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Smart Circular Economy: CIRCit Workbook 4

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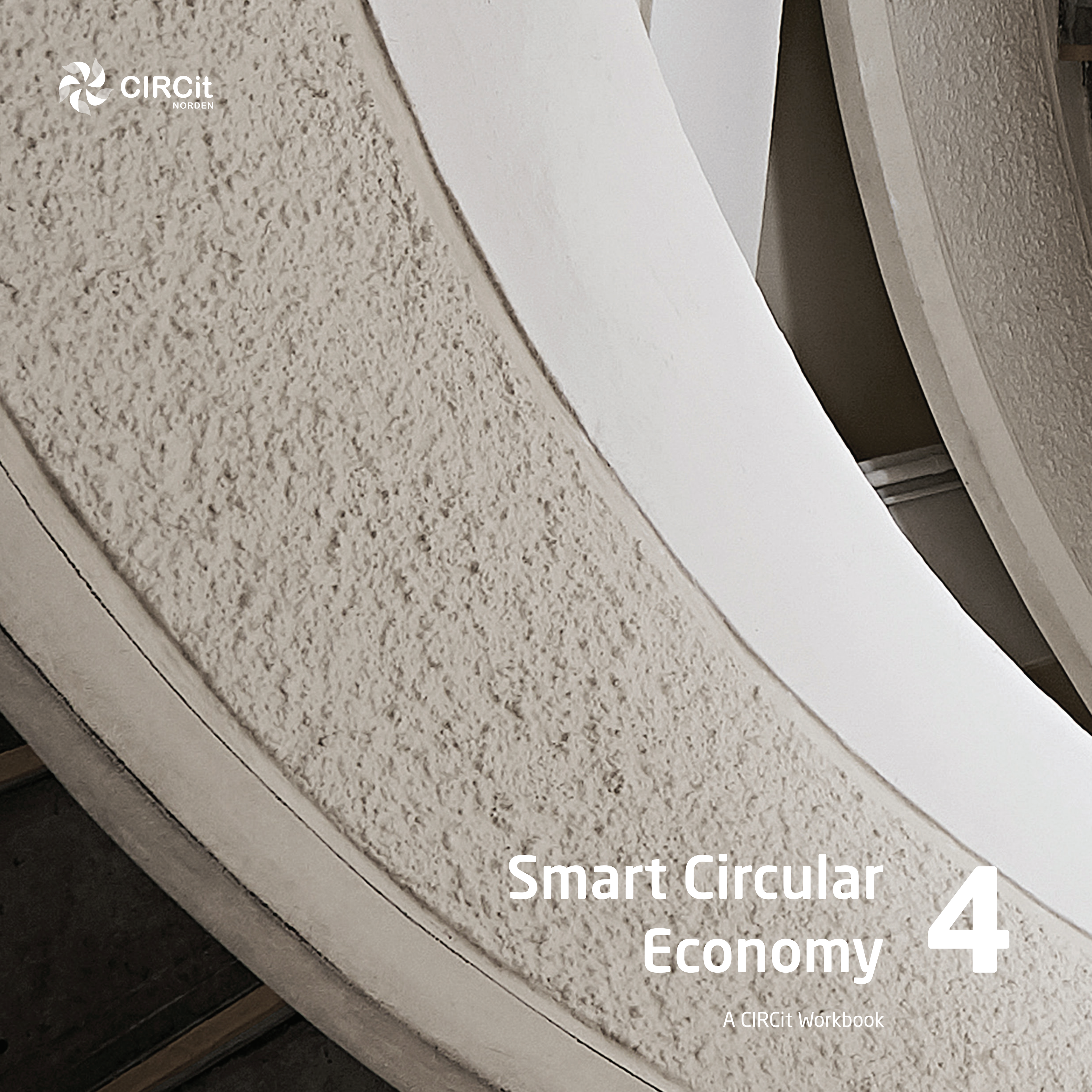

CIRCit NORDEN

Smart Circular Economy 4

A CIRCit Workbook

1 **Circular Economy Sustainability Screening** A support for decision-making through the sustainability screening of alternative circular solutions in terms of environmental, social and business potential. e-ISBN: 978-87-7475-601-9

2 **Circular Economy Business Modelling** A guide to the creation of circular business models based on a step-by-step approach, best practice and success cases.
e-ISBN: 978-87-7475-603-3

3 **Circular Product Design and Development** An approach to assess product circularity and a set of circular design guidelines for early product development.
e-ISBN: 978-87-7475-605-7

4 **Smart Circular Economy** A look at how digitalisation and smart products can play a role in facilitating the transition to a Circular Economy.
e-ISBN: 978-87-7475-607-1

5 **Closing the Loop for a Circular Economy** An assessment tool and guidelines to support the identification of the best circular strategy for products at end-of-use.
e-ISBN: 978-87-7475-609-5

6 **Collaborating and Networking for a Circular Economy** An approach to support circular value chain configurations, seeking innovation through collaboration.
e-ISBN: 978-87-7475-611-8

What are we exploring in this workbook?

For many product types, the optimal circular strategy is to extend the active life of the product. Do you have a way of evaluating whether this is the case for your company and products? Tracking, tracing and monitoring of materials and products is important for performing repair or preventative maintenance and for recovering and recycling materials. But what technologies to use and how to turn the generated data into a competitive advantage? This workbook helps you to evaluate the above questions, and helps you to investigate how digitalisation and smart products can play a role in facilitating a Circular Economy.

Smart Circular Economy
A workbook in the CIRCit Series

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E-book version and more information at www.circitnord.com

In this workbook

Introduction to Circular Economy

What is Circular Economy?
Circular Economy is a concept, based on the principle of decoupling value creation from resource consumption. The basic idea of Circular Economy is to move away from the so-called linear mindset, where value creation is based on the 'take-make-use-dispose' dogma.

Circular Economy has the potential to achieve maximum value by increasing resource productivity, enhancing energy efficiency, lowering resource consumption and decreasing waste. To do this, we should continue to extract value from resources for as long as possible, by extending their productive lifetimes. This means, for example, increasingly enjoying product and service offerings that are not necessarily based on one-time ownership, and not necessarily based on single-lifetime products.

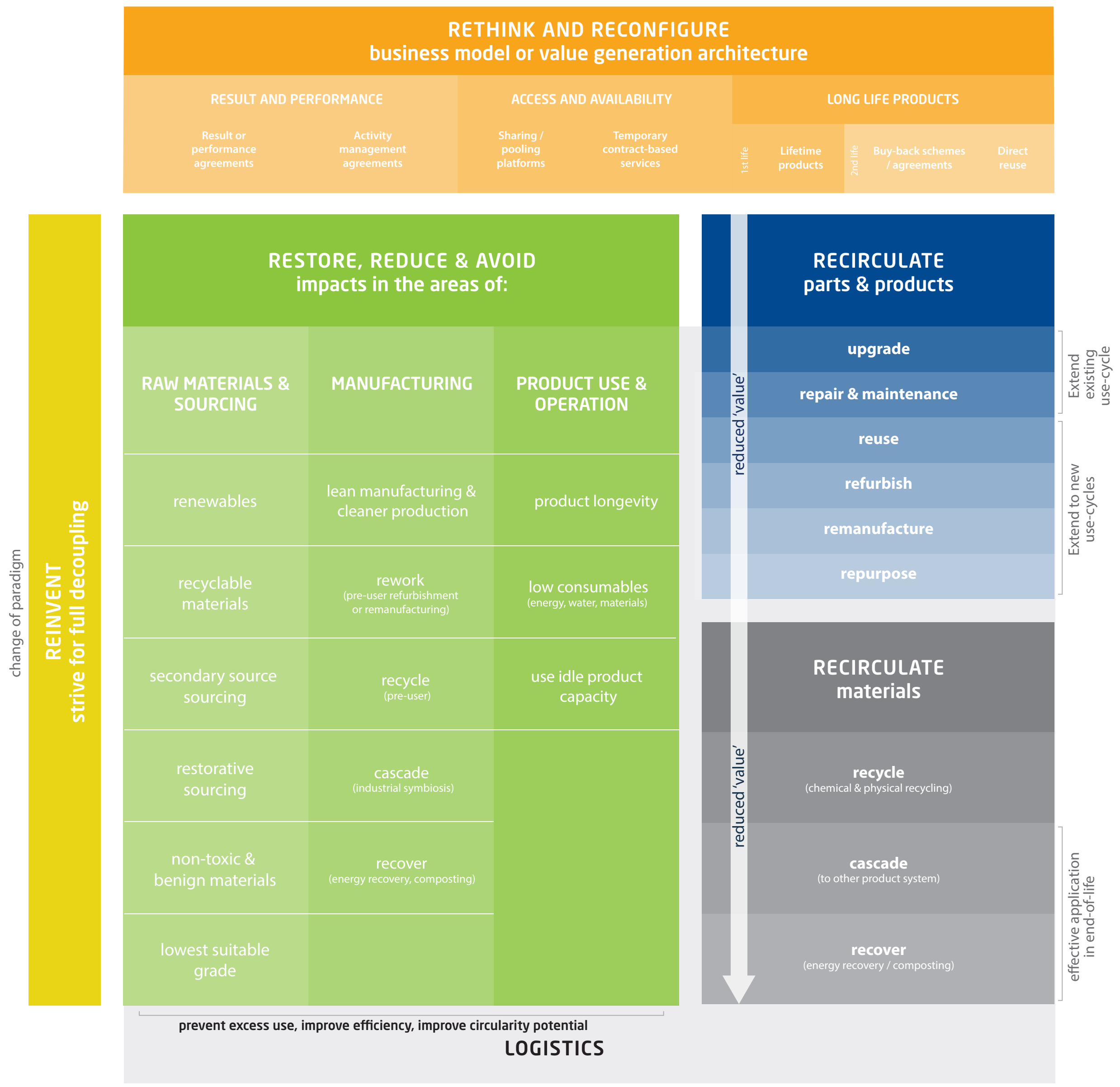
On first thought, many might equate Circular Economy to recycling of old and used products and materials. And indeed, *material recirculation* is a possibility, whether it be via recycling, cascading or recovering. Alternatively, and more valuable again, one could consider *product recirculation*, by applying tactics such as upgrade, repair & maintenance, reuse or remanufacturing. Even greater potential could also be achieved, by rethinking whole new ways of generating value, via integrated product/service business approaches, shared-access products, or new service offerings for long life products.

Achieving a Circular Economy requires a fundamental shift in mindset through business model, product design, support of the active product life cycle and closing the product loop, when the user no longer has a need for it. At the core of a Circular Economy lies collaboration, within and across value chains and with different societal stakeholders than we've maybe been used to.

And there's no use being circular, if the outcome is less sustainable than the starting point. Therefore we need to be able to estimate the sustainability benefits and drawbacks of our actions.

For many companies, there will be obvious low-hanging fruits, such as reduction of single-use packaging in the production facility, or making small design changes to the product, to ease its disassembly at end-of-life. But for most, there will be a necessity to re-think the way in which business is done, materials and components are sourced, and new types of solutions are developed and marketed, in order to achieve maximum value and circularity from the resources used.

The good news is that there are increasing numbers of examples, in all types of business sectors and within civil society, in general. Circular Economy is a movement that is currently under rapid development, and the many necessary components to shift our mindset from a linear to a circular economy are increasingly manifesting themselves.



*The **Circular Strategies Scanner** can help you to map which strategy or strategies are already being implemented by your company and to identify opportunities of complementary strategies to maximise the value created for as fewer resources as possible. We will refer to this Scanner throughout the six workbooks.*

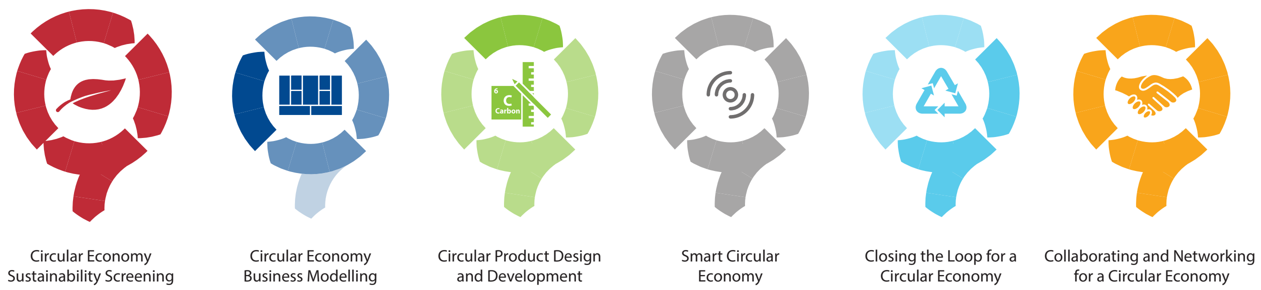
Photo Nick Jio, Unsplash

How to make the transition

The basic concept of Circular Economy is easy to grasp for many. It is appealing from a business perspective, as it connects good business sense to good environmental stewardship. After all, which business would not like to reduce the consumption of cardboard boxes in internal production shipping; fully utilise its logistics capacity; or make its product easier to produce, maintain and upgrade?

The tricky part for many companies, however, is in knowing which steps to take first. How ready is your customer and the market in general, to embrace circularity and what role can your company play? Are there drivers or barriers to be found in the way in which regulations are composed in your area of operation – and if so, are there ways of exploiting the drivers or removing the barriers? Should we design the product for upgrade, or should we develop a new business for leasing? Should we make a new partnership for materials sourcing, or should we be better at monitoring our product in-use? As with many new phenomena and business trends, it is often easier to admire and envy the existing good case examples than it is to actually get started on the journey within one's own business.

This workbook is one in a series of six proposed areas to begin the transition to a Circular Economy.



Introduction to CIRCit

The CIRCit research project was a 3½-year research project, spanning the five Nordic countries, Denmark, Norway, Finland, Iceland and Sweden. Using a number of action research methods, CIRCit's objective was to support the Nordic industry to discover and implement the opportunities of Circular Economy, through the development, testing and implementation of science-based tools.

The project spanned six main areas, corresponding to the workbooks that you are currently reading, as follows.

Circular Economy Sustainability Screening

This workbook supports decision-making by providing sustainability screening of alternative circular solutions in terms of environmental, social and business potential.

Circular Economy Business Modelling

This workbook supports the creation of circular business models, based on a step-by-step approach, best practice and success cases.

Circular Product Design and Development

This workbook presents an approach for assessing product circularity in the conceptual design stage, plus practical design guidelines to support early product development decisions.

Smart Circular Economy

This workbook helps to evaluate how digitalisation and smart products can play a role in facilitating the transition to a Circular Economy.

Closing the Loop for a Circular Economy

This workbook provides an assessment tool and guidelines to support the identification of the best circular strategy for products, taken back at end-of-use.

Collaborating and Networking for a Circular Economy

This workbook presents an approach to support various circular value chain configurations, seeking innovation through stakeholder collaboration.

Digitalisation for the Circular Economy

To date, digitalisation and emerging digital technologies, such as the Internet of Things (IoT), Big Data, Machine Learning, and Artificial Intelligence (AI) have received much attention for their potential to leverage the transition towards a Circular Economy, and sustainability in general.

The correct utilisation of these technologies and the massive volumes of data available throughout the value chain may enable the step change needed, to move towards a more sustainable mode of business and industry operation, by connecting the material and information flow.

Content and expected insights

This workbook provides insights into which technologies to focus on, depending on the level of organisational readiness and Circular Economy strategies to be adopted.

Acknowledging that the workbook covers two emerging and complex fields (Circular Economy and Digitalisation), this workbook attempts to make sense of the many terms and digital buzzwords (that may or may not mean the same).

The workbook should be seen as a supplement to many other readings about potential smart solutions to support Circular Economy. Our aim is to go one step deeper into: (i) the terminology and how to understand it; and (ii) provide some examples of how to proceed with smart Circular Economy strategies in real life cases.

In part 1 of the workbook, we provide a short introduction to digitalisation for the Circular Economy. This is first and foremost targeted at managers, to help demystify the process of digitalising for the Circular Economy. We present the core concepts and technologies relevant for a circular transition, along with the concept of a *Smart Circular Economy*, with example strategies.

Next, we take a deep dive into *Smart Circular Economy strategies*, and the *data science process*, as ways to support the transformation to Circular Economy, through data analytics and smart systems.

We also discuss core challenges that are apparent with data analytics and smart products, as well as the connection to the cutting edge of AI research on deep learning architectures.

In part 2 of the workbook, we present five exemplary cases, describing a selection of important experiences and lessons learned from using digital technologies and big data analytical approaches to implement Circular Economy strategies, such as predictive maintenance, anomaly detection, product lifetime prolongation and upgrade.

This mostly targets individuals with an IT-background that are familiar with data analysis in general, but also provide valuable insights for non-technical individuals.

1 The Smart Circular Economy

Digitalisation and digital technologies

So-called 'digital technologies' form the operational building blocks of a more efficient and effective Circular Economy.

The term 'digital technologies' covers emerging new technologies, such as the Internet of Things, Big Data, and Artificial Intelligence, which have encouraged a paradigm shift for industrial production, known as the 'Fourth Industrial Revolution' or 'Industry 4.0'. These digital technologies are seen as one of the key enablers for wider adoption and accelerated transition to the Circular Economy.

Defining the technologies

The term *digital technologies* or *digitalisation* spans a wide range of concepts, from Internet of Things, through Big Data, Artificial Intelligence, Cloud Computing, Cyber-Physical Systems, to Blockchain. With all these concepts comes enormous promises and possibilities, but also confusion. The figure here shows how these concepts and terms relate to each other.

For the purpose of this workbook, we focus specifically on the collection, processing and analysis of data and information. For this scope, three concepts stand out.

Internet of Things

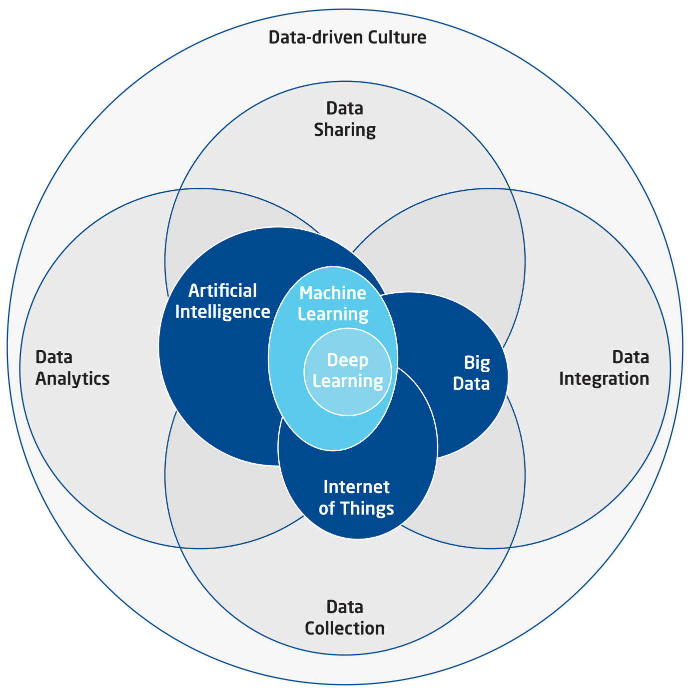
The Internet of Things (or IoT) is a system of interconnected objects that are provided with unique identifiers and have the ability to automatically transfer data over a network and communicate with other objects.

With this functionality, these objects are often perceived as linking the physical and virtual worlds by providing everyday products with sensing and actuating capabilities. IoT plays a central role for data collection.

Big Data
Big data is data with very high volume and complex data that cannot be easily processed or analysed with traditional tools. Big data requires more advanced techniques for processing, storage, distribution and management of the collected data, in order to transform data into contextualised information. Sources of big data include: the internet (e.g. web-traffic or social media data); large amounts of machine sensor data; and supply chain information.

Artificial Intelligence
Artificial intelligence (AI) can be defined as a collection of technologies and methods that simulate the human cognitive process, including reasoning, learning, and so on. We have seen a renewed interest for artificial intelligence in recent years building on the massive amounts of data available. At its core, artificial intelligence is, much like data analytics, concerned with turning data into information and actionable insights. Various approaches exist, from more traditional statistics to machine learning and deep learning. The two latter approaches enable the machine to perform a specific task without using explicit instructions, relying on patterns and inference instead.

Data integration
Data integration involves combining and structuring all the disparate data sources into one unified view. As such, it combines both technical and business processes to create a single-source-of-truth that can be trusted and adopted for several different uses. For the Circular Economy, connecting data from various external stakeholders throughout the value chain may prove to be a huge challenge, both from a technical and business perspective.



Data sharing
Data sharing is the process of making data and information available to internal (i.e. across departments and business units) and/or external stakeholders (both upstream and downstream). Data sharing relies heavily on nicely structured data and thus increases the need for data integration.

For the Circular Economy, the sharing of data and information is fundamental. Similarly, as no one company can adopt the Circular Economy by themselves no one company holds all the data they need to enable the necessary strategies.

Data analytics
Data analytics is the actual analysis of data, where it is transformed into information and insights. This information and insights can be further observed, measured, improved, and compared, relative to a number of target audiences.

Target audiences can range from individuals, departments, institutions or enterprises, groups of organisations, and/or entire industries. Data analytics spans a range of methods and techniques, from traditional statistics to new and advanced artificial intelligence, machine learning and deep learning methods.

For the Circular Economy, data analytics can support a number of strategies. Evident in this workbook is the support to analyse and provide condition data of assets through predictive maintenance.

For this workbook, we will be focusing mainly on *Internet of Things (IoT)*, *Big Data* and *Artificial Intelligence (AI)*, plus their closely related approaches of *machine learning* and *deep learning*.

Photo Markus Spiske, Unsplash

Smart Circular Economy and example strategies

Digital technologies, when deployed with Circular Economy principles, have the potential to propel the application of sustainable resource management in a significant manner.

For instance, digital technologies can contribute to restorative strategies for land use and bio-goods production by:

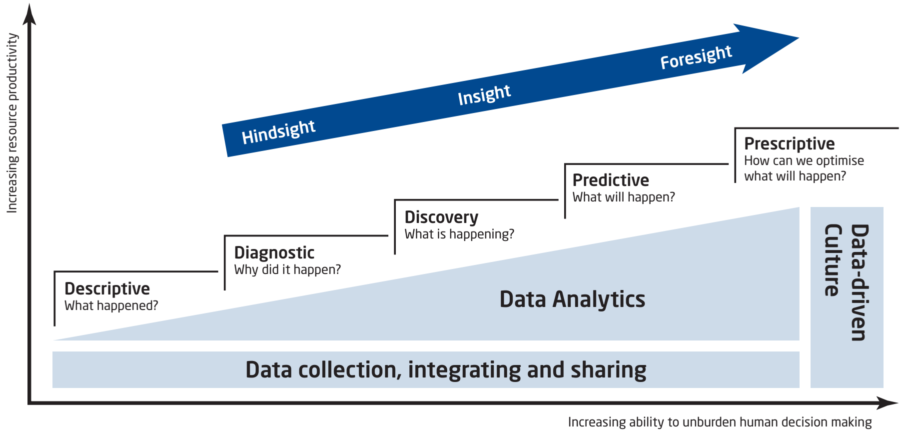
- condition monitoring
- reducing the amount of lost or damaged perishable goods by transport monitoring
- enhancing transport efficiency by smart route planning
- increasing manufacturing yield by tracking material flows
- reducing disturbances in a supply chain due to unforeseen spikes in demand by continuous feedback
- reducing downtime
- supporting life cycle extending operations by predictive maintenance.

When deployed intentionally, digital technologies can keep materials, components and products in use for longer, which improves efficiency, enhances effectiveness, and facilitates the implementation of Circular Economy strategies at scale.

There is a general consensus, both in industry and academia, that digital technologies have the ability to connect the physical and virtual worlds to provide capability to observe, analyse and discover new interventions that may improve the outcomes of Circular Economy.

Furthermore, digital technologies can be thought of as the 'glue' we need to link trillions of assets with the changes that a Circular Economy needs in consumer behaviour, product recovery, material separation and remanufacturing.

However, organisations struggle to fully understand how digital technologies can support the implementation of circular strategies. The Smart Circular Economy overview we provide here is an attempt to guide companies on their journey to integrating 'smart' and 'circular' into their business.



Levels of the Smart Circular Economy

Depending on the overall organisational readiness and the experience with implementing artificial intelligence solutions, various levels of analytics insights may be achieved.

The levels of the *Smart Circular Economy* overview range from 'descriptive analytics' that provide hindsight into what has happened in the past, all the way to 'prescriptive analytics' that give foresight into what could happen in the future, and how to mitigate problems. The higher up on the Smart *Circular Economy* 'ladder' one aims to climb, the greater potential to unlock increased resource productivity one can achieve.

However, climbing the ladder may come at the cost of greater technological and organisational challenges. Implementing a prescriptive analytics solution, for example, sets new requirements for managers to not only develop a mature IT infrastructure to handle the data collection and integration, but it also puts the organisational data-driven culture to the test.

Having a data-driven culture is key to succeeding with most all digitalisation efforts and particularly the strategies involving advanced artificial intelligence, such as predictive and prescriptive analytics

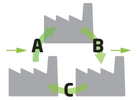
Example strategies

Smart Circular Economy strategies, where digital technologies can leverage, optimise and enhance the overall resource productivity, span all the major Circular Economy strategies. These can range from strategic categories, such as *reinventing* and *rethinking business models*, to operational categories, such as *recirculating parts*, *products, and materials*.

The figure (opposite) provides an illustrative example of the connection between these different levels of digital technologies implementation and a corresponding Circular Economy example strategy. Part 2 of the workbook provides a detailed look at some of these examples.

Smart Circular Economy strategies

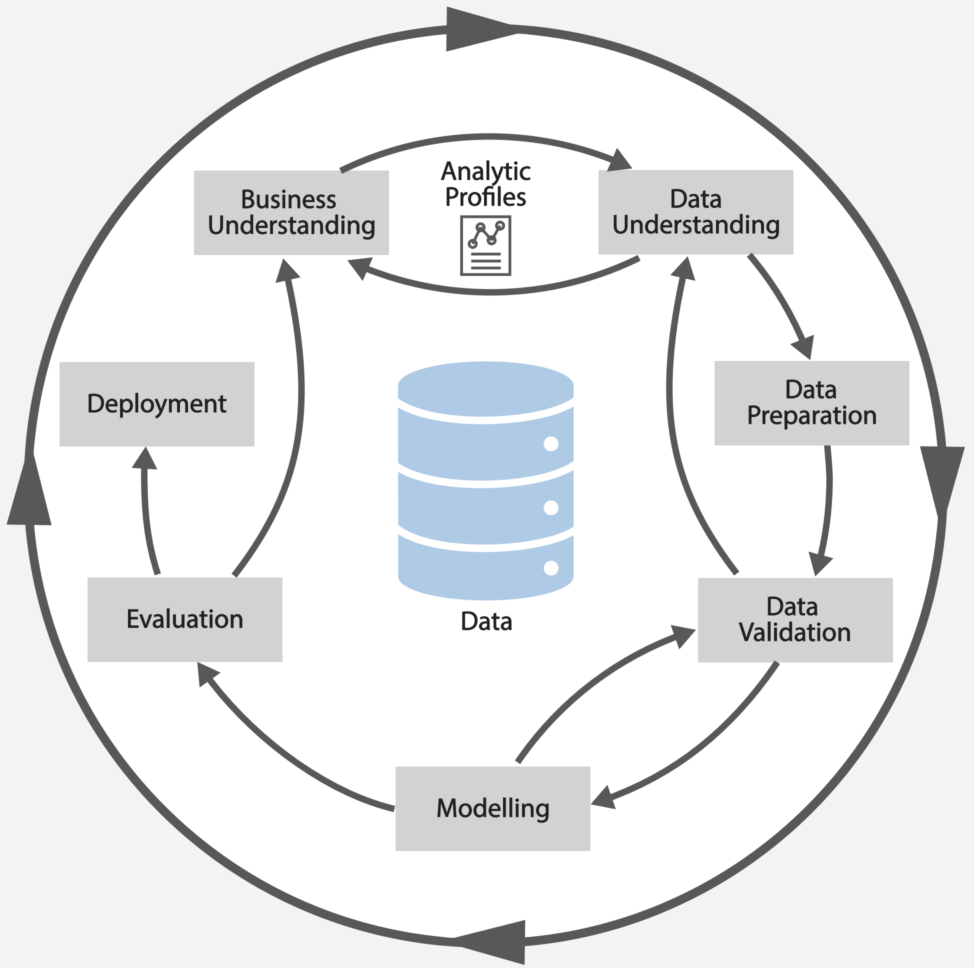
	Restore, reduce & avoid impact in the areas of: Raw materials & sourcing	Recirculate parts & products Extend existing use cycles	Recirculate materials
Prescriptive	**Automatic gathering and processing of real-time and aggregated information** in self-managing and adaptive sourcing plans or configurations. ***Requires:*** self-optimisation algorithms (e.g. swarm intelligence), open data and well-functioning eco-networks with extensive resource coverage	**Autonomous determination by parts/ products of the need for and scheduling of the appropriate life cycle extending operations**. E.g. through predictive maintenance. ***Requires:*** deep learning (e.g. long short term memory network), live operation data streams paired with maintenance logs and failure modes	**Autonomous cost-benefit analysis and execution** of end-of-life strategy of parts/ products based on material quantity, composition and quality. ***Requires:*** self-optimisation and reliability algorithms (e.g. swarm intelligence and long short term memory network) and openly accessible material databases
Predictive	**Anticipate changes to sourcing and value chain dynamics** and alert for potential upcoming issues. ***Requires:*** value chain analysis and value stream mapping	**Prediction and/or automated planning of product/part life-cycle extending operation** based on condition data (i.e. Product health) and aggregated (failure) data for product (group) and taking into account user-activity cycles for minimal disruption of operations. ***Requires:*** condition monitoring, machine learning, and signal processing.	**Predict the impact of recycling and cascading on material composition and quality** and Direct materials to appropriate treatment systems. ***Requires:*** impact measuring, analysis of recycling activities
Discovery	**Identify new and alternative waste-to-resource matches and possible eco-networks for their application.** ***Requires:*** factor analysis algorithms, openly accessible input and output resource flows from multiple actors in the value chain	**Explore different options for product/part life cycle extending operations.** E.g. through with condition-based maintenance. ***Requires:*** representation learning or reliability analysis algorithms, predetermined maintenance rules and operation data with failure modes	**Identify and explore new and effective material cascades** with a minimum environmental impact. E.g. digital material market places. ***Requires:*** data mining methods and openly accessible material databases
Diagnostic	**Identify new scenarios for the application of raw materials** that optimise sustainability impact (environment, social, economic) and reduce (the impact of) quantity, quality and timing fluctuations. ***Requires:*** self-optimisation algorithms and impact analysis	**Determine the need for life-cycle extending operations** based on elapsed time and use statistics for product. ***Requires:*** statistical analysis and operation management	**Determine material quantity and health** by means of analysing purity, constitution, and quality. ***Requires:*** purity analysis and quantity analysis
Descriptive	**Identify quality, quantity and timing etc. of current input flows.** ***Requires:*** aggregated information from internal sourcing, inventory, and logistics databases	**Trigger request for repair based on alert of sudden product failure.** E.g. through with reactive maintenance. ***Requires:*** root cause analysis algorithms and an Internet of Things device, or corresponding sensor/machine data	**Automatic identification of materials and material grades for correct selection of end-of-life strategy**. E.g. automated waste sorting. ***Requires:*** an Internet of Things device, or barcode to scan and recognise material, predetermined rules of material degredation linked with end-of-life srategy choices



for example:
Industrial Symbiosis

for example:
Maintenance

for example:
Recycling



Adapted from Shearer (2000)

The data science process

The importance of digital technologies to transition to a Circular Economy is clear. However, adopting them is more than a technical challenge or a 'simple' procurement process.

To use digital technologies to transition to a Circular Economy requires a clear data- and business analytics strategy, the right people to effect a data-driven cultural change, and willingness in the organisation to appropriately structure itself to align the analytics capability with the overall business strategy.

To achieve such a strategy, it is necessary to establish data-oriented management systems, both to make sense of the increasing volumes of data and, more importantly, to create the capability to transform the insights into business value and competitive advantage. Supporting this transformation through the use of these analytics methods, is called the *data science process.*

Why data science?

Data science is a multidisciplinary field encompassing tools, methods, and systems from statistics and artificial intelligence. These are applied to large volumes of data with the purpose of deriving insights for decision-support. As such, data science may include the collection and use of data to:

- better understand the business operation and provide current-state evaluation of performance
- transform the organisation from a reactive to a proactive stance, with respect to business decision-making, through the use of predictive analytics
- improve customer service through the use of data to build a more coherent knowledge base and thus a better understanding of customer needs
- optimise circular infrastructures, business models and product/service-systems.

The process

Business Understanding

The first and very important step within the data science process is to understand the business and Circular Economy objectives. The current situation must be assessed, together with domain- and business experts to understand the problem at hand, plus to decide how to analyse it and how to measure success.

Data Understanding

Initial data, facts, and figures are collected to create a deeper understanding of the problem. The properties, amount and quality of the data are examined, to verify that the target goal and analysis is achievable.

Often, a lot of time is spent iterating between *Business Understanding* and *Data Understanding*.

Data Preparation

After the data sources are completely identified, the data are collected and pre-processed (formatted, etc.), in order to prepare it for modelling. A great deal of data exploration is also carried out at this stage, to observe and uncover any patterns in the data, in light of the business understanding.

Data Validation

Another important step to carry out, before moving on to data *Modelling*, is to validate the data, by re-involving the business- and domain experts. The aim here is to validate that a proper understanding has been reached, of the data and problem in hand, together with proper Circular Economy objective alignment.

Modelling

In the *modelling* phase, the data scientist moves over to the actual algorithm- and artificial intelligence development. Often, multiple models and solutions are tested and evaluated for quality, precision, and best fit, with respect to the initial business goal.

Evaluation

In this phase, the results of the modelling phase are evaluated, according to the business initiative and Circular Economy objectives. This entails the re-involvement of the business- and domain experts. Often, new business and Circular Economy objectives may occur, as a result of the new patterns and insights discovered.

Deployment

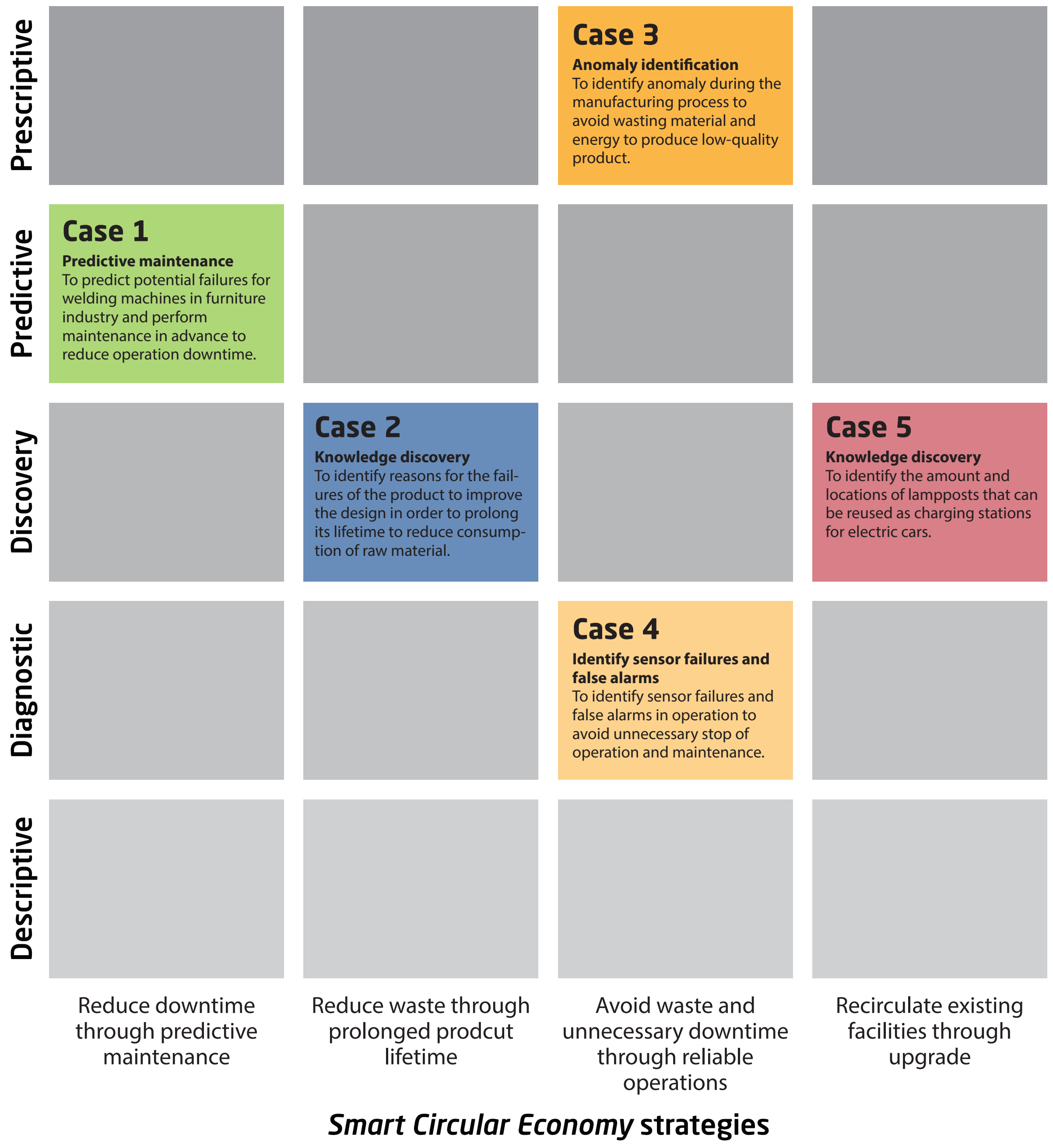
Finally in the data science process, final information from the evaluation phase is gathered and the artificial intelligence solution is deployed to production, before offering to customers and, stakeholders.

Analytic Profiles

The last part of the *data science process* model to describe is the *analytic profiles*. These are structures that are meant to consolidate the learnings, methods and techniques achieved, allowing the organisation to more easily reuse their own experience to catalyse the development of future artificial intelligence solutions.

Analytic profiles can be understood as structures that standardise the collection, application and re-use of all artificial intelligence related methods and tools. Examples of the information include:

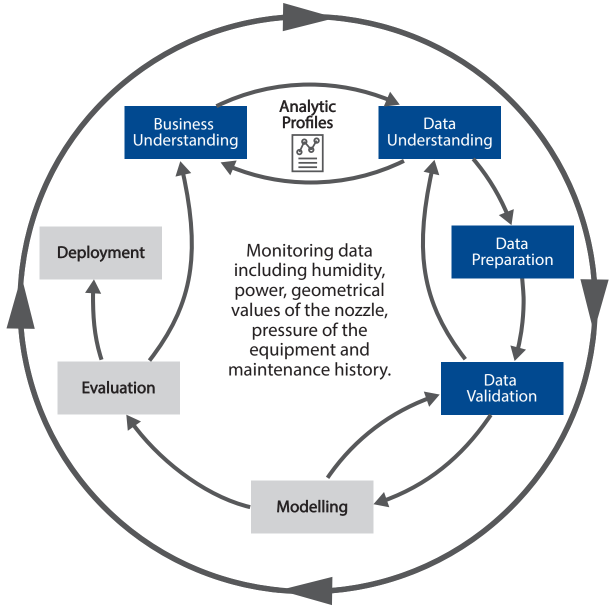
- use-case description defining the business goal, e.g. predict the remaining useful life of a product
- domain-specific insights important for the use case, e.g. knowledge about typical product failures and causes
- data sources relevant to the use case, e.g. time-series data of product operation and service data with failure modes
- key performance indicators or metrics for assessing the analytics implementation performance, e.g. product failure rate, downtime and maintenance costs
- analytics models and tools with proven conformity for the given problem, e.g. long or short-term memory networks and deep-belief networks
- short description of previous implementations with lessons learned, e.g. deep-belief networks for backlash error prediction in machining centres.



2 Cases

This part of the workbook presents five case to exemplify how to use digital technologies to enable specific Circular Economy strategies. The cases are a selection from the cases of Smart Circular Economy strategies performed during the CIRCit project and are chosen to describe how the data science process can be used to enable and facilitate Smart Circular Economy strategies, together with some experiences and lessons learned from the cases, derived by analysing data of the chosen cases.

The data analytic applied and the corresponding Circular Economy strategies enabled or developed are shown in the figure, opposite .



Case 1: Reduce downtime through predictive maintenance

The data science process

The case company for the first case is a leading manufacturer of furniture for parks and outdoor public spaces in cities and towns. Their products contribute to creating social meeting places.

The data science process of this company includes *Business Understanding*, *Data Understanding*, *Data Preparation*, and *Data Validation*.

Based on the available data and the planned analyses, we propose data analysis strategies and methods to guide the company to collect more data and to perform corresponding analyses in the future.

Business Understanding

The case company's products are manufactured in Norway and Sweden using high-end materials, in order to live up to the company's high standards. To ensure a long lifespan for their products and achieve Circular Economy, the company cooperated with us to study the potential of predictive maintenance of a welding machine in their factory. The purpose was to reduce the downtime of their production.

Data Understanding

The available data from the welding machine could be classified monitoring data or maintenance information. The monitoring data mainly included humidity, power, geometrical values of the nozzle, and other condition values, such as gas type, thickness, and pressure of the equipment. The maintenance information included the maintenance log, holding records of the maintenance history of the machine.

Data Preparation

The data provided by the company was collected for diagnostic use when problems occured during production.

Data Validation

In the data validation phase, two major issues were identified:

1. Lack of documentation of the parameters' meaning in the operation data of the welding machine

Some of parameters in the operation data were guessable, such as pressure, gas type, and thickness. Some other parameters were difficult to guess without detailed documentation or support from the welding machine manufacture, which was reluctant to share additional information due to intellectual property issues.

2. Limited occurrences of failures of the welding machines were observed, and the reasons for the failures were not analysed or classified.

Proposals for enabling predictive maintenance
Since the currently available data were not fully interpretable nor sufficient, the study focused on proposing a high-level data modelling strategy and corresponding deep learning algorithms for the company to achieve predictive maintenance in the future.

Our first suggestion to the company is to collect and analyse sufficient failure data, which is critical to predict failures in the machine operation. If possible, the company should also analyse and classify the failures. For example, the failures can be classified into (i) failure leads to a full stop of operation; (ii) failure leads a short-term pause of the operation; or (iii) failure does not impact the operation. The failures can also be classified into (iv) mechanical component failure, (v) electronic component failure, or (vi) another component failure.

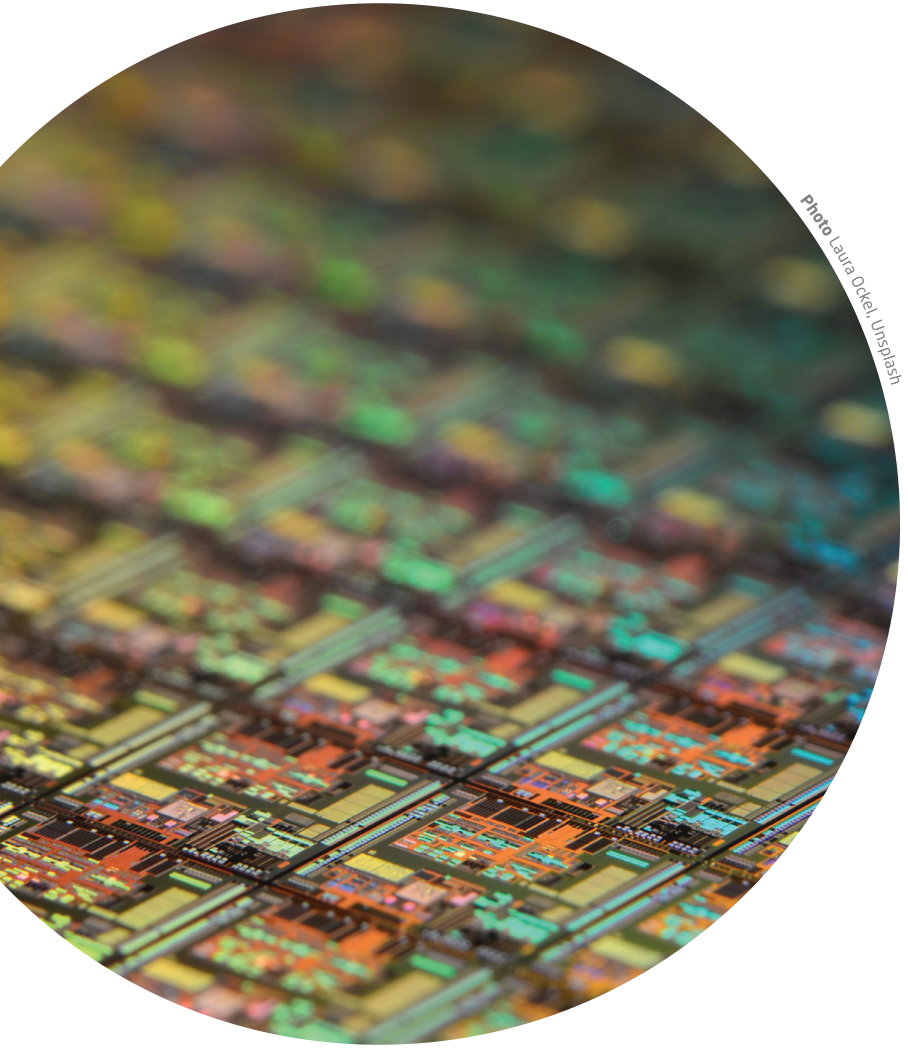
By having classified failures, the predictive maintenance algorithms can predict not only the occurrence of the failure but also the failure type. Once more failure data has collected, the collected data can be divided into two data sets. One data set is to use to develop deep learning analysis algorithms, and the other data set is to verify the accuracy of the algorithms. For example, the company can use 80% of the collected data to train the deep learning algorithms to predict the welding machine failures based on the sensor data of the welding machine. The other 20% of the data can be used to verify how well the trained deep learning models can predict failures.

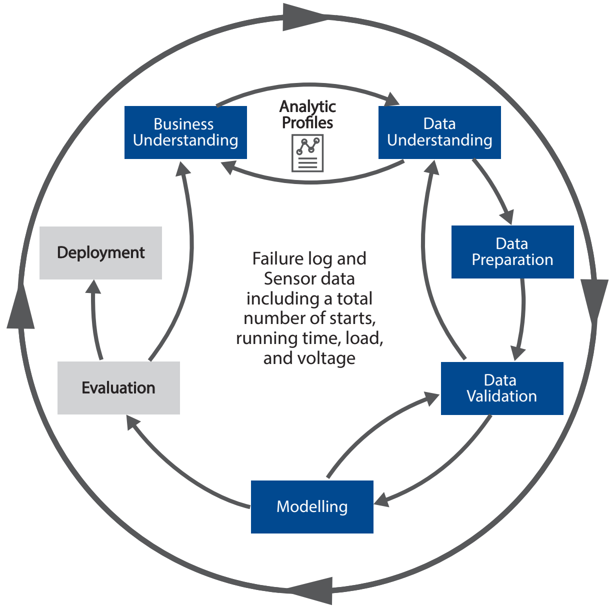
Subsequently, supervised deep learning approaches can be used to perform failure prediction. Supervised deep learning is used to identify the relationships between the input vector (i.e. sensor data of the welding machine, such as pressure, gas type, and thickness) and the labelled output variable (i.e. failure categories).

Lessons learned
In this case, we performed the *data understanding*, *data preparation*, and *data validation* steps of the data science process. It was, however, not possible to perform *detailed data modelling*.

Lessons learned from this case study show that predictive maintenance requires a sufficient understanding of the data available to perform the corresponding analyses.

Advice for good practices
Many companies want to follow the development of IT and data science technologies to support the implementation of Circular Economy. Some companies have already collected some data and want to use the data to enable new businesses or to improve current businesses. However, the data owned or collected by the company may not be sufficient in terms of quantity and quality from the beginning. We would like to advise the company who want to implement smart Circular Economy strategies to start with a gap analysis of the data they have and the data they will need to perform the desired analyses as early as possible to be prepared for later data analyses. No matter how advanced the deep learning algorithms are, sufficient and high-quality data are always the pre-requisites.





Case 2: Reduce waste through prolonged product lifetime

The data science process
The second case company produces heavy machines, such as cranes. The company has already collected data for some purposes, such as analysing the cost of production and maintenance. However, the company wants to create more value from the collected data.

In this case, the data science process goes from *Business Understanding*, *Data Understanding*, *Data Preparation*, and *Data Validation*, to *Modelling*.

Business Understanding
The second case focused on helping a company to analyse the operation and failure of its product, to discover the conditions that most likely lead to product failures. The purpose was to help the company to identify weaknesses in the design and usage of its product.

Based on the identified weaknesses, the company intended to improve its product design and user training to prolong the product´s lifetime and reduce waste of materials and energy in producing and maintaining the product.

Data Understanding
The company collected product failure logs and sensor data (such as actual load and line voltage of cranes) from the daily operation and use of the product. The failure logs were collected to explain the purpose of the maintenance, and the sensor data were collected in order to monitor abnormal or unsafe conditions.

It is important to highlight, however, the data have not been collected for the purpose of identifying the relationship between the sensor data and the failures.

Data Preparation
The company has collected a lot of historical data for many years, from 2009 to 2017. The data provided by the company contained 247,269 sensor data records and product failure logs.

Data Validation
The types of sensor data collected (e.g. total number of starts, running time, load, and voltage) varied greatly over

the years, from 57 in 2009 to 197 in 2017.

To prepare for the data analysis, it was important to clean the data first. Insufficient data (e.g. lack of enough historical data sets), low quality data and irrelevant data to the purpose of the analysis were excluded.

In the end, a total of 42 types of sensor data, which were relevant and were collected continuously during the sampling period, were selected for data modelling and data analysis.

Modelling
In this case, a deep learning-based model was employed to map the relationship between the observed monitoring data and failure record in the failure log.

With the help of the model, some samples that had very different sensor data with other records were identified, which resulted in a discovery of conditions that potentially lead to failures of the product.

Lessons learned
In this case, a lot of sensor data were obtained. However, most of the sensor data were collected under normal working conditions. As the product is highly reliable, the number of collected failure data was limited. It was, therefore, challenging to validate the data analysis results, i.e., the relationship between the sensor data and the product failure, with only a limited number of failure scenarios.

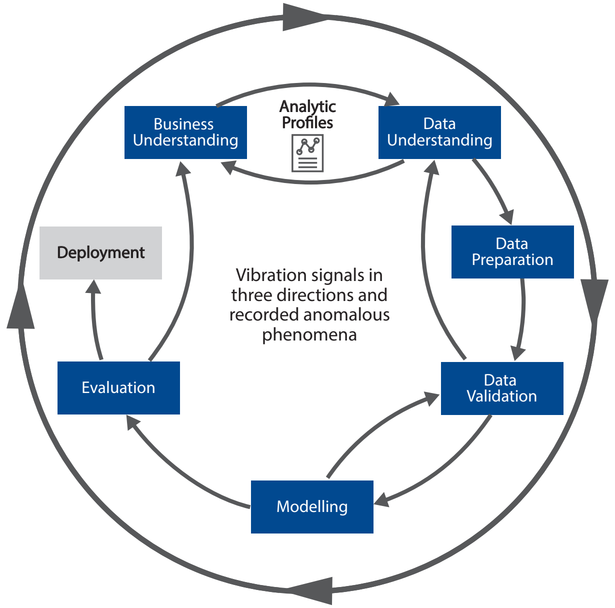
Another lesson learned is that the sensor data of the company were initially not collected to understand the reasons for the failures. Thus, the data analysis showed that many collected sensor data were irrelevant to the product failures. Although the domain engineers of the company hypothesise that some other data can be more relevant to the product failures , those data are not yet collected and are, therefore, not available to analysis.

Advice for good practices
There are two different data collection and data analysis strategies. One strategy is to define the questions to be answered by the data and collect only data for answering the defined questions. Another strategy is to collect as much data as possible with the hope that some knowledge can be discovered from the data given a lot of data are collected.

There are pros and cons to both strategies. For the first strategy, the data collection will be cost-effective because only relevant data are collected. The data analysis is also straight-forward because it has been defined before data collection. However, people may not find extra knowledge from the collected data.

For the second strategy, by using explorative data analysis approaches, the data analysts may identify unexpected knowledge from a large amount of data. However, data collection can be ineffective because many irrelevant data may have been collected and stored.

A good practice could be that a company can collect some data based on pre-defined questions to answer and then perform some pilot analyses to justify whether the data are relevant to the questions after some data are collected. After the data are proven to be useful, more data can be collected and stored for later large-scale analysis.



Case 3: Avoid waste through reliable operation

The data science process

The third case focuses on identifying failures in manufacturing to avoid producing large amounts of low-quality products. The data science process went all the way from *Business Understanding* to *Evaluation*. However, within the timeframe of the CIRCit project, the collaborating company has not deployed our data analysis results yet.

Business Understanding

The company wanted to have an automatic analysis of the sensor data to help generate alarms when the production machine began to deviate from the expected operation.

By enabling to identify failures of the machine early and automatically, the company could stop manufacturing to fix the machine and avoid producing low-quality products that should be discarded.

Data Understanding

As real data were not available, the study was performed in an experiment that simulated the working condition of rotating equipment.

Data Preparation

Vibration signals were collected in both normal and abnormal conditions of the simulated machines.

The operation and failure of the rotating machine were simulated based on information provided by the case company. Failures were introduced by adding weights on the mass-adjustable load to simulate load imbalance.

Data Validation

As the data were collected in an experimental environment, data quality can be controlled, resulting in high-quality data for later analysis.

Modelling

500 data samples were collected, including data in normal and abnormal conditions.

Two advanced deep learning approaches were applied to identify failures of the machine early based on abnormal vibration data of the machine.

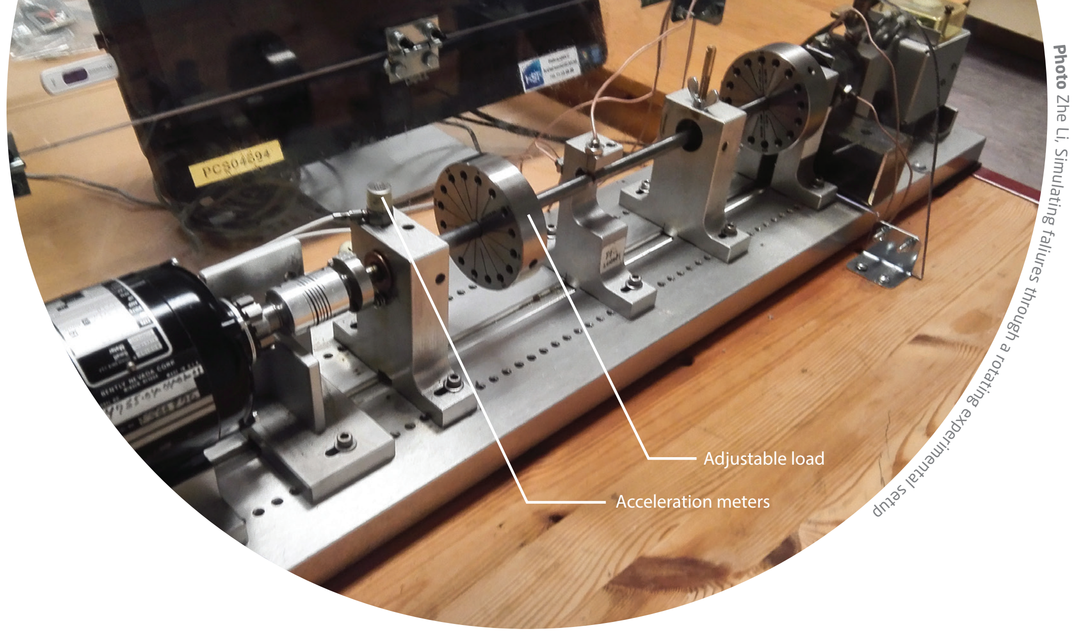


Photo Zhe Li, Simulating failures through a rotating experimental setup

Evaluation
To evaluate the performance of the proposed method, a selection of 200 samples, constructed of 150 samples in normal condition and 50 samples in abnormal condition, were leveraged for testing. According to the numerical results, 99% detection accuracy was achieved in the simulated environment.

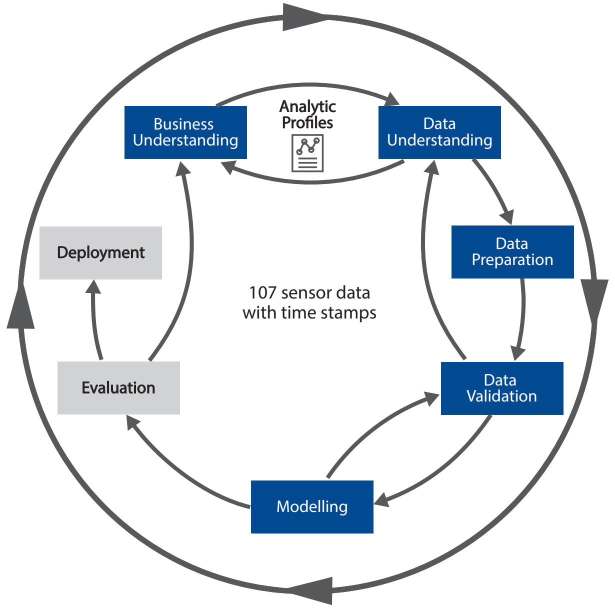
Lessons learned
In this case, sensors were mounted and collected data under various simulated conditions. The anomaly conditions were also introduced intentionally during the experiment.

In many industrial applications, however, it is challenging to obtain high-quality data due to various noise sources that can influence the quality of the data.

Thus, further data and on-field experiments will be needed to deploy the studied data analysis approaches in full industrial (non-experimental) contexts.

Advice for good practices
Due to the development of machine learning technologies, many advanced data analysis approaches have recently been proposed. However, most of the data analysis approaches are invented from academia with a lot of assumptions about the application contexts.

To understand the algorithms well and to apply the machine learning approaches successfully in the industrial context, small experiments in labs or simulated environments are always the first step. It can be risky to apply a certain new data analysis approach without knowing its pros and cons.



Case 4: Avoid unnecessary downtime and maintenance through reliable operation

The data science process
In this case, an international energy company, operating multiple large turbines to produce oil and gas, wanted to find a solution to verify the sensor values of its machines. The data science process goes from *Business Understanding* to data *Modelling*.

Business Understanding
The company had experienced several sensor failures and false alarms caused by sensor failures. False alarms can lead to unnecessary stop and maintenance of the operation, which leads to a high amount of waste of effort and spare parts. Thus, the company was seeking to develop a system to double-check sensor values and to alert sensor failures.

Data Understanding
The studied turbines had more than 100 sensors, continuously monitoring the health of the turbine. There are implicit internal relationships among those sensors, but the relationships are too complex and impossible to be represented by physical models. In addition to this fact, there were no records that logged the reasons for historical sensor failures.

Data Preparation
The data provided by the company included 107 types of sensor data, collected between 2013 and 2018. The data were collected without any labels indicating whether the data were linked to turbine failures, planned downtime & maintenance, or unplanned downtime & maintenance.

Data Validation
The sensors had different collection frequency with unique timestamps, which raised the need to merge the data into slipping time windows with 30 seconds as each window size.

Modelling
Machine learning approaches were applied to predict the value of each sensor by the value of other sensors that are possibly relevant.
Once the derivation between the predicted and actual sensor values exceeded the threshold, a sensor failure alarm will be triggered.

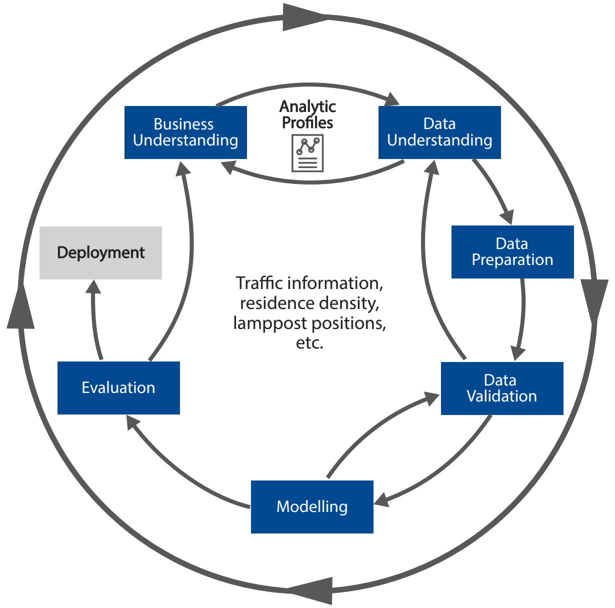
Lessons Learned
In this case, our data analysis approach was able to identify and report sensor failures from the historical data

obtained from the company. However, it was necessary to compare reported sensor failures with the logged failures, to evaluate the accuracy of our algorithms.

The data to log the downtime and maintenance of the turbines did not clearly indicate whether the downtime was due to the sensor failure or false alarm. It was, therefore, impossible to evaluate the accuracy of the established model and data analysis results by reading the downtime and maintenance logs.

The accuracy of the algorithms can be evaluated by domain experts, which are able to identify whether a certain sensor data indicate false alarm or not.

Advice for good practices
Data analytics is always a joint effort of data scientists and domain experts because the data scientists will need to support from domain experts to interpret the data and to evaluate data analysis results. Without support from the domain experts, the data analysis may lead to misleading results.



Case 5: Recirculate through reuse of existing lampposts as charging stations for electric cars

The data science process
In this final case, the company that produces lampposts found that it was possible to retrofit lampposts to have them double as charging stations for electric cars, not least due to the existing electricity supply inside the lamppost, which is usually high enough voltage for this purpose.

The data science process in this case starts from *Business Understanding*, *Data Understanding*, *Data Preparation*, *Data Validation*, *Modelling*, and *Evaluation*. A data analysis tool is developed and evaluated through interviewing the possible users of the tool. We are in the process of finding opportunities to deploy and sell the tool to the market.

Business Understanding
The company needed a data analysis tool to help them to identify the amount and the location of lampposts needed for this purpose, based on the charging needs.

Data Understanding
We needed data to calculate the charging capacities of the lamppost and the needs of the charging station based on the number of residents, the number of lampposts, the traffic situation, and the number of the existing charging stations within specific areas.

Data Preparation
Some data were available as open data, such as the number of buildings and the type of buildings in specific areas.

Based on the number and types of buildings, it was possible to estimate the number of residents. In addition, the parking spaces and the location of lampposts were also available as open data in the Norwegian governmental open data repository, such as the Nordic smart city network (**https://nscn.eu/Stavanger/OpenData**). The voltage of the lampposts is defined in available standards.

Other necessary or desirable data for this case (such as the traffic situation of specific areas, and the number of existing charging stations in specific areas) were owned by commercial companies and therefore not available. In these cases, simulations were created based on assumptions and estimations of the

Photo Zaptec

average number of cars pass a busy main street per day and the average number of charging stations per resident in a specific city.

Data Validation
To attempt to validate the simulated data as far as possible, interviews were held with industry experts of lamppost designers, city planners, and electricity providers, in order to test assumptions and estimations as far as possible, so as to arrive at as reality-close simulations as possible.

Modelling
The goal of the data analysis was to compute how many lampposts would be needed, based on the (sometimes estimated) number of residents, traffic, and other relevant factors. Not all lampposts could be used as charging stations, due to their location or voltage supply restrictions. For lampposts that could not be upgraded, the model re-calculated to distribute the needs of the charging stations to other nearby lampposts.

The results of the analysis were used to create a tool, which was grafted on to a Google map. The tool had functionality to allow the user to remove a specific lamppost as a candidate charging station, for whatever reason. The tool was also created with an open data interface, allowing the simulated data to be replaced with real data or actual use data, should these become available in the future.

Evaluation
The planning tool was presented and demonstrated to several relevant industrial and governmental players in order to evaluate its applicability. Both the collaborating case company and other key stakeholders appraised the tool's functionality and potential to aid such a planning task, based on real and simulated data.

Lessons learned
The main lesson learned was that data integration and data availability could be a bottleneck of using digital technologies for the Circular Economy.

However, a sound combination of simulated data and available real data can create useful models of real-life situations, to aid Circular Economy relevant actions, strongly aided by the data science approach.

Advice for good practices
When developing data analytic tools, many companies want to collect data themselves or to utilise the data they have collected, even if the data are collected for other purposes. There are many open data repositories from government or academia.

Through utilising existing open data or through simulating some data to experiment and evaluate, data analysis algorithms can help the companies to choose the proper data analysis methods and tools. Putting effort into collecting data to be very relevant to the data analysis method is a lot more cost-efficient than collecting a lot of data without knowing how to use it later.

Smart Circular Economy: Take-home messages

- Along with the development of *IoT, big data*, and *machine learning* technologies, the Circular Economy can be smarter by utilising the state-of-the-art data analytic algorithms and tools.
- There are different kinds of data analytics approaches, namely, descriptive, diagnostic, discovery, predictive, and prescriptive methods. All the data analytic approaches have pros and cons and require different data, skills, and domain knowledge. Companies planning to implement smart circular strategies should understand their business needs, the data they own, and the data they need to collect to choose the proper data analytic strategies and approaches.
- It is important to find the data analytic approach that fits the business purpose rather than using the approach that is cool and advanced but needs data or skills that the companies do not have.
- Many modern *machine learning* approaches analyse data as black boxes, i.e. the input and output relationship of the data analysis is not interpretable. Thus, data analyses usually require a large number of preliminary experiments and evaluations. One Circular Economy companies should not underestimate the effort needed in the experiments and evaluations.
- The data quality and relevance are critical for successful data analytics. Although people can pilot and explore the machine learning algorithms to try to find bonus knowledge from data they collect for other purposes, the more cost-effective approach is to collect data for the purpose.
- The data analysis is always a joint effort of data scientists and domain experts. Without sufficient support to interpret the data and the analysis results from domain experts, the data analysis results can be useless and misleading.
- Without enough own data to pilot data analysis approaches and algorithms, open data or simulated data can be a good complement

References

Blomsma, F. *et al.* (2019) 'Developing a circular strategies framework for manufacturing companies to support circular economy-oriented innovation', *Journal of Cleaner Production*, 241. doi: 10.1016/j.jclepro.2019.118271.

Shearer C., *The CRISP-DM model: the new blueprint for data mining*, J Data Warehousing (2000); 5:13—22.

Nordic
Green Growth

This workbook helps to evaluate how digitalisation and smart products can play a role in facilitating the transition to a Circular Economy.

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