Deliverable D3.1
Current Best Practices, Stakeholder Analysis and Pilot Scenarios for Energy Efficient Manufacturing Systems

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D3.1: Current Best Practices, Stakeholder Analysis and Pilot Scenarios for Energy Efficient Manufacturing Systems

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Executive Summary

Deliverable 3.1 presents an analysis of the current best practice in energy efficient manufacturing systems with particular emphasis on the role of digital technologies. The objective is to collate a comprehensive review of current practice, industry needs (via DENiM pilot definition) and engagement with external experts. A requirements review was conducted based on this analysis and alignment with the DENiM innovation pillars. These will be used to inform the architecture specification for the proposed solutions, the implementation of the DENiM components and tools and the evaluation plan in the context of the DENiM pilots.

Keyword list

Best Practice, Requirements and Stakeholder Analysis, Pilot Scenarios, Energy Efficiency Management, Lifecycle Assessment Lifecycle cost assessment, Energy Auditing, Digital Twin, Energy Modelling, System Architectures

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Glossary

AAS	Asset Administration Shell
AHU	Air Handling Units
ANP	Analytic Network Process
CHP	Combined Heat
CSR	Corporate Social Responsibility
DER	Distributed Energy Resources
DER	Distributed Energy Resources
DRSA	Dominance-based Rough Set Approach
EED	Energy Efficiency Directive
ELECTRE	Elimination and Choice Expressing Reality
EnBs	Energy Baseline(s)
EnMS	Energy Management Systems
ESS	Energy Storage Systems
EWMA	Exponential Weighted Moving Average
FDD	Fault Detection and Diagnosis
GHG	Green House Gases
HVAC	Heating Ventilation and Air Conditioning
IoT	Internet of Things
LCC	Life Cycle Costing
LCCA	Life Cycle Cost Analysis
LSSVR	Least Squares Support Vector Regression
MAUT	Multi-Attribute Utility Theory
MCDM	Multi-Criteria Decision Making
MRV	Monitoring, reporting & verification
OEF	Organisational Environmental Footprint
OEFSR	Organisation's Environmental Footprint Sector Rules
PCA	Principal Component Analysis
PEF	Product Environmental Performance
PEFCR	Product Environmental Performance Category Rules
PROMETHEE	Preference Ranking Organisation Method for Enrichment of Evaluations
RBF	Radial Basis Function
RES	Renewable Energy Sources
SBTs	Science-based targets
SEUs	Significant Energy Uses

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Definitions

Precision	It is the fraction of relevant patents among the retrieved patent of the patent set. For the precision evaluation it is possible to perform a selection of a random subset and evaluate the number of relevant documents P’ for the field of interest.
Recall	It is the fraction of the total amount of relevant patents included in the set.

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1 Introduction

The industrial sector was responsible for 37% of the total global energy use in 2017, representing a 1% annual increase in energy consumption from 2010, with growth of 1.7% in 2017 following much slower growth of 0.1% the previous year[1]. The increase in energy consumption is driven by escalating production in energy-intensive industry subsectors. The primary characteristic of Industry 4.0 is the digitisation of manufacturing processes, which offers opportunities for energy saving through the optimisation or replacement of technologies, the application of new software tools for energy efficiency management or adaptation in existing business processes. Energy efficiency remains one of the most effective short to medium term targets to reduce industry carbon footprint and needs to be considered at all stages of the manufacturing process. It is therefore crucial that product designers, production managers' and right through to operators are supported and advised on how to incorporate energy efficiency as a fundamental input to their decision-making process. Recent innovations in digital technologies (big data, IoT, cloud, machine learning), manufacturing processes (automated control, advanced materials), renewable and distributed power generation all provide opportunities for the creation of sustainable factories and value chains. However, the convergence of digital technologies and energy management in the manufacturing sector is still maturing and requires further development to realise the potential benefits.

The overarching objective of DENiM is the development of an interoperable digital intelligence platform to enable a collaborative approach to industrial energy management. DENiM will provide an integrated toolchain to provision advanced digital services including secure edge connectivity leveraging IoT, data analytics, digital twin, energy modelling and automation culminating in the delivery of continuous energy impact assessment, together with energy control and optimisation across existing production facilities, processes and machines.

From a DENiM perspective, digital intelligence refers to the ability to transform digital data extracted from heterogenous sources (shop floor, machines, planning, quality, maintenance) into real-time, actionable, energy-centric insights. This will enables industry to take advantage of digital technologies to improve their energy efficiency and competitiveness by gaining better knowledge of the actual energy demand of their machines/systems/plants as well as further automating production processes. This in turn provides opportunities for developing human competences in terms of digital skills in synergy with technological progress. This will allow the manufacturing sector to maximise the potential promised by Industry 4.0 (and towards Industry 5.0 paradigm), by reducing the gap between the technological capabilities (e.g. Digital Twin, Big Data Analytics) and achievable impact (energy reduction, cost reduction, sustainability). DENiM will leverage the convergence of innovative digital technologies including Digital Twin, IoT, Cloud/Edge Computing, Machine Learning, Modelling and Simulation to provide advanced services, which enables more sophisticated business practices and data processes, thus improving the understanding, capacity and efficiency of the manufacturing processes.

1.1 DENiM Innovation Pillars

DENiM is focused on innovation across four pillars: i) *DENiM Digital Platform:* Reliable Data Integration and Sharing, ii) *DENiM Digital Twin:* Accurate Modelling and Verification iii) *DENiM Decision Support:* Decision Support Systems for Sustainability, iv) *DENiM Digital Skills:* Digital Maturity and Workforce Development. The following provides a summary of each pillar addressed by DENiM:

i. Development of enabling technologies to support **Reliable Data Integration and Sharing**: Access to reliable data is critical to understand energy performance. There is a need to

[1] International Energy Agency (IEA) tracking report 2019 https://www.iea.org/reports/tracking-industry-2019#

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develop a digital platform that is grounded on existing reference architectures in Industry 4.0 that supports interoperability and extensibility. It requires a secure integration solution that provides a “plug and play” approach to extract data from legacy equipment and leverage current protocols utilised in the manufacturing domain. This must be supported by state-of-the-art software paradigms to enable rapid deployment of digital services that automates ingestion, contextualisation and analysis of large datasets with a focus on energy related data. Having a common semantic model is necessary to support the sharing of energy and process data across systems, tools and business functions.

ii. **Accurate Modelling & Verification**: Utilising data from a manufacturing site, it is then possible to create models that represent performance of machines, processes and products. This requires new tools and mechanisms to support the creation and composition of digital models to support accurate energy performance assessment and support model driven identification of energy saving potential. These models can be leveraged to provide an independent and accurate measurement of energy for manufacturing process for verification of energy efficiency initiatives while also contributing to online monitoring to detect faults or provide optimal control of processes from energy perspective.

iii. **Decision Support System**: The availability of robust models and performance data will drive the enhancement of existing methodologies for optimising energy efficiency such as energy auditing. Tools such as Lifecycle Assessment, Lifecycle Cost Assessment, process control and optimised scheduling can be enriched through the integration of real-time data. There are opportunities to support automated assessment tools that can be utilised across the manufacturing value chain supported by context-driven visualisation that captures a common view of energy flows that supports continuous energy performance management.

iv. **Digital Maturity and Workforce Development**: A mechanism to assess the readiness of an organisation to maximise the opportunities digital technologies can bring to the company is needed. The convergence of digital technologies and energy management in the manufacturing sector must consider the human factor and the digital skills required to enable workers make informed decisions with clarity. There is a need to identify skills gaps within industrial sectors and deploy education and training approaches for developing skills and building competences to support energy awareness and sustainability as part of smart manufacturing processes through the seamless integration of digital technologies, education and training activities.

The objective of this deliverable is to capture the current practice for energy efficient manufacturing systems with particular emphasis on the following: the role and use of digital technologies, identifying the skills gaps and reviewing existing and future regulations from an energy policy perspective and will be used to inform the DENiM technological developments and pilot site interventions.

1.2 Requirements Analysis Approach

The multifaceted nature of manufacturing systems makes improving energy efficiency a complex task. A holistic approach is required to encapsulate parameters that collectively influence the energy performance of a manufacturing system\plant such as environment, components, use of materials, machines, cells, lines and supply chains. The manufacturing industry is striving to be more proactive in addressing the need to produce products using an eco-friendly and sustainable approach and ultimately become active participants in the energy transition. Many opportunities remain for industrial sectors to leverage and integrate cost-effective, energy-efficient technologies, processes,

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and practices into EU manufacturing which must stem both from **broader use of current best practices** and from a range of **advances enabled by future innovations** spurred on by digital transformation.

To support this, **four** fundamental strategies have been identified that are common across sectors, these should be applied to enable energy efficient management of manufacturing systems:

Strategy 1 Reliable Extraction, Exchange, and Sharing of Data: Systems need to collaborate across technologies, industries, and business units to uncover energy flows and unlock energy efficiencies.

Strategy 2 Accurate Monitoring & Verification: Continuous performance auditing is essential to ensure precise predictions and efficient energy target management.

Strategy 3 Adaptation and Decision Support: Manufacturing systems must evolve and adapt to changing operation conditions, requirements & system configurations to support & promote sustainability.

Strategy 4 Workforce Development: the role of digital technologies in manufacturing is evolving rapidly, as such workers and employees require new skills to take exploit new opportunities to manage energy more effectively.

The above-mentioned strategies will form the basis for the requirements analysis, this will consist of the following steps (Figure 1):

1. Four industrial pilots will be used to demonstrate the applicability of the proposed solution. This will offer insight to the practical needs across different industry sectors and will provide a set of demonstrable scenarios that illustrate how the DENiM solution will address identified stakeholders' needs and as such maximise the impact of the DENiM outcomes. The pilot definitions will be used to define a set of user-level requirements of the proposed platform.
2. A review of the state of the art will be completed to establish what the current practice is from a technology, energy efficiency, skills and standards perspective that align to the DENiM innovation pillars outlined previously.
3. The project will solicit advice from industry and academic experts in the fields relevant to the DENiM project. A particular focus will be placed on conducting a Strengths, Weakness, Opportunities and Threat (SWOT) analysis of the proposed solution. The outcome of this analysis will facilitate the identification of the current challenges and opportunities that DENiM will address.
4. The culmination of steps 1 – 3 will provide a set of key requirements that will drive the realisation of the DENiM vision.

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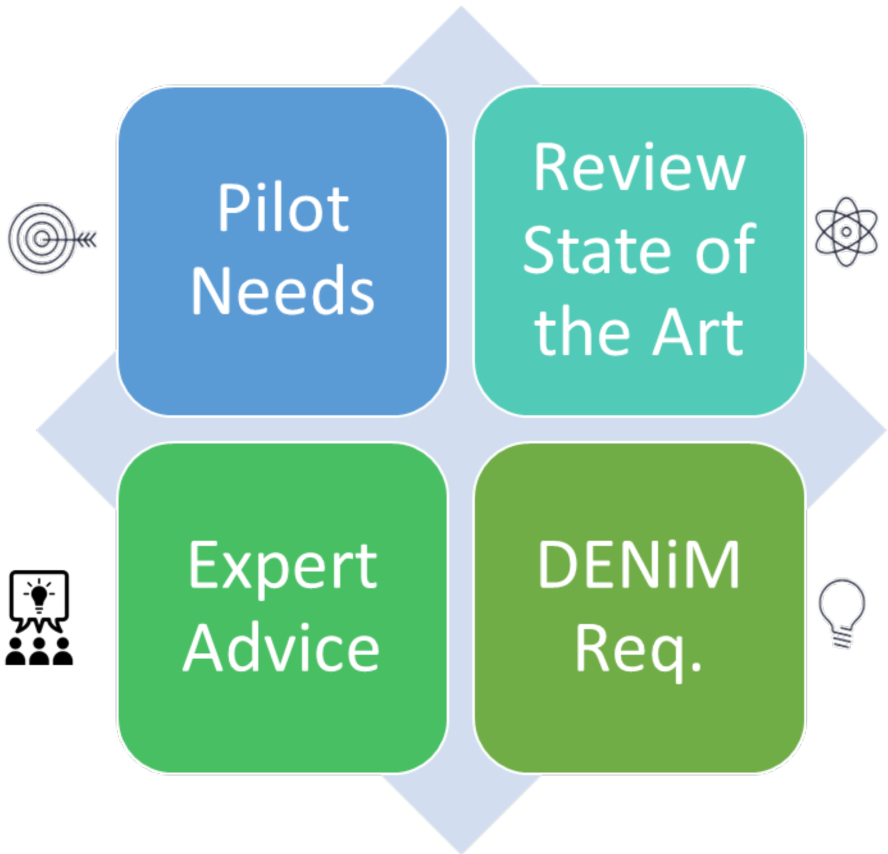

Figure 1: Requirements Analysis Steps for the DENiM project

The outcome of this deliverable will provide the basis for the specification of the DENiM platform architecture (WP4) and inform the development of energy centric models and tools (WP5 & WP6). In addition it will formalise the baseline and evaluation plan (WP8) for the DENiM project.

The remaining of the deliverable is structured as follows, Section 2 provides an overview of the DENiM pilot sites identifying the challenges and scope the project will address. This will inform the focus for state of the art analysis as presented in Section 3. Section 4 presents a SWOT analysis carried out in collaboration with the DENiM External Expert Advisory Board and the identification of specific requirements that will be addressed by the DENiM solution. Section 6 will conclude the deliverable.

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2 DENiM Pilot Site Overview

2.1 Introduction

DENiM is focused on accelerating the potential for improving energy efficiency with cost-effective solutions in four major energy-consuming industries. By validating the deployment of the DENiM digital intelligence platform and ecosystem of smart manufacturing energy efficiency and optimisation services in these complex real operational pilot sites, through key stakeholders (early adopters, relevant experts, industry alliances, dedicated workshops) and market feedback (industry networks & alliances, dedicated workshops). At the core of the DENiM development will be close collaboration with the industrial pilot partners who represent the end user stakeholders within the project across four complex industrial sectors as identified in Figure 2. This cross-sectoral, co-design process will act as an enabler to encourage a joint approach in addressing the energy efficient challenge faced by the manufacturing industry. The DENiM evaluation across these sectors will demonstrate the applicability of key enabling digital technologies as a solution for effective energy management, thus contributing to best practices that can firstly, enable industrial partners to demonstrate leadership in both the uptake of digital technologies to support sustainable manufacturing and secondly, promote replication across other energy-intensive sectors.

2.2 DENiM Validation Ecosystem

DENiM will create and apply design-based research using a “communities of practice” approach, to enable the collaborative development and validation of new digital technologies and practices in conjunction with the pilot sites and their employees thus making relevant stakeholders jointly responsible and involved in the development of the DENiM solution. The pilot sites provide both synergies and differences that enable replicability, flexibility, and adaptability of the DENiM digital intelligence platform.

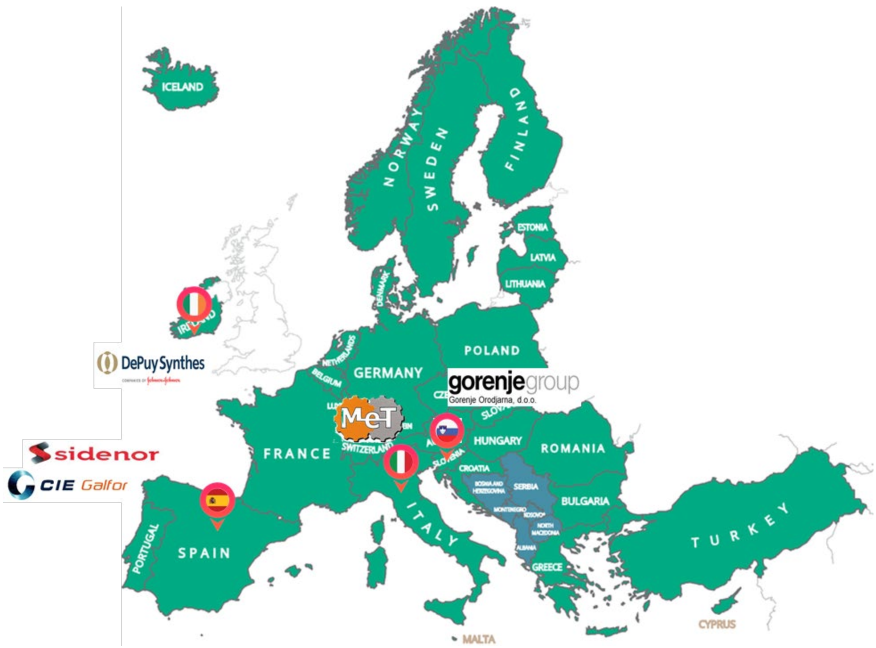

Figure 2: DENiM Pilot Sites supporting Demonstration & Evaluation.

An overview of the pilot cases and sectors covered by the DENiM project are presented in Figure 3. They cover four very different sectors and varying levels of energy intensity, including steel

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manufacturing, medical devices, appliance manufacturing and plastic mechanical components. In addition each industrial partner are at different stages of the energy management journey, from implementing a standards based approach, smart metering to no visibility of energy performance across current processes and products. This offers a significant opportunity for DENiM to demonstrate both cross-sectoral replicability but also its value for industry at different levels of maturity (energy management, digitisation and skills).

	Ireland	Spain	Slovenia	Italy
Sector	**Medical Devices /Life Science**	**Steel Manufacturing For Automotive Industry**	**Tooling for Appliance Manufactures**	**Mechanical Components for Industrial Machines**
Company	**DePuy Synthes**	**SIDENOR/CIE GALFOR**	**Gorenje Orodjarna**	**MET Srl/SCMGroup**
Energy Intensive Process	Poly Value Stream	Steel making and Metal Forging	Tool and Mould Production	Machining of Composite Parts
Product	Knee Implants	Crankshaft	Industrial Tooling	Large screws, flanges, bushings
Energy Management	ISO 50001/IMPVP	Energy Meters & LCA	Plant wide aggregation of Energy Metrics	None
Overall Energy Profile	Electricity: 33,613 MW/h Gas: 15,131 MW/h Local Generation (wind): 15,878 MW/h	Electricity: 551,000 MW/h; Gas: 310,000 MW/h; **85%** of Electricity on Steelmaking	Electricity: 1,800 MW/h Thermal: 1,200 MW/h	Electricity: 450 MW/h

Figure 3: DENiM Pilot Summary

The following provides an overview of the use case scenarios for each pilot site that will be addressed within DENiM:

Pilot No:	**DP01**
Pilot Name:	Digitisation to support sustainable production planning and maximising the use of renewable energy
Industry Partner:	DePuy Synthes
Location:	Cork, Ireland

Background & Motivation

As a medical device manufacturer, DePuy Synthes is mindful of their impact on the environment and the facilities in Cork, Ireland have received Johnson & Johnson Sustainability Awards for their environmental leadership. However, there is still potential to further improve energy-efficiency and ensure it is considered holistically across a specific value chain. DePuy Synthes Cork consumed over 56,000 MWh in 2019 with production responsible for almost 40% of this figure.

Currently the main driver for optimisation of the production process is cost, energy has not factored in as it is not collected at the production asset level. Depuy have made great strides to date within the manufacturing facility emphasising the generation of clean energy, however, there is a need to shift the priority from generation to conservation and ensure production systems maximise every unit of energy produced. Depuy Synthes is looking to integrate knowledge and understanding into existing decision processes from supply chain level through to production attainment.

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Current Practice for Energy Management	
The site is certified to ISO:50001 and utilises the IPMVP standard for all energy projects as a means of Measurement and Verification (M&V). Currently, evaluating KPIs is a heavily manual and flawed task in terms of data collection and analysis. Renewable Energy is key to the strategic objectives to reduce CO2 with a commitment to increase on-site clean energy capacity. The general trend for energy demand is increasingly linked to higher production demands, hence it is essential the company finds further efficiencies in existing process to achieve expected targets: • Sourcing 100% of electricity needs from renewable sources by 2025. • Carbon neutrality operations by 2030. • Reducing upstream carbon footprint by 20% by 2030.	
Product/Process	**Poly Value Stream:** The Poly manufacturing process is responsible for the production of over 20 distinct product parts. Parts are manufactured from UHMWPE (ultra-high molecular weight polyethylene) through a process that includes block cutting, CNC machining, inspection, laser marking, industrial cleaning and packaging.
Pain Points 1. Limited monitoring of asset data from an energy perspective, data collection is manual and labour intensive. 2. Low visibility of energy performance of value stream at process level, requires additional monitoring. 3. Significant gaps in existing energy performance data, with little historical data available. 4. Disparate data sets that remain siloed across multiple systems and business functions. 5. Weak understanding of production energy impact at value stream level. 6. Unreliable energy metering with data that requires validation. 7. Basic energy modelling reliant on regression analysis.	
Pilot Objectives 1. Increase the monitoring of assets associated with the poly process that impact the efficiency of the process (energy, waste, and cost). 2. Provide capabilities to visualise asset energy use in "real-time" for the poly value stream. 3. Enable fault detection and diagnosis on key assets and equipment to maximise lifetime and minimise impact on energy usage. 4. Optimise the use of CNC machining by minimising idle time (driven by production planning, scheduling and energy usage). 5. Increase awareness of energy efficiency within the manufacturing environment and providing upskilling and knowledge sharing as appropriate. 6. Identify opportunities reduce scrap production and minimise material waste. 7. Offer decision support when new assets are to come on site from an energy and sustainability perspective. 8. Establish more effective modelling protocols for energy consumption and prediction that maximise the potential for onsite generation.	

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Pilot No:	DP02
Pilot Name:	Reduction of environmental footprint of a crankshaft production by energy-efficient steelmaking and forging processes management.
Industry Partners	SIDENOR & CIE Galfor
Location:	Biscay, Spain

Background & Motivation

Being an energy-intensive industry, the steel sector accounts for a significant consumption of energy within Europe. Despite the 50% energy reduction achieved by the sector in the last 40 years, there is still margin for further improvement. The automotive sector has improved its energy consumption from 43.5 MWh/year in 2005, to the 38.8 MWh/year utilised in 2018, resulting in a 10.8% reduction. Nonetheless, further improvements in both energy consumption and environmental impact can be made, at both the vehicle and industrial levels.

While visibility on energy consumption is generally available, this data needs to be made more accessible in real-time to allow for inline optimisation of the workflow and parameters of energy intensive stage of steel product manufacturing. This also requires more accurate models of consumption and integration into decision support tools.

Current Practice for Energy Management

Currently SIDENOR is monitoring energy consumption using various energy meters and have implemented LCA at SIDENOR based on historic data and average values (in accordance to ISO standards, ISO 14040, ISO 14044 ISO 14025 and International EPD System PCR 2015:03). CIE GALFOR is currently monitoring energy consumption but does not have any LCA tool for the forging process. Several specific energy consumptions can be measured depending on the mass of material chosen as reference (denominator). This is a common practice in steelmaking, since, along the process, the steel in being constantly transformed and mass is normally being lost (or gained, i.e. with the addition of ferroalloys).

Product/Process	**Crankshaft Production:** This involves two key aspects, firstly steel making which involves sub-processes such as electric arc furnace (EAF), secondary metallurgy, continuous casting. The second process is forging of the crankshaft part, that involves heating and forging sub processes.

Pain Points

1. Limited exploitation of the available data from an energy perspective.
2. None and/or limited collection of some influential variables.
3. Unavoidable reliability uncertainty of important physical measurements.
4. Manual collection of some variables, where human errors are expected.
5. Lack of trust on data-based models for process optimisation in mature industries.
6. Resistance to change.
7. Fear to become obsolete at a job position replaced by automatic process control systems.
8. Achieve a complete and successful integration of the advanced tools within production processes during the project duration.

Pilot Objectives

This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 958339.

1. Increase the monitoring of environmental impact of the production of a crankshaft for the automotive sector.
2. Provide Digital Twins of the most energy consuming process steps, capable of predicting their energetic performance.
3. Achieve a deep understanding and thorough analysis of the variables involved in the EAF steel melting process, as the biggest energy consumer in the steelmaking process.
4. Optimise the electrical energy consumption in the EAF steel melting process, by increasing its efficiency on thermal energy provided to the raw material (scrap) while ensuring product quality.
5. Analyse the role of every process variable involved in the induction heating process, as the biggest energy consumer in the forging plant.
6. Optimise the electrical energy consumption of the induction heating furnace used for heating the billets at the forging temperature, by getting an accurate and homogeneous thermal distribution inside the billets.
7. Increase awareness of energy efficiency within the manufacturing environment and provide upskilling and knowledge sharing as appropriate.
8. Promote the use of data-based decision support systems as a trustworthy tool for process optimisation.
9. Provide capabilities to visual asset energy use in “real-time”

Pilot No:	**DP03**
Pilot Name:	Digital Twinning of machining processes to improved planning, design and programming of operations for manufacturing of tooling for Appliance Manufacturing
Industry Partner:	Gorenje Orodjarna, d.o.o.
Location:	Velenje, Slovenia
Background & Motivation GORENJE ORODJARNA, d.o.o. is a major tool making company in Slovenia. The company specialises in the development, manufacturing, marketing and maintenance of a variety of tools for sheet metal processing, progressive and transfer tools and injection moulding tools (among other products). Some customers leave the tool made by Gorenje Orodjarna in factory as they provide also serial production of sheet metal parts for the automotive industry. The main customers of Gorenje Orodjarna are home appliances manufacturers and the automotive industry. Gorenje Orodjarna is part of the Gorenje group, one of the leading European manufacturers of household appliances, which accounts for about 9,000 employees and a revenue of €1,184 billion in 2018. Gorenje Group is owned by Group HISENSE, which accounts 75,000 employees. The manufacturing process at Gorenje facilities is very high energy-intensive with a special focus on electrical energy consumption. This process is currently driven by the delivery time, quality, and production cost. To ensure the proper production of the products, Gorenje consumes about 150.00 kWh per month of electricity (including 350.000 Nm3/month of compressed air) and almost 100.000 kWh per month of thermal energy. For that reason, Gorenje, is focusing its efforts on enhancing sustainability and energy efficiency across existing processes. This requires improving digitisation of machining process, reduce energy consumption and cost of operations.	
Current Practice for Energy Management	

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<table>
<tr><td colspan="2">Currently Gorenje is monitoring energy consumptions based on historic data and average values. Current main drivers for operation are time to delivery (key in this business), quality and mainly production costs. Nonetheless, sustainability and energy efficiency are becoming more important, not only for their impact in production costs but also for the increased interest of the customers on ensuring a low-carbon footprint production. The company already has several sustainability indicators monitored including overall energy consumption, water and compressed air. All these consumptions are monitored for the whole company but not currently related to the individual production jobs.

Gorenje has monitoring quantity of waste secondary material (in kg, in EUR) distributed among: scrap – other iron particles, waste sheet metal, scrap iron, other non-ferrous material metal particles (other non-ferrous particles, Aluminium scrap and Brass wire. Gorenje has data about price of secondary waste raw material per kg.</td></tr>
<tr><td>Product/Process</td><td>Tool making for sheet metal parts:

Orodjarna, d.o.o. use numerous processes in tool making including milling, grinding, drilling, turning, WEDM and EDM, measurements and laser processing. These processes are energy intensive with special focus on electricity energy consumption but also compressed air consumption.</td></tr>
<tr><td colspan="2">Pain Points

1. The current energy consumption is measured at facilities' level, not at machine level.
2. Additional sensors and monitoring systems are required to fill the gap of machining energy consumption and optimisation.
3. There are historical data about each machine being on or off at a certain moment, but the power consumption cannot be extracted from those measurements.
4. There are a high variety of production routes, which increases the uncertainty regarding the production energy impacts.
5. Relevant energy-oriented models of the company's machine are not available.</td></tr>
<tr><td colspan="2">Pilot Objectives

1. Implement machine-based energy and compressed air consumption monitoring (milling, grinding, drilling, turning, WEDM and EDM). Integrate new sensors with existing monitoring systems (time, quality, planning) to feed this to digital twin models.
2. Develop models to estimate load-dependant energy consumption of pieces depending also on process parameters, tools and machine used. Study and understand the power curves (energy consumption) of particular machines. Identify the machining process's relationship with compressed air to integrate all processes in the analysis of energy savings.
3. Analyse and eliminate the gaps in energy efficiency regarding the machining routes.
4. Integrate digital twin of the manufacturing infrastructure with decision support systems.
5. Provide insight for deciding on when individual machines should be switch off based on available planning data.
6. Provide information about actual production cost of each piece, which will have a direct impact on Gorenje's commercialisation plan.
7. Provide decision support to Gorenje personnel on most efficient approaches, for example to allow planners for selecting the most efficient machine for a specific task, embed energy as a key metric in overall design and planning optimisation.</td></tr>
</table>

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8. Extend existing reporting capabilities with additional information to inform commercial/ quoting department, providing individual estimations of actual costs (LCCA) realized in the manufacturing of each piece as well as LCA analysis of the manufactured parts. 9. Optimisation of auxiliary services from a facilities perspective (e.g. heating and cooling) 10. Improve Gorenje's customer relationship and transparency by being able to provide more accurate information on energy and cost of product manufacturing.

Pilot No:	**DP04**
Pilot Name:	Edge Intelligence for continuous energy optimisation in manufacturing of composite components for industrial machines.
Industry Partner:	MET snc
Location:	Mantova, Northern Italy
Background & Motivation MET snc, is a highly dynamic SME focusing on the production of mechanical components for the machinery industry. It is located near Mantova, in Northern Italy, a densely industrialised area specialised in instrumental machinery and mechanics, machine tools and packaging-processing machines for the food, beverage and pharmaceutical industry. MET supplies critical components for format change and semi-finished product handling, such as large screws, flanges, bushings, etc., made of diverse composite materials such as polyethylene, polypropylene, polyzene, nylon and its derivatives. The objective of the pilot is to adopt a holistic energy optimisation approach for machining operations in production leveraging edge intelligence for the calculation of KPIs linked to energy efficiency and the integration of digital twin for process parameter optimisation. In addition, the pilot will provide MET an opportunity to formalise and implement an energy management system using existing standards.	
Current Practice for Energy Management The dominant factor in this sector is the quality and delivery of orders in a short time, but this has not prevented the company from applying some improvements to reduce the energy consumption of production such as the optimisation of the use of vacuum pumps through accumulations, of centralized suction systems on each single machine, of centralized compressed air to avoid the continuous work of the compressor. Currently there is very limited visibility on energy performance of production processes. Energy efficiency is not monitored for the manufacturing of a specific production and it is not considered as a variable in production planning and parameter setup.	
Product/Process	**Mechanical Component Production:** Each component is manufactured across 2-3 machining steps, eventually combined with assembly operations. There is no standard process, and each machine operates as a single cell, although their combination varies continuously depending on the desired shapes, mechanical properties and surface treatments needed. Relevant machinery include CNC machining, waterjet machine, optic fibre laser cutting system; metal sanding machine and a compact deburring-finishing machine.

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Pain Points
1. Energy efficiency of machine processes is currently not accessible and therefore not considered in production planning. 2. Limited monitoring of asset data from an energy perspective, data collection is manual and is labour intensive. 3. Lack of visibility of energy performance at value stream at process level and requires additional monitoring. 4. Disparate data sets that remain siloed across multiple systems and business functions, integration of legacy machines 5. Job management is the responsibility of machine operator, a manual process with limited automation.
Pilot Objectives
1. Acquire visibility on the energy-related elements influencing production cost, to quote each order more accurately. 2. Introduce the energy optimisation variable in the choice for the optimal production set up and schedule. 3. Develop a "Smart Energy" app within the SCM MAESTRO Ecosystem, to deploy a set of aftersales services to its present customer base. 4. Expand the smart energy service to the range of customers using Accord machines, and in general CNC working centres, to produce wood panel-based furniture. 5. Increase the monitoring of environmental impact of products 6. Provide capabilities to visualise asset energy use in real-time and integrate Digital Twin to predict performance.

Table 1 provides a summary of some of common current barriers and pain points ("TODAY" column) identified from analysis of each pilot site that are hindering significant energy reduction across all sectors of the manufacturing industry. It also highlights the opportunities to address these by using DENiM digital intelligence platform ("WITH DENiM" column). And finally, the DENiM innovation will aim to establish and inform best practices for energy-efficient manufacturing system management ("BEST PRACTICES" column).

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Table 1: DENiM cross-cutting barriers, opportunities, and best practice for Energy Efficient Manufacturing Systems

TODAY	WITH DENiM	BEST PRACTICES
Disparate Data Sets across Systems & Roles	Secure and real-time data collection, aggregation and processing	Digital Technologies for reliable data collection and sharing
Energy Efficiency Independent of Production Processes	Holistic Approach to Energy Efficiency	Sustainable Driven Manufacturing System Management
Manual “what-if” Scenario Creation and Analysis	Continuous Event-Driven Analysis based on Accurate Models	Digital Twin for Sustainable Manufacturing Processes
Cadence-based Planning and Decision making	Digitization Supporting Collaborative Decision Making	Digital Maturity and Collaborative Energy Management
Limited Interaction with Grid	Integration of Renewables with Production Process	Active Participation in the Energy Transition
Digital Skills Gap between Energy , IT & Data Experts	Assessment of soft skills, upskilling & improved awareness	Digital Skills for Energy Efficient Management

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3 Current Practices for Energy Efficient Manufacturing

To ensure industrial goals and needs are addressed by DENiM (as captured in Section 2), the first step is to review current state of the art within the scope of the *DENiM Innovation Pillars* (Section 1.1). Under the each subsection the following is provided, i) a review of the state of the art on the topic relevant to the DENiM and ii) where appropriate provide reference to current industry practice and tools that are being used.

3.1 Reliable Extraction, Exchange, and Sharing of Data

3.1.1 Secure Integration

Security is of the utmost importance for the integration of manufacturing systems, as intelligence driven automation solutions often involve components that are geographically distributed and heterogenous in nature. Addressing security is a multifaceted task and requires consideration of the following functions: Authentication, Session Management, Authorization, Input and Data Validation, Sensitive Data (privacy), Cryptography (confidentiality and integrity), Configuration Management, Exception Management, Auditing and Logging. These categories must be considered for each individual component and the overall integrated system (Wressnegger, et al., 2016). As such in the context of DENiM, to support a collaborative approach to energy efficiency requires a systems-of-systems approach, as the number of systems that become open, connected, and integrated increases, the security threat surface also expands drastically. Therefore a holistic view of the global system is mandatory when security is concerned, and the security posture of a system is equal to its weakest point. This requires manufacturers to tackle a broad aspect of security, starting from the basic and general security principles and subsequently expanded to a review of the currently existing standards, institution, documentation and processes that can be applied to validate and improve the global security of manufacturing systems. This review will then focus on two key points regarding integration, namely authentication and secure communications that are key to the DENiM approach.

Table 1 provides an overview of the main application security categories that should be considered when dealing with security.

Table 2: Security Categories

Category	Description
Authentication	Authentication is the process where an entity proves the identity of another entity, typically through credentials, such as a username and password.
Session Management	A session refers to a series of related interactions between a user and the Web application.
Authorization	Authorization is how the application provides access controls for resources and operations.
Input and Data Validation	Input validation refers to how the application filters, scrubs, or rejects input before additional processing.
Sensitive Data	Sensitive data refers to how the application handles any data that must be protected either in memory, over the network, or in persistent stores (database).
Cryptography	Cryptography refers to how your application enforces confidentiality (i.e., keeping secrets) and integrity (i.e., tamper-proofing).

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Configuration Management	Configuration management refers to how the application is administered and how its settings are secured.
Exception Management	When a method calls in your application fails, what does your application do? How much do you reveal? Do you return friendly error information to end users? Do you pass valuable exception information back to the caller? Does your application fail gracefully?
Auditing and Logging	Auditing and logging refer to how your application records security-related events.

There are many standards that currently exist to define security rules, threats and remedial actions to take. A non-exhaustive list of such institutes, groups and some of their relevant publications regarding secure integration include:

- The Open Web Application Security Project (OWASP) is a non-profit foundation that works to improve the security of software. It provides community-led open-source software projects, with extensive number of members and contributors and is seen as a source for developers and technologists to secure the web:
    - Security verification for IoT integration
    - Application security verification
    - Wiki for securing your IoT system

- Internet Engineering Task Force (IETF) is a large open international community of network designers, operators, vendors, and researchers focused on Internet architectures, they have the following activities relating to security:
    - Authentication with Oauth
    - IoT Security: State of the Art and Challenges
    - Software update recommendation

- International Organization for Standardization (ISO) / International Electrotechnical Commission (IEC):
    - ISO/IEC 27001: is an international standard on how to manage information security.
- There are many more standards pushed by industrial or technology providers (non-exhaustive) that are relevant to DENiM conepts:
    - Open Supervised Device Protocol (OSDP)
    - Building Security In Maturity Model (BSIMM)
    - Security Industry Standards Council (SISC)
    - Health Industry Cybersecurity Practices

- EU / National institutions
    - French National Agency for the Security of Information Systems (ANSSI):
    - European Union Agency for Cybersecurity
        - List of publications related IoT security
        - Industry 4.0 - Cybersecurity Challenges and Recommendations
        - ENISA Good Practices for Security of IoT in the context of Smart Manufacturing
        - ENISA Good Practice for IoT and Smart Infrastrcture

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3.1.1.1 Authentication

Authentication is the first and mandatory step to allow Session Management and Authorization. When integrating multiple systems, it is required be able to authenticate the user at every step of the interaction. If a user is a human, he/she needs to log into the system, with a login/password, a personal token or any authentication method (several can be combined to increase the security). However, when using several systems, the user must not be forced to log on to every part of the system, for every action, he/she must login once and then his/her identity is kept safe and shared across the whole system. This can be supported with mechanisms such as **Single Sign On** (SSO), which is an authentication scheme that allows a user to log in with a single ID and password to any of several related, yet independent, software systems. True single sign-on allows the user to log in once and access services without re-entering authentication factors. It should not be confused with same-sign on (Directory Server Authentication), often accomplished by using the Lightweight Directory Access Protocol (LDAP) and stored LDAP databases on (directory) servers. **Json Web Token (JWT)** is an Internet standard for creating data with optional signature and/or optional encryption whose payload holds JSON that asserts some number of claims. The tokens are signed either using a private secret or a public/private key. For example, a server could generate a token that has the claim "logged in as admin" and provide that to a client. The client could then use that token to prove that it is logged in as admin. The tokens can be signed by one party's private key (usually the server's) so that party can subsequently verify the token is legitimate. If the other party, by some suitable and trustworthy means, is in possession of the corresponding public key, they too can verify the token's legitimacy. The tokens are designed to be compact, URL-safe, and usable especially in a web-browser single-sign-on (SSO) context. JWT claims can typically be used to pass identity of authenticated users between an identity provider and a service provider, or any other type of claims as required by business processes.

When authenticating machines, the login process to a server is not required, regardless, the login information must be stored and accessible from the machine. To identify the machine a secret is generated and then used to authenticate the machine. Session management plays a key role in maintaining the security posture of a system, tokens generated after the human users log in the system MUST be limited in time. For JWT, a typical configuration is to have a 15 minute duration for access token and between 1 hour to 1 month duration for the refresh token. The tokens duration is a balance between security (the shorter the better) and the associated cost (user action, communication to refresh tokens, token sever usage). Secret keys used by a machine to authenticate MUST also be renewed, typically between 1 day and 1 year. The choice here will be made considering the cost to update the secret (can be remotely done without service interruption or does it require a physical connection with down time?). Once the users are authenticated several authorization levels MUST subsequently be defined. Groups are usually defined for users (admin, user, guest). For machine groups may be defined based on location or other relevant criteria. Each group or single user is then associated to an authorization on ever component (or group of components in the system): WRITE, READ, NONE.

3.1.1.2 Secure Communication

Once the users in the system are authenticated it is mandatory to secure the communication between the component. This is done with cryptography techniques. The most common approach is to rely on HTTPS (Hypertext Transfer Protocol Secure). In HTTPS, the communication protocol is encrypted using Transport Layer Security (TLS) or, formerly, Secure Sockets Layer (SSL).

The communications are encrypted with a public / private key cryptography algorithm. Hence it is not possible to read or modify the content of a communication unless the attacker knows the private key of one of the participants. The participants in the communication (e.g., a web server, a remote proxy) are identified by a certificate. Hence it is not possible for an attacker to claim to be the real web server to control the factory. To trust a certificate, a participant trusts the certificate authority (CA) that

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generated the certificate. Certificate standards are generally based on RFC 5280 – PKIX Certificate and CRL Profile[2] . The certificates are generated with an expiration date usually between a few months to a few years.

There are public and widely used Certificate Authorities (CA) on the Internet (e.g., Lets encrypt, IdenTrust, Digicert). All the main computers trust these entities. Hence a secure communication is started thanks to these CAs. However, to validate a certificate the CA MUST be accessible. This is easy when browsing the web, however, it can be more challenging or not feasible to implement in the private network of a company. To generate a certificate, the CA MUST have access (temporarily) to the participant requiring the certificate. This again is not reasonable to assume for private networks. Hence a private CA MUST be used in the systems targeted in the context of manufacturing environments. When using a public CA it is easy to trust it, but when a private CA is used, this assertion is not so easy to make. Essentially, if a CA is compromised every communications and certificates generated by this CA is compromised. Several measures MUST be taken to secure a private CA:

- The machine hosting the CA MUST be as secure as possible and monitored.
- The CA SHOULD be updated as frequently as possible.
- Multiple CA can be used to avoid the impact of a compromised CA
- An off-line CA may be used: this is very secure however it cannot invalidate certificates making it exposed to attack on some participants getting unnoticed and even if noticed they cannot be countered.

3.1.2 Edge/Cloud Architectures for Scalable Data Processing and Sharing

DENiM digital intelligence relies on the ability to extract, analyse and interpret large volumes of data, as such it is critical to consider the most appropriate architectural approach that allow for scalable data processing and sharing to support data driven decision making. Edge and cloud computing represent key technologies to bridge between the field devices (sensors, actuators) and data analysis platform (big data) (Khan & Turowski, 2016). It is critical to reach a high level of convergence between both to avoid the risk of data silos and enable the development of intelligent algorithms, models and adaptive approaches for process monitoring and control.

Often the scale and volume of data to be extracted from manufacturing systems suggest that cloud-centric approaches is an appropriate architecture for data management. However, there are some associated challenges including the cost of network bandwidth along with the potential connectivity and reliability issues that can occur in communication systems (Group, 2017); impact on the scalability of the transferred data and availability of services (Agency, 2012), and delayed response-time and reliability of actuation due to the high communication latency of cloud solutions. In addition to these operating challenges, there are also some difficulties associated with industry companies not willing to let their private data into the cloud environments (e.g. public clouds) as it could pose a risk in sharing commercially sensitive data on infrastructure they may not have control over.

An alternative is to use edge or on-premises solutions (i.e. deploy data processing capabilities to devices in the field). This would enable real-time (or near real-time) data analysis, reduced network traffic and lower operating costs over cloud services and data centres. However, the limited resources of edge devices restrict large-scale data storage and intensive processing. Another major challenge is that these solutions are often bespoke, which restricts cooperation and data sharing across

[2] https://www.ietf.org/rfc/rfc5280.txt

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heterogeneous systems and limits the integration across business verticals that is essential for holistic energy management.

A **hybrid edge-cloud architecture** can address the complexity of interconnecting multiple manufacturing systems (and data sources) where data processing modules can be deployed either on edge or cloud and is entirely transparent to the system behaviour. This approach also enables redundancy to mitigate against having a single store of data that could potentially be a point of failure (e.g. due to unforeseen failure at cloud providers[3]).

There are a number of existing reference architectures, open standards and technologies within the IoT domen that have been applied in industrial settings, these can provide a firm base for managing large volumes of data to support energy efficiency in manufacturing. The following section provides a general study on the reference architectures in the context of Industry 4.0.

3.1.2.1 State of the Art & Beyond: Industry 4.0 reference architectures

Recent developments on reference architectures for Industry 4.0 are focusing on standardisation to facilitate interoperability and simplify the development of new features. A fast-growing number of initiatives are working in parallel but with similar objectives, which can be summarised in identifying and structuring a common model to serve as a general guideline for developers. The following table provides a brief overview of the existing initiatives developing architecture models and relevant standards.

Table 3: Industry 4.0 reference architectures and standards

Type	Initiative	Description
Reference architecture models	Reference Architecture Model Industry 4.0 (RAMI 4.0)	A reference model that provides a common basis and terminology for new products and business models development. Released in 2015 by ZVEI, the German Electrical and Electronic Manufacturers' Association. Since then, it has become the base standard for the connected factories.
	Industrial Internet Reference Architecture (IIRA)	Provides an N-Tier architecture (edge, platform and enterprise) that targets a common model for the deployment of Industrial Internet of Things across industry verticals
	Internet of Things – Architecture (IoT-A)	Provides a reference model and functional view that aims to provide a common grounding to address interoperability at the communications and service levels across different platforms.
	Standard for an Architectural Framework for the Internet of Thigs (IoT)	The IEEE P2413 project has a working group on the IoT's architectural framework, highlighting protection, security, privacy, and safety issues.

[3]https://www.datacenterdynamics.com/en/news/after-strasbourg-fire-ovhcloud-plans-power-servers-starting-week/

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	Arrowhead Framework	This initiative enables collaborative automation by open-networked embedded devices. It's a major EU project to deliver best practices for cooperative automation.
Relevant Machine-to-machine (M2M) standards	European Telecommunications Standards Institute Technical Committee (ETSI TC) for M2M	oneM2M architecture provides a layered model comprising of three layers, the Application, Common Services and Network Services Layer that can encapsulate a set of entities that representative functional blocks.
	International Telecommunication Union Telecommunication Standardization Sector (ITU-T)	The ITU-T has coordination activities on aspects of identification systems for M2M.

3.1.2.2 State of the Art & Beyond: **Hybrid Cloud computing architectures**

A hybrid cloud consists in the combination of on-premise (company-owned) and off-premise (owned by a third party provider) cloud infrastructures. Usually, the utilisation of off-premise resources is a response to the necessity of achieving a minimum Quality of Service (QoS), fulfilling a given deadline or dividing data processing between on- and off-premise to enforce security compliance requirements. Hybrid cloud architectures require the dynamic, seamless integration of both owned and third-party nodes. There are few references in the literature to this kind of hybrid networks. Both cloud and on-premise computing are getting more common in big data applications, but the combination can still be considered a research topic.

(Loreti & Ciampolini, 2015) proposed a layered architecture based on the concept of Hybrid Infrastructure as a Service (HyIaaS). The HyIaaS layer consists in a software layer that implements the integration of both on-premise and off-premise infrastructures by merging their resources into a series of clusters of Virtual Machines (VMs). The partitioning of those VMs between the internal and the external networks must be transparent to the final users. The HyIaaS layer takes care of provisioning off-premise resources when the on-premise ones are no longer enough for a given task or desired QoS. This term is usually known as "cloud bursting", and has been analysed by several authors. In (Guo, et al., 2014), an architecture named Seagull is presented. Its main purpose is the implementation of cloud bursting by migrating VMs between clouds. This approach is quite expensive, and so the authors employ optimisation techniques based on intelligent pre-copying mechanisms.

An alternative is to eliminate the migration of VMs and avoid the shortcomings of this technique. A common approach is to implement the batch processing on-site while deploying the stream processing platform, which usually presents a more demanding scenario in terms of computational capacity, to the external network.

Since the first authors started talking about hybrid clouds, the world of virtualisation, networking and big data technologies have gone through a relevant evolution. More recent works on the field like (Zhang, et al., 2018) have started analysing the seamless integration of edge and cloud resources by applying dynamic scheduling mechanisms. This technique showed promising results in a real application from the State Grid Corporation of China (SGCC) where the data of tens of thousands of Data Acquisition Terminals (DATs) from electric transmission lines was used to analyse interferences and predict power quality disturbances. The followed approach consisted in scheduling the

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lightweight part of the analysis, like the detection of a disturbance, into the edge element and the heavyweight part, like the identification of the source of the disturbance (which relies on recurrent neural networks) on the cloud. More recently, the authors in (Yang, et al., 2020) explored edge-cloud architectures for Cloud Manufacturing Systems (iCMfg). In their work, they propose an edge-cloud architecture that supports optimal collaborative utilisation of edge and cloud computing resources with optimal efficiency.

3.1.2.3 Current Commercial Practices in Hybrid Computing

There are several commercial solutions for hybrid clouds and edge-cloud integration from the big players in the sector. Intel and Google Cloud have been collaborating to offer a joint solution for IoT applications that make use of hybrid and multi-cloud Deployment. In November 2020, they revealed their reference architectures for enterprises to be able to deploy their cloud business models using their on-premise self-managed hardware (Intel, 2020).

Azure, one of the biggest solution provider for cloud services and infrastructures, also offers hybrid and multi-cloud compatibility through a holistic, seamless and secure approach to on-premises, multicloud and edge environments. Dell EMC Ltd has a solution called Dell Technologies Cloud, which offers the possibility to run cloud-native applications across multi-cloud environments. Dell refers to this solution as a Data Center-as-a-service that allows bringing the advantages of a public cloud into the edge computing locations. Many other large companies are starting to provide similar solutions to the market. The combination of both cloud and edge computing as well as on- and off-premise infrastructures seems to be the key to leverage the advantages from both of them. But this requires a secure and robust development in terms of seamless integration of the two approaches.

3.1.2.4 Related EU Initiatives

The following provides a non-exhaustive list of EU projects investigating the edge-cloud computing field:

ACCORDION – Adaptive edge/cloud compute and network continuum over a heterogeneous sparse edge infrastructure to support nextgen applications (2020 – 2022)
ACCORDION will intelligently orchestrate the compute & network continuum formed between edge and public clouds, using the latter as a capacitor. Deployment decisions will be taken also based on privacy, security, cost, time and resource type criteria.
DECENTER – Decentralised technologies for orchestrated cloud-to-edge intelligence (2018 – 2021)
DECENTER aims to realise a robust Fog Computing platform, covering the whole Cloud-to-Things Continuum, that will provide AI application-aware orchestration and provisioning of resources. The project will enrich existing Cloud and IoT solutions with advanced capabilities to abstract features and process data closer to where it is produced.
CLASS – Edge and CLoud Computation: A Highly Distributed Software Architecture for Big Data AnalyticS (2018 – 2021)
CLASS aims to develop a novel software architecture to help big data developers to combine data-in-motion and data-at-rest analysis by efficiently distributing data and process mining along the compute continuum (from edge to cloud) in a complete and transparent way, while providing sound real-time guarantees.
PrEstoCloud – Proactive Cloud Resources Management at the Edge for Efficient Real-Time Big Data Processing (2017 – 2019)

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PrEstoCloud project will make substantial research contributions in the cloud computing and real-time data intensive applications domains, in order to provide a dynamic, distributed, self-adaptive and proactively configurable architecture for processing Big Data streams. In particular, PrEstoCloud aims to combine real-time Big Data, mobile processing and cloud computing research in a unique way that entails proactiveness of cloud resources use and extension of the fog computing paradigm to the extreme edge of the network.
CHARITY – Cloud for Holography and Cross Reality (2021 – 2023)
CHARITY leverages an innovative cloud architecture that exploits edge solutions, a computing and network continuum autonomous orchestration, application-driven interfacing, mechanisms for smart, adaptive and efficient resource management, strong community involvement, and overreaching compatibility with all infrastructure vendors.
PLEDGER – Performance optimization and edge computing orchestration for enhanced experience and Quality of Service (2019 – 2022)
The EU-funded PLEDGER project aims to provide a new architectural model as well as a set of software tools that will prepare the future development of the next generation of edge computing. The project will allow edge computing providers to secure the stability and effective performance of the edge infrastructures. It will also allow edge computing users to understand the nature of their applications, research understandable quality of service metrics and optimise the competitiveness of their infrastructures.
RECAP – Reliable Capacity Provisioning and Enhanced Remediation for Distributed Cloud Applications (2019 – 2019)
RECAP goes beyond the current state of the art and develop the next generation of cloud/edge/fog computing capacity provisioning via targeted research advances in cloud infrastructure optimization, simulation and automation. Building on advanced machine learning, optimization and simulation techniques. The overarching result of RECAP is the next generation of agile and optimized cloud computing systems.

It is not the intention for DENiM to provide a new architectural approach but rather ground the developments with existing reference architectures and approaches that allows for the creation of a scalable, flexible data processing platform.

3.1.3 Data Quality for Robust Energy Modelling

In the recent years, many organizations have begun to realise that data is critical asset in there organisation. The Industry 4.0 paradigm relies on the idea of providing services with highly automatized procedures and data is at the very heart of this revolution. From a manufacturing perspective high quality, reliable data management is the main premise to support the optimisation and efficient management of production. Energy savings is one of the most attractive targets to achieve improved energy efficiencies with the technologies of Industry 4.0, the advantages of the use of the data, addressing the digital-twin paradigm is viewed as one of the most promising approaches to model and to plan the industrial processes in order to optimize energy (Teng, et al., 2021). The authors (Teng, et al., 2021) divide the problem of the digitalization of the Industry in four categories: Data Acquisition, Data Pre-processing, Modelling and Analysis, and Industrial Implementation. The article shows that the more popular category in the scientific research, in terms of number of publications, is the Modelling and Analysis; conversely, the Data Pre-processing problem seems to have less attention in literature. Nevertheless, they identify that data pre-processing is one of the main challenges in industrial modelling and energy optimization problem, particularly with trying to

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build digital twins. It is often referenced in the literature that the data pre-processing problem sometimes represents 40% of the total work involved in leveraging the data to create added value.

The DENiM data-driven models for industrial energy savings will rely heavily on sensor data, experimentation, and knowledge-based data. Data is key to end-to-end visibility of any process, as such data integrity and reliability play an integral role in being able to create accurate models both from an energy estimation and automated control. Generally once models have been obtained, they are taken as valid and they are used for the estimation of variables that quantify their quality, that is, through the models we can know the expected (or predicted) value of other variables and use them as comparison with measured values. Distributed estimation and control are currently very attractive research fields for applications in large-scale and highly complex plants where centralized data and control structures become very expensive and difficult to implement (Garwood, et al., 2018). Currently, the use of simulation tools is becoming increasingly important in the manufacturing industry. Many of the tools focus either on throughput and productivity (Manufacturing Process Simulation (MPS)), or on the energy consumed by the general system of the factory building (Millán et al. (2015)).

Manufacturing processes tend to focus more on maximising production at the time of process simulation (MPS) although, possibly, considering energy constraints. However, energy consumption is typically done in the first simulation stage and subsequently, the company typically do not use energy meters in the plant to check and verify these simulations. To holistically manage energy there is a need to allow simulation and modelling approaches focused on predicting energy to adapt to the dynamic nature of manufacturing environments and processes utilising distributed estimation and control mechanisms to detect and classify data quality obtained, this is an important factor in supporting online energy efficiency modelling of manufacturing plants since anomalies need be detected dynamically and in real-time.

(Jugulum, 2014) presents a basis of the Data Quality (DQ) techniques. They describe how to build and to execute DQs program with operating models involving four steps: Define, Assess, Improve and Control. The topics of the book provide a powerful combination of academic/intellectual expertise and learning from applied business experience. They state that there is an associated loss when a quality characteristic deviates from its target value. The quality loss function (QLF) concept can easily be extended to the data quality world. If the quality levels associated with the data elements used in various decision-making activities are not at the desired levels (specifications or thresholds), then calculations or decisions made based on this data will not be accurate, potentially resulting in huge losses to the organization. The DQ component is responsible for cleaning the data and making sure that it is fit for the intended purpose, so it can be used in various decision-making activities. Research in the DQ field has focused on defining methodologies that help the selection, customization, and application of data quality assessment and improvement techniques. (Batini, et al., 2009) present a review of methodologies in the literature and provides a comparison between many of these methodologies regarding the methodological phases and steps, the strategies and techniques, the data quality dimensions, the types of data, and the types of information systems. Furthermore, (Batini, et al., 2009) propose open problems in DQ methodologies mainly concerned to the identification of more precise statistical, probabilistic, and functional correlations among data quality and process quality, and the vali-dation of methodologies. Often, a methodology is proposed without any large-scale specific experimentation and with none or only a few, supporting tools. There is a lack of research on experiments to validate different methodological approaches and on the development of tools to make them feasible.

To support DQ for decision making, it is essential to assess the data quality level by means of well-founded metrics. However, if not adequately defined, these metrics can lead to wrong decisions and economic losses. (Heinrich, et al., 2018) presents a set of five requirements for data quality metrics:

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(i) Existence of Minimum and Maximum Metric Values, (ii) Interval-Scaled Metric Values, (iii) Quality of the Configuration Parameters and the Determination of the Metric Values, (iv) Sound Aggregation of the Metric Values, (v) Economic Efficiency of the Metric. These requirements are relevant for a metric that aims to support an economically oriented management of data quality and decision making under uncertainty. (Heinrich, et al., 2018) demonstrate the applicability and efficacy of these requirements by evaluating five data quality metrics for different data quality dimensions and discuss practical implications when applying the presented requirements.

An updated state of the art review linked to Digital Twin in industry by (Tao, et al., 2018) identifies the problem of Data Fusion as one of the main challenges in the industrial digitalization. Digital Twins must handle a massive volume of data, including physical data, virtual data, and fusion data between them. Data fusion is the process of combine the massive volume of data collected from a variety of channels such as machine, physical environment, virtual space, historical database, etc. Data fusion involves three processes—data pre-processing, data mining, and data optimization. Therefore, it is necessary to perform DQ pre-processing that includes data cleaning, data conversion, and data filtering. (Tao, et al., 2018) claim that there are few research works conducted in the context of Digital Twins. The reviewed literature shows the developing of DQ methods for robust modelling and industry digitalization remains an open research topic. There have been a number of European projects that specifically have involved topics on industrial digital simulation, data quality and robust modelling that will be considered to address the DQ within DENiM:

- **Arrowhead Tools:** Create advanced new digitisation and automation tools for the European engineering industry. The project is expected to reduce the costs of developing and introducing flexible and secure digitisation and automation solutions by about 20 to 50%.
- **OPTIMISED:** Develop novel methods and tools for deployment of highly energy-optimised and reactive planning systems. Incorporate extensive factory modelling and simulation based on empirical data captured using smart embedded sensors and pro-active human-machine interfaces.
- **DIGIMAN4.0**: Propose innovative technological solutions for high quality, high throughput and high precision production (zero-defect precision mass-manufacturing of high-performance products) for the manufacturing industry. Validation of different digital manufacturing technologies by integration into process chains for the production of advanced components in several sectors.
- **iDev40:** Propose to achieve a disruptive step toward speedup in time to market by digitalising the European industry, closely interlinking development processes, logistics and manufacturing. The project aims at suitable digital technology advancements to strengthen the electronic components and systems industry in Europe.
- **REFLEX:** Analyse and evaluate the development towards a low-carbon energy system with focus on flexibility options in the EU to support the implementation of the SET-Plan. The analysis are based on a modelling environment that considers the full extent to which current and future energy technologies and policies interfere and how they affect the environment and society while considering technological learning of low-carbon and flexibility technologies.
- **Productive4.0**: Achieve improvement of digitising the European industry by electronics and ICT. Ultimately, the project aims at suitability for everyday application across all industrial sectors – up to TRL8. It addresses various industrial domains with one single approach of digitalisation.
- **TWIN-CONTROL:** Development of a simulation and control system that integrates the different aspects that affect machine tool and machining performance.

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- **BOOST 4.0:** Demonstrate in a measurable and replicable way, an open standardised and transformative shared data-driven Factory 4.0 model through 10 lighthouse factories.
- **SMART 4.0**: Fellowship Programme aimed at providing world-class training and research opportunities to 16 post-doctoral fellows in Smart Manufacturing.
- **COGNITWIN:** Investigate how today's plants can learn from historical data and adapt. It will partner with numerous industries and research groups from around Europe to create a platform that includes a sensor network for monitoring and collecting data from various plant processes.
- **TwinERGY:** Introduce a new digital twin framework for the energy market. It will incorporate the required intelligence for optimising demand response at the local level without compromising the well-being of consumers and their daily schedules and operations.

An analysis of the application and implementation of Industry 4.0 patents in the world, with special attention to the European Union is conducted by (Karabegović, et al., 2020). The authors state that in the period between 1990 to 2016, the trend of patent applications and implementations involving Industry 4.0 moved by an exponential function. The analysis was conducted by industry sectors and leading companies in the application and implementation of Industry 4.0. The article shows that the latest available patents application concerning mainly with five base technologies of Industry 4.0: Cloud computing, Robotics, Sensors, 3D Printing, RFID (radio frequency identification).

DQ and Robust Estimation problems are involved in the five base technologies of Industry 4.0 mentioned in the article. Each of these categories deals with a very large amount of data, the fault-tolerant modelling of processes is based on accurate data prepossessing algorithms. (Karabegović, et al., 2020) mention the obstacles in the implementation of Industry 4.0 patents, such as reliability problems with machine-to-machine (M2M) communication, the security of information technologies, etc. Examples of Patents involving Data Quality and Robust Estimation are the following:

- (Jr., et al., 2007) propose systems and methods that provide for adaptive processes in an industrial setting. They create a process trend component that can access historian data to determine/predict an outcome of a current industrial process. Such enables a tight control and short reaction time to correct process parameters.
- (Ho, et al., 2011) propose systems and methods for automatically and/or systematically include more data sources and/or more detailed data in the analysis, prediction, and model building to reduce the reliance on inconsistent and expensive human experts.
- (Markham, et al., 2006) provides quality management and intelligent manufacturing with labels and smart tags in event-based product manufacturing.
- (Bidlack, 2012) addresses data quality issues by standardizing, verifying, matching, consolidating, and merging data records using powerful inexact matching logic and search reduction technologies. These technologies aloud to improve the quality of data and/or resolve quality data issues such as incomplete, inaccurate, and duplicate data records.
- (Hood, et al., 2010) present an industrial automation device comprises a data storage component that retains at least a portion of a schema, the schema facilitates usage of a hierarchically structured data model by the industrial automation device. The industrial automation device can be employed to execute a workflow.
- (Nixon, et al., 2019) patent a data modelling studio that provides a structured environment for graphically creating and executing models which may be configured for diagnosis, prognosis, analysis, identifying relationships, etc., within a process plant.
- (Hood, et al., 2010) present a system that facilitates tracking and tracing products in an industrial environment.

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- (Bera & Marcade, 2002) disclose a system and method are disclosed for generating a robust model of an industrial system based on data and machine learning techniques.
- (Rollins & Venkatesh, 2012) patent system, method, and program product for interpreting, optimizing, and customizing data mining models using statistical techniques that utilize diagnostic measures and statistical significance testing.
- (Wojsznis, et al., 2010) present a robust method of creating process models for use in controller generation, such as in MPC controller generation, adds noise to the process data collected and used in the model generation process. Process models created using this technique generally have confidence intervals, therefore providing a model that works adequately in many process situations without needing to change the model manually or graphically.
- (Dwarakanath, et al., 2009) combine two robust forecasting techniques to automatically detect anomalies in observed data and/or use of a multi-user computer system.

3.2 Accurate Monitoring & Verification

DENiM intelligence and decision supports will have a foundation in its ability to provide an accurate representation of energy flows, product and process performance as such this requires innovation to support energy modelling, simulation and analysis towards providing energy-centric digital twins that can be leveraged to provide a holistic view of sustainability and cost performance (e.g. via LCA). This has to be correlated and integrated with the use of current standards and approaches for energy auditing to formalize the approach to energy efficiency management of manufacturing systems. As such the following subsections provides insight into the current state of the art covering these topics.

3.2.1 Energy Performance Modelling and Simulation

The core of the data-driven energy-saving pipeline is the procedure for modelling and analysis. Mathematical modelling is fundamental for manufacturing and consists of two branches: principles modelling and empirical modelling. Empirical modelling is modelling that is based on empirical observations that are then used to develop mathematical equations for data analysis. Empirical models are well used in the manufacturing industry and due to the recent advancements in computational technologies, specifically machine learning and cyber physical systems, their capabilities have increased significantly, so much so that now it encompasses the field of data-driven modelling. Adaptability, accuracy, predictivity and simplicity are the main advantages of data-driven modelling and it has proven to be much superior to traditional mathematical modelling methods. The rise in data driven modelling has mirrored the rise in the vast sum of manufacturing data being generated due to Industry 4.0 enabling technologies. Cost, computational power, and lack of storage were some of the constraints limiting the use of data driven modelling. However, Industry 4.0 has now given data driven modelling access to the processing power and storage required to handle the volume of manufacturing data. Subsequently, data driven models are becoming prevalent across industry for modelling and monitoring of plant-wide industrial processes. (Fisher, et al., 2020) gives an overview of data driven modelling in the manufacturing industry.

Predictive analytics is the branch of the advanced analytics which is used to make predictions about unknown future events. Predictive modelling is one of the many techniques used in manufacturing for applications such as energy savings implementation and fault detection. Self-learning algorithms underpin data based predictive models which include but not limited to, Regression Analysis; Artificial Neural Networks (ANN); Least Squares Regression and Decision Tree Modelling.

Traditionally, linear regression analysis has been the most popular modelling technique in predicting energy consumption. Linear regression attempts to model the relationship between two variables by

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fitting a linear equation to observed data. The most popular performance metrics used for the regression problems are, root mean square error (RMSE); mean absolute error (MAE) and coefficient of determination (R2).

ANN have grown in popularity with its ability to provide predictive analysis and highly nonlinear modelling accuracy. They are forecasting methods that are based on simple mathematical models of the brain. Decision tree modelling is the model of computation in which an algorithm is a sequence of queries or tests that are done adaptively, so the outcome of the previous tests can influence the test is performed next. A comparison of these models and algorithms when it comes to predicting energy consumption in (Tso & Yau, 2007). An overview of machining energy models for improving the sustainability of machine tools is provided in (Sihag & Sangwan, 2020). CRISP DM (Wirth & Hipp, 2000) offers a structural approach to developing a data driven model. It is the most widely used methodology for developing data driven models and it is considered the standard method in the industry.

Machine learning is another technique used in descriptive analytics that can be broken down into three categories of learning: supervised, unsupervised and reinforcement. In supervised learning the computer program derives a function between the input and the output from a set of labelled training data. Unsupervised learning does not require labelled data. Reinforcement learning deals with the problem of learning the appropriate action or sequence of actions to be taken for a given situation to maximize payoff. Self-learning algorithms are the bedrock of machine learning, (Mahdavinejad, et al., 2018) outlines the frequently used machine learning algorithms in manufacturing. Machine learning is a useful technique when it comes to energy efficiency in manufacturing. (Narciso & Martins, 2020) gives an overview of applications of machine learning tools for energy efficiency in industry and introduces big data and machine learning to enhance the energy saving strategy, in addition, an extensive review of machine learning, and data mining applied in the context of manufacturing can be found in (Dogan & Birant, 2020).

Modelling is a key technique in predictive analysis and many different methods exist in the field. When it comes to energy efficient modelling, the methods such as traditional regression analysis, decision tree and neural networks are more commonly used. Regression analysis remains the most popular used method when it comes to energy prediction. However, the use of alternative analytic methods such as decision tree models, can prove to be more useful and effective as shown from the (Tso & Yau, 2007) case study. It also indicates the importance of comparing and analysing the various modelling methods and not relying on traditional regression analysis when it comes to selecting the most effective method for predicting energy consumption and identifying energy saving measures. Machine tools, such as Computerized Numerical Control (CNC) machining, contribute to a large part of the high emissions outputted in the manufacturing industry and therefore, the analysis of energy consumption by the machine tools and machining processes is primarily important to understand their complex and dynamic energy consumption behaviour. In a review (Sihag & Sangwan, 2020) of machining energy models it has been found that computational self-learning models, such as ANN, support vector machines (SVM) and neural networks (NN) are a much more efficient way to predict and measure energy consumption in machine tools than traditional mathematical based models. Mathematical models involve many physical variables, which makes it more difficult to accurately predict faults. This outlines the growing importance of self-learning data driven models in predicting energy consumption and how the industry is shifting its focus based on self-learning techniques. (Teng, et al., 2021) enforces the point that data driven models are at the forefront of energy saving in manufacturing due to is superiority over other traditional models and its potential possibilities in smart manufacturing.

3.2.2 Digital Twin Platforms

The concept of Digital Twin (DT) has multiple definitions across the literature. Different authors propose different definitions. Thus, it is necessary to establish a common approach to this concept

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within the DENiM project. A review from (Negri, et al., 2017) went through 16 studies and found some common points that all the definitions of Digital Twins have the following characteristics:

i. a monitoring functionality of the physical system through sensors and data logging,
ii. a mirroring of the life of the physical asset,
iii. virtual simulations of the physical system, and
iv. decision-making capabilities for optimisation during design and across the system's lifecycle.

The steps needed to build a functional Digital Twin are outlined in (Tao, et al., 2019), these include:

i. build a virtual representation of a physical product using CAD or 3D modelling
ii. process data to facilitate design decision-making
iii. simulation of physical systems in the virtual environments
iv. test the physical system to calibrate the virtual world
v. establish real-time bi-directional secure connections between physical and cyber system
vi. collect more related data for continuous system integration

DT are being explored for a wide range of applications in manufacturing including maintenance, optimisation, planning and identifying potential energy savings. A review of DT and associated challenges in manufacturing can be found in (Kritzinger, et al., 2018), (Uhlemann, et al., 2017) and (O'Sullivan, et al., 2020). An analysis from (Kritzinger, et al., 2018) revealed the importance of distinguishing between Digital Shadow and DT. The first is defined as a virtual version of the asset with only one data flow from changes in the physical object to updates of the digital twin. However, a Digital Twin must have bi-directional automatic data flow so that decisions made from simulation data can produce automatic adjustments in the real system. Thereby, the Digital Twin is richer in data than the Digital Shadow. Detailed DT started to be used in the industry over a decade ago. The literature considers NASA to be the first to apply a detailed DT in 2010 (Shafto, et al., 2012). It consisted of a physical element with its virtual representation and the corresponding connections for a bidirectional exchange of information. Since then, DTs have experienced tremendous development within the digitalisation trend in manufacturing 4.0. The current trends seem to evolve to the digital enterprise concept as referred to by the big actors in the industry such as Siemens, CSC (DCX technology), Deloitte and Oracle in their latest published whitepapers.

The evolution of the DT concept is highly related and has built on learnings from another digital manufacturing technology called Cyber-Physical Systems (CPS). This term was first used in 2006 by Hellen Filler from the US National Science Foundation to refer to a system in which both a physical component and its virtual counterpart are connected to sensors, controllers, and algorithms. In this way, the physical elements can be automatically monitored and controlled by the virtual side. Outside of their similarities (physical-digital connection, real-time interaction, etc.), CPSs and DTs differ in the level of representation of the assets. Cyber-Physical Systems are mainly focused on control and automation, and the virtual part consists of algorithms, not of digital representations. However, Digital Twins rely on virtual models of the real assets, which can provide simulations on top of real-life data. In this sense, a CPS can be part of a Digital Twin, and in those cases, it is referred to as CPS twinning. Having said that, both CPS and DT concepts are emerging as separated yet related R&D efforts.

Considering a wide variety of different digital and physical assets, a standard digital framework is needed for information and data sharing. This framework can be understood as a DT Platform, an infrastructure containing a set of tools for building and utilising digital twins. There are several interpretations for what can be considered as a DT platform. From the technical point of view, a DT platform involves a set of digital technologies that are used as a base upon which other applications,

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processes or technologies are developed. On the other hand, from the business perspective, a DT platform can be considered as a model that creates value by facilitating exchanges between two or more interdependent groups, usually consumers or producers. Thus, the combined interpretation is that a DT platform is used for data management and information flow, which together are also the source of the added value they create and their competitive advantage.

3.2.2.1 State of Art & Beyond for Digital Twin Platforms

ICT technologies such as big data and analytics, IIoT and cognitive systems have enabled significant advances in different industries as well as the development of DT for improved forecasting and analytics. Nonetheless, the practical application of DT is still in its infancy, and the literature mainly consists of concept papers with few concrete case-studies. Only 18% of them are really describing a DT with a bidirectional data transfer (Kritzinger, et al., 2018). Most of the application focus on manufacturing planning and maintenance (Aivaliotis, et al., 2019). Nonetheless, the presence of commercial software tools to support DT creation demonstrates its importance for the industry with a focus on the acquisition and combination of real-world heterogeneous data. Below, a non-exhaustive list of commercial software that implements industrial DT technology is presented (Damjanovic-Behrendt & Behrendt, 2019):

- **General Electric Digital**: GE developed a DT for their wind turbines with individual configuration capabilities prior to the construction phase. Later, the models were enriched with data from the real devices. The DT is based on the Predix platform. Furthermore, GE released the DT Starter Kit, an open-source toolset designed to teach software engineers in the DT development.

- **Siemens Simcenter** and **Simcenter 3D**: This DT suite contains software of three categories, i) a product DT for the design phase, ii) a production DT representing the factory floor assets that is used during the manufacturing process, iii) a performance DT evaluating big data from IIOT products in smart plants to improve the production systems efficiency.

- **AssetWise Digital Twin Services**: The company Bentley offers services for the creation of DT within their platform AssetWise. Its capabilities include the visualization and analysis of data from multiple sources and formats to support decision making with a digital twin approach.

- **Schneider's Enterprise Asset Performance Management**: From its own documentation: "*Schneider Electric offers an end-to-end solution that manages the collection of data from any number of sources, incorporates advanced analytics technology that combines machine learning with analytic rules and provides a complete enterprise asset management platform to manage asset lifecycle and maintenance processes. It also includes a variety of interactive visualization capabilities for presenting this information in intuitive ways on mobile devices and platforms.*"

- **PTC Windchill**: Product Lifecycle Management software. Windchill is mainly designed for digital product definition and for linking the digital world data to product data.

- **Dassault Systèmes 'Build To Operate':** DT for production used to evaluate "what if" scenarios to address market demands. It connects planning to the shop floor through the use of "virtual twins" for predictive actions.

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- **DXC**: The company uses digital twins for hybrid cards during their entire lifecycle. Their DT uses ML solutions, particularly the Microsoft Cortana Intelligence Suite.

- **Bosch IoT Things**: Platform for managing digital twins. Its applications are able to store and modify data, properties and relationships of the assets. Furthermore, notifications are generated for relevant changes.

- **Microsoft Azure Digital Twins**: Azure DTs is a IoT platform for the generation of digital representations for real-world things. It also includes features like real-time data analytics, connection with the real-world assets data, visualization and predictions of performance.

- **Seebo Digital Twin**: Seebo has a set of Industry 4.0 solutions for Condition Monitoring, Predictive Maintenance, Digital Twin and Smart Factory. Its main application is the prevention of process-based production losses in manufacturing using process-based AI.

- **Autodesk Tandem Digital Twin Platform**: Commercial software for digital twin platform which is focused on architecture, engineering, and construction industry

The open-source community has started developing DTs software, however, only a few solutions are currently available including: Eclipse Ditto; CPS Twinning; Equinox and ScaleOut DigitalTwin Builder. The following provides a summary of the existing EU Initiatives involving DT that are relevant to the DENiM approach:

SPHERE – Service platform to host and share residential data, (2018 – 2022)
SPHERE aims to provide a BIM-based Digital Twin Platform to optimise the building lifecycle, reduce costs and improve energy efficiency in residential buildings. SPHERE will provide a set of tools and services integrated in a platform based on BIM models facing construction projects.
COGITO – Construction-phase digital twin model, (2020 – 2023)
COGITO proposes a digital construction 4.0 toolbox that harmonises Digital Twins with the building information model concept to allow a semantic and pragmatic alignment between novel data capture techniques and value-adding end-user services.
IoTwins – Distributed digital twins for industrial SMEs: a big-data platform, (2019 – 2022)
IoTwins project plans to build testbeds for digital twins in the manufacturing and facility management sectors. The digital models will integrate data from various sources such as data APIs, historical data, embedded sensors and open data.
DUET – Digital urban European twins for smarter decision making, (2019 – 2022)
DUET project is leveraging the advanced capabilities of cloud and high-performance computing to evolve the traditional public policymaking cycle using large open-data sources. The use of digital twins will make it easier for city managers to react quickly to real-time events and ensure long-term policy decisions are more effective and trusted.
Ashvin – Assistants for healthy, safe, and productive virtual construction design, operation & maintenance using a digital twin, (2020 – 2023)
Ashvin project will establish an open-source digital twin platform integrating IoT and image technologies for a European digital twin standard. The project will deliver instruments and demonstrate procedures of platform applications to guarantee improvements in the construction industry that will optimise and increase productivity, reduce costs, and ensure safe work conditions and privacy.
iDev40 – Integrated development 4.0, (2018 – 2021)
iDev40 project aims at suitable digital technology advancements to strengthen the electronic components and systems industry in Europe. It addresses various industrial domains with one and

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the same approach of digitalisation towards competitive and innovative solutions. The concept introduces seamlessly integrated development together with automation and network solutions as well as enhancing the transparency of data, consistence, flexibility and overall efficiency that leads to a significant speedup in the time to market race.
Edge Twins HPC – Bringing digital twins to the edge for mass Industry 4.0 applications, (2020 – 2021)
Edge Twins HPC project will develop an open-source software tool to produce digital twins that are installed on the physical asset they represent and operate in very constrained compute environments. The aim will be to facilitate a new breed of novel real-time applications – from autonomous vehicles to small devices.
COMPOSITION – Ecosystem for collaborative manufacturing processes – intra- and inter-factory integration and automation, (2016 – 2019)
The goal of COMPOSITION was to develop an integrated information management system (IIMS) which optimises the internal production processes by exploiting existing data, knowledge and tools to increase productivity and dynamically adapt to changing market requirements.
MAESTRI – Energy and resource management systems for improved efficiency in the process industries, (2015 – 2019)
Aim of the MAESTRI project was to advance the sustainability of European manufacturing and process industries by providing a management system in the form of a flexible and scalable platform. Platform was based on IoT approaches to share and integrate re-sources information among heterogeneous platforms, systems and sub-systems.
COCOP – Coordinating optimisation of complex industrial processes, (2016 – 2020)
The objective in COCOP was to enable plant-wide monitoring and control by using the model-based, predictive, coordinating optimisation concept in integration with plant's automation systems. Especially design and implement of efficient data management and optimisation methods to monitor and control large industrial production processes was investigated.
Modelling Factory – Collaborative modelling, simulation and decision making through shared modelling factory, (2016 – 2018)
Modelling Factory is a virtual working space, where individuals and organisations can test and share their ideas on how to advance material efficiency and sustainable circular economy by creating different types of computational models and design solutions and validating them against measured and simulated data.
Productive 4.0 – Electronics and ICT as enabler for digital industry and optimized supply chain management covering the entire product lifecycle, (2017 – 2020)
The aim of the Productive 4.0 innovation and lighthouse program was to create a user platform across value chains and industries, thus promoting the digital networking of manufacturing companies, production machines and products. Optimization of industrial processes using a scalable platform to support plant wide capturing of data from device and system configuration and production operations was one the central themes.
FAR-EDGE – Factory automation edge computing operating system reference implementation, (2016 – 2019)
FAR-EDGE is a joint effort of leading experts in manufacturing, industrial automation and future internet technologies towards the smooth and wider adoption of virtualized factory automation solutions based on future internet technologies. It provides the reference implementation architecture (RAMI4.0, ICC) along with simulation services for validating automation architectures and production scheduling scenarios.
knowlEdge – Towards AI powered manufacturing services, processes, and products in an edge-to-cloud-knowlEdge continuum for humans [in-the-loop], (2021 – 2023)
knowlEdge project will address the need for new AI solutions that are agile, reusable, distributed, scalable, accountable, secure, standardised and collaborative. The proposed new framework will

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ensure the secure management of distributed data and facilitate knowledge exchange. To achieve its goal, the project will combine innovative technologies from data management, data analytics and knowledge management.

3.2.3 Sustainability Assessment (LCA, LCCA)

Sustainability is a growing concern for manufacturing companies, however, one of the main challenge's organizations are facing is understanding the cause-and-effect relationships between critical indicators of sustainable manufacturing. To overcome this problem several indicators-based frameworks have been developed (Bhanot, et al., 2020). Indicators are vital to define sustainable development, these are typically numerical measures that provide quantitative information going beyond simple data to show trends or cause-and-effect relationships. Currently, several tools, assessment methods and indicators exist, but they differ in their goal and scope and are intended for various uses and stakeholders such as companies, consumers, or authorities to support policy planning and evaluation. Additionally, different tools are focused on different levels of assessment: product, company, industry or society. An analysis carried out by the recently concluded SAMT project analysed an extensive set of methods and tools suitable to assess sustainability impacts of a production process. An analysis of existing methodologies has been carried out in the SAM project (Marzio Sorlini, 2014) and identified a broad range of tools covering lifecycle, hybrid and integrated methods. The tools and methods analysed provide a set of instructions describing how to calculate a set of indicators, or artefact that assists with the implementation of these instructions as such they rely heavily on the validity of the indicators utilised. (Bhanot, et al., 2020) revealed that most of the sustainability-related frameworks in the manufacturing literature were primarily focused at product level with limited attention to processes. However, a growing number of authors have been integrating multiple level-based analysis for addressing sustainability within companies (Jenny, et al., 2019); (Schmidt, et al., 2016). Furthermore, another relevant classification consists of the difference between product and corporate indicators. While the former are mainly used to communicate the environmentally sustainable performances to stakeholders (usually through labels), the latter are used to inform the public about the impacts of firms' activities regarding their contribution to environmental protection areas, social development and economic sustainability. The following sections provide an overview of the most widely adopted sustainability indicators to assess products' and processes sustainability is provided. Considering the scope of the DENiM project, an emphasis will be placed on energy performance indicators, however, to ensure a holistic approach that promotes sustainability an overview of environmental, economic and social indicators is provided.

3.2.3.1 Energy Performance Indicators

One of the major success factors in energy management in manufacturing industries is the implementation of effective energy performance indicators (EnPIs) that enables comparison between systems and provides historical data analysis to support decision-making workflows. According to literature EnPIs can be divided into 3 categories: consumption, efficiency and renewability (Andersson & Thollander, 2019); (MAY, et al., 2013); (Mayer, et al., 2020).

Consumption incorporates a set of indicators for the evaluation of energy consumption within a manufacturing company (Andersson & Thollander, 2019). Indicators such as *cumulative energy demand*, *non-renewable cumulative energy demand*, *fossil-based energy use*, *primary fossil use* and *secondary energy use* are typically utilised for life cycle assessment. Further analysis carried out by (Mayer, et al., 2020) discusses the previous set identifying gaps and suggesting the use of *net energy indicator* to calculate losses within the system under study. The authors also introduce *specific energy consumption* indicator, which is one of the most used and standardized EnPI for measuring energy consumption based on a normalization factor. Similarly, (Shim & Lee, 2018) discuss the importance of measuring energy related to each company subsystems to have a more structured overview at an

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organizational level. (Yi, et al., 2020) highlighted the relevance of evaluating losses within a process system by measuring the *energy waste per task* and *specific output net energy*. Regarding energy efficiency (Coroiu & M. Chindris, 2014) and (Wu & Chen, 2007) introduce respectively *energy saving potential* and *energy savings* to assess the relation between energy performances and best practices. The first also highlight the importance of *energy intensity* indicator for measuring energy efficiency from an economic point of view. Research carried out by (Perroni, et al., 2018) discuss energy efficiency within a process system considering the ratio between output and input energy used.

(Thiede, 2012) explains how the term “energy efficiency” has different meaning depending on the context. He showed that in manufacturing it is defined as the ability to produce the same quantity while consuming less energy. The author thus introduces the *energy efficiency* indicator for measuring the yield of each kWh of energy consumed. In relation to energy renewability indicators (Mayer, et al., 2020) introduces the *renewable factor* as a metric from measuring renewability of a process. Even though this is still an open topic in the literature many authors consider this to be , in manufacturing contexts, the indicator used to calculate the renewability of a given system and is generally expressed as the ratio between renewable energy in input and the energy consumed within a process or company (Arvidsson, et al., n.d.); (Mayer, et al., 2020); (Cîrstea, et al., 2018).

3.2.3.2 Environmental Performance Indicators

Environmental impact is the core of sustainability dimension and represents the ability to safeguard the reproducibility of natural resources and preserve fundamental functions of the environment over time. Hence, it encompasses the fundamental role of natural resources and their use, and the reduction of non-renewable resource and material degradation of nature and natural processes. To achieve sustainable targets and goals companies have to base their strategies on Key Performance Indicators (KPIs). Based on several papers analysed, the most used indicators fall into the following four categories: (1) gas emissions, (2) renewable resources, (3) resource consumption and (4) waste (Hristov & Chirico, 2019); (Zarte, et al., 2019); (Fan, et al., 2010); (Winroth, et al., 2012); (Pavláková Dočekalová & Kocmanová, 2016).

According to this classification different sets of KPIs have been developed in the literature. Regarding gas emissions several authors define the *air emission* or *GHG emissions indicator*, measured in eq. kg of CO_2, as the reference KPI for assessing the amount of pollution in the air (Amrina & Lutfia Vilsi, 2015) (Hristov & Chirico, 2019); (Patil & Javalagi, 2020); (Zarte, et al., 2019). More in-depth analyses introduce indicators such as *emission of ozone-depleting substances* and *emissions causing acid rain* respectively measured in kg or m^3 of ozone depleting substances and kg or m^3 of emission of NO_x, taking into consideration the harmfulness of gases relating these to the mid-point impact categories during the Life Cycle Impact Assessment (LCIA) analysis (Fan, et al., 2010); (Winroth, et al., 2012); (Pavláková Dočekalová & Kocmanová, 2016); (Kocmanová, et al., 2017).

Different indicators to evaluate the use of renewable resources have been developed in the literature. Usually measured in %, kg, m3 or even kWh over a normalization factor, these indicators allow to better understand what resources are used and how they are managed within a company. In terms of energy usage different authors introduce the *renewable energy use* indicator that, measured in kWh/nf[4], represents the portion of renewable energy used over the total (Winroth, et al., 2012); (Park & Kremer, 2017); (Patil & Javalagi, 2020). In terms of material usage, more authors introduce the *percentage of renewable material* as an indicator for assessing renewability of material resource consumption (Linke, et al., 2013); (Zarte, et al., 2019).

One of the most important aspects manufacturing companies are dealing with is how to effectively measure resource consumption in terms of energy, water, land and material usage. A first overview

[4] Most of the indicators previously cited need a normalization factor(nf) to compare different systems.

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of resource consumption indicators is provided by (Amrina & Lutfia Vilsi, 2015), (Patil & Javalagi, 2020) and (Zarte, et al., 2019). Based on the Organization for Economic Co-operation and Development (OECD) they identify a list of KPIs that includes *energy intensity* and *water intensity* respectively measured in kWh/nf and m^3/nf, and *land use* indicator which, measured in m^2, allows to evaluate of the amount of soil removed from the natural environment by the plant. In terms of energy use (Akbar & Irohara, 2018) provide a more complete list of indicators introducing aspects such as *energy efficiency* and *energy savings*.

Regarding material usage, further analysis presented by (Winroth, et al., 2012) introduce other indicators such as *material usage*, measured in kg or m3 per unit, *scrap rate*, rate of packaging material and *use of process additives* measured in % of material usage. In the same context, (Park & Kremer, 2017), introduces the concept of Resource productivity, resource efficiency and resource sustainability.

According to the papers analysed a short list of indicators has been provided to assess wastes within a manufacturing company. Several authors introduce as one the most common indicator the *total production waste* that, measured in tonnes over a normalization factor, allows the quantification of the total wastes of a system (Zarte, et al., 2019); (Akbar & Irohara, 2018); (Winroth, et al., 2012). In addition, another common indicator introduced by (Dočekalová & Kocmanová, 2016) is the *weight of hazardous waste* that is measured in kg or m^3 of hazardous waste.

3.2.3.2.1 Social Performance Indicators

Social performance indicator provides a sustainability dimension to represent the capacity of providing for citizens' welfare with equal distribution among different classes. Many researchers have discussed the role of social indicators to address social performance value. (Saka & Oshika, 2014) highlighted the relevance of social indicators in the value creation process. (Amrina & Lutfia Vilsi, 2015) provides empirical evidence of the importance *of occupational health and safety* indicator in manufacturing companies. (Patil & Javalagi, 2020) shows the relevance of *training & education* within an organization. (Linke, et al., 2013) discussed how the indicator *labour intensity,* which accounts for the number of worker hours needed per normalisation factor, effects the productivity. (Zarte, et al., 2019) explains the importance of work environment for employees and time of training. (Akbar & Irohara, 2018) provides a list of updated social indicators divided into three categories: (1) community, (2) customer and (3) employee. (Kravchenko, et al., 2019) discussed the tradition of the manufacturing sector of concentrating social performance measurements on "inside-out" social aspects. (Fan, et al., 2010) highlight how social impacts is considered a controversial area due to the results of questionnaires showing almost every social indicator as not used and not important in different companies. As for the environmental dimension, according to (Hristov & Chirico, 2019) all social indicators selected from literature have been divided into the following strategic goals: (1) to encourage employees to accept cultural change, (2) to improve the quality of work conditions, (3) to guarantee respect for human rights and (4) to participate in social initiatives.

3.2.3.2.2 Economic Performance Indicators

In the manufacturing sector there is a strong need to create indicators able to both support decision making and control performance of enterprises. According to (Linke, et al., 2013) indicators rarely have the same relevance for the user and the company. Companies might also put more weight on economic aspects rather than environmental and social sustainability. Survey-based statistical analysis made by (Amrina & Lutfia Vilsi, 2015) highlights how economic sustainability is the most important among the triple bottom line (social, environmental & economical). They also identify the *inventory cost* indicator as the most important within the economic category. Similarly, (Patil & Javalagi, 2020) confirms the economic sustainability being the most important aspect from companies' point of view. In this case, they identify *profitability* as the most important indicator within the economic category.

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(Akbar & Irohara, 2018) provides an updated list of economic KPIs divided into financial performance, delivery reliability and manufacturing cost. (Kravchenko, et al., 2019) discusses the most prevalent economic aspects in corporate reporting, providing a set of economic KPIs distributed according to business processes. Global Reporting Initiative (GRI) guidelines (Winroth, et al., 2012) developed a set of economic indicators to be integrated on a factory level to communicate economic performances. In conclusion, the respect for the economic dimension is guaranteed by ISO 9001 and UNE 166002, which allow the quality of financial and economic performance to be certified. Company certification has a direct influence on its performance and management, this allows companies to have better reputations and improves relationships with stakeholders.

3.2.3.2.3 Circularity Indicators

For what concerns the transition to circular economy (CE), the state of art still shows a lack of research on indicators to measure the adoption of the CE paradigm, especially at micro level. According to (De Pascale, et al., 2021), an overview of circular economy indices in literature is provided. (Ellen MacArthur Foundation and Granta Design, 2015) introduces Material Circularity Indicator (MCI) which focuses on the restoration of material flows at product and company level. (Huysman, et al., 2017) explains the relationship between the actual obtained environmental benefit and the ideal one, defining Circular Economy Performance Indicator (CEPI). (Di Maio, et al., 2017) conduct research regarding the value of resources introducing the Value-based Resource Efficiency Indicator which estimate resource efficiency and circularity. Finally, (Adibi, et al., 2017) introduce the Global Resource Indicator that considers quantitative variables (scarcity and recyclability) as well as qualitative variable (geopolitically availability). For energy efficiency, (Elia, et al., 2017) reports energy assessment methodologies are mainly focused on energy usage and resource consumption, including renewable and not, at product and process level. (Huijbregts, et al., 2017) introduces Cumulative Energy Demand (CED) as an indicator for the evaluation of a system based on the estimation of direct and indirect energy use throughout its life cycle. (Dixit, et al., 2010) explains the importance of Embodied Energy (EE) for measuring the quantity of non-renewable energy. (Brown & Ugliati, 2004) defines EMergy Analysis for assessing energy of one kind that is used up in transformation directly and indirectly to obtain a product or service. Finally, (Apaiah, et al., 2006) establishes the EXergy Analysis as an indicator of energy quantity and quality, explaining it can be useful to identify energy inefficiencies in a process.

3.2.3.3 Life Cycle Cost Analysis

Life cycle cost analysis (LCCA) is a process to determine the sum of all expenses associated with a product, process, sub-process, or project, including acquisition and all associated costs, operation, and maintenance (O&M), refurbishment and retirement costs. The definition of lifecycle costing (LCC), as quoted from the IEC standard on Life cycle costing (IEC 60300-3-3:2017), is:

> *"Life cycle costing (LCC) is the process of performing an economic analysis to assess the cost of an item over a portion, or all, of its life cycle in order to make decisions that will minimise the total cost of ownership while still meeting stakeholder requirements".*

As the lifetime of a manufacturing system could be traverse several decades, operating and maintenance costs can end up being several times higher than the original acquisition price. In practice, the acquisition costs are often visible as they relate to purchasing assets. Therefore, they are commonly emphasized in decision-making. This problem is often visualized using the well-known "LCC iceberg", which highlights that the acquisition cost is only a small part of the total cost of ownership. (Figure 4).

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Figure 4. The LCC Iceberg model.

A typical case for LCC calculation is a decision-making situation where the aim is to select an optimal alternative among different options. By considering life cycle costs, decision makers have a better opportunity of optimizing the total cost of ownership and achieving better profitability in the long term. The costs over the lifetime of the solution are discounted to current values. Typically, the main potential for life cycle cost savings in manufacturing systems and processes are on the use of energy, water, and fuel, on the maintenance and replacement and on the disposal costs.

3.2.3.3.1 Key LCC Standards

There is an array of standards for assessing life cycle costs available. The following provides a non-exhaustive list of key international standards, which provide companies and their stakeholders with a means to develop strategies and solutions designed to reduce the life cycle cost of manufacturing systems.

- Standard for general use IEC 60300-3-3: 2017: Lifecycle costing for technological systems
- Standard for construction sector ISO 15686-5:2017 Buildings and constructed assets — Service life planning — Part 5: Life-cycle costing
- ISO 15663-1:2000: Petroleum and natural gas industries — Life cycle costing
    - Part 1 (2000): Methodology, Part 2 (2001): Guidance on application of methodology and calculation methods, Part 3 (2001): Implementation guidelines
- ASTM F1675 - 13(2017): Standard Practice for Life-Cycle Cost Analysis of Plastic Pipe Used for Culverts, Storm Sewers, and Other Buried Conduits

In industrial applications concerning the technological systems, LCC typically follows the process presented in the IEC 60300-3-3:2017 and it consists of five main steps (Figure 5).

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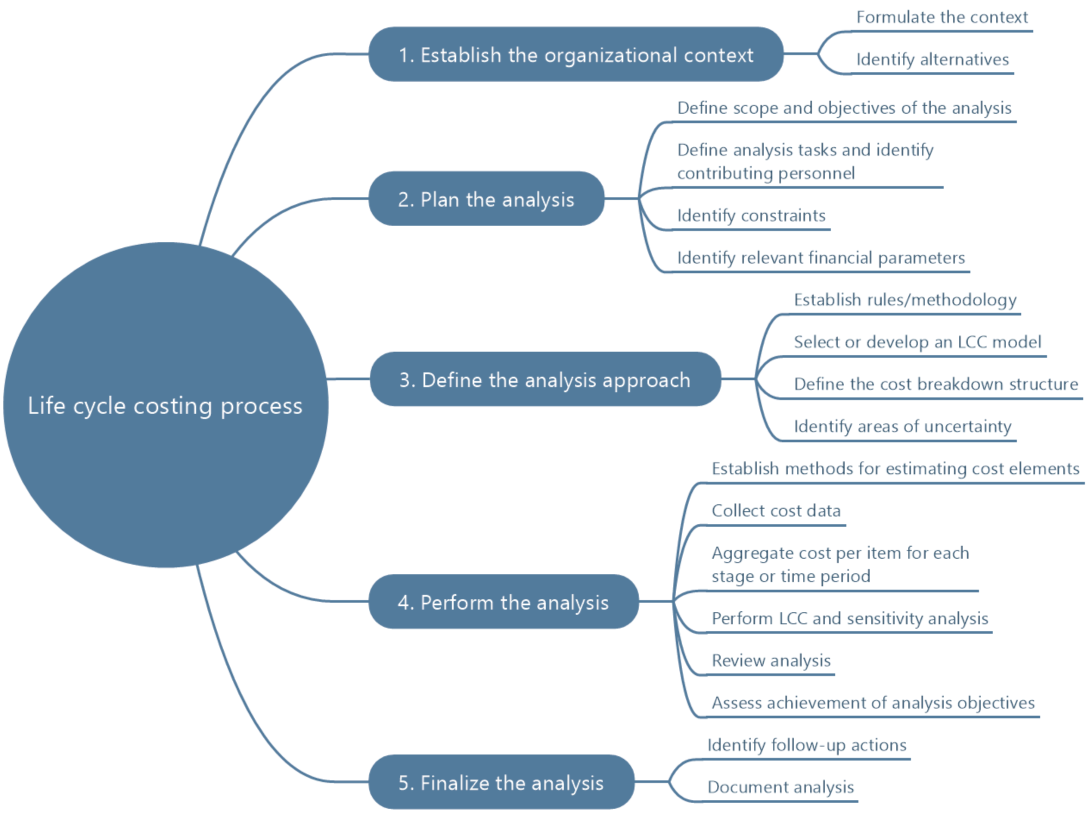

Figure 5. Life cycle costing process according to the IEC 60300-3-3:2017.

3.2.3.3.2 LCCA Key Performance Indicators

The results of LCCA can be characterized by KPIs. The list below gives the overview of the indicators which support judging and decision making with respect to economic and cost impacts of industrial energy management and the cost savings potential related to energy efficient production and production assets.

- **Total life cycle costs and cost savings** are the sum of discounted costs and cost savings for the calculation period (lifetime).
- **Net Present Value (NPV).** NPV is the difference between the present value of cash inflows and the present value of cash outflows.
- **Present Value of Benefits (PVB), Present Value of Costs (PVC)** is the estimated current value of a future amount to be received or paid out, discounted at the specified discount rate.
- **Benefit Cost Ratio (BCR)** is a ratio attempting to identify the relationship between the cost and benefits of analysis options. BCR is calculated as the NPV of benefits divided by the NPV of costs where BCR >1 is good.
- **Internal Rate of return (IRR) (%)** is the discount rate resulting NPV=0. The higher the IRR, the better the solution is according to CBA.
- **Pay Back Period (years)** is the length of time required to recover the cost of analysed solutions. The shorter the pay-back time, the better the solution is. The costs and benefits are not discounted.

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- **Discounted Pay Back Period (years)** is the amount of time that it takes to cover the cost of analysis options, by adding positive discounted cash flow coming from the benefits of the implementation. The shorter the pay-back time, the better the solution is.

In practise, the definition of economic and cost related KPIs should be done hierarchically. LCCA is typically based on cost breakdown structure (CBS) that is a representation of costs related to the case in question and divides a rather abstract life cycle cost in to more concrete and thus more easily estimated cost elements. The hierarchical way to define cost structure promotes recognition of all relevant cost elements. Finally, the breakdown of the cost elements into lower cost items is needed to be able to make the calculations.

3.2.3.3.3 Differences Between LCCA and LCA

To deal with financial, environmental, and social concerns, four LCC types have been introduced (Hoogmartens, et al., 2014):

- *financial LCC (fLCC).* Conventional LCC assessment that only focus on private investments from one actor is categorized as financial LCC (fLCC). Only costs borne by the actor matter, and environmental costs or external end-of-life costs are omitted. fLCC does not always consider the complete life cycle as only the economic lifetime matters.
- *environmental LCC (eLCC).* An Environmental LCC (eLCC) builds upon data of fLCC and extends it to life cycle costs borne by other actors. The full life cycle of a product is considered. The focus remains on real cash flows that are internalized or expected to be internalized. There is no conversion from environmental emissions to monetary measures.
- *full environmental LCC (feLCC).* The full environmental LCC (feLCC) is not a commonly accepted sustainability assessment tool. feLCC extends eLCC with monetized, non-internalized environmental costs that can be identified by an environmental assessment method.
- *societal LCC (sLCC)*. In Societal LCC (sLCC) all costs borne by anyone in society, whether today or in the future, and associated with the life cycle of a product are considered.

These concepts should not be confused with LCA that is internationally standardised in ISO 14040 and 14044. The environmental LCA does not address the economic elements of the product, system, service life cycle, which are the main focus of LCC (Estevan & Schaefer, 2017). Market prices do not reflect environmental and social values. Therefore, fLCC or eLCC cannot cover all environmental impacts associated with a product. LCC only covers environmental and societal costs that have been internalized into the economy. In addition, these costs must be assigned to specific actors directly associated with products or solution's lifetime (Kambanou & Sakao, 2020).

Both LCA and LCC belong to the family of life cycle tools. There are, however, major differences among them which create challenges on adopting an integrated method for LCC and LCA analysis (Miah, et al., 2017). The main differences are presented in Table 4.

Table 4. Differences between LCC and LCA (adopted from Miah et al. 2017)

Characteristics	LCC	LCA
Purpose	To evaluate cost-effectiveness of business decisions and alternative investments	To systematically evaluate the environmental impacts of products and processes
Scope	Only direct costs and/or benefits incurred during the life cycle of an investment	Full system boundary covering cradle-to-grave

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Modelling feature	Primarily based on quasi-dynamic models. Steady-state models can be used.	Primarily based on steady-state models
Flows considered	Monetary flows representing direct costs and benefits impacting the decision maker	Material and energy flows including pollutants
Units for tracking flows	Monetary units	Primarily mass and energy
Time treatment	Adjusting cost over a time horizon is critical to reflect cost evolution and risks. Different discounting techniques are used, e.g Net Present Value	The consideration of time on environmental impacts is ignored, especially discounting for future impacts. Some environmental impacts are presented as fixed time.
Aggregation	Most LCC's use discount rates to aggregate different costs.	Future environmental impacts are generally not discounted in the results
Allocation	Allocation is based on economic flows	Common allocation techniques are based on mass or energy flows

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Examples of Use Cases and Tools

The European Commission has developed a series of sector specific LCC calculation tools which aim to facilitate the use of LCC amongst public procurers. (European Commission, no date). LCC is being applied by an increasing number of public authorities across the EU and in a range of sectors. Under the 2014 EU procurement rules a contract must be awarded based on the most economically advantageous tender. Cost or price will form part of the assessment of any procedure and is usually one of the most influential factors. Costs may be calculated based on a product's life cycle. Further details on how LCC approaches can be used as part of public procurement procedures are presented in the Article 68(2) of Directive 2014/24/EU and Article 83(2) of Directive 2014/25/EU.

- **SMART SPP** – innovation through sustainable procurement was a three-year European project which promoted the introduction of new, innovative low carbon emission technologies and integrated solutions onto the European market. The project has published guidelines for public authorities for driving energy efficient innovation through procurement (Clement, et al., 2011). The project has published a MS Excel based SMART SPP LCC-CO2 Tool for calculating the life cycle costs and CO_2 emission of various products and services to assist in procurement decision making. The tool is available for download at https://www.smart-spp.eu/. In addition, accompanying guidance for using the tool has been published (Adell, et al., 2011).
- **The Clean Fleets** EU project has developed an LCC tool which directly combines a standard total cost of ownership calculation with the operational lifetime cost (OLC) methodology from the Clean Vehicles Directive. This is available on the Clean Fleets website: www.clean-fleets.eu (Clean Fleets , 2014).
- **Sustainable Construction and Innovation Through Procurement** (SCI-Network) has published a guide for European authorities. This guide includes a section on the use of LCC in construction projects (Clement, et al., 2012)
- **German Environment Agency** (Umweltbundesamt – UBA) has published tools for calculating LCC in procurement decision making. The general Excel tool of the German Environment Agency can be used to assess up to five different procurement options. It considers all essential cost categories, such as cost of acquisition, operating costs and costs of disposal. A product-group specific Excel tool of the German Environment Agency aids in the calculation of life cycle costs of computers, multi-functional devices, monitors, computing centres, floor coverings, refrigerators and dishwashers. (Umweltbundesamt, 2017)
- **CRAVEzero** Horizon 2020 project has published a repository of LCC calculation tools (Pernetti, et al., 2018).

Table 5. Overview of LCC tools (modified from Pernetti et al. 2018)

Tool	Developer	License	Perspective
LCC tool for procurement	Swedish national agency for public procurement	Free (available in Swedish)	Contracting authorities, suppliers
SMART SPP LCC-CO_2	SMART SPP consortium	Free	Contracting authorities, suppliers
Gabi	Sphera Solutions GmbH	Free 30-day trial	Designers
OpenLCA - Life Cycle Costing module	Greendelta	Free	Designers

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LCC tools developed by the EC	European Commission	Free	Contracting authorities, suppliers
CRAVEzero Life Cycle Cost Tool	CRAVEzero project	Free (web-tool and MS Excel)	Designers
Econ Calc	Energy Institute of Vorarlberg	Free (available in German)	Designers
General and product-group specific LCC tools	German Environment Agency	Free (available in German)	Contracting authorities, suppliers
LEGEP-Lebenszykluskosten	LEGEP Software	Free trial	Designers
RETScreen Expert	Government of Canada	Advanced premium version of the software, is available in Viewer mode free-of-charge.	Designers
BLCC5	National Institute of Standards and Technology (NIST	Free	Designers
Harvard LCC	Harvard University	Free	Designers

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3.2.3.4 Data for LCCA

The realisation of a robust assessment methodology (such as LCA, LCCA) requires current and accurate data necessary to create a knowledge base to support the calculation of the lifecycle impacts to be assessed. Both quantitative and qualitative data could be used, but for monetary valuation, quantitative data is a necessity. Quality of data is important, without accurate data quality, the reliability of value assessment results is inadequate and poor.

However, despite advances in (open source/free) databases and software platforms supporting the gathering and calculation of these parameters, the procedure of evaluating a detailed and transparent performance assessment is still remarkably labour intensive and time-consuming. Moreover, the complexity associated with data acquisition, organisation and integration with assessment tools becomes exponential with the extension of the value network boundaries. Additional challenges with current assessment methodologies include but are not limited to (Barni, et al., 2018):

(i) complexity of assessment methodologies does not enable companies to directly apply them, but often require the support of consultancy companies in the set-up and maintenance of studies with related costs and timings;
(ii) need of a strong rework of the acquired data due to the different possible levels of focus to be applied in the assessment approach;
(iii) limited or no visibility on supply network data mostly deriving by the complexity associated with data retrieving;
(iv) an increasing number of stakeholders to be mapped in the aim of assessing a complete value network.

The integration of digital technologies can have a relevant impact in streamlining the assessment process by enabling the collection of real-time data (e.g. energy and carbon input/outputs) associated with objects via network of sensors, that can make sustainability assessment much more precise and automated compared with today's conventional methods (Tao, et al., 2014). The integrated evaluation of environmental, social, and economic positive and negative impacts goes towards a Life Cycle Sustainability Assessment (LCSA) approach (Finkbeiner, et al., 2010).

(Kambanou & Sakao, 2020) have developed a guideline based on LCC to help companies to select and implement circular measures and to help them understand the financial outcomes. Based on case study research and literature review they present strengths, limitations, and considerations for using LCC in circular decision-making, and is shown in Table 6.

Table 6. Strengths. limitations and considerations of using LCC in circular decision making (adopted from Kambanou and Sakao 2020).

Scope	Strengths	Limitations	Considerations
Relevance	Suited to product or functional unit level decision-making Familiar monetary metric Broadens decision makers perspective	Only valid on micro level	fLCC for simplicity or eLCC for a comprehensive view of the life cycle As an assessment method needs to be part of a framework or a guideline

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	eLCC has a life cycle perspective and helps avoid burden shifting		
Implementation	Low to medium complexity Limits knowledge and time input Availability of data	Other stakeholder data hard to obtain Need to build cost models Uncertain discount rates	Discounting rates vs steady state
Financial aspects and profitability	Assessment of profitability if alternatives are functionally equivalent and of equal value Focus on costs that can be influenced (fLCC)	Uncertainty attached to calculations	Revenues and customer costs may need to be included if alternatives are not functionally equivalent and of equal value Profit maximization vs profit optimization
Environmental impacts	Can be used with LCA	Cannot comprehensively cover environmental impacts e.g., due to market and information failures	The offering's physical characteristics e.g., durability determine the CE measures that are applicable
Circularity performance	Indicator of material reduction in comparative context (eLCC) Employment indicator Includes labour costs Identification of cost barriers to CE measures e.g. post use transport	Upstream costs are not detailed Only relevant for comparison of alternatives fLCC cannot be a measure of circularity performance due to burden shifting	Categorization required to promote cost exchangeability of materials and energy costs with labour costs

3.2.4 Standards, Certification and Audit Methodologies for Energy Efficiency in Industry

European policies for energy efficiency in general and specifically relevant to the industrial sector along with the standards which formalise operating procedures stem from European Directive 2012/27. Member states have transposed EN 2012/27 into national regulations. In addition, several standards have been developed and updated during the last decade with the aim being to harmonise the processes and compare the performances. Concerning energy auditing in industrial settings, different standards can be considered depending on the level of the interventions, in general the following must be considered:

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- EN 16247[5]-1: 2012 Energy audits - Part 1: General requirements
- EN 16247-2: 2014 Energy audits - Part 2: Buildings
- EN 16247-3: 2014 Energy audits - Part 3: Processes
- EN 16247-4: 2014 Energy audits - Part 4: Transport
- EN 16247-5: 2015 - Energy audits - Part 5: Competence of energy auditors
- EN ISO 50001[6]: 2011 Energy management systems - Requirements and guidelines for use
- EN ISO 50002[7]: 2014 - Energy audits - Requirements with guidance for use
- EN ISO 14001[8]: 2004 Environmental management systems - requirements and guide for use
- EN 16212: 2012[9] Calculations of savings and energy efficiency – Top-down methods (descending) and bottom-up (ascending)
- EN 16231: 2012[10] Energy efficiency benchmarking methodology

This chapter presents an overview of the main aspects of the important steps necessary to improve an energy audit that will be utilised in the context of the DENiM pilots to formalise the energy assessment process and promote the use of existing standards.

3.2.4.1 Energy Efficiency Directive 2012/27/EU

Energy Efficiency Directive (EED) 2012/27/EU[11], is the main European legislative act that establishes a common framework of measures and targets in terms of energy saving and Green House Gases (GHG) reduction and sets binding measures to help in achieving targets for Members States. EU countries are required to use energy more efficiently at all stages of the energy chain, including energy generation, transmission, distribution and end-use consumption.

The goal defined in the 2012 was 20% of energy saving with respect to the overall consumption measured in the 2007. In terms of energy, it means an overall consumption equivalent to around 1483 million tonnes of oil. In 2018, under the Clean Energy for all Europeans package, the EU has set binding targets of at least 32.5% energy efficiency by 2030 (1128 Mtoe considering the UK exit from the EU). Under the amended directive, EU countries will have to achieve additional energy savings of 0.8% each year for the 2021-2030 period. A possible upward revision was set for the 2023 due to potential energy efficiency cost reductions and technological development, but the economic restriction due to the COVID19 situation will need to be considered. The European climate ambition increases again as part of the European Green Deal and aims to transform the EU into the first climate-neutral continent by 2050. This will drive a review of legislation to meet the 2030 GHG emission target including the EED.

The key article for energy efficiency in the industrial sectors is the Article 8. It requires Member States to implement mandatory energy audits for large enterprises and to safeguard the availability of audits for SMEs by the end of 2015. Therefore, it makes a distinction for obliged subjects (energy intensive subjects and large enterprises), define the key figures (qualified editors) and defines the procedures and the reference tools:

[5] The European Standards of the EN 16247 series for Energy Audits https://www.cencenelec.eu/News/Press_Releases/Pages/PR-2015-06.aspx

[6] ISO 50001 Energy Management https://www.iso.org/iso-50001-energy-management.html

[7] ISO 50002:2014 Energy audits — Requirements with guidance for usehttps://www.iso.org/standard/60088.html

[8] ISO 14001 Environmental Management https://www.nsai.ie/certification/management-systems/iso-14001-environmental-management/

[9] Energy Efficiency and Savings Calculation, Top-down and Bottom-up Methodshttps://www.en-standard.eu/bs-en-16212-2012-energy-efficiency-and-savings-calculation-top-down-and-bottom-up-methods/

[10]Energy efficiency benchmarking methodology https://standards.cen.eu/dyn/www/f?p=204:110:0::::FSP_PROJECT:34105&cs=16431317A08F15A67C5804E1917CBC0C3

[11] *Guidance note on Directive 2012/27/EU https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32012L0027&from=EN*

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Article 8.1: An 'energy audit' means a systematic procedure with the purpose of obtaining adequate knowledge of the energy consumption profile of a building or group of buildings, an industrial or commercial operation or installation or a private or public service, identifying and quantifying cost-effective energy saving opportunities, and reporting the findings; [Guidance note on Directive 2012/27/EU].
Article 8.2: The energy audits are an essential tool to achieve energy savings. They are necessary to assess the existing energy consumption and identify the whole range of opportunities to save energy [Guidance note on Directive 2012/27/EU].

An energy audit is a technical report drawn up by an accredited expert (article 8.16), that collects information from buildings and the processes that contribute to the existing energy consumption (electricity and thermal energy). It aims to identify and assess the range of opportunities to save energy. In this way, energy audits tackle the information gap, which is one of the main barriers to energy efficiency.

Article 8 clearly defines the role of the member states in the energy audit development process in national legislation. For this purpose, member states must activate promotional campaigns carried out in an independent manner and by qualified expert under the national legislation. The energy audit process is defined in the European normative EN 16247.

3.2.4.2 EN 16247 – Energy Audit

EN 16247 is a European Standards that specify the requirements, common methodology and deliverables for an energy audit process. It applies to all forms of establishments and organisations. The standard is divided into 5 parts: (i) General Requirements, (ii) Buildings, (iii) Processes, (iv) Transport, and (v) Competence of energy auditors. The standard applies to commercial, industrial, residential and public-sector organisations. EN 16247 part 1 describes the general requirements and define the terminology and the steps to conduct and energy audit.

Where the scope of the energy audit also must also consider the building envelope, the reference standard to use is EN 16247 part two. This will not be considered here because it is outside the scope of the DENiM project.

EN 16247 part three best aligns with the scope of DENiM project. It describes in detail the application of the energy audit methodology to production processes. The quality of the audit process depends strictly on the knowledge of the industrial processes and the available data and information from the site; therefore it is essential that there is close collaboration between the auditor and the organisation. It is important that the definition of a process as outlined in the standard is adhered to to define the limits for the audit:

A process could include one or more production lines, offices, laboratories, research centres, packaging and warehouse sections with specific operational conditions and site transportation. An energy audit could include the whole site or a part of a site

The standard lists seven elements for the entire audit process:

1. **Preliminary contact**: This is the starting point where objectives, expectations, scope and boundaries are defined. The energy auditor shall obtain a preliminary description of the site and the processes. A timescale is drafted with the criteria for the evaluation of the efficiency measures in output of the audit.
2. **Start-up meeting**: In this step, the responsible persons are named and decision are made regarding access to the sites, safety rules are outlined and the non-disclosure agreement is signed. The systems, processes relevant to energy KPIs that will be used in the audit are agreed.

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3. **Collecting data**: In cooperation with the organisation, data relating to the site and production processes are collected. This step can be carried out in several stages in an iterative process of measure, verify and calibrate. At the end of the data collection period, preliminary data analysis is carried out.
4. **Field work**: This step represents the physical inspections where the auditor can carry out additional measurements, confirm specific conditions, settings or ask for additional measurement data.
5. **Analysis**: During this phase, the energy auditor establishes the existing energy performance and calculates the relevant KPIs. A useful tool for this step is the use of a Sanky diagram.
6. **Report**: The results of the previous steps are reported in the final document as described in the standard for the output.
7. **Final meeting**: This step involves the presentation of the results to the customer and an analysis of the proposed efficiency measures.

The energy audit process is described in Figure 6:

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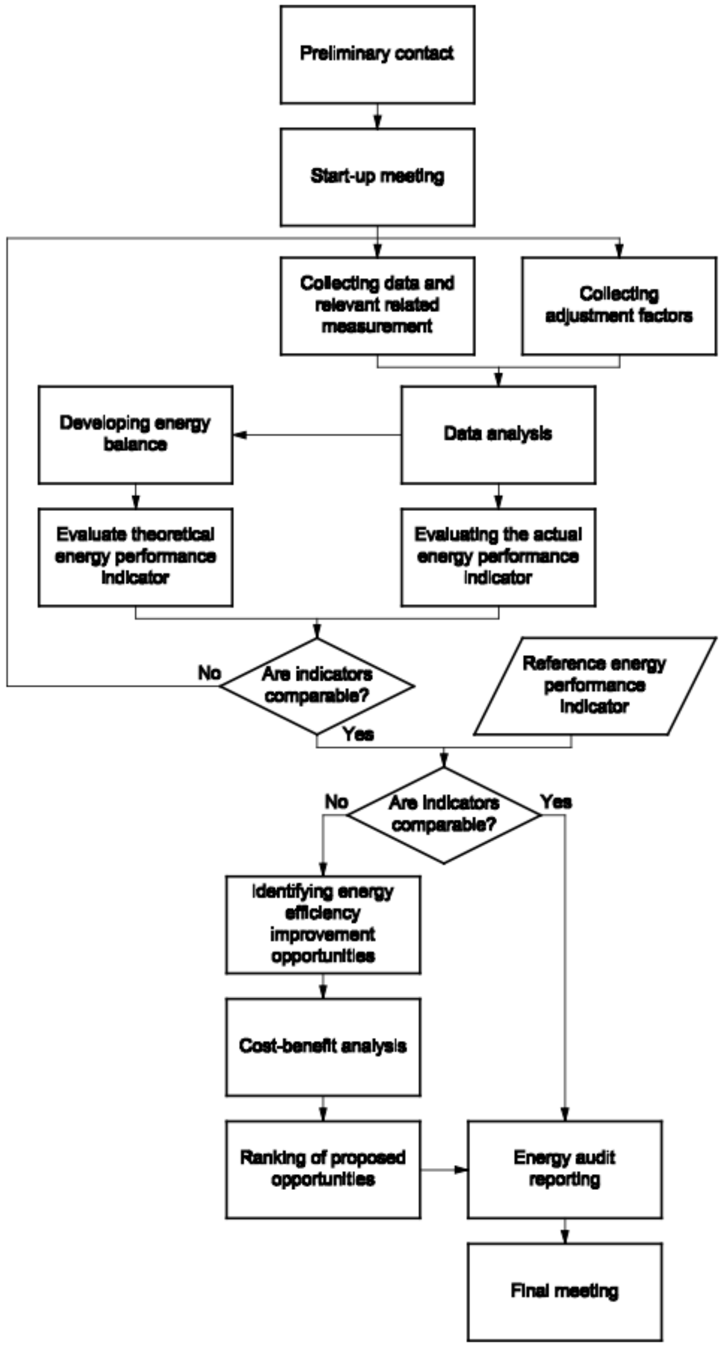

Figure 6: Energy Audit process (EN 16247-part 3)

3.2.4.3 ISO 50001 – Energy Management Systems

The ISO 50001 standard is a voluntary certification process designed to support organisations from all sectors to improve their energy use through the implementation of a continuous monitoring and management system (EnMS). Initially drafted in 2011 it exploits a systematic approach to defining and implementing energy policies with the objectives being to guarantee energy performance targets. It follows the model used for the ISO 9.001 Quality Management System and ISO 14.001 for Environmental Management Systems (EMS). ISO 50001 effectively replaces an energy audit and therefore companies certified in ISO 50001 are not subject to obligatory periodic energy audits.

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The implementation of an EnMS according to ISO 50001 establishes a process for continual improvement and can provide organisations with several benefits such as a reduction in energy costs and subsequent increased competitiveness, achieving environmental goals, sustainable long-term progress, innovation triggering, productivity and operational improvements.

The ISO 50001 standard is based on Plan-Do-Check-Act (PDCA) approach, as shown in Figure 7, a widely used iterative management process for continual improvement. The PDCA approach applies to EnMS elements and activities in the following way:

Plan*: understand the context of the organisation, establish an energy policy and an energy management team, consider actions to address risks and opportunities, conduct an energy review, identify significant energy uses (SEUs) and establish energy performance indicators (EnPIs), energy baseline(s) (EnBs), objectives and energy targets, and action plans necessary to deliver results that will improve energy performance in accordance with the organization's energy policy.*

Do*: implement the action plans, operational and maintenance controls, and communication, ensure competence and consider energy performance in design and procurement.*

Check*: monitor, measure, analyse, evaluate, audit and conduct management review(s) of energy performance and the Energy Management Systems (EnMS).*

Act*: take actions to address nonconformities and continually improve energy performance and the EnMS*

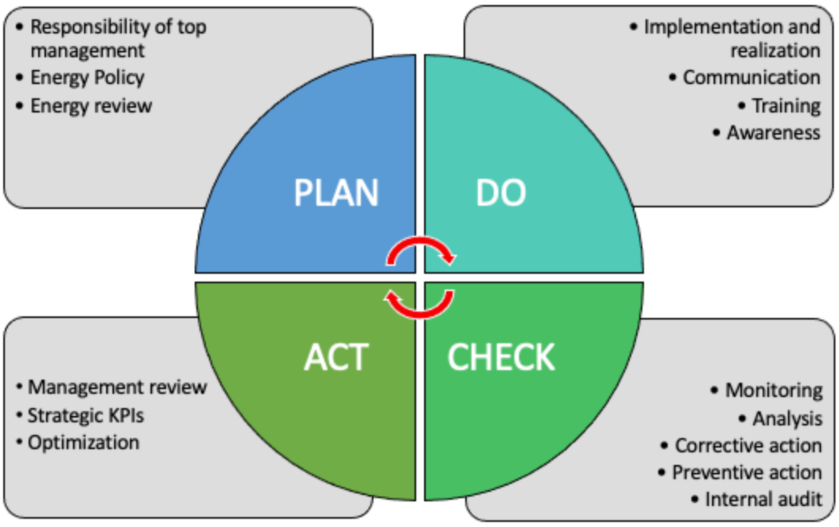

Figure 7: Plan, do, check, Act process

An important principle for ISO 50001 is the development of an energy management document that can be used to improve communication between different actors, roles and levels in an organisation in relation to energy management. This aspect, improved in the updated ISO 50001 edition 2018, can also be implemented with the support of digital tools to support data management, tracking of decisions and managing responsibilities.

3.3 Decision Support and System Adaptation

3.3.1 Fault Detection, Diagnosis and Prognosis for Energy Efficiency

Fault Detection and Diagnostics (FDD) is an area of investigation concerned with automating the processes of detecting faults with physical systems and diagnosing their causes. Prognostics address

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the use of automated methods to detect and diagnose degradation of physical system performance, anticipate future failures, and estimate the remaining life of physical systems operating in an acceptable state before faults or intolerable degradations of performance occur. Together these methods provide a cornerstone for condition-based maintenance of building systems (Katipamula & Brambley, 2005). The primary objective of an FDD system is early detection of faults and diagnosis of their causes, enabling correction of the faults before additional damage to the system or loss of service occurs. This is accomplished by continuously monitoring the operations of a system, using FDD to detect and diagnose abnormal conditions and the faults associated with them, then evaluating the significance of the detected faults, and deciding how to respond. (Katipamula & Brambley, 2005). By automating and integrating FDD into systems has the potential to reduce the quantity of unplanned downtime of manufacturing machinery by identifying and diagnosing issues as and even before they occur. This has the potential to increase output productivity, reduce scrap and rework and improve the energy efficiency of the manufacturing sector. With the increased proliferation of innovative digital technologies and the consequent increase in data available for analysis, FDD implementation can be accelerated into manufacturing systems which were once islanded in terms of their data and wider network integration. There is even potential for FDD to be utilised on the grid integration side by allowing manufacturing companies to enter the energy market providing Distributed Energy Resources (DERs). The first step in the FDD process is to monitor the physical system or device and detect any abnormal conditions. This step is generally referred to as fault detection. When an abnormal condition is detected, fault diagnosis is used to evaluate the fault and determine its causes. Following diagnosis, fault evaluation assesses the size and significance of the impact on system performance (in terms of energy use, cost, availability, or effects on other performance indicators). Based on the fault evaluation, a decision is then made on how to respond to the fault. Prognostics focus on predicting the condition of an engineering system or equipment at times in the future. As with FDD, prognostics are used along with evaluations of impacts to make operation and maintenance decisions. The use of prognostics enables transition from maintenance based on current conditions of engineered systems and equipment (condition-based maintenance) to predictive maintenance.

Figure 8 from (Bruton, et al., 2014) details the main methods and subcategories of FDD as expanded from an initial schematic compiled during a comprehensive review of FDD applied to HVAC systems conducted by Katipamula and Brambley (Katipamula, 2005).

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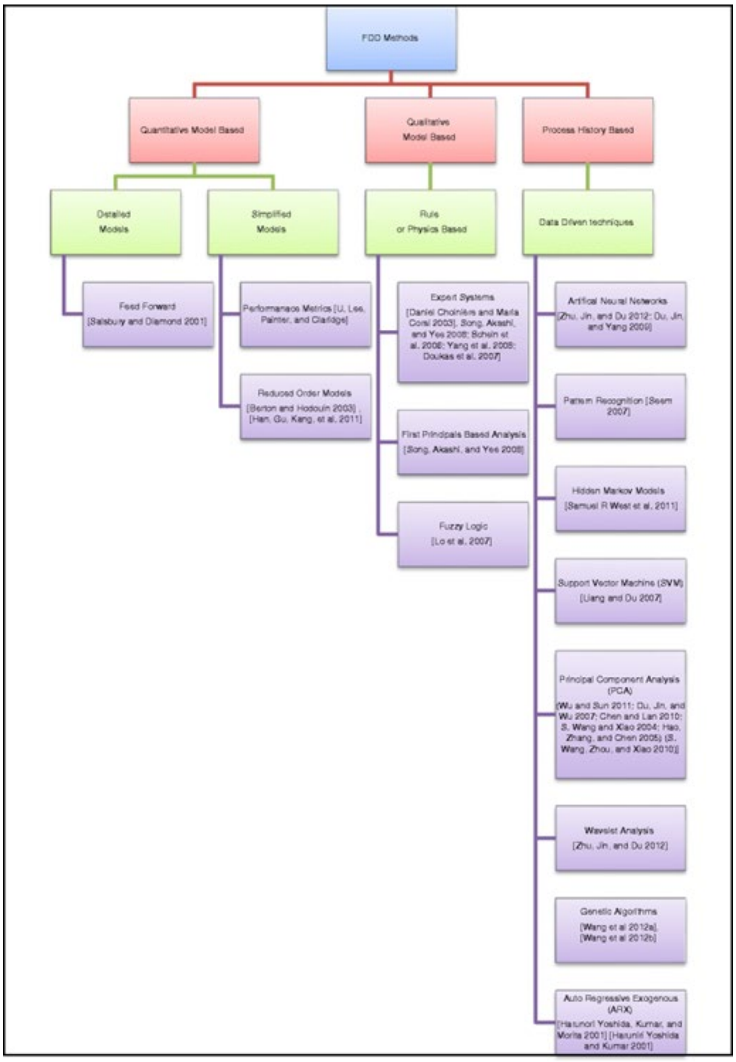

Figure 8: Taxonomy of FDD Methods

Automated FDD has been applied across the manufacturing in various guises to date. A semiconductor manufacturing system is one of the most complicated high-tech manufacturing systems. The key characteristics of this process includes the high complexity of wafer processing, non-linearity of most batch processes, multimodal batch trajectories due to product mix, large-scale systems and the high degree of measurement uncertainty, which all together have posed great difficulties to these traditional fault detection methods. Therefore, designing effective fault detection technologies to improve product quality, reduce scrap rate and wafer quantity, and ensure the safety during the production process is the key point of the semiconductor manufacturing process. Data-driven based statistical process control methods have been widely applied in semiconductor manufacturing processes, because of large amounts of trace or machine data generated and collected by process equipment's in modern industry. Among all fault detection methods, multivariate statistical process control (MSPC) method as the effective data-driven method, has been successfully applied to on-line process fault detection, in particular, chemical processes, biochemical processes, semiconductor processes, etc. (Li & Zhang, 2014)

Faults in chemical plants can be immensely detrimental to companies as they increase plant downtime (Peng and Zhu, 2017), decrease product yield, cause environmental issues, and increase exposure to plant safety hazards. A fault in chemical plant systems is defined as any unpermitted deviation from normal plant operating behaviour. In general, they can be defined as a departure from a design-

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defined acceptable range of values for a given parameter (Severson, et al., 2015). Data-driven fault detection techniques provide insight to how the plant is operating, even without any engineering-based process knowledge or first-principle models ((Alzghoul, et al., 2014); (Yuan, et al., 2017)). Knowledge-based process monitoring requires existing process knowledge and depend on a contrived fault tree or process expert ((Ayodeji, et al., 2018); (Cheliyan & Bhattacharyya, 2018)). It is often assumed that abundant historical data are available spanning all types of fault. Often, this is not a good assumption as new faults are likely to occur. Data-driven process monitoring strictly invokes methods derived directly from process data ((Beghi, et al., 2016); (Naderi & Khorasani, 2017)) and thus are easier to implement and more efficient. FDD has also been implemented on an equipment specific basis in the manufacturing sector, below outlines some of these approaches that can significantly impact energy efficiency:

Chillers: With the development of machine learning and artificial intelligence, an increasing number of researchers have begun to apply intelligent methods to the FDD of commercial chillers, and have produced some research results and diagnosis models (Fan, et al., 2020). There are two typical fault diagnosis methods for chillers that are proposed: One is model-based, and the other is data-driven.

The **model-based diagnosis** method is mainly based on the first principles physical model. Researchers have established dynamic linear black box models which identifies each of the system's relevant characteristic features during the normal functioning of the chiller, and use an online methods and a decision table to identify chiller faults as well as presenting a fault diagnosis strategy for centrifugal chillers that is based on a simple regression model and a set of general rules (Cui & Wang, 2005). **Data-driven methods** use black-box models that do not need to understand the system, such as principal component analysis (PCA), NN, support vector machines (SVM), Bayesian network, and so on. When researching the algorithm, researchers choose the characteristic parameters to optimize the chiller's fault diagnosis model. Researchers have used fuzzy modelling and artificial neural networks to select characteristic parameters for FDD. Researchers have also proposed FDD strategies that are based on support vector regression (SVR), non-linear radial basis function (RBF), and least squares support vector regression (LSSVR), and are combined with the exponential weighted moving average (EWMA). According to a recent survey (Wang, et al., 2018), the most frequently installed sensors are the:

- entering evaporator water temperature
- leaving evaporator water temperature
- entering condenser water temperature
- leaving condenser water temperature
- evaporating temperature/pressure
- condensing temperature/pressure
- compressor input power
- refrigerant discharge temperature

The use of key feature selection to minimise sensor requirements and ensure more practical implementation of FDD in the field has been evident in recent research (Fan, et al., 2020).

Heating Ventilation and Air Conditioning (HVAC): Buildings rarely perform as well in practise as anticipated during design due to improper equipment selection or installation, lack of commissioning or improper maintenance to cite but a few reasons. It is estimated that HVAC energy consumption accounts for 10–20% of total energy consumption in developed countries with Air Handling Unit (AHU) associated energy use accounting for the majority of this. Studies have indicated that savings of 20–30% in building system energy consumption are achievable by recommissioning HVAC systems, and more specifically AHU operations, to rectify their faulty operation. In a study of FDD application in 36 organisations spanning 200 million square feet, users achieved a median whole building savings of 8%

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with one organisation exceeding 30% energy savings (Lin, Kramer and Granderson, 2020). HVAC FDD methods range from those based on physical and analytical models to those driven by analysis of historical performance data using either artificial intelligence or statistical techniques. A significant number of research works have attempted to determine the most effective combination of techniques. Researchers have suggested that process knowledge should be used in conjunction with a knowledge-based system in a combination with data-driven approaches for maximum efficiency. Researchers have also attempted to reduce the number of data inputs to FDD systems by using fewer physical parameters to simplify the detection and diagnosis process. Results have shown that some features had more significance in terms of effectively diagnosing faults. Bruton et al successfully enacted this philosophy in the development of an FDD tool which was successfully implemented and tested across a range of different manufacturer equipment on a number of different manufacturing sector HVAC equipment (Bruton, et al., 2014).[i]

3.3.1.1 FDD focussed EU initiatives targeting industrial and building domains

PRONTO (Process NeTwork Optimisation) is concerned with the efficient and sustainable operation of assets already installed and running in Industry. The research topics of the consortium partners are 1) data analytics to extract information from large, heterogeneous assemblies of data to determine machinery condition and process performance and 2) optimization of operations, materials, energy and wastes taking machinery condition and process performance into account. FDD was performed using Bayesian Kalman filtering. Grant agreement ID: 675215

Mosycousis Project is an intelligent monitoring system based on acoustic emissions sensing for plant condition monitoring and preventative maintenance. Software was developed to utilise specific algorithms to exploit signal processing and acoustic emission theory to correlate acoustic emissions to faults in machinery, to perform machine prognosis and to calculate life expectancy. Grant agreement ID: 285848

ENERGY-SMARTOPS (Energy savings from smart operation of electrical, process and mechanical equipment) focussed on reducing manufacturing industry energy consumption by 25% for 2020 through equipment and process monitoring, integrated automation and optimisation for energy savings. Utilising condition monitoring techniques and optimisation frameworks, the system efficiency of a gas compressor increased while reducing overall operating costs. A 10% reduction in operating costs and 37% decrease in energy consumption can be found using a scheduling approach in production processes. Grant agreement ID: 264940

ENERGY IN TIME (*Energy in Time*, 2021) developed a smart energy simulation-based control method. Researchers created a control tool for the building energy management systems, which could be automatically and remotely operated. Grant agreement ID: 608981

PERFORMER (Portable, Exhaustive, Reliable, Flexible and Optimised approach to Monitoring and Evaluation of Building Energy Performance) developed a holistic energy monitoring methodology based on performance indicators, information models and simulation tools, to achieve building energy performance targets. The project goes beyond simple data visualisation by using prediction algorithms and fault reporting to help users target ongoing opportunities for effective improvements. Grant agreement ID: 609154

HIT2GAP (Highly Innovative building control Tools Tackling the energy performance GAP) aims at linking enabling technologies and approaches used in the commissioning and operation phases of construction to improve the comparative predictions of the models and simulations that drive design and the actual performance of new and retrofitted buildings. Principal component analysis was applied as an AI based FDD method in the project. Grant agreement ID: 680708

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3.3.2 Integration of Renewable Energy in Production Processes

Currently new approaches of energy procurement and usage, which are both economically and technically available worldwide, are adapted to the local contexts (Resource Development Ltd., 2013). Concerning renewable technology options, over 200 projects are identified across the globe, involving various sectors, and deploying renewable systems, ranging from the traditional cases such as photovoltaic to innovative solutions such as hydrogen generation from a RS. The industries that can take advantage of this innovation include energy intensive industries such as Iron, steel, and non-ferrous metals, Chemical industry and petrochemical, Minerals (Non-metallic), Food, Tobacco, Paper industry and pulp, Textile, Leather Mining, quarrying, transport, and machinery industries.

Table 7 presents some example projects in Europe, the US, and Canada (IEA RETD TCP, 2017), (IRENA, 2014):

Table 7: Examples of industrial projects involving integration of RES.

Industry Name & Sector	Description
Diavik Diamond Inc: Mining of diamond	Installed 9.2 MWe onshore wind farm in its off grid mine
Volkswagen Chattanooga: Automobile assembly plant	Purchases 100% of generated electricity from a 9.5 MWe solar PV park adjacent to the manufacturing plant
Brewery Vestyfen: Danish brewery	Replaced an oil-fired boiler with a 4 MWth wood boiler
Tenon Manufacturing Ltd: Sawn wood processing (wood and paper)	Modified its natural gas-fuelled kilns to run on geothermal steam (27 MWth)
Jain Irrigation System Ltd: Irrigation systems, pipes, and fittings, plastic sheets, etc.	Transforms by-products of the tomato transformation process into biogas in the plant, digestate is then valorised on secondary markets as bio-compost
Nuova Sarda industria casearia: Manufacture of dairy products	Solar CSP, 470 kWth, 600 kg/h steam at peak production
Munster Joinery: Manufacturing – building systems	4 MWe of wind power 3 MWe and 12 MWth from CHP
Colruyt: Logistics	800 kWe of Solar PV 1.5 MWe of wind power 120 kW of Fuel cell
BMW Spartanburg: Car manufacturing	landfill gas CHP, and hydrogen 11 MWe and 21 MWth turbines. 96 kWe of solar PV
Heineken: Austrian brewery	Hydro of 1.3 MWel Solar thermal of 1.0 MWth CHP of 0.45 MWel / 0.47 MWth

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	Biogas of 15 GWh produced per year

It is evident that renewable energy integration in the industrial assets brings direct profits to the industry, further than what could be expected from the direct purchase of renewable-based power. Generally, industrial players' drivers and their motivation to install renewable assets are:

- Energy supply reliability improvement concerning insecure supply of electricity due to their distances from the main distribution nodes.
- Energy costs reduction and price hedging from foreseen increases of fuel and electric network prices.
- Productivity Increment.
- Providing opportunities for further revenue.
- More coherence with corporate environmental and local commitments.

However, several barriers still hinder full renewable development in industries (IRENA, 2014). Several concerns already identified that can hinder an industry to/or get them away from deploying renewable generation assets in their facilities. Some of them are as the following:

- **The Regulatory System for Energy Production**: By the current norm, it is hard to produce energy using self-governing players, and valorise energy through self-consumption and/or the right to sell the generated energy. Policymakers should ensure that these two regulatory necessities are implemented within the energy generation regulatory system.
- **Investment:** Third-party energy generation schemes bring a substantial opportunity for industries who deficient in the equity capital/cash needed to launch renewable projects. Renewable energy projects require substantial up-front investment costs compared to the power purchase option and traditional fossil fuel generators. Having mechanisms for investment support can lower the industry side upfront costs.
- **Payback Times and Return on Investment:** Compared to the fundamental activities of an industry, integration of RES projects mostly come with longer payback times, and lower investment return. Preferential rates for purchasing of decentralized renewable energy production should be provided by public authorities to industries, guidelines, and a regulatory framework for the valorization of by-products that can increase their investment return. In this regard, the industrial company can take advantage of the following approaches:
    - Investment transferring the to the third-party producer of energy.
    - Oversizing of Installations in order to sell surplus energy to energy utilities and/or other industries.
    - Increase value of by-products (predominantly in the biomass projects).
    - Anticipate and enhance heat/power synergies and energy efficiency.
- **Technology Maturity:** Technologies applicable in the industries such as tri-generation scheme (generation of electricity, heat, and cooling) or renewable heat integration still are under development. Investing in a non-mature renewable energy technology brings risks that industries are not willing to take.
- **Operability and Integration:** A renewable energy integration project must bring either higher productivity or easier operability to the targeted industry. Sufficient integration of renewable energy generation assets in an industry requires a deep knowledge of renewable energy systems, industrial processes and environmental, health and standards for safety.

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- **Contractual Scheme Complexity:** Contractual complexity of heat/power purchase agreements and participation in the retail or wholesale electricity market can prevent industries from considering their application. Third-party power producers look for 20-year PPA contracts, whereas an industrial player normally has shorter period activities that is mainly determined by their market cycles. New, shorter-term contractual schemes that fit better with industrial players' constraints need to be developed.
- **Awareness:** Communication on existing support mechanisms (incentives, guarantee, etc.), costs, and best practices are essential to fill the gap between knowing the subject and concrete implementation on the ground. Public entities are required to facilitate sharing relevant information on RE technologies and existing public financial and technical support. Industries and OEMs should consider joining groups such as inter-professional associations to share their knowledge with counterparts.

For each RES technology, the potential should be estimated based on the analysis of the following (IRENA, 2014):

- **Realizable Technical Potential:** Realizable technical potential considers neither the costs of technologies nor the availability of resources to reach the related potential. Rather, they serve as an indication of the maximum extent to which renewable energy technologies can be deployed given their existing technical constraints.
- **Economic Potential:** After the estimation of the realizable technical potential, the additional costs of heat production by renewable technologies compared to fossil fuel counterparts should be taken into account by estimating the CO_2 abatement costs of each RES technology relative to the fossil fuel-based counterpart, thereby taking into account the fuel mix in each region, heat production costs, and regional CO_2 prices.
- **Realizable Economic Potential:** In the last step, the demand for RESs according to the economic potential will be compared to the regional resource supply potential. This applies to geothermal and biomass since access to supply could be limited in some regions because international biomass trade is excluded.

From a DENiM perspective the integration of RES at the pilot sites will be considered to enable industry partners understand the potential opportunities that can be achieved through leveraging renewable energy sources. This will be based on the successes achieved in other industries as well as the criteria outlined above.

3.3.3 Sustainability Labelling and Decision Support Tools

Decision support systems (DSS) can be used to supplement uncertainty around potential opportunities for energy efficiency by equating and providing visibility of relevant indicators to generate suggestions, driven from a sustainability perspective, for improvements in the production process. The primary methodologies defined in the literature that are relevant to DENiM are highlighted hereunder:

Elimination and Choice Expressing Reality (ELECTRE), Preference Ranking Organisation Method for Enrichment of Evaluations (PROMETHEE) and Dominance-based Rough Set Approach (DRSA) are non-compensatory approaches that consent to use a strong sustainability concept, accept a variety of thresholds, but suffer from rank reversal. It is interesting to highlight that the analysis of the literature pointed out that despite the increasing efforts of researchers, scheduling that considers sustainability should still be urgently addressed. There are no realistic, full-scale manufacturing systems available for researchers to test and validate, in real-time, the degree of sustainability of their scheduling method. There are many benchmarks in classical scheduling, but no planning system currently exists

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which considers input and output flow of production to schedule the production (Maximilian Zarte, n.d.).

Multi-Criteria Decision Making (MCDM) is widely adopted in the sustainability field; in particular, methods hybridised with group decision-making techniques are frequently used and is of transversal nature. PROMETHEE was the most employed method in the references reviewed, followed by ELECTRE; AHP and Analytic Network Process (ANP) were also popular, especially for structuring a problem and determining weights. However, Multi-Attribute Utility Theory (MAUT) and AHP are simple to understand and have good software support. Still, they are cognitively demanding for the decision-makers and can only embrace a weak sustainability perspective because trade-offs are the norm.

3.3.3.1 Analysis of Tools Supporting LCA and Decision Making

Currently there are many solutions in the market and European research focused on impact assessment software concerning product LCA and Environmental Footprint. These solutions make it possible to determine the impacts of the product throughout its life cycle, from the extraction of raw materials to the demolition or recycling phase at the end of its life, including all impacts generated by the transport and the use of the good throughout its lifetime. In addition, to assessing the impacts on the environment, these tools also provide a method for showing the results, allowing comparison. To have a complete overview of the most renewed LCA software, a study concerning eight LCA tools (Umberto LCA+, EIME, Gabi, SimaPro, Air e LCA, OpenLCA, Sutainable e ApparelcoalitioSun and One click LCA) has been conducted and each tools has been analysed under a set of functional and non-functional requirements. Between the eight tools identified, the most complete and suitable for DENiM are:

- **Umberto LCA+:** is a software tool recommended by industries, consulting and education experts. In addition to standard LCA analysis, this tool can also account for the costs of material flows.
- **GaBi:** is a professional software used for complete life cycle assessment projects. GaBi's modelling phase is based on plans used to assemble processes in the product system. The software has several environmental indicators to assess the impact of the product.
- **SimaPro:** An LCA software can calculate the environmental impacts of a product throughout its life cycle, from the extraction of raw material to the final disposal. Once the processes have been created it is necessary to identify the inputs and outputs. The software allows the evaluation of the different life cycle phases of a product based on many indicators.

3.3.3.2 Labelling and Reporting

Since the 1990s, the global community has been developing a series of guidelines and standards to support organisations in assessing their emissions and environmental impact to meet the targets set by European (EU 2030 climate targets - Paris agreement) and international institutions (Kyoto pact). In this context, the optimisation of energy consumption is a crucial activity to reduce environmental impacts and improve production processes. It is essential to use tools and standards that allow an organisation to report and analyse the current situation. Furthermore, it could be useful to calculate the carbon footprint, a measure of the total amount of GHG emissions, expressed in CO_2 equivalent, caused directly or indirectly by the organisation or one of its products. There are different standards and guidelines for reporting greenhouse gas emissions and determining the carbon footprint, depending on whether it talks about products and services or organisations. Approaches to take this further includes corporate social responsibility (CSR) standards, the implementation of which has increased in number and popularity in recent years. A review of the literature has identified more than 300 global corporate standards, each with its own history and criteria. The following outlines the most relevant standards concerning DENiM project objectives.

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3.3.3.2.1 The GHG Protocol

The GHG Protocol was created in the late 1990s as an international standard for greenhouse gas accounting, which was needed in view of the evolution of international policies on climate change[12]. The standards are designed to provide a framework for businesses, governments, and other entities to measure and report their greenhouse gas emissions in ways that support their missions and goals. The GHG Protocol considers the emissions of the following six climate-altering gases (capable of contributing to global changes in the Earth's climate): carbon dioxide (CO_2), sulphur hexafluoride, methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons.

According to the protocol, the emissions of these climate-changing gases are divided into two macro groups: direct emissions, those coming from the organisation's sources, and indirect emissions, those that are the consequence of the organisation's activity but whose source is controlled by other organisations (Institute, 2004).

3.3.3.2.2 ISO 14064

In March 2006, the ISO completed its four-year development of ISO 14064 (Wintergreen, 2007), a three-part international standard for GHG management activities, including developing entity emission inventories. The standards include minimum requirements for GHG inventories, which provide a basic structure for credible and consistent independent auditing. ISO 14064 offers organisational users' opportunities for improved consistency, increased flexibility and decreased effort associated with voluntary GHG inventories. The Structure of ISO 14064 consists of three parts, each with a different technical focus.

Part 1 of the standard addresses conducting greenhouse gas emission inventories of organisations using a bottom-up approach to data collection, consolidation, and emissions quantification. Part 2 of the standard addresses quantification and reporting of emission reductions from project activities. Part 3 of the standard establishes a process for verifying a greenhouse gas statement, including organisation inventories, regardless of whether the inventory was developed under Part 1. This verification process is also applicable whether the verification is being conducted by an independent third party verifier or by an organisation's internal auditors.

3.3.3.2.3 Global Reporting Initiative (GRI)

The GRI is a principle-based standard focus on changing corporate reporting standards to help firms communicate information on their social and environmental impact in a comparable way[13]. The GRI Standards create a common language for organisations to report their sustainability impacts consistently and credibly. This enhances global comparability and allows organisations to be transparent and accountable. The GRI standards are designed as an easy-to-use modular set, starting with the universal Standards. Topic Standards are then selected based on the organisation's material topics: economic, environmental, or social. This process ensures that the sustainability report provides an inclusive picture of material topics, their related impacts, and how they are managed.

It should be noted that the GRI guidelines are not a simple summary of a variety of performance indicators. A considerable part of the guidelines is devoted to selected principles defining how the report is supposed to be compiled (Marimon, 2012) (Rasche, 2011).

3.3.3.2.4 Science Base Target

Science-based targets (SBTs) are GHG emission reduction targets whose ambition is in line with the decarbonisation level required to keep the global temperature increase below 1.5°C, as described in the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, and the Paris Climate

[12] https://ghgprotocol.org/

[13] https://www.globalreporting.org/

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Agreement. Science-based targets provide a clearly defined pathway for companies to reduce GHG emissions, helping prevent the worst impacts of climate change and future-proof business growth. The SBTs allows businesses to choose from seven target-setting methods, in order to set targets that are most relevant to them and account for the dynamics of the sector they operate in. As part of the criteria for setting a science-based target, the target boundary must be company-wide, covering all emissions included in the Greenhouse Gas Protocol. Moreover, the commitment period must cover a minimum of five years from the target announcement date. Companies are also required to annually disclose their greenhouse gas emissions annually and any other data that shows progress against their targets[14].

3.3.3.2.5 O-LCA: Organisational Life Cycle Assessment

By the directive ISO/TS 14072, the O-LCA is being described as: "a collection and evaluation of inputs, outputs and potential environmental impacts of the activities associated with the organisation adopting a life cycle perspective and since the portfolio of an organisation usually includes more than one product, all goods and services provided by the organisation are evaluated simultaneously" (International Organization for Standardisation, 2014). O-LCA follows the same four-step methodology as LCA, thus requiring clear definitions, reference units, a defined system boundary, lots of high-resolution data, allocation procedures, identification of hotspots, etc. The O-LCA approach is considered multi-impact environmental, which means that a full range of environmental issues relevant to the specific system is considered, representing the organisation's activities' potential environmental impact profile. Martinez-Blanco (BLANCO, et al., 2015) organises the O-LCA goals into three groups: analytical objectives, management objectives and social objectives. Furthermore, the guidance document defines the so-called "experience-based implementation pathways" and provides particular methodological support according to the organisation's previous experience with other environmental tools. Eight sectors and four regions are represented in the case studies.

3.3.3.2.6 Organisation Environmental Footprint (OEF)

OEF originates from the European Commission Recommendation 2013/179/EU of 9 April 2013 and is defined as a multi-criteria measure of the environmental performance of organisations providing products/services from a life cycle perspective. The normative act's general objective is to introduce standardised methodologies at the European level, suitable for identifying environmental impacts related to organisations' activities while considering the activities of the supply chain and integrating tools currently used by organisations. The method requires a reference unit for assessment, parallel to the concept of "functional unit" in an LCA study. Still, in this case, the organisation is the reference unit for an OEF analysis. As part of this European initiative a sector-specific guidance (EU-Joint Research Centre-Institute for Environment and Sustainability, 2018) has been developed for calculating and reporting organisations' life cycle impacts, the organisation's environmental footprint sector rules (OEFSR). The OEFSRs help focus OEF studies on those aspects that are most relevant in determining an organisation's environmental performance in each sector, thereby reducing the time, effort, and money needed to do an OEF study.

3.3.3.2.7 Product Environmental Footprint PEF

In parallel to the OEF and OEFSR project, the European Commission has developed and studied a method to measure and communicate products environmental performance (PEF). The European Commission also established instructions to defined PEF category rules (PEFCR), a ruleset describing how to calculate a specific product group's environmental footprint (Sustainability, 2018). The resulting rules have been being applicable in the entire EU market thanks to 26 pilots. Based on a European Commission Communication in 2013, the PEF and OEF guides used during the pilot phase

[14] https://sciencebasedtargets.org/

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until 2018, can now be applied during the current transition phase until 2021. About 20 Product PEFCR and OEFSR documents have been developed in this process, together with industry producers and other private sector and governmental organisations.

3.3.3.2.8 Environmental Labels

Recent research carried out by Eurobarometer shows that 80% of European consumers are interested in purchasing products certified as ecological. It also shows that only 50% of consumers fully trust information relating to the environmental performance of a product. The ISO has introduced a set of rules to ensure that environmental declarations are considered reliable by consumers and effectively exploited by companies to their full potential. The ISO divides environmental labels into 3 types:

- Type I (ISO 14024:2018): labelling program based on third party certified criteria, which assigns a license that authorises the use of an environmental label to products that guarantee better environmental performance within a product category, considering the entire life cycle.
- Type II (ISO 14021:2016): environmental self-declarations for which third party verification is not required.
- Type III (14025:2010): environmental labels that report declarations based on established parameters and subject to independent control.

The environmental labels described above are based on the LCA methodology, which allows the environmental impacts of a product to be objectively analysed by measuring specific indicators. To facilitate comprehension, product labels are generally included in a classification system that makes it possible to compare them with others within the same product category. Over the last decade, there have been numerous public and private initiatives aimed at communicating environmental sustainability. Ecolabelindex.com has more than 459 labelling programs in 197 countries and 25 industrial sectors. Product labelling programs have both advantages and disadvantages, the competition brings to the creation of more sustainable products which also helps the creation of new value chains with the aim of influencing behaviour towards greater respect of the environment. Finally, the development of these issues is an opportunity to constantly monitor environmental declarations with a view to constant revision of standards.

Despite the important benefits, labelling programs can also have downsides. A rather widespread phenomenon in this field is known as greenwashing. That is the practice whereby companies focus more on advertising their products as green, even with fake labels, rather than actively operating to reduce environmental impacts. Other issues may come with consumers and producers who may be disinterested in paying more for sustainable products, showing the difficulty of companies to demonstrate positive impacts also given the high certification costs, especially for small producers.

3.4 Analysis of Digital Skills for Energy Efficient Manufacturing

This section will identify the technologies that are utilised to support energy management within the manufacturing field, with particular focus on the technological sectors and productive processes of the DENiM project pilot scenarios (outlined in Section 2). A list of technologies were identified and the correlation among these with the technical problem those technologies are used to solve and/or the field they are related to will be presented. The technologies identified as described above will be used to identify the specific job profiles to create the skills gap matrix and to define the related job profiles.

Patent literature, consisting of published documents including both granted and application patents, is a unique source of technical information. Several studies ((Terragno, 1979), Kütt 1998) have shown that about 80% of the technical information contained in patent documents is not available elsewhere. As such patent literature is a necessary complement to a traditional and scientific technical literature

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review. Moreover, patents are a significant cost for companies and are thus generally filed to protect only innovations that are considered relevant to an enterprise: there is a direct correlation between patents and the impact of innovation in terms of costs and revenues; for those reasons, technologies presented within patents and patent applications have a high level of maturity and feasibility (higher than the ones presented, for example, in the papers and non-patent literature). The formal structure of patents documents means it is possible to select only documents focused on specific technologies of interest. In fact, patents mandatory describes the technical problem the invention is aimed to solve: this allows for the identification of key aspects (characteristics, technologies, solutions, embodiments, components) that are more related to the object of the analysis, avoiding considering false positive signals or taking into account documents where a specific aspect is just mentioned.

It is also possible to classify patents from a functional point of view (Bonaccorsi et al, 2019): this means that functions and behaviours extracted from patent documents can be very useful element for identify skills (and job profiles) needed to manage the related technologies. Furthermore, patents include detailed information on developing of technologies, and forecasting the introduction of a promising technology is a relevant opportunity for companies and countries. By observing the trend of filing patent applications (the number of applications filed over years), together with other parameters, it is possible to understand the maturity level of a technology and estimate its evolution in the next future. The first part of a typical technology trend (the so called S-curve) is shown in Figure 5: in early stages of a technology the number of patents issued is very limited. Then, a fast-growing period follows where the number of patents filed and issued increases. The reason is that the general concepts of a technology are studied and patented.

After this phase, the number of inventions over years decreases, because the R&D activity is focused on the implementation of the general concepts: a second fast-growing period follows the decrease, reaching a number of patents generally higher than the number of documents filed during the first period. Those are patents related to specific solutions. Finally, the technology becomes mature and/or obsolete.

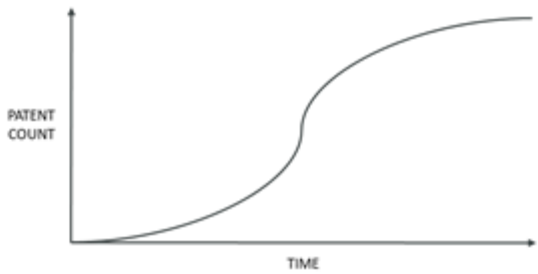

Figure 9: Patent count for specific technology (S-Curve)

Altshuller’s four trends (Figure 6) validate a system’s position on the S-curve and helps identify its evolutionary potential within the current system as well as predict developmental paths to increase the system’s maturity.

The four technology maturity steps are:

- Birth: New product created via radical innovation
- Childhood: First cycle of incremental innovation; slow development due to lack of profits.
- Growth: Benefits of the product are recognised; positive cycle performance, profits, R & D investments.
- Maturity: High profitability but saturation in terms of possibilities of innovation and improvement.

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- Decline: Limits of product evolution have been achieved, profitability decreases. Technology is no longer necessary.

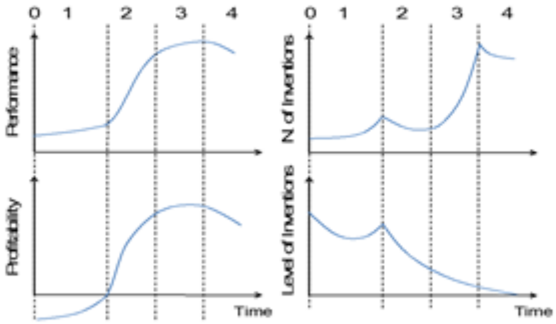

Figure 10: Altshullers Four Trend Validation

This is the reason why it is possible to use historical patent data to determine objectively and quantitatively what the promising technologies of the future may be. Finally, patents data are very useful also because patent applications anticipate the launch in the market and very often publication too (as publishing may compromise patentability of an invention): signals coming from patents allow to observe the technological evolution earlier than the analysis of the products on the market or their description within the non-patent literature.

3.4.1 Workflow and General Methodology

In is possible, among other things, to extract the list of technologies related to a specific problem. After defining a set characterized by proper levels of precision and recall (Glossary), by using dedicated tools and applying specific methods (for example, Functional Analysis), it is possible to extract from the text of patents the "chunks" describing a technology, that is, keywords, multi-words, expressions, also identifying the functions there are related to and if they are subjects of that function, or objects or if they describe the function itself (verbs). The number of patents related to those chunks over years (the so-called filing trend) can also be evaluated, to define the technology maturity level. The analysis allows for evaluation of (and how much) those text signals are related to the problem in suit (even weak signals) and, thus, to select only relevant elements. A software aided procedure is then performed, to compare and cluster signals and build the final list of technologies. Table 6 describes the workflow activities in detail:

Table 8: Workflow Summary for Technology Analysis

Activity	Description
Ontology creation and keywords	As the first activity, the keywords were researched to define a set on which to go and track down the technologies.
Document set creation	After creating the ontology and selecting the related keywords and expressions, patent documents focused on the energy management systems, methods and devices used in the four technological sectors in which the four pilots operate has been selected. The technological sectors are listed below: - **DP-01** related to Medical Device Manufacturing - **DP-02** related to Crankshaft Manufacturing (Steelmaking & Forging Processes)

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	- **DP-03** related to Tooling and Mould Production for Appliance - **DP-04** related to Machining and Production of Composite Products Because all the four pilots operate in the mechanical processing technological field, the global set of patents related to the energy management systems for this field was used for the analysis. The technologies identified were then associated to each of the individual pilot sectors. The global patent set is composed by 22402 patent families. The patent documents set defined has been managed via semi-automatic tools and algorithms, performing several iterations, to improve both the precision and the recall (please see Glossary) of each final set. Such iterations are useful to reduce considerably the text ambiguity (please see the precision definition in Glossary) and reduce the risk of not including documents of interest. Once the document set was selected, it was then possible to retrieve statistical data, to acquire further information and evaluate the level of precision and recall of the document set. At the end of the patent set definition, recall and precision reached values higher than 90%.
Technologies identification and Clustering	After defining the final document set, the technologies for the energy management have been identified and then clustered, to obtain a list with a homogeneous level of detail. A hybrid approach, both bottom-up and top-down has been followed: the clusters have been defined both according to the information retrieved from the texts of the patent documents and thanks to functional analysis, through an iterative activity. Once the technologies were identified, statistics were carried out to obtain the trends of the technologies and understand which ones may be emerging and which ones are obsolete.

3.4.2 Technology Analysis

The list of technologies has been provided, highlighting the correlations among them and with the problem those technologies are used to solve and/or the field they are related to. The list of technologies identified in the patent documents is shown in Table 7.

The percentage of patents for each technology is also presented with respect to the initially identified total patent set of 22402 patent families.

Table 9: Technologies identified and the relative percentages within the patents

Technology	% Patents for each technology
Air conditioning	35%
Computer device	33%
Heating device	22%
Switching electrical device	20%
Energy storage device	15%
Communication device	14%
Heat exchanger	11%

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Light sensor	11%
Network device	10%
Temperature sensor	9%
Wireless sensor	8%
Integrated circuit	8%
Control valve	8%
Electric motor	7%
Motion sensor	6%
Rechargeable battery	6%
Drive transistor	5%
Control module	5%
Pressure sensor	5%
Printed circuit	4%
Storage battery	4%
Solar panel	4%
Heat pump	3%
HVAC system	3%
Humidity sensor	3%
Energy management data	2%
Wind turbine	2%
Power converter	2%
Occupancy sensor	2%
Torque sensor	1%
Fuel cell system	1%
Load control system	1%
Thermal actuator	0%

3.4.2.1 Correlation Between Technologies and Pilots' Sectors

It was found that all the technologies identified can be applied into all the four pilots' field: there is no specific technology for just one or some of them. This interesting aspect can be explained by considering that the four pilots' sectors are very similar: they can all be traced back to a unique general filed, that is, the machining production field.

3.4.2.1.1 Technology vs Technical Problem

The technical problems solved by each technology were extracted from the text of the patent documents. After clustering the signals, five main technical problems were identified:

- **Monitoring of indirect measures**: the technology allows to measure and monitor some parameters.
- **Control system/Data management**: the technology can be used for managing data, both in control systems and for analysis.
- **Power generation**: the technology is used for generating power in efficient way.
- **Energy storage**: the technology allows to store and manage energy.

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- **Communication system:** the technology is used for communicating data in integrated systems.

Table 8 shows, for each technology, the main technical problems which it contributes too. This information can be used for defining the best skills (and the job profiles) for managing those problems (and related technologies) and for understanding if one skill can be useful for more technologies and/or problems and vice versa.

Table 10: Correlation matrix technology vs technical problem

	Monitoring of Indirect Measures	Control System/Data Management	Power Generation	Energy Storage	Communication System
Temperature sensor	X				
Pressure sensor	X				
Light sensor	X				
Motion sensor	X				
Occupancy sensor	X				
Torque sensor	X				
Air conditioning			X		
Control valve	X				
Control module		X			X
Heat exchanger			X		
Thermal actuator			X		
Integrated circuit		X	X		X
Heat pump			X		
Rechargeable battery			X	X	
Storage battery			X	X	
Drive transistor			X	X	
Printed circuit		X	X		X
Hvac system			X		
Communication device					X
Electric motor			X		
Computer device		X			X
Network device		X			X
Energy storage device				X	
Wireless sensor	X	X			X
Heating device			X		
Power converter			X		
Switching electrical device			X		
Load control system	X	X			X
Fuel cell system			X	X	
Solar panel			X		

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Humidity sensor	X				
Wind turbine			X		
Energy management data		X			X

3.4.2.1.2 Technology vs Technology

It was analysed if two or more technologies were simultaneously present within a patent and also if they were correlated in some way (for example, if they were referred to the same function, technical problem or behaviour). If many technologies are present within the same document, they can be alternatives to each other or used in combination to solve the same problem. To identify and investigate in more detail the relationship between technologies, a matrix was created indicating, for each technology, the other technologies present in the same documents. The presence of two technologies in a patent allows us to understand if and how those technologies are correlated and to identify which skills are needed to manage them. An extract of this analysis is shown in Figure 11.

	Temperature sensor	Pressure sensor	Light sensor	Motion sensor	Occupancy sensor	Torque sensor
Temperature sensor	*	X	X	X	X	X
Pressure sensor	X	*	X	X	X	X
Light sensor	X	X	*	X	X	X
Motion sensor	X	X	X	*	X	X
Occupancy sensor	X	X	X	X	*	X
Torque sensor	X	X	X	X	X	*
Air conditioning	X	X	X	X	X	X
Control valve	X	X	X	X	X	X
Control module	X	X	X	X	X	X
Heat exchanger	X	X	X	X	X	X
Thermal actuator	X	X	X	X	X	
Integrated circuit	X	X	X	X	X	X
Heat pump	X	X	X	X	X	

Figure 11: Correlation Matrix Technology vs Technology

3.4.2.1.3 Technology Trends

For each technology, the temporal trend was calculated: the trend is the number of patent applications related to each technology filed over years. The technological trends were calculated for all 33 technologies. Based on these trends it is possible to evaluate the maturity level of each technology, thus if it is emerging, growing, mature or obsolete. Examples from this analysis are shown below.

The first trend (Figure 12) is related to **Power converter** technology, and it is possible to observe that there was a peak in 2012 and then the trend is starting to decrease: the technology seems to be in the phase 2: the main general aspect of the technology has already been investigated, and a new growth is expected related to specific implementations.

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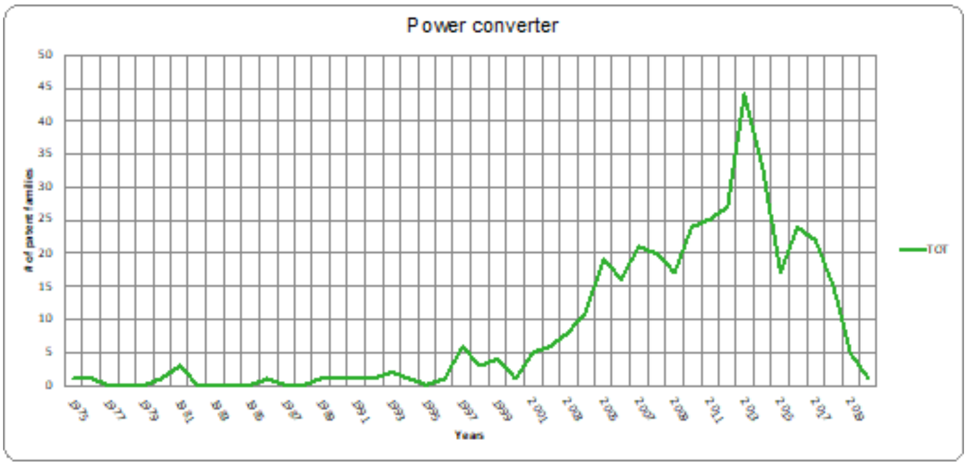

Figure 12: Trend of Power converter technology.

The second trend (Figure 13) is related to **Energy management data** technology and it is possible to observe that is emerging. The peak was in 2018, but the trend is probably still growing: the decreasing trend after 2018 should not be considered as suggesting that the technology is mature, because patents relating to this technology are relatively few due the so called "**blind period**": patents are secret for 18 months after they have been filed, and thus the values for 2019 and 2020 are as such **underestimated**.

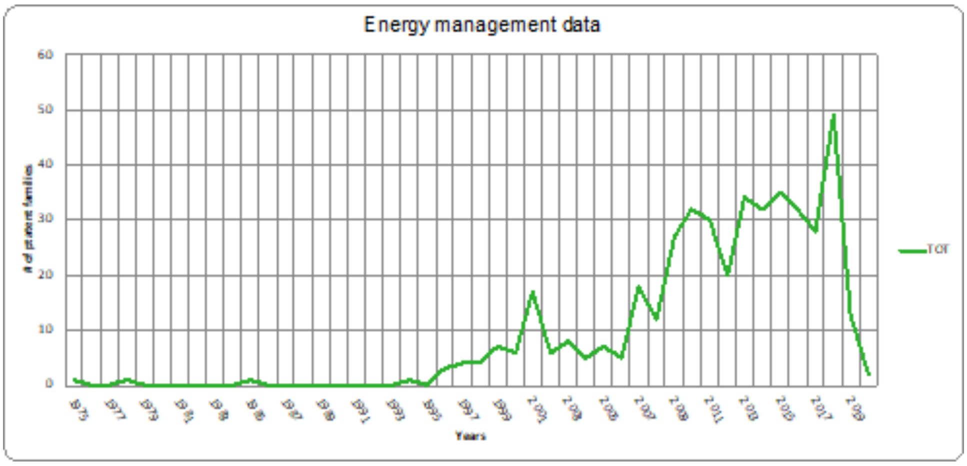

Figure 13: Trend of Energy management data technology.

This technology is most likely growing because the topic of energy management is pertinent at present. In recent years companies focused their attention on energy savings and consumption, therefore it can be surmised that they are likely aiming to develop technologies which allows them to address this. Among those technologies there is of course **energy management data**.

In general, for some trends it is possible to give more precise information on the technology and therefore to establish whether it is emerging or not, for others this is not possible due the low number of significant patents, which leads to a low statistical consistency. Almost all trends **show growing technologies.** This behaviour can be explained based on the technologies identified are enabling technologies for the Industry 4.0 transition and can be all used in integrated systems and for collecting, managing, and communicating data. All the technologies are needed to realise the concept of a smart factory. Finally, it has to be considered that the trends of technologies in energy management for manufacturing were calculated: it is also possible that some single technologies are mature if considered by their own, but their application into the field of interest can ben new and growing in

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the next future: some of those technologies have already been developed in other fields and they start to be used for the energy management and/or in the manufacturing sector thanks to crossover operations.

To conclude, the technologies and categories collected above represent the starting point to define existing archetypes (i.e. Job profiles) and to design new profiles suitable to manage digital revolution in Energy Management field. In further steps, the technologies will be detected in International competence databases, finding what is currently present and what is missing. In parallel, the categorisation of technologies, built according to problems they contribute to solve, will be used to define the foundation of new Archetypes.

3.5 Digital Maturity Assessment

Digital maturity assessment is used to support organisations in their digital transformation journey by first assessing where they are on that journey and then by setting goals to enable them to progress on that journey. As part of the assessment organisations identify where they are in relation to the use of digital technologies as part of their business process, where they want to go and how this can be enabled. This process looks at a number of dimensions across the business from whether or not there is buy-in across the organisation, what are the factors pushing for digital transformation (for example, is it regulatory, market forces, product innovation, customer demand?), what is the current level of digital maturity in the market and the organisation's relative position, what is the customer experience, what is the level of digital skills and awareness within the organisation. With industry 4.0 and (now Industry 5.0) continuing to challenge the manufacturing sector through increasing digitalisation there is a need to understand the Industry 4.0 readiness of organisations and digital maturity models are commonly used to quantify the maturity of an organization or a process with regard to some specific desired target state. The authors in (Schumacher, et al., 2016) review a number of Industry 4.0 digital maturity models as well as proposing their own and these are summarised in Table 9 based on (Schumacher, et al., 2016) along with a sample of other digital maturity tools stepping from commercial and scientific fields.

Table 11: Digital Maturity Models & Tools

Digital Maturity	
Model/Tool	**Assessment Approach**
The Digital Maturity Assessment Tool – DMAT[15]	Online non-commercial and free to use tool based on a questionnaire that assesses digital maturity across six dimensions (with each dimension having a number of sub-dimensions): Strategy, culture, organisation, processes, technology, customers and partners.
Deloitte Digital Maturity Model (2018)[16]	Describes itself as being the *first industry-standard digital maturity assessment tool* with digital maturity being based on 5 core business dimensions (with 28 sub-dimensions and 179 digital criteria): Customer, Strategy, Technology, Organisation & Culture and Operations in order to create a holistic view of digital maturity across an organisation.
The Smart Industry Readiness Index - SIRI[17]	The SIRI Framework and accompanying matrix tool is made up of a higher layer that is composed of: Process, Technology, and

[15] Dr. Annabeth Aagaard Aarhus University https://dbd.au.dk/about-dmat/

[16]https://www2.deloitte.com/content/dam/Deloitte/global/Documents/Technology-Media-Telecommunications/deloitte-digital-maturity-model.pdf

[17] https://siri.gov.sg/

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	Organisation. These are identified as the core building blocks for Industry 4.0 and these layers are supported by 8 pillars that are across 16 dimensions which are used in the evaluating the current maturity levels of an organisation. A self-assessment can be carried out with comparison against industry benchmarks or a SIRI certified assessor can be engaged to perform the assessment.
Industry 4.0 (Schumacher, et al., 2016)	
IMPULS – Industrie 4.0 Readiness (2015)	6 dimensions using 18 items to indicate readiness across 5 levels; and barriers for progressing to the next stage along with advice on how to overcome them
Empowered and Implementation Strategy for Industry 4.0 (2016)	Assessment of Industry 4.0 maturity as a quick check and part of a process model for realisation; gap-analyses and toolbox for overcoming maturity-barriers are intended; limited details available.
Industry 4.0 / Digital Operations Self-Assessment (2016)	Online-self assessment measuring digital maturity across 6 dimensions and 4 maturity stages, limited details available.
The Connected Enterprise Maturity Model (2014)	Maturity model integrates information technology (IT) with operations technology (OT) to improve performance and minimise risk as part of a five-stage approach to support the realisation of Industry 4.0; technology focused assessment in 4 dimensions; limited details available.
I 4.0 Reifegradmodell (2015)	Assessment of maturity in 3 dimensions including 13 items for maturity indication; maturity is assessed over 10 levels; limited details available.
Industry 4.0 Maturity Model (2016)	Assessment is defined based on 9 dimensions with 62 items being used to assessing Industry 4.0 maturity. The dimensions: Products, Customers, Operations and Technology are used to assess the basic enablers with the dimensions: Strategy, Leadership, Governance, Culture and People being used to facilitate the inclusion of organisational aspects as part of the assessment.

DENiM is focused on energy sustainability in smart manufacturing and as such will concentrate on readiness and maturity models and tools that focus specifically on energy rather than the broader case of digital maturity for Industry 4.0. DENiM promotes the implementation of sustainable energy policies to increase process efficiency and to create a pathway towards the adoption of sustainable renewable technologies with the aim of reducing energy consumption.

3.5.1 Energy Management Maturity Assessment

As part of the energy management process, there must be an understanding of the readiness and maturity of an organisation to effectively implementing energy management strategies. The authors in (Finnerty, et al., 2017) carried out a comprehensive review of energy maturity models across the main works stemming from both industry (standards, guidelines and best practice) and academia (scientific literature) and their findings are summarised in Table 10, including the EM^3 model they proposed.

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Table 12: Energy Management Maturity Models based on (Finnerty, et al., 2017)

Type	Model Name/Description	Maturity Levels	Comments
Industrial Guidelines	Carbon Trust Energy Management Matrix	5	High-level assessment of strengths & weaknesses across six areas of energy management aligned with plan-do-check-act continual improvement framework.
	Carbon Trust Energy Management Assessment	0-100%	Provides a detailed appraisal of energy management performance across twelve key areas grouped in 5 dimensions aligned with plan-do-check-act cycle.
	Sustainable Energy Authority of Ireland (SEAI)	Emerging Defining Integrating Optimising Innovation	Model built around the four domains of the plan-do-check-act cycle. The output is a single graph illustrating the strengths and weaknesses of each domain and each pillar within that domain, enabling organisations to plan in terms of energy management.
	EDF	None Emerging Developing Leading Advancing	The EDF survey targets all types of organisations regardless of size and sector. It evaluates the whole organisation at a high level without considering the multi-site organisation scenario and the associated dynamics.
Scientific Literature	(Ngai, 2013) Model provides a series of steps for organisations to follow in implementing energy management practices		Model does not analyse the maturity of an organisation but provides a description of the phases an organisation will go through during the evolution of its energy management.
	(Antunes, et al., 2014) Framework provides maturity models and continuous improvement steps for an organisation implementing energy management activities.		The model is based on clearly defined and understood activities, the movement from one maturity level to the next follows the plan-do-check-act cycle.
	Similar to above (Introna, et al., n.d.) also provides a questionnaire and the process that are required to be implemented to assess the energy management		The model consists of 40 questions & is complementary to the implementation of ISO 50001 (aligning with the plan-do-check-act cycle and targets single-site organisations.

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	maturity of an organisation		
	(Jovanović & Filipović, 2016) model aligned with ISO 50001		The model is directly linked to the ISO 50001 standard aiming at directly evaluating the level of maturity of an organisation in implementing the standard aligning with the plan-do-check-act cycle.
	EM^3 (Finnerty, et al., 2017) for multi-site organisations		Targets industrial multi-site organisation, aims to characterise and benchmark individual site performance and then the network of sites with respect to the technical and non-technical readiness to implement energy efficiency actions.

(Finnerty, et al., 2017) summarise that the energy management maturity models reviewed have for the majority considered similar key areas when assessing an organisation with the EDF and Carbon Trust Energy Matrix being more a high-level quick assessment approach and do not provide recommendations in terms of improvement. The Carbon Trust Energy Management Assessment and the SEAI maturity models are identified as being comprehensive methodologies that provide detailed recommendations, but this incurs the need for additional time and resources. In relation to the models stemming from the scientific literature follow the plan-do-check-act cycle are aligned with ISO 50001. The EM^3 model proposed by (Finnerty, et al., 2017) is a multi-site model and more comprehensive with respect to the other models listed as it provides the criteria to be used in the maturity evaluation and evaluates multiple sites as well as the network of sites associated with a particular organisation; it provides a continuous improvement path while also supporting benchmarking with respect to a database of external peers.

From a DENiM perspective in relation to energy maturity assessment the key dimensions of interests are: management commitment; energy information systems, monitoring measurement and analysis, training and awareness, energy planning, energy baselining, energy key performance indicators, energy efficiency integrated within processes, and benchmarking. From the table above based on (Finnerty, et al., 2017) the energy maturity models we will consider for further investigation within DENiM are: (i) Carbon Trust Energy Management Assessment, (ii) (Jovanović & Filipović, 2016) and (iii) EM^3. These approaches are aligned with the plan-do-check-act cycle ingrained in ISO 50001 and they concentrate on identifying the current situation with respect to energy performance, identify a course of action, implementing the measures to derive improvement, followed by measuring the effectiveness of the interventions, and finally identifying opportunities for further improvement opportunities.

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4 DENiM Requirements Analysis

Based on the review of current practice and engagement with relevant industry and academic experts, many opportunities remain for industrial sectors to leverage and integrate cost-effective, energy-efficient technologies, processes, and practices into EU manufacturing which must stem both from broader use of current best practices and from a range of advances enabled by future innovations spurred on by digital transformations. From a DENiM perspective, digital intelligence refers to the ability to transform digital data extracted from heterogenous sources (shop floor, machines, planning, quality, maintenance) into real-time, actionable, energy-centric insights. This enables industry to take advantage of digital technologies to improve their energy efficiency and competitiveness by gaining better knowledge of the actual energy demand of their machines/systems/plants as well as further automating production processes. This in turn provides opportunities for developing human competences in terms of digital skills in synergy with technological progress. This section provides an overview of the actors that will utilise and interact with the DENiM solution and the outcomes of a SWOT analysis of the proposed solution. Finally, a summary of the key requirements of the DENiM project will be presented.

4.1 DENiM Actors and Stakeholders

To manage energy effectively requires a holistic approach that involves information sharing and a representative view of performance across business functions and systems. Figure 6 presents the DENiM actor diagram and the interaction between the identified innovation pillars.

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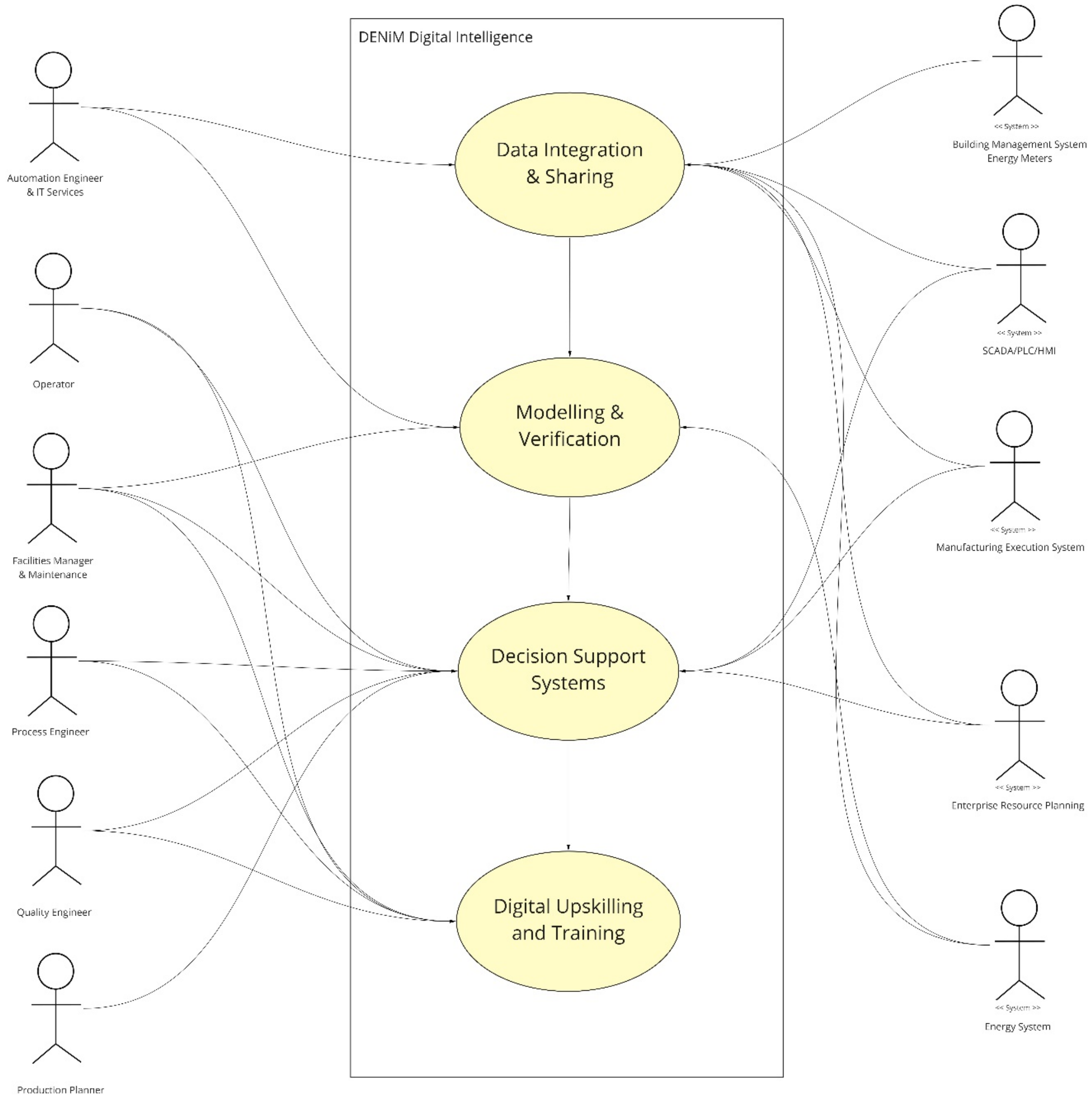

Figure 14: DENiM actors and Interaction with Innovation Pillars

The following table captures the role of the different actors as identified across the DENiM pilot sites, each actor can represent a person or a system that interacts with the DENiM solution.

Actor	Role	Interaction
Automation Engineer	Integration with asset\automation network Sensor Installation Software Validation	Integration and data extraction from machines and processes on automation network.

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IT Services Engineer	Network Infrastructure Sensor Integration (Network) Security Management Software Validation	IT Network Integration and security management Software Systems integration and change management
Operator	Asset Identification Operational Knowledge Requirements and needs assessment. Verification of data (e.g. scrap, usage)	Decision Support System (production scheduling, parameter optimisation) Digital upskilling and training
Energy Manager	Energy Systems Integration Asset Identification (Significant Energy Users) Awareness and Policy implementation Energy Auditing and Performance Verification	Energy Performance Models & Verification of energy savings Decision Support System (Visualisation of Energy flows, performance metrics, reports)
Facilities Manager	Asset Identification Auxiliary Services	Asset Performance Models Decision Support System (Fault Detection and Diagnosis, performance metrics, reports) Digital upskilling and training
Maintenance	Asset Identification Operational Knowledge – procedure	Asset Performance Models Decision Support System (Fault Detection and Diagnosis, performance metrics, reports) Digital upskilling and training
Process Engineer	Asset Identification Operational Knowledge	Decision Support System (Production Planning & Scheduling) Digital upskilling and training
Quality Engineer	Quality Assurance Quality Impact Assessment	Decision Support System (Production Planning & Scheduling)
Production Planner & Product Managers	Setting Boundary Conditions Scheduling and Impact Assessment	Models – LCA & LCCA Decision Support System (Production Planning & Scheduling, Key Performance Indicators)

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Finance	Cost Assessment & Verification Boundary Conditions	Models: Use and verification of verification of Lifecycle Cost Assessment Decision Support System (Sustainability Key performance indicators)
Building Management System	Building Asset Data, usage patterns	Data Integration
Energy Meters & Management System	Energy and Power Meters	Data Integration
SCADA/PLC	Asset Integration and Management Process data	Data Integration Decision Support Tools (Model Driven Control Services)
Manufacturing Execution System Laboratory Information Management System (LIMS) Computerised Maintenance Management System (CMMS)	Lifecycle Data Asset & Process data Performance Metrics Maintenance Data	Data Integration Decision Support Tools (connectivity for better decision making based on energy efficiency and KPIs)
Enterprise Resource Planning	Enterprise Asset Management Data Analytics (Business Intelligence)	Data Integration Decision Support Tools (connectivity for better decision making based on energy efficiency and KPIs)

4.2 DENiM Stakeholder Workshop

To validate the DENiM approach and to explore DENiM with respect to current status quo in relation to the role of digital technologies and energy efficiency in manufacturing systems the project team held an online workshop with the DENiM External Expert Advisory Board (EEAB) on March 18th, 2021. The advisory board consists of international experts across the various fields and topics covered by the DENiM project. The workshop was organised as an open discussion on the practical challenges, roadblocks and solutions for energy efficient manufacturing and as part of this workshop we introduced the DENiM objectives & ambition, presented the DENiM solution & vision, and sought the experts' opinion in relation to current best practices with respect to DENiM's related activities ("Innovation Pillars"). The DENiM innovation pillars are categorised as "Digital" relating to the

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technical solutions and "Human" relating to the role of the worker in energy efficient smart manufacturing.

In order to capture the experts' feedback a SWOT analysis was used to synthesise their observations and to draw out relevant insights to analyse the relevance of the DENiM objectives and proposed solutions and to identify ways to improve or enhance the DENiM offering if needs be. To capture a broad range of opinions and diverse insights the DENiM EEAB profile is itself diverse in nature with respect to their expertise and alignment with the DENiM innovation pillars and is described as follows:

Innovation Pillar	Category	Expert Profile
Reliable Data Integration & Sharing	**Digital**	Systems & software architectures for industrial Internet of Things, information semantics and interoperability, integration, interoperability and automation for smart energy systems.
Accurate Modelling & Verification		Energy modelling, sustainability, climate change mitigation, digital twin and process optimisation.
Decision Support and Adaptation		Business process optimisation, standards based workflows, life cycle assessment, circular economy and resource efficiency.
Workforce Development	**Human**	Industry 4.0, digital skills, training, upskilling, worker centric solutions.

4.2.1 DENiM Solution Analysis

4.2.1.1 Energy Efficient Manufacturing Current & Future Needs

As part of the analysis of the DENiM Digital Innovation Pillars with respect to current needs, barriers and future needs, we examined each of the Digital innovation pillars and identified how the DENiM solution meets the current and future needs.

4.2.1.1.1 Reliable Data Integration & Sharing

Current Needs	Barriers/Future Needs	DENiM Offering
Theme: Collaboration (sharing of best practise, insights, models, data sharing & analytics)		
• A collaborative approach across industry is required to sharing best practices	• Sharing data on energy consumption alone does not bring value need incentive, e.g. collective demand response • Sharing of experience may be more beneficial and less threatening than sharing of data • Collaborative sharing of energy efficiency models, digital twins as opposed to data • Challenge is different assets, processes and disclosure of trade secrets – need to balance	• State of the art software paradigms to enable rapid deployment of digital services that automates ingestion, contextualisation and analysis of large datasets with a focus on energy related data and collaborative data spaces

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• Need to increase the visibility of what is happening across EU projects/initiatives (e.g. build on EFFRA innovation portal in terms of project insights)	• Need more public deliverables and innovation to share experiences across projects • Demonstrators are a key aspect of this, situate the scope of the demo eg: advanced technologies, factory floor, energy efficiency etc., ongoing effort by EFFRA	• DENiM will support sharing of best practice and demonstrator impact as part EFFRA innovation portal
Theme: Integration & Interoperability		
• Legacy systems - integration of them must be taken into account • Need to identify the "practical" challenges for interoperability for energy • Shift from current infrastructure to new End-to-End Digital infrastructure • Focus on digitalising supply chain not organisation as a whole	• Bubbles of IT staff to support Digitisation is not the way forward – need IT & OT integration • Interoperability still remains a significant challenge. • Convergence of IT/OT still requires some effort.	• DENiM uses a common semantic model for sharing energy and process data • DENiM incorporate a secure middleware solution that provides a "plug and play" approach to integrating current protocols utilised in the manufacturing domain for specific process
Theme: Standards		
• For factory level information - focus on standards eg. - link to TC65 AAS work • A consolidated approach to interoperability challenges is needed	• Asset Administration Shell (AAS) is an opportunity and provide a common semantic model • Inform and feed into the current standards development • Need higher-level reference architecture that is applied in the context of project	• DENiM will develop a digital platform built on well-established reference architectures in the Industry4.0 space and utilize standards based approaches for integration, interoperability, energy auditing, determining energy savings, & KPIs

4.2.1.1.2 Accurate Modelling & Verification

Current Needs	Barriers/Future Needs	DENiM Offering
Theme: Energy data, optimisation, savings, efficiency, reduction		
• Monitor energy from a business case/cost perspective rather than sustainability point of view • Savings to be made in optimizing existing processes, target energy reduction	• Carbon intensive targeting savings rather than reductions • Reduction may occur but demand increases • Capital investment required for optimising existing processes	• DENiM will provide model driven identification of energy savings potential • DENiM will provide independent and accurate measurement of energy for manufacturing process

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Theme: Monitoring, Reporting, Assessment, Legislation		
• Ability to verify energy standards/auditing are implemented correctly in practice and in the right form • Formal approach to definition of Energy efficiency, i.e. what does it mean and how is it measured in different processes and situations • Eliminate the barrier between cost of energy and need to be more efficient. • Integrated Processes – for example informing maintenance processes from energy perspective. • Realisation of directive targets • Carbon neutral planning • Digital tools to support Monitoring, Reporting & Verification (MRV) methodologies • Approach to define LCA methodology for energy efficiency early. • Clear definition of the boundary for LCA - strategy for energy efficiency can impact other aspects	• Legislation can drive industry to take energy efficiency seriously • Industry Carbon Pledges - Sustainable and efficiency of Supply chain • Carbon Neutral Planning • Boundaries used for LCA are broadening • Flexible approach to how often can LCA be done - repetitive fashion taking various production dynamics into account. • The carbon pledges that many companies are signing up to are currently moving swiftly from commitments based on emissions savings to commitments based on emissions reductions, i.e. absolute reductions relative to a particular time • Energy is too cheap for industry - link to financial gain or legislation is alternative	• DENiM will create tools and mechanisms to support the creation and composition of digital models to support accurate energy performance assessment of assets, systems or processes • DENiM provides fault detection and optimal control from an energy perspective

4.2.1.1.3 Decision Support and Adaptation

Current Needs	Barriers/Future Needs	DENiM Offering
Theme: Decision Support		
• Carbon footprint can be misleading so more lifecycle approach is needed • A balanced approach to LCA implementation, i.e. LCA may be too complex for specific challenges\scenarios - clear LCA indicators are needed • Ease access to data for LCA assessment	• LCA needs to be brought online and methodology that helps decide when it is appropriate or not • Not just energy people but process people are involved in making decisions • KPIs - Turn data into local context • Getting access to company data can be challenging and	• DENiM will enhance existing methodologies for optimising energy efficiency such as energy auditing, LCA, LCCA, process optimisation, scheduling through the integration of real-time data • The DENiM decision support tools will cover production planning and scheduling,

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• For product lifecycle management need a view that embodies what LCA provides (i.e. environmental and/or energy indicators) • LCA not always needed for "quick" decision, need to identify where LCA indicators are appropriate	result in assumptions that reduce effectiveness of assessment • Data is under different silos and roles	fault detection and diagnosis of assets
Theme: Adaptation		
• Machine Manufacturing - Device to directly measure the power consumption were not built in • IoT to measure machinery indirectly is starting to be rolled out - but this data is disconnected from process changes • Link LCA & LCCA showing cost benefits for encouraging energy savings	• LCA being part of the optimization - but requires specific expertise, s/w, data • Data should lead to more Interaction between services and production process for holistic view on performance	• DEMiN will provide automated assessment tools that can be utilised throughout the value chain • DENiM supports the Integration of renewable energy in production processes • DENiM will provide common visualisation of energy flows to support continuous energy performance auditing

4.2.1.2 DENiM SWOT Analysis

S STRENGTHS	W Weakness	O Opportunities	T Threats
Reliable Data Integration & Sharing			
• Support integration and interoperability	• Given multitude of systems & protocols it is difficult to identify best approach for Interoperability • What reference architecture/protocols to adhere to - links to standards	• Demonstrate practical implementation of Standards (e.g. AAS) • Promote use of Digital Twin for industry • Contribute to Standards & initiatives e.g. on interoperability	• Availability of Data • Rapid evolution of technology
• Demonstrators from different sectors (process and	• Are pilots willing to share data, experience?	• Pilot diversity an opportunity or challenge - opportunity as they	• Are pilots too diverse for cross industry learning - is replication possible?

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<table>
<tr><td>discrete manufacturing)</td><td></td><td>are not competitors, should allow for open discussion</td><td></td></tr>
<tr><td colspan="4">*) DENiM Response: Within DENiM interoperability and integration will leverage industry standards based methodologies and protocols with RAMI4.0 and Asset Administration Shell being considered initially in the DENiM architecture specification, implementation and common data model formats.</td></tr>
<tr><td colspan="4">Accurate Modelling & Verification</td></tr>
<tr><td>• Use of data across business functions</td><td>• Clarify what we mean by savings - is it savings or reduction or both?</td><td></td><td>• Is there enough energy data available to build effective models?
• Is energy data gathered easily and effectively?</td></tr>
<tr><td>• Online LCA approach</td><td></td><td>• Transition to zero carbon targets drive energy efficiency & use of renewables</td><td>• Carbon neutral can reduce drive to reduce energy</td></tr>
<tr><td colspan="4">*DENiM Response: To support accurate modelling and verification as part of process optimisation to support energy efficiency (saving energy) and energy reduction with respect to an existing baseline a comprehensive baseline audit will be conducted to understand what data insights & knowledge can be extracted/inferred based on existing instrumentation or marginal upgrades. Approaching carbon neutral targets can reduce the focus on energy reduction, but DENiM will integrate energy related data flows as part of the lifecycle assessment methodologies making it an intrinsic part of lifecycle assessment rather than an add-on and will inherently drive continuous energy reduction and improvements.</td></tr>
<tr><td colspan="4">Decision Support and Adaptation</td></tr>
<tr><td>• Covering from shop floor to factory level digitisation</td><td>• Pure digitisation will not be able to reduce carbon /zero carbon</td><td>• Supporting reporting needs, certification, product passports, & digitalisation</td><td>• Is the DENiM solution scalable - what level of digital maturity is needed
• Ambitious targets have been set - are they achievable</td></tr>
<tr><td colspan="4">*) DENiM Response: DENiM will use digitisation to integrate energy data flows within the manufacturing process and as part of the lifecycle assessment methodologies to effectively address energy sustainability. The heterogeneity, capabilities and needs of the DENiM pilot sites will allow for investigation of the scalability and replicability potential of the DENiM solution. The DENiM solution will be based on a suite of tools, services and components that can be customised for sites based on its current and future levels of maturity.</td></tr>
<tr><td colspan="4">Workforce Development</td></tr>
</table>

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• Bringing experts from the shop floor to inform innovation	• Lack of social science expertise in the project • Incentives/willingness of operator to be more involved	• Have engagement that is not superficial across sectors • Involving the operator to inform innovation	• Procedure to engage with people
*) **DENiM Response:** A community of practise methodology will be used to understand the workers needs in terms of skills development and to enable sharing of knowledge & best practise as part of engaging the worker in the innovation process.			

*) *The DENiM response is to address weaknesses and minimise threats while taking advantage of opportunities.*

4.3 DENiM Platform Requirements

This section provides a summary of platform specific requirements that have been extracted from the current practice, pilot needs assessment and DENiM SWOT analysis. These general requirements will be used to drive the DENiM system specification and architecture. To support this, the requirements can be grouped under the DENiM strategies and associated functional grouping as set out below:

Innovation Pillar	Functional Group	Description
DENiM Digital Platform: Reliable Data Integration and Sharing	Digital Integration (DI)	Supporting and enabling the digitisation of existing processes
DENiM Digital Twin: Accurate Modelling and Verification	Digital Twin (DT)	Provide reliable modelling and data driven approaches for energy performance assessment
DENiM Decision Support: Decision Support Systems for Sustainability	Decision Support Systems (DSS)	Integrate energy and sustainability into existing and new business processes and workflows
DENiM Digital Skills: Digital Skills and Workforce Development	Digital Skills (DS)	Ensure industry are ready to take advantage of digital technology and that workforce are embedded in the process.

Each requirement definition will adhere to the following structure consisting of the following attributes:

- ID – This element is a unique identifier of each requirement and can be used as a short reference to a given requirement. Generally, it consists of literal identifier linking to the functional group and a numerical sequence.
- Name – Requirement name is a short representation of the actual content, it should be short to allow better orientation in the text and related mapping tables, but still representative of the content.

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- Description – This attribute is an actual content of the requirement. It should give a clear outline of the requirement objective.
- Priority – There are three levels of requirements priority that have been considered, selected based on alignment with project goals and SWOT analysis:
    - High – it is necessary to deliver the features described in the requirement.
    - Medium – in certain conditions this requirement could be omitted, but the reasons for this must be clearly explained and justified.
    - Low – requirements with this priority are optional.

4.3.1 DENiM Digital Platform: Reliable Data Integration & Sharing

DI-RQ-01: Digitisation of existing machines and processes	
Description	The DENiM system must support the integration of legacy equipment. The complexity of integration should be reduced and allow for easy addition of further communication protocols (e. g. : OPC, REST, Modbus, MBus, KNX …)
Priority	High

DI-RQ-02: Allow secure integration of device and other systems (data sources)	
Description	DENiM must support secure communications, access control and authentication of devices and data sources across systems to enable coordinated performance monitoring. The system should be easily extensible with components that allow integration with other business systems (e.g. ERP) through the use of data connectors.
Priority	High

DI-RQ-03: Supporting binding between devices distributed across different physical networks	
Description	Devices located on different physical network segments (or across sites, operational process/line) can be bound together as if they were located on the same physical segment. This is relevant to remove existing silos that impact integration and provide a holistic view on data used to understand energy flows holistically.
Priority	Medium

DI-RQ-04: Common Data Model to promote data sharing and interoperability	
Description	To promote interoperability a common data model should be defined and utilised across all DENiM modules. This should capture system configuration data, raw data and relevant meta-data that captures configuration and formatting. This should enable easier ingestion and integration of disparate data sources. Due to the high variety of data and data types, there is need to store this common model (semantic reference) that can be accessed via open interface.
Priority	High

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DI-RQ-05: Provide adaptive stream processing	
Description	DENiM must support (cross-device) data processing in near-real time; It should provide reusable components to provide “plug and play” data services such as to support data producers and consumers as well as distributed analytic services. This layer will provide a coordination layer across the DENiM solution.
Priority	High

DI-RQ-06: Ensure data integrity	
Description	The DENiM solution should ensure that data integrity is maintained throughout the lifecycle of the solution to support DENiM modelling and services. This should cover ALCOA+ data integrity principles (i.e. Attributable, Legible, Contemporaneous, Original, Accurate, Complete, Consistent, Enduring, Available)
Priority	High

DI-RQ-07: Provide scalable distribution and orchestration of data processing (Hybrid Cloud)	
Description	The system must scale across large sites covering multiple machines and processes; this includes processing of large amounts of data. It should be possible to distribute the integration and data processing functionality over different physical nodes (RTU, edge servers, BMS Machines, Cloud, etc.), to support scaling across large sites potentially across multiple physical buildings as well as supporting resource management. This distribution should be transparent to other tools and modules of the DENiM solution.
Priority	High

DI-RQ-08: Alignment of the solution with existing standards	
Description	The specification of the DENiM architecture and module functionalities should be in line with current standard definitions to support regulation and quality assured approach requested by many legal authorities.
Priority	Medium

4.3.2 DENiM Digital Twin: Accurate Modelling & Verification

DT-RQ-01: Energy Performance Models (Energy Twins)	
Description	The DENiM system must provide capabilities to integrate energy performances models. This includes existing tools, simulation environments that are applied to model and predict energy demand across products, machines and processes. Modelling approaches should facilitate the creation of digital twins that capture the current performance and are enriched by real-time data extracted from the DENiM system.

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Priority	High

DT-RQ-02: Support appropriate selection of approaches for performance modelling	
Description	Tools and methodologies are required that allows users to reduce the complexity associated with selecting techniques, creating, validating and deploying accurate models used for energy performance assessment and prediction.
Priority	High

DT-RQ-03: Formalise data integrity strategies to ensure continuous data quality for models	
Description	Approaches are required to ensure the quality of data models are maintained throughout their lifetime. This is to ensure robust models can be provided and maintained that are used in decision support systems.
Priority	High

DT-RQ-04: Provide online lifecycle assessment (LCA)	
Description	DENiM should enhance existing LCA methodologies by integrating real-time data to enable a more accurate and "online" assessment given site specific boundary conditions. Focus on integrating sustainability criteria as key drivers of the assessment process.
Priority	High

DT-RQ-05: Provide online lifecycle cost assessment (LCCA)	
Description	DENiM should enhance existing LCCA methodologies by integrating real-time data to enable a more holistic representation of cost impacts that supports energy efficiency management driven by site specific boundary conditions.
Priority	High

DT-RQ-06: Develop enhanced energy performance indicators (EnPI)	
Description	To support continuous auditing of energy performance there is a need to extend and enhance current energy performance indicators to allow the DENiM solution to provide a representative view of overall performance (energy, cost, sustainability) and that accurately reflects the current situation.
Priority	High

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4.3.3 DENiM Decision Support: Decision Support Systems for Sustainability

DSS-RQ-01: Enhanced energy performance indicators (EnPI)	
Description	To support continuous auditing of energy performance there is a need to extend and enhance current energy performance indicators to allow the DENiM solution to provide a representative view of overall performance (energy, cost, sustainability) and that accurately reflects the current situation.
Priority	High

DSS-RQ-02: Enable production planning that has sustainability as key criteria	
Description	DENiM should utilise energy performance models and sustainability assessment tools to support production planning from the perspective of analysing the impact planning and scheduling has on overall energy efficiency.
Priority	Medium

DSS-RQ-03: Allow autonomous fault detection and diagnosis	
Description	The DENiM solution must encapsulate functionality to support the management of fault detection and diagnosis methods for significant energy consuming assets at a particular site. A particular focus is the need to reduce failure rates, downtime, and energy waste. In case of faulty devices, there is the need for adequate support to inform maintenance strategies to ensure that the assets are working correctly and fulfil the functional requirements of the system.
Priority	Medium

DSS-RQ-04: Enable the integration of onsite renewables with production processes	
Description	The DENiM solution should be extensible to enable adaptation of production processes that facilitate the integration of onsite energy generation. The approach should be cognisant of the need to support future smart grid services such as demand response or demand peak shaving.
Priority	Medium

DSS-RQ-05: Common front-end for performance monitoring	
Description	Visualisation of energy performance data extracted by DENiM solutions is required. This should provide a consolidated view of energy performance and energy flows via a common user interface that is intuitive, easy to use and adaptive. This will allow multiple stakeholders to effectively manage their products, production and machines and processes. This includes visualisation of real time performance data, energy prediction, model outputs and effectiveness of energy saving strategies.
Priority	High

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DSS-RQ-06: Assessment of digital maturity of an industrial site	
Description	There is a need to acknowledge that not all industrial sectors are at the same level in terms of implementation and use of advanced digital technologies. As such it is critical for DENiM to provide a mechanism to assess the maturity of the pilot sites and to evaluate their ability to maximise the potential of the DENiM solution (from a technology and energy perspective). This can include the role of the DENiM system in advancing the digitisation of a manufacturing site.
Priority	High

4.3.4 DENiM Digital Skills: Digital Skills and Workforce Development

DS-RQ-01: Effective implementation of standard energy auditing approaches	
Description	DENiM should provide support for the effective implementation of standard based energy auditing processes (e.g. ISO 50001). DENiM should offer mechanisms that allow for independent verification of energy savings at the pilot sites and provide confidence in any energy saving measures that may be undertaken at a specific site. Where appropriate, training should be given at the pilot sites.
Priority	High

DS-RQ-02: Identify any skills gap across pilot sectors.	
Description	DENiM should identify any needs or opportunities for upskilling (as required) to ensure all workers are provided with sufficient knowledge to leverage advanced digital technologies that support managing energy efficiency.
Priority	High

DS-RQ-03: Provide appropriate training to support digital upskilling	
Description	Based on the skills gaps that may be identified at the pilot sites, DENiM should provide support to identify and match appropriate training .
Priority	High

DS-RQ-04: Facilitate the sharing of experience and knowledge across representative industry sectors	
Description	To ensure the use of best practices, DENiM should put in place structures that enable knowledge sharing and communication across pilot sectors. This should create a community that drives industry actors to distribute their own experiences in addressing energy efficiency enabling a collaborative approach to maximise opportunities across sectors.
Priority	High

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5 Conclusion

This deliverable provides a set of high-level use cases and requirements by focusing on the DENiM's innovation pillars and the requirements that DENiM solution needs to fulfil to address the current challenges faced in the domain of energy efficient manufacturing systems.

The innovation pillars, discussed in Section 1.1, reflect the DENiM approach to energy efficiency management and incorporate common functionalities that are needed across different sectors:

- Reliable Data Integration & Sharing
- Accurate Modelling & Verification
- Decision Support and Adaptation
- Skills and Workforce Development

Do drive the requirements definition and to ground the scope of activities for the DENiM project, four pilot cases were presented in Section 2. For each of the pilot use cases, the context and expectations were presented as well as an outline of the use case challenges that DENiM will address was provided. This approach allowed the project to identify the cross-cutting and site-specific challenges faced by industry and inform the needs for the DENiM approach. This will be used to map the overall DENiM solution to allow each pilot achieve energy efficient targets and performance improvement in the context of their individual needs while also being able to share best practice as they tackle common challenges.

This combined with the innovation pillars were used to guide the analyse of the state of the art and allowed the project to identify the current practices being applied in these areas. Emphasis was placed on a review of the current literature; industry works and related EU initiatives. As such, a comprehensive review of the technologies, tools and methodologies relevant to the DENiM approach was conducted and presented in Section 3. This will be used to guide the implementation work of the project to ensure they have a foundation in the current state-of-the-art and can demonstrate advancement beyond this.

The requirements analysis process was supported through engagement with an external expert advisory group. The group members consist of individuals with significant expertise that cover the various technologies and innovations of the DENiM project. This group provided participated in open dialog through a dedicated workshop where a SWOT analysis (Section 4.2) was conducted to allow the DENiM project to gain an understanding of current needs, trends and challenges being faced by the industrial sector.

The culmination of the approach described above resulted in the identification of specific requirements that will be addressed by the DENiM. This content of this deliverable will form a basis for the transition from user requirements to the architecture specification and subsequent component-specific requirements while being cognizant of the implication of the DENiM pilot use cases on the approaches of implementing the different modules and tools of the architecture definitions.

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