Fraunhofer IZFP

Avoiding defects before they arise

AI-based Sensor Systems for Predictive Quality & Predictive Maintenance

Introduction

AI for NDT 4.0

The term "Artificial Intelligence" was coined back in the 1950s when British mathematician Alan Turing published a paper that asked whether machines can think. Shortly thereafter, a seminar entitled "Artificial Intelligence" was held at Dartmouth College in New Hampshire. But the development of successful AI applications reached its familiar breathtaking pace only in the last few years. Some of this is certainly due to the rapid improvements in computing power – today's smartphones, for instance, are as powerful as the best computer in the world 25 years ago. At least as important for the current AI boom is the data explosion of the last few years. The intelligence of a machine is primarily dependent on the data at its disposal. This data is delivered by the sensors that today dominate almost every technological sector. A good example are modern smartphones with their integrated proximity sensors, fingerprint readers, GPSes, gyroscopes, accelerometers, barometers, and heart rate monitors.

More and more sensors are being used in manufacturing companies as well. As part of "Industry 4.0" and the Industrial Internet of Things (IIoT), they serve to improve product and process quality and flexibility and increase productivity. Such sensors must have not only great data availability, but also sufficient data quality; that is, they must ensure that the data are correct, consistent, and free of disruption. The more advanced and powerful a sensor, the more relevant and valuable the data it generates. For almost 50 years, Fraunhofer IZFP has been developing powerful sensors that deliver relevant information about materials, semi-finished products, and components without destroying them. These sensors become "cognitive" when they are linked to AI.

AI can use analysis of nondestructive sensor data to return substantially more precise forecasts and more robust classifications than conventional assessment methods such as physics-based analytical models. This has been studied at Fraunhofer IZFP as part of various projects. Their results are described below.

AI is used in advanced image processing applications (X-ray, ultrasound, thermography. Unlike classical imaging methods, AI also allows the processing of low-grade images, which results in lower hardware requirements (positioning accuracy, contrast, resolution, etc.). Images can be assessed in situ (that is, immediately by the cognitive sensor). Image content, such as defects and anomalies, but also false indicators, are detected and assessed automatically. This allows functional defects to be automatically distinguished from merely cosmetic ones. The interpretation of the testing results (that is, the diagnostics) in particular is still a challenge and requires a highly qualified tester. AI-based assistance systems allow even personnel with little training to perform complicated testing tasks and return results of suitable quality. AI is used to automatically analyze structured and unstructured sensor data and thus generate models that describe the links between product characteristics that can be detected by nondestructive means and those that can be measured by destructive means only. The correlation established in this way allows material properties such as hardness to be determined nondestructively.

AI then optimizes such indirect measurements for reliability and precision. If process emissions detected with sensors are processed with AI in real time, defects can been detected early – even before they are arising.

Furthermore, by continuously comparing current results with historical data, the AI identifies patterns that make it possible to predict future results and trends. Defects, bottlenecks, downtimes, and losses of productivity can thus be detected in good time and suitable corrections ultimately made to avoid them. Defects are avoided before they are made. AI-based sensor systems thus ensure that rejects are not even produced (predictive quality) and that machines no longer fail unplanned (predictive maintenance).

A current study by the Capgemini Research Institute shows that Germany is leading the world in introducing AI in manufacturing industry. Of German manufacturing companies, 69% have at least one AI application in use. In the U.S. it is only 28%, and in China it is 11%. Fraunhofer IZFP's research is contributing to expanding this lead in innovation.

Dr. Bernd Wolter
Fraunhofer IZFP

Content

3D SmartInspect

Smart assistance system with interactive visualization for the manual testing

Application

Smart system for quality assurance of safety-relevant components or large surfaces

Situation

Manual testing is widely applied in inspection of safety-relevant components. The testing quality is greatly dependent on personnel and environmental conditions. An accurate analysis of measured values and a complete coverage of the test area require a high level of personal expertise. In addition, companies face considerable challenges with regard to conducting inspections. Up until now, test reports have been hand-written and detected abnormalities have been marked on the components themselves. However, this method does not establish a digital connection between the test object and the test procedure.

Fraunhofer IZFP has tackled this topic and developed the intelligent assistance system "3D SmartInspect" with cognitive signal processing. The inspection process is recorded optically; the tracking module follows the movement of the probe and records measurement signals and inspection positions. The measurement signals are automatically processed by AI, evaluated, and merged with spatial coordinates in the live image. The detected indications are displayed on a control screen (notebook or tablet). An Augmented Reality (AR) software also enables visualization with a HoloLens™. The results can then be transmitted digitally to a server or data center.

AI approach: AI-supported analysis

AI-supported analysis of eddy current and ultrasound signals

Advantages

- Reliable defect detection in measurement signals
- Interactive support of testing personnel in the manual testing process
- Big Data: Automatic documentation of inspection results to show that the test was performed correctly and according to quality assurance requirements, including transfer and storage of the analyzed measurement data
- Can be combined with collaborative robotics
- Integration of other sensors based on point testing principles

Fields of application

The assistance system is designed for all manual testing application areas, including

- Aerospace (safety-relevant components)
- Energy systems (turbines, generators, high-pressure vessels, etc.)
- Large component systems

Maturity level

The 3D SmartInspect prototype has been successfully set up; industrial validation is in progress.

Sensors in use

- Ultrasound
- Eddy current
- Optical

AcoustiX

Acoustic sensor system for final assembly inspection or operation monitoring by means of cognitive signal analysis

Application
Final assembly inspection for the cutting tools of harvesters

Situation
Noises emitted by machines and systems in the industrial environment change when faults arise. Experienced specialists can detect defective components based on these changes. However, such inspections are at the mercy of subjective influences such as personnel fatigue and interference from ambient noise, making detection unreliable. To solve these problems, Fraunhofer IZFP has developed "AcoustiX", an acoustic sensor system with cognitive signal analysis.

AI approach: Algorithms
The cognitive approach is similar to subjective human noise analysis, but returns objective, reproducible results. Operating vibrations and/or noises are detected by suitable sensors and digitalized, then split up into short segments, filtered, and transformed. Consecutive signal segments are then compared by means of suitable mathematical methods.

Unexpected vibrations or noises return characteristic differences between segments, and these differences are displayed by the system. The algorithms developed require no previous knowledge. All that is needed for basic software parameterization is a few signals for comparison.

The algorithms can thus detect anomalies without tiresome learning-in. Instead, the algorithm uses the signal history to evaluate consecutive signal segments in order to assess the signal as a whole.

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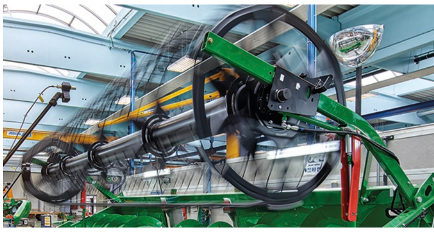
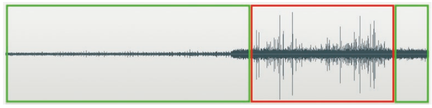
Advantages
- Great testing reliability by means of objective, simultaneous evaluation of signals from multiple sensors
- Cognitive quality assessment without explicit calibration
- Many possible applications
- Allows sustained quality monitoring
- Greatly reduces set-up effort
- Quick online assessment
- Individual, tailored system design
- Evaluation algorithms can be integrated into existing inspection systems
- On-site feasibility studies with a portable system
- User-friendly, adaptable software that can be tailored to the customer

Fields of application
- Final assembly inspection of machines or systems with moving parts
- Operation monitoring at regular intervals or constant quality monitoring for large, autonomously operated machines and systems
- Quality assessment of individual assemblies, including those operated on test benches

Maturity level
The system is in continuous operation on a customer's production line, where it fulfills the tasks it is given with optimal reliability and to the customer's fullest satisfaction.

Sensors in use
Microphones and structure-borne sound sensors





An acoustic signal with anomalies in the area marked red

AM SoftND

Quality assurance and regulation for additive manufacturing (AM) with cognitive online monitoring

Application
Control of manufacturing parameters of an additive manufacturing system for adjusting desired component quality

Situation
Conventional AM systems provide little information about component quality during the process. Occurrence of anomalies such as pores, bonding defects, and cracks is verified only after the component has been manufactured, and detection requires metallography or X-ray computer tomography (CT). The manner in which anomalies detected in AM components by sensors affect their functionality (such as mechanical strength) is still not sufficiently understood.

Current Fraunhofer IZFP research projects are aimed at developing AI-based processes for detecting defects early and adapting AM processes.

AI approach: Algorithms
An important point in finding a solution is the consideration of the entire manufacturing chain, from the technological foundations to the manufactured assembly. Starting with the CAD model, initial simulation values are taken from the manufacturing plans. The resulting data pool is continuously expanded with the machine and sensor data collected during the manufacturing process. The assembly is then assessed in a downstream, nondestructive inspection and in stress tests. This provides a database with comprehensive information about the component.

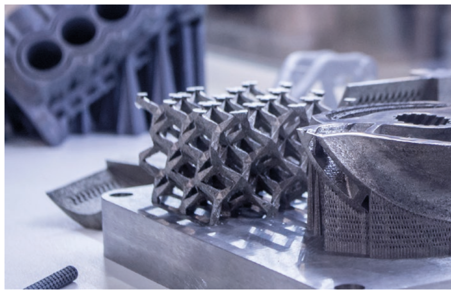
The results are then analyzed and relevant influencing values identified and classified. Design, simulation, machine, and sensor data is combined to create a digital twin of the component and used to determine defect types, sizes, and positions and resulting component properties by means of suitable ML algorithms.

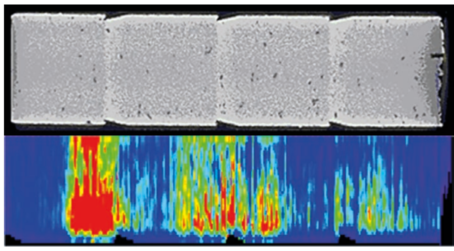
Advantages
- Reduction of required follow-up inspections
- Improved component quality
- Early detection of functional component defects
- Reduction of preliminary process optimization tests
- Reduced costs thanks to shorter product development times

Fields of application
- Powder-bed-based AM processes (LBM, EBM, SLS, etc.)
- Deposition-based AM-processes (FFF, LMD, 3DMP, etc.)

Maturity level
The system is currently under development.

Sensors in use
- Sensors for measuring high-frequency acoustic emissions
- Thermography
- Eddy current
- Ultrasound
- Computer tomography





Cross section of an X-ray image of an AM reference part consisting of four cubes (top); cross section of the structure-borne sound amplitudes in volume representation (bottom)

FML Calibration

Optimized prediction models for 3MA PHS systems based on federated machine learning

Application
Optimization of distributed 3MA inspection system calibration

Situation
Press-hardened steel (PHS) is used in the automotive industry to manufacture sheet metal components with extremely high strengths (up to 2000 MPa). They are deployed in the body as reinforcing elements. 3MA PHS is an inspection system that can, in a non-destructive manner, predict the strength properties of steel and the coating thicknesses in these components. The prerequisite is a so-called calibration, or prediction model, with which the target values (such as hardness) can be determined from measurements of the up to 41 electromagnetic parameters from 3MA (predictive analytics). For optimal predictability, it is necessary to locally adjust the prediction model.

AI approach: Machine Learning
Multiple linear regressions are usually used to determine the prediction model. Here, the 3MA calibration is a typical task for supervised machine learning. Data sets that each consist of a certain value for the target magnitude determined with the help of a reference process and the values of the associated 3MA parameters. Almost 200 installations worldwide have generated more than 50,000 training data sets (Big Data) distributed across many locations.

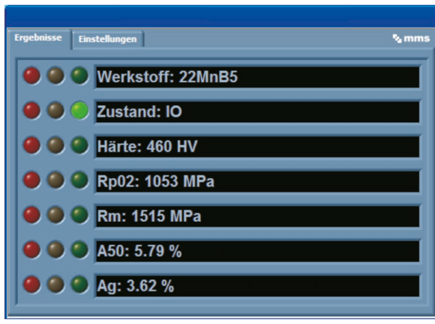
Federated learning allows multiple inspection systems at different locations to learn a common prediction model while the training data itself remains locally stored. This means that machine learning no longer requires all data to be stored on a central server. The individual system is given the current master model, which can be adapted individually based on the local training data. This individual model is also stored centrally and ultimately serves to optimize the jointly used master model.

Advantages
- Continuous improvement of all prediction models with new local data
- Only models, but no sensitive measurement data, are centrally stored
- Small data quantities result in low hardware requirements

Fields of application
- So far, only car body manufacture
- Transferrable to other 3MA calibrations

Maturity level
- 3MA PHS is established in industry
- Federated learning is still in development

Sensors in use
3MA-PHS



Result display

FSW Monitoring

Real-time monitoring of process stability and joint quality during friction stir welding via data fusion

Application
Real-time monitoring of process stability and joint quality during friction stir welding (FSW) via data fusion of process parameters, acoustic emissions, and expert knowledge

Situation
Because of its advantages, friction stir welding is gaining significance as an industrial solid-state joining process. The process's complex kinematics and the mechanical interaction of welding tool with components to be joined are a major reason why a reliable process monitoring strategy is especially important for FSW. Fraunhofer IZFP has developed such a strategy.

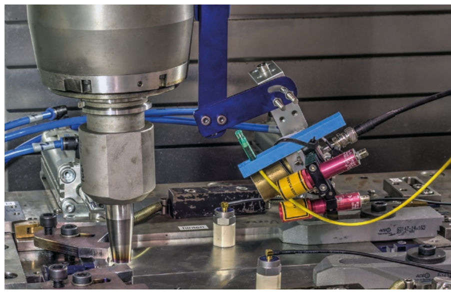
AI approach: Data fusion
Data fusion of process data (e.g. welding forces, temperatures) with the sound emitted by the process as well as expert knowledge allows the detection of instabilities in the process even before irregularities outside of tolerance arise in the joining area. Any process fluctuations can be detected based on acoustic emissions of the process leaving the previously defined tolerance range. AI-based data assessment, coupling to machine data, and applied expert knowledge allow conclusions to be drawn about the location, dimensions, and type of impending quality deficiencies (predictive quality) and the state of welding tool wear (predictive maintenance). Real-time capability ultimately allows this information to be used to implement strategies for process control and maintenance of the system.

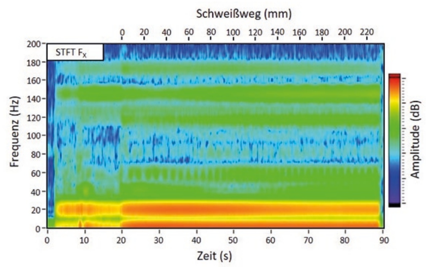
Advantages
- Holistic monitoring approach (process, components, systems, tools, etc.)
- Real-time capability
- Basis for process control concepts
- Great reliability due to various signal sources
- Simple transferability to alternative machines and manufacturing processes
- Increased production efficiency via reduction, reject and downtime avoidance, and set-up time plannability

Fileds of application
- Automotive, aerospace, rail, and shipbuilding
- Assessment of joint quality and process stability in joining processes
- Currently observable in the example of friction stir welding, but can be transferred to almost any manufacturing process

Level of maturity
Result of an internal research project; initial studies on industrial implementation are being planned

Sensors in use
- Use of existing process sensors (temperature, torques, forces, etc.)
- Structure-borne and airborne acoustic piezo sensors
- Laser microphones





Example of the frequency spectrum (STFT) of the process force in the feed direction

inspECT-PRO

Sensor system for quick, AI-based screening inspections

Application
Quick component check for various production steps to ensure product quality and a smooth production process

Starting situation
Efficiency and economy are among the characteristics determined by product quality in automated manufacturing processes. Mass-produced parts are primarily delivered as bulk material and fed into machines that process them further. To avoid system malfunctions and ensure the required quality, it is crucial to inspect each part, and statistical QA methods cannot do this. Defects, material composition, and the status of the treatment process (hardening) can all affect quality, and they can be monitored with the eddy current process.

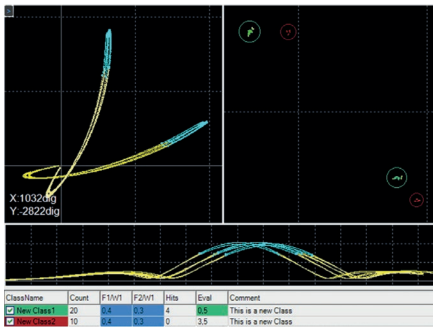
AI approach: Machine Learning
Machine learning algorithms allow inspection hardware to perform real-time assessment. Among other things, multiple linear regression is used here. The resulting regression hyperplanes serve as prediction values for the target values to be monitored, such as electrical conductivity, hardness, and coating thickness. Classification algorithms tackle a further goal: If the regression offers a prediction about the target magnitude of the measured value, the classification provides information about the group to which a measured value belongs. For instance, faulty screws with cracks can be assigned to a different class than fault-free screws. OPC UA (Open Platform Communication Unified Architecture) allows results to be fed quickly to the appropriate hubs. The combination of the two methods allows various component properties to be distinguished quickly and reliably.

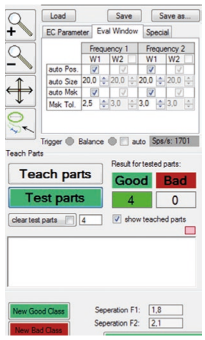
Advantages
- Simple classification of relevant component properties
- Very quick testing (within a few milliseconds),
- Gapless documentation of all components
- Quick integration of product lines via OPC UA
- Low-maintenance operation
- Simple transfer of information to other production machines, allowing process optimization

Application areas
- Inspection of mass-produced parts in the production process to ensure quality throughout the process
- Monitoring of component specifications to ensure no downtimes in downstream manufacturing steps
- Capability of optimizing production by implementing a feedback path for process control

Level of maturity
Sorting inspection systems have seen continuous operation for many years and have proven low-maintenance.

Sensors used
Electromagnetic eddy current sensor systems





Machine Learning Software

Traceability

Sensor-based fingerprint by means of Artificial Intelligence

Application
Identification, tracking and tracing of semi-finished products and components in production lines

Situation
Production processes often prevent conventional object marking (such as barcodes and RFID) from remaining permanently and in an undamaged condition on the object to be identified. In general, there are limited traceability applications for optically detectable characteristics on the object surface. If the surface changes too greatly during a processing step, identification is no longer possible afterwards. There is no sensor-based concept that allows component traceability throughout all steps if, during their processing, objects are greatly changed via such methods as forming, machining, or coating.
Fraunhofer IZFP is working on this problem by using sensor-based concepts to identify components based on intrinsic characteristics such as material properties or tolerable "faults" in the volume of a component. Any irregularity in the microstructure of the component such as grain boundaries, grain size, inclusions, stresses, etc. influences the measurement signal and allows recording of the individual component's intrinsic structure.

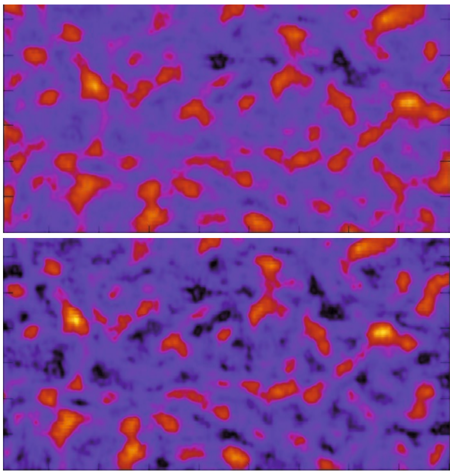
AI approach: Machine Learning (ML)
The intrinsic structure data recorded can be used to extract features that represent striking characteristics of the component structure. Comparing these features with those of other components allows a suitable classifier to identify the component. This can be done with neural networks for automatically extracting features while identifying the component, or with classical ML processes that extract features according to expert knowledge and pass them to a classifier for identification. The greater abstraction of features in the use of neural networks promises more precise results given suitable training. The AI approach used is being developed jointly with the Fraunhofer Institute for Machine Tools and Forming Technology and the Fraunhofer Institute for Industrial Mathematics as part of a WISA project.

Advantages
- Component traceability
- No additional object marking necessary
- Reliable detection of product counterfeits
- Complete documentation of component history
- Significant optimization potential for quality assurance

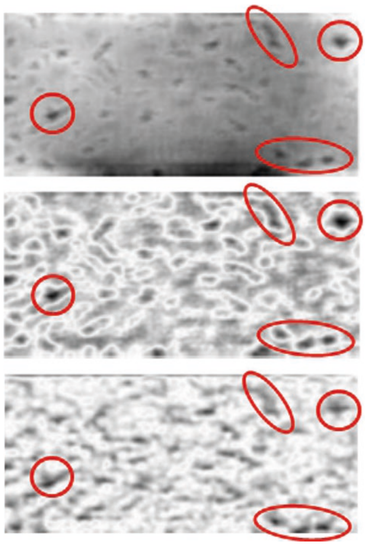
Fields of application
- Potentially any electrically conductive component
- Formed parts (currently)
- Can be implemented in any process chain (prospectively)

Maturity level
Research project with promising initial results

Sensors used
Electromagnetic sensors



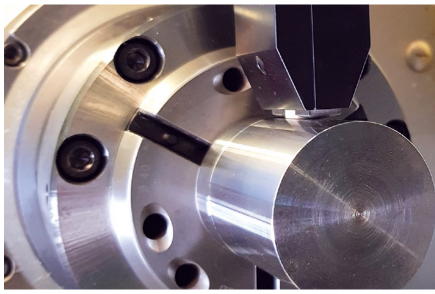
Electromagnetic measurement of a tensile specimen prior to deformation (top); same after the specimen has been stretched about 5% (right)



Identification of a component after various forming steps based on certain microstructure characteristics

WL SoftND

Multi-modal sensors for targeted influencing of surface characteristics during machining



Application
Real-time capture of surface characteristics of 42CrMo4 during the turning process

Situation
The industrial environment subjects machines, systems, and raw materials to natural fluctuations that directly influence the manufacturing process.
The challenge during machining is avoiding accumulation of white layers (thermally induced layers near the outer layer) and the associated detrimental tensile residual stress states. Mechanically induced white layers associated with compressive residual stresses, on the other hand, are advantageous.
To solve this problem, Fraunhofer IZFP is developing real-time-capable monitoring systems.

AI approach: Soft sensor
The holistic approach links simulation, process, and expert knowledge. Moreover, nondestructive sensors allow data fusion, which forms the basic structure for setting up a soft sensor that includes the relevant fused machining system model.
Statistical experiment design allows determination of all relevant process statuses, from fault-free statuses (OK) to faulty statuses (NOK). The soft sensor is trained with the machining process data.
The soft sensor can now be deployed and forms the cognitive element that can serve as an observer to estimate the statuses of the dynamic system and intervene to perform "predictive maintenance".

Advantages
- Targeted setting of the required surface characteristics (white layer and/or residual stresses) by means of turning process control
- Inspection reliability, completeness, precision, and consistency with multi-dimensional soft sensors
- Real-time/online quality monitoring
- Interfaces to MESs, inspection systems, or machine tools
- Individual, tailored system design
- Multi-dimensional soft sensor integration into the existing systems

Fields of application
- Constant operation monitoring and quality monitoring of individual machines/systems or entire production lines
- Quality assessment of individual assemblies, including those operated on test benches

Maturity level
Joint research project with partners as part of the SPP2086 DFG priority program (SCHU 1010/65-1, LA 2351/46-1, WO 903/4-1)

Sensors used
- Micromagnetics (3MA)
- High-frequency airborne sound sensors
- High-frequency structure-borne sound sensors
- Dynamometer with multi-dimensional force measurement
- Temperature sensors

X8 Sensor System

AI-based steel mill process optimization – multi-modal, multi-intelligent sensor system for detecting hardspots on heavy plate

Application
Steel mill process optimization

Situation
Local hardspots have been shown to reduce the gas pipeline lifespan. Natural gas escaping due to leaks pollutes the environment; pipeline replacement and associated production downtimes cause billions in economic damage. Detecting these hardspots early allows the heavy plates affected to be reworked at the steel mills, or discarded if necessary, before they are delivered to the end customer.

AI approach: Smart signal processing
Fraunhofer IZFP is developing the AI-based micromagnetic X8 sensor system with the goal of steel mill process optimization. The sensor uses the effects of magnetic hysteresis and extracts from the available raw data magnetic fingerprints and characteristic identifiers for monitoring basic material and detecting hardspots. The development of an intuitive "nearest neighbor algorithm" combined with smart signal processing allows reliable detection of hardspots, even under the conditions that prevail at steel mills.
Smart signal processing means that the X8 sensor system requires no a priori training – it learns during operation. Unfamiliar types of steel and hardspots can thus be detected and evaluated during the process.
An online plausibility test is also performed in the system. If sensor liftoff is outside of the specified range and needs to be re-adjusted, are there gradual sensor degradations? The X8 sensor system detects all these statuses and forwards them with the evaluation of the heavy plate to the operator.

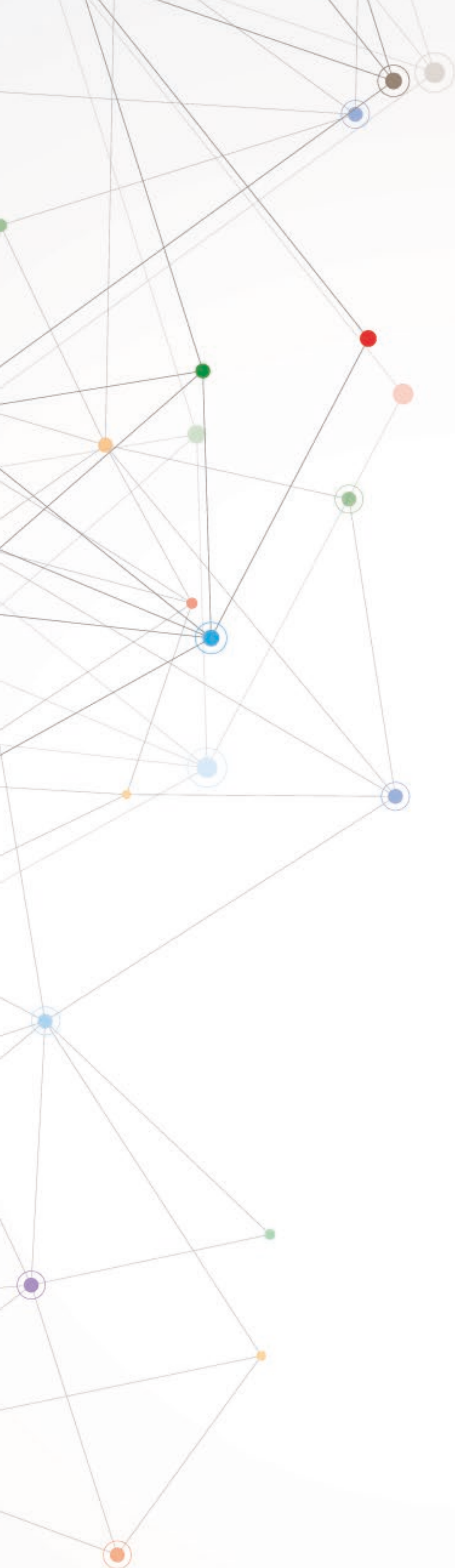
Advantages
- Reliable online detection of hardspots on heavy plates in steel mills.
- Intuitive evaluation of hardspots (AI algorithms easily explained)
- No a priori training; X8 sensor system learns during operation
- Number of sensor channels can be freely scaled

Application areas
- Online hardspot detection on heavy plates
- Transfer to other applications with the goal of detecting inhomogeneities

Level of maturity
Qualified system with verification of functionality in the area of application (TRL 8)

0Sensors used
- 3MA-X8
- Infrared temperature sensor

Top: extracted characteristics for the basic material (green) and hardspot (red);
bottom: results display for an eight-channel X8 sensor system



Cognitive Sensor Systems. Efficient Processes.

Glossary

Some important definitions

42CrMo4

A common chromium-molybdenum steel (Steel Number 1.7225); usually used after tempering, with high intensity and hardenability

3D

Three-dimensional

3DMP®

A 3D printing process by GEFERTEC whose starting material is in the form of wire instead of powder

3MA

"Micro-Magnetic Multi-Parameter, Microstructure and Stress -Analysis" – an inspection technology developed by Fraunhofer IZFP for nondestructive edge layer characterization

Additive Manufacturing (AM)

Summarizing term for technologies to build up 3D objects by applying material layer by layer (so-called "3D printing")

Assistance System

All information and functions that support a user in the use of a product

AI

Artificial Intelligence: Sub-discipline of informatics that deals with machine learning and the automation of intelligent behavior; more broadly, methods or machines that work on the basis of these two processes.

Augmented Reality

Computer-supported broadening of human reality perception

EBM

Electron beam melting, an additive manufaturing process for manufacturing metallic components from the powder bed

FFF

Fused Filament Fabrication, freely usable synonym for the "Fused Deposition Modeling"® (FDM) 3D printing technique in which a workpiece is built up layer by layer from meltable plastic or molten metal

Hysteresis, magnetic

Describes the strongly nonlinear relationship between the magnetic flux density B and the magnetic field strength H in ferro-magnetic materials

Calibration

In this context the generation of the correlation function, which describes the causal relationship between a target quantity and nondestructive measurement quantities. If the correlation function is known, values of the target quantity can be determined from the measured values of the nondestructive measurement quantities. Correlation functions are usually determined by experiments.

Cognition

Transformation of information by a behavior-controlling system; the sum of all processes of thought and perception and their mental results (knowledge, opinions, convictions, expectations). Cognition can be conscious (in the performance of a calculation, for instance) or unconscious (in the forming of an opinion, for instance).

Collaborative Robots

Industrial robots that can work in close proximity to and together with humans. This assumes the reliable prevention of robot-induced hazards to humans. Fences and other protective devices are then not required.

Friction Stir Welding

A welding procedure from the pressure welding group in which two parts that are touching each other are moved relative to one another under pressure. The resulting friction heats the contact surfaces so that they plasticize.

LBM

Laser Beam Melting, an additive manufacturing process to build up components from metallic powders

Linear Regression Analysis

Statistical analytical method to determine relationships between a dependent variable and one or more independent variables in a model

LMD

Laser Metal Deposition, an additive manufacturing process using a laser to generate a molten bath on a metallic component surface, into which metal powder is introduced

Machine Learning

Generation of knowledge in a machine by means of experience and its processing on the basis of statistical models; the system learns from examples (training data), which it is able to generalize at the end of the learning stage.

Federated machine learning strives for using decentralized data sources for the training data.

MES

Manufacturing Execution System; computer-based system for support and documentation of the transformation of raw materials into finished goods in the production process

Monitoring

Surveillance of processes; in an industrial context usually performed by technical devices

Multi-modal

The ability of a sensor-based inspection system to simultaneously -integrate sensors that use different physical principles

Predictive Maintenance

The proactive maintenance of machines and systems based on measured values and data collected by sensors with the goal of keeping downtimes low or eliminating them completely if possible

SLM

Selective Laser Melting, an additive manufacturing process, wherein spatial structures are produced from a powdery metallic host by complete melting with a laser

SLS

Selective Laser Sintering, an additive manufacturing process used to produce spatial structures from a powdered host (usually plastic) by sintering with a laser

Tracking

Tracing or dynamic allocation; encompasses all individual methods used to trace objects

TRL

Technology Readiness Level, a scale for estimating a product’s level of technical maturity during its development phase

WISA

“Science-oriented strategic alliances“ (Wissenschaftsorientierte strategische Allianzen), a special internal project funding system of the Fraunhofer Society

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