Quick Guide

Machine Learning in Mechanical and Plant Engineering
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Drivers of innovation in the mechanical engineering industry

Everybody is talking about machine learning and artificial intelligence. These technologies and their tools are constantly being improved, expanding rapidly from the consumer into the industrial sector and thus to the mechanical and plant engineering industry.

For years, or even decades, this field was the preserve of academics and only gained a foothold in select sectors. Over the past ten years, falling prices for computing power and storage have led to rapid advances in cloud and big data technologies. These two factors quickly led to the development of various software technologies that had an impact on artificial intelligence.

Machine learning is an important field of computer science and a subdiscipline of artificial intelligence. Computer programs based on machine learning can use algorithms to autonomously find solutions for new and unknown problems. Artificial systems recognize patterns and regularities in the training data they are supplied with. Tools that are already established on the market assist in finding the algorithms. New frameworks and platforms are aiding the widespread application of this previously rather academic subject matter in work on everyday projects. For mechanical engineering in particular, this technology offers many new and exciting ideas.

With the aid of machine learning, software and information technology are becoming increasingly important drivers of innovation in the mechanical engineering industry.

This Quick Guide was written by the machine learning expert group at the Software and Digitalization Association. Its primary audience is managers at mechanical engineering companies who are interested in evaluating machine learning’s potential for their businesses. It provides information on opportunities, challenges and possible solutions. But above all, this Quick Guide is intended to aid readers in approaching the subject with the right questions and drawing their own conclusions. Given the pace of change in the field, this Quick Guide cannot address the topic exhaustively and in depth. The members of the expert group at VDMA are available to provide advice about machine learning and will continue to follow developments in this demanding field.

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1. What is machine learning?

Machine learning (ML) and artificial intelligence (AI) are omnipresent — in the media in the workplace, and in private life. Digitalization is dramatically changing all aspects of society, including the manufacturing industry. The German mechanical engineering industry in particular will need to address the resulting challenges if it is to maintain and expand its current global product leadership role in many sectors.

But just what is ML? It is literally that: machines that learn. Machines, in this case computers, gain the ability to learn autonomously. ML deals with algorithms that learn from data and predict outcomes that will occur with a certain probability. Such algorithms do not follow rigid programs and rules laid down by humans, they make data-based predictions by generating knowledge based on examples — in other words, learning.

As early as 1959, the pioneering American computer scientist Arthur Samuel defined ML as a field of study that “gives computers the ability to learn without being explicitly programmed.” Like data mining, it comes from statistics. The difference is that statistics explains what has happened, data mining explains why something has happened, and ML determines what will happen and specifies how certain situations can be improved or avoided.

ML is an independent field that is often confused with AI (artificial intelligence). Originating in 1956, the latter term is thus only slightly older and is used to designate the efforts of duplicating human intelligence. ML can be an initial important step along this path, which is why it is often viewed as a subset of AI. But not only do the goals of these two disciplines differ in magnitude, there is a much more significant difference. ML is already here among us, but when that can be said of artificial intelligence is a matter of speculation.

Another term is often mistakenly used in conjunction with machine learning: big data. Big data refers to the processing of large...
amounts of heterogeneous data, and their speeds and data types both with or without ML.

This document does not address AI or big data but concentrates on ML.

What role can ML play in product leadership for the mechanical engineering industry? Maintaining and expanding it in many areas as a prerequisite.

There are many possibilities, and the majority of the applications is not yet foreseeable. However, there are already many obvious practical applications and solutions that enable businesses in the mechanical engineering industry to get a quick start in ML and also to expand their capabilities. There are possibilities in process optimization as well as in maintaining and expanding leadership in product innovation.

However, some key issues are cause for uncertainty, such as the necessary knowledge about how to select, develop and configure the relevant algorithms, how to acquire and prepare the data, and not least the indispensable experience with these factors. Unclear legal aspects and implications also deter businesses from making meaningful investments in ML. Many machinery manufacturers find it difficult even to investigate and define a specialized application or project.

ML is already used to support critical decision-making in medical diagnosis, financial markets and the energy sector, or even to make decisions automatically. Our everyday life is also shaped by ML; one need only think of all the product recommendations we receive daily. They are based on our previous purchases, our search behavior, and the terms we enter into the devices we use. But ML is increasingly finding its way into the mechanical and plant engineering industry and enabling new applications, which will be discussed in chapter 3.

Why is ML becoming so important just now? The answer is as simple as it is complex. What was still impossible yesterday is now routine. Computing power on a scale inconceivable ten years ago is now affordable. When this computing power for large amounts of data is combined with the ability to learn, algorithms can be continuously improved. All of these are further important contributors to rapid progress.

This Quick Guide is for decision makers who want to learn more about ML. First we explain what is meant by ML and the opportunities and risks this technology brings to the mechanical engineering industry. Then we present a few typical applications.

We explain the importance of data for ML, describe the basic process in ML projects, and explain how to make a successful start with ML. The Guide concludes with an outlook on future developments.
1.1 Learning from data

ML enables technical systems to do something previously only possible for living beings: learn from experience. ML algorithms learn patterns and structures in sample data prepared by humans and then apply this new knowledge to new and unknown cases. For example, from a large number of sample images, ML algorithms learn how a good part looks in a camera image. The system then uses these self-defined views to detect and separate out bad parts. In this way, the machine learns to distinguish good parts from bad ones.

But how does learning from data and then applying the learned knowledge work in practice? Let us begin by explaining a few terms. A fundamental concept for learning is the model, which contains the learned knowledge and is used to make predictions. As a rule, models are only designed for a single task. For example, using sensor data (input), the probability of a malfunction is predicted (output). Another important concept is model training, in which the model is taught through data input. Models are normally trained once and then used for predictions. ML algorithms can be differentiated by the way they learn from data or how their models are trained, with three categories used:

- Supervised learning
- Unsupervised learning
- Reinforcement learning
1.2 Supervised learning

In supervised learning, the model is trained with examples from input and output values. For the example of malfunction analysis, one would feed sample sensor data into the system along with information about upcoming malfunctions. The system learns the relationship between sensor data and malfunctions. This learning process is called supervised because the correct output is known for each input and the model can be corrected when predictions are false.

To train the model, a large quantity of sample input and output data is needed. Creating this data can be very expensive or difficult since expert knowledge usually has to be learned. The quality of the sample data is also important. If the model is supplied with incorrect sample data, it will learn incorrect correlations.

1.3 Unsupervised learning

In unsupervised learning, the system also learns from sample data, however, the sample data do not include known output data. Instead, the examples are used to learn how “typical” data or data clusters appear. For the example of sensor data, the model would learn how typical sensor data for the machine appear. In the event of deviations from this data, it would assume a malfunction.

In a different approach to unsupervised learning, the data are automatically classified into clusters. Examples of such clusters could be “machine producing,” “machine malfunction” or “machine standstill.”

The advantage of unsupervised learning is that the sample data can be created with little effort. The disadvantage is that unsupervised learning is unable to cover all possible cases.

1.4 Reinforcement learning

In reinforcement learning, models are trained by reward and punishment. Every solution or step in a solution is typically scored by assigning points. Rewards are expressed by an increase in points, penalties by a decrease. The goal is to maximize the score. During training, trial and error are used to generate new proposed solutions, which are increasingly refined to continuously improve the score. Challenges for reinforcement learning: Suitable reward mechanisms need to be found and short-term benefits need to be balanced against long-term ones. This form of learning is called reinforcement learning because it is reminiscent of human learning by praise and criticism.
1. **Benefits, opportunities and risks for the mechanical engineering industry**

In many mechanical engineering companies, there is still uncertainty about whether ML is relevant to their business. Due to the increasing interchangeability of individual machines in many areas, future sales will involve supplementary services and not only the machines themselves. That will result in fundamental changes for the industry and explains why ML is a very salient issue for management and specialists at mechanical engineering companies.

ML offers unprecedented opportunities for Germany’s mechanical and plant engineering industry to optimize existing business and production processes, with the machines maturing to become process service providers that operate almost autonomously. We provide a structured analysis of the benefits, opportunities and risks of important aspects and use examples to place them in a business context. The aim is to assist readers in making an initial business assessment of ML’s relevance from which they can derive their own approaches and strategies.

ML has potential benefits for both product characteristics and internal process optimization. This applies for processing incoming payments and preparing bids, as well as for production planning.

The ML properties also differ in product-related areas, on the one hand in products themselves, for example in expert systems for machine operator support, and on the other hand in machine-related processes such as maintenance or other value-added services.

Since it is not always possible to differentiate the properties effectively, they should be defined in the context of specific application scenarios.

**“Zero-defect quality and maximum adherence to schedules”**

It should be possible to clearly describe and quantify the economic benefits in each case. An example of this could be automated comparison of incoming payments with invoices with potential savings of over ten percent. Another example: inquiries about pricing for complex machine configurations.

Extensive ML-based automation would enable much faster responses to requests for quotes, with a corresponding increase in the number of new contracts. Scenarios of this type for a business’s core processes are already available for use as part of ERP, marketing or sales systems.

**“Machine learning boosts leadership in costs and product innovation”**

Besides its benefits for core business processes, the product leadership benefits of ML as part of a business’s own products are a further application area. Two potential benefits can be addressed here: On the one hand, direct added value can be created for the customer when operating the machine; on the other hand, the available machine data can be used for the creation of value-added services.
An example for improving a company’s own products with ML is predictive maintenance. Using the large amount of information gathered while operating a machine, problems can be recognized early and their maintenance can be planned — before a customer’s production has to be unexpectedly interrupted at a usually inopportune time. The machine manufacturer’s customer can therefore plan and integrate the machine’s maintenance efficiently in its internal processes. If the sensors for predictive maintenance are used in combination with software, it would enable fine tuning of the machine’s efficiency for additional optimization.

Another field for ML: simplifying machine operation with expert systems. This results in reduced familiarization time, training costs and set-up times, while simultaneously increasing efficiency. ML can enable both the machinery manufacturer and its customers to optimize their processes.

“Reduce training costs and set-up times”

But how is a successful start in this field possible? Studies show that many companies make their first projects too large and complex while failing to successfully address many relevant aspects. The following questions should be answered before starting a project: What application scenario is available as an entry project for my company? How can we gradually build up the required knowledge in our company? Which ML technologies and algorithms are relevant for me? How can the results of ML algorithms avoid business risks - or at least mitigate them early? The availability of the required data is also crucial and plays an important role.

There is one more important question to answer: Who is responsible when people delegate decisions to machines? For example, if a model is formally correct but delivers incorrect or negative results due to learning using incorrect or unsuitable data?

If a successful ML project is to be set up, experts must first examine these questions in a structured manner and then answer them in detail, particularly with regard to relevance, risks and the need for investment for the company. At the same time, one must avoid being discouraged by the scope of the issues resulting in missing the starting gun. As always, it is important to simply get started.
3. Use cases in mechanical and plant engineering

In this chapter, we present a few typical use cases for ML in mechanical engineering. Each of the use cases is described briefly and a possible implementation strategy explained. Then we discuss the benefits, the required capabilities, and the costs, opportunities and risks.

Listed risks. We will go into the technical implementation of these use cases in more detail in chapter 6.

3.1 Human-like machine vision

Judging surface textures is a task in which traditional image processing systems reach their limits, while the human eye can recognize textures, patterns, objects and structures and can reliably judge and classify them visually after only a brief training period. With only a few examples, humans can learn to distinguish permissible variations from defects, even in natural objects of which no two are identical.

All kinds of sensor can be used for the imaging process used with human-like machine vision, including 2D, 3D, ultrasound, X-ray and shape from shading. The ML application works from a training phase with good parts; in contrast, extensive defect catalogs must be used with traditional image processing applications. With ML, the desired result – and not the deviation from it – is thus the standard.

The process-secure solution for such tasks is ML-based image processing systems which are specially developed and optimized for the industrial analysis of images.

The use of such systems based on ML opens up further potential applications for reliable automated inspection with very high detection levels. Where traditional vision systems reach their limits and human judgment is the best solution in spite of its risks and limitations, human-like machine vision based on ML algorithms currently offers a state-of-the-art solution. New products can be learned without great effort and even new and unknown characteristics can be detected without extensive defect libraries, resulting in considerably shorter development and product launch periods.

Except for experience with traditional image processing and in designing optical camera systems, the modeling requires no additional software development and no understanding of the algorithms.
Despite all of the possibilities, ML has limitations and is not the tool of choice for every case.

Important limiting factors can include:

- Accessibility of required training data
- Availability and influence of expert feedback for evaluation of results
- Image resolution and size of the files to be transmitted and/or stored
- Vulnerability of the ML system to tampering or sabotage

In some cases, a combination with traditional image processing is also necessary. Interdisciplinary expertise, an extensive portfolio of image processing solutions, and careful consideration of the opportunities and risks are needed to profitably utilize the potential of ML systems.

### 3.2 Adaptive control for process optimization

In this use case, we discuss the optimization of the start-up procedure for an offset web press as a representative example of the optimization of complex physical machine processes. Due to its numerous parameters and influencing factors, the start-up process is complex. An important factor is the fine adjustment of the solid density, which has to be manually parameterized before every production run. The effects of parameter changes can only be evaluated after a full run of the press; this process is associated with a dead time during which waste-quality products may be produced.

At the same time, other parameters such as consumables, physical factors and the condition of the machine also influence the printed products in an unknown way.

[Figure 4: Adjustment process (source: Fraunhofer)](image)

[Figure 5: Start-up (controlled and uncontrolled) (source: Fraunhofer IGCV)](image)

Technical systems such as these, with behavior which is influenced by numerous variables and unknown relationships, are difficult to model with physical formulas and thus often defy process optimization. Machine learning processes can be helpful in this case. They learn the system’s behavior and can subsequently make predictions about the process, something known as adaptive control.
The dead time can be bridged with model-based adaptive control. The relationship between sensor data and the quality of the solid density is learned from historical data and used as a feedback variable in the control system. This enables adjustment of the process parameters even before measured values for the density are available. Use of predictive control increased productivity and resource efficiency significantly. On average, waste during start-up was reduced by 37% and the required time by 39%. This kind of control is called predictive control.

Developing an adaptive control system requires an in-depth understanding of the process. It also calls for knowledge about the use of machine learning processes for time series regression. The process of model-based predictive control can be also be applied to other problems. An approach involving machine learning processes is always promising when many measurable variables influence the process in an unknown way. As in the other use cases, sufficient data is an absolute requirement for adaptive control.

This variety of machine configurations is also a major challenge for the tendering process. For very complex machines, the tendering process with different machine versions and their pricing can drag on for weeks, often leading to delays in preparing bids and possibly endangering sales. A smart tendering system can automate parts of the tendering process, making it faster and reducing costs.

Information and comprehensive data about previous bids, machine configurations and prices can be used for the semi-automated preparation of future bids. Assuming that a similarly configured product would result in a similar cost structure, ML algorithms are used to train a model that learns the correlations between machine configurations and costs. Then this model is used to estimate the costs for a machine configuration and prepare an initial bid (see figure 6). Rapid preparation of bids can increase the likelihood of sales and thus increase revenues. Other advantages include simplification of the tendering process and reduced scope for errors.

### 3.3 Smart tendering

The trend of product customization continued over the past decade. With on-demand production and lot size 1 production, product version diversity is increasing disproportionately, and with it, the complexity. This complexity is also reflected in the available machine configurations. A large number of machine models with options and dependencies among the options can quickly lead to a confusing variety of possibilities for both manufacturers and customers.
As in the other use cases, a sufficient set of historical data about machine configurations and costs is also needed for smart tendering. The bids must be available in a structured form that can be read by an algorithm. The greatest effort required here is to clean up the data and normalize the historical data sets. A data scientist should be consulted regarding the development of a predictive model.

Other ways of using ML for the tendering process include the following:

- **Searching for similar configurations**: ML algorithms can be used to find machine configurations that result in similar costs/results.
- **Guided configuration**: Based on historical data, permissible configuration variants can be determined and successively suggested to the person preparing the bid.
- **Augmented configuration**: Based on the current machine configuration, the most popular supplementary machine options are proposed.
- **Avoiding or reducing overspecification when configuring the machine**: ML algorithms can be used to find the relevant options for the price/performance ratio.

### 3.4 Data-driven innovation

At the beginning of an industrial analytics project to improve overall system effectiveness (availability, performance, quality), the optimization potential of a system or machine is determined. From this, the commercial value of the data can be derived as part of the general business understanding process. In the collection phase, data are gathered from automation components and field devices. In the analysis phase, the data are processed and modeled and then analyzed using ML algorithms. Once a problem has been analyzed and understood, it is solved — if possible by modifications in production. If the problem cannot be permanently solved, it should at least be recognized in advance. To do this, a solution is looked for using a streaming analytics implementation, such as anomaly detection, and then deployed during the implementation phase.

Experience has shown that machinery manufacturers and system operators typically make an existing machine or system available first or improve the quality with a reactive industrial analytics project. Only after this method has proven successful is its application considered during the development of the next generation to improve the performance. The method is basically the same, but not the goals are not.
With the traditional sequence of algorithms -> data -> decisions, overall system effectiveness cannot be better than the person who programmed it. Contrastingly, ML algorithms which are applied to large amounts of production data recognize causalities that had previously been hidden from machinery manufacturers and system operators, but improve overall system effectiveness. This means that quality and availability can be improved reactively, while the performance of future machines can also be improved proactively.

The current industrial analytics solution can only suggest possible correlations in the supplied data. The domain expert of a machinery manufacturer or system operator assesses the correlations recognized by the ML algorithms as chance or as actual causality. Based on these correlations which domain experts recognized as causalities in the data, decisions about production optimization are now made. In the future, a domain expert will initiate data analysis in the field of guided analytics, but the process will otherwise continue automatically; in autonomous analytics the entire data analysis process is automated.

Figure 7: Malfunction detected. (source: Softing GmbH)
4. Data as a raw material

Data are becoming the most important currency of the 21st century and are the foundation of ML. More data were generated in the last two years than in all of human history. Data are increasingly becoming a factor in production along with land, capital and labor. They enable cost reductions and new business models. The increasing importance of data is causing a change in the sequence from algorithms -> data -> decisions to data -> algorithms -> decisions (figure 7), a factor that represents the revolution that is currently taking place.

Since the first programmable chip — the Intel 4004 was launched in 1971 — software development has always followed the same pattern: First the problem is defined, then objectives and work steps are specified, and finally the application is programmed as a sequence of algorithms. In practice, these algorithms are supplied with data, and users reach decisions based on the results. This approach is currently undergoing a structural change; the data are now gathered in advance and analyzed with generally valid algorithms in the second step. This results in causalities, upon which decisions are made, for example to optimize production, and these decisions are increasingly often being made autonomously.

System data were often collected in the past but not processed. Today, they are used in production optimization to increase overall system effectiveness, called overall equipment efficiency (OEE). Data from a normally functioning machine or system are used to train a model with limit values. As soon as the model receives with deviating data, it sounds the alarm because the deviating data represent defective components, machines or processes.

If ML algorithms are the engine for future development, data are the fuel.
ML does not find its solution with rule-based software code written by humans, thus differing from traditional applications. It is important to know the nature of machine learning: There is a pattern in the form of data that we cannot grasp using "IF THIS THEN THAT" lines of program code. But algorithms find this pattern in the data. In production it is typically a causality between component status and physical measurements.

With the traditional sequence of algorithms -> data -> decisions, the OEE cannot be better than the understanding of the person who programmed the OEE influencing factors. In contrast, ML algorithms applied to large amounts of production data can find causalities that can improve the OEE, but have always been hidden from system operators.

Which data do we need for ML? And in what quantity? What role does big data play? Big data is a collective term for large amounts of data – with different data types from different sources that are provided at different rates.

The amount, the rate and the variety of current production data exceed the abilities of the operating staff and call for new, data-based approaches. But access to high-quality data is a prerequisite for even being able to use ML. This includes data from control systems, data from sensors, actuators and databases, and production flow data or weather data from additional sources. But how can we tell whether the amount of data from automation components and field devices is enough? The answer is simple: Once algorithms detect patterns, they have been fed enough.

This means it is impossible to predict which data are needed for the required model quality and precision. More data do not necessarily lead to more patterns, at best to more correlations, but in any case not necessarily to more causalities, as these can only be confirmed by a domain expert.

At the beginning of an ML project, the optimization potential for a system or machine is determined, and along with it, the commercial value of the data as part of the general business understanding process. In the collection phase, data are gathered and processed. Outliers are deleted, erroneous entries eliminated, time stamps compared, metadata added, and the cleaned data formatted. In the analysis phase, the data are processed, modeled and analyzed. In the implementation phase, a data-based production optimization is installed, for example a model used to detect anomalies.

Data are everything for machine learning. Without data there is no ML.
5. **Data-driven modeling**

No refinery without crude oil. No cosmetics and no gasoline without refineries. Once the prerequisite has been created and data are available, the next question swiftly follows: How can useful information be gleaned from them? American high-tech companies active in the B2C sector were able to provide an entire sector with a one-size-fits-all solution for applications such as online retail and web searches. In doing so, they followed a top-down approach. However, these solutions do not work for the highly diversified B2B sector in the mechanical and plant engineering industry. Processes and procedures differ from one company to another, as do the use cases, the business cases and the types of sensors used. All of this calls for a solution that has to be tailored to individual companies and their business objectives. A bottom-up approach must therefore be selected on the way to data-driven value creation. A model that has proven itself in practice in many projects offers ways to simplify the sequence of an ML process.

The multi-sector standard process for data mining, commonly known by its acronym CRISP-DM, is well suited for this purpose. This data mining process model describes common approaches used by analytics experts to tackle problems, a process which can be easily applied to ML projects.

CRISP-DM divides the ML analytics process into six phases. In a structured approach, this process can be repeated without limitations, making it suitable for agile development based on the scrum method since it can be divided into sprints.

The sequence for the phases is not strict; what is needed is constant switching between the various phases. The arrows in the process diagram show the most important and most common dependencies between the phases. The outer circle in the diagram symbolizes the cyclical character of the ML approach itself. After a cycle, the insights gained can trigger new and often focused business questions; subsequent ML processes benefit from the experiences of previous processes.

The individual phases are as follows:

**Business understanding**
This first phase involves understanding the project objectives and requirements from the business perspective. This knowledge is used to define the data mining problem and draw up a preliminary plan for achieving the objectives.

**Data understanding**
This phase begins with initial data collection, followed by familiarization with the data, identification of data quality problems, and the first insights into the data to discover interesting subsets. This subsequently enables the development of hypotheses on hidden information.
Data preparation
This phase includes all activities for creating the final set of data, in particular data fed into the modeling tools from the original raw data. The tasks include selecting tables, data sets and attributes, and cleaning and transforming data for modeling tools. This is the largest task of the entire analytics project, with 50 to 75 percent of the effort.

Modeling
The modeling techniques are selected and applied in this phase and their parameters are calibrated to optimum values. There are typically several techniques for the same type of problem. Some techniques have special requirements for the form of the data, meaning it is often necessary to return to the data preparation phase. Once the data have been correctly prepared, several hundred thousand proposals or a wide range of models can be generated in a short time. That is why only about 10% of the total effort of the entire CRISP-DM-based analysis phase originates in this step. However, if the data preparation was only mediocre, the results of modeling will also be mediocre and it will not be possible to generate any more valid results after the next phase.
**Evaluation**
In this phase of the project, one or more models are created that appear to have high quality from the data analysis. Before final deployment of the model can proceed, the model has to be carefully evaluated and the steps in its construction must be examined. This is the only way to ensure that it satisfies the company objectives. One main objective is to determine whether an important business problem was insufficiently accounted for. Decisions about whether and how to use the analytics results are made at the end of this phase.

**Deployment**
A finished model is usually not the end of the project. Even if the purpose of the model is to increase knowledge about the data, the knowledge gained needs to be organized and presented to benefit the customer. Depending on requirements, the implementation phase can be as simple as preparing a report or as complex as implementing repeated data scoring, for example a segment assignment. In many cases, the customer and not the data analyst performs the deployment steps. Even if the analyst uses the model, the customer needs to understand the actions to be performed in order to be able to use the created models.
6. Technical implementation of the use cases

In this chapter, we describe the technical implementation of the use cases from chapter 3.

6.1 Human-like machine vision

Traditional image processing systems often reach their limits with tasks that can be performed easily by humans. Human-like machine vision was developed with the aim of reproducing the strengths of humans in a technology for industrial image processing. This technology was developed by experts in image processing, data processing and neural networks. The basis was formed from insights into the workings of the human brain that were gained by neuroscientists. Human-like machine vision was developed and optimized specifically for industrial image analysis and operates on a self-learning basis. It is based on multistage neural networks that can be configured with only a few parameters. Human-like machine vision includes three industrial image processing tools that were developed and optimized for different tasks:

- Discovery of quality anomalies for quality inspections
- Localizing and identifying single or multiple features
- Classification of objects or entire scenes

Traditional vision systems are trained with images of defects, objects or scenes. The system can detect and classify exactly these – and only these – defects in the objects or scenes; it does not recognize deviations as defects. In human-like machine vision, the algorithms are trained with images of typical good parts and correct objects or scenes. The system learns, similarly to a human, how a good part or an object or a scene can appear, with all allowed variations and deviations. Anything that deviates from these expected images will be recognized by both a human and the system as an anomaly. Conversely, anything that corresponds to the expected images of good parts and typical objects or scenes will be classified by both a human and the system as meeting expectations.

6.2 Adaptive control for process optimization

In adaptive control, an ML model is trained with historical data to recognize the relationship between process-influencing factors and the process quality resulting from them. This estimated process quality is then controlled via process parameters without actually being measured. Supervised learning algorithms are used to train the model.
In the example of controlling solid density, over two dozen parameters such as humidity, temperature and color properties served as input variables. The input variable for the model is the estimated solid density, which is controlled via process parameters even before actually being measured. Measured values for the influencing parameters and the corresponding quality results from several months were used for training. Suitable preliminary data processing eliminates inconsistent or ambiguous data sets and generates suitable characteristics. A condition is that the data sets include only examples for which the solid density was set satisfactorily for the influencing parameters.

The model is then able to correlate the complex and nonlinear relationships between the numerous influencing parameters and the solid density. Using the model enables suitable settings to be predicted successfully in many cases, even under previously unknown influences or an unknown combination of influencing parameters. Not only can the model reproduce knowledge, it can also impart some of its knowledge to new cases.

### 6.3 Smart tendering

In smart tendering, an ML model is trained with historical bid data to learn the relationship between machine configurations and costs. These estimated costs are then used for the bid. Supervised learning algorithms are used to train the model. The training is performed at regular intervals to ensure that as many current data as possible are taken into account.

Input variables for the model are all cost-relevant configuration options for the machine. From this, the model learns the sometimes very complex relationships between the options and their effects on the resulting costs, enabling it to estimate an approximate price for a machine configuration. After this initial approximate bid, of course an expert calculates the exact costs for the official price. This approach allows more than just estimates for the costs of machine configurations; with the same approach, historical data can be used to estimate expected project durations or a system’s output.

To train the model, the bid data have to be available in a structured, machine-readable form. A collection of bids in PDF format is normally insufficient. What is needed is a database of machine configurations and bid prices that takes changes and corresponding versions of machines and machine options into account. The price structure for machine options can change over time; this must also be taken into account. For smart tendering, along with training there is also a focus on data deployment and data cleanup.

### 6.4 Data-driven innovation

Many decision makers are uneasy with the thought of storing their production out in the cloud. The alternative is an “edge” solution in which the data are stored on a standard IPC where they originate in the system or machine. This minimizes the danger of data theft or data loss.
Some cloud providers now have a “cloud on-premises” or edge analytics solution in their portfolio. This involves preliminary analysis of data on a gateway in the system; the data are then compared with several systems and locations in the cloud. In the edge-based industrial analytics approach, data are collected, analyzed offline and fed into a model. The model is then brought back to the system to evaluate the incoming data streams there.

“Analytics at the edge” takes place inside the firewall in the system without additional security measures. Only the results of the locally performed real-time analytics can be gathered in a public or a local cloud. For training the models, the cloud ideally keeps a larger selection of powerful machine learning algorithms available than the system on-site or the edge analytics provider. And production parameters for multiple systems can be compared in the cloud. Analytics at the edge, on the other hand, processes the data in real time (figure 10).

Figure 10: Real-time data processing (source: Softing GmbH)
7. **Build or buy**

Once the decision has been made to use ML in the company or for one’s own products, the next question follows: What do I have to do myself and what can I buy? This chapter provides an overview of this issue using the CRISP-DM analytics process in chapter 5 and discusses hardware and software components currently available on the software market.

### 7.1 Overview

**Business understanding**

Business understanding is a company’s in-house knowledge and as such need not be bought from outside. However, there is more to it than understanding one’s own business. Particular attention must go to the opportunities and risks accompanying digitalization and ML. Here, it can be useful to consult external sources to fill in knowledge gaps in the organization and develop the right business strategy.

**Data understanding**

Knowledge about a company’s data is generally internal to the company. Still, this knowledge is often insufficient for developing new solutions immediately; it needs deepening first, something for which there are generally no buyable solutions. Knowledge about in-house data and their importance, availability and quality needs to be gathered in interdisciplinary cooperation involving application experts, data scientists and management experts. A number of software solutions can assist with data analysis, but they are no substitute for the actual compilation of knowledge.

**Data preparation**

Preparing the data is often the most time-consuming part of the process. Software products can aid in saving time. However, the time taken for data preparation and the quality that results always depend on the in-house data and need to be adjusted to the plans for them. The buyable products are just tools to be used by data specialists to speed up the process.

**Modeling and evaluation**

There are also buyable products to develop algorithms that can be used to analyze previously gathered data. They include developer tools as well as finished algorithms. Only rarely can one find finished solutions. Normally, existing solutions are adapted, but they are also developed from scratch for complex problems. The algorithms should be developed by an in-house expert or a service provider. A team of application experts and data scientists then assesses the resulting models. Most tools for the development of algorithms also include tools to assess the developed algorithms.

**Deployment**

Integrating the developed models in existing processes is often a major challenge for machinery manufacturers. They need to establish an IT infrastructure that gathers the required data, processes it automatically using the models, and feeds the results back into the process. Gathering the data can be simple or extremely complex, depending on the in-house IT infrastructure.
Analyzing the data on-site is simpler than gathering them from data sources scattered around the world and then analyzing them together.

There are products on offer for these challenges which aid in gathering the data and executing the algorithms, such as devices for collecting machine data or cloud platforms with hardware and software solutions for ML. Integration in the in-house processes has to be performed by IT experts and software developers and has to be customized to meet the company’s needs. There are also many other things to consider, such as the legal aspects regarding how data are handled. Here too, there is usually no off-the-shelf solution. Every company will need its own special solutions.

### 7.2 Available hardware and software modules

The following table lists examples of software and hardware modules for ML. With these proven modules, in-house ML projects can be implemented quickly and economically. They are categorized as follows: hardware, programming languages, libraries, frameworks, services, cloud platforms and products. The categories are briefly explained below.

**Hardware** refers to physical devices, such as for executing algorithms or for gathering and transmitting machine data.

**Programming languages** are used to write ML algorithms. Speed of execution and ease of implementation of the algorithms are important criteria for programming languages. **Software libraries and software frameworks** include algorithms as finished modules. The available algorithms differ in scope, execution speed, and the programming language used (e.g. C++ or Python).

**Services** are finished software services to be integrated into in-house applications by a software developer. An example of a service is the detection of objects in an image. A special feature of such services is that often no data scientist is needed in order to use their functionality. The services in the table show the numerous ML possibilities that can be implemented without in-depth ML expertise.

**Platforms** offer additional functionalities such as automatic scaling of the required hardware for a large number of users, worldwide online availability of services, or easy integration of existing software products into in-house applications.

**Products** are specially tailored solutions for a specific problem and only need minimal adaptation.
<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Supplier</th>
<th>Type</th>
<th>Ability</th>
<th>Environment</th>
<th>URL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon Machine Learning</td>
<td>Amazon Machine Learning is a service with which developers can implement the technology for machine learning.</td>
<td>Amazon AWS</td>
<td>Platform</td>
<td>Data scientist</td>
<td>Cloud</td>
<td><a href="https://aws.amazon.com/de/aml/">https://aws.amazon.com/de/aml/</a></td>
</tr>
<tr>
<td>Azure Machine Learning</td>
<td>Application for creating, deploying and releasing predictive analytics solutions</td>
<td>Microsoft</td>
<td>Platform</td>
<td>Data scientist</td>
<td>Cloud</td>
<td><a href="https://azure.microsoft.com/de-de/services/machine-learning-studio/">https://azure.microsoft.com/de-de/services/machine-learning-studio/</a></td>
</tr>
<tr>
<td>Caffe</td>
<td>Deep learning framework with a stronger focus on configuration opposed to hard-coding</td>
<td>Berkeley AI Research</td>
<td>Framework</td>
<td>Developer</td>
<td></td>
<td><a href="https://caffe.berkeleyvision.org">https://caffe.berkeleyvision.org</a></td>
</tr>
<tr>
<td>Cognitive Services</td>
<td>Services for image analysis, speech recognition, speech input, translation etc.</td>
<td>Microsoft</td>
<td>REST service API</td>
<td>Developer</td>
<td>Cloud</td>
<td><a href="https://azure.microsoft.com/de-de/services/cognitive-services/">https://azure.microsoft.com/de-de/services/cognitive-services/</a></td>
</tr>
<tr>
<td>Keras</td>
<td>Python deep learning platform</td>
<td>Open source</td>
<td>Library</td>
<td>Developer</td>
<td></td>
<td><a href="https://keras.io/">https://keras.io/</a></td>
</tr>
<tr>
<td>Knime</td>
<td>Konstanz Information Miner, a data analytics, reporting and integration platform</td>
<td>Open source</td>
<td>Platform</td>
<td>Data scientist, developer</td>
<td></td>
<td><a href="https://www.knime.com/">https://www.knime.com/</a></td>
</tr>
<tr>
<td>Matlab</td>
<td>Commercial solution for various mathematical problems including AI and ML</td>
<td>MathWorks</td>
<td>Platform</td>
<td>Students Data scientist</td>
<td>On-premise</td>
<td><a href="http://www.mathlab.mtu.edu/">http://www.mathlab.mtu.edu/</a></td>
</tr>
<tr>
<td>Mindsphere</td>
<td>Connectivity, tools for developers, data analysis, industry applications and services</td>
<td>Siemens</td>
<td>Platform</td>
<td>Developer</td>
<td>Cloud</td>
<td><a href="https://siemens.mindsphere.io/">https://siemens.mindsphere.io/</a></td>
</tr>
<tr>
<td>Movidius</td>
<td>Framework for developing deep neural network applications</td>
<td>Intel</td>
<td>Hardware</td>
<td>Developer</td>
<td></td>
<td><a href="https://www.movidius.com/">https://www.movidius.com/</a></td>
</tr>
<tr>
<td>NumPy</td>
<td>NumPy is a Python package for scientific calculations and machine learning.</td>
<td>Open source</td>
<td>Library</td>
<td>Data scientist, developer</td>
<td></td>
<td><a href="http://www.numpy.org/">http://www.numpy.org/</a></td>
</tr>
<tr>
<td>Name</td>
<td>Description</td>
<td>Supplier</td>
<td>Type</td>
<td>Ability</td>
<td>Environment</td>
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</tr>
<tr>
<td>Pandas</td>
<td>Library (BSD license) that provides high-performance, easy-to-use data structures and data analysis for Python</td>
<td>Open source</td>
<td>Library</td>
<td>Data scientist</td>
<td></td>
<td><a href="https://pandas.pydata.org/">https://pandas.pydata.org/</a></td>
</tr>
<tr>
<td>Predix</td>
<td>Platform for simple development and operation of industrial solutions</td>
<td>GE</td>
<td>Platform</td>
<td>Developer, Data scientist</td>
<td>Cloud</td>
<td><a href="http://Predix.io">http://Predix.io</a></td>
</tr>
<tr>
<td>Python</td>
<td>Programming language, widespread among data scientists</td>
<td>Open source</td>
<td>Language</td>
<td>Developer</td>
<td></td>
<td><a href="https://www.python.org/">https://www.python.org/</a></td>
</tr>
<tr>
<td>R</td>
<td>R is a free programming language for statistical calculations and graphics</td>
<td>Open source</td>
<td>Language</td>
<td>Data scientist</td>
<td></td>
<td><a href="https://cran.r-project.org/">https://cran.r-project.org/</a></td>
</tr>
<tr>
<td>Veles</td>
<td>Distributed platform for rapid deep learning application development</td>
<td>Samsung</td>
<td>Framework</td>
<td>Data scientist</td>
<td>On-premise and cloud</td>
<td><a href="https://velesnet.ml/">https://velesnet.ml/</a></td>
</tr>
<tr>
<td>Watson Cloud</td>
<td>Services for image analysis, speech recognition, speech input, translation etc.</td>
<td>IBM</td>
<td>REST service API</td>
<td>Developer</td>
<td>Cloud</td>
<td><a href="https://www.ibm.com/watson/developer/">https://www.ibm.com/watson/developer/</a></td>
</tr>
</tbody>
</table>
ML is a powerful tool, but not a cure-all. At the beginning of an initial project, it is necessary to consider the opportunities and risks and to gauge and quantify the costs and benefits – always with a clearly defined objective. If ML is being rolled out or used for the first time, there will most likely be a learning curve and some lean times to get through.

Everybody is talking about ML nowadays, but experience and expertise are still largely absent. New processes need to be developed, verified and validated, and experience has to be gained. Nearly every algorithm is a well-protected black box; as a result, the outcomes are not always easily understood or explained, which in turn can lead to longer rollout times. During rollout and initial use of an ML project, reliable backing from management is extremely important, and so is demonstrable success. They keep up the motivation of the team and the leadership and weaken the arguments of doubters.

To develop ML and/or successfully roll it out, expertise in three areas is indispensable for the participating staff:

- Developing algorithms, and developing solutions based on existing algorithms
- Use of the algorithms by operating staff and managers
- On the market, with customers and along the entire supply chain

The question is now for which problems does it make sense to consider introducing ML? The answer is currently generally those questions that call for detailed knowledge of the application – domain expertise. This knowledge is often limited to only a few experts; they need to be challenged and promoted. Expertise and a willingness on the part of experts to accept responsibility are the foundation of a successful ML rollout.

Another requirement for a successful ML rollout is data in sufficient quantity and quality, and access to it through a suitable network. The data need to be prepared so that incorrect data are corrected or deleted and missing data are added. A consistent and precise time stamp mechanism is also required so that chronologically correct conclusions can be drawn subsequently. Before a project begins, all sources should be known, as should the levels on which ML will be at work. A data map can aid in identifying the required data, as well was the types of data and the places where data are generated. If a map like this does not yet exist, it must be created at the beginning.

In industry, we mainly rely on quantitative instead of qualitative statements when working with conventional systems. Today, systems count as conventional when they are not based on ML algorithms, e.g. production systems, measurement systems or software systems. They are tangible and easily and conclusively analyzed.
In the field of ML algorithms, we mostly find only "human experiences and impressions." They are very difficult or impossible to measure or can only be made measurable with great effort, which is why it is so important to assess experiences and impressions. Possible assessment criteria are good/bad, valid/invalid or sufficient/insufficient. The results of such assessments play a central role in preparing and implementing ML systems, after all, the system can only learn what it is taught. Conversely, this means that if a system is based on incorrect information, it can or will learn incorrect things.

Along with data formats and the required connectivity with uniform standards, data content and the issue of its links to individuals are important criteria for further processing and handling. Personal data must be defined, along with the resulting obligations related to collecting, transferring, processing, storing and deleting them. This issue plays a role of increasing importance, especially in data analytics and thus also in ML since statutory requirements can strongly affect business models.
9. **Outlook**

It is only now becoming clear how some machinery manufacturers view digital value creation and what path they have taken toward a data-driven future. That also explains why they have been able to build out their lead over the competition. Valuable expertise develops with remarkable speed, building up its own momentum after a rather short initial phase. With this momentum, their lead over hesitant competitors increases exponentially, exceeded only by the increase in the amount of data available for analysis.

“Uncharted territory is where nobody has any experience because nobody has been there yet.”

Even for fast followers, it is not too late. These businesses are also beginning to regard data as a refined product of their own value creation chains and not mere “crude oil.” In its current technological phase, ML is reaching its first significant breakthrough with solutions that can be applied on a large scale, and the ability to economically process data in parallel provided the foundation. In the next phase, ML will expand into all segments of the mechanical engineering industry, for example in self-optimizing process control systems.

The mechanical and plant engineering industry is in an early phase of the ML application cycle with its enormous dynamism and potential, resulting in a severe shortage of data scientists. This shortage can only be countered with more efficient ways of using ML.

This is why the new discipline of self-service or guided analytics has the defined objective of minimizing both the need for and the dependence on data scientists. In this way, the major gap between the sea of data and data analytics tools can be closed. Today the data science approach is largely manual and exploratory, which is why most of the tasks performed by data scientists need to be automated. In the case of guided analytics, for example, this would mean that data analysis is merely initiated by domain experts but otherwise proceeds automatically, enabling the domain experts to find the added value in “their” data themselves. In a more advanced phase, the entire data analysis process will be automated by “autonomous analytics” – from data entry to presentation of the results.

Viewed from the current state of the art, the path there is a long one, full of both challenges and opportunities. Those who fail to set out on this path now, who do not concern themselves with ML and initiate the transition to a data-driven business will be even farther behind in a few years when the next stages arrive.
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Members who made significant contributions to this Quick Guide with their contributions in the expert group. We thank them for their creative ideas and fruitful discussions.

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