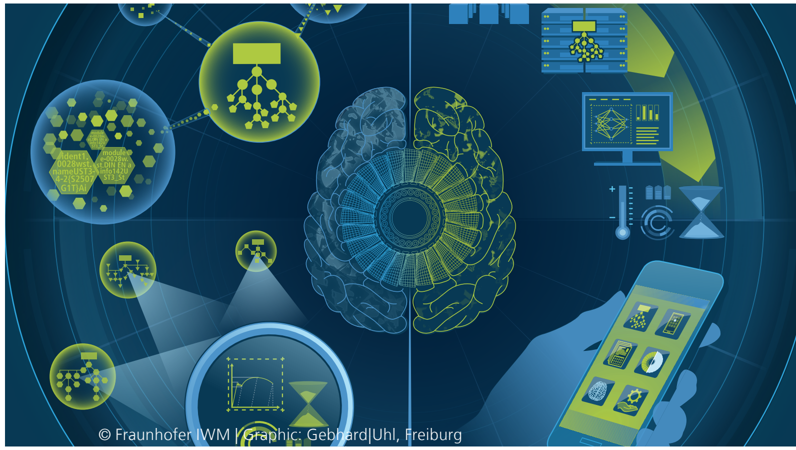

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Making materials knowledge and data digitally usable and accessible for corporate decision-making.

We create the prerequisites for greater value creation from materials data and materials knowledge. Our aim is to make the development history and all influencing factors that have led to a final product with its properties traceable and transparent.

Our R&D offerings

Structuring data and integrating data islands

By semantically structuring heterogeneous materials data, we create a productive connection between various information from the entire product life cycle.

Implementing data streams

We integrate measurement data, machines, and devices into a digital workflow and design digital paths, for example, from testing machines to simulation tools.

Analyzing and using data sets

We use machine learning to curate data sets and derive recommendations to optimize product development, manufacturing, and component use.

Developing data products

We develop digitized materials, digital twins, and web-based evaluation tools to predict operating behavior and service life.

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The **Fraunhofer IWM** is passionate about sustainability in industrial value creation. Through its research and development, it opens up new pathways and design opportunities for durability and safety in components, resource efficiency in process chains, and energy efficiency in machines. The institute makes materials within process chains, components, and machines predictable in terms of their behavior and properties.

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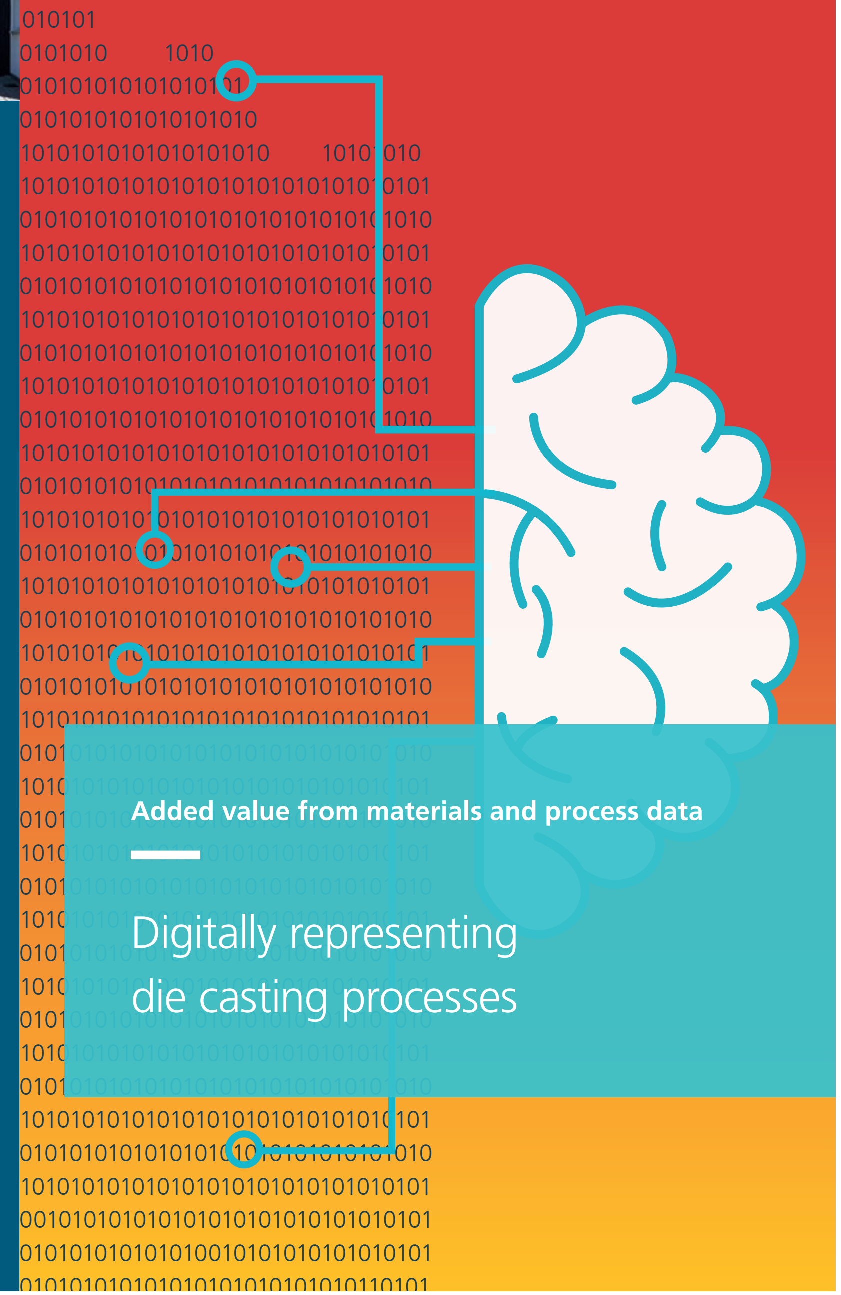


Added value from materials and process data

Digitally representing die casting processes

Traceability and prediction through digitalization and AI

Decarbonization, cost increases, pace of development, pressure to innovate – without a comprehensive product-related knowledge base, these challenges, some of which conflict with each other, cannot be overcome. This applies especially to technology-intensive products that must meet high requirements in terms of safety, reliability, and service life, as well as to cast components.

On the one hand, systematic traceability is required, i. e., knowledge of the many influencing factors – technological, ecological, economic – that have led to a materials and component state, and on the other hand, quantitative relationships between process conditions and parameters are needed, which lead to the microstructure of the cast material and ultimately to the component properties.

This complex process chain is described in detail in a knowledge graph. This graph links materials related information for all sub-processes of die casting.

- It allows queries for specific information and the derivation of cause and effect relationships in the casting process.
- It provides insights for process optimization and for predicting component qualities.
- It is the starting point for the digital product passport, in which information regarding the sustainability and circular economy of products and materials is digitally accessible.

Virtual assessment chains, which are set up with a knowledge graph, lead to new opportunities for materials efficiency, cost reduction, time savings, and risk minimization.

Procedure for developing a digital twin for die casting processes

Every die casting process is different, and even more so are the specific information requirements of foundries, designers, and users of cast components.

The configuration of the digital twin begins with a comprehensive inventory of the process steps and the necessary and available data.

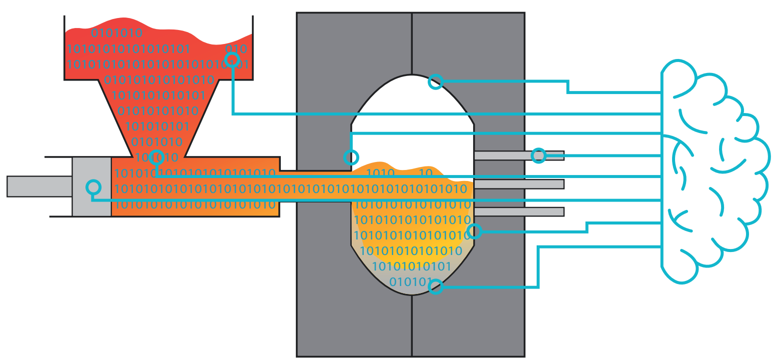
For the process description, existing knowledge graph modules are adapted, expanded, and newly created.

The data packages are converted into semantically structured data sets and finally into the knowledge graph.

Once the data structure has been created, the queries are programmed so that the digital knowledge base can lead to greater added value and quality.

For the live operation of the digital twin, data must be collected directly at the production plant, via automation if possible, and transferred to the data space.

The digital twin can ultimately provide information for each product about which machines, parameters, and raw materials were used to manufacture it.



FAQs

How complex does a knowledge graph need to be?

A knowledge graph must map the relationships that are crucial for the component and the process. For many questions, a few clearly defined information nodes are sufficient at first – for example, regarding alloys, tools, process parameters, microstructure, and test results.

What data does a digital twin need?

A digital twin combines process data from the machine control system, sensor data (e.g. temperatures, pressures), materials and batch information, and test and inspection results. More important than the amount of data is the quality of the data and its consistency.

How can the digital twin take economic and ecological aspects into account?

The knowledge graph can be supplemented with key figures such as scrap rates, energy and materials usage, cycle times, or carbon footprint. This allows process variants to be compared in terms of cost and sustainability.

What data is needed for predictions and to gain new insights from production?

What happens in the process should be consistently measured and recorded — from machine data and materials batches to environmental influences. The variance of the actual values collected is crucial, because only the natural dispersion in the process provides the basis for valid evaluations.

What are the benefits of data-driven predictions?

The aim is to streamline quality control processes and identify outliers and anomalies. A well-designed digital data structure uses the actual measurements collected from ongoing production to provide probability forecasts for the quality of each casting. This enables foundries to optimize components for which the algorithm indicates a high risk of defects.