GF Machining Solutions

AI Application in Machine Tools

S. Schurov, U. Maradia, R. Perez
Bern, May 2019
Transition to Industrial Reality
We are industrial pioneers

Founded +200 years ago

On the Swiss Stock Exchange since 1931

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

S. Schurov: "Speed of Development"
Presentation at Matlab World Expo 2016
4th 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
  - AI and ML reinforce models with powerful algorithms using both EDGE and cloud-based technologies

*Development cycles defined by numerical models, less by mechanical prototypes*
Smart adaptive solutions as process building blocks
Smart adaptive solutions as process building blocks

AI brings value across entire manufacturing value chain
Unique Technology Portfolio

- Milling
- EDM
- Laser
- Additive Manufacturing
- Micromachining
- Spindles
- Tooling and Automation
- Digital Transformation

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<table>
<thead>
<tr>
<th>Founded</th>
<th>Headquartered</th>
<th>Employees worldwide</th>
<th>Sales CHF million</th>
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Key figures (2018)

- Countries: 33
- Companies, service and sales centres: 140
- Productions plants: 57
Three divisions

GF Piping Systems

GF Casting Solutions

GF Machining Solutions
Value-Added Solutions across Market Segments

Aerospace

ICT

Automotive

Medical

Electronics

Energy
Failure detection
Big data analytics
Defect recognition
Supervised learning
RUL estimation
Machine in-service availability
IVU
Surface interpreter
Intelligent consumables
Pro-active maintenance
Learning machines
Stochastic optimization
DEVELOPMENT
OPERATION
MAINTENANCE
AI for Zero Defect Manufacturing

Defect recognition
Supervised learning

OPERATION
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

<table>
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<th>Segment size</th>
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<th>50ms</th>
<th>100ms</th>
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- Apply three-layer feed forward back-propagation neural network: RBF
- Success rate with control data
- 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

OPERATION
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- Failure detection
- Big data analytics
- Intelligents consumables
- Pro-active maintenance
- IVU
- Surface interpreter
- Learning machines
- Stochastic optimization
- Defect recognition
- Supervised learning
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DEVELOPMENT
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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)

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
AI in Proactive Maintenance

RUL estimation
Machine in-service availability
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

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 semi-supervised 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*

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

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AI for Integrated Metrology

IVU
Surface interpreter

OPERATION
Functional Surfaces – Mother Nature’s Magic

- 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

Hydrophobic Surface example: **Lotus Leaf**

- Self cleaning
  - Domestic appliances
  - Automobile
  - Turbine/Jet engine

- Anti-microbial
  - Medical

- Anti-icing
  - Aerospace and defense

- Anti-adhesion
  - Domestic appliances
  - Turbine/Jet engine
  - Manufacturing

*In-situ surface characterization is required to achieve desired properties*
Our approach: Surface Interpreter

Image analysis use Convolutional Neural Networks to recognize fingerprints

- **Regressor** derives surface roughness using training data
- **Classifier** estimates the technology used to produce a surface and identifies defects

**Prepare Training set**
- Known Ra
  - 2.09
  - 1.21
  - 0.64
  - 0.37
  - 0.17

**Process image pattern**

**Classify results**

**New image input**

Ra = 0.69 ± 0.11 µm
Image captured using built-in CCD – then classified

Estimated technology: Standard (Pb 99.3%)

Estimated technology: Standard (Pb 99.9%)

Estimated technology: Functional (Pb 92.7%)

Estimated Ra value map

Ra = 0.23 ± 0.03

Ra = 0.52 ± 0.04

Ra = 1.28 ± 0.22

Technology probability

Data processed using EDGE PC with access to cloud-based machine learning data set
AI for Integrated Metrology

IVU
Surface interpreter

OPERATION
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

- AI 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”

All three domains share AI competencies and tools
Conclusions

Can we afford not to AI?

1. Accelerating customer demands for application-specific solutions and on-demand configurations
2. 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. AI empowered by IOT tools has proven its capabilities; enables huge worldwide investments into this field
5. Competitors in Asia driving ahead at full speed

The choice already made: AI is self-enabling and accelerating!
Industry 5.0 is already here!
Thank you

GF Machining Solutions
Passion for Precision