



# Transition to Industrial Reality





# We are industrial pioneers

Founded +200 years ago

On the Swiss Stock Exchange since 1931



Johann Conrad Fischer 1773-1854



Georg Fischer I 1804-1888



Georg Fischer II 1834-1887



Georg Fischer III 1864-1925

Georg Fischer was among the first to transition from hand production methods to machines

# ... through "Build to Stock" serial production methods to present day adaptive "On-demand" manufacturing



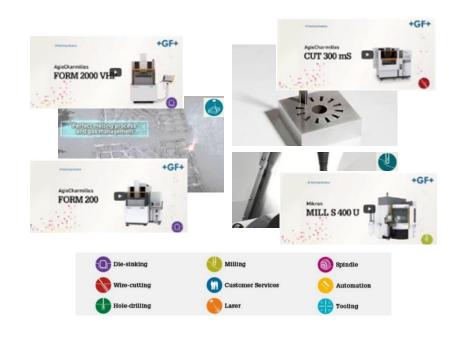


"People can have the Model T in any color - so long as it's black"

Henry Ford (1913)

#### From "Standardized Products" ...

Few materials and technologies, lengthy to establish, costly to move from pre-defined set up ...



#### ... to "Mass Customization"

Seemingly limitless choice of materials and technologies with growing sophistication and flexibility

Conventional manufacturing methods no longer meet expectations of fast product cycles

### Our Expectations in 2016



#### What is next?



### Step 4: Complete machine simulation

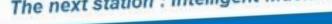
#### Deeply integrated systems

- "System in Silicon" complete machine modelling
  - + Physical systems, control processes, user applications
- Late decisions based on market feedback
  - + Field test inputs 'just in time' to optimise at pre-launch phase

#### Industrial Internet : Industry 4.0

- Smart factories with
  - + Automated production process flow optimisation
- Self learning machines
  - + Eliminate process tuning from user prospective

The next station: Intelligent Machines





Speed of Development: The Future of Machine Building | 23/06/2016 | Sergel Schurov

S. Schurov: "Speed of Development" Presentation at Matlab World Expo 2016

# 4<sup>th</sup> industrial revolution not only brings connectivity, it transforms organizations and value creation chain



#### Agile everywhere

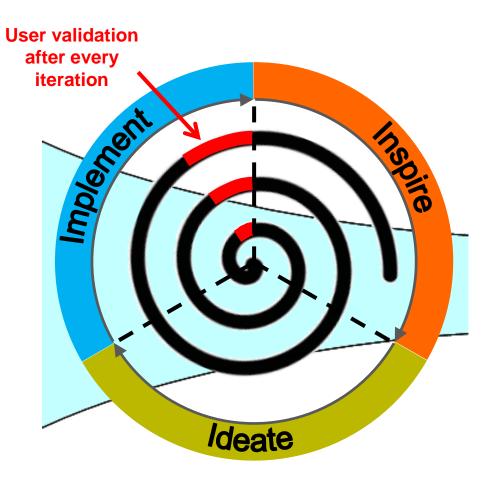
- Each development is a "mini-cycle" or short "sprint"
- Delivers functional solution ready for user testing

#### Design Thinking

- Iterations help validate multiple ideas in rapid succession
- Specifications are continuously refined based on agreed use-cases and customer feedback

#### Modelling and simulation

- Mode order reduction techniques cut simulation times transforming modeling into design tool, not just validation
- All and ML reinforce models with powerful algorithms using both EDGE and cloud-based technologies

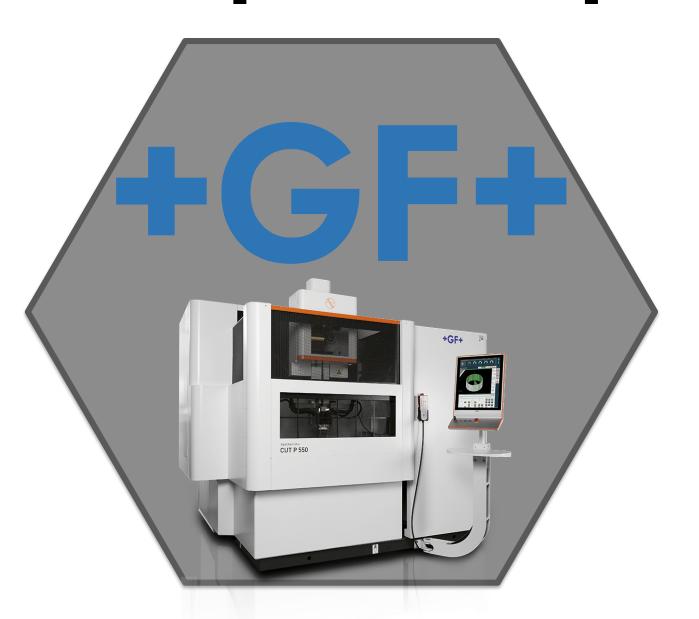


ITERATIVE IDEA DEVELOPMENT

Development cycles defined by numerical models, less by mechanical prototypes

#### Smart adaptive solutions as process building blocks

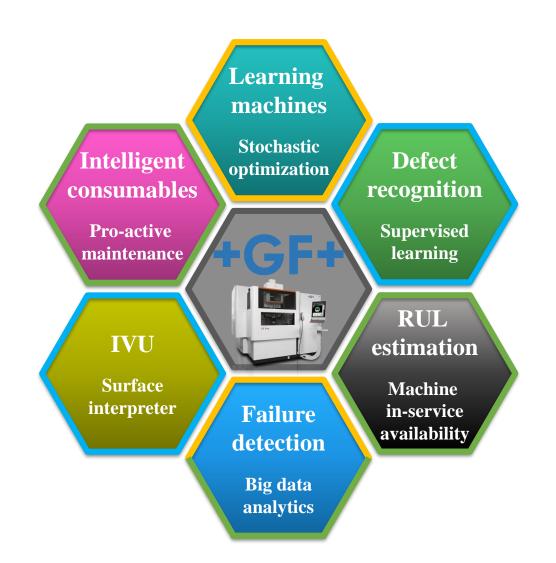






#### Smart adaptive solutions as process building blocks









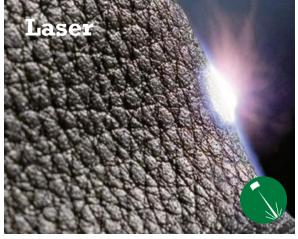
Al brings value across entire manufacturing value chain

#### **Unique Technology Portfolio**



















**Key figures** (2018)



Switzerland 15 027 1802 4572 

**Key figures** (2018)







**GF Piping Systems** 

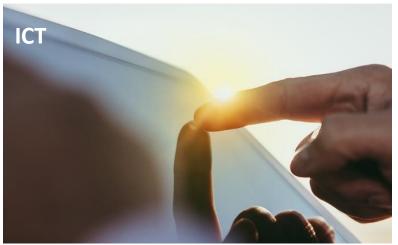
**GF** Casting Solutions

**GF Machining Solutions** 

#### Value-Added Solutions across Market Segments









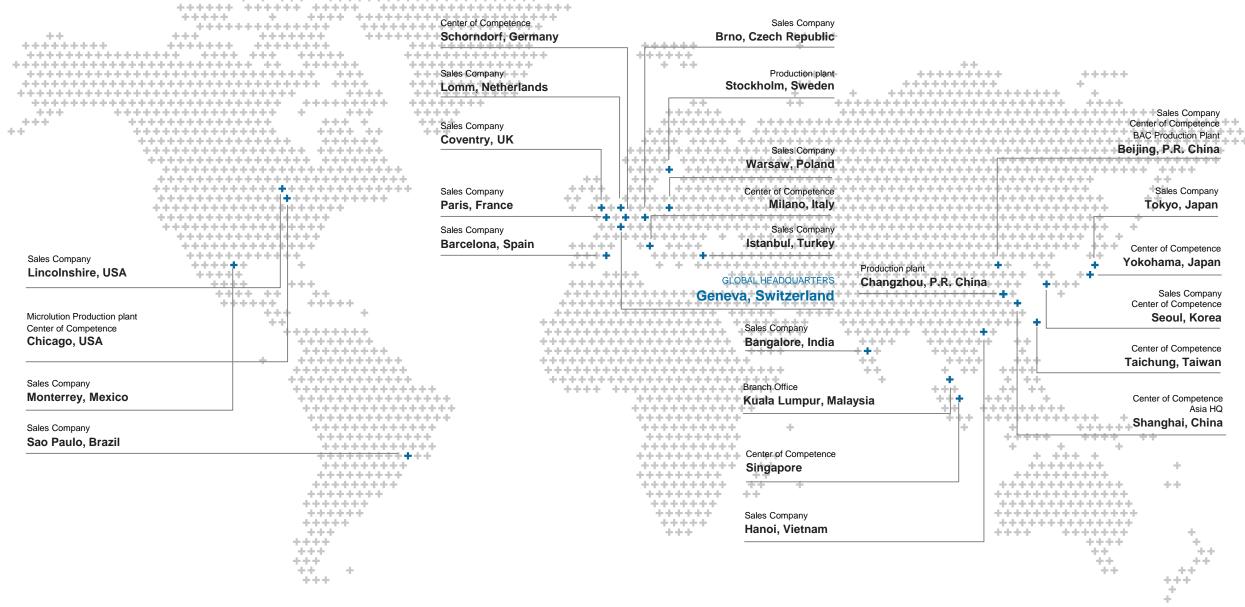




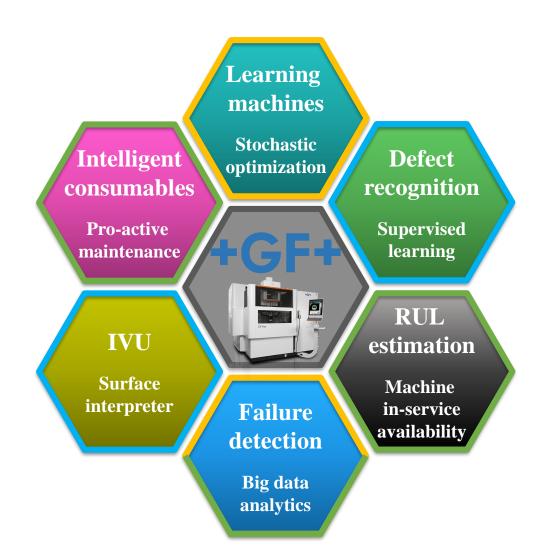


#### Global Reach









## **DEVELOPMENT**



#### **AI** for Zero Defect Manufacturing

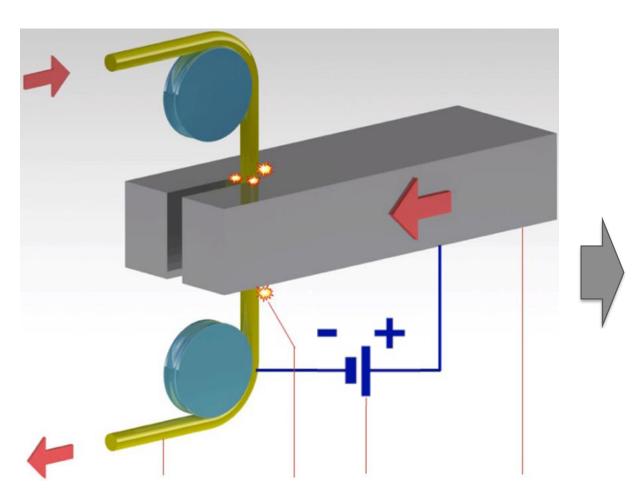


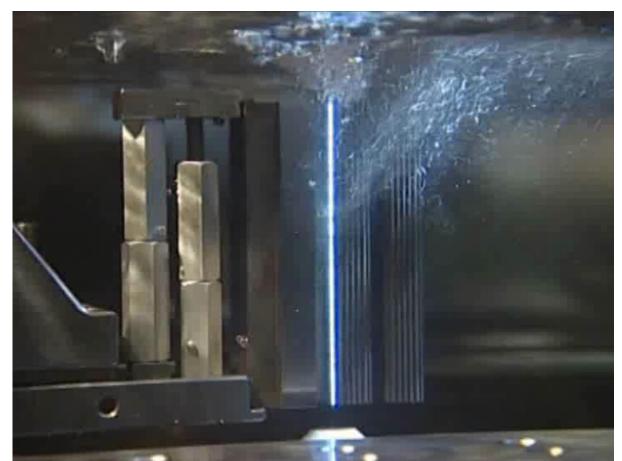
Defect recognition Supervised learning



#### EDM is preferred technology for tough materials



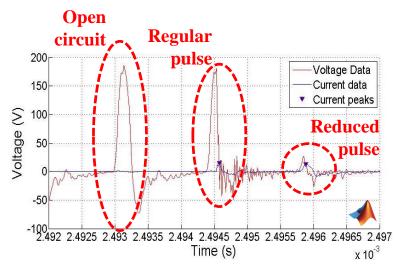




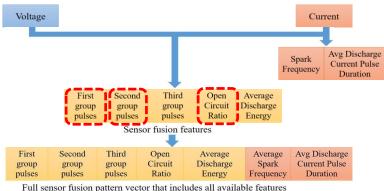
Process abnormalities must be identified in advance for correction to avoid failures later

#### Our approach: Neural Networks analytics



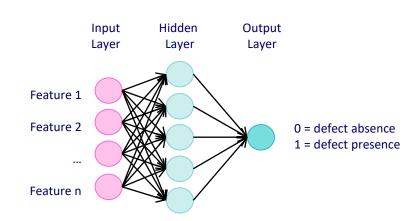


- Direct pattern analysis does not correlate automatically with surface defects
- Features must be extracted by grouping data of different type or source



 Full feature set from 50 parts (example) divided into training and test sets

30 20 parts parts		
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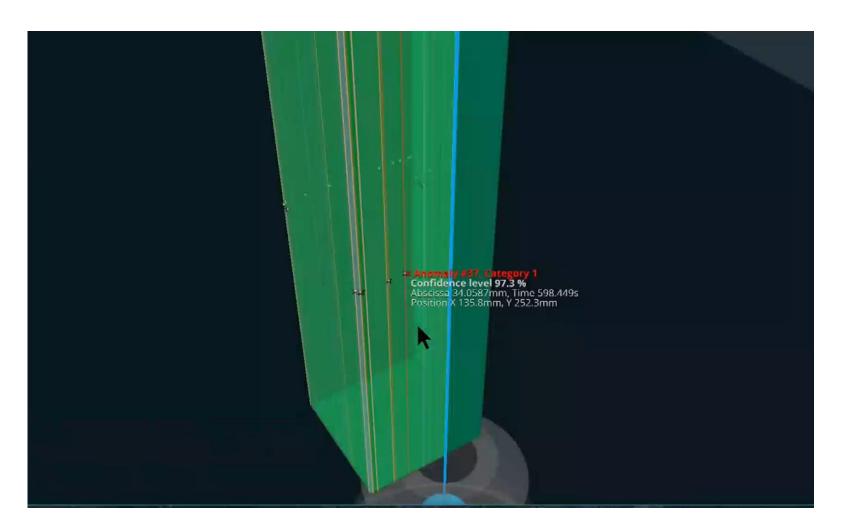
 Apply three-layer feed forward back-propagation neural network: RBF Success rate with control data

	Segment size			
NN Architecture	20ms	50ms	100ms	
7-7-1	88%	97%	96%	
7-14-1	81%	96%	97%	
7-21-1	87%	97%	96%	
6-6-1	87%	100%	96%	
6-12-1	87%	96%	93%	
6-18-1	86%	99%	97%	
\'				

 Optimise nodal architecture and segment size to find best accuracy

# Anomalies visualised by superimposing on the CAM image of the part





- Each machine has its unique ML signature
  - Training required for each new geometry and specific for each machine
- Neural Network algorithms evolve with increasing dataset
  - The best accuracy of the model does not always increase with node count

ML correlates abnormal conditions with defects by NN analytics of the fused sensor data

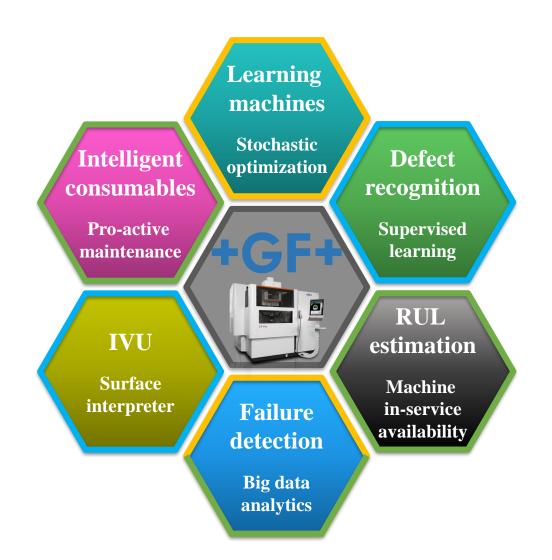
#### AI for Zero Defect Manufacturing



Defect recognition Supervised learning







## **DEVELOPMENT**



#### **AI** for Customized Applications



Learning machines

Stochastic optimization

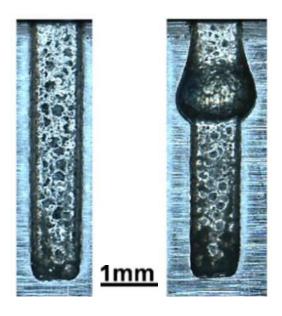


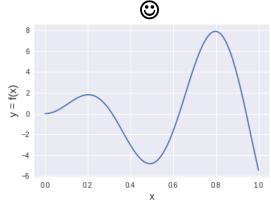
#### EDM Drilling: A unique solution for hard materials



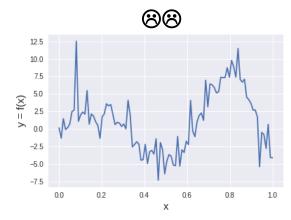


- Turbine blades can exceed 1200°C unless cooled
- Each part: 250+ cooling holes x 40+ blades x 8+ stages
- Machining time ~10s per hole every second counts
- EDM process has over 100 interdependent variables
- DOE unreliable, full factorial unrealistic
  - n=15,  $n^3 = 3375$  (brute force)
  - n=200, n\*3=600 (parsimonious gridding)

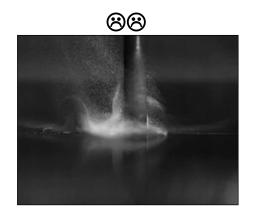




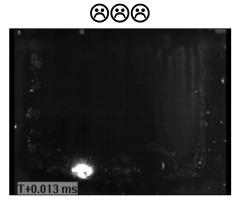
Local minima



Process noise



Material specific



Unpredictable behavior

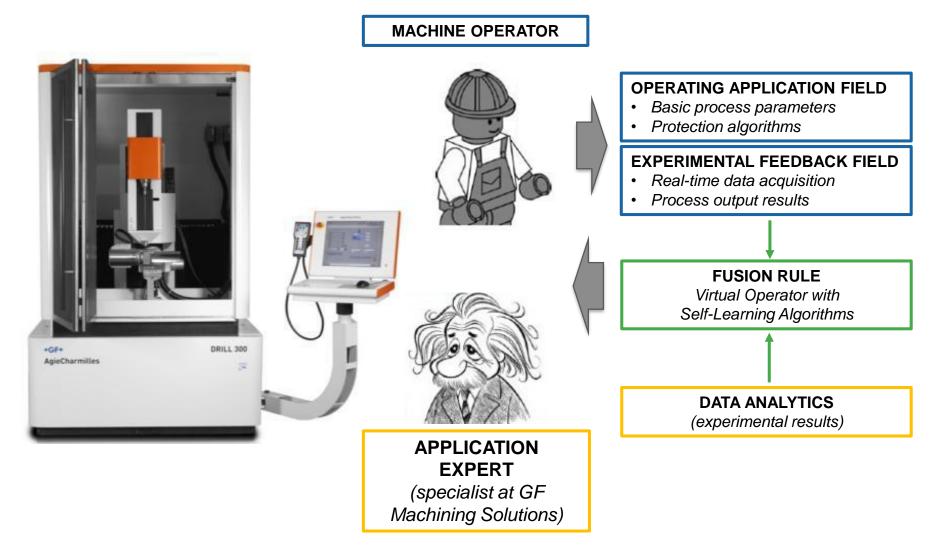
The process must be optimized to maximize cutting speed without loss of quality

#### Our approach: Learning Machines



- EDM Process
  - Expert system
  - Adaptive control

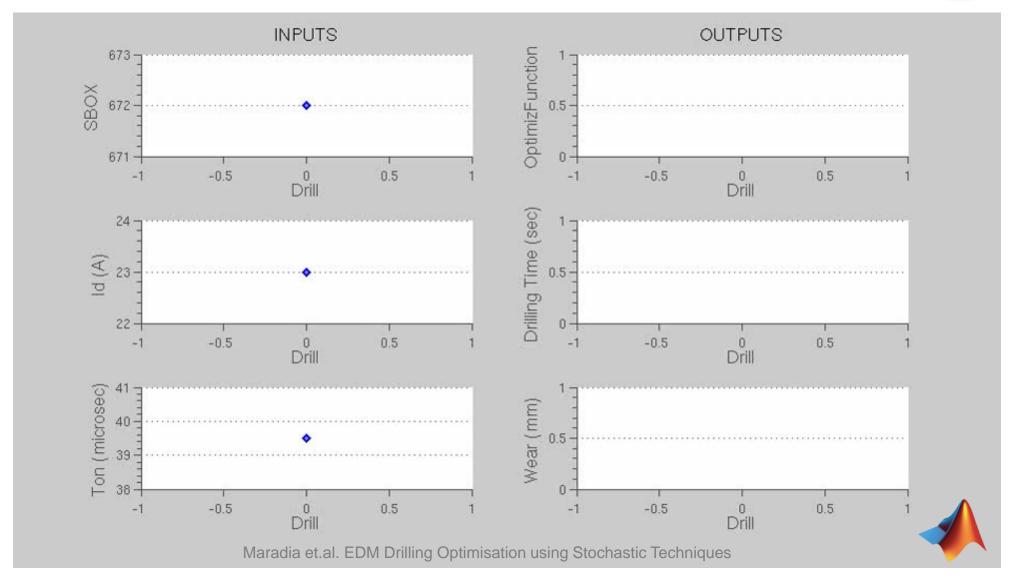
- ML Input
  - Self-learning algorithms
  - Fusion rules



Stochastic optimization algorithm finds process optima

#### Results: Improvement over expert set-up





For three main process inputs, the AI algorithm requires ~40 iterations

#### **AI** for Customised Applications

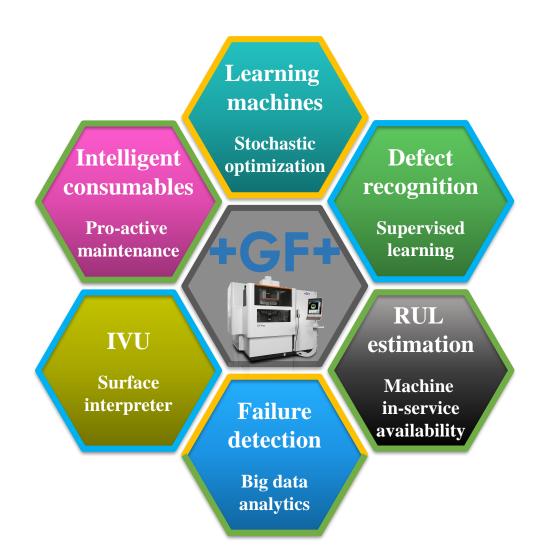


Learning machines

Stochastic optimization







## **DEVELOPMENT**



#### **AI** in Proactive Maintenance



RUL estimation

Machine in-service availability



**MAINTENANCE** 

#### Preventive maintenance: mandatory for reliability





From CAD/CAM to final product: workflow planning relies on guaranteed machine availability for uninterrupted process

#### **User Expectations**

Pro-active advice on m/c maintenance periods

No extra costs: service fees included in the purchase contract

#### **OEM Constraints**



No maintenance annotation

Heterogeneous data sources

Limited options for data analytics

Difficulty of data fusion/processing



Interventions ahead of time increase costs unnecessarily

#### Our approach: Hybrid Condition Monitoring



Path 1: Maintenance annotation available:

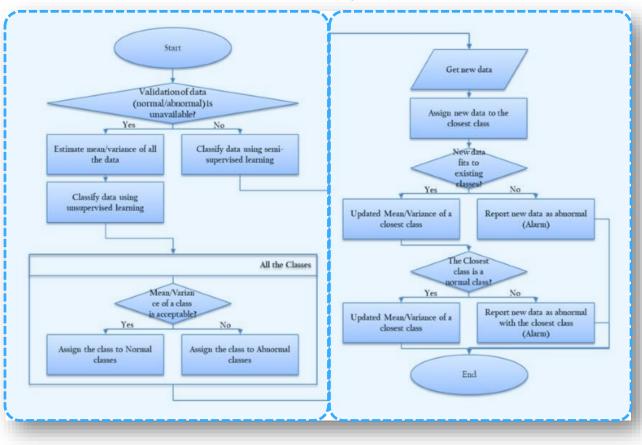
#### **Supervised learning**

- Main purpose : Data classification and Estimation of Residual Useful Lifetime (RUL)
- Hard assignment maintenance assumptions can not be changed with upcoming data

# Path 2 : Maintenance annotation *not* available : **Unsupervised learning**

- Main purpose : Anomaly detection
- Soft assignment maintenance assumptions can change depending on upcoming data

#### Combine two analytical paths



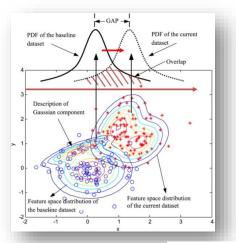
Both methods can run concurrently to calculate RUL and detect early failures

# Apply Adaptive Gaussian Model to visualise deviation from normal

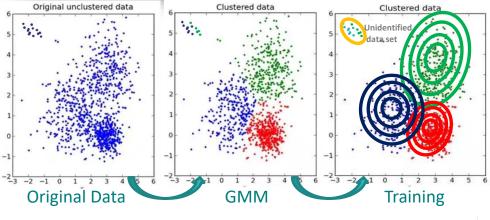
- Step 1: Gaussian Mixture Model (GMM)
  - Convert symmetrical Gaussian "Bell Curve" distribution to probabilistic "Mixture Model"
- Step 2: Predictive Maintenance Algorithm
  - Apply GMM to original dataset using semisupervised learning to cluster data
- Step 3: Calculate Residual Useful Lifetime (RUL)
  - Calculate Mahalanobis Distance-Residual from regression calculated mean as a failure probability measure

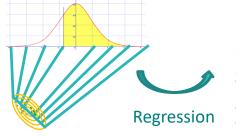
Model accuracy improves with larger datasets

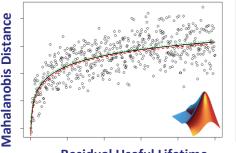




Yu, J., 2012. Machine tool condition monitoring based on an adaptive Gaussian mixture model. *Journal of Manufacturing Science and Engineering*, 134(3), p.031004. https://ict4sm.epfl.ch/

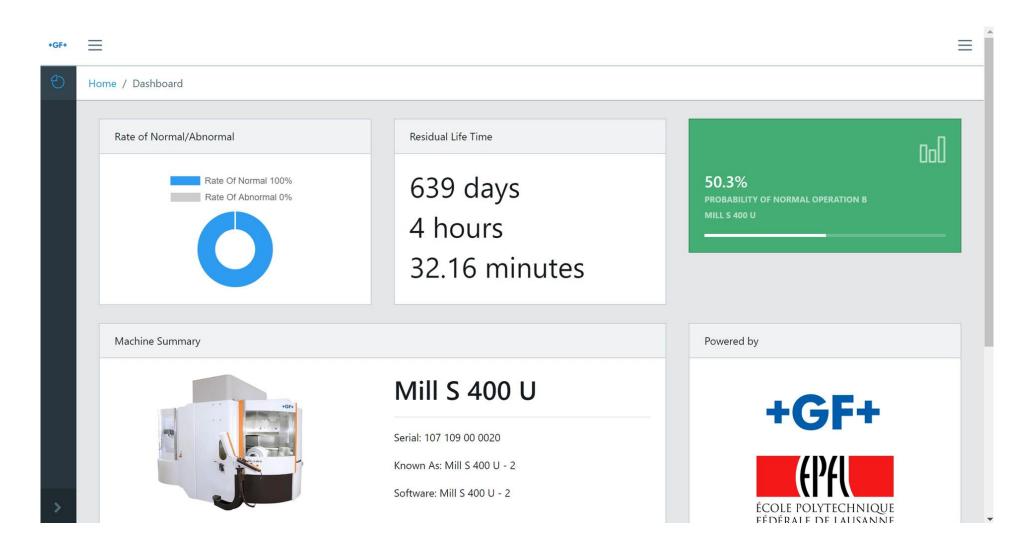






#### Dashboard to visualize maintenance needs





Customer can see maintenance alerts as well as accompanying process data

#### AI in Proactive Maintenance



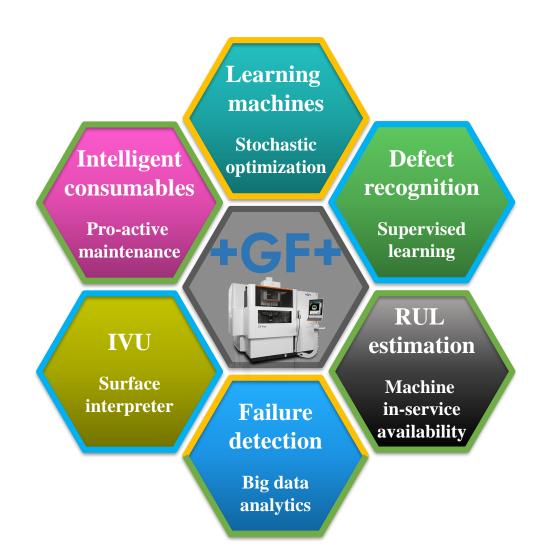
RUL estimation

Machine in-service availability



**MAINTENANCE** 





## **DEVELOPMENT**



#### **AI** for Integrated Metrology



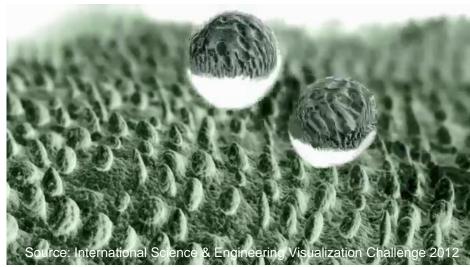
IVU
Surface
interpreter



**OPERATION** 

#### Functional Surfaces – Mother Nature's Magic





Hydrophobic Surface example : Lotus Leaf



#### Self cleaning

- Domestic appliances
- Automobile
- Turbine/Jet engine



#### Anti-icing

Aerospace and defense



#### Anti-microbial

Medical



#### Anti-adhesion

- Domestic appliances
- Turbine/Jet engine
- Manufacturing

Classical methods measure roughness (Ra)



- Similar Ra value, different behavior
- Measure workpiece without removing it from the machine allows:
  - Detect defects: micro cracks, burns, pitting
  - Correct errors automatically
  - Optimize using self-learning automation

In-situ surface characterization is required to achieve desired properties

#### Our approach: Surface Interpreter



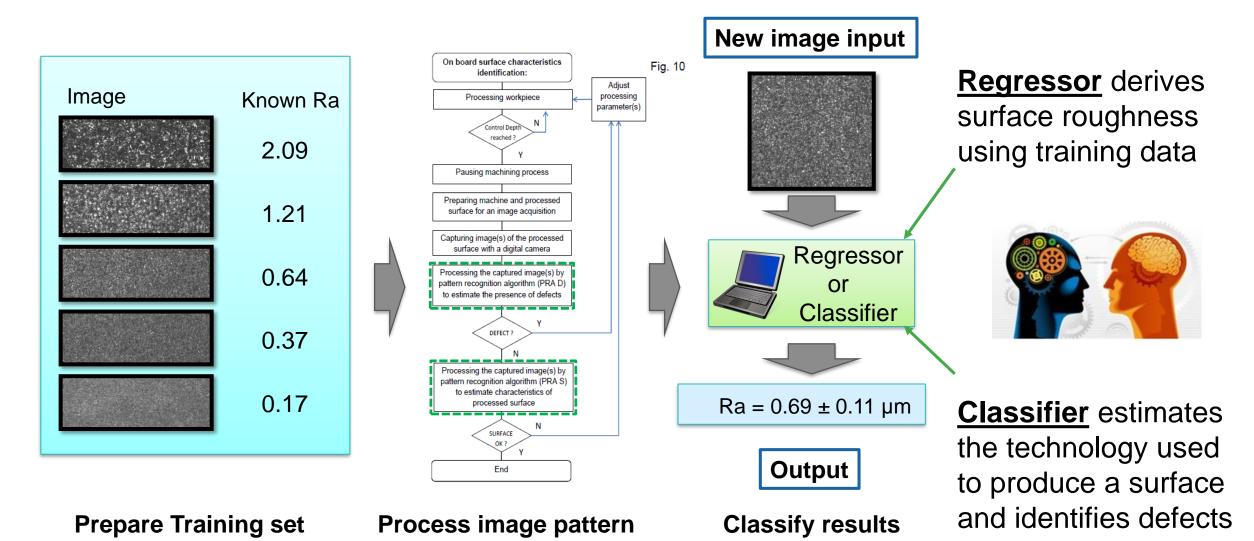
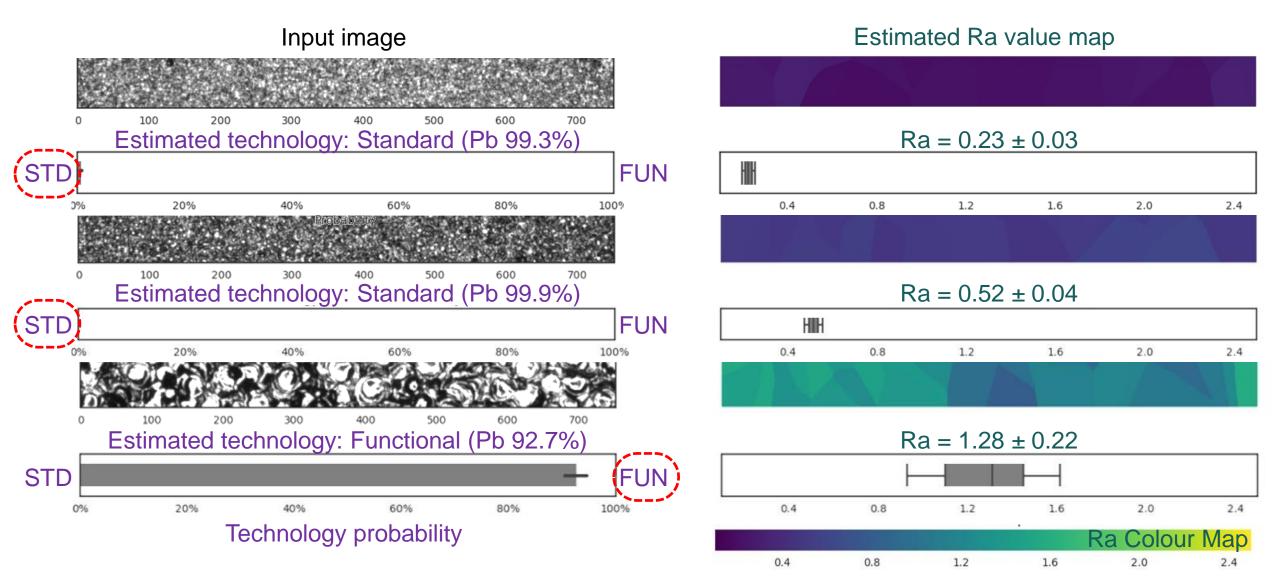


Image analysis use Convolutional Neural Networks to recognize fingerprints

#### Image captured using built-in CCD – then classified w +GF+





Data processed using EDGE PC with access to cloud-based machine learning data set

#### **AI** for Integrated Metrology

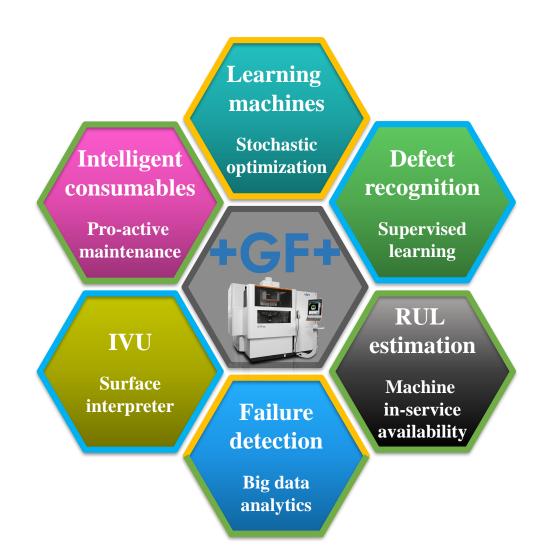


IVU
Surface
interpreter



**OPERATION** 





## **DEVELOPMENT**



# AI applications find use across entire manufacturing value chain



- R&D Development team applies ML to fast-track technology development
  - Make customised applications a reality
  - Technology adaptation on-demand
- All applications in the field improve customer flexibility and operational effectiveness
  - Eliminate setting errors by using built-in metrology
  - Instant defect recognition with process data analytics
- Customer care teams support end users throughout product lifetime with proactive maintenance tools
  - Anticipate issues before they become a problem
  - Intelligent consumables "just in time"

### **DEVELOPMENT**

**OPERATION** 

**MAINTENANCE** 

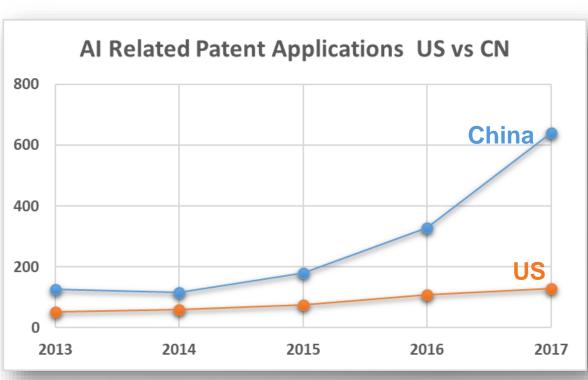
All three domains share Al competencies and tools

#### **Conclusions**



#### Can we afford not to Al?

- Accelerating customer demands for applicationspecific solutions and on-demand configurations
- Manufacturing value chains growing in complexity and need to be adaptive
- 3. Relentless push for higher performance/productivity without costly (and error-prone) human intervention
- 4. All empowered by IOT tools has proven its capabilities; enables huge worldwide investments into this field
- 5. Competitors in Asia driving ahead at full speed



Data: CB Insights

The choice already made: Al is self-enabling and accelerating!

#### What comes next?



# Industry 5.0 is already here!





Thank you

**GF Machining Solutions** 

Passion for Precision