4E Electric Motor Systems EMSA

Classification of digitalisation technologies for electric motor driven systems

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Abstract:
One difficulty in assessing the policy measures required to increase efficiency through digitalisation technologies relates in particular to the definition and delimitation of these technologies. This report therefore provides a classification of digitalisation technologies that forms a basis for further analysis of energy effects and the elaboration of case studies and policy recommendations. The classification included the analysis, definition and description of digitalisation technologies in the field of motor systems and an estimation of the effects on energy consumption (as far as possible). The following technologies could be categorised by definition, description and application in motor systems: smart sensors, Internet of Things, smart control, motor and production level data analytics, real-time monitoring, digital twins, cloud based services, artificial intelligence and augmented reality. Drones, advanced robotics and additive manufacturing were also described.

About the IEA 4E Electric Motor Systems Annex (EMSA):

Electric motor systems consume about 10,700 TWh annually worldwide and were responsible for 53% of the global electric energy consumption in 2016. This corresponds to approximately the combined electricity consumption of China, the European Union (28 countries) and the USA. The goal of the Electric Motor Systems Annex EMSA is to increase energy efficiency and reduce greenhouse gas emissions worldwide by promoting highly efficient electric motor systems in the EMSA member countries, industrialised countries, emerging economies and developing countries.

Further information on EMSA is available at: www.iea-4e.org/emsa/

About the IEA Implementing Agreement on Energy Efficient End-Use Equipment (4E):

The Technology Collaboration Programme on Energy Efficient End-Use Equipment (4E TCP) has been supporting governments in coordinating effective energy efficiency policies since 2008. Fourteen countries and one region have joined under the 4E TCP platform to exchange technical and policy information focused on increasing the production and trade in efficient end-use equipment. However, the 4E TCP is more than a forum for sharing information: it pools resources and expertise on a wide range of projects designed to meet the policy needs of participating governments. Members of 4E consider this an efficient use of scarce funds, which results in outcomes far more comprehensive and authoritative than can be achieved by individual jurisdictions. The 4E TCP is established under the auspices of the International Energy Agency (IEA) as a functionally and legally autonomous body.

Current members of 4E TCP are: Australia, Austria, Canada, China, Denmark, European Commission, France, Japan, Korea, Netherlands, New Zealand, Switzerland, Sweden, UK and USA.

The main collaborative research and development activities under 4E include the

- Electric Motor Systems Annex (EMSA)
- Solid State Lighting (SSL) Annex
- Electronic Devices and Networks Annex (EDNA)
- Power Electronic Conversion Technology Annex (PECTA)

Further information on the 4E TCP is available from: www.iea-4e.org

Disclaimer:

Most text in this report is derived from various literature sources and references to these are included. Some text is written by EMSA authors who are experts on electric motor systems, these sections are not referenced.

Executive summary

One difficulty in assessing the policy measures required to increase efficiency through digitalisation technologies relates to the definition and delimitation of these technologies. This report therefore provides a classification of digitalisation technologies that forms a basis for further analysis of energy effects and the elaboration of case studies and policy recommendations.

Therefore, this report is meant as a preparatory study building the base for further discussion and analysis of digital technologies in industrial motor driven systems. It explains terminologies commonly used. It is not meant as a guideline for industry to start with digitalisation in this area (EMSA is currently working on such a guideline).

The report focuses on digital technologies that enable energy efficiency in motor driven systems especially during the use phase. It also considers technologies that are of further interest and potential energy effects in the future.

The following technologies were analysed: sensors, Internet of Things, intelligent control, data analytics on equipment level, data analytics for production line or on company level, real-time monitoring, artificial intelligence, digital twins, cloud based services, augmented reality, additive manufacturing, robotics, drones.

Level of data collection and analysis	**Technology**	**Short definition**
Intelligent components, connected to each other	Sensors	A sensor measures a physical, biological, or chemical parameter and converts it into an electrical signal, which is sent to an electrical instrument, which enables reading the measured parameters (Xing Liu & Baiocchi, 2016; Yan, 2015).
	Internet of Things	Internet of Things (IoT) is a group of infrastructures, interconnecting connected objects and allowing their management, data mining and the access to data they generate (Dorsemaine, 2015).
	Intelligent control	An intelligent control system has the ability to comprehend, reason and learn about processes, disturbances and operating conditions in order to optimize the performance of the process under consideration." (Åström, McAvoy, 1993)
Analysis of data & optimisation of operation	Data analytics on equipment-level	Data analytics generally deals with turning the volume, variety, velocity and veracity of data into actions and insights within a manufacturing system (Mittal et al., 2019). In this case it is used for the optimisation of electric motor systems.
	Data analytics for production line or on company level	Data analytics is the science of analysing raw data in order to make conclusions about that information. Many of the techniques and processes of data analytics have been automated into mechanical processes and algorithms that work over raw data for human consumption (Frankenfield, 2020). In this case, it is used for optimisation of the energy consumption in companies.

	Real-time monitoring	The real-time monitoring or online monitoring describes mainly online processing, analysis and visualisation of indicators for decision support, which are extracted out of the electrical power use of a machine (Emec, S. et al., 2016).
Technologies adding further advantages	Artificial intelligence	"Artificial intelligence is the branch of computer science seeking to simulate the human capacity to reason and make decisions." (UNIDO, 2019)
	Digital twins	Digital twin describes a digital version of a physical asset and/or process. The digital twin contains one or more sensors that collects data to represent real-time information about the physical asset (Webopedia, 2021).
	Cloud based services	Cloud based services provide information technology (IT) as a service over the internet or a dedicated network with delivery on demand and payment based on usage over time. (https://www.cleo.com/blog/knowledge-base-what-is-cloud-computing)
	Augmented reality	Augmented reality (AR) refers to "Images produced by a computer and used together with a view of the real world" (Cambridge dictionary, 2021).
Other relevant technologies	Additive manufacturing	Additive manufacturing is a digital technology for producing physical objects layer by layer from a 3D computer aided design (CAD) file producing a final three-dimensional product (Engineering Product Design).
	Robotics	Robots are machines that are programmed by computers and are capable of automatically carrying out a series of more or less complex actions (Oxford English Dictionary).
	Drones	A drone is an unmanned aircraft. Drones are more formally known as unmanned aerial vehicles (UAVs) (Earls, 2019).

Figure 1: Summary of digital technologies analysed

Based on analysis of the different technologies the following conclusions can be drawn:

- All major digital technologies, which have been identified and analysed, are already used in the field of electric motor systems.
- Digital technologies are mainly used for reasons other than energy efficiency, such as higher production efficiency, a more flexible system, better control and predictive maintenance.
- All identified and reported digital technologies can be used to increase the energy efficiency in electric motor systems and save energy.
- As it is the interrelation of different digital technologies that often leads to energy savings, it is difficult to attribute concrete savings to specific single technologies. Currently, there is little knowledge about the energy consumption for data collection, processing and preparation.
- While digital technologies can help identify opportunities, energy savings will only be realised once this information is acted upon.
- Examples of specific applications with concrete evidence of energy savings are rare.

- Limited data is available on the energy consumption of digital communication and data analysis applications used for energy optimisation, since this is often not possible to be distinguished from energy used for other process and quality-related analysis.

EMSA is currently undertaking further research to provide more information and clarity especially on concrete examples of specific applications as well as on the energy consumption of digital communication and data analysis applications used for energy optimisation.

Content

1. Introduction, methodology

Digitalisation brings 'smart' applications to all kinds of industrial energy systems, of which electric motor driven systems take the largest part of industrial electricity use. Electric motor driven systems are currently responsible for some 53% of global electricity consumption (IEA 2016), and approximately 70% of industrial electricity use.

An optimal motor system includes optimal aligned system components (motor control, motor, mechanical equipment and application) engineered and operated for the right process demands in a specific timeframe. The application of digital technologies to electric motor driven systems can enlarge the scope and accessibility of optimisation, leading to efficiencies in operation (operational cost, flexibility, procurement, footprint), energy, materials (circularity) and emissions.

The International Energy Agency (IEA) Technology Collaboration Programme 4E EMSA (Electric Motor Systems Annex) works on the assessment of specific developments in the field of industrial digitalisation. The target is to identify the relevant different technology fields (areas), their potential impact on energy use and efficiency and the potential need for policy measures.

This report is a preparatory study building the base for further discussion and analysis of digital technologies in industrial motor driven systems. It explains terminologies commonly used but it is not meant as a guideline for industry to start with digitalisation in this area. It is written for EMSA to further their work in defining policy recommendations and to develop guides for industrial users to start using digital technologies to improve the efficiency of motor driven systems.

2. Background

The Electric Motor Systems Annex is part of the Technology Collaboration Programme 4E on Energy Efficient End Use Equipment within the IEA. The target is to share information and support effective policy development for energy efficient equipment. Participating countries include Australia, Austria, Denmark, the European Commission, Netherlands, New Zealand, Sweden, Switzerland and the US.

The goal of the Electric Motor Systems Annex (EMSA) is to raise awareness of the large saving potential of motor systems, while simultaneously presenting its method of realisation. The different tasks within EMSA currently deal with digitalisation in motor systems, international standards and testing, tools and outreach.

This report was prepared within Task 3 "New Industrial developments". Participating countries are Austria, the Netherlands, Switzerland and Sweden. The first target is to define the key technologies in this field, to describe the potential effects on energy use and further benefits (non-energy benefits, also known as NEBs), and report on some key examples for application in motor driven systems.

3. Overview of digitalisation technologies

The digitalisation technologies included in this report were based on a long list of different technologies and applications of digital technologies in industry, that also included for example big data, algorithms, human machine interface, energy analytics, condition monitoring, cyber physical systems.

The technologies included in the report were selected based on their potential effect on efficiency in motor driven systems.

Topics like block-chain, cybersecurity, data sharing, and machine worker security were not included, as the focus of the report lies on energy efficiency. Though, these topics are considered as very important prerequisites.

Applications like demand response were not included as the focus was more on the use phase of efficient motor driven systems and not on effects on the grid.

Figure 1 summarises the technologies analysed in this report.

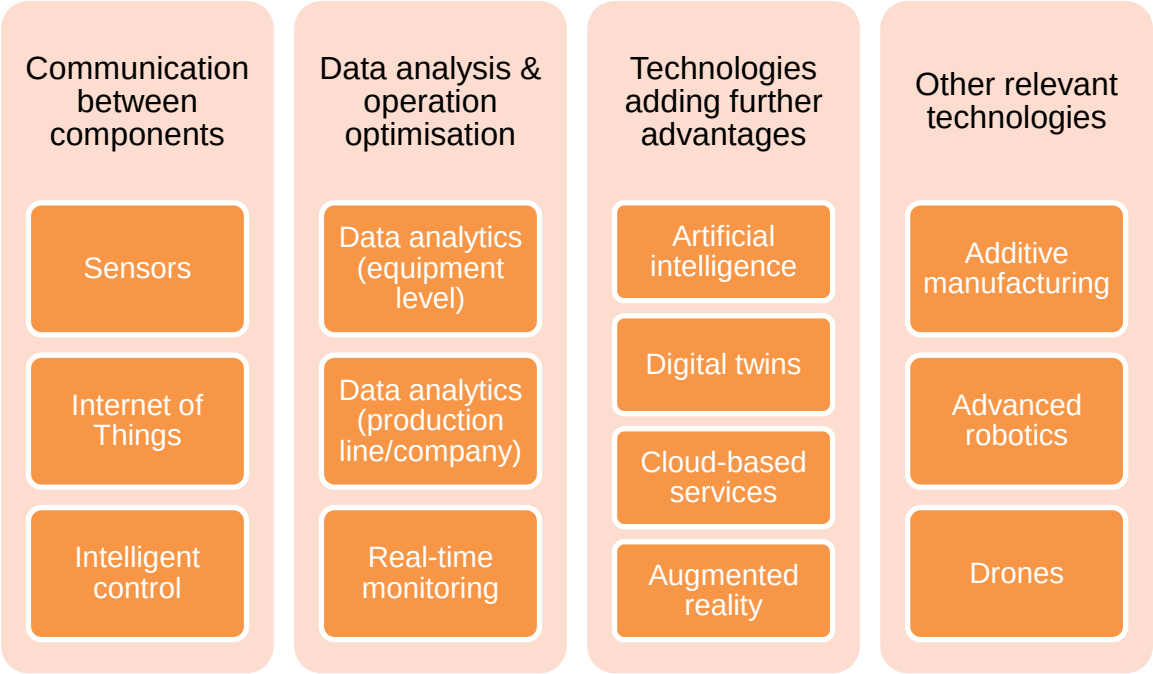

Figure 2: Technologies associated with Energy Efficiency, Digitalisation and Motor Systems analysed within EMSA Task 3

Starting on the left-hand side in Figure 1 on the level of machines, the technologies sensors, intelligent control and the Internet of Things enable communication between the different levels and components.

Furthermore, the next level is the use of possibilities to analyse data and optimise operation. This includes data analytics on both the level of motor systems and on the level of production lines or even the whole company. Real-time monitoring of the different appliances is also significant.

Technologies adding advantages to these applications are artificial intelligence, digital twins, cloud-based services. Augmented reality can help to implement the suggested measures.

Three technologies that are not directly related to the optimisation of motor driven systems, but which are of further interest include additive manufacturing, advanced robotics and drones (at the right side of Figure 1).

The following chapters list in most cases definitions, descriptions, applications for motor driven systems and energy and further effects for each of these technologies. In some cases, not all information was available, e.g. for the energy effects of other relevant technologies.

4. Different digitalisation production technologies

4.1 Sensors

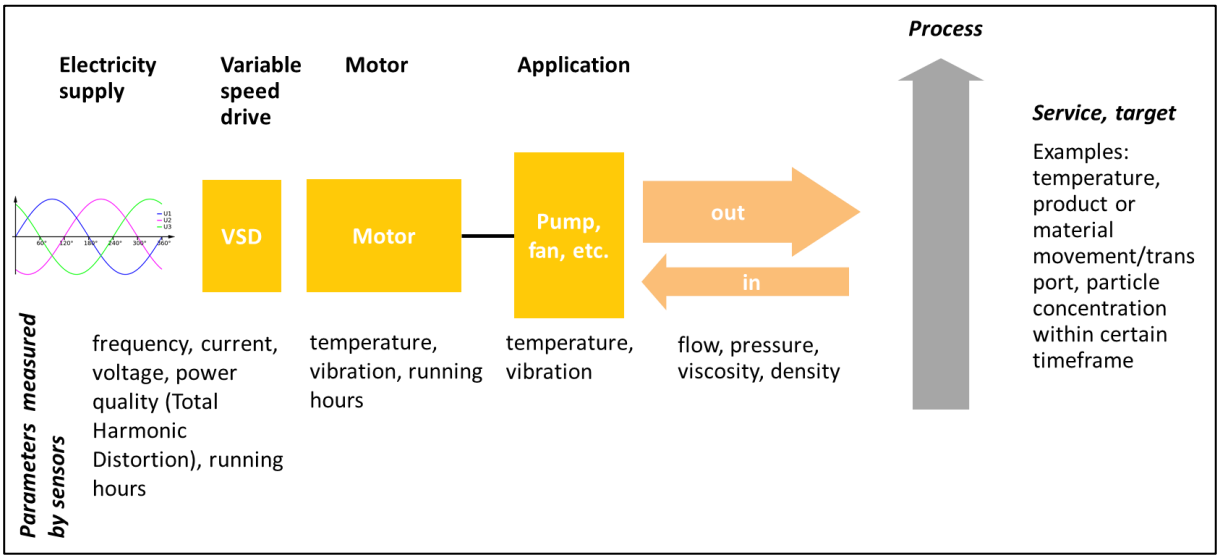

Figure 3: Potential areas of measurements and of application of sensors in motor driven systems, source: Austrian Energy Agency

Definitions

Using the broadest possible definition, a sensor can be described as a technology used to detect changes in its environment or an event and converts this information into a signal, which in turn, is sent to another electronic device, usually a tool with processing power (Meijer et al., 2014; Schütze et al., 2018). A sensor measures a physical, biological, or chemical parameter and converts it into an electrical signal, which is sent to an electrical instrument, which enables the reading of the measured parameters (Xing Liu & Baiocchi, 2016; Yan, 2015).

Fourth generation sensors, usually referred to as smart sensors, have received increased attention in the last decade; however, there is a lack of consensus regarding the definition of a smart sensor (Schütze et al., 2018; Xing Liu & Baiocchi, 2016). The Smart sensors can be seen as the next generation of sensors that not only simply measure one variable at a time, but also have other functions. It has the capability of: (1) measuring multiples values, (2) performing one or more logic functions, (3) store information for future analysis, (4) make decisions, and (5) signalize processed data (Islam et al., 2017; Morales-Velazquez et al., 2017; Schütze et al., 2018).

Description of technology

In principle, sensors (and meters) in connection with motor driven systems can be used to monitor the:

- Machine (motor and/or driven equipment) through measurements of temperature, speed, vibration
- Power supply through measurements of frequency, power quality, energy consumption
- Delivered output through measurements of torque, speed, flow, pressure
- Supplied process or even delivered service through measurements of required flow, pressure, existing humidity, moisture, CO, O2, temperature or occupancy

Sensors are therefore the basis for most applications for improving energy efficiency and detection of faults in motor driven systems. For instance, with vibration or temperature sensors damage on bearings or windings and connections can be detected. In combination with variable speed drives, sensors in supplied processes can be used to adapt speed and therefore energy consumption to the necessary needs.

Applications in electric motor driven systems, examples

One example of sensor usage is in their involvement in the use of frequency converters in a factory's fan system. Sensors could examine the temperature and airflow inside the factory and then send a signal to the frequency converters connected to the electrical motors controlling the fan system through the Industrial Internet of Things (IIoT). This is done in order to adjust the speed of the motors, depending on the state of the factory. Such a system could result in notable energy savings in the fan systems, since they then only run at full capacity if it is required.

Positive and negative energy effects

In a study on the impact assessment of Information and communications technology (ICT) on energy consumption, the current stock of sensors in industrial motor driven systems is estimated to be at 50 million in Europe, with 150 million additional sensors to be installed by 2030. These sensors would bring potential savings in electricity use by 5-10 % in motor driven systems, meaning 50-100 TWh /year (VHK and Viegand Maagoe, 2020).

Positive energy effects:

- Improved operations: Sensors are necessary to connect data. In combination with transparent data on systems and devices coupled with big-picture analytics and insights, they enable higher operational efficiency. For example, incorrect scheduling leads to running during off-hours. The companies can save a considerable amount of energy by using the motor at the optimal speed, power, and performance. Digitalisation has also allowed the customer to start the motors one after another, where with the help of sensors the system decides to communicate what motor to start or not. This allows companies to save a high amount in operating costs. Another example would be sensors collecting data that can be used as a basis for recommendations on how to improve the factory's performance.
- Advanced failure detection: Sensors connected to a monitor displaying information on energy-consumption patterns of motor-systems can be used to identify problems in the system. For example, one can see when a bearing is about to break, and the user can then replace the bearing in the first available timeslot they have. In other words, they can schedule maintenance when something is about to break. The digitalisation allows the user to look at the entire chain and identify its condition with regards to, for example, the quality of sensor signals. Through a detailed analysis it can be determined when maintenance is needed. Predictive maintenance will prevent the process operation from stopping.
- Sensors on every device and system can deliver granular data in real time, which can justify the need for behavioural change and can demonstrate the positive effect to employees.
- Energy efficiency: Using a smart sensor, one can measure voltage, current, and speed, and thereby calculate the efficiency of the motor. After that, a solution can be found to improve this efficiency. It is also possible to make a system with several

motors more energy efficient. For example, if there is a motor driving a pump and both have efficiency specifications, it is possible to find the best compromise in the system, such as reducing the speed. This could result in an efficiency decrease in the pump, but the overall energy efficiency would be higher. Another practical example is in large facilities. In the past a room could have presence detectors, but it could not differentiate if there were 5 or 100 people in the room. Today, some heat-cameras can calculate how many people are inside a room and there are light sensors that report if there is a need to light the lamps. By using a variety of technologies and adding up the energy efficiency contributions, more efficient systems can be created.

Negative (overall) effects:

- Energy consumption by industrial sensors: neutral. The energy use for data measuring, communications, storage and processing is insignificant, e.g., in the EU 50 million sensors equals to the electricity use of 25 EU households (VHK and Viegand Maagøe, 2020).
- Sensors require considerations regarding security: Integrity (prevent any actor from interfering and sending false information); Confidentiality (the information sent in their systems is classed confidential, and it is, therefore, essential to protect themselves from espionage attacks); Authentication (outsourcing some parts of the production chain to third parties in manufacturing industries).
- Risk with data quality: The risk of lower data quality could occur if a sensor is malfunctioning. A broken sensor will not send a signal, whereas a partially broken sensor could send corrupt data. This will affect the performance of the systems and makes identifying faulty sensors more difficult. Corrupt or altered data could for example affect predictive maintenance. One solution for this could be to use intelligent fusion sensor solutions, where one can combine different sensors and calculate some variables instead of measuring them. By combining sensors, it could make it easier to identify where the abnormal measurement comes from, thus reducing the maintenance time.
- Lack of standards: The lack of standards refers to all of the products and systems coming with different sensors and software from the suppliers. It would be very complicated for the factory to build a communication standard that includes all the different technologies. The lack of standards means therefore a risk regarding control systems.

4.2 Internet of Things (IoT) and Industrial Internet of Things (IIoT)

Figure 4: Internet of Things, source: Adobe Stock

Definition

There are numerus definitions for Internet of Things (IoT) in literature, but with different levels of accuracy. A definition with high relevance to the concept is the one by Bruno Dorsemaine (Dorsemaine, 2015):

"Internet of Things (IoT) is a group of infrastructures, interconnecting connected objects and allowing their management, data mining and the access to data they generate where connected objects are "sensor(s) and/or actuator(s) carrying out a specific function that are able to communicate with other equipment."

The IoT concept is broad and includes a wide range of areas. To narrow down to an area with close relevance to electric motor systems, we need to consider Industrial Internet of Things (IIoT) which is defined by Hugh Boyes (Boyes, 2018) as:

"A system comprising networked smart objects, cyber-physical assets, associated generic information technologies and optional cloud or edge computing platforms, which enable real-time, intelligent, and autonomous access, collection, analysis, communications, and exchange of process, product and/or service information, within the industrial environment, so as to optimise overall production value. This value may include; improving product or service delivery, boosting productivity, reducing labour costs, reducing energy consumption, and reducing the build to- order cycle."

Gloss (2021) distinguishes between the two concepts in the following way:

"The architectural components of IoT and IIoT are quite similar but are used for different purposes. IoT covers connected device applications more broadly in many verticals, while IIoT connects devices in manufacturing and utilities that deal with more critical processes than general IoT." (Gloss, 2021).

Description of technology

A basic IoT system consists of four main components: sensors and devices, connectivity, data processing and user interface. Sensors & devices collect data with various degrees of complexity from the surrounding environment. In the second step (connectivity), the collected data is sent to the cloud through a transport medium such as cellular networks, satellite networks, Wi-Fi, Bluetooth, wide-area networks (WAN), low power wide area network and some others. Each of these media has different specifications and trade-offs between power consumption, range, and bandwidth. In the third step, the data in the cloud is processed in the

cloud system software. Data processing can be very simple, such as temperature reading on a device, or very complex such as identifying movement through computer vision on video. The fourth and last step is “user interface” which is about making the information available to the user through for example, triggering alarms on the user’s phone or notifications via texts or emails (Data-flair, 2021).

IIoT systems are generally more advanced than the basic IoT systems and have an intermediate step for data pre-processing, the so-called edge computing. In this step, data is processed close to its generation point, especially when data processing is time sensitive. In these systems the sensors connect to gateways that support a variety of connection methods, including wired, Wi-Fi, cellular and low-power WAN. These gateways collect data from industrial equipment and send it to cloud management systems, such as Microsoft Azure, IBM Cloud and RackWare Hybrid Cloud Platform. By running the data through an analytics algorithm when it is created at the edge of a corporate network, companies can set parameters on what information is worth sending to a cloud for later use. Some systems use fog compute as another intermediary step before cloud computing. While in the edge computing data compute strictly happens within network endpoints, in fog computing, data exists outside the edge but not in the cloud yet. Fog computing reduces the bandwidth, latency and amount of data sent to the cloud (Internet of things agenda, 2020).

Cloud computing services in the form of infrastructure, platforms or Software as a Service (SaaS) are used for fully managed scalable compute resources in addition to information storage as a backup, which can reduce the cost of building data storage infrastructure in-house for companies (Chai, W).

Challenges and issues

One of the biggest challenges faced by the IoT industry is cyber security. Many of the IoT connected devices were left with vulnerabilities, which had to be mitigated during development phases. However, several methods that secure businesses, such as firewalls, also secure IoT systems, although connecting devices to the internet demands other security measures as well (Ani, U et al 2016).

The lack of industry-accepted standards is another problem, as enterprises have to choose from a broad framework without clear guidelines. There are some initiatives for standards development, but all are still in progress. Currently, it is challenging to facilitate communication between different devices from different manufacturers due to competing standards.

Another issue that is worth mentioning is the vulnerability of IoT systems when it comes to operation of connected devices. Any bugs in a single device can potentially affect the entire IoT system. In addition, security and privacy concerns increase as the number of connected devices and shared information increases.

Further, the devices produce huge amounts of data which sometimes are difficult to collect, manage and get insight from for the business (Cognizant, 2014).

IoT energy application

IoT systems create value with the enormous amount of data they generate and compute thereby enabling a smarter way of working. They also offer a wide variety of monitoring and energy control functions, particularly when it comes to:

- Ensuring system reliability through actionable insights and analytics (Data-flair, 2021).
- Promoting efficient energy and resource consumption by preventing the system from getting throttled or overloaded as well as through protection against losses such as equipment damage, downtime, and injuries through detecting threats to system performance and stability as well as through simplification of energy monitoring and management processes (Data-flair, 2021).

Applications in electric motor driven systems

Electric motors in industrial factories, which deploy IIoT are equipped with one or several sensors that are connected to a control database, which continuously collects data about the motors. Artificial intelligence (AI) can be applied in the control database to learn about the motors normal behaviour. When the system becomes familiar with the motor behaviour patterns, it can generate alerts when deviations from normal conditions occur. This means that IoT combined with AI not only predicts problems, but it continuously scans for problems (Augury inc., 2021).

Examples of IIoT include predictive maintenance, supply chain traceability and asset tracking. One interesting application of IIoT is machine health monitoring systems that manage equipment and diagnose problems to keep manufacturing lines running via remote control during crises (Augury Inc., 2021). They use IIoT sensors to monitor machines as they operate, then sending the data to a cloud, where AI algorithms analyse the data in real time and provide steps to resolve potential problems. The system also has the ability to collaborate with Augury's machine health experts in real time to identify and troubleshoot issues.

IoT-based predictive maintenance is another IIoT technology that can be used for electric motor systems. IIoT based predictive maintenance in manufacturing processes makes use of the IIoT sensors, gateway and management system to predict potential equipment failure occurrences. IIoT sensors monitor machinery metrics, such as vibrations, leaks and fuel levels, to detect whether the equipment operates at its full potential. Sensor data together with real-time analytics help to uncover the overall equipment effectiveness (OEE) of machines used throughout the manufacturing process. This way, information is gathered on issues such as current health levels, machine performance and location of hold-ups in the production line. The speed at which data is collected and analysed is critical to the successful implementation of this technology. Engineers still must explore the predictive maintenance formula, in particular in the area of machine learning. AI technology takes predictive maintenance a step further and advises on actions to take to solve issues before they occur, based on analytical insights (Jones 2020).

Many companies already use or have considered implementing predictive maintenance hardware and software across large and small worksites. Industries that benefit from the advancement in predictive maintenance are, among others, the oil and gas industry, manufacturing firms, IT services, and the energy sector. One example here is predictive maintenance that can be performed by deployment of wireless sensors that record vibration, temperature and magnetism metrics from motors, compressors and pumps. These sensors can be used to upload the data to cloud software, which reports back on the machine's health (Augury Inc., 2021).

Positive and negative energy effects

No specific positive or negative effects were identified in the literature on this topic.

4.3 Intelligent control

Figure 5: Intelligent control, source: Adobe Stock

Definition

There are several definitions for intelligent control, but the most widely used definition is the one from Åström and McAvoy, which is:

"An intelligent control system has the ability to comprehend, reason and learn about processes, disturbances and operating conditions in order to optimize the performance of the process under consideration." (Åström, McAvoy, 1993).

Description of technology

Intelligent controls are applied when classical control systems fail in building a suitable and reliable model. This occurs due to complexities such as nonlinearity, distributed sensors/actuators, dynamic mutations, multiple time scales, complex information patterns, big data process, strict characteristic indicators, etc.

In contrast to classical control, which requires a mathematical model with all dynamics of the system to be controlled, intelligent control systems develop models abstractly themselves, based on the designer's input of the behaviour of the device or plant to be controlled. This means that the designer of the intelligent control system does not need to know the internal dynamics of the device or plant to be controlled.

Intelligent control is not always a better alternative to the classical control with well-developed mathematical models, since the latter are comprehensible and easy to integrate into other models. Rather, intelligent control becomes a better alternative, when the mathematical model fails to describe the physical system due to system complexities (Gabbar, 2016).

Furthermore, according to Gabbar (2016), Intelligent control systems become a better alternative to classical control systems when:

- human knowledge cannot be described sufficiently in analytical models
- relevant information about the problem domain cannot be derived from the collected data
- the problem domain is too complicated, with many inputs and outputs making the analytical solutions inaccurate and unfeasible

For electric motor systems, it is essential to develop control strategies to achieve features such as suitability for all kinds of machines. This should be realised without too many adjustments, versatility for different applications, possibility for expansion, robustness, high operation efficiency, rapid convergence for calculation, low power loss for machine control, easy implementation for practical application and reasonable cost for hardware implementation (Chunhua, 2017). Within electric motor systems, intelligent control applications could be integrated via frequency converters.

For electric motors, need for intelligent control systems (as alternative to classical control systems) becomes vital when (Smith, B (2002); Gabbar (2016); Chunhua, 2017; Hu, M (2017)):

- the application of conventional control theory and control algorithm results in complex computation. For example, the vector controls are seldom used in practical drive systems due to these computation complexities and the associated computation time delays. In state estimation controls (for example speed sensorless control) and parameter identification, the computation will be even more complex.
- the presence of nonlinearities in an induction motor drive complicates the control problem. Current research on efforts in nonlinear control theory focuses on differential geometric methods and attempt to extend well-known results in linear control theory to the nonlinear domain. Despite the great interest in this area, many fundamental theoretical issues related to nonlinear control are currently not well understood. Consequently, many of the well-established theoretical results cannot be used for practical control.
- certain essential information required in the mathematical models of the induction motor drive system such as load, exact values of machine parameters and noise, is unknown. Although some parameter identification and state estimation algorithms have been proposed to resolve the problem at the expense of more complex computation, the uncertainty issue has not been completely solved in practical applications.

In many cases, intelligent control systems have been shown to improve the performance of electric motors with respect to dynamics, accuracy, disturbance rejection, in addition to increasing the efficiency of the electric motors. But because of the points mentioned above, intelligent control is not yet widely used in electric motor systems.

Types of intelligent control:

Expert systems

Expert systems (ES) are based on sets of boundaries and rule-based formed if-then statements. It has the ability to encode multiple expertise into its knowledgebase (Gabbar, 2016).

Fuzzy-logic control scheme

Fuzzy logic (FL) is built on principles that mimic human brain reasoning, which is approximate, non-quantitative, and non-binary. The technique is based on using fuzzy rule sets and linguistic representations of human knowledge to describe the controlled device or plant.

In general, fuzzy logic control (FLC) is made up of the following steps:

1. Input and output variable definition
2. Subsets' interval definition
3. Choice of membership functions
4. Condition rules (IF-Then) definition
5. Calculation performance and rules adjustments

Some fuzzy-logic controllers have already been designed for induction motor control, such as Field-Oriented Control (FOC), with fuzzy efficiency optimisers, and fuzzy-logic based Distributed Secondary Control (DSC).

Fuzzy logic is a tool to handle imprecise or ambiguous knowledge. It is similar to expert systems in its structure and inference mechanism. However, in FL, classical sets are replaced by fuzzy sets that have gradual boundaries, allowing gradual transition between sets. Consequently, FL is less sensitive to uncertainty and noisy inputs, offering better presentation of systems with those characters. Like Expert Systems, the FL knowledgebase is made of linguistic variables and if-then rules at the rule-base structure that preserve the ability to inject knowledge directly from expertise and comprehend conclusions and decisions (Gabbar, 2016).

Neural-network control scheme

Neural networks (NN) try to mimic biological processes in order to learn about their environment and account for it to improve overall performance. Neural-networks control schemes with inherent capabilities in classification and pattern recognition have achieved great success in classification. Pattern recognition schemes are considered general model-free controllers, as they function with no need for mathematical models of the controlled plant.

There are two main classes of neural networks for control applications: open-loop identification, which resembles signal processing and classification - so most of the techniques and algorithms appropriate to these fields will still apply -, and closed-loop feedback control. In contrast to open-loop, in this case the NN reside inside the control loop, which requires special care to ensure the tracking error and NN weights remain bounded in the closed-loop system.

Neural-networks have been used for parameter identification and state estimation of induction motor drive system. Hybrid fuzzy and neural controllers (neural-fuzzy) have been designed to control a 100 kW induction motor. Neural networks with the advantage of parallel computation can be used to describe the controller time-delay caused by complex computation (Gabbar, 2016).

Genetic algorithm (GA)

Genetic algorithm (GA) is a stochastic global search method that mimics the metaphor of biological evolution. The technology is based on a methodology to select the most suitable solution with the highest fitness within certain constraints. The implementation starts with the generation of a random group of functions, where each function is constituted of a computer program and terminals that are inputs and outputs to the programs. The programs are executed and labelled with a fitness value based on the programs ability to solve the problem. This is then followed by the execution of a so-called "mutation operator", which involves randomly changing functions and terminals of a program and the crossover operator, which swaps functions and terminals of one program with functions and terminals of another program.

Finally, using the reproduction function in several iterations the algorithm presents the results with the highest fitness.

In contrast to conventional search techniques, which look for local minima in the calculations, GA identify global minimums in highly nonlinear search surfaces. It searches a population of points in parallel instead of a single point and does not require derivative information or other auxiliary other than the objective function and the corresponding fitness levels. Despite these advantages, GA is not suitable for on-line processing due to their sequential processing nature. However, they work well in off-line processing in higher level of optimisation and control hierarchy (Gabbar, 2016).

Hybrid intelligent system (HIS)

In this control technique, different knowledge implementation schemes, decision-making modules and learning strategies are combined to handle the computational application. In this way, the constraints of individual techniques can be conquered. Many HIS contain three necessary models: artificial neural networks, fuzzy inference systems, and genetic algorithms. The combination of fuzzy interference and artificial neural network allows adding human experience to machine learning (Gabbar, 2016).

Applications in electric motor driven systems, examples

No studies which have studied specific applications have been found in the research for this report, however it is clear that most control systems help control energy use.

Positive and negative energy effects

No specific postive or negative energy effects have been found in the literature on the topic.

4.4 Data analytics on equipment-level

„With the advent of the Internet of Things and other advances in information technology, we now have the capability to store and analyse a more complete picture of asset health, based on a more complete set of data drawn from a variety of sources“ (Dunn, 2020).

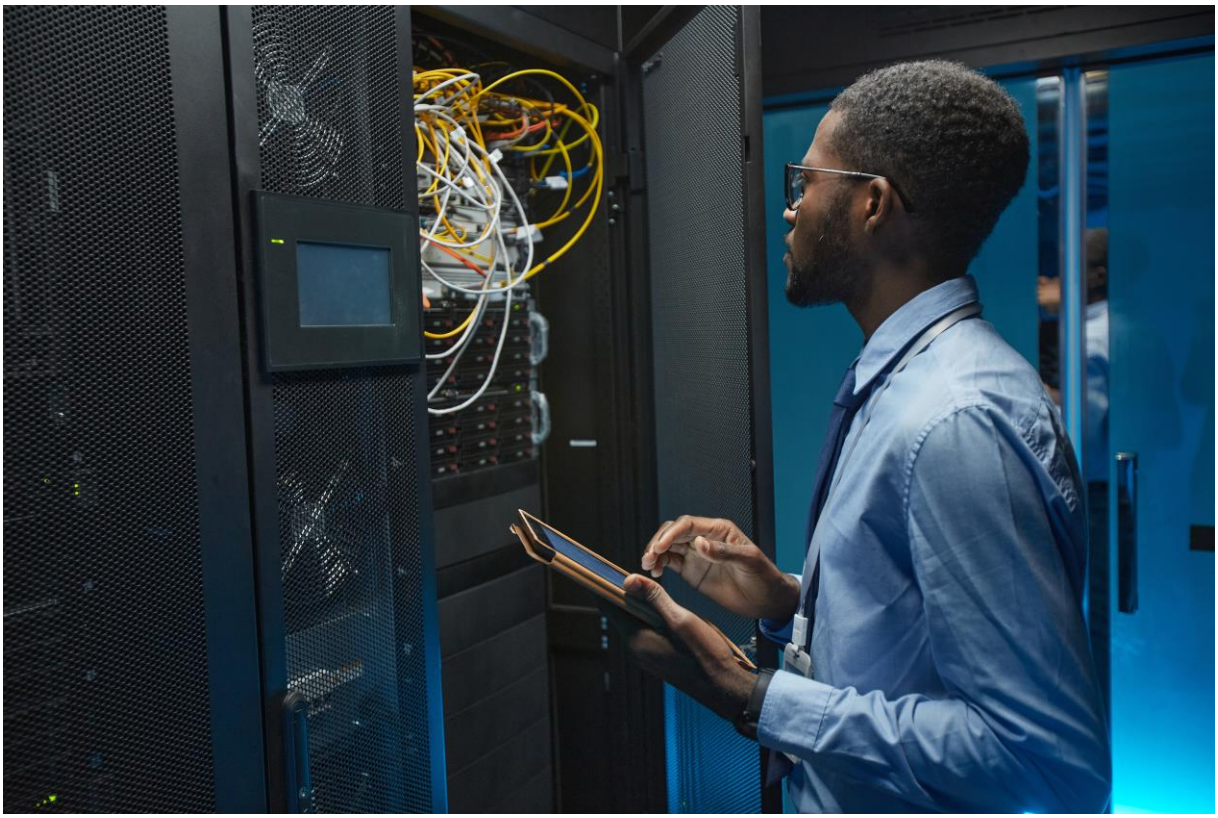

Figure 6: Data analytics on equipment level, source: Adobe Stock

Definitions

The term “big data” describes the large amounts of data that are available from disparate systems. Traditionally, these datasets have been stored and analysed independently of one another (Dunn, 2020). Data analytics generally deals with turning the volume, variety, velocity and veracity of data into actions and insights within a manufacturing system (Mittal et al., 2019).

Description of technology

According to the Cross-Industry Standard Process for Data Mining (CRISP-DM) the following steps have to be considered during a data analytic project: Business understanding, data understanding, preparation, modelling, evaluation and deployment (Smart Vision Europe, 2020). Motor system manufacturers have to find general solutions applicable for a broad range of customers, even in different sectors to build economic business models.

First, the objective and the scope of the data analytics exercise (project) has to be defined. Based on that definition, the target and project plan are developed.

Data sources (Instrumentation data) that can be used for delivering data analytics include (Heggemann, 2018; experience of authors):

- Manufacturer datasheets, nameplate
- Instrumentation of the application, e.g. a pump or a fan itself (integrated data collection)
- Programmable logic controllers (PLCs)
- Installed supervisory control and data acquisition system (SCADA)
- Energy sub-meter data
- Newly installed meters
- Data from a data storage system (process history data)

- Other databases

This data has to be described in quantity and quality before using it further during the analysis.

Then, the data is transferred to different storage solutions:

- Local data storage, which is the most common method in the industry to handle its storage.
- Fog computing, which is a local cloud solution that is located inside of the factory (by using edge devices or clients inside of the factory).
- Cloud, meaning data centres available to many users via the internet, usually separated from the internal network within the industry. The customer can contract cloud computing on demand.

Some companies have chosen to combine local data storage with cloud or fog technologies to reduce the risks with regards to cybersecurity and data loss (Hakansson, Höckerman, 2020).

Before data of multiple sources is analysed, it is necessary to perform a selection for relevance, cleansing and preparation for avoiding duplicate records, outliers, or missing values (Bari et al., 2020).

Data mining tools are used to extract useful information or knowledge from the data.

Main data mining methods include (Lee et al., 2017):

- Statistics and classification (Regression Analysis, neural network, deep learning, support vector machines, decision tree)
- Clustering (K-Means, density-based spatial clustering, affinity propagation)

One important difference in the context of digitalisation is the use of statistics and machine learning:

Regression analysis is used for the estimation of relationships between a dependent variable (e.g. energy consumption) and one or more independent variables (e.g. heating degree days, production output, occupancy). It has been an important tool in energy analytics within energy management and energy saving calculation for the last decades and is recommended by the International Performance and Measurement protocol and the ISO 50001 series, for example in the ISO 50015 standard. The result of such an analysis is a formalisation of relationships between variables in the form of mathematical equations (a statistical model). (EVO, 2012; ISO 50015)

Machine learning, a subfield of artificial intelligence, is an algorithm that can learn from data without relying on rule-based programming and is used for a high number of attributes and a high number of observations, for detecting and describing relations in a more complex environment. Machine learning can complement traditional physics-based understanding of equipment performance and enables improvement in both speed and accuracy of pump performance predictions (Gomaa, 2018).

Reasons for using artificial intelligence instead of or in addition to statistical or formula driven approaches are (Deep mind, 2016):

- The equipment, the mode of operation and the environment interact with each other in complex ways. Formula-based engineering cannot capture this interaction.
- Systems can currently not adapt quickly to internal or external changes, because there are no rules or control strategies for every operating scenario.

The model is trained with datasets and tested with another dataset to verify the model's output. Actual (observed) output data is compared with predicted output data and the algorithms (in

the case of ML) aim to minimize the difference. At this stage, different algorithms can be used and different models can be developed and used simultaneously (Gomaa, 2018).

Ideally, machine-learning models are trained on data gathered during operation, covering a full range of load situations. For all labelled failure modes present in the historical data, models can be trained to detect similar events. Problems occur for new installations or old equipment equipped with new sensors. Therefore, it is difficult to build analytical solutions based on limited operational data to estimate a performance baseline (e.g. for condition assessment) (Gomaa, 2018).

After the model is deployed, the performance of the model has to be monitored and continuously improved or updated with new data.

Presenting the data in the shape of graphs (data visualization) on screens or on mobile devices can provide real-time insights about the assets in a plant. This can include e.g. current and historic values of parameters, current, flow or pressure within a pumping system, efficiency, trends or probabilities to fail or alert if e.g. vibration level is too high. Operators can select the most meaningful key performance indicators and track the performance and condition of their motor driven systems. This makes it possible for the operator or the energy-manager to act upon this information. Furthermore, graph patterns can be used for automatic analysis of the data.

Then automatically generated recommendations can for example provide guidance about which part should be replaced and when.

Finally, reports can present performance indicators, summaries of past events, or lists of underused devices. This information may help facility managers in their decision-making process (Da Silva, 2016).

Examples of application on a general level include:

- Information on efficiency and load characteristics derived from measuring electric input data
- Forecasts of future conditions based on industrial devices' historical working patterns (e.g. an individual working pattern of a motor according to power and application characteristics) (Da Silva, 2016).
- Data display against known performance curves (Gankema, n.d.)

Applications in electric motor driven systems, examples

Data analytics on equipment-level is very often used in combination with real-time monitoring with the target of condition monitoring.

In general, condition monitoring continuously observes the operating status and detects unfavourable operating conditions. These include, in particular, increased vibrations, increased power consumption, increased number of starts, irregular transit times, etc. Through appropriate evaluation (also via algorithms), it can identify various causes (e.g. inadequate lubrication, clogged air filters, fouling of pumps and pipes, worn gearboxes). Change of requirements and appropriate countermeasures are initiated. This can be done via warning signals to the automated ordering of the replacement component and appointment request for replacement or maintenance (Gankema, n.d.).

Load conditions and current motor efficiency can be extracted from current and voltage signals. This information is used to save energy by resizing oversized and therefore inefficient motors. As one example, a smart condition monitoring system for AC induction motors, pumps, compressors and conveyors measures current and voltage with six high-frequency sensors from the motor control cabinet. The self-learning artificial intelligence algorithm analyses the resulting signals to detect equipment faults as soon as they start to develop, and identify the specific failure mode. Therefore, 90 percent of developing faults are detected up to five months

in advance, increasing uptime, energy efficiency and overall equipment effectiveness (Gankema, n.d.).

For e.g. pumping installations the following data is already collected by different manufacturers: Operational status, rotating direction, differential pressure, volume (calculated), energy consumption, power [W], current [A), media temperature, density of viscosity of media, running hours, speed, vibration, errors such as: pump, motor, over- and low- voltage , system pressure too high, too low, sensor-error, max. speed, min speed, control mode (e.g. constant pressure, const. volume) (Rauch, 2018, Heggemann, 2018).

For predictive maintenance models further data is used (Dhingra, 2018):

- Data about the equipment (producer (brand), model (=manufacturer data), configuration, operation settings) which does not change on a regular basis.
- Usage history: running hours.
- Maintenance data about parts replaced.
- Environmental data (outside temperature, humidity, rainfall)

Also in the field of pumping systems, expected performance curves are used to train a machine learning model on the extracted data set. For given operating conditions (speed, flow rate) the model returns the expected performance at ideal conditions. By applying the model to live operational data, the deviation between expected and actual performance can be assessed. Deviations occur because real performance curves differ from manufacturer performance curves. This might be because of interaction with the installed system, because operational equipment wears over time, resulting in performance degradation, or because of equipment failure. This information allows operators to for example improve operation settings or other counter measures (Gomaa, 2018).

In terms of more complex analytics, the clustering of certain failures in specific areas allows the use of clustering as an indicator to label different failure modes. With the collection of more data, the setting up of new performance benchmarks is possible (Gomaa, 2018). For example, a higher vibration level of a pump can indicate increased wear and tear, cavitation or bearing problems. Experience is necessary to determine the critical vibration level for a specific pump type. If vibration is over the threshold limit, operators can investigate the root cause to avoid failures (Heggemann, 2018).

The long-term goal is that each individual component monitors itself. An example would be a solenoid valve on a valve terminal, which detects when a coil needs too much power and thus recognizes when an exchange or repair is required. In general, machine manufacturers will increasingly evaluate and use the data on the operation of their systems by the plant operator (Kulterer, 2019b).

Positive and negative energy effects

Positive energy effects are for example (Vardi, 2015):

- Improved operations: The combination of transparent data on systems and devices coupled with big-picture analytics and insights, enables higher operational efficiency. For example, incorrect scheduling leads to running during off-hours.
- Advanced failure detection: Monitor energy-consumption patterns of motor systems and benchmark them against similar devices and locations leads to identifying problems.
- Interrelated systems performance: Problems that affect more or multiple systems (e.g. air conditioning unit, water pumps) can be detected by device-level monitoring in combination with data analytics. Interrelated problems can be detected and solved.

- Monitoring the energy print: through monitoring the energy consumption of motors in real time, it is possible to detect faults, like belt- or bearing problems, when machinery begins to draw more electrical power.
- Energy optimisation and cost savings: device-level monitoring enables companies to identify inefficiencies in real-time, pinpointed and corrected.
- Real time granular energy data for every device and system can explain the need for behavioural change and can show the positive effect to employees.

Negative energy effects are for example:

Increase in energy consumption due to:

- Energy consumption for data collection (e.g. sensors), data transfer and storage
- Energy consumption for data analysis (computing power)
- Energy consumption for data visualization (screens, mobile)

Other advantages include (Heggemann, 2018):

- Operation optimisation
- Targeted preventive maintenance
- Increased reliability
- Process safety
- Fast reaction
- Targeted actions
- Increased efficiency
- Energy savings
- Cost savings

4.5 Data analytics for production lines or on company level

This chapter refers to energy analytics on the level of a whole company, plant or production line. It describes possibilities and concepts to increase efficiency and save energy by production and energy data analytics.

Figure 7: Data analytics for production line, source: Adobe Stock

Definitions

„Data analytics is the science of analyzing raw data in order to make conclusions about that information. Many of the techniques and processes of data analytics have been automated into mechanical processes and algorithms that work over raw data for human consumption.

Data analytics techniques can reveal trends and metrics that would otherwise be lost in the mass of information. This information can then be used to optimize processes to increase the overall efficiency of a business or system" (Frankenfield, 2020).

Description of technology

Energy analytics generally describes the process of collecting electrical data and applying sophisticated analytical software and algorithms to deliver insights around consumption and time of use. It is a combination of concepts from traditional industrial energy management systems (e.g. ISO 50001) with digital technologies and advanced software applications. (enertiv, 2019)

In the context of energy analytics for energy management, data used on this level include the following information (Schneider Electric, 2019):

- Utility bills/utility data
- On-site meters/devices that collect resource consumption data (water, electricity, gas)
- Facility sub-metered interval data (lighting, cooling, compressed air compressors)
- Supplier information and ratings
- Efficiency goals, performance
- Efficiency project details
- Energy cost metrics (price, tariffs, rates)
- Related data for analysis: production, financial, occupancy, weather

As algorithms are fed with more aggregate data, energy analytics are being combined with machine learning to ensure maximum performance, optimal scheduling, equipment fault detection, and peak demand load shifting and saving (Enertiv, 2019).

The following key-topics can be delivered:

- Developing reports on the most important energy consumers (share and absolute values), displaying total energy consumption of plant per week, trend of total or specific energy consumption of the plant and on key performance indicators (KPIs) on a monthly or weekly basis
- Monitoring energy consumption and KPIs in real-time
- Forecasting energy consumption and comparing real values, for detecting periods with higher energy consumption and enabling fast reaction.
- Specific information on the different assets can be transferred and displayed within the central energy management system (see example for compressed air systems below).

IT based production management include: Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), Computer-aided design (CAD) and Computer- aided manufacturing, CAM.

Process industries generate enormous volumes of data. Production analytics uses advanced data-driven analysis for different purposes.

Companies record product quantities and qualities, product parameter and production time to control their production. Companies can use this information (and information on for example

ambient conditions, raw material quality, machine availability and downtime) to optimise the processes and identify bottlenecks or unprofitable production lines (Kulterer, 2019a).

Furthermore, they record the runtime, downtime, and work queue for various machines and then analyse the data to better plan the workloads, so that the machines operate closer to peak capacity. In addition, they conduct root-cause analysis for product quality improvement, by creating a baseline, and diagnose and correct process flaws and thereby achieving optimal output and improving performance. Other examples include KPI charts for the manufacturing floor and root-cause analysis for predictive maintenance (Frankenfield, 2020).

Advanced analytic techniques, e.g. neural networks, help companies sort through millions of possible interdependencies among variables, such as the quality of raw materials, the configuration of equipment or process technologies. Specific days and events, when the yield should be higher, can be found, analysed and the process parameters changed (Hammer, 2015).

Main applications of advanced data analytics in the process field include (Dilda, 2017):

- Quality issues (fault/error detection, root-cause analysis, fault-avoidance)
- Predictive maintenance based on condition monitoring
- Process optimisations (improving performance and quality)

One indicator monitored in some production companies with close relation to energy consumption of a company is the Overall Equipment Effectiveness (OEE). The OEE assesses speed, quality, and downtime of individual machines. The improvement of the OEE reduces time periods when no valuable output is generated by the machines. Therefore, the machines are used more effectively and motors are running only when needed (Kulterer, 2019a).

Another tool in this area is Yield-energy-throughput (YET) analysis, which balances yield, throughput and material costs to maximize the profitability of each process step. The target is to increase the yield and throughput and reduce the amount of energy consumed by individual machines (Dilda et al. 2017).

As mentioned above, a plant´s sensors produce a huge set of data. Advanced data analysis identifies critical through-put drivers and allows a model of the process to be built. A model can quantify the interdependence of key variables and provides a better understanding of the process. With a new understanding of the process and its key drivers, the company can set up experiments to optimise production and e.g. tweak a recipe in a steel plant. According to Dilda et al. (2017) “the analysis can build a performance dashboard in the control room with live data from operations, enabling production personnel to change operating conditions as indicated by the analysis.”

Challenges

For data-analytics to have an impact, the right personnel is required: For the retrieval, cleansing, and structuring of data considerable effort by data scientists may be necessary. IT experts, e.g. platform specialists, have to aggregate data from different sensors and store the information in various platforms. Process technology and asset maintenance experts are needed for their expertise in their area.

Furthermore, manufacturers have to change processes e.g. spare-parts, supply-chains, deployment of technicians, and integrate new solutions into day-to-day operations and the way of working (Dilda et al. 2017).

Applications in electric motor driven systems, examples

A manufacturer of car motors found the optimal arrangement of the machines and conveyor technology to optimise throughput and throughput times. By simultaneously simulating the energy requirements in the individual operating states of the machines and systems, it was

possible to avoid peak loads and to reduce standby consumption. Energy savings of 3 GWh p.a. were achieved (ZVEI, 2018, p 6).

Another example is the display of energy data, e.g. for air-compressors on the 3rd level of the automation pyramid. For compressed air systems, it might make sense to display the following data in the energy-data management software (Kulterer, 2019a):

- Total compressed air consumption
- Operating pressure
- Power consumed by the compressed air system
- Used heat by heat recovery
- Dew point
- Specific compressed air consumption

For the efficiency analysis of the compressed air plant the following curves can be displayed (Weidmüller, 2018):

- Compressed air system power [kW] over time
- Delivered quantity [m^3 / h] over time
- Energy consumption per delivered quantity

Positive and negative energy effects

The following list gives examples of advantages of different applications and their possible energy effects:

- Device-level sub-meters coupled with big data analytics improve real time operational efficiency and system performance management (ZVEI, 2018)
- Transparency, meaning detailed understanding of energy use (lower implementation effort for measuring/monitoring systems and data evaluation) (ZVEI, 2018)
- Permanent monitoring of assets (incl. machines, production lines) (Kulterer, 2019a)
- Reporting of consumption, trends, KPIs for dashboards on different levels (machine, production line, facility, company) (Kulterer, 2019a)
- Self-learning systems in combination with pattern recognition processes enable an automated evaluation of the development of the energy efficiency of a machine or system (ZVEI, 2018)
- Intelligent break management by merging production planning, energy requirements of equipment in certain conditions (load, stand by energy consumption) and dependencies in production management and production process (e.g. Start-up time) (ZVEI, 2018)
- Specification of minimal energy consumption as an optimisation criterion of the production control system (Manufacturing-Execution-System). For this, information on energy consumption of different process steps and interrelation is needed. (ZVEI, 2018)
- Optimised process control by calculating process parameters to reach certain energy consumption values (WKO, 2019)

Energy savings of over 10-30% depending on industrial processes and technology are possible (IEA, 2019).

4.6 Real-time monitoring

Definitions

According to EN 13306, monitoring is an activity performed manually or automatically, with the intention of observing the actual operating state of a machine (Emec, S. et al., 2016).

The real-time monitoring or online monitoring describes mainly online processing, analysis and visualization of indicators for decision support, which are extracted out of the electrical power use of a machine (Emec, S. et al., 2016).

Figure 8: Real-time monitoring, source: Adobe Stock

Description of technology

For electric motor driven systems, different parameters or indicators are relevant. Very often data for electrical power are transferred, from which other parameters are derived.

In the simplest case, the current drawn from different motors is measured and displayed in real-time on the control board and transferred to a control centre. Here, e.g. the energy manager has access to similar data of all connected machines in an industrial plant. In combination with data analytic-methods applied also in the context of cloud-services several further options are possible:

Various operating states of plants and processes are continuously analysed against the basis of recorded data, and with the aid of suitable software solutions and deviations are marked and reported. Constant monitoring and analysis can help avoid unexpected system failures, but also situations with high energy consumption. Incorrect settings, misuse and incorrect operation by the operator or machine operator are detected at an early stage. Wear parts are operated until the actual usage limit instead of replacing them early on. Condition monitoring prevents machine failures and damage situations, and thereby defective productions (VDI ZRE 2017).

To assess the energy efficiency of electric motors and to improve the overall performance of industrial systems, it is essential to identify energy losses and to monitor in real-time the efficiency and load factor. Assessing the energy efficiency and load factor requires field

measurements of the shaft power, which is very costly. Therefore, different methods are available for estimations on the energy efficiency.

Three-phase asynchronous motors usually do not have sensors equipped. In recent years, most important motor manufacturers have launched so-called “sensor boxes”. These boxes can be installed directly on the motor without wiring, sometimes even during operation, e.g. with magnet or glue. Essentially, they measure the parameters of the magnetic field, vibration and surface temperature.

In many cases, these boxes have been developed for use on motors from the respective manufacturer. Based on the stored motor data and measured values, further values can be calculated. For example, the motor winding temperature is calculated based on the surface temperature. A magnetic field is used to infer the current load on the motor and thus the power. The vibration can indicate faulty bearings. Other application examples include: overload, problems with power supply, problems with the insulation of the stator, motor imbalance, eccentricity of the stator or the shaft, motor alignment, lack of lubrication, problems in the area of the bearings, etc. (e.g. Test Motors, o.J., Siemens, 2017, ABB, 2019). In some cases, data is transferred via a Bluetooth-gateway or smartphone to a secure server.

Another method of collecting data is to use the motor protection unit to monitor the motor current in the control cabinet of electric motors. Extensions can enable voltage detection and thus, in combination with measuring the current, detect active power and monitor further measured variables. Additional sensor connections can enable process monitoring of e.g. fill levels, flow rates, dry running or filter contamination.

In addition to Profibus and Modbus, the connection to higher-level automation systems also takes place via Ethernet / IP and Profinet and via the offline communication standard Unified Architecture (OPC UA). The information can therefore be displayed in the motor control centre, at the control room or via the cloud and thus on all mobile devices. In addition to various status messages (operating data, downtimes, overload, over-symmetry) and fault and maintenance messages, measured values (current and voltage for each phase, active and apparent power) can also be displayed. Combined with other data that are delivered directly from the process to the cloud, efficient energy management, predictive maintenance and resource optimisation can be implemented across systems (Siemens, 2019).

Applications in electric motor driven systems, examples

Application examples include:

Dry run protection: The pump status can be determined by monitoring the motor's power consumption. If the value falls below a certain defined threshold value, the pump can be switched off.

Pump cleaning: When monitoring the value of the absorbed motor current, it can be concluded (based on previous experience) when the pumps are dirty and the pump's self-cleaning mechanism can be activated by changing the direction of rotation. The number of pump starts can also be monitored (Siemens, 2019).

A condition monitoring system can detect irregularities in electric motors, pumps, fans, and their rolling bearings, and is able to report potential fault causes in a plain text message after they have been identified. With the integration of the system into the control room visualization, the maintenance personnel is informed of incipient damage at an early stage and can immediately initiate maintenance measures and procure any replacement parts that might be needed (Bearing News, 2018).

A frequency converter records or regulates the speed of a motor via the amplitude and frequency of its output voltage. The converter receives a large number of data in real time via the voltage and current sensors. The frequency converter records the speed and the current rotor position (angular position) of the driven motor via further sensor inputs. In addition, a frequency converter can record vibration, pressure (air, water) and temperature via additional

inputs. The frequency converter can correlate this data with the speed and load, process and analyse the signal. Basically, knowledge on the state of the industrial processes can be gained on the basis of the recorded data and the system can thus be optimised. Subsequently, services and analyses will be developed from this (Hanigovszki, 2018).

One example is the so-called "condition monitoring", applied to avoid conditions that lead to increased losses (Hanigovszki, 2018):

- Inadequate lubrication
- Clogged air filter
- Fouling on pumps and pipes
- Worn gearboxes

In ventilation systems, a frequency converter makes it possible to record the operating status of fans in real time via the motor without additional sensors. For example, clogged filters reduce the volume flow, thereby reducing the current value. Based on a defined warning threshold, the user can be informed about the time of the necessary filter change (Yaskawa, 2019).

In compressed air systems the control system can continuously and in real time supply all operating and environmental parameters to the data centre. With the help of specially programmed expert tools, abnormalities are identified early on and operational disruptions prevented. The necessary maintenance is therefore based on actual needs rather than on defined service intervals, thereby lowering costs. Furthermore, through real-time transmission and evaluation or monitoring of important operating parameters, such as compression end temperature, pressure dew point or differential pressures, the energy efficiency of the compressed air system can always be kept in the optimal range, also for short-term production adjustments (KAESER, 2019).

Positive and negative energy effects

As mentioned above, constant monitoring and analysis can help to detect situations with high energy consumption caused by incorrect settings or incorrect operation. In addition, maintenance issues as leakages or worn-out equipment can be detected early. The saving effect is depending on the use case.

4.7 Artificial intelligence

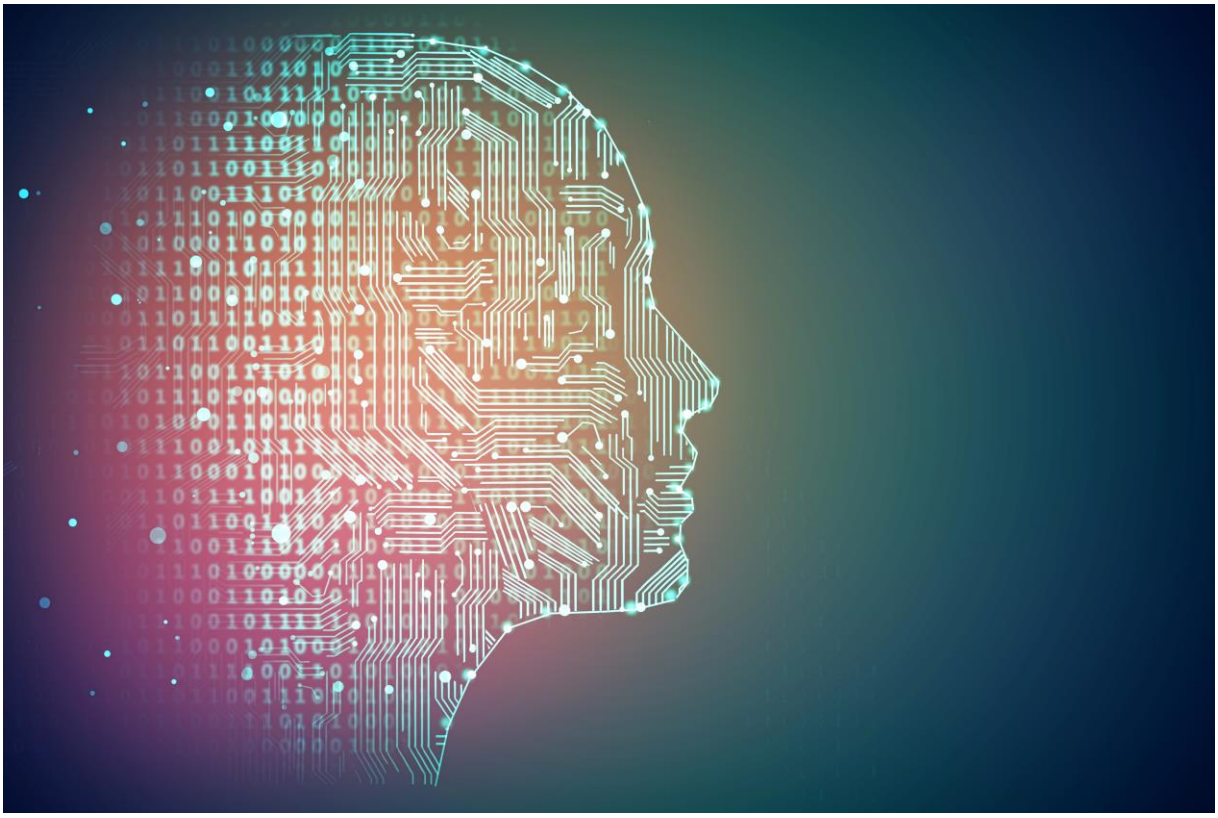

Figure 9: Artificial intelligence, source: Adobe Stock

Definitions

"Artificial intelligence is the branch of computer science seeking to simulate the human capacity to reason and make decisions. The term usually refers to such AI techniques as machine learning, deep learning, neural networks, fuzzy logic, computer vision, natural language processing and self-organizing maps to provide machines and systems with human-like cognitive capabilities, such as learning, adapting, perceiving and solving problems." (UNIDO, 2019).

Machine learning, one example of application of artificial intelligence, involves the self-teaching of computer programs based on their experiences and pattern recognition. Machine learning uses general algorithms to determine on their own how to map inputs to outputs, typically being fed by very large sample datasets. It recognizes patterns when exposed to new data, therefore it can be part of data analytics (Brynjolfsson et al., 2017, Mittal et al., 2019).

These systems can improve their performance in a given task over time by collecting experience and large volumes of data such as big data (UNIDO, 2019).

Description of technology

The transition from general computer science to AI is fluid, so that a clear distinction is not possible. Machine learning differs from non-learning AI methods in that the algorithm learns from data. The difference to classic methods is that the algorithms do not map the knowledge of a programmer in the form of rules in program code, but the algorithm independently develops rules in a defined framework (Hatiboglu et al., 2019).

Neuronal networks are based around the concept of having highly intelligent data analysis being done over different levels of the system to extract higher-level results from input data progressively. The process is comparable with the neural networked inside of a human brain.

This emerging technology is complicated to adapt in an industrial environment because of the vast amount of different types of data (Hakansson, Höckerman, 2020, Kahng et al. 2018).

In deep learning the algorithm also learns using examples, however, the characteristics or attributes on which learning is based are not explicitly specified here. Instead, the AI determines the characteristics itself. It is therefore a specific sub-area of machine learning (prominent examples are image processing algorithms) (Hatiboglu et al., 2019).

Deep neural networks are neural networks with a large number of neuron layers, which makes it difficult to train them (high computing effort, large training sets). However, their structure enables them to learn very abstract relationships between input data and desired outputs (iit, 2018).

Deep learning can only be implemented using neural networks; for machine learning also other methods such as support vector machines tree models can be used (Hatiboglu et al., 2019).

Artificial intelligence-tools relevant for the user are: Text and language processing (e.g. for human machine interfaces), image and sound processing, pattern recognition, knowledge representation and semantics, action planning and optimisation, emotion detection and intent analysis (Hatiboglu et al., 2019).

Artificial intelligence is already used in different areas in the industrial context: Maintenance, logistics, quality management, product- and process-development, digital assistance systems, process-optimisation and –control, resource planning, and automation technology.

As one example, AI applications in maintenance currently focus on the need-based optimisation of maintenance intervals. The time of maintenance schedule is determined based on the wear of the equipment. The AI continuously monitors machine and process parameters and signals maintenance requirements according to the condition of individual components. Monitored parameters can also be generated using image processing applications. For example, sensors monitor the condition, temperature, vibration and forces in the bearings of machines. The data obtained are used to create a virtual image of the current status and control automated maintenance activities, such as adding lubricants. If this does not improve the system status, further sources of error are inferred and a maintenance engineer is informed via smartphone (Schaeffler AG, 2020, Hatiboglu et al., 2019).

Applications in electric motor driven systems, examples

As the first example of AI application for energy efficiency there is one interesting use case mentioned:

The main energy consumer in data centres are motor driven systems like pumps, chillers and cooling towers. However, dynamic environments like data centres make it difficult to operate optimally for several reasons:

- The equipment and the environment interact with each other in complex, nonlinear ways.
- Traditional formula-based engineering and human intuition often do not capture these interactions.
- The system cannot adapt quickly to internal or external changes (like the weather) because there are no rules and heuristics for every operating scenario.

Therefore, Google applied machine learning to operate its data centres more efficiently. Using a system of neural networks trained on different operating scenarios and parameters within data centres, the team created a more efficient and adaptive framework to understand data centre dynamics and optimise efficiency. They used the historical data, such as temperatures, power, pump speeds, and set points, to train an ensemble of deep neural networks on the average future PUE (Power Usage Effectiveness, the ratio of the total building energy usage to the IT energy usage). Two additional ensembles of deep neural networks were trained to predict the future temperature and pressure of the data centre over the next hour to simulate

the recommended actions from the PUE model. The machine learning application achieved a reduction of the amount of energy Google data centres use for cooling by up to 40 percent, which equates to a 15 percent reduction in overall PUE (Deepmind, 2016; Google, 2019).

As a second application area for AI, the development of new products is mentioned here: With the analysis of laboratory and field data regarding surface quality, lubricants, kinematics and geometries, data mining methods can be used to make predictive statements regarding new products. Developers can reduce the friction of rolling bearings, plain bearings and other mechanical components, or to prevent corrosion. Through widespread collection of raw data and the intelligent interpretation of results, the energy efficiency of these components and systems can be increased further (Schaeffler AG, 2020, Hatiboglu et al., 2019).

The third example is predictive maintenance: With the knowledge of interrelationships between the design of a machine, the external conditions, and the loads occurring during operation, it is possible to provide precise predictions regarding failure probability with the help of learning algorithms. Maintenance intervals and even the machine control system can be precisely adjusted according to this information (Schaeffler AG, 2020).

Positive and negative energy effects

IEA estimates that Artificial intelligence algorithms can save 10% of energy in energy intensive industrial applications. The effect comes from predicting the future performance of industrial equipment and alerting plant operators to potential faults before they disrupt production (IEA, 2019).

Further effects could come, as described in this chapter, from the possibilities of improved control, and designing new more efficient products. One can use machine learning for optimisation of manufacturing processes. In these examples, the system automatically determines the ideal behaviour (setting) within a specific context to maximise performance (Dhingra, 2018).

4.8 Digital twins

Figure 10: Digital twins, source: Adobe Stock

Definition

Digital twin is the phrase used to describe a digital version of a physical asset and/or process. The digital twin contains one or more sensors that collects data to represent real-time information about the physical asset (Webopedia, 2021).

Description of technology

A digital twin is a virtual representation of a physical asset, plant or system in operation, based on simulation technology, which is connected to the real product.

For instance, a digital twin can be developed for the purpose of monitoring, therefore the following steps are necessary:

Modelling: CAD models from the design phase can be used for setting up model-based operation support. Potential faults must be included in the model if diagnosis of faults is required.

Model order reduction techniques, which preserve important properties of the original model, need to be applied to run the final model in parallel to operation and achieve fast simulation.

Identification: the simulation results of the model has to be compared to the sensor data. Thereby, faults or degradation laws can be identified.

Prediction of degradation: the development of a fault can be predicted.

Model Predictive Control: based on the prediction a control of the performance versus early downtime may be developed (Stocco, 2020).

By means of attached or integrated sensors, data like temperature, pressure, flow rate, etc. are continuously collected. This simulation reflects all the circumstances, operating conditions and events of the real asset. For instance, the digital twin experiences the same wear and tear as the physical device, but virtually on a computer. It enables optimised system design, real-time prediction, predictive maintenance, improved industrial plant management, and overall plant and system performance improvement of plants and systems (Haidari, 2019).

Thanks to the IIoT, combined with the development of smart, connected assets and the widespread availability of sensors, it is now possible to develop accurate maintenance and operating ranges for each piece of equipment in a given plant under real operating conditions. These can be used for plant performance and inspection and operational monitoring, among other things. Digital twins are also used in this process to analyse failures due to fatigue, vibration, erosion and other operating conditions in equipment and systems (Haidari, 2019).

Furthermore, engineers can use this accurate model to use simulation to test different operating conditions before exposing the plant to them or make the next version of the object much more efficient (Haidari, 2019).

Applications in electric motor driven systems, examples

In an electric motor it is not possible to place sensors everywhere, e.g. in the rotor.

Therefore, some electrical values are usually estimated or described by constants, as for example the rotor's resistance, trying to follow the real motor behaviour without an appropriate feedback interaction.

Though, in reality, this value varies with the different temperature or load conditions. Therefore, the motor is not controlled properly and this can lead to a loss of efficiency when the motor runs at a condition different to the nominal terms, like working with a wrong electromagnetic flux.

With a digital twin it is possible to evaluate any physical value of the electric motor (temperature, flux, current, friction, vibration, etc.) by knowing the instantaneous currents and following the real electromechanical and thermal behaviours of an induction motor in real-time.

In this way, the control is continuously updated with the newest motor's values, allowing to get a reliable drive fitting exactly with the real engine conditions.

For instance, by applying virtual sensors where necessary, with only measuring the three-phase stator currents, a digital twin can simulate the stator voltages, the induced rotor currents,

the generated torque, and all the parameters necessary for the Field Oriented Control (FOC) (Stocco, 2020).

Another application of the digital twin technology is to develop a prediction of the future trends, or to improve the behaviour by analysing the data collected by sensors or by previous simulations (Stocco, 2020).

It is not easy to measure or even estimate the temperature of electric motors in real-time. But high temperatures can increase the probability of efficiency problems and failures. If the working condition (load torque and rotation speed) are constant and stable for a long time, a thermal model within a digital twin can calculate the future temperature and resistance values. As a result, the cooling system can be activated only when necessary (Stocco, 2020).

For electric motor systems a digital twin is often applied for fault detection. Independent from physical sensors only by measuring currents the calculated torque is compared to certain thresholds, used to show warning messages according to the type of detected anomaly (Stocco 2020).

Other applications of digital twins are for energy monitoring and making in time decisions: The digital twin provides a dashboard to the energy manager or engineer with which they can monitor every individual meter at every location from a remote place. The asset efficiency can be easily monitored by analysing the voltage, current, etc. readings. For any breakdown or tripping in the facility, automated alerts are sent to the operators as mails or message alerts at the exact time it happened. It makes it easier for the company to quickly manage the situation and get back the plant running. The previous energy consumption data can be analysed to check for fluctuations in the consumption or any unnecessary use of energy or to maintain the power factor (SmartSense 2018).

Positive and negative energy effects

The digital twin parameters estimation allows to obtain a more reliable drive response, which is able to adapt to the estimated motor's parameters value step by step. The control performance is improved and the FOC control condition is guaranteed. Therefore, the control follows better the different load torque and speed requirements for all motor parameters (Stocco, 2020).
Even if constant values are guaranteed, a more performing system behaviour can be obtained by applying the digital twin estimated values. The absorbed current with adoption of estimated values is lower than in the constant cases, with an improved drive response. Savings of the absorbed power can be achieved in this way reducing energy consumption, costs and achieving lower stress of the electrical components (Stocco, 2020).

This chapter described mainly the use of digital twins for motor control, but digital twins can be used for several applications in industry. Accenture (2021) estimates that the use of digital twins in the manufacturing industry can reduce the baseline of the primary energy consumption by 5-8% between 2020 and 2030, with a theoretic saving potential of 20% (to be multiplied with the implementation rate).

4.9 Cloud based services

Figure 11: Cloud Based Services, source: Adobe Stock

Definition

Cloud based services provide information technology (IT) as a service over the internet or a dedicated network with delivery on demand and payment based on usage over time (https://www.cleo.com/blog/knowledge-base-what-is-cloud-computing).

Description of technology

Cloud based services are scalable solutions using digital technologies like sensors and other devices for data acquisition, connectivity to bring the data to the cloud and back, and technologies like data storage, high-performance computation, artificial intelligence and visualization tools to develop solutions for the customer. The solutions deliver a translation of the computed data into physical actions with either automated or manual actions through interfaces to achieve meaningful output for the system with the help of additive manufacturing and autonomous robots (Hakansson, Höckerman, 2020). These scalable solutions are offered and managed by a third party.

When the amount of data to be sent to the cloud and back to the sensors/actuators is excessive, part of the computation can be moved closer to the industrial facility/the sensors by allying fog computing. This alleviates the resources consumed in the network and the cloud (Magadan, Suarez, 2020). Fog computing or a fog layer consists of Local Networks, gateways or e.g. 'smart' converters (VFDs) deploying (pre)data analysis, control response and virtualization and standardisation.

Cloud based services offer a broad range of different solutions e.g.:

- Software as a Service model, e.g. for customer relationship management, to remotely manage customer databases and update records.
- Scalability and connectivity as a service, e.g. enterprises can increase demand based on business need without adversely affecting performance. This is particularly helpful for enterprises whose usage may experience peaks and troughs (declines/dips).

- Data storage to the cloud, including security, enterprises can save significant costs on building infrastructure and maintenance by moving data storage to the cloud. A third-party cloud service provider is responsible for the data and ensures security including compliance and legal matters.
- Big data analytics, enterprises and data scientists may access any system or process data for analysis using cloud computing. Cloud solutions allow users to manage large amounts of data remotely with open-source big data tools.

Applications in electric motor driven systems, examples

Cloud based services are applied for different applications and include elements of the technologies described in the preceding sections 4.1 – 4.8.

Real-time monitoring is one of the bases of industrial digitalisation and many systems have been developed to monitor currents, pressures, temperatures and other variables in industrial plants. The digital solutions refer to process control (for operational purposes and optimisation cycles) and condition monitoring (for maintenance and operational purposes) (see section 4.6).

Cloud based services deliver the last of the three levels, i.e. providing the data integration platform for data analytics such as benchmarking, predictive maintenance, reporting and data storage.

Different business models are applied by the service providers; some supply the hard- and software as extra asset for their asset portfolio, e.g. electric motors, pumps, converters, etc. These manufacturers originate from the electrical and/or mechanical industries.

Other service providers originate from the digital world, e.g. start-ups with an origin in university and research, with a high profile in the development of artificial intelligence and information and data research.

Examples: a pilot project has been dedicated to monitor, diagnose and predict failures on less-critical, but widely utilized rotating equipment, such as motors and pumps, using low-cost sensor technologies (vibration), machine learning and a software solution for collecting data, analytics and visualization. The pilot delivered positive results.

4.10 Augmented reality

Figure 12: Augmented reality, source: Adobe Stock

Definitions

Augmented reality (AR) refers to “images produced by a computer and used together with a view of the real world” (Cambridge dictionary, 2021). The technology can be described as “a technology that superimposes a computer-generated image on a user's view of the real world, thus providing a composite view” (Google dictionary).

Description of technology

AR incorporates three features (Azuma, 1997):

- a combination of real and virtual worlds,
- real-time interaction, and
- accurate 3D registration of virtual and real objects

In the following section, some of the main hardware components and functionalities of AR are explained:

Processor

The processor controls the display and manages the virtual information. The AR software can build augmented reality experiences with functionalities like environment understanding, motion tracking or light estimation. Based on the scanned environment the computer generates images or a video and shows it on the display.

These functionalities rely on computationally intensive computer vision algorithms with high latency requirements. Therefore, they have to offload data processing to an external machine via different communication tools (Chen, R. 2021), (AnyMotion GmbHa).

Sensors

The creation of any AR elements requires capturing of the real-world objects to augment them realistically on the display. For this purpose, a variety of sensors can be used: mechanical sensors to determine the objects' position, weight and movements, biological sensors (e.g. temperature, heart rate), acoustic sensors (frequency, volume), optical sensors (emissivity, light wave frequency), environmental sensors (temperature, humidity) and infrared sensors (Litslink, 2019).

Tracking and markers

Tracking methods determine the position and scale of the AR marker relative to the user and sensor input, respectively. The most important factor is the position and orientation of the user's head.

The term augmented reality markers refers to everything that triggers the display of additional virtual information. Typical markers are visual or optical markers or objects, for which the system is trained. Examples are pictures and objects e.g. QR codes: By pointing your mobile camera at one of these markers, the system recognises it (incl. position, scale and orientation) and superimposes the digital image on the screen. They need a camera to recognize the marker and distinguish it from other objects (AnyMotion GmbHb (b), (Chen, R. 2021), (VRketing GmbH 2021).

By using GPS data as markers (referred to location-based AR) GPS, digital compass, velocity meter, or accelerometer provide data about the location and the augmented reality visualizations are activated based on these inputs. Technologies like digital cameras, optical sensors are also used for motion tracking (Kuprenko, 2021).

Next to the technologies and sensors mentioned above, input techniques include speech and gesture recognition systems.

Display and information

In the industrial environment, tools like eyeglasses, cameras, but also mobile phones or tablets and other technologies such as Head-up-displays (HUP) or eye lenses are used. For several applications in industry, it is useful to have both hands free and not to have to touch the screen of such devices during the working procedure. Therefore, eyeglasses are used. For other applications, tablets are sufficient.

Examples of virtual information that can be displayed via AR include texts in 2D in front of the user or pictures and videos also projected on real surfaces as 3D models (AnyMotion GmbHa).

Industrial applications

Augmented reality can be used for the following industrial applications:

Assistance

- Video-based work, maintenance and safety instructions are provided for the production worker on a device to guide him or her step-by-step through the process (Bouveret, Human, 2019).
- Ability to visualize complex work steps and instructions, information about necessary tools and spare parts to assist the technician and enhance the speed of assembly (VRketing GmbH, 2021).
- Assisting workers in finding and identifying components, various locations and wires (using their voice) (Startus-Insights, 2021).

- Displaying infrastructure such as pipes, lines, cables and other assets in-field and in real time (Myriadglobalmedia, 2017).
- Displaying construction plans, circuit diagrams or maintenance instructions to the worker in a visualized form (VRketing GmbH, 2021).
- Scanning and identifying faulty components & machinery and providing guidance in repairing them (Startus-Insights, 2021).
- Remote on-site guidance of junior workers from colleagues or general in case of problems (Startus-Insights, 2021).

Plant design and commissioning (Bouveret, Human, 2019)

- With the visualization of complex products and plants, sites can be checked for their suitability in advance. Entire plants can thus be tested before a production chain is finally put into operation.
- With the help of an iPad application systems can be visually positioned true to scale in the customer's machine park. Space requirements, connections or possible collisions can be analysed in advance.
- Video conferencing with real and virtual participants can simplify group work with different location-independent teams.
- Several people can also work directly on a 3D model.

Supervision and maintenance (Myriadglobalmedia, 2017)

- Live access to the right manuals and service documents, overlaying planned preventative maintenance.
- Overlaying 3D models and real-time maintenance directions on a piece of equipment onsite.
- Virtually monitoring and supporting several locations at once.

Real-time analytics & display of results (Startus-Insights, 2021)

- Collecting and analysing vibration data to detect and identify problems with a machine's operation.
- Monitoring and overlaying the real-time temperature of various machines during the maintenance process.

Training and learning (Bouveret, Human, 2019)

- AR also facilitates the training of employees when, for example, new machines are integrated into production or for other things like laying cable harnesses.

Applications in electric motor driven systems, examples

Most of the applications mentioned above are relevant for Electric Motor Driven Systems. Two specific examples are given here:

For configuration of an air distribution system and a connected, efficient compressor room, AR systems can be used to measure compressor room or production floor area and calculate the amount of piping needed. Based on this information, the system can be designed more efficiently, reducing pressure drops and losses. Using the latest CAD systems, the system design can be completed in perhaps 20% of the time it took ten years ago (Ottewell, 2020).

A major pump system provider is offering service support for pumps via augmented reality. The service is based on data glasses linked with the internet or with a smartphone app.

An expert of the company can assess the situation through the data glasses of the person on site and can guide users and technicians during their service work through video and audio.

They can instruct technicians to carry out common maintenance measures, step by step. Further, the glasses can transmit exploded views or screenshots. The required spare parts can be identified without a visit of an expert, the procurement process can be started much earlier or it may be revealed that the specific action can wait until the next revision.

The data glasses can serve to check in advance whether the installations are actually ready for commissioning (KSB, 2018).

Positive and negative energy effects

No source on energy effects was found (by time of research, 12.5.2021).

The advantages of AR are that with AR-equipped mobile device or glasses an expert can advise the field technician lacking the knowledge, experience or access to data required to decide on what steps to take (Bouveret, Human 2019).

For example, AR in connection with the relevant data, could be used during energy audits to identify the equipment/application with the highest/lowest energy consumption and collect their relevant technical information: nominal power, current drawn, annual energy consumption, temperature of in- and outflow for heat and cold applications. Infrared information could be used for showing potential points of loss.

In virtual site visits a “Kiber Helmet” was used already. The external auditor was able to virtually walk through the plant, make the visual inspection of the different areas and equipment, was able to understand the different functions of machines, could check the presence of control system and understand how energy is typically managed, similarly as if he had been there in person (Bonvicini, 2020).

Furthermore, AR applications can increase efficiency in almost all areas of operational work through visualization of work steps during repair, or e.g. in the warehouse or assembly. Several cases and studies prove an average increase in productivity of 32 percent (Bouveret, Human, 2019).

According to another source, it is expected that the utility segment can achieve a 15 -20% increase in efficiency with use of augmented reality (Global Data Energy, 2019).

Further advantages:

- Safety: improves operational safety, allowing for better visualisation of underground assets and complex components, reducing accidents (Global Data Energy, 2019).

5. Other relevant technologies

5.1 Additive manufacturing

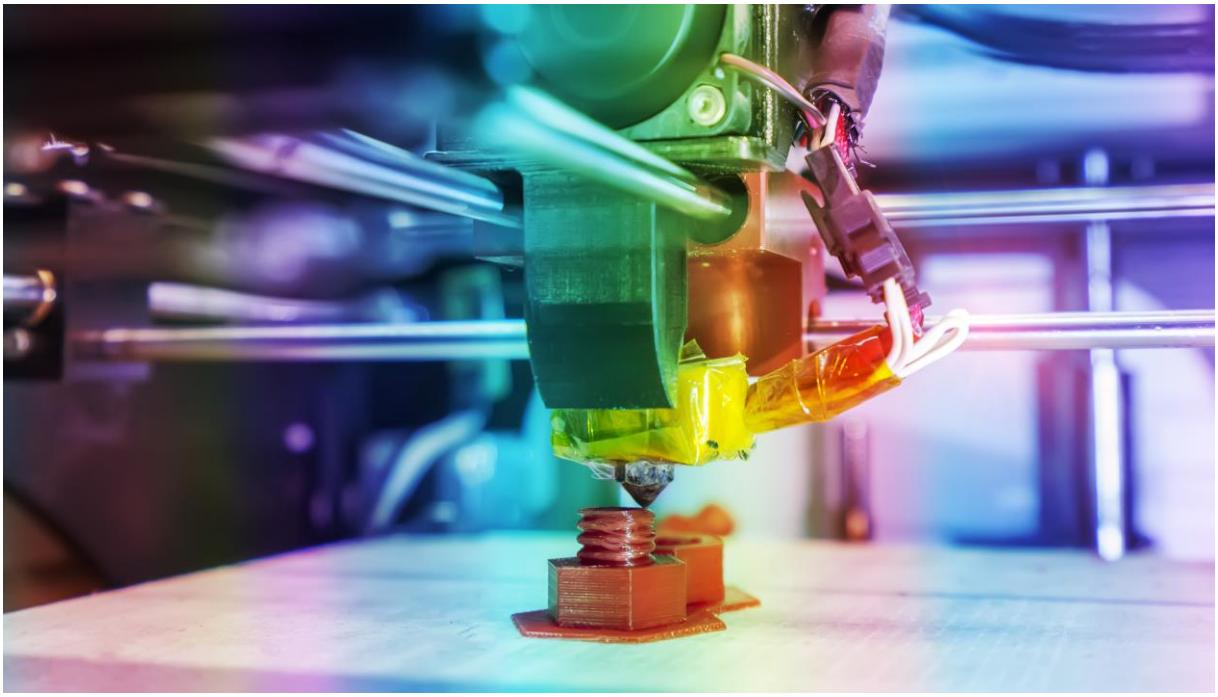

Figure 13: Additive manufacturing, source: Adobe Stock

Definition

Additive manufacturing (AM) is a digital technology for producing physical objects layer by layer from a 3D computer aided design (CAD) file producing a final three-dimensional product (Engineering Product Design).

Description of technology

Additive manufacturing is commonly known as 3D-printing and is the process of manufacturing parts or products layer-by-layer, directly from digital product data. 3D-printing facilitates the construction of complex geometries, e.g., honeycombs and lattices that are impossible to create by using conventional manufacturing methods. After a re-design, existing products can be built by AM-technologies in a way that reduces the use of raw materials, while possibly enhancing product properties in terms of weight and functionality. Expensive and exotic materials may be printed with minimal waste. Additive manufacturing does not suffer from the cost penalties - namely machining, moulding, casting, and/or specially made tooling - incurred by conventional manufacturing methods. Key benefits of AM over traditional manufacturing are therefore: Cost, speed, quality, innovation/transformation, and impact. AM will not replace existing conventional production methods. However, it is expected to revolutionize many niche areas (Magisetty et al, 2019 and Khajavi et al, 2014).

Additive manufacturing has recently transformed from a rapid prototyping technology to a manufacturing technology (Silbernagel, 2019). However, most of this transformation has been only for structural materials and not for functional materials. AM for functional materials production, e.g., AM to produce soft and hard magnets for electric motors/ transformers or other complex components is still in its infancy.

Additive manufacturing is a hypernym covering several technologies with specific characteristics in terms of material selection, printing accuracy, speed, price of equipment, and finishing quality among others.

The process begins with generating a three-dimensional CAD model of the object with all its details and dimensions. Next, the three-dimensional CAD file is sliced into very thin two-dimensional (2D) cross sections (layers) by a computer program. Then, the 2D layers are sent to the three-dimensional printing machine one layer at a time. The machine produces the object by building each layer on top of the previous one, utilizing different solidification methods of raw material in its production chamber. The entire production process can take from a few hours to several days, depending on its size and required production precision (Magisetty et al, 2019 and Khajavi et al, 2014).

Multinational companies, e.g., General Electric (GE), Siemens, HP, Wipro, etc. are developing AM systems and producing complex parts using AM processes (Attaran, 2017). Laser based additive manufacturing is one promising method for processing components of complex geometry and compositionally graded alloys and components. There are several review papers on the AM of structural materials, however, to date, there is no comprehensive review of AM of magnetic materials. AM using a feedstock consisting of either blended elemental powders, pre-alloyed powders or metallic powders blended in a suitable polymer, is a viable manufacturing process to develop magnetic parts (Chaudhary et al, 2020 and Lamichhane et al, 2020).

The future of AM technology will include integrated systems coupling (i) thermal sensors which can provide in situ diagnostics during printing; (ii) temperature controlled building platforms, which can control the thermal gradient during printing; (iii) robotic arms for removing the support materials and surface finishing; (iv) high temperature furnaces, which can be used for post printing heat automated treatments, and most importantly (v) an improved interface between hardware and software to control every step of the 3D printing process. Such an integrated system can substantially accelerate AM usage for magnetic material processing (Attaran, 2017).

AM has a design freedom that is not as constrained as traditional manufacturing. This design freedom enables several principles that can be taken advantage of because of AM. These principles include reducing assembly part counts by consolidating multiple parts into one, improving performance by creating complex internal geometry, reducing weight by removing excess material, and automating some of these processes by means of topology optimisation.

AM also opens a wider range of freedom not currently experienced in electric motor design. Many improvements can potentially be achieved by AM, such as higher conductor utilisation and higher fill factors, better thermal management via controlled cooling and ventilation, and unique flux path geometry to reduce losses. Once a motor designer feels confident in the material properties of AM parts, they then need to embrace a design for additive manufacturing mentality to move away from the traditional manufacturing mentality and help the electric motor industry incorporate AM (Lamichhane et al, 2020).

5.2 Robotics and advanced robotics

Robots are machines that are programmed by computers and are capable of automatically carrying out a series of more or less complex actions (Oxford English Dictionary).

Robots can be differentiated into industrial robots and service robots.

According to World Robotics, in 2019 (due to global economic downturn and trade tensions) global robot installations dropped by 12% to 373,240 units. “The global economic crisis attached to the COVID-19 pandemic will shape industrial robot sales in 2020. A major contraction must be expected in the short run. In the medium term, this crisis will be a digitalisation booster that will create growth opportunities for the robotics industry worldwide. The long-run perspectives remain excellent” (IFR, 2020).

The operational stock of robots was 2,722,077 units. Annual installations grew from 2010 with 120.000 to 400,000 units in 2018 (IFR, 2020).

The main sectors are the automotive industry with 28% of all installations and the electrical and electronics industry (24%), metal and machinery (12%). The share of newly installed robots in Asia was about two thirds of global supply with China, Japan, Republic of Korea under the top 4 nations (IFR, 2020).

Figure 14: Robotics and advanced robotics, source: Adobe Stock

Definition

“An industrial robot is an automatically controlled, reprogrammable multipurpose manipulator in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications” (ISO 8373:2012, cited after IFR, 2019).

Reprogrammable means designed so that the programmed motions or auxiliary functions can be changed without physical alteration; multipurpose means capable of being adapted to a different application with physical alteration (alteration of mechanical systems), axis is the direction used to specify the robot motion in linear or rotary mode (ISO 8373:2012, cited after IFR, 2019).

Description of technology

Robots are used within manufacturing processes (welding, painting, and cutting), material-handling (machine-loading, material transfer), assembly and inspection, such as depositing, sorting, and packing processes.

An industrial robot consists of manipulator which moves and performs different tasks, a controller which actuates and controls the manipulator, and a programming pendant which teaches the manipulator movement (Yaskawa, 2020).

Robots are classified by mechanical structure.

Cartesian robots

Linear robots consist of a serial arrangement of at least three linear axes, usually linked at right angles. The basic unit of the portal systems are driven linear axes with movable carriages, to

which additional axes, grippers or tools are attached. The carriage is typically driven by electric motors with power transmission through toothed belts, toothed racks or spindles; linear motor direct drives or pneumatic drives without piston rods are also used (translated from Xpertgate, 2018a).

While they are unable to perform complicated movements, their precision level is high, and they are easy to control (Yaskawa, 2020).

Articulated robots

"Multiple joints of Horizontal Articulated Robots and Vertical Articulated Robots are connected through links, each of which makes rotary movements around the joints. The greater the number of joints, the greater the level of freedom, which enables these robots to make complicated movements including roundabout moves. Many robots today are multi-jointed. The makeup of Vertical Articulated Robots is similar to that of human arms, which makes it possible to say that they are probably the most rational form of robots to use for work to be done "in the place of humans." (Yaskawa, 2020).

"As Multi-Joint robots comprise structures where the joints that are operated by motor and the links are connected in a series circuit, they are sometimes called Serial Link Robots" (Yaskawa, 2020). Since the drives are integrated in the wrist axes and arm joints, the mass of all drives must also be moved with the axes and, in many cases, requires a weight compensation for the drive. "This, also, leads to a limitation of the load at the end of the arm due to the need to carry drives or power transmission systems and to a lower accuracy due to the accumulation of tolerances." (translated from Xpertgate, 2018b).

Parallel/delta robots

Robots with a structure consisting of multiple axes (motors) at their tip that move in parallel are called Parallel-Link Robots. For high forces, which are typically required in hexapod robots, the movement of the arms in the longitudinal direction is generated by the use of spindle drives in the axes.

With delta robots for quick handling, the drive motors for the upper arm are firmly mounted in the base frame and are articulated to the non-powered forearms, which reduces the moving mass of the arms to a minimum (translated from Xpertgate, 2018b).

Cylindrical robots

"A cylindrical robot has at least one rotary joint at the base and at least one prismatic joint to connect the links. Along the joint axis, the rotary joint uses a rotational motion; along the prismatic joint, it moves in a linear motion" (Gonzales, 2016).

Their field of operation is broad; they are not very suitable for complicated tasks that require them to make roundabout movements (Yaskawa, 2020).

Service robots

Service robots are machines that have a degree of autonomy and can operate in complex and dynamic environments that require interaction and coordination with individuals, objects and other devices (for example, when used for transportation, surveillance, cleaning) (Eurostat, 2017). Cobots are robots intended to physically interact with humans (UNIDO 2019).

Advanced robotics

Advanced robotics are defined as:

"Devices that act largely, or partly, autonomously, that interact physically with people or their environment and that are capable of modifying their behaviour based upon sensor data" (itiTechmedia, 2008).

Conventional industrial robots work within a highly structured industrial environment and are capable of only small modifications to their programmes (e.g. sensing potential collisions and halting or performing a programme motion with a small offset). In contrast, advanced robots have their own perception through cameras and sensors, the ability to process this data and derive their own conclusions from it (itiTechmedia, 2008; Küpper, 2019).

Advanced robots have superior perception, integrability, adaptability, and mobility. These improvements permit faster setup, commissioning, and reconfiguration, as well as more efficient and stable operations (Küpper, 2019).

"Recently, robots have expanded in appeal and presence in not only industrial but also other fields by advancing speed, accuracy improvement, response to complex movements, and strengthening of safety functions toward coexistence with humans" (Yaskawa, 2020).

Applications in electric motor driven systems, examples

Motors used for robots are brushless DC motors, AC motors, and step-motors.

Very often servomotors are used. This term does not specify a motor-technology but these motors consist of motor, encoder and brakes. The motor is applied in a closed-loop control system using position feedback to control position, velocity (speed) and acceleration.

Servomotors use optical or magnetic rotary encoders to measure the speed/motion of the output shaft and a variable speed drive to control the motor speed.

Robot requirements for servomotors are (Bartenschlager et al. 1998, Faulhaber Group, n.d.):

- High continuous torque in relation to motor volume and weight
- High efficiency
- Small size, low weight
- Robustness, shock-resistance (inspection robots)
- High angular acceleration and high braking
- Large speed setting range
- High positioning accuracy, precision
- High degree of protection, no maintenance and reliability

Selection criteria for servomotors are (Bartenschlager et al. 1998, Faulhaber Group, n.d.):

- High short-term overload capacity
- Low mass moment of inertia (rotor moment of inertia) and
- Small time constants

Trends towards more efficient motors include improved technology, more compact design and thus lower mass and lower power consumption (Kulterer, 2019a).

Possibilities to increase efficiency or robots are for example:

- Reduction in weight and size (e.g. for lifting arms) by advanced lightweight materials (Barnett, 2018)
- Reduction in stand-by consumption (Senft, 2012)
- Energy recovery during braking and lowering movements (Senft, 2012)
- Currentless holding mechanisms (FANUC, 2021)
- Optimised dimensioning of robots, e.g. an 80 kg instead of an oversized 250 kg payload robot saves 25% energy, with 20% reduction of cycle time (Yaskawa in: Sonnenberg, 2017).

- Simulation models can calculate optimised trajectories (and acceleration profiles). Eliminating jerky motions and accelerations can achieve 40% reduction in energy usage, unnecessary stress and peak loads are also avoided (Barnett et al., 2017).
- Avoiding unnecessary movements (e.g. due to incorrect installation height, evasive manoeuvres) (Stolber, 2014)
- With a visualization software it is possible to display the current energy consumption per cycle and compare it to the expected (Kuka Systems GmbH in: Sonnenberg, 2017).
- Optimised production planning and machine utilisation allows, for example, to reduce the waiting times of individual machines and thus standby consumption. Optimised clamping and tool changing devices etc. also make it possible to reduce such times.
- Changing from AC to DC grid (600 V) to directly use solar, keep kinematic energy within system (KUKA, 2017).

Positive and negative energy effects

For a robot with 210 kg load capacity, a reach of 2.7 m, full load power of 3.5 kW and detailed load profile (approx. 19 % of time 3 kW, 10 % in waiting position 0.7 kW; remaining time, incl. weekend-stops and waiting, braking: 0.2 kW) Brunner calculates a 7.000 kWh energy consumption per year. This would correspond to an average load of 0.8 kW or 2,000h full load hours (Brunner, 2015).

In another case, Barnett et al. calculate 21 915 kWh annual electricity consumption based on 20 full-load daily working hours, 365 working days per year for a 3 kW robot, which seems to be on the high end (Barnett et al., 2017).

The global final electricity consumption in the industrial sector was 9 362 TWh for 2018 (IEA 2020). Using the data of Brunner and Barnett and multiplying it with the 2.7 million units would mean a total energy consumption for industrial robots of around 20-60 TWh or 0.2 to 0.6% (IFR, 2020; Barnett et al. 2017; Brunner, 2015).

Though, in specific sectors and applications, e.g. in automotive assembly and welding lines, robots consume half of the total energy consumption (Weber, 2014).

Other effects that need to be accounted when considering robot energy consumption:

- Annual growth rates in energy consumption for robots of 15% are possible (corresponding to the numbers of installation compared to installed base, see above) (IFr, 2020).
- As robots take over human-powered tasks and human-machine collaboration increases, the energy consumption increases as well.
- On the other hand, robots may replace other machinery and consume less energy than the out-dated equipment, due to highly efficient control systems, motors or replacement of multiple machines. Industrial robots may operate in unlit, unconditioned environments, which allows facilities to eliminate heating and lighting (Barnett et al., 2017).

5.3 Drones

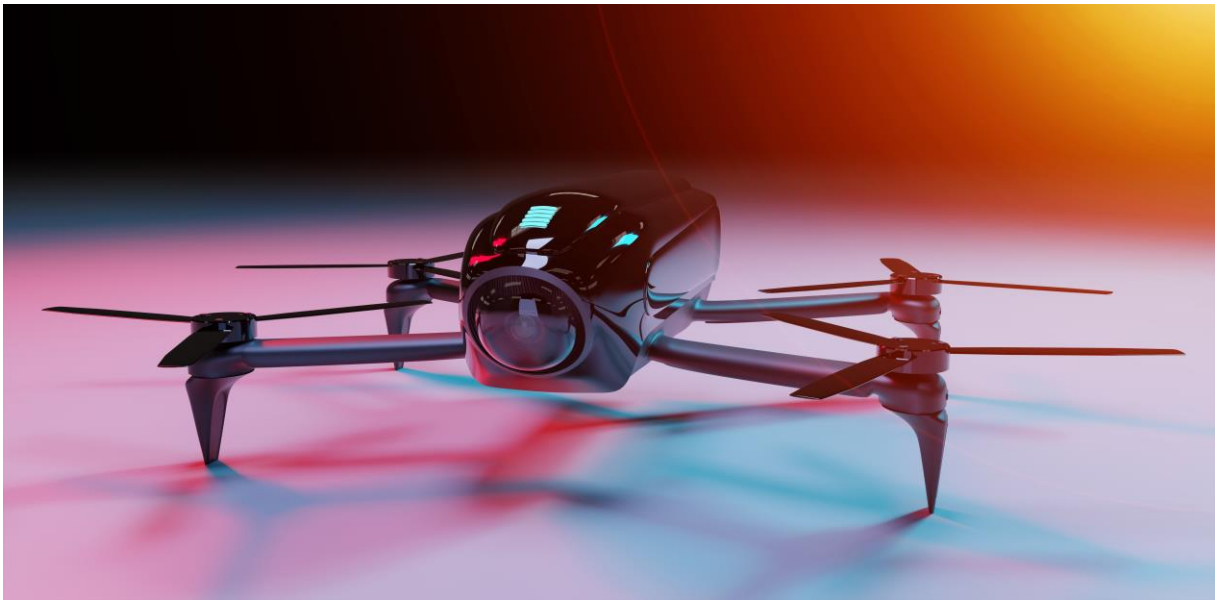

Figure 15: Drones, source: Adobe Stock

Definition

A drone is an unmanned aircraft. Drones are more formally known as unmanned aerial vehicles (UAVs) (Earls, 2019).

Description of technology

A drone can be controlled remotely or fly autonomously through software-controlled flight plans working in conjunction with on-board sensors and GPS (Earls, 2019).

Drones consist of a battery (or fuel), motors, propellers and a frame made of lightweight, composite materials. An operator uses a remote controller that communicates with the drone using radio waves to launch, navigate and land the drone remotely. (Earls, 2019)

The flight controller takes in inputs from the remote controller, the GPS module, compass, and for some drones from obstacle avoidance sensors and processes it into information to the Electronic Speed Controllers (ESC). This is an electronic circuit that controls a motor's speed and direction. The GPS module is used to determine the position of the vehicle and enables the drone to fulfil functions such as position hold or autonomous flight. Further components include antennas, accelerometer and altimeter to measure speed and altitude (Dronefly, 2022).

Special features of drones include weight, camera type, maximum flight time and speed, hover accuracy, altitude hold and others.

Depending on the application drones can be equipped with thermal cameras or infrared cameras, DSLR (digital single-lens reflex) and cinema cameras and a number of other sensors, including distance sensors (ultrasonic, laser, lidar), time-of-flight sensors, chemical sensors, and stabilisation and orientation sensors. Visual sensors include RGB sensors collecting visual red, green and blue wavelengths, multispectral sensors collecting visible and non-visible wavelengths, such as infrared and ultraviolet. Further sensors are accelerometers, gyroscopes, magnetometers, barometers (Earls, 2019), (Altigator, 2021).

According to the Swiss company flyability (flyability, 2021) the primary types of data currently collected by drones in industrial context are:

- Visual data: by flying over objects, things can be detected otherwise not visible.
- Thermal data: can help inspectors to identify problem areas.

- LiDAR data: A LiDAR (Light detection and ranging) targets an object with a laser and measures the time for the reflected light to return to the receiver. It can create 3D maps of an area used for project planning and tracking.
- Other data includes multi- and hyperspectral data used for example for crop monitoring.

Applications in electric motor driven systems, examples

Drones are applied for several functions and sectors:

In the energy, real estate, rental and leasing and in industrial plants drones are mostly used to carry out inspections that could be life-threatening to a human or would be very expensive, for instance, climbing a tower or walking inside a tank to collect visual data. For construction, drones are mostly used for mapping and surveying. Examples include aerial planning, inventory management, topographic mapping, 3D reconstruction of sites or ongoing construction projects (McNabb, 2021).

Other applications include measuring and recording the height of crops, express shipping and delivery, aerial photography for journalism and film or building safety inspections and many other (Earls, 2019), (Insider Intelligence, 2021).

Examples of using drones to save energy include the following:

Drones could be used for leakage detection in compressed air or pumping systems. Roof inspection by drones can help to reduce the amount of energy used for heating the building. For irrigation systems, crop monitoring can provide detailed information on the amount of water to be pumped to the fields. Infrared sensors can help to detect malfunctions in motors or fans not easily detected, otherwise.

Wien Energie (a Vienna based energy utility in Austria) uses drones already to inspect wind farms, photovoltaic plants, district heating pipelines and industrial chimneys. Drones take pictures of the plant using RGB and thermal imaging cameras. Wien Energie's trained personnel analyse the images live. In addition, artificial intelligence subsequently examines the data to identify possible damage.

In the city, drones are used in particular for the maintenance of district heating lines. In the event of a leak, the images taken by the thermal imaging cameras show an increased temperature of the ground without having to carry out excavations.

The use of drones minimizes plant downtime and avoids excavation work. Evaluation using artificial intelligence guarantees objective data assessment. The archived data helps improve plant documentation, allowing plants to be monitored over a longer period of time and changes to be detected automatically. In addition, the drones save time during data collection (Wien Energie, 2021).

Positive and negative energy effects

When used for inspection services, drones can have a positive energy effect by detecting leakages or fault equipment otherwise not recognized.

Drones are equipped with batteries and need energy for re-charging. But they are not in continuous use and therefore the energy consumption is not a severe problem for the cases mentioned here. This could be different, for purposes like delivering packages.

6. Energy effects

Within the project, work has been dedicated to estimate the energy effect of digitalisation technologies. Project members assigned the type of effect on energy savings to the individual technologies and investigated information on the quantification of this effect.

The following potential effects were selected and were to be rated as high, medium or low (Rogers, E., 2014):

- Efficient components instead of standard products
- Device operating only as needed to meet demand (instead of switching on/off)
- Process operating as needed to meet production targets (instead of switching on/off)
- Past performance instructing current performance rather than best guess settings
- Smart Design (instead of conventional design process)
- Connected systems and business units instead of isolated systems
- Energy consumption of specific equipment in digitalisation technology, e.g. sensor, control, other data collection system
- Energy consumption of data processing (incl. external servers) (data process intensity)

However, the produced overview proves not to be presentable and sound enough in this stage, for the following reasons:

First, there is no data, no database available to assign saving effects to a single digitalisation and motion technology.

Secondly, one result of this study is that there is no data available to assign saving effects to a single digitalisation technology. The reasons are:

- Several technologies interact with each other and cannot easily be assessed independently.
- Digital technologies are seldom used for the purpose of saving energy.
- Once data has been collected through these technologies, there needs to be an action taken to increase energy efficiency. It often happens that data is collected without being followed by an energy saving activity, leading to no saving being made.

For example, Artificial intelligence assisted data analysis of real-time data collected by sensors and transmitted through IoT can indicate increased energy consumption. This already includes five of the technologies mentioned above. Beyond that, however, the savings effect only materializes when this information is acted upon appropriately and the causes for the increased energy consumption are eliminated.

On the energy consumption side, too, there is limited data available on the energy consumption of digital communication and data analysis. In addition, data collection, storage and analysis are often carried out together with other process- and quality-related data collection, making it difficult to assign them to energy analysis.

Two other sources report specific estimates of savings effects for digital technologies in motor systems and for industrial sensors in the EU:

a) The EMSA survey listed a weighted average saving estimate of 18% by applying digital technologies in motor systems, an estimate based on interviewing 82 experts and users (K. Kulterer, et. al, 2021).

b) A preparatory study on potential Ecodesign measures for industrial sensors in the European Union, published in 2021, shows a considerable saving potential: ‘even at a conservative estimate of 5-10% savings from sensors, this comes down to a potential of 65-130 TWh/year electricity saving in 2030 in the EU. This savings number relate to the energy use of the industrial stock of electric motors without small and special types of motors; in total 1’294 TWh/year in 2030 (VHK and Viegand, 2021).

The reason for including industrial sensors in the EC preparatory study for Ecodesign measures lies mainly in their energy and resources saving potential in the connected products, i.e. mainly electric motors (>0.75 kW) and electric motor applications like pumps, fans, air compressors and machines. The Ecodesign measure could be applied to new and existing

equipment. This means the impact of the measure would not be slowed down by the stock replacement dynamics (VHK and Viegand, 2021).

The EU market for industrial sensors for electric motors is estimated at around 100 million units (>0.75 kW, no special motors). Around 25% of the installed stock of pumps, fans, compressors could benefit of an (additional) sensor, i.e. 70 million units. Together with an extra 30 million bearing sensors (for machines) the total EU market potential for industrial sensors is estimated at 200 million sensors (VHK and Viegand, 2021).

The current stock of installed sensors in the EU is around 50 million. The potential market size for new industrial sensors amounts to 150 million units. When applied in the market these 150 million sensors can bring 50-100 TWh electricity savings per year by 2030, together with additional benefits such as lower maintenance and production costs (VHK and Viegand, 2021).

In general, considering all sources of this study, digitalisation can contribute to the following savings opportunities:

- Switching on/off according to actual demand
- Switching to different operating states according to demand
- Time scheduling (timer)
- Control of output according to actual demand (%) (optimised speed, flow...)
- Remote control
- Improvement of electrical supply (power quality)
- Real time data on actual output
- Display of current energy efficiency
- Analysis of past performance to improve current performance (e.g. settings)
- Regular data transmission on energy consumption, running time, delivered power to central energy management system
- Linking with other data/production planning
- Adaptation to other processes, data transfer from and to other supplied processes
- Possibility to integrate external knowledge (e.g. via AR)
- Remote access to assets (difficult to access, remote, dangerous)
- Possibility of automated re-actions

Design, rebuild, retrofit:

- Better design/simulation of system, experimentation with other solutions
- Correct dimensioning
- Intelligent design of the component itself

7. Outlook

As explained in the introduction, this report is meant as categorisation of digital technologies and describes potential effects on energy use in motor driven systems.

In the next phase from 2022 to 2024 within the EMSA Task dedicated to this subject, the following activities are planned:

A report will be created that makes it easier for users to grasp the various possibilities for using digitalisation to increase efficiency in electric motor systems. Use cases of Industry 4.0 technologies in energy efficient motor systems will be described and technical possibilities of digitalisation for increasing energy efficiency will be shown. The aspect of energy consumption due to the digitalisation of motor systems will also be analysed.

Furthermore, a detailed survey of barriers to the use of digitalisation among users and providers will be conducted through interviews. Existing programmes in the areas relevant to the barriers (standardisation, training, etc.) will be analysed. Nationally, "best practice" programmes in this area will be described, complemented with international programmes and policy recommendations will be identified.

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