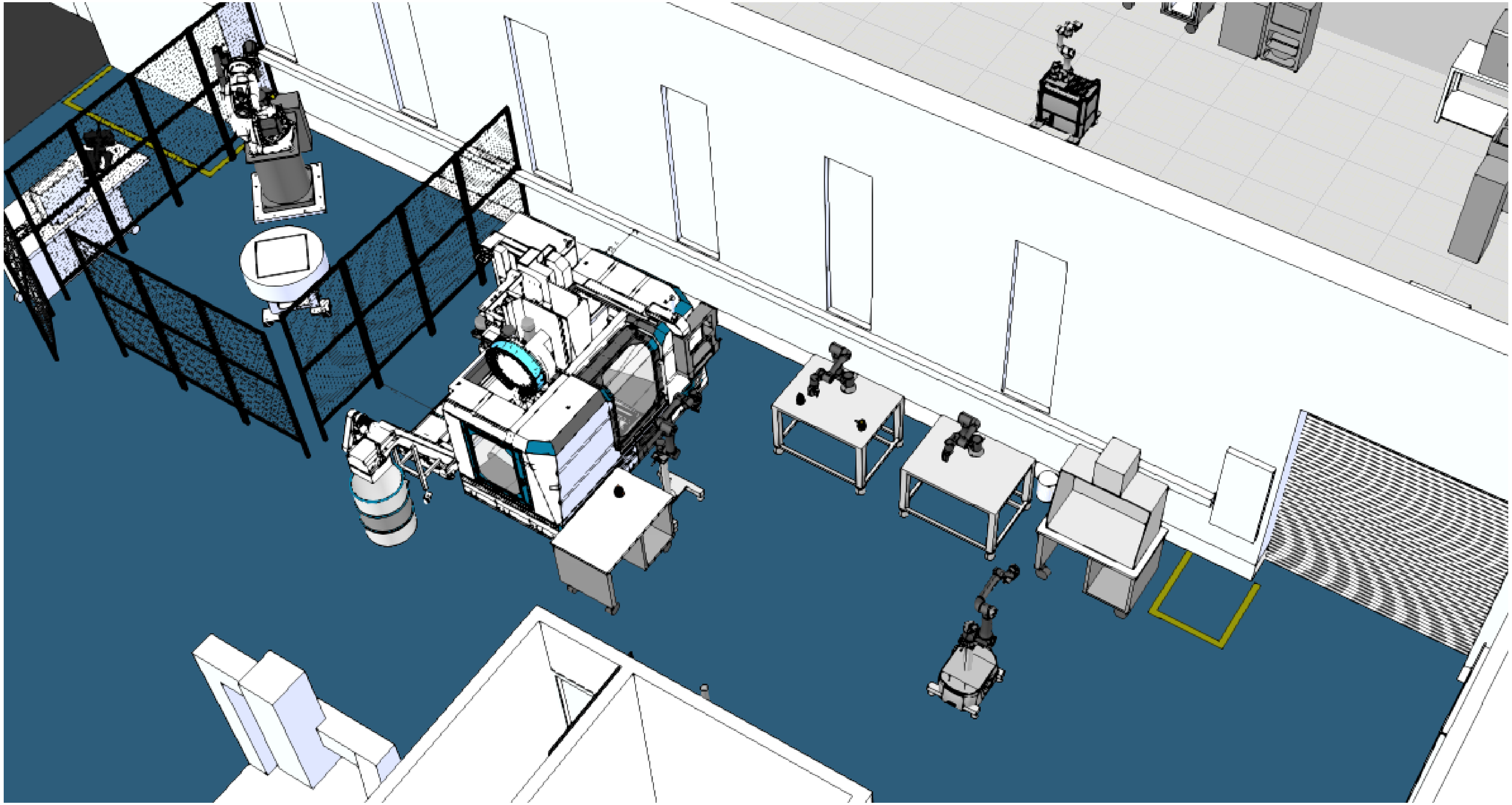
Next Steps

- Causality Analysis – Failure modes
- Corrective Action Algorithm
- Edge Device Software Development – Consume ML Model
- Establish high frequency communication with machine controller
- Establish high frequency machining controller parameter adjustment
- Manufacturing process simulation using Digital Twin
- Compare Digital Twin with actual measured data

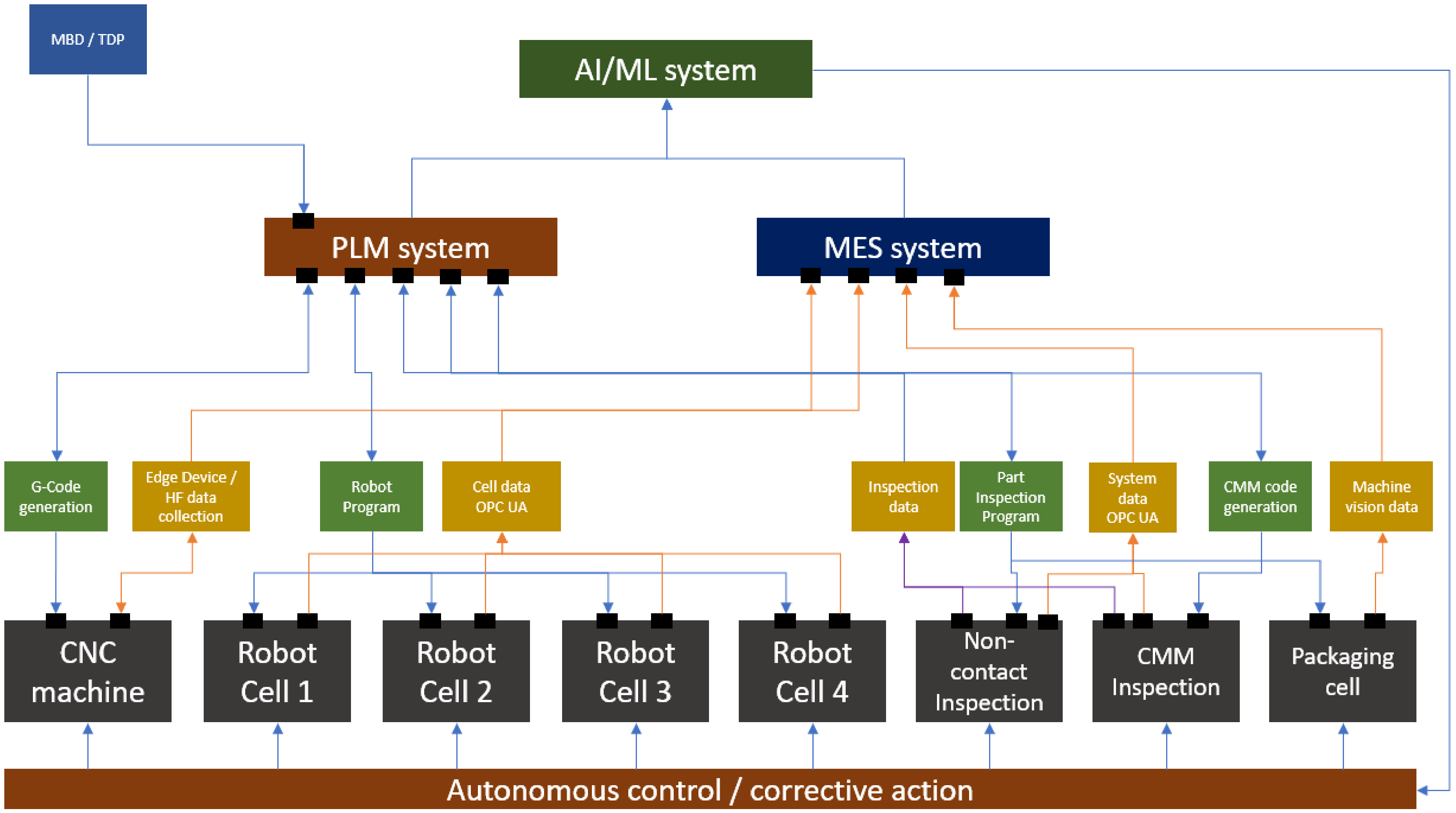
Work in Progress: Autonomous Manufacturing Cell

Connecticut Center for Advanced Technology, Inc.

CCAT Autonomous Manufacturing Cell



CCAT Autonomous Manufacturing Cell



Resource for Manufacturing Companies

- Regularly held technology demonstration workshops
- Access to training videos and on demand workshops
- Company specific technology demonstration projects
- Process development and validation
- Support with technology adoption

Connecticut Center for Advanced Technology, Inc.

Thank you

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Industry 4.0 AI Forum

Artificial Intelligence in Manufacturing

Jeff Orszak, Director, Business Technology & Innovation

CONNSTEP

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Artificial Intelligence in Manufacturing

CONNSTEP is Connecticut’s NIST MEP

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** The Upjohn Institute for Employment Research study (2019)*

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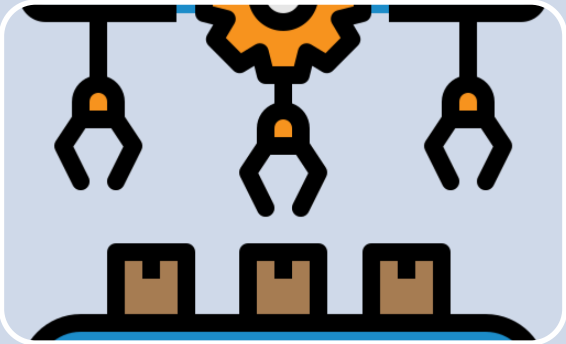
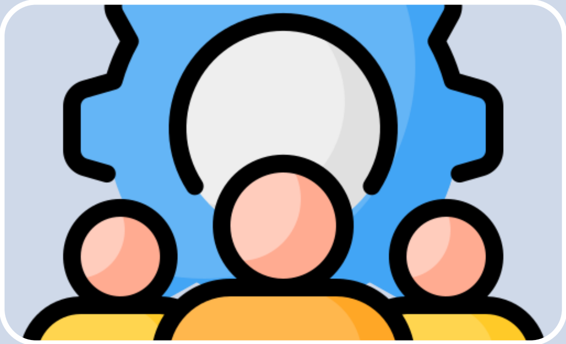
- **Continuous Improvement**
- **Quality Management**
- **Workforce Development**
- **Cybersecurity**
- **Technology and Industry 4.0**

Benefit Creation





Operations

↑ Performance
↑ Throughput
↑ Quality

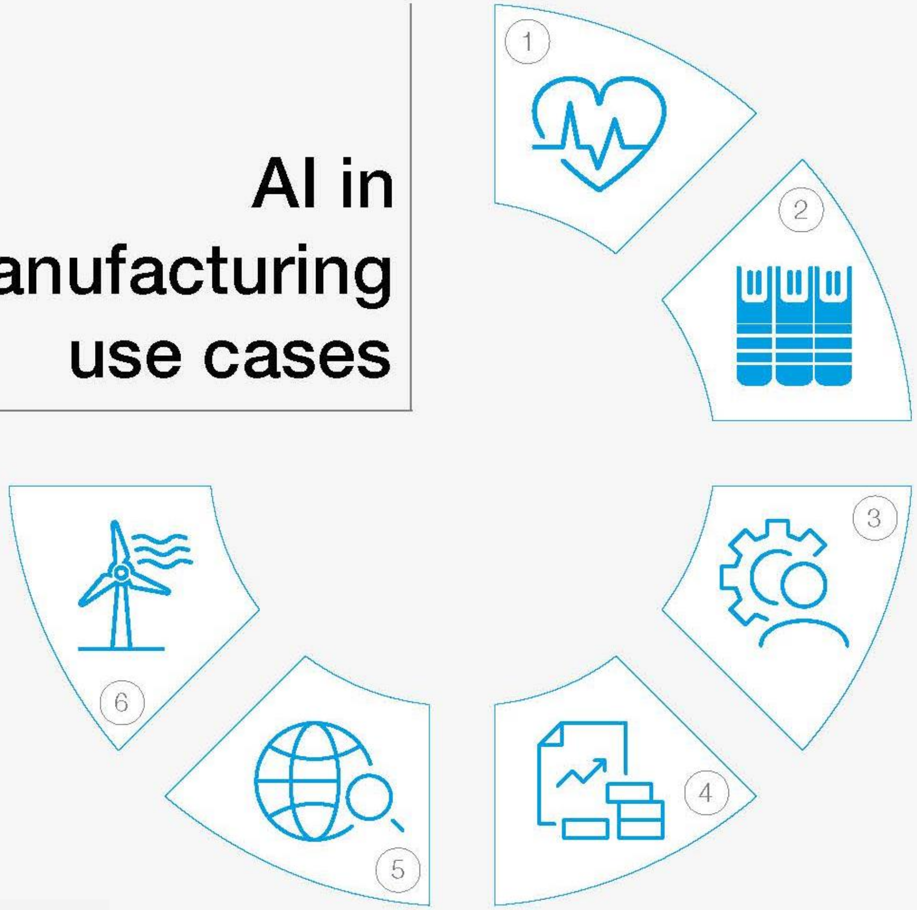
Workforce

↑ Decision Making
↑ Collaboration
↓ Risk

Sustainability

↓ Scrap Rate
↓ Material Used
↑ Machine lifetime

AI in manufacturing use cases



Source: WEF

Health and safety

- Employee health & safety: incident prevention
- Process safety: advanced alarm analytics

Quality

- Quality inspection in assembly
- Quality assurance/ defect inspection
- Quality testing
- Quality prediction

Maintenance

- Machine health monitoring: predictive maintenance
- Maintenance planning

Energy management

- Energy optimization
- Electricity demand forecasting
- Heating and cooling optimization

Supply chains

- Future demand and price forecasting
- Supply chain control tower
- Warranty and service management

Production process

- Process optimization
- Line balancing
- Product design and development
- Process parameter optimization
- Production planning/ decision support

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by assessing your company's situation

Make recommendations for opportunities where technology solves problems or generates the greatest benefit

Help you develop a business case

Rigorously measure results

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Jeff Orszak
Director, Business Technology & Innovation

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Connecticut Center for Advanced Technology, Inc.

Thank you

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