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ACCURATE

Frameworks for Resiliency- and Sustainability-Oriented Production Digital Twins

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Accurate

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Achieving resilience through manufacturing as a service, digital twins and ecosystems

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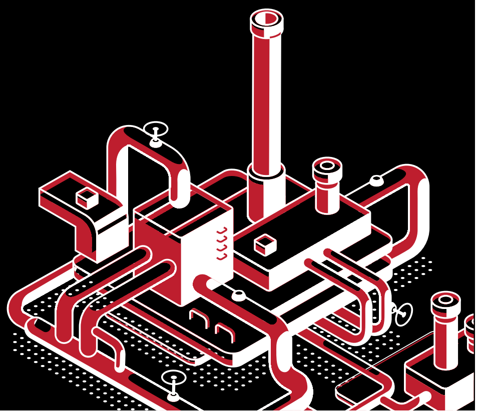

DELIVERABLE FACTSHEET

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Dissemination level	
x	PU = Public
	PP = Restricted to other programme participants (including the EC)
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	CO = Confidential, only members of the consortium (including the EC)

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Terms and abbreviations

ABS	Agent Based System
BFO	Basic Formal Ontology
CE	Circular Economy
CMS	Component Mounting System
DES	Discrete Event Simulation
DSS	Decision Support System
DT	Digital Twin
EF	Environmental Footprint
eLCA	Environmental Life Cycle Assessment
ERP	Enterprise Resource Planning
GUI	Graphical User Interface
GWP	Global Warming Potential
ILCD	International Life Cycle Data System
IOF	Industry Ontology Foundation
IPCC	The Intergovernmental Panel on Climate Change
ISO	International Standards Organisation
KPI	Key Performance Indicator
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LCSA	Life Cycle Sustainability Assessment
MaaS	Manufacturing-as-a-Service
MES	Manufacturing Execution System
MCDM	Multi-Criteria Decision-Making
MRP	Material Requirements Planning
MSA	Manufacturing Sustainability Assessment
MTBF	Mean Time Between Failures
MTTF	Mean Time To Failure
MTTR	Mean Time To Repair
OEE	Overall Equipment Effectiveness
OEF	Organisation Environmental Footprint
OEM	Original Equipment Manufacturer
OTD	On-Time Delivery
OWL	Web Ontology Language
PCB	Printed Circuit Board
PEF	Product Environmental Footprint
RQ	Research Question
SC	Supply Chain
sLCA	Social Life Cycle Assessment
SMT	Surface Mount Technology
UC	Use Case (as pertaining to the ACCURATE project)
UI	User Interface
UNEP	United Nations Environmental Protection

VBA	Visual Basic for Applications
WIP	Work-In-Progress
WP	Work Package

Public Summary

This deliverable is a part of the ACCURATE project which aims to increase the competitive abilities of European manufacturing through manufacturing-as-a service (MaaS), digital twins (DTs), and decision support systems (DSS).

One of the primary objectives in ACCURATE is investigating the resilience of MaaS systems during disruptions and the impact of such disruptions on the short- and long-term sustainability of such systems. Work Package (WP) 3 aims to addresses this research question, within the scope of individual nodes (i.e., manufacturing facilities) within a MaaS system. The overall ambition in WP 3 is to deliver the knowledge and tools for supporting the adaptation and reconfiguration of production processes within MaaS nodes from the perspective of resiliency, sustainability, and human-centricity. WP 3 will enable the creation of create DT modelling frameworks and associated DSS, with the above goals supporting MaaS nodes to perform simulation-based performance prediction, robust optimisation, and consequently responsive control of production processes.

This deliverable covers reports the progress in WP 3 towards establishing a conceptual basis for measuring and subsequently optimising the resiliency and sustainability performance of production processes and establishing the functional requirements for developing production-level simulation models within MaaS nodes. The deliverable covers work performed in Task 3.1, Task 3.2, and partially in Task 3.3. Results from these tasks, coupled with results from WP 2 and WP 7, have established a basis for quantitively assessing resilience, sustainability, and circularity performance for MaaS nodes, considering factors including, stakeholder priorities, data collection burdens, and applicability to simulation-based modelling. Results have also identified specific indicators to measure the above performances for each pilot in the ACCURATE project. Methodologies and results reported in this deliverable will be subsequently implemented in the ACCURATE project in the form of discrete-event based simulation (DES) models of capable of measuring resilience, sustainability, and circularity performance of production lines for MaaS nodes under nominal operating conditions and under disruptions. These DES models will be used as a basis for developing production-level DT models.

1 Introduction

1.1 Project Context

The ACCURATE project vision is to realise manufacturing-as-a-service (MaaS) value chains whose capacity, profitability, and sustainability are robust to longer- and shorter-term exogenous disruptions. The ACCURATE mission is to deliver a federated MaaS framework, data space and ecosystem, powered by multi-level digital twin models of MaaS value chains, to enable a collaborative, human-centred decision support system (DSS) for robust planning, resilient operation and responsive value networks and industrial systems recovery. The concepts, methods, and tools developed in the ACCURATE project will be applied, demonstrated and validated in three pilot partners

1.2 Deliverable Scope and Key Outcomes

The scope of this report is to present the work done as a part of Work Package (WP) 3, *Digital Twins Supporting MAAS Production Adaptation*. The overall ambition in WP 3 is to deliver the knowledge and tools for supporting the adaptation and reconfiguration of production processes within MaaS nodes (individual manufacturing facilities) from the perspective of resiliency, sustainability, and human-centricity. The work reported in this deliverable covers results from Task 3.1, Task 3.2, and partially from Task 3.3.

First, the deliverable reports results on the functional requirements for developing the ACCURATE digital twin (DT) models across the nine use cases (UCs) identified in ACCURATE. In this regard, the integration and interoperability framework has been established, defining technical requirements for DTs, including structured outputs, containerisation, and data exchange responsibilities. Model requirements have been developed to capture process dynamics, assess disruptions, and support decision-making based on key performance indicators (KPIs). Scenario configuration capabilities have been examined to facilitate disruption analysis, time-scale planning, and performance evaluation. Additionally, requirements for assessing sustainability and resilience have been established, ensuring alignment with production system requirements.

Next, the requirement and data required for developing and usage of resilience-oriented production-level simulation models based on discrete event simulation (DES) have been established across the three different pilot partners. The development and implementation of production models across various cases have been structured around shared data sources, including products, bills of materials, processes, resources, material handling, and production planning.

Simultaneously, the methodology for quantifying resilience, circular economy (CE), and sustainability performance was investigated, with the goal of coupling such indicators to the above simulation model. Indicators were identified using a scientific literature review, and narrowed down based on applicability to individual nodes in MaaS systems as well as information provided by the ACCURATE pilot partners on data availability, measurement complexity, and internal priorities. Two indicator screening tools were created to screen for resilience and circularity indicators. An ontology was also created to integrate the selection of circularity, sustainability, and resilience indicators into a manufacturing as a service context.

Finally, this deliverable lays out a recommended framework for resilience, circularity, and sustainability assessment for the nine distinct UCs across the three ACCURATE pilot partners.

1.3 Deliverable Structure

This report is split into six additional chapters, as follows.

- Chapter 2: Functional Requirements Engineering.
- Chapter 0: Circular Economy Circularity Indicators for a MaaS System
- Chapter 4: Resilience Indicators for a MaaS System
- Chapter 5: Sustainability Indicators for a MaaS System
- Chapter 6: Ontologies for Architecting Circular and Sustainable Manufacturing-as-a-Service System
- Chapter 7: Circularity and Sustainability Assessment Framework for a MaaS System

In Chapter 2, the functional requirements for the DTs are discussed. This discussion includes integration and interoperability between models, functional requirements for the models and an overview for the planned models for each ACCURATE pilot partner. Results from Chapter 2 are used as a basis for formulating the requirements for resilience, circularity, and sustainability assessments in Chapters 0-5.

In Chapter 0, an overview of a circularity indicator screening tool is presented, along with consideration of the circularity indicators presented for the UCs in the ACCURATE project. These indicators are linked to ACCURATE UCs in Chapter 7.

Chapter 4 presents a literature review on resilience indicators and details an indicator selector tool that aids the user in choosing resilience indicators for their own scenario. These indicators are linked to ACCURATE UCs in Chapter 7.

Chapter 5 provides an overview of the methodology for estimating environmental and sustainability indicators using the life cycle assessment framework, and their applicability to MaaS nodes. These indicators are linked to ACCURATE UCs in Chapter 7.

Chapter 6 discusses a novel ontology model created in the ACCURATE project for assessing circularity and sustainability in MaaS systems. The ontology models were developed from the assessment methodologies discussed in Chapters 5-6 and will be used for eventually extending ACCURATE matchmaking services.

Chapter 7 provides a conceptual framework for future work on the DTs models, specifically highlighting indicators for circularity and sustainability assessment for each UC. It builds on results from Chapters 0-5 which identify a general methodology for screening indicators for resilience, circularity, and sustainability performance, as applicable to individual nodes in MaaS systems.

2 Functional Requirements Engineering

In order to achieve the main goal of the project the Digital Twins must integrate across multiple scales, from individual manufacturing processes to entire supply chain networks. This requires well-defined functional requirements that ensure interoperability, adaptability, and reliability. Chapter 2 outlines these critical requirements, establishing the foundation for the development and implementation of DT models across ACCURATE's pilot cases.

This chapter is structured in three main sections:

1. **Integration and Interoperability Requirements** – This section defines the essential requirements for seamless communication between DT models and external systems. As DTs must interact with various data sources, simulation models, and decision-support tools, standardization in structured output delivery, orchestration, containerization, and data exchange is necessary.
2. **Models needed to be developed** – This section presents the output of Task 3.1, detailing the identified models that need to be developed and their mapping to the relevant use cases where their added value will be demonstrated.
3. **Resilience-oriented production models** – This section details how DT models will incorporate resilience mechanisms into production planning. By simulating disruptions, assessing recovery strategies, and optimizing reconfiguration processes, these models contribute to maintaining operational stability even under uncertain conditions. The chapter highlights key resilience-related KPIs and the methodologies for evaluating them.

2.1 Integration and Interoperability Requirements

To ensure seamless integration and interoperability, the models, DTs must support the following requirements:

1. **Structured Output Delivery:**
   - Models should deliver outputs in a structured format compatible with other user tools/models as requested by the client tool.
2. **Orchestration and Status Declaration:**
   - Models intended for use in orchestration with other systems must declare their status to facilitate automatic data exchange.
3. **Invocation and Execution Requirements:**
   - **Containerised Deployment:**
     i. If a DT is to be invoked by an external function or client, it should be provided as a container that includes all dependencies required for its execution.
   - **Configurable Data Exchange Location:**
     i. DTs should support access through a configurable data exchange location for communication with external functions or clients.
   - **Control Bus Implementation:**
     i. DTs should implement a control bus to support single-point evaluation, streamlining integration with external systems.
4. **Data Exchange Responsibility:**
   - **Black Box DTs:**
     i. Responsible for managing data exchange with the data sources required for their execution.
   - **White Box DTs (e.g., DSS):**
     i. The client (e.g., DSS) is responsible for orchestrating data exchange with the data sources required for the DT's execution.

2.2 Models needed to be developed

The models developed to support the adaptation and reconfiguration of production processes are designed to:

- Accurately capture and simulate critical dynamics at both the process-chain and higher-level nodes.
- Incorporate key events and disruptions across multiple nodes and hierarchical levels using a parametric approach.
- Enable quantitative assessment of the impacts of both **known unknowns** and **unknown unknowns** on output performance and system resilience.
- Provide actionable insights for decision-making through sustainability-focused and performance-oriented KPIs.

Functional Requirements

Scenario Definition and Configuration

Models must enable users to configure and change inputs for scenario creation. These scenarios should support:

1. **Disruption Event Introduction:**
    - Address disruptions and their impacts across hierarchical levels, including:
        - **Machine/Equipment Level:** Variables such as machine speed, reliability, scheduled stops, setups, energy consumption, and other resource usages.
        - **Process-Chain Level:** Incorporate aggregated impacts from equipment-level variables.
2. **Time Scales and Horizons:**
    - Support planning across different time scales:
        - **Short-Term (Days/Weeks):** Analyse initial production status, machine condition, deadlines, and potential delays.
        - **Medium-Term (Weeks/Months):** Evaluate medium-term production efficiency and planning adjustments.
        - **Long-Term (Months/Years):** Assess average productivity and long-term performance during design and reconfiguration phases.

Output and Result Requirements

Models must provide robust output capabilities to meet various performance evaluation needs:

1. **Quantitative Measurements:**
    - Assess and measure performance under specific scenarios defined by user inputs.
2. **Key Performance Indicators:**
    - Supply a comprehensive list of available KPIs to ensure the model aligns with task requirements.
    - Compute performance metrics across the following categories:
        i. **Process-Chain Level:**
            - KPIs such as availability, production rate, equipment utilisation, work-in-progress, lead time, and resilience metrics.
        ii. **Circularity and Sustainability:**
            - Provide methods to directly and indirectly compute sustainability-related KPIs.

A clear overview of the models developed under the ACCURATE project, including their implementation, interaction, and demonstrated value in the UCs, is presented in the table below:

Pilot	Use-case *(All use-cases are described in detail in D7.1)*	Model type/ Methodology *(Indicates the category of models used)*	Explanation Methodology *(Refers to specific models or tools applied)*	Expected Outcome/Benefits *(Purpose of applying each model)*	Task under which the model has been identified/developed *(Responsible task for developing the model)*
AIRBUS ATLANTIC	UC1: Supply Chain (SC) disruption monitoring by DT-based simulation	DES	SC stress test a part	Measure performance impact of defined set of disruptions	T4.1 SC components and process definition & Data collection T4.2 SC stress-testing simulation T4.6 Design of a resilience- and sustainability-oriented DT-based DSS
	UC2: SC design support by identification of hidden critical suppliers/material	ABS, DES, and Network science	SC stress test for a part with systematic experiment design features	Identify critical nodes for unknown disruptions	T4.1 SC components and process definition & Data collection T4.2 SC stress-testing simulation T4.6 Design of a resilience- and sustainability-oriented DT-based DSS
	UC3: SC design recommendations for better absorption and swift adaptation	Analysis methodology, Optimisation	Coordinate the SC and manage risk	Enhance multi-criteria decision-making (MCDM) in supplier selection by incorporating sustainability, quality, reliability, resilience, stability, and other critical factors	T4.6 Design of a resilience- and sustainability-oriented DT-based DSS
	UC4: Integrated assessment of supply and internal value chains by means of DTs	Analysis methodology, Probability and statistics, Optimisation	Manage demand, solve lots of size problem, integrate external and internal SCs	1. Demand-driven material requirements planning (MRP) to smoothen the deliveries (e.g., via thresholds, summaries of daily consumption, parametric models for replenishment) 2. Add buffers to strategic critical points of the supply and internal production workflow 3. Include prediction on delivery dates to anticipate missing components	T4.3 Optimisation of material flow in MaaS SC T4.6 Design of a resilience- and sustainability-oriented DT-based DSS
		DES	Capture both material flow and disruptions at SC and shopfloor level	Enhance decision making by considering both SC level and shopfloor level factors	T4.6 Design of a resilience- and sustainability-oriented DT-based DSS

Pilot	Use-case *(All use-cases are described in detail in D7.1)*	Model type/ Methodology *(Indicates the category of models used)*	Explanation Methodology *(Refers to specific models or tools applied)*	Expected Outcome/Benefits *(Purpose of applying each model)*	Task under which the model has been identified/developed *(Responsible task for developing the model)*
TRO	UC1: SC stress-test and optimisation: *Inventory management under fluctuating demand forecasts*	DES and ABS	Simulate the SC with customised SC policies	1. Improve inventory management policies 2. Minimise delays, reduce inventory costs, reduce dead stock, ensure timely availability of resources	T4.1 SC components and process definition & Data collection T4.2 SC stress-testing simulation T4.6 Design of a resilience- and sustainability-oriented DT-based DSS
		DES and ABS	Simulate the SC with decision-making process and allow complex adaptive system approach	1. Improve inventory management policies 2. Improve fab performance	T4.1 SC components and process definition & Data collection T4.2 SC stress-testing simulation T4.6 Design of a resilience- and sustainability-oriented DT-based DSS
		Probability and statistics	Model demand forecast fluctuation	1. Represent and model the fluctuations of demand forecast for different time horizons (long-term, mid-term, short-term); 2. Instantiate the simulation and optimisation models under uncertainty	T4.3 Optimisation of material flow in MaaS SC
	UC2: Production planning: *Batching optimisation*	DES	Simulate the behaviours of batching practices/approaches and formalise decision analytics (optimisation)	Increased efficiency through optimal batch sizing	T3.4 Robust Optimisation & Control of Production DTs
	UC3: Production planning and control: *Scheduling, dispatching, monitoring for lot excursions*	Modelling methodology, probability and statistics	Track, trace, and monitor lots of excursions	Estimate the waiting time/processing time distributions between workshops; Estimate the cycle time	T3.4 Robust Optimisation & Control of Production DTs
		Optimisation, DES	Monitor and optimise the fab performance under uncertainty	1. Align global (fab-wide)-local (workshop) decision/targets 2. Demonstrate an approach to addressing suboptimal production performances	T3.4 Robust Optimisation & Control of Production DTs T4.6 Design of a resilience- and sustainability-oriented DT-based DSS

Pilot	Use-case *(All use-cases are described in detail in D7.1)*	Model type/ Methodology *(Indicates the category of models used)*	Explanation Methodology *(Refers to specific models or tools applied)*	Expected Outcome/Benefits *(Purpose of applying each model)*	Task under which the model has been identified/developed *(Responsible task for developing the model)*
		Ontology, simulation models	Ontology is required for achieving semantic interoperability and simulation is required for analysis	DT-based scheduling optimisation	T 2.2 Ontology-based matchmaking T3.2 Resilience-Oriented Circularity & Sustainability Assessment T 3.3 Resilience-Oriented Production Modelling and Simulation
CONTI	UC1: SC stress-test in the very high complexity context	DES	SC stress test for a defined product	SC stress test, measure performance impact of defined disruptions	T4.1 SC components and process definition & Data collection T4.2 SC stress-testing simulation T4.6 Design of a resilience- and sustainability-oriented DT-based DSS
	UC2: Optimisation of material flow along the SC	Analysis methodology, Optimisation	Map and optimise the circulation of material along the supply chain in terms of quantities to order/produce/distribute for different time horizons	1. Minimise materials stock (particular attention will be paid to obsolete materials) 2. Maximise customer satisfaction and minimise the associated logistic costs	T4.3 Optimisation of material flow in MaaS supply chain
	UC3: Integration of production planning with production control	DES, Probability and statistics	1. Analyse historical disruptions/disturbances 2. Enhance the robustness of production planning under disturbances/disruptions and the performance of production control 3. The material flow behaviour and equipment reconfiguration of the production system can be effectively captured using DES modelled.	1. Ensure consistency between production planning and production control 2. Demonstrate an approach to addressing suboptimal production performance: Reduction of downtimes resulting from reconfiguration activities	T3.4 Robust Optimisation & Control of Production DTs T4.6 Design of a resilience- and sustainability-oriented DT-based DSS
		Ontology, simulation models, optimisation algorithms	Ontology is required for achieving semantic interoperability and	Estimation of capacity at a given time or alternatives to achieve	T 2.2 Ontology-based matchmaking T3.2 Resilience-Oriented Circularity & Sustainability Assessment

Pilot	Use-case *(All use-cases are described in detail in D7.1)*	Model type/ Methodology *(Indicates the category of models used)*	Explanation Methodology *(Refers to specific models or tools applied)*	Expected Outcome/Benefits *(Purpose of applying each model)*	Task under which the model has been identified/developed *(Responsible task for developing the model)*
			simulation is required for analysis	the defined capacity at a given time	T 3.3 Resilience-Oriented Production Modelling and Simulation
ALL	MaaS: Proof Of Concept	Modelling methodology, semantics	Analysis of semantic relations/interdependencies between information elements.	Foundation for ontology-based matchmaking of services to requirements (mainly determined by to-be produced products)	T 2.2 Ontology-based matchmaking T2.3 Semantic services development
		Modelling methodology, Optimisation	Dynamic pricing for MaaS	1. Endow the MaaS framework with a dynamic pricing functionality 2. Demonstrate the feasibility of enhancing the responsiveness, flexibility, and scalability of manufacturing industries via MaaS 3. Extend the scope of the conventional disruption mitigation strategies	T4.4 Dynamic Pricing for MaaS
		Modelling methodology, Optimisation	Schedule a set of on-demand manufacturing jobs on shared manufacturing resources	1. Endow the MaaS framework with a scheduling functionality 2. Demonstrate the feasibility of enhancing the responsiveness, flexibility, and scalability of manufacturing industries via MaaS 3. Extend the scope of the conventional disruption mitigation strategies	T4.5 Design a MaaS SC robust to disruptions
	Towards adoption of MaaS (dispersion of manufacturing services across both	Survey	Understand the barriers affecting the MaaS adoption in life-critical sectors: A case	Facilitate the adoption of MaaS at the ecosystem level — spanning companies, countries, the EU, and globally — under	T4.4 Design of a resilience- and sustainability-oriented digital DT-based DSS

Pilot	Use-case *(All use-cases are described in detail in D7.1)*	Model type/ Methodology *(Indicates the category of models used)*	Explanation Methodology *(Refers to specific models or tools applied)*	Expected Outcome/Benefits *(Purpose of applying each model)*	Task under which the model has been identified/developed *(Responsible task for developing the model)*
	geographical and logical boundaries)		study of AIRBUS ATLANTIC, CONTINENTAL, TRONICO	both: Normal Operating Conditions (driven by economic and environmental values), and Abnormal Operating Conditions (driven by survival and recovery motivations)	

Table 1: Overview of models needed to be developed for each UC in the ACCURATE project

All the models listed in the table will be described in detail in the corresponding deliverables, primarily those from WP2, WP3, and WP4. Some of these deliverables have already been submitted, while the remaining ones are scheduled for delivery in M22.

2.3 Resilience Oriented Production Models

This section provides a concise summary of resilience-oriented production models being developed to address the challenges identified for each UC, considering specific scenarios and disturbance factors.

The underlying concepts of individual production models, along with the challenges they aim to resolve within the internal value chain, are briefly outlined. Despite their unique objectives, these models share a common architectural structure, as illustrated in Figure 1 below.

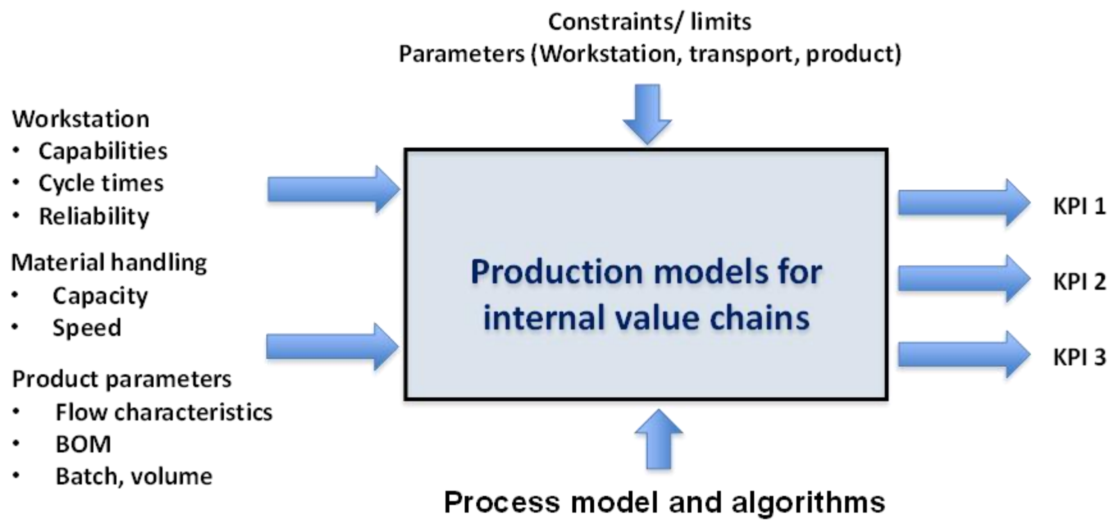

Figure 1: IDEF-0 model representation of the main entities and relation with the production models

Data sources

The data required for both the development of the models and their subsequent usage cycle follows a shared classification or taxonomy across most use UCs, as illustrated in Figure 2. Below is a list of the primary entities for which data collection is essential.

In the input side for the production models summarized parameters of workstations, Material Handling and Products are processed fed.

Workstation related parameters characterize main behaviour or a workstation such as:

Capabilities – what the workstation can perform in terms of processes required by the product process plans to transform the input to output.

Cycle times – the times necessary to carryout operations.

Reliability – the probability or percentage that availability that machines are available without being subject to failure.

Material handling related parameters characterize the capacity of transporting parts and work in progress in the factory. These include:

Capacity – the maximum quantity or units of materials that the equipment can handle at a moment

Speed – The speed in which the transporters can cover distances in the factory

Product parameters in relation to the system are also key inputs such as:

Flow patterns and routes – define the logic and sequence of parts movements from input material until the end of the processing.

Bill of materials – the list of sub-components and their hierarchical structure to form the product

Batch and volumes – define if products are produced in minimum lots or required quantities per time period.

In order to calculate the above-mentioned parameters, data collection templates are prepared as partially shown below:

Product and Families

Product SKU	Product name	Product family

Bill of materials

Component #	Component name	Quantity	Process #	Component Weight	Component Material	Unit Type

Processes

Process #	Process name	Short description	Flow time (s/pcs)	Flow policy	Condition

Workstation and resources

Workstation No	Resource name	Total available	Average Utilization	Planned maintenance	Unplanned shut downs	Scheduled shifts	Tool changeover time

Material Handlers

Handler No	Resource name	Capacity	Speed	Availability

Figure 2: Structure of the template used for data collection about internal value chains of the UCs.

- Products and families
- Bill of materials
- Processes
- Workstation and resources
- Material handlers and transportation
- Production planning and flow logics

The production models being developed are as follows:

1) Integrated assessment of supply and internal value chains by means of DTs for AIRBUS ATLANTIC

In this UC the production models developed for are designed to facilitate robust planning capabilities that dynamically adapt to changes in internal value chain parameters and external supply chain factors affecting performance. Examples of such changes include shop floor disruptions at equipment and workforce level such as unforeseen failures, planned stops or external factors such as transportation delays impacting material arrival dates, and last-minute customer specification updates. In order to achieve the UC objectives, the production models integrate comprehensive assessments of Airbus Atlantic's supply and internal value chains, enabling rapid adjustments that enhance resilience related KPIs. The primary focus is on improving both short-term and long-term resilience, as measured by KPIs.

Targeted KPIs and Data Sources

Various data sources are utilised to gather information for the development of DES models. This includes data on internal processing stages, production resources, production flows of selected product types, supply chain and logistics for component supply, and historical reliability data of suppliers. Additionally, the bill of materials—capturing the internal component flow from the Manufacturing Execution System (MES) and external component supply from the Enterprise Resource Planning (ERP) system—is leveraged to develop the models. Furthermore, availability and timing data for production resources are also collected. Integrating these diverse data sources into the models ensures a comprehensive and accurate representation of the factory's operations, facilitating precise analysis and optimisation of the target KPIs.

Some of the output KPIs that will be calculated/forecasted by the models are:

- Short term output KPIs that can be calculated are:
  - Lead time
  - Work in progress
  - On-time delivery (OTD) or delays
- Medium term
  - Production rate (cumulative for a relatively longer period)

2) Production planning reconfiguration under disruption for CONTINENTAL

This production model emphasises the robustness and reconfigurability of production planning at CONTINENTAL's factory in Timisoara (Romania), considering the effects of various internal and external factors. The primary objective is to develop models that enable the production scheduling system to adapt effectively to changes and disruptions while maintaining efficiency and meeting demand.

The main factors impacting on planning robustness and that should be captured by the production model include: 1. Demand fluctuation, 2. Missing components / insufficient inventory, 3. Unusable components, 4. Warehouse space constraints, 5. Capacity and utilisation challenges, 6. Machine breakdowns and 7. Variability in production yield and process duration.

Targeted KPIs and Data Sources

The production models will use data obtained from the CONTINENTAL systems, e.g. the system status, work in progress and fulfilled production orders to model relevant aspects of the manufacturing system. The data exchange may be asynchronous and initiated by the user.

Decision variables include allocation of production orders towards manufacturing resources as well as selection of material flow options; the main DTs focus is the logical reconfiguration of the production system.

The UC will target the following KPIs:

- Resilience
- Delivery rate
- Lead time and OTD
- Sustainability

Additional KPIs will be included in future versions of the production models.

3): Production scheduling optimisation and shop floor control for TRONICO.

In this case the production models aim to improve production scheduling and shop floor control. The models focus on supporting efficient scheduling to handle disruptions efficiently and optimising the production flow in TRONICO production system considering the short term and medium-term planning needs. The models should lead to significantly reduced downtimes arising from product changes and reconfigurations and improve overall efficiency. The manufacturing system level models could allow to propose the best strategies to manage scenarios that arise from internal disruptive events and managing them through the right size of work-in-progress (WIP) and prioritisation of production tasks. The models will contribute to shift from the currently adopted infinite capacity planning approach towards a finite capacity scheduling approach.

Targeted KPIs and Data Sources

Historical data is collected on the macro-stages of the TRONICO production system. This data is cleaned and restructured according to the DES requirements and approximations are made where details are missing in the historical data.

The target KPIs that are calculated by the production models

- Resilience
- Blocked production orders
- OTD
- Lead Time
- Sustainability KPIs

4) Production planning batching optimisation for TRONICO.

This production model focuses on defining the ideal batch size for production, considering TRONICO's production capacity and necessary tools. This approach seeks to determine the most efficient batch sizes for different stages of production, such as larger batches for component mounting systems (CMSs) and smaller batches for subsequent manual operations. The current practice lacks a standardised method for determining batch sizes, relying instead on individual experience and intuition.

Targeted KPIs and Data Sources

Although the decision variable in this production model is different compared to the model number 3, the output KPIs and the data sources used are similar.

3 Circular Economy Circularity Indicators for a MaaS System

This chapter discusses the methodology for measuring CE performance of MaaS systems in the ACCURATE project. The chapter provides a general overview of product-level CE indicators, and the recently published ISO standards for CE measurement. Finally, the chapter describes the circularity indicator screening tool developed in the ACCURATE project.

3.1 Introduction to Circularity and Sustainability Indicators

The transition from traditional linear economic models to CE approaches is essential as global resources diminish, and environmental damages increase. Traditional linear models, i.e. 'take-make-use-dispose', economic models are proving to be unsustainable, this in turn promotes for society a shift towards a circular economy that tries to minimise waste and maximise resource efficiency through so-called restorative and regenerative processes. This approach tries to help to maintain materials and value over time, thereby creating a model that reduces the need for new raw materials and minimises waste production. Circularity involves the reutilisation of resources to reduce waste by maintaining products and materials in closed loops of production and reuse. A CE seeks not only to reduce environmental impacts but also to enhance economic benefits by transitioning from finite to renewable material sources (Lieder & Rashid, 2016).

Indicators play a crucial role in managing and evaluating the implementation of CE strategies, allowing for the quantitative measurement of sustainability progress across various metrics. These indicators provide the metrics needed to track performance improvements, inform decision making, and perhaps even policy development, all in all addressing the challenges of resource use and environmental pollution. CE indicators are thus of high importance to the entire transition. The selection of appropriate CE indicators has many challenges due to the diversity of metrics and the complexity of their applications. Implementation of a CE framework relies on choosing the right indicators that reflect the sustainability goals of the organisation at hand and this can be a challenge for most organisations to even find what data availability they possess. Furthermore, the lack of standardisation and complex measurement frameworks can prevent and delay utility (Goddin et al., 2019).

3.2 ISO Standards on Circular Economy

The ISO 59000:2024 series of standards are designed to provide comprehensive guidelines and frameworks for implementing CE principles across various industries (Standardization, 2024a, 2024b, 2024c). These standards aim to promote sustainable development by encouraging the efficient use of resources, minimising waste, and enhancing the overall sustainability of products and processes throughout their life cycles.

3.2.1 Measurement and assessment of circularity performance

ISO 59020, a part of the ISO 59000 series, specifically focuses on the measurement and assessment of circularity performance within organisations (Standardization, 2024c). It provides a standardised, comprehensive framework that includes core indicators for evaluating resource inflows and outflows, energy and water use, and economic factors. These indicators are crucial for ensuring consistency and comparability across different organisations and sectors, enabling a holistic view of circularity performance. Utilising the core indicators of ISO 59020 facilitates the ability of companies to reference, share, and benchmark their circularity results against others. This standardisation ensures that the assessment framework is robust and methodologically sound, helping organisations track and improve their circularity performance. Moreover, adhering to ISO 59020 helps organisations comply with international standards of measurement, supporting transparency, and promoting best practices in CE initiatives.

The core indicators of ISO 59020 are divided into several categories, each focusing on different aspects of circularity performance, mass inflows, mass outflows, water, energy, and economic. These categories ensure that all critical aspects of circularity are covered, enabling organisations to comprehensively assess and improve their circular economy practices.

A list of mandatory and optional indicators from the ISO 59020 were compared with the list of product circularity indicators from Jerome et al. (2022). It was found that the product level indicators already identified adequately covered the mass inflow, outflow, and energy indicators outlines in the ISO 59020 standards, however there were key gaps that the ISO indicators filled, specifically in the category of water, which was not covered by the product level circularity indicators.

3.2.2 Circular Economy Actions

As organisations shift towards a CE, the ability to measure and trace this transition towards circularity becomes increasingly important. Many circularity indicators are used as tools in this process, providing knowledge, in the form of various KPIs, into how well a company or production system is performing regarding many aspects linked with circularity. However, given the broad scope of these indicators, many could potentially fit into so-called circular action categories within the circular economy framework. These CE actions are defined in ISO 59010, guidance on transition of business models and value networks (Standardization, 2024b). These actions help define what each indicator can contribute towards reducing the impacts of maintaining a linear economy.

It should be noted that these actions are generally used to describe what a company or organisation can do to mitigate the linear economy and strengthen its transition to a CE. The CE framework is built on several core actions that drive the transition from a linear to a circular model. These actions are defined to try and maximise resource efficiency, minimise waste, and promote circularity across all stages of a product's life cycle.

3.3 Circular Economy Indicators and Actions Categorisation

On reviewing the different indicators for CE measurement, it was evident that not all indicators are applicable towards CE measurement for MaaS nodes and the selection of indicators for assessment of CE performance can vary, depending on the priorities of the manufacturer and data availability. Due to lack of a systematic approach for categorising indicators in an easy-to-use manner, the ACCURATE project has developed a tool for screening CE indicators (further elaborated in Section 3.4). The tool focuses on screening resource-based product level CE indicators based on the requirements for simulation models establishes in the UCs. The following sections describe the methodology for developing the tool.

In order to create a tool that screens for indicators based on the data available to the user, indicators need to be categorised and presented by category. To create such a tool, the methodology used, behind the current framework, stems from an iterative approach to finding the more efficient and feasible ways of implementing a tool that from a set of criteria can selectively choose the indicators that match those. The original paper that the product circularity indicators were gathered from Jerome et al. (2022), grouped each indicator together by their class and measurements. The proposed tool instead categorises indicators and data by the data types used in the calculation of these indicators. This was considered to be a better method for the purposes of the ACCURATE project, as many of these indicators do not necessarily include the same ways of quantifying them, referring to the exact measurement terms included in their formulas. The selected indicators for the screening tool use linearised formulas, that do not require any numerical approach to quantify.

All indicators use terms of measurements that fall into three general groups of physical measurements of mass, time and energy (Aher & Ramanujan, 2024). This is seen throughout each indicator present, however, small deviations in forms of mass fractions of a product or subassembly and alike are also used. Although not directly a mass parameter, they can be very closely aligned and related to that of regular mass terms measured in units of mass (kg).

By choosing to categorise based on terms, e.g. mass terms such as mass of products (Mprod) regardless of what measurements the indicators quantify on their own, it is possible to group each of the three general terms of mass, energy and time, that is included in each of the indicators, into larger groups for which they generally belong in and conform to. This procedure was done by analysing the flows that each of these terms are defined by in the flowchart, as each indicator has a unique flowchart (Jerome et al., 2022).

The reason for grouping these terms together in this way is that one of the main ideas behind the framework is to create criteria for which each indicator is conditioned by. These criteria are more or less just the terms themselves, however, a question regarding the criteria is added. This question will often just be whether the user can estimate data regarding the different measures that the terms quantify. This will be explained further in the later sections.

These criteria needed to be grouped together because each of them constituted one of the terms used in the indicators. If each term was assigned to a criterion, and each criteria needed to be given a question, then there would be 40+ criteria that one should respond to and address. This would in turn also make the selection process simpler. This would suddenly be a very long list of criteria, and thus it was decided that creating these groupings/categorisations of terms/criteria would make the process of addressing them more convenient. The convenience appears from creating an overall criterion for each of these groups, corresponding to each of the categories. Each of these overall criteria has underlying criteria that is associated with that category. If one cannot fulfil the overall criterion, then they would not be able to fulfil the underlying criteria either. This does, however, make some overall criteria broad, in the sense that it needs to cover all the underlying criteria. In the end, the user might have to answer far fewer questions if they have limited data (as expected in many cases) and thus would only be exposed to a lesser number of questions.

All the criteria themselves are listed as a question, specifically they are set up to inquire the user regarding the data they can gather. Most criteria start with a question: *Can you estimate data on* ____, followed by the nature of the indicator term that the criteria refer to. For example, the criteria regarding the product mass term of Mprod is listed as: *Can you estimate the data on the total mass of the product?* Each criterion is followed by a description of what is meant by the question itself, which is usually short in nature due to the rather simple quantifications of these terms. For example, the description of the Mprod criteria is: *"Total mass of end-products"*. Having established the list of indicators and the criteria, along with a description explanation of each in regard to the flowchart, they could then be implemented together to form the framework of the tool.

By narrowing down the categorisation to the more core functionality of each indicator in terms of their action contribution, one can provide a less cluttered and more focused view of how they contribute to specific circular actions. For example, an indicator that measures recycling rates is categorised under actions that contribute to value recovery because its primary function is to assess material recovery through recycling.

Furthermore, the indicators used in the screening tool were mapped onto each category. There are five categories of CE actions defined in the ISO 59010 standards, that are adopted in the screening tool as follows:

1. **Create Added Value**: These actions focus on optimising processes, improving resource efficiency, and enhancing sustainability to increase the overall value derived from materials, products, and services.

Indicators in this category typically measure efficiency improvements that reduce costs, waste, and environmental impacts, thereby directly adding value to the production process.

2. **Contribute to Value Retention**: This group of actions is concerned with extending the lifespan of products and materials through reuse, maintenance, refurbishment, and remanufacturing. Indicators here assess how well a system retains the value of resources by keeping them in use for as long as possible.
3. **Contribute to Value Recovery**: These actions are focused on recovering value from products, components, and materials that have reached the end of their initial use. Indicators in this category typically measure the effectiveness of recycling, material recovery, and reintroduction into the production cycle.
4. **Regenerate Ecosystems**: This category encompasses actions that contribute to the regeneration and sustainability of natural ecosystems. Indicators here might measure the use of renewable resources, the reduction of environmental impacts, or the adoption of regenerative practices in production.
5. **Support a Circular Economy Transition**: These actions facilitate the broader shift towards a circular economy by guiding strategic changes, measuring overall circularity, and demonstrating the economic viability of circular practices. Indicators in this category provide insights into the overarching progress of an organisation or system towards circularity (Standardization, 2024b).

Given the broad applicability of many indicators, it might seem that they could fit into several, if not all, of these action categories. Many indicators do implicitly contribute to multiple areas of circularity, especially those that enhance process efficiency, which could be seen as adding value in a broad sense. However, to avoid overlap and ensure that each indicator is recognised for its primary function, it was chosen to categorise them based on what they explicitly measure and the most direct action that they support and contribute towards. This involved defining the explicit contribution and the core function of an action. While indicators often contribute to various circular actions implicitly, this categorisation focuses on the explicit outcomes they are designed to measure. This approach tries to identify the primary, and more explicit role each indicator plays within the CE framework.

3.4 Description of the ACCURATE Circularity Indicator Screening Tool

The product-level circularity indicators used in the ACCURATE project quantify the circularity of a product by assessing different aspects of its production, use, and disposal phase, as shown in Figure 3. This image specifies system boundaries and important material flow throughout a manufacturing system.

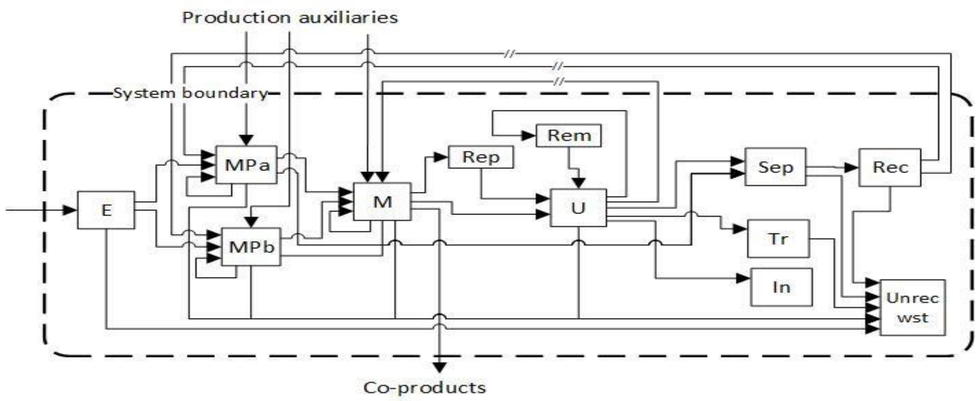

Figure 3: System Boundaries of Product Lifecycle Used for Circularity Indicator Calculation (Jerome et al., 2022).

The ACCURATE project has developed a CE Indicator Screening Tool to address these challenges by simplifying the process of screening appropriate CE indicators. This tool is designed to help various stakeholders choose relevant indicators, with a focus on product- level indicators, through a series of questions that reflect specific terms included in the CE indicators. The main objective of the study is to create a robust indicator framework by systematically classifying indicators into a comprehensive list and establishing a methodology to narrow them down. This framework will aid in screening the most relevant indicators for evaluating progress towards circularity and sustainability.

Microsoft Excel, with its already established graphical user interface (GUI) and interactive capabilities through macros and Visual Basic for Applications (VBA), was chosen to implement the tool. The core functionality of the tool is to organise a selection of CE indicators based on the user's input regarding what indicators are accessible for their particular data availability. This is achieved through a criteria selection process where users tick checkboxes to indicate which criteria they can fulfil, as seen in Figure 4.

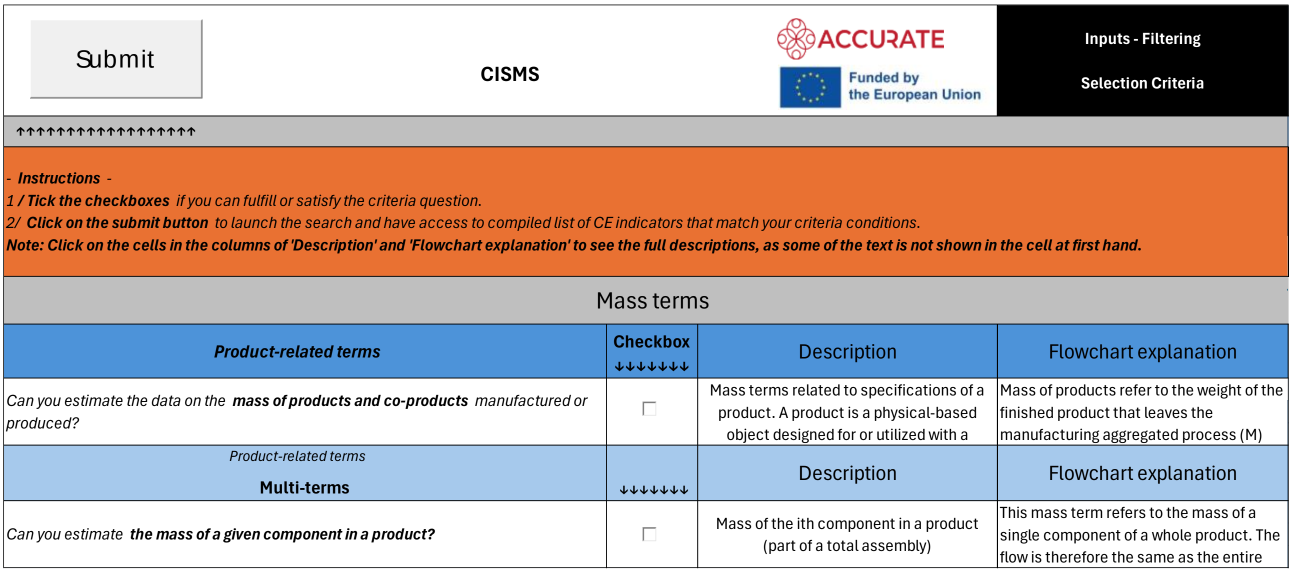

Figure 4: Circularity Indicator Screening Tool Criteria Input Selection Tab.

The user interface (UI) of the ACCURATE CE Indicator Screening Tool is crafted to be intuitive and user-friendly, ensuring users can easily navigate through the process of selecting appropriate circular economy indicators. The tool's layout is structured to ensure logical flow and ease of use. It comprises:

- *Input Section:* Where users input their criteria and select relevant checkboxes.
- *Criteria Sheet:* Displays all possible indicators and their corresponding criteria.
- *Output Section:* Shows the results after criteria submission.
- *FlowChartReadMe Sheet:* Provides a comprehensive guide to the flowchart model used for the indicators.

Each section is clearly labelled and logically arranged to guide the user through the selection process seamlessly.

The *Input Section*, shown in Figure 4 allows users to provide their specific data and select relevant criteria. Key components include:

- *Checkboxes:* Represent different criteria that users can select based on available data. These are grouped into categories for easy access.

- *Dynamic Rows:* Implemented using VBA code, dynamic rows show or hide based on checkbox states, ensuring only relevant options are displayed. This helps guide the user towards illustrating what indicators they both can and cannot calculate with the information they have at hand.

Each criterion is linked to a checkbox. These checkboxes contain the logic for the criteria and store this information in the far-right corner of the sheet. This is because VBA cannot access information across different objects.

To implement the hierarchical branching of the criteria, effective visual formatting is required. When a criterion is fulfilled, additional criteria should become visible to the user. This effect is achieved by utilising macros through VBA in Microsoft Excel, essentially through the logic of each of these checkboxes. These checkboxes are part of the developer tool in Microsoft Excel and are interactive objects that can be placed arbitrarily, but more importantly, within a given cell.

The information that the checkbox stores is the name of the term in each indicator formula that they represent. For the criterion*, Can you estimate the data on the total mass of the product?,* this refers to the mass term: *Mprod*. A separate macro, acting as the way of submitting the answer to the criteria, is created to locate all the terms of the criteria that have been stored. If it finds a term, it will also register that criterion to be fulfilled.

The *Criteria Sheet*, shown in Figure 5 functions as the taxonomy of the indicators, listing all possible indicators along the rows and the criteria along the columns. If an indicator contains the term that the criteria are defined by, a *'check'* is placed in the cell that corresponds to the row of the indicator and the column of the term, as shown in Figure 4. This sheet uses visual cues like colour coding to show which criteria are fully or partially met, aiding users in understanding their data compatibility. Indicators with all terms/criteria fulfilled are shown in green, those with at least one or more criteria fulfilled are shown in yellow, and those with no criteria fulfilled do not change colour.

Indicator Taxonomy				
Circularity Indicators (C-Indicators)	**Access Link**	**Description**	Flowchart Adapted From: Jerome et al. (2022) Link ***Push to show*** ↓↓↓↓↓↓↓↓↓↓	**Formula**
Energy Intensity (EI)	https://doi.org/10.1039/c9gc02992c	The EI is a fraction of the total energy demand during extraction and production E_demand, compared to the total mass of end-products		E = (E_demand-E_int) / (M_prod + M_co.prod)
Waste Factor (WF)	https://doi.org/10.1039/c9	Waste factor (WF) and measures the ratio of the total mass (kg) of solid, liquid or gaseous waste, generated as process wastes or lost from the		WF = M_waste / (M_prod+M_co.prod)
Feedstock Intensity (FI)	https://doi.org/10.1039/c9	Feedstock intensity (FI) quantifies raw material consumption and is the ratio of the total amount of the main raw materials used to the total		FI = M_primary.mat / (M_prod + M_co.prod)
Process Material Circularity (PMC)	https://doi.org/10.1039/c9	Responsible material circularization strategies employed to recover and reuse some or all of the process auxiliaries consumed during the product		PMC = Σ (from i=1 to n) [(M_rec.prod.aux,i / M_prod.aux,i) × (100 / n)]

Figure 5 Circularity Indicators Screening Tool Criteria Sheet Example

The *Output Sheet*, shown in Figure 6 illustrates the selection of indicators that fully match the answers to the criteria in the InputSheet. The information shown here is copied from the *Criteria Sheet*. It is thus a sheet dedicated to the indicators that have all criteria fulfilled by the inputs.

Circularity Indicators (C-Indicators)	Access Link	Description	Formula
Actions that create added value			
Actions that contribute to value retention			
Actions that contribute to value recovery			

Figure 6 Circularity Indicators Screening Tool Blank Output Sheet

The *FlowChartReadMe sheet* provides a comprehensive guide to the flowchart model, shown in Figure 3, used for the indicators, detailing the phases and processes each indicator measures. It includes an explanation based on Jerome et al.'s paper and outlines key phases like the extraction phase (*E*) and material production phases for both non-renewable (*MPa*) and renewable materials (*MPb*); these phases are shown in Figure 3. This sheet serves to clarify the model and its components, which enhances the user's understanding of the indica- tor measurements. The main flowchart model description was sourced from the supplementary materials provided in Jerome et al. (2022).

The user interaction flow begins with selecting criteria in the *Input Section*, followed by reviewing the matched indicators in the Criteria Sheet, and finally viewing the tailored results in the *Output Section*. This flow ensures a streamlined and efficient process for identifying relevant indicators.

4 Resilience Indicators for a MaaS System

This chapter presents a systematic literature review aimed at identifying and organising resilience indicators for MaaS systems. The goal was to provide a comprehensive overview of resilience metrics applicable to both academic research and the industry pilots of the ACCURATE project. To support the identification and application of these metrics, a corresponding screening tool was developed to filter and select resilience indicators based on specific user needs in the ACCURATE project.

4.1 Introduction to Resilience

Resilience is a widely used, but rarely agreed upon, topic in the discipline of engineering. It is a key design principle and system attribute in engineering which is only just gaining popularity. Many engineered systems will experience some sort of failure or disruptive event during their lifetimes, but the concept of resilience is relatively new in the engineering field compared to other fields of study. Designing with resilience in mind and calculating different resilience metrics can help mitigate adverse effects from disrupted events. Resilience plays a key factor in reducing the occurrence and impacts of these events (Bhamra et al., 2011; Wied et al., 2020).

There are a wide range of definitions for resilience, encompassing many different aspects. For the purposes of this review and future work regarding the resilience of a production facility we will define resilience as a system's ability to avoid, withstand, and recover from a disruptive event (Bhamra et al., 2011; Francis & Bekera, 2014; Wied et al., 2020). These disruptive events can be many things, specific to the ACCURATE project, these could be supply chain disruptions due to geopolitical events or a machine breakdown at a facility. This definition was chosen because it touches on three time periods surrounding a disruptive event. Figure 7 can be used as a reference in noting the timeline of a disruption. Figure 7shows a resilience curve, this is the performance of a system over a duration, during which a disruption to functionality occurs. The first period is the time before a disruption occurs, shown in green in Figure 7Figure 7. Here, the inherent properties of a system may allow it to avoid being impacted by a disruption. The next period of interest in the time in which a system is negatively impacted by a disruptive event, shown in orange in Figure 7. Here, the system must be able to absorb the negative effects. This time period encompasses the decline of system functionality up until the point where the final period, recovery begins. This final time period, shown in blue is the period in which a system recovers from the event and achieves a new normal state of functioning (Bhamra et al., 2011; Chatterjee et al., 2024; Wang et al., 2022).

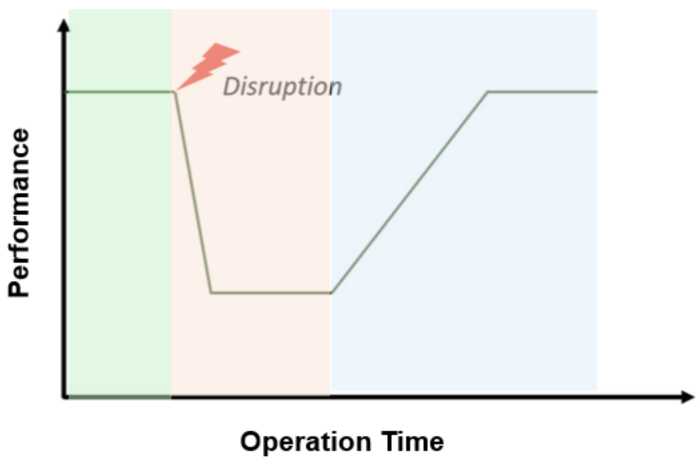

Figure 7: Resilience curve adapted from Chatterjee et al. (2024).

The first time period, before a disruptive event happens is the time when latent properties of a system protect it from a disruption. These properties are passive and pre-built into a system. The other two time periods are when the system is actively working to slow, and stop a disruption from affecting the system, as well as actively working to recover the system's functionality. These passive, attributional and active aspects of a system are both needed to predict and strengthen the resilience of a system (Hosseini et al., 2016).

Disruptions can affect different layers of the supply chain, resulting in a given company potentially being pressured from multiple sides, which could be decreased customer demand or supplier shortages (Sheffi, 2017). Within WP3, the scope of disruptions are limited to those *directly affecting* a single manufacturing facility where a MaaS service is provided. Herein, the term *directly affecting* refers to problems or solutions that are created by a disruption that disturb the planned operation of a manufacturing facility. Furthermore, such effects can be examined and controlled within the said facility using in-house solutions, therefore excluding disruptions such as decreased customer demand and supplier shortages—situations that would be typically solved by increased marketing or making better agreements with suppliers. The bounds of a single facility are in this instance defined as the facilities that a manufacturer or MaaS provider has direct control over. In other words, a company with multiple facilities all producing the same product (but at different stages) is counted as a single facility, just separated by the limitations of physical space. Productions running in parallel (i.e., producing the same product/component, but in multiple locations) are not as a single facility, as they can potentially operate independently and not be directly affected by disruptions hitting one facility.

This following part of this chapter discusses results from a literature review on resilience indicators which can be applied to a single manufacturing facility. As such, it is important to talk about the nature and function of indicators. Indicators are tools used to demonstrate particular traits or tendencies of a system. These traits and tendencies must be observable and measurable in some form whether it be qualitative, quantitative or a mix of both. Indicators for resilience must be able to show partially or totally the ability of a system to adhere to the definition of resilience previously indicated, a system's ability to avoid, withstand, and recover from a disruptive event. The resilience indicators that we are searching for in this paper are indicators meant to be used by important decision makers for a production facility (Turksezer et al., 2020; Valenzuela-Venegas et al., 2018).

4.2 Resilience Indicator Literature Review

There is a gap in understanding in current literature between resilience studies of SC level systems and single manufacturing facilities. SC level resilience is well-defined by current resilience indicators, where some might be relevant to single facilities, but no clear distinction has been made yet as to separating indicators based on controllable parts of the supply chain (Sheffi, 2017). With the world changing politically, culturally and environmentally, are efficient resilience strategies more important than ever. Manufacturing facilities are no different from normal businesses in their need for optimal preparation and response to potential disruptions, but they do differ in the ideal strategy for doing so. This paper will therefore explore the current state-of-the-art on resilience metrics by classifying and categorising conventional resilience metrics which are relevant and controllable by single facilities. To do this are three research questions (RQs) are asked:

- RQ 1: How are resilience indicators conventionally categorised?
- RQ 2: Which categorises of indicators are the most relevant to manufacturing facilities?
- RQ 3: Which are the current best applicable resilience indicators for single manufacturing facilities?

In this review paper a systematic literature review was completed, assessing resilience indicators in the context of MaaS systems. To do this, a two-step article search approach used for gathering data. The search engine used was Scopus[1], limiting the search to English articles written after the year 2000. The research scheme consists of a preparation phase, where the research question was determined and aligned with industry partners, followed by a two-fold article search, where search criteria were expanded upon as existing literature was examined.

To determine which indicators were most useful for a MaaS systems we entered in a dialogue with the three ACCURATE pilots partners. The resulting main research questions (RQ) from those discussions were:

- RQ 1: What prior research exists assessing the resilience of single facilities and which of these indicators can be apply to a MaaS system?
- RQ 2: What are the limitations to indicator complexity for usefulness in industry?
- RQ 3: How can we categorise resilience indicators in MAAS systems?

To answer the RQ 3 a baseline is needed for defining resilience in a manufacturing facility. Therefore, going back to RQ 1 and RQ 2 a categorisation of conventional resilience indicators is needed to properly identify metrics which are usable in a manufacturing facility under the scope of being manufacturing solutions. To answer the three RQs a systematic literature review was done using Scopus. The review was thereafter split up into multiple searching stages. These stages aimed to understand parts of the RQs continually, to direct further searches in a way that had the highest probability of answering the RQs. The literature search was split up in three stages, with the first stage providing a bigger scope of articles, then the second narrowing it down and the third expanding it again to encapsulate the most possible relevant articles. During each of the searching stages some articles were discarded based on their availability, relevance to engineering, and relevance to resilience. Articles of interest were picked out and used to direct further stages of the literature search. All three stages of literature search were therefore done before a complete exclusion scheme was set up to limit the articles worked with.

The first literature search stage aimed to understand general resilience indicators related specifically to manufacturing to answer RQ 1 and RQ 2. To do this a keyword search was set up using Scopus excluding non-English papers. As shown in Table 2, the keywords were specifically focused on resilience or manufacturing terms or indicator terms. A focus was also made on circularity, sustainability and life cycle assessment so as to make the indicators more compatible with WP 3 goals.

Table 2: Initial Keyword Search.

Search category	Search string	Articles found
Initial search terms	TITLE-ABS-KEY((resilien*) W/5 (manufacturing OR production OR design) AND ((circular* OR sustainab* OR "life cycle a*") W/2 (indicator OR metric OR measurement OR result)))	54

From the first literature search, one article of interest was found that defined resilience in a manufacturing facility (M. El-Halwagi et al., 2020). This definition of 12 categories of resilience of an efficient manufacturing

[1] https://www.scopus.com/home.uri

facility was used to direct the second literature search, which became a 12-fold search with keywords relating specifically to each of the 12 categories of resilience, as can be seen in Table 3. The second literature search resulted in a total of 76 articles being found, with some of them being duplicates. There were categories such as reconfigurability, recoverability, modularity and reliability that were much more present than others. The significant difference in available literature across categories suggested that some of the 12 different indicator categories were less relevant to the RQs.

Table 3: Secondary Keyword Search.

Search category	Search string	Articles found
Fail safe by design	TITLE-ABS-KEY("Fail-safe design" AND "Indicator")	4
Recoverability/Restorability	TITLE-ABS-KEY((Recovera* OR Restora*) W/10 Manufacturing AND "Indicator")	8
Redundancy	TITLE-ABS-KEY(Redunda* W/10 Manufacturing AND "Indicator")	3
Reconfigurability	TITLE-ABS-KEY(Reconfigur* W/10 Manufacturing AND Indicator AND quantita*)	8
Modularity/Mobility/Distributability	TITLE-ABS-KEY((Modular* OR Mobility OR Distribut*) W/10 Manufacturing AND Indicator AND quantita*)	18
Flexibility	TITLE-ABS-KEY(Flexibility W/10 Manufacturing AND Indicator AND quantita*)	8
Controllability	TITLE-ABS-KEY(Controllability W/10 Manufacturing AND Indicator)	6
Reliability	TITLE-ABS-KEY(Reliability W/10 Manufacturing AND Indicator AND quantita*)	15
Repurposability	TITLE-ABS-KEY(Repurpos* W/10 Manufacturing AND Indicator)	1
Rapidity	TITLE-ABS-KEY(Rapidity W/10 Manufacturing AND Indicator)	2
Robustness	TITLE-ABS-KEY(Robustness W/10 Manufacturing AND Indicator AND quantita*)	1
Resourcefulness	TITLE-ABS-KEY(Resourceful* AND Manufacturing AND Indicator)	2

The third literature search was a more general search without specific categories of resilience indicators, as seen in Table 4. Here the focus was kept on a single facility, but the search criteria on sustainability, circularity and life cycle assessment was removed as it severely limited the number of articles.

Table 4: Third Keyword Search.

Search category	Search string	Articles found

General resilience & manufacturing	TITLE-ABS-KEY(("resilien* metric" OR "resilienc* assessment" OR "resilienc* indicator") AND (" manufact* " OR " facility " OR " production " OR " factory " OR "plant")) AND (LIMIT-TO (SUBJAREA,"ENGI") OR LIMITTO (SUBJAREA,"DECI") OR LIMIT-TO (SUBJAREA,"ENER")) AND (LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English"))	164

With the reduced focused on sustainability was a total of 164 articles found, with some being duplicates of previous searches. Additional articles which were articles not found in the literature search were added by. The overall literature search resulted in a total of 259 articles, excluding duplicates.

Given the large number of retrieved articles, we performed two filtering rounds to narrow the corpus to articles relevant to the RWs. The first filtering round excluded articles that were not relevant to resilience of manufacturing systems. This was determined based on the title, abstracts, and conclusions section of the article. The relevance to resilience criteria was chosen based on RQ 1 and to keep within the scope of the ACCURATE project. The second filtering round excluded articles that did not correspond to research applicable to a single facility or contained indicators deemed to be difficult to reproduce. The criteria on applicability to a single facility (MaaS node) was defined based on the scope of WP 3. The exclusion criteria on reproducibility was used as several articles contained indicators which were hard to reuse in another context, or were hard to test be used in a practical context by decision makers in manufacturing facilities. After the two filtering step, the corpus narrows down to a total of 32 articles. These articles were fully read through, and if they had indicators of interest, they were they logged and classified into either the main category *Preventative* or *Active/Reactive*. Under these primary categories, the indicators were also classified into one or more of of several subcategories

Under the category '*Preventative'* the sub-categories included *Modularity*, *Redundancy*, *Robustness* & *Reliability*. The modularity subcategory exemplifies a manufacturing facility built in such a way that sections can be easily replaced, moved or reused elsewhere. The redundancy subcategory highlights facilities where parts of the facility are functional even if other parts fail under a disruption. The robustness subcategory corresponds to how well a facility can withstand changes from its ideal state. The reliability subcategory refers to how long a facility can be expected operate in its ideal state.

Under the category *'Active/Reactive'* the sub-categories included *Reconfigurability*, *Absorption*, *Recovery/Rapidity* & *Repurposability/Flexibility*. The reconfigurability subcategory refers to the degree of changeability after a disruption has happened. The absorption subcategory corresponds to the magnitude of 'stress' a manufacturing facility can withstand before reaching a failure state. The recovery/rapidity subcategory combines the terms of recovery and rapidity from the previous 12 resilience categories to describe how the facility recovers from a disruption and how fast the recovery occurs. The repurposability/flexibility subcategory combines two categories from the 12 resilience categories, which focus on the ability to be used for other tasks after a disruption has happened, which are not necessarily related to the existing production.

Resilience indicators from the literature search were also classified based on their:

- evaluation method, which included *method*, *equation*, *survey,* and *simulation*.
- evaluation type, which included *quantitative*, *qualitative* and *hybrid*.
- external data requirements (by source), which included *downstream*, *upstream* or *no external data*.
- Validation type; whether the indicators were validated using a hypothetical or real case study.

4.3 Literature Review Key Findings

As described in the previous section, all indicators found in the evaluated literature were categorised based on the aspect of resilience they covered, evaluation methods used, evaluation type, data sources necessary and type of validation case used. A total of 86 resilience indicators were identified by reviewing the articles, and are listed in Table 5, Resilience Indicators List

Table 5: Resilience Indicators List.

Indicator	Description	Resilience Category	Evaluation Method	Data Source	Validation Case
Human Intensity (Stocker et al., 2022)	A ratio describing how many process paths in a facility that requires human input. This can describe the degree of automatization.	Robustness	Equation	Upstream	Real
Machine Intensity (Stocker et al., 2022)	A ratio describing how many process paths in a facility that requires machines for execution. A higher ratio can mean increased machine-related vulnerabilities.	Robustness	Equation	Upstream	Real
Model Redundancy (Stocker et al., 2022)	A ratio describing how many of the resource paths have redundant resources for replacements.	Redundancy	Equation	Upstream	Real
Resource Redundancy Degree (Stocker et al., 2022)	A ratio focusing on a single resource path and seeing what degree of redundancy it has in resource replacements.	Redundancy	Equation	Upstream	Real
Resource Redundancy Intensity (Stocker et al., 2022)	This metric shows the relative resource redundancy of a process path. A higher value indicates that the process is redundant and resilient.	Redundancy	Equation	Upstream	Real
Composite Net Resilience Index (Yazdanie, 2023)	The net resilience index is a framework for doing linear optimization of multiple resilience indices in energy systems (But can be used generally as long as the sub indices are qualitative and linear).	Every category except absorption	Equation and Simulation	Upstream and Downstream	Real
Decision Making Framework for Reconfiguration (M. Mabkhot et al., 2020)	This is not a single indicator but three different methods on how to reconfigure a given setup to make it more resilient based on quantitative measurements such as utilization, wait time and module state.	Reconfigurability	Expert Evaluation	Upstream and Downstream	Hypothetical
Reconfiguration Smoothness Factor (Yang et al., 2022)	This index is used to evaluate the cost, time, and effort required for reconfiguring a production line. It takes into account both the reconfiguration smoothness and the feasibility of the project	Reconfigurability	Equation	Upstream and Downstream	Real
Reconfiguration Productivity (Yang et al., 2022)	This index is used to evaluate the production capacity and scalability of a production line.	Reconfigurability	Equation	Upstream and Downstream	Real
Lifecycle Cost (Yang et al., 2022)	This index is used for evaluating the facility investment and operating cost compared to the investment budget	Robustness & Reconfigurability	Equation	Upstream	Real

Space Efficiency (Yang et al., 2022)	An index used to assess how efficiently a space is used based open the area of the line compared to the constrained space where the manufacturing line can be configured.	Reconfigurability	Equation	Upstream	Real
Integrated Reconfiguration (Yang et al., 2022)	A single value calculated from the previous four indices to give one combined estimate for the reconfigurability resilience of a factory.	Reconfigurability	Equation	Upstream and Downstream	Real
Customization (Kombaya Touckia, 2023)	Customization is a metric determining the flexibility of producing different types of products depending on the operations flexibility, the products flexibility and the product point of differentiation. This indicator is used in a combined simulation.	Reconfigurability & Repurposability / Flexibility	Equation and Simulation	Upstream and Downstream	Real
Adaptability (Kombaya Touckia, 2023)	Adaptability ensures the convertibility of the system between products by acting on the functionality as well as the production capabilities of the system. The adaptability measure is achieved by adjusting the production system in terms of functionality and by changing the production rates. This indicator is used in a combined simulation.	Robustness & Reconfigurability & Repurposability / Flexibility	Equation and Simulation	Upstream	Real
Modularity (Kombaya Touckia, 2023)	Modularity corresponds to the ability of the system to be divided into subunits and to integrate new elements. This indicator is used in a combined simulation.	Modularity & Reconfigurability	Equation and Simulation	Upstream	Real
Integrateability (Kombaya Touckia, 2023)	Integratebility corresponds to the ability to include new components on the line using adapted interfaces. This indicator is used in a combined simulation.	Modularity & Reconfigurability & Repurposability / Flexibility	Equation and Simulation	Upstream	Real
Diagnosability (Kombaya Touckia, 2023)	Diagnostic capacity corresponds to the speed of detection of a failure on the system or a quality defect and its root cause. This indicator is used in a combined simulation.	Reliability & Recovery / Rapidity	Equation and Simulation	Upstream	Real
Mission Reliability (Dai et al., 2014)	Mission reliability describes the amount of rework needed in a reconfigurable system to make it run as a new process. It is based a on simple logistic function to measure the expected reworking time.	Reconfigurability & Repurposability / Flexibility	Equation	Upstream	Hypothetical

Overall Equipment Effectiveness Flex (Ginste et al., 2022)	It merges information of equipment usage, process yield and product quality like the original OEE measure but includes flexibility measured by mobility, uniformity and range.	Repurposability / Flexibility	Equation	Upstream and Downstream	N/A
Condition Indicator (Hoseyni & Cordiner, 2024)	The condition indicator measures when a condition-based maintenance threshold has been reached a maintenance should be done for a single machine	Reliability	Equation	Upstream	Real
Negentropy (Durán et al., 2023)	An indicator applied to time series and frequency histograms of disruptions, used to measure how resilient a response is based on tendencies in a normal system availability graph	Recovery / Rapidity	Equation	Downstream	Hypothetical
Response Time (Wang et al., 2022)	The time between a disruption and the beginning of performance decline.	Robustness	Equation and Simulation	Downstream	Real
Disruption Time (Wang et al., 2022)	The amount of time between the beginning of performance decline and the beginning of recovery.	Absorption	Equation and Simulation	Downstream	Real
Rapidity in the Disruption Phase (Wang et al., 2022)	An index that quantifies how quickly the system declines.	Absorption	Equation and Simulation	Downstream	Real
Robustness (Wang et al., 2022)	An index that quantifies the lowest system performance.	Absorption	Equation and Simulation	Downstream	Real
Recovery Time (Wang et al., 2022)	The time it takes a system to recover from the lowest point of performance to a new steady state.	Recovery / Rapidity	Equation and Simulation	Downstream	Real
Rapidity in the Recovery Phase (Wang et al., 2022)	An index that quantifies how quickly a systems performance increases during the recovery phase	Recovery / Rapidity	Equation and Simulation	Downstream	Real
Recoverability (Wang et al., 2022)	The size between performance achieved by the system in the new stable phase and the initial phase.	Recovery / Rapidity	Equation and Simulation	Downstream	Real

Loss of Performance (Wang et al., 2022)	Total lost performance during a disruption and recovery.	Absorption	Equation and Simulation	Downstream	Real
Time Averaged Loss of Performance (Wang et al., 2022)	An average loss of performance per time step.	Absorption	Equation and Simulation	Downstream	Real
Probability of Failure (Lounis & McAllister, 2016)	An index that quantifies the probability of failure of a system.	Robustness	Equation and Expert Evaluation	N/A	Real
Probability of Loss (Lounis & McAllister, 2016)	An index that quantifies the probability of loss in a system.	Absorption	Equation and Simulation	N/A	Hypothetical
Functional Service Loss Matrix (Moslehi & Reddy, 2018)	The total functional service loss due to a disruption.	Absorption	Equation and Simulation	N/A	Hypothetical
Imposed Cost Matrix (Moslehi & Reddy, 2018)	Cost imposed on the system due to a failure mode.	Robustness	Equation and Simulation	N/A	Hypothetical
Resilience Index (Moslehi & Reddy, 2018)	The difference between maximum imposed cost possible and current imposed cost, divided by the maximum imposed cost.	Absorption	Equation and Simulation	N/A	Hypothetical
Fraction of Simulations that result in Resilience Operation (Matelli & Goebel, 2018)	Probability that a design has resilient operations (there is a failure, but it still operates at a reduced standard).	Absorption	Equation and Simulation	N/A	Hypothetical
Resilient Operation Time (Matelli & Goebel, 2018)	A weighted average of the operating time of all simulations were a component failed.	Absorption	Equation and Simulation	N/A	Hypothetical
Time until Failure (Matelli & Goebel, 2018)	Average total operating time for all simulations that result in failure.	Robustness	Equation and Simulation	N/A	Hypothetical

Fractions of Simulations that result in Failed Operations (Matelli & Goebel, 2018)	An index that quantifies the probability of a system design failing.	Robustness	Equation and Simulation	N/A	Hypothetical
Normalized Resilience Index (Matelli & Goebel, 2018)	A weighted average of all simulation operating time normal or failed normalized by time.	Robustness & Absorption	Equation and Simulation	N/A	Hypothetical
Resilience (Bhusal et al., 2020)	The ratio between recovered functionality to actual functionality.	Recovery/Rapidity	Equation and Simulation	N/A	N/A
Daily Reliability Level (Ba-Alawi et al., 2020)	Probability of failure of a component on a daily level.	Reliability	Equation and Simulation	N/A	Real
FTA Probability of Failure (Ba-Alawi et al., 2020)	Probability of failure based on a fault tree analysis.	Robustness & Reliability	Equation and Expert Evaluation	N/A	Real
Supplier Delivery Rate (Sambowo & Hidayatno, 2021)	The percentage of orders delivered on or before the due date for a certain supplier.	Reliability	Equation and Survey	Upstream	N/A
On Time Delivery (Sambowo & Hidayatno, 2021)	The percentage of orders delivered on or before the due date	Reliability	Equation and Survey	Upstream	N/A
Supplier Delivery Lead Time (Sambowo & Hidayatno, 2021)	An index that quantifies the time between receiving an order and delivering.	Reliability	Equation and Survey	Upstream	N/A
Manufacturing Lead Time (Sambowo & Hidayatno, 2021)	The complete time it takes to manufacture a product	Reliability	Equation and Survey	N/A	N/A
Capacity Utilization (Sambowo & Hidayatno, 2021)	An index that quantifies how much of the total capacity is currently being used.	Redundancy	Equation and Survey	N/A	N/A

Stock Level (Sambowo & Hidayatno, 2021)	The number of goods that are able to be stored and delivered in a storage facility.	Redundancy	Equation and Survey	N/A	N/A
Reserve Funds (Sambowo & Hidayatno, 2021)	An index that quantifies how many reserved resources an organization has.	Redundancy	Survey	N/A	N/A
Employees (Sambowo & Hidayatno, 2021)	An index that quantifies the number of employees working at an organization.	Redundancy	Survey	N/A	N/A
Robustness Loss (Juan-García et al., 2021)	The maximum value of performance lost during a time series.	Robustness	Equation and Simulation	N/A	N/A
Speed to Recovery (Juan-García et al., 2021)	Time between detection of a failure and returning to acceptable levels of operation.	Recovery / Rapidity	Equation and Simulation	N/A	N/A
Global Resilience Index (Juan-García et al., 2021)	A compound metric consisting of the integral of the functionality minus the compliance limit of functionality dived by the speed to recovery for normalization.	Reconfigurability & Repurposability / Flexibility	Equation and Simulation	N/A	Real
Resilience of a Scheduling System (Feng et al., 2022)	The resilience of a scheduling system takes the time efficiency of a scheduling completion and a correction factor based on available resources.	Recovery / Rapidity	Simulation	Upstream	Hypothetical
Time Series System Cyber Resilience(Simone et al., 2023)	This indicator defines the best case and an actual case time series metric and evaluates the differences using the area from their integrals to define how close the system performs to the resilient strategy.	Robustness & Absorption	Equation and Simulation	Downstream	Real
System Absorption Performance (Pawar et al., 2022)	This indicator measures the performance during a disruption and describes how much of a disruption the system absorbs while continuing safe and low failure rate operation.	Absorption	Simulation	Downstream	Real
System Adaptation Performance (Pawar et al., 2022)	Adaption is defined as intervention in a system automatic or manual and the system adaption performance defines how the systems reliability changes during an adaption phase.	Reconfigurability & Absorption	Simulation	Downstream	Real
System Recovery Performance (Pawar et al., 2022)	The recovery performance measures the systems need for maintenance and how close it is to normal operations.	Absorption & Recovery / Rapidity	Simulation	Downstream	Real

Availability Resilience (Durán et al., 2021)	This indicator defines resilience by the availability of the machine through different stages of the production and gives the probability of a machine not working at different times.	Reliability	Equation and Simulation	Downstream	Real
Resilience Index (Singhal et al., 2022)	The resilience index takes account of the repair time and a step wise recovery function to describe time until full recovery.	Recovery / Rapidity	Equation and Simulation	Upstream and Downstream	Hypothetical
Robustness Resilience Index (Wu et al., 2024)	This index requires a failure mode analysis and then the index is calculated based on the probability of failure and importance of each failure mode.	Robustness	Simulation	Upstream	Real
Recovery Resilience Index (Wu et al., 2024)	The index requires a recovery model and a system performance simulation of the recovery process and then the index is calculated as the difference in area by a time series integral of the best case vs recovery case scenario.	Recovery / Rapidity	Simulation	Downstream	Real
Function Performance Index (Wu et al., 2024)	This index requires performance curves of different recovery situations and the probability of those situations to calculate the expected performance.	Recovery / Rapidity	Simulation	Downstream	Real
System Resilience (Tong & Gernay, 2023)	This indicator defines resilience as a metric dependent on a network of machines which can all experience disruptions affecting each other using the probability of individual failures.	Absorption & Recovery / Rapidity	Simulation	Downstream	Real
Resilience (Patriarca et al., 2019)	This metric combines simple metrics for absorption, recovery and adaptive capacities of the system.	Reconfigurability & Absorption & Recovery / Rapidity	Equation and Simulation	Upstream and Downstream	Real

Results show that the most common *preventive* indicator subcategory was *robustness* and the least common was *modularity.* We found no indicators specifically evaluating *modularity*, but some multi-issue indicators still considered this category. The most common *active/reactive* indicator was *absorption*, with repurposability/flexibility being the least common. We found an almost even distribution of indicators across the main categories of *preventative* and *active/reactive.*

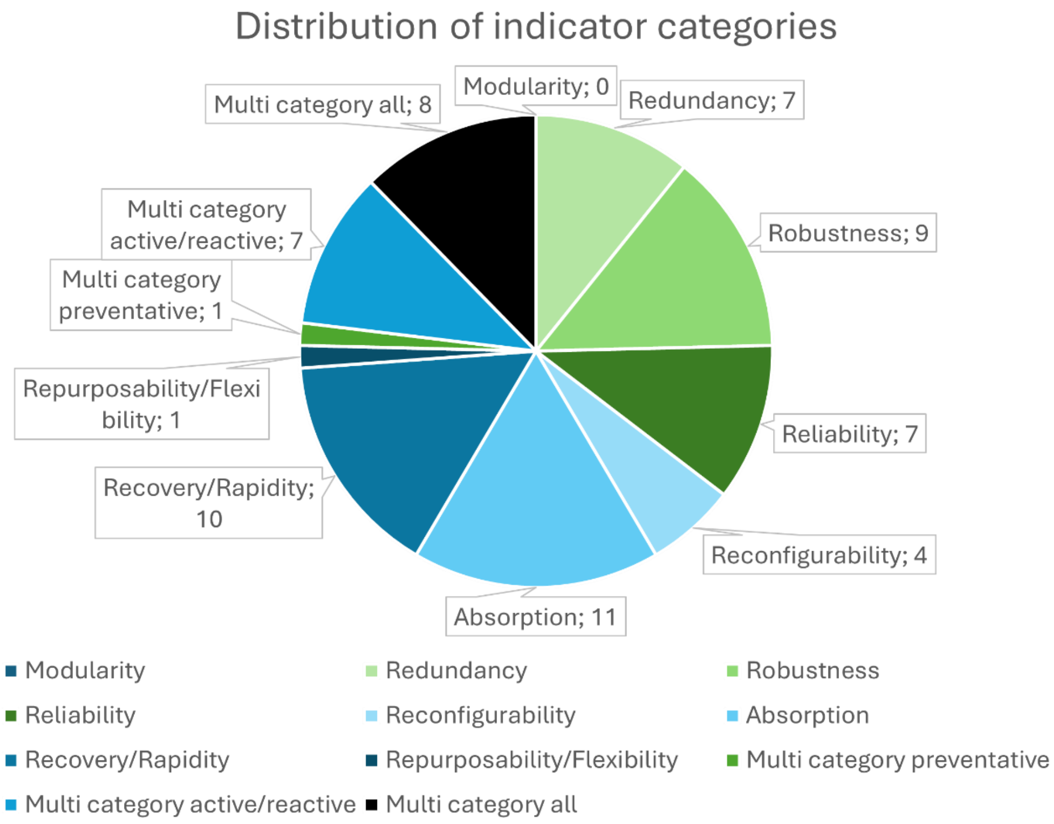

Figure 8: Distribution of Resilience Indicator Categories.

The different distributions of the indicators in the previously mentioned categories, are shown in a pie chart form in Figure 8. Each colour indicates the aspect of resilience which the indicators fall into, with a specific colour scheme showing if the subcategories are *reactive* or *preventative*. Multiple indicators were also found, which were a combination of different categories. What can be seen from the multiple category cases is that *active/reactive* indicators are often grouped together, while *preventative* multicategory indicators also had *active/reactive* aspects.

It is important to discuss why certain resilience categories were not heavily utilised, despite them being initially included in the classification criteria. For all indicators, the category *modularity* was never found to be a singular indicator category. The subcategory *repurposability/flexibility* was represented as a singular category in only one indicator. The *modularity* category was in a multicategory three times, and the *repurposability/flexibility* was in a multicategory seven times. For *modularity*, this small number of indicators seem to be because making production lines modular becomes a priority when a disruption has occurred, therefore becoming a *reconfiguration* rather than a baseline modular system. This decreased focus on *modularity* in the *preventative* stage might make production lines less prepared for reconfiguration, even if the manufacturing facility performs well in reconfigurability indicators. The gap of sufficient indicators in the *modularity* category leads us to conclude that this may be a more difficult system attribute to measure, especially if it is not a focus in the initial design of a system.

A hypothesised reason for *repurposability/flexibility* only being present once as the sole indicator category but seven times as a multicategory indicator is because the found indicators do not clearly distinct between reconfiguration of a setup compared to repurposing a setup. This unclear distinction can therefore mean that two separate categories are not relevant for future groupings of those indicators in manufacturing. It may also be the case that *repurposability* and *flexibility* are an indicator category that should be focused on in the *preventative* stage, where a design can be made with the ability to be repurposed in mind. Additionally, *flexibility* being a broad topic could possibly benefit from having greater precision in its definition. The reason for there being few sole *repurposability/flexibility indicators* is also the reason why there are an increased amount of multicategories for *active/reactive* indicators.

It can be seen in Figure 8, that a clear distinction exists when categorising *preventative* indicators, but the *active/reactive* categories are more spread across the different indicators. An issue with indicators that rely on many categories is that they are often complicated to calculate, but more importantly complicated to understand. A truly useful resilience indicator is one that can be acted upon to improve a system; when a conglomeration of resilience attributes are weighted into one indicator it is difficult to find the true meaning in the number that is presented. The review also shows that complexity of calculating different resilience indicators can significantly vary. Indicators that are solely in the category of *absorption* are some of the simpler indicators, and serve as a base for other indicators. Such indicators include, *Probability of Loss* and *Probability of Failure*, both of which are important factors on their own, but also often serve as a contributory term in more complex simulation-based indicators which aim to minimise losses and failures in a facility. The fact that complex indicators are build on top of simpler indicators, provides an implementation strategy for manufacturing decision makers in gathering data for simple indicators first and thereafter using that information in the more complex models.

The indicators based on *probability of loss* often look at four different types of losses: *time losses*, *human losses*, *machine losses,* and *economic losses*. The *reliability* category mainly focuses on *time loss* and *economic loss* with indicators such as *Supplier Delivery Rate*, *On-Time Delivery* and *Manufacturing Lead Time,* which aim to increase the reliability of production and reduce the potential time spent, and therefore the *economic loss*. The *robustness* category mainly focuses on *machine loss*, aiming to make the facility as robust as possible to different kinds of disruptions. Here, indicators include *Machine Intensity* and *Time series system cyber resilience*, and *Human Intensity*. *Human loss* indicators are scarce, and were therefore not clearly in one main category of indicators. Finally, the *active/reactive* indicators didn’t seem to be as clearly distinct in the across different types of losses.

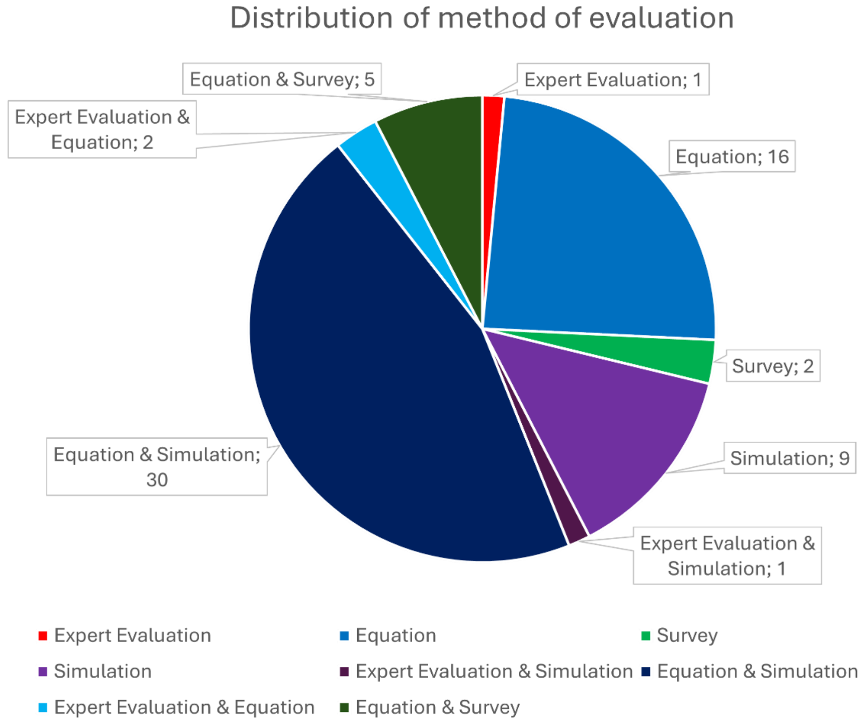

Figure 9: Distribution of the Method of Evaluation for the Surveyed Resilience Indicators.

The distribution of the method of evaluation for the surveyed resilience indicators can be seen in Figure 9. The methods of evaluation include *equations*, *expert opinions*, *surveys*, and *simulation models*. Please note that in situations where indicators used two or more methods to be calculated, these are listed as their own category. The most prevalent methods of evaluation are *equations* and *simulation models* (individually and also in combination). This is expected since all of the surveyed resilience indicators were quantitative; no qualitative or hybrid indicators present in the filtered list of indicators as the aim of WP 3 is to identify indicators that can be subsequently linked to the production-level DTs developed in ACCURATE.

There is an even distribution of *preventative* and *active/reactive indicators* based on *equations* or *simulation models*, suggesting that there isn't a clear difference in complexity of indicators when looking across these main categories. The indicators using only *equations* as the method of evaluation often are simpler indicators, which can be calculated with few terms. Indicators based on *simulation models* often require minimising for one of the different losses as described earlier. Indicators based on *simulation models* are mainly split into two groups, those that focus on *minimisation of loss* and those using simulation as a means of testing the theory the indicator is based on.

Comparing equation and simulation-based resilience indicators, it is possible to establish an ease-of-implementation hierarchy for the surveyed indicators. *Equation-based* indicators are the simplest to use, followed by mixed methods indicators that use *equations* and *simulation models* that are decoupled from each other. Indicator based on *simulation models* alone are not easy-to-implement with complexity being one of their defining features. *Survey-based* resilience indicators can be easy to implement as they typically require querying workers of the given facility questions. However, they are harder to implement when external data is required, either from upstream or downstream stakeholders. Lastly, resilience indicators based on *expert evaluations* can be easy to use if the access to relevant experts is available, but can potentially become expensive to implement as external experts and consultants may need to be hired.

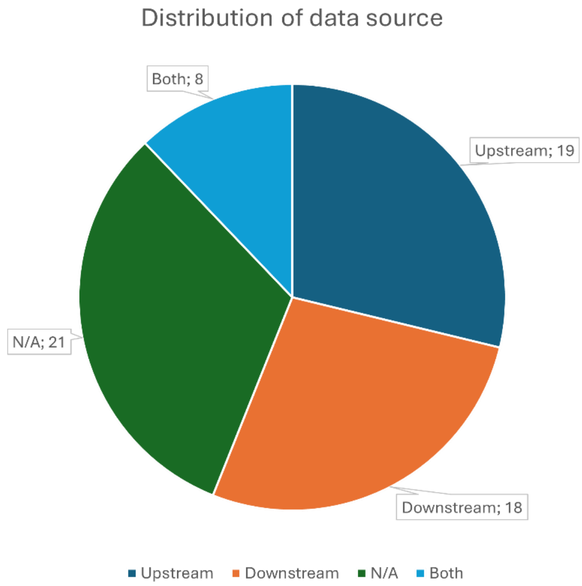

Figure 10: Distribution of External Data Source for the Surveyed Resilience Indicators.

The distribution of the external data requirements (by data source), and validation type can be seen in Figure 10 and in Figure 11respectively. As shown in Figure 10, we found an almost even distribution of indicators needing *upstream data*, *downstream data,* or *no external data*. There were also some cases where both *upstream data* and *downstream data* were needed to compute the indicators, but such cases were rare.

Resilience indicators requiring *no external data* sources potentially require lesser implementation effort, when compared to the ones requiring either *upstream* or *downstream* data. Combining results shown in Figure 10 with those in Figure 8 reveals that *preventative* indicators most often needs *upstream* information, as they plan against future disruptions by strengthening the production's ability to withstand stress. This is seen in indicators such *as Supplier Delivery Rate* and *On-Time Delivery* where information from suppliers are needed to prepare the manufacturing floor most efficiently to variance in delivery rate or time of delivery. The opposite is true for *active/reactive* indicators, which most often require *downstream* data, as the simulations either need to know the response from customers or the people which the manufacturing facility caters to. This is the case because resilience in these scenarios are often defined by the ability to meet customer demand in a disruption. Therefore, without an understanding of changing customer demand during a disruption is it not possible to calculate the extent of the loss. Resilience indicator categories that require the least external information are *reliability* and *absorption* indicators, because these often can be calculated from the failure rate of the equipment within the facility, wherein limits for maximum output or variance in delivery can be estimated.

Looking at Figure 11, we can see that the validation method for most indicators was done using *real case studies*. Roughly two-thirds of the indicators mentioned were validated using *real case studies,* with the usage of *hypothetical* or *no case studies* having been comparable to each other. A potential reason is that most surveyed resilience indicators were established in relation to specific industries. The few hypothetical case studies were found in complex theoretical simulation-based resilience indicators and indicators which require very specific types of disruptions (e.g., one-off large-scale disasters). Indicators that were not validated using case studies were often simpler *absorption*-based indicators which serve as the basis for other indicators.

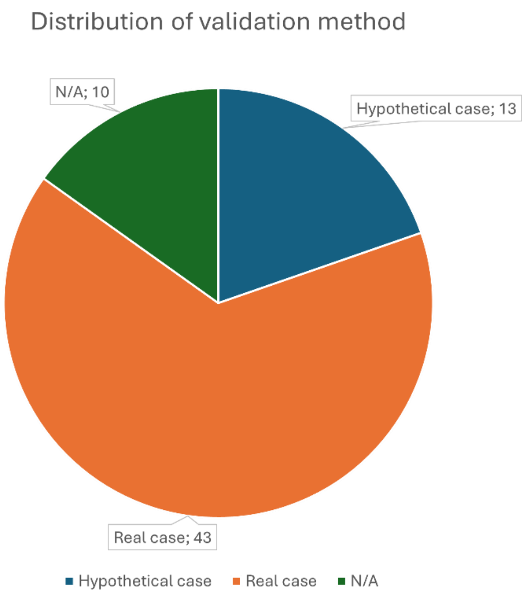

Figure 11: Distribution of Validation Method for the Surveyed Resilience Indicators.

4.4 Resilience Indicator Selector Tool

Results from the literature review were implemented in the form of an easy-to-use screening tool usable by industry and academia, to explore different resilience indicators. As discussed earlier, the resilience indicators were sorted into 12 categories (M. M. El-Halwagi et al., 2020). Additionally, the tool also categories the resilience indicators based on their relevance to sustainability and circularity assessment. Thes screening tool allows users to filter the indicators by their resilience category, the calculation method used for obtaining the indicators (i.e. analytical, empirical or simulation based), whether the indicators are quantitative or qualitative and if the indicator is preventive or detection based. The selection tool was implemented using Microsoft Excel for ease-of-access with an accompanying *Read Me* page (see Figure 12) containing information on how the screening tool can be used.

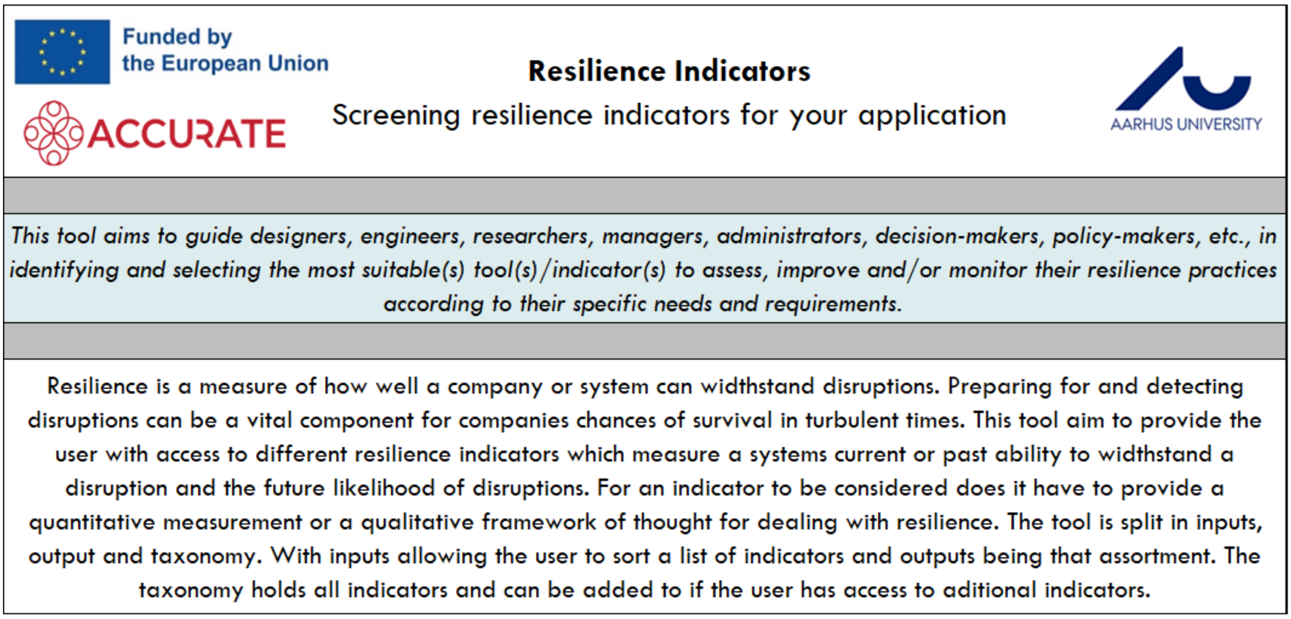

Figure 12: 'Read Me' Page of the ACCURATE Resilience Indicator Screening Tool.

An *Input sheet* (Figure 13) allows users to screen the resilience indicators by the aforementioned categories and indicator attributes. Accompanying the sorting buttons are in depth descriptions of each category to improve the understanding for the user for finding the best fitting indicator.

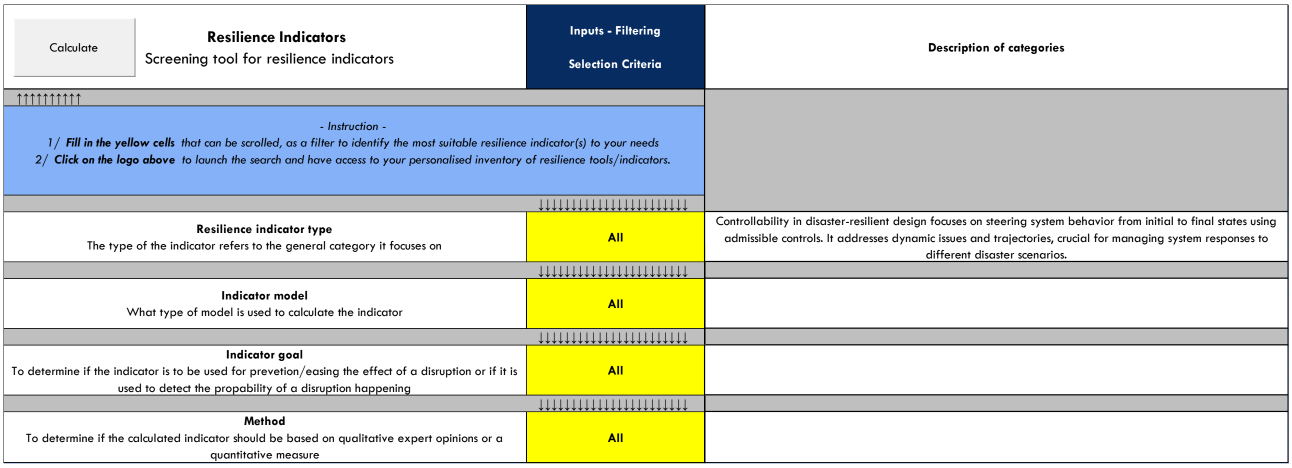

Figure 13: Input Sheet in the ACCURATE Resilience Indicator Screening Tool.

After a selection has been made the user is provided with meta data about the indicators satisfying the filtering criteria, including the name of corresponding research article, author names, access link to the article, application and scope and type of assessment (see Figure 13: Input Sheet in the ACCURATE Resilience Indicator Screening Tool.). The screening tool does not directly provide formulas or information on how to calculate each indicator; it primarily serves as a tool for finding relevant resilience indicators and points users to an appropriate source.

Resilience Indicators	Description-Working Principles	Indicator model			Indicator goal		Method	
		Analytical	Empirical	Simulation /Optimization	Prevention	Detection	Qualitative	Quantitative
Product Recyclability	In the procedure of product develop	-	-	X	X	-	X	-
Pollution Production Capability	In the manufacturing process, supplie	-	-	X	X	-	X	-
Environmental Management	Suppliers should implement a set of	-	-	X	X	-	X	-
Safety and health	Supplieres should have the potentia	-	-	X	X	-	X	-
Eco-design and green image	In the procedure of product design,	-	-	X	X	-	X	-
Production facilities	It is a maximum conceivable output	-	-	X	X	-	X	-
Trustworthiness	The Reliability indicator measures tl	-	-	X	X	-	X	-
Supply chain density	Supply chain density measures the c	-	-	X	X	-	-	X

Figure 14 Resilience Screening Tool Output Example

The above figure shows an example of the outputs of the resilience indicator screening tool. For the given criteria, the tool will output a list of applicable indicators, a description of the indicator, the type of model used to assess the indicator, the method of assessing the indicator and the goal of the indicator. Additionally, the source of the indicator is given in the output sheet, it is just not shown above for the sake of space.

5 Sustainability Indicators for a MaaS System

This chapter describes the methodology, indicator selection criteria, and recommendations for evaluating the sustainability performance of MaaS systems in the ACCURATE project. The chapter discusses the assessment methodology and relevance of both environmental sustainability indicators as well as social sustainability indicators to the ACCURATE project.

5.1 Environmental Sustainability Indicators

5.1.1 Environmental Life Cycle Assessment

Environmental Life Cycle Assessment (eLCA) has emerged as one of the most widely used tools for quantifying the lifecycle environmental impacts of products and production systems. As shown in Figure 15, according to the ISO 14040 standard (Standardization, 2006), eLCAs consist of four stages.

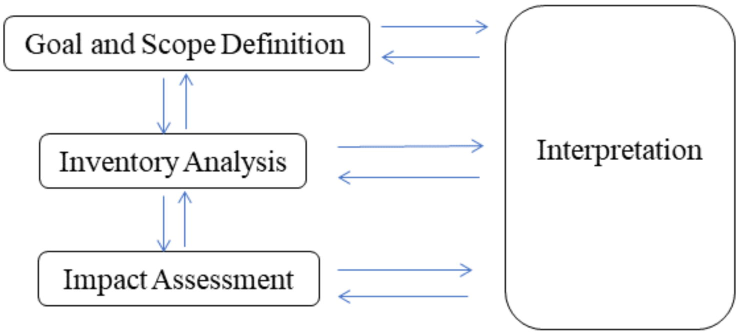

Figure 15: Stages in an environmental life cycle assessment according to the ISO14040 standard.

1. *Defining the goal and scope of the study*: In this stage, practitioners set the boundaries of the system, specify the assumption to be used, and set the functional unit of the product or process to be studied.
2. *Conducting the Life Cycle Inventory (LCI) data collection:* During this stage, all input and output flows linked to each life cycle stage of the product or process are collected. Such flows include inputs regarding resources and materials and outputs in emissions, waste and downstream material.
3. *Assessing the life cycle impact (LCIA):* This stage analyses LCI data and links them to the environmental impact categories and indicators.
4. *Interpretation of the results:* During this stage, practitioners interpret the results according to the defined goal and scope and address all the uncertainties and accuracy of the results.

It should be noted that these stages should be applied in an iterative manner, and the assessment methodology should be refined based on the obtained results and their interpretation. Several commercial software are available for conducting eLCAs, with notable examples including GaBi[2], SimaPro[3], and OpenLCA[4]. This report does not aim to provide an in-depth introduction to eLCAs; it primarily discusses the generation of metrics for assessing the sustainability performance of MaaS systems based on eLCAs. Readers interested in obtaining an in-depth understanding of the various stages in eLCAs are directed to the LCA compendium book series (*LCA Compendium - The Complete World of Life Cycle Assessment*, 2014-2023).

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[2] www.sphera.com
[3] www.simapro.com
[4] www.openlca.org

5.1.2 Manufacturing Sustainability Assessment

When quantifying the environmental impacts of manufacturing systems and identifying potential improvements that can be made to system from an environmental sustainability point of view, eLCAs can be used to establish both qualitative and quantitative measures of sustainability performance. The process of planning activities and/or actions that improve the sustainability of manufacturing processes has been defined as *manufacturing sustainability assessment* (MSA) (Ramanujan et al., 2022). From an operational perspective, Lee and Lee (2014) derive an operational definition for MSA by defining manufacturing sustainability as a *"measure of manufacturing performance metrics of product design, process plan, and production system with respect to the environment, economy, and society, when executing a process plan for a product design in a given production system."* Extending this definition, the authors define MSA as a process *"determine a value of the manufacturing sustainability metric, which is a balanced performance of product design, process plan, and production system with respect to environmental, economic, and social aspects of sustainability".*

The primary goal of performing MSA in the ACCURATE project is to identify,

1. the magnitude of change in environmental sustainability performance of production systems (operating in MaaS systems) under potential disruptions and,
2. the effect remedial actions (e.g., changing production planning, reconfiguring production lines) on the environmental sustainability performance of production processes within MaaS systems.

For this, DT models that can model functional performance of the production systems (e.g., WIP, lead time, production rates) need to be extended to also quantify their environmental sustainability performance. With this goal, only *quantitative* environmental sustainability metrics are investigated in the the ACCURATE project. Quantitative sustainability metrics in MSAs typically take the form of environmental impact indicators based on eLCAs, and KPIs that can encode specific dimensions of environmental impacts. They are distinguished in further detail below.

5.1.3 Quantitative sustainability metrics for manufacturing sustainability assessment

<u>Environmental impact indicators based on eLCAs:</u>

Results from eLCAs are expressed using environmental impact indicators that typically quantify the environmental impact of the analysed system on one or more impact categories. Based on the LCIA method considered, the methodology can be classified into:

1. ***<u>Single issue methods:</u>*** Single issue methods only address one impact category (e.g., climate change, water scarcity) and ignore the environmental impacts of the analysed system on other impact categories. For example, the LCIA method IPCC 2013 GWP 100a (Ometto et al., 2014) only computes potential climate change related impacts due to the global warming potential (GWP) of green house gases emitted from the analysed system. Single issue methods are not in compliance with ISO 14044 standard as it is not allowed to leave out impact categories that may have a significant environmental impact.

2. ***<u>Multiple issue methods:</u>*** Multiple issue methods have broad (yet limited) coverage of impact categories. For example, a multiple issue method such as ReCiPe 2016 midpoint (Huijbregts et al., 2017), can compute multiple environmental impact indicators, including, GWP, ozone depletion potential, terrestrial acidification potential, fine particulate matter formation, etc. Several, established multiple issues methods such as a ReCiPe 2016 midpoint, ReCiPe 2016 endpoint, CML (baseline), USEtox, Environmental Footprint, are incorporated in to commercial LCA software. Interested readers are referred to Table 1, Page 7 of the openLCA documentation on LCIA methods for a comparison for a comparative analysis of the above methods (Acero et al., 2015). The European Commission has introduced two environmental footprint methods, comprising the Product Environmental Footprint (PEF) and Organisation Environmental Footprint (OEF) for harmonised assessment of environmental indicators, with the aim of improving transparency in reporting and decision-making. The technical details of the EF methods are laid down in the Commission Recommendation (EU) 2021/2279 (Annexes I-II-III-IV). Additional guidance documents on the EF methods have been developed during the first applications of the PEF/OEF in the pilot phase (2013-2018) and in the transition phase (2019-2022) (European Commission: Joint Research et al., 2022).

When discussing the choice of single issue and multiple issue methods for quantifying environmental sustainability indicators, specific attention should be given to the representativeness and the comprehensiveness of the data that needs to be collected in the LCI stage. In terms of data collection burdens, multiple issue methods typically require that a more comprehensive LCI model of the production system in constructed, when compared to a single issue method. To illustrate, if the aim of performing MSA is to assess climate change related impacts of the system using a method such as IPCC 2013 GWP 100a, the LCI model for the production system only needs to include any direct greenhouse gas emissions as well as energy/resource flows (e.g., electricity usage, lubricating oil, materials) whose production entails significant greenhouse gas emissions. In several production systems, greenhouse gas emissions from electricity use outweigh other flows, which can simplify LCI data collection. On the other hand, applying multiple issue methods typically requires a more comprehensive analysis of energy/resource flows in the production system, as different flows can contribute to different environmental impact categories disproportionality (Campitelli et al., 2019).

An associated consideration is the need for primary LCI data collection, so that the resulting environmental sustainability indicators accurately characterise the analysed system. Conducting process-based eLCAs requires collecting and quantifying LCI data of the employed processes, e.g., energy use, water and material consumption, and process emissions (Seghetta & Goglio, 2020). Background data, e.g., from commercial LCI databases such as ecoinvent[5], is especially useful when primary data (i.e., actual data from production) collection is challenging, or during early design stages when primary data is not available at all. On the other hand, background data is inherently uncertain and therefore affects the accuracy of the results, which must be taken into account during the analysis (Blok et al., 2007). That is because, in practice, there is considerable variation between manufacturing process implementation, depending on the specific process parameters and the used machine tools (Boettjer et al., 2021). Thus, background data does not fully account for process variations, which can significantly impact resource consumption and emissions production. In cases where sufficiently representative background LCI models are unavailable, primary LCI data should be collected to increase the accuracy of the computed environmental sustainability indicators. The choice of indicators consequently dictates primary data collection burdens from the production system. Recent research projects have aimed to address data collection challenges through improving product and process digitalisation. The s-X-AIPI project aims to build artificial intelligence enabled sustainability monitoring tools for process industry (*self-X Artificial Intelligence for European Process Industry digital transformation*, 2022). The RECLAIM project (*RE-manufaCturing and Refurbishment LArge Industrial equipMent*, 2019) and the METAFACTURING project (*Data and METAdata for advanced digitalization of manuFACTURING industrial lines*, 2022) explore the use of Industry 4.0 technologies such as digital twins and computer vision for automated estimation of life cycle inventory data and computation of streamlined environmental sustainability performance metrics. Even so, the adoption of digital technologies for automated manufacturing sustainability assessment remains challenging and is not yet widely adopted (e.g., by industrial partners in the ACCURATE project).

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[5] https://ecoinvent.org/database/

Lastly, the interpretation of results based on computed environmental sustainability indicators is a significant concern. In other words, decision-makers should be able to understand

1. the significance of the computed environmental sustainability indicator(s),
2. the implications on the manufacturing system and activities/processes that significantly contribute to the indicators, and
3. available decision-levers in the systems to mitigate the environment impacts of the system.

This can be challenging in the case of eLCA based indicators as they present results in measurement units not directly related to manufacturing systems, and correlations between the indicators themselves can be hard to discern (Glisic et al., 2024).

Recent research has focused on advancing indicator selection, assessment and interpretation for advancing eLCAs. The ORIENTING project (*Operational Life Cycle Sustainability Assessment Methodology Supporting Decisions Towards a Circular Economy*, 2020) performed a critical review of LCA methodologies, with the aim of advancing life cycle sustainability assessment (LCSA) towards the integrated assessment of environmental, social, and economic impacts. Results from the project (Horn et al., 2021) discuss the relevant merits and weaknesses of LCIA methodologies and recommend specific data quality requirements, e.g., for compliance with the PEF method. To illustrate, if a process is run by a company, e.g., an original equipment manufacturer (OEM), company-specific data on both the manufacturing activity and direct emissions is recommended. In the case of a process run outside the company, with access to specific information, company-specific data is preferred, but an EF compliant secondary dataset from trusted LCA data sources is also acceptable. Finally in the case of of a process run outside the company, without access to specific information, an EF-compliant secondary data set (in aggregated form) or a secondary data set compliant to the International Life Cycle Data System (ILCD) should be provided. Given the challenges with primary data collection mentioned in the previous paragraph, sourcing high-quality, process-specific inventory data can be challenging. Such challenges are further compounded in the case of MaaS, where portions of the manufacturing process takes place outside the physical boundary of OEMs. Therefore, process-specific data for sustainability critical manufacturing activities may be unavailable as they occur outside the facilities owned by an OEM.

Key-performance index based sustainability metrics: KPIs have been proposed as an approach for supporting sustainability-related decision-making in manufacturing. KPIs, when appropriately formulated, can overcome certain limitation in eLCA based indicators including, high time-and cost-burdens for computation, limited relevance for decision-making, and interpretability. A KPI, or more broadly, an indicator, can be defined as a parameter that provides more information on significant phenomena, relevant to the specified performance objectives (Feng & Joung, 2010). Prior literature has identified two broad approaches for defining relevant KPIs in sustainable (Kibira et al., 2017).

- *Bottom-up approach:* In this approach, metrics that are either currently in use or deemed necessary to be measured, are to define KPIs that are a basis for continuous development. KPIs defined using the bottom-up approach are typically directly quantified based on operational data from manufacturing systems. Examples for such KPIs include, *energy efficiency* of manufacturing systems, *percentage of recycled materials* used in manufacturing, *waste produced* in manufacturing, etc. Thus, such KPIs are typically formulated from unit process-level life cycle inventory data measurements. Given that bottom-up KPIs are defined in close association to the manufacturing system being analysed, they are often easier to interpret, and valuable for modelling and improving system- and process-level sustainability performance (Smullin et al., 2016). However, a shortcoming of KPIs defined using a bottom-up approach is that they do not necessary estimate the global performance of the system; multiple KPIs may be required for this purpose. Furthermore, such KPIs can be in conflict with each other, requiring MCDM and trade-off analysis for improving system-scale performance. Furthermore, KPIs defined using a bottom-up approach may not necessarily capture an oranisations' sustainability goals or targets.

- *Top-down approach:* In contrast to the bottom-up approach, in the top-down approach, the definition of KPIs in sustainable manufacturing is based on the overall sustainability goals of an organisation. Therefore, KPIs defined using the top-down approach often measure the sustainability performance over a collection of unit manufacturing processes (as opposed to a single process) in the dimensions relevant to the overall organisational goals (Kibira et al., 2017) . Consequently, such indicators may not be easy-to-interpret when the objective is to improve the performance of a specific unit process or a process parameter. However, KPIs defined using the top-down approach are well-suited for reporting sustainability performance of manufacturing systems, given they are defined at a system-level, and incorporate dimensions of quantification relevant to the specific organisation.

In both the approaches discussed above, a generalised procedure for defining relevant KPIs involves the following (Garetti & Taisch, 2012; Rakar et al., 2004).

1. Defining the overall sustainability goals and objectives
2. Identifying and defining KPIs (based on the selected approach)
3. Shortlisting and selection of relevant KPIs
4. Implementing data collection systems for quantifying the defined KPIs
5. Implementing a monitoring plan for the KPIs, ensuring continuous process improvement.

In this process, it is important to consider the which dimensions of environmental sustainability are being measured by the selected KPIs, and if they are a significant source of environmental impact for the manufacturing system being analysed. It is also important to clearly specify the boundaries of measurement (as per the selected KPI), and if it includes all components of the process/system that affect the selected KPI. Finally, it is important to note that in practice, the selection of relevant KPIs is often limited by the requirements on data collection and reporting. Therefore, a critical evaluation of the challenges and benefits of implementing and monitoring selected KPIs is often necessary.

5.1.4 Recommendations for Manufacturing Sustainability Assessment in ACCURATE

To understand the availability of data for performing LCA based manufacturing sustainability assessment within the scope of the ACCURATE project, the following activities were conducted across all three ACCURATE pilot partners.

- Detailed interviews were conducted with the ACCURATE pilot partners to understand the importance of sustainability-related process performance in terms of the current manufacturing setup, as well as extensions to a MaaS system.
- A data collection template (Section 7.1) was distributed to the pilot partners to understand the availability of primary and secondary LCI data. Follow up discussions were also conducted to understand challenges in collecting LCI data requested in the data collection template.
- Finally, multiple discussions were conducted with WP3 meetings (Task 3.1) to understand requirements for integrating MSA assessment into the DES-based production DT models being developed in WP3.

Results from these discussions revealed that,

- Climate change-related impacts were prioritised by the ACCURATE pilot partners
- Due to the lack of existing infrastructure for primary inventory data collection, process specific-company data is currently unavailable. This knowledge gap should be filled through additional measurements made on the manufacturing lines, as well as through using high-quality secondary datasets (e.g., using commercial data providers).
- ACCURATE pilot partners did not have existing agreements with upstream/downstream suppliers regarding sharing process-specific inventory data. Furthermore, it was suggested that it would be challenging such information for potential MaaS providers. Consequently, high-quality secondary datasets (e.g., commercial data providers) should be used to fill existing data gaps.
- Finally, due to the lack of complete visibility on processes, the use of streamlined indicators (not based on LCA) for critical processes (identified by OEMs) were suggested as a means for quantifying and monitoring sustainability performance related to material use. Such indicators include:
    - Process wastes (e.g., expired components, scrap, other wastes) produced per component/process.
    - Consumption of materials (e.g., consumables, tools, etc.) per component/process.

The selection of environmental sustainability indicators for each UC is discussed in Chapter 7.

5.2 Social Life Cycle Analysis (sLCA) Indicators

5.2.1 Introduction to SLCA

Social Life Cycle Assessment (sLCA) has become an important methodology within the framework of LCA, allowing for the evaluation of social and socio-economic impacts in the entire life cycle of products and services, from raw material extraction to end-of-life disposal. While eLCAs primarily focus on environmental effects such as resource use and emissions, sLCA extends the evaluation to social aspects, such as labour conditions, community well-being, and human rights. sLCA is increasingly recognised as vital to achieving comprehensive sustainability (Haslinger et al., 2024). sLCA adopts the so-called 'life cycle thinking' approach. This perspective ensures that all stages of a product's life, such as extraction, production, distribution, use, and disposal—are considered for their social impacts in each of these different stages. The United Nations Environmental Protection (UNEP) guidelines on sLCA establish a more structured framework to categorise stakeholders and assess these social impacts, focusing on groups such as workers, local communities, consumers, and society as a whole (Andrews et al., 2009). These stakeholder groups have impacts through different aspects of production and also consumption processes. This makes this tool important to measure the 'social' footprint of businesses and organisations alike. The sLCA methodology typically follows four main steps (Andrews et al., 2009):

1. defining the goal and scope,
2. performing life cycle inventory analysis,
3. conducting an impact assessment, and
4. interpreting the results

This process often requires both qualitative and semi-quantitative data, which often makes it difficult to measure. While some impacts can be quantitatively measured (such as absenteeism or injury rates), others, such as worker satisfaction and social equity, require interpretative frameworks to measure efficiently (Haslinger et al., 2024).

The application of sLCA to MaaS stakeholders introduces a new set of complexities. MaaS enables companies to lease manufacturing capacity on-demand rather than engaging in full-scale production themselves. This also includes the lease of data and software digitally as the formal definition refers to MaaS as a distributed system of production in which resources (including data and software) are offered as services, allowing manufacturers to access distributed providers to implement their manufacturing processes. Such servitisation of manufacturing resources contributes significantly to production flexibility and responsiveness, enabling production on demand for many product categories. Suppliers of manufacturing systems and of integration technologies design and offer interoperable services in close partnership with manufacturing companies, while other providers in the value chain can offer additional services. Secure, real-time data exchange between the companies involved enables quick response times (*Twin Green and Digital Transition 2024 (Horizon-CL4-2024-Twin-Transition-01)*, 2024).

While this model offers flexibility and scalability, it complicates the traditional approach to identifying and engaging stakeholders in sLCA frameworks (Andrews et al., 2009). In traditional manufacturing, stakeholders are typically easy to identify due to direct involvement in production processes. In contrast, the model in MaaS introduces layers of indirect relationships, particularly between those leasing manufacturing capacity and users of these services. Performing sLCAs for MaaS systems can also considered to be more complex than similar assessment on traditional manufacturing value chains. This stems from the fact that,

- In traditional value chains, OEMs have long-term agreements and relationships with suppliers, which eases data collection on stakeholder impacts. On the other hand, MaaS systems are designed to be more agile and flexible, implying that stakeholders and associated impacts significantly vary over time.

- System boundaries are more well-defined in traditional manufacturing. For example, in the case of in-house manufacturing, boundaries can be drawn around stakeholders that have a direct involvement with the OEM. In the case of multi-tiered suppliers, boundaries for sLCAs are set based on specific degree (e.g., 1st-degree suppliers, 2nd-degree suppliers, etc.) based on the visibility on the value chain and ease of data collection. However, in the case of MaaS, where stakeholders and beneficiaries can vary (temporally and geographically), it is more challenging to define consistent system boundaries, identifying stakeholders in manufacturing SCs.

Regulatory developments, e.g., the Corporate Sustainability Reporting Directive (The European Parliament, 2022), Ecodesign for Sustainable Products Regulation (The European Parliament, 2024) can potentially ease data collection burdens for sLCAs by mandating reporting on specific social impacts on stakeholders. However, to develop a realistic sLCA framework for MaaS systems in the current environment, it becomes essential to develop a more focused perspective, i.e., assessing the social sustainability performance from the perspective of individual MaaS providers.

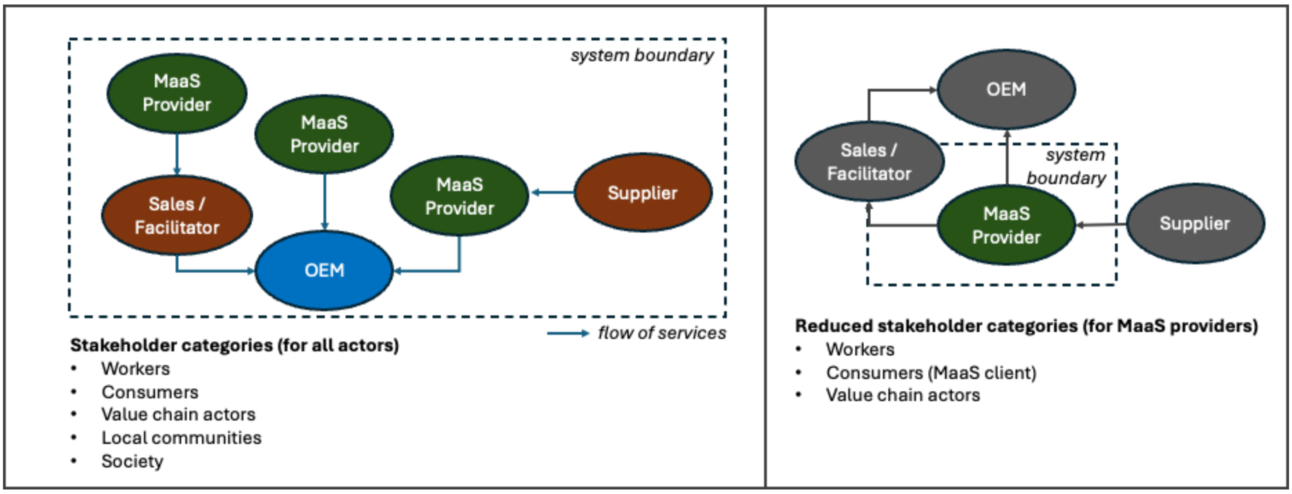

Figure 16: System boundary and stakeholders included in sLCA of MaaS systems. Scope for holistic analysis is shown in the left panel the focused scope of analysis in the ACCURATE project is shown in the right panel.

As shown in Figure 16, for a holistic sLCA of MaaS systems, multiple actors in the system should be taken into account, including OEMs, MaaS providers, MaaS facilitators, suppliers to MaaS providers, and OEMs. Furthermore, stakeholders such as workers, consumers, value chain actors, local communities, and society need to be identified with respect to each actor in the system. As described earlier, framing and analysing social sustainability performance with such a broad scope is highly information and time intensive, further complicated by the fact that the MaaS system can change over time. To reduce complexity, and enable a feasible methodology, the ACCURATE project restricts the sLCA assessment to a single MaaS provider as shown in the right panel in Figure 16. Such analyses could be potentially extended to cover the MaaS system, through combining assessments for individual actors. However, this aspect will not be investigated within the scope of the ACCURATE project, due to the inability to collect social sustainability related data for a complete MaaS system. Furthermore, in the suggested scope of the analysis, stakeholders associated with a MaaS provider, including workers, consumers (clients of the MaaS provider) and specific value chain actors are taken into account, while stakeholders not directly involved with the provision of the MaaS service are excluded. The exclusion criteria for stakeholders are further explained below.

5.2.2 Exclusion Criteria for MaaS Stakeholders

To maintain a clear focus on leasing manufacturing capacity, it is necessary to establish exclusion criteria that filter out stakeholders not directly relevant to a MaaS provider. This narrows down the considered stakeholders and ensures the sLCA remains focused on MaaS providers. Specifically, two inclusion/exclusion criteria are specified in our analysis

1. The scope of the analysis only includes stakeholders directly interacting with the analysed MaaS provider. Thus, stakeholders for all other actors in the MaaS system are excluded.
2. For the analysed MaaS provider, only stakeholders that are directly involved in maintaining or supporting the leasing of manufacturing capacity for the MaaS provider (i.e., primary function of a MaaS provider) are included.

This targeted approach ensures that the analysis captures relevant social impacts, rather than addressing broader or unrelated aspects of traditional manufacturing processes. It also ensures that the analysis remains centred on a MaaS provider, which in return also simplifies the evaluation process and improving the accuracy of social impact assessments. The following stakeholders are <u>not</u> considered as being directly involved in maintaining or supporting the leasing of manufacturing capacity:

- *Supply and distribution (upstream and downstream) stakeholders:* Stakeholders involved in the SC (upstream) and distribution and sales (downstream) processes are excluded from our analysis as they are external to the MaaS provider. Upstream stakeholders are involved in supplying raw materials and components, which are important to production but not directly related to leasing manufacturing capacity. Downstream stakeholders handle the distribution and sales of finished products, which are also important for market delivery but do not directly relate to the leasing of manufacturing facilities.

- *Full-Service manufacturing stakeholders*: Full-service manufacturing companies that provide end-to-end production processes (i.e., contract manufacturers) are excluded from the scope of our analysis unless they offer leasing services. Only including stakeholders that provide leasing services ensures the analysis remains concentrated on MaaS providers.

Other stakeholders relevant to sLCA were identified based on the UNEP sLCA guidelines (Andrews et al., 2009) and classified based on their direct relevance to a MaaS provider, i.e., assessing whether they directly involved or support the activity of leasing manufacturing capacity. The following stakeholders were analysed.

Value chain actors

- *Manufacturing and production providers:* Comprises of stakeholders representing those that offer these leasing services for manufacturing equipment, facilities, or capacity. These stakeholders are central to the concept of a MaaS provider and are therefore included in the analysis.
- *Service providers:* Comprises of stakeholders providing integration services, such as software solutions, maintenance, or technical support essential for leased facilities. These stakeholders ensure the smooth operation and maintenance of leased manufacturing capacity and are therefore included in the analysis.
- *SC & logistics providers:* Such stakeholders are excluded unless they offer services essential towards maintaining manufacturing capacity, i.e., they are directly involved with the internal manufacturing activities of a MaaS provider.
- *Financial & legal service providers:* These stakeholders facilitate the necessary contractual and financial structures to support leasing agreements that maintain the manufacturing capacity of MaaS providers; they are included in the analysis.

Consumers

- *Clients of MaaS providers*: Comprises of stakeholders that lease the actual manufacturing capacity from a MaaS provider. Therefore, these stakeholders represent end users, i.e., businesses and organisations that utilise the MaaS systems to meet their manufacturing needs. These stakeholders are included in the analysis as they are the primary reason for the existence of MaaS providers.

Society & Local Community

- *Society and local community*: Stakeholder groups corresponding to broader society and local communities are excluded as they are not directly involved in maintaining or supporting the leasing of manufacturing capacity for a MaaS provider. Local communities might experience indirect effects such as changes in local economic activities or environmental impacts, due to the activities of a MaaS provider. Similarly, broader societal impacts such as shifts in industry standards or public policy may influence MaaS providers. Analysing such interactions is beyond the scope of the proposed analysis,

Workers

- *Workers:* Comprises of stakeholders that provide human capital essential for maintaining manufacturing capacity of a MaaS provider. Therefore, they are included in the analysis scope.

5.2.3 UNEP Guidelines and Alignment with sLCA Analysis of MaaS

The proposed stakeholder inclusion/exclusion criteria for performing sLCA of MaaS providers is compared with the UNEP sLCA guidelines (Andrews et al., 2009) to evaluate the prioritisation and limitations of the proposed framework. The UNEP guidelines provide a standardised framework for conducting sLCA and identifying and evaluating the social impacts of various stakeholders. It should be noted that this framework is context-agnostic. The UNEP sLCA guidelines outline the following stakeholder categories:

1. *Workers*: Individuals directly involved in production pro- cesses.
2. *Local Community*: Residents affected by manufacturing activities.
3. *Society*: Broader societal impacts, including social and economic effects.
4. *Consumers*: End-users of the products.
5. *Value Chain Actors*: Suppliers, distributors, and partners in the production process.

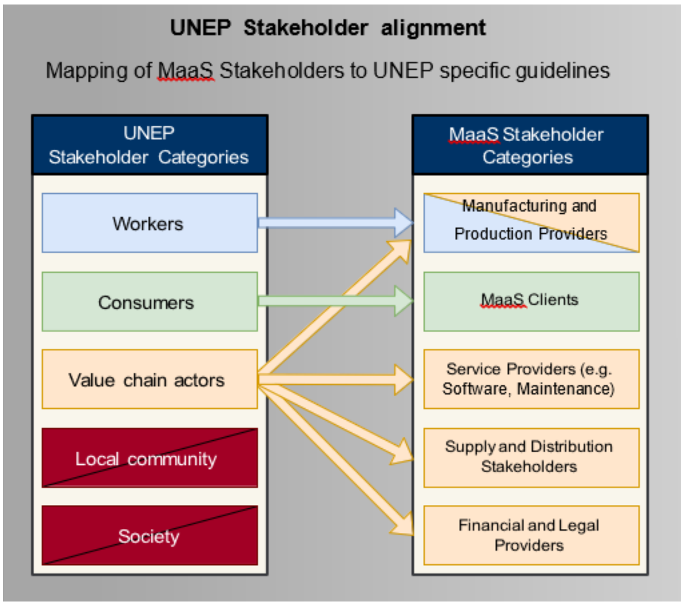

Figure 17: Mapping of Maas Stakeholders to UNEP Specific Stakeholders.

Figure 17 shows the mapping of stakeholder categories from the UNEP guidelines to those suggested for performing sLCA of MaaS providers, and they are summarised below. This mapping aims to ensure that relevant social impacts are considered, and that the assessment is both robust and comparable to other sLCA studies. This approach not only enhances the reliability and transparency of the assessment but also facilitates ongoing compliance with best practices in social sustainability (Andrews et al., 2009).

- **Manufacturing and Production Providers:** *UNEP Stakeholder mapping: Workers & Value Chain Actor* - These stakeholders correspond to the *Workers* and *Value Chain Actors* in UNEP guidelines, focusing on those directly involved in production, thus aligning with the core service providers in the MaaS model.
- **Service Providers (e.g., Software, Maintenance):** *UNEP Stakeholder mapping: Value Chain Actor* - Service providers in MaaS systems can be mapped with *Value Chain Actors* in UNEP guidelines, focusing on essential support services necessary for maintaining leased manufacturing capacity.
- **Supply and Distribution Stakeholders:** *UNEP Stakeholder mapping: Value Chain Actors* - Value Chain Actors such as *suppliers* and *distributors* are included in UNEP guidelines. However, the proposed criteria exclude these stakeholders unless they are directly related to leasing services, aligning the focus with on MaaS providers.

- **Financial and Legal Providers:** *UNEP Stakeholder mapping: Value Chain Actors* - While not explicitly detailed in UNEP guidelines, in the context of MaaS providers, these actors offer essential support for maintaining operations, including financial and legal frameworks important for leasing arrangements in the MaaS model.
- **MaaS Clients:** *UNEP Stakeholder mapping: Consumers* - These stakeholders lease the manufacturing capacity and are direct stakeholder beneficiaries of the MaaS model, similar to consumers in traditional business settings.

As discussed above, the sLCA model for MaaS providers interprets the stakeholder categories of workers and consumers as manufacturing/production providers (i.e., human capital) and clients for the MaaS provider. Furthermore, value chain actors in the perspective of the MaaS provider, include stakeholders that are directly interacting with a MaaS provider, and are necessary for provisioning of the intended MaaS services. Thus, for these subcategories, stakeholder impacts, including labour conditions, health and safety, business ethics, relationship with clients, and service impact can be assessed. Stakeholder groups related to society and local communities are not present in the proposed sLCA framework for MaaS providers, in line with the inclusion/exclusion criteria suggested above. This simplification limits the scope of impact assessment, i.e., impacts on society and local communities (e.g., job creation, upskilling, increasing societal resilience, etc.) cannot be assessed by the proposed framework. However, it is viewed as necessary to retain the focus of the analysis on the provision of MaaS services, and limit data collection burdens (e.g., due to large geographic dispersion of MaaS providers).

5.2.4 Implementation of sLCA in the ACCURATE project

The implementation of this framework involves several steps to identify and evaluate the relevant stakeholders effectively. sLCA typically measures stakeholder impacts using both qualitative and quantitative measures. However, in the context of the ACCURATE project a significant challenge is (quantitatively) evaluating stakeholder impacts as result of specific changes made on the production floor. To illustrate, if a production line is reconfigured with a view of making it more resilient to supply disruptions, the resulting impact on worker well-being (e.g., due to changes in shifts, adjustments of tasks) is challenging to quantify from a purely simulation-oriented approach. On the hand other outcomes, e.g., on-time deliveries, can serve as a reasonable proxy for impact on stakeholder such as MaaS clients. Considering such challenges, the following conceptual approach is proposed for conducting sLCAs within the scope of the ACCURATE project.

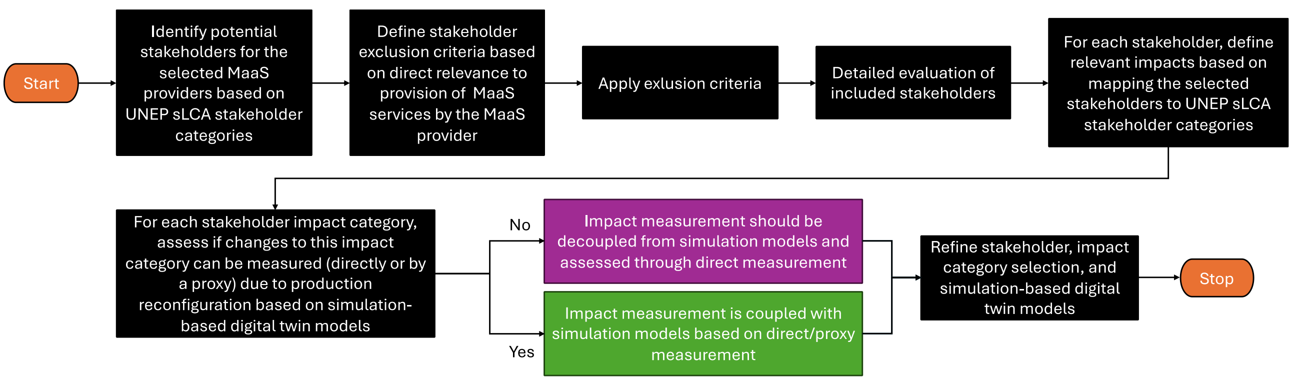

Figure 18: Proposed conceptual approach for implementing sLCA for MaaS providers.

As shown in Figure 18, the process begins with identifying potential stakeholders based on the selected MaaS provider(s). A preliminary list of stakeholders can be based on industry reports and the UNEP sLCA guidelines to ensure that all potential stakeholders are considered in the initial phase. Then the proposed exclusion/inclusion criteria is finalised (based on data collection burdens, intended analysis goals, etc.) and applied to arrive at a final stakeholder list. A detailed review of capacities and industry focus of these stakeholders is performed to identify their role in the MaaS systems and to identify potential impacts on these stakeholders due to production-specific changes made by the MaaS provider(s). Next, the ability of existing/feasible simulation production models to capture changes in the identified impact categories is assessed, and the scope of the overall analysis, including the selected stakeholders, impact categories, and simulation models are subsequently refined.

TRO UC2: Production planning and control: Scheduling, dispatching, monitoring for lot excursions

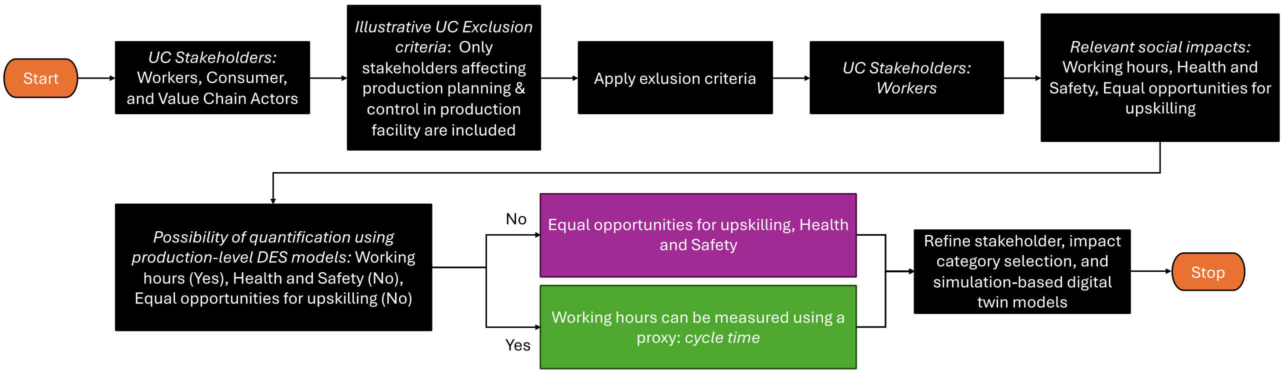

Figure 19: Illustrative application of proposed sLCA methodology to TRO UC2.

Figure 19 presents an illustrative application of the proposed conceptual model to TRO UC2. Herein, the focus in on supporting production planning and control under disruptions, including scheduling, dispatching, and monitoring for lot excursions. In this illustrative example, we consider that decision-making support is provided using a production-level DT using DES modelling. Based on the UC, workers, consumers, and value chain actors are identified as potential stakeholders through the UNEP sLCA framework described earlier. Due to the fact that the UC primarily focuses on monitoring and reconfiguring TRO's internal production planning to better deal with disruptions, the selected exclusion criteria limits stakeholders to those that can directly affect the production process (i.e., workers). Following this, relevant social impact categories are identified for this stakeholder group, with an analysis on whether such impacts can be quantified using the proposed DES-based DT. Finally, proxy metrics are identified for quantifiable metrics and further refinement of stakeholder impact categories are conducted.

Subsequent efforts in the ACCURATE pilots (WP 7) will explore the implementation of the proposed conceptual model across the identified UCs.

6 Ontologies for Architecting Circular and Sustainable Manufacturing-as-a-Service Systems

This chapter outlines a methodology for achieving circularity and sustainability in MaaS systems. The complexity of MaaS systems, which arises from the need to consider all possible combinations of MaaS providers, potential suppliers, machinery, and process configurations, and to assess the sustainability of each combination, is proposed to be addressed in two steps. The first step involves information integration and retrieval using ontology as a core model, with a sustainability score as the target. To this end, the initial ontology model, which integrates the concept of MaaS, is implemented by extending the Industry Ontology Foundry (IOF) ontology and is evaluated using a use case. The second step, which involves the derivation of an optimised manufacturing ecosystem using DTs, is considered future work.

6.1 Introduction

The CE concept aims to decouple value creation from resource consumption, governed by the principles of reduce, reuse, recycle, refuse, rethink and repair (6R) (Jawahir & Bradley, 2016). Achieving circularity within manufacturing industries has been a topic of research for many years (Aher & Ramanujan; Blomsma et al., 2019; Pieroni et al., 2021). The concept of circularity can be applied to various dimensions of a manufacturing system, such as business, production processes, or products (Aher & Ramanujan). An important aspect of circularity is that it must also be sustainable to be meaningful (Blomsma et al., 2019; Pieroni et al., 2021). Therefore, state-of-the-art approaches for establishing a CE typically use a bottom-up method, identifying potential initiatives first and then quantifying their circularity and sustainability performance. (Blomsma et al., 2019; Pieroni et al., 2021).

At the same time, manufacturing companies are increasingly adopting agile methodologies in production to meet the changing customer requirements and the demands of global markets (Vathoopan et al., 2021; Zhang et al., 2020). They are incorporating approaches like MaaS to achieve greater flexibility and reconfigurability in their ecosystems (Cheng et al., 2017). The goal of MaaS is for manufacturers to provide manufacturing capabilities as a service, which other manufacturers can utilise on demand (Cheng et al., 2017). Given that circularity is increasingly becoming an essential requirement in manufacturing, several companies are experimenting with CE initiatives (Blomsma et al., 2019; Pieroni et al., 2021). However, the complexity and variability of agile manufacturing ecosystems make assessing circularity and sustainability a challenging and time-consuming task. This highlights the need for systemic modelling approaches and automated assessment techniques.

This research aims to address the above problem from a top-down approach, assuming that a company aims to introduce a circularity initiative with a targeted sustainability (performance) score. Thus, the main goal is to identify an ecosystem that achieves the targeted sustainability score by evaluating all combinations of suppliers, production systems, and MaaS providers. Consequently, this paper addresses the following research question: How can sustainability be systematically achieved in a MaaS-based flexible and circular manufacturing ecosystem by evaluating all possible combinations of participating entities? It introduces a two-step method for addressing this question. The first step involves integrating and retrieving information on all possible manufacturing ecosystem combinations for the given sustainability score using an ontology. The second step calculates and derives an optimised ecosystem by evaluating all possible ecosystem combinations from the previous step.

6.2 Background and Related Work

6.2.1 Manufacturing as a Service

The term MaaS is mostly associated with cloud manufacturing in literature, as cloud manufacturing is seen to enable MaaS. Cloud manufacturing refers to making available manufacturing and associated services on the cloud, to the consumers on a demand basis (Bouzary & Frank Chen, 2018; Cheng et al., 2017; Zhang et al., 2020). Most of the works in this direction addresses the technologies for virtualisation of manufacturing resources, and services, service descriptions for optimal discovery, service matching and composition, and business models (Cheng et al., 2017; Zhang et al., 2020). MaaS, when considered as a term by itself can be understood as a some companies offer their manufacturing ecosystem as a service, and some companies avail and integrate this service in their manufacturing ecosystem (Cheng et al., 2017; Diedrich et al., 2022).

6.2.2 Ontology and Knowledge Graph

The term ontology has been originated in the domain of philosophy, however it has been adopted and evolved within the domain of computer science (Staab & Studer, 2013). According to Hurtado and Nudler (2012), the term ontology is a description or formal specification of a program, that include the concepts and relationship of the participating agents or a community of agents. Ontologies were introduced to achieve semantic and syntactic interoperability among heterogeneous enterprises and systems (Hurtado & Nudler, 2012; Staab & Studer, 2013). They provide a systematically curated vocabulary that is both machine and human readable (Hurtado & Nudler, 2012; Staab & Studer, 2013). The concept of ontology when combined with a graph data model yields a knowledge graph that is a form of knowledge base. A knowledge graph can be understood as an instance of ontology that comprises specific information of real-world entities (Kasie et al., 2017).

Ontologies are classified into four hierarchical level (Sapel et al., 2024). Ontologies that lie in the first layer are top level ontologies, that are highly generic and applicable to various domains. The ontologies that lie in the second layer are the core ontologies that describe common entities of a specific domain. The third layer, domain specific ontologies describe properties specific to some sub-domains. Application level ontology that lies in the fourth layer describes task specific ontology within a specific domain.

6.2.3 Ontologies for Knowledge Management

Knowledge curation and derivation are vital components of decision-making. A systematic study by Martins et al. (2019) reveals that ontologies have been applied for knowledge curation and derivation since the early 2000s. Their study clarifies that the application of ontology for knowledge management spans various domains, with only a few works found within the manufacturing domain. However, there has been an increase in research in this direction since 2017.

In one of the earliest approaches of applying ontology for sustainability assessment, Giovannini et al. (2012) proposed a product centric ontology for supporting the design of sustainable products. Their ontology captures the relation between products and processes and identify processes that yields more sustainable products. Benabdellah et al. (2021) proposes a similar approach for instituting an ontology for designing green products. In their approach ontology is used for managing knowledge about various design techniques and their relations to strategies of organisations. However their approach employs an ad-hoc ontology developed for this specific use case. Echefaj et al. (2023) applied ontology for supplier selection in the circular economy, developing criteria for sustainable supplier selection with an ad-hoc ontology. Psarommatis et al. (2023) extended the IOF standard ontology for zero defect manufacturing, however did not focus on overall circularity or sustainability of manufacturing systems.

6.3 Problem Description

The ACCURATE project envisions an agile manufacturing ecosystem, facilitated by the seamless integration of various entities from inside and outside of the factory. This implies that all stakeholders involved in the value chain, or the overall ecosystem are connected with seamless interoperability. To ensure trusted and secure communication and data exchange among partners within the manufacturing ecosystem, a Gaia-X based framework, as shown in Figure 20, is proposed.

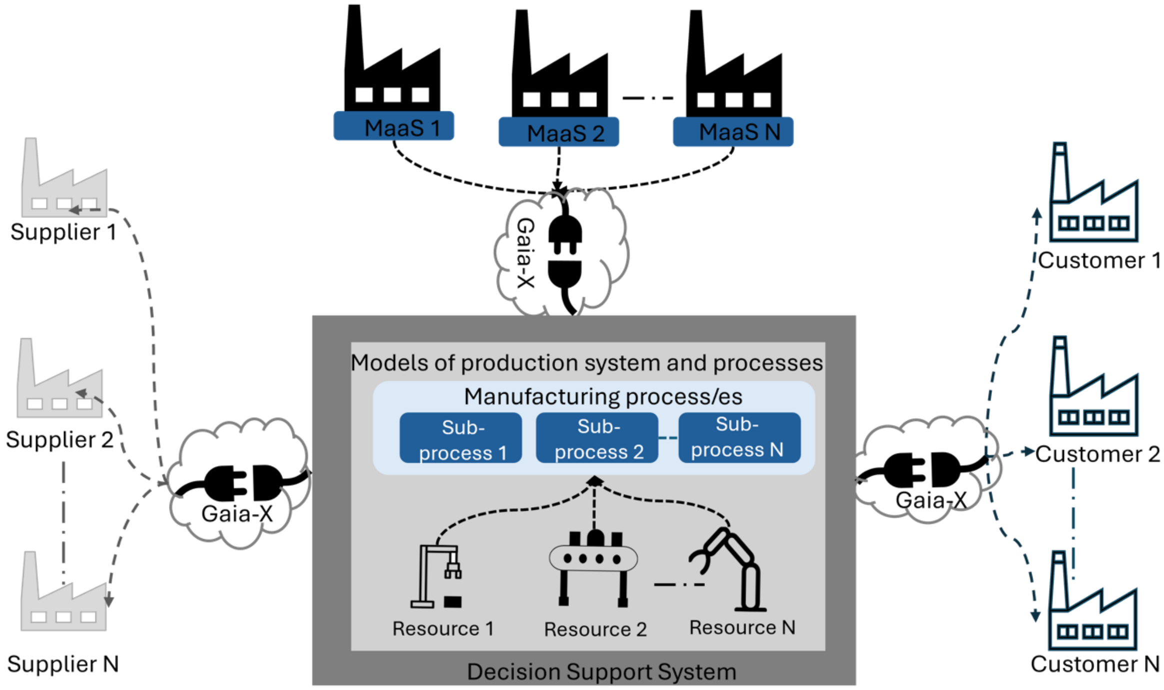

Figure 20: A simplified representation of the ACCURATE framework.

An agile production environment allows for the dynamic discovery and contracting of raw material suppliers and MaaS providers globally. Therefore, an agile production environment can have potential raw material suppliers, potential MaaS providers, potential customers, other supply chain stakeholders, governmental agencies, etc. At the same time, we can assume that the production system itself has the flexibility and reconfiguration capability to capture varying requirements from customers and market fluctuations, including potential discrepancies. The introduction of a CE initiative within an agile production environment, hence, needs to consider all possible combinations of different machinery configurations, raw material suppliers, and MaaS providers. Additionally, their interdependencies need to be defined, and correlations need to be mapped. This has to be followed by a circularity and sustainability performance assessment. Therefore, the overall process can be seen as a complex problem for a human, making it challenging, time-consuming, and error prone.

From a technical point of view, the problem can be seen as a decision-making problem that requires information from different stages such as design, development and operation stage of a manufacturing ecosystem. The decision making must consider information retrieved from various stakeholders, associated tools, production resources, supporting systems, operational information, economic information, etc., that take part in these stages. This leads to the requirement of having the technical characteristics as shown in Table 6 for the proposed DSS.

Table 6: Required characteristics of the proposed decision support system

Label	Requirement
RQ1	Semantic interoperability among humans, tools and various systems
RQ2	Ability to model information from various disciplines and their interaction
RQ3	Ability to capture dynamic and evolving knowledge
RQ4	Scalability

6.4 Ontology as a Core Enabling Technology

A systems engineering process consists of interconnected methods and models (Estefan, 2008; Kranabitl et al., 2024). A method is a well-defined procedure for achieving a specific objective and may include a sequence of steps and their procedures. Thus, a method defines "HOW" an objective can be achieved (Kranabitl et al., 2024). A method takes one or more models as input and generates the required objective as output. Depending on the use case, the method will also incorporate associated models for supporting the generation of the required objective. Additionally, a method must be implemented in a tool. Choosing the right method is critical for the success of a project (Kranabitl et al., 2024).

Inspired by the systems engineering process (Estefan, 2008; Kranabitl et al., 2024), we define our method to consist of two sequential steps, as shown in Figure 21. The first step is information integration and retrieval, and the second step is the derivation of optimised configuration. The methods have input models, as depicted on the left-hand side of the figure, and out-put models, as shown on the right-hand side. The associated model of a method is illustrated above the method, and the tool where we expect to implement the method is shown below the method.

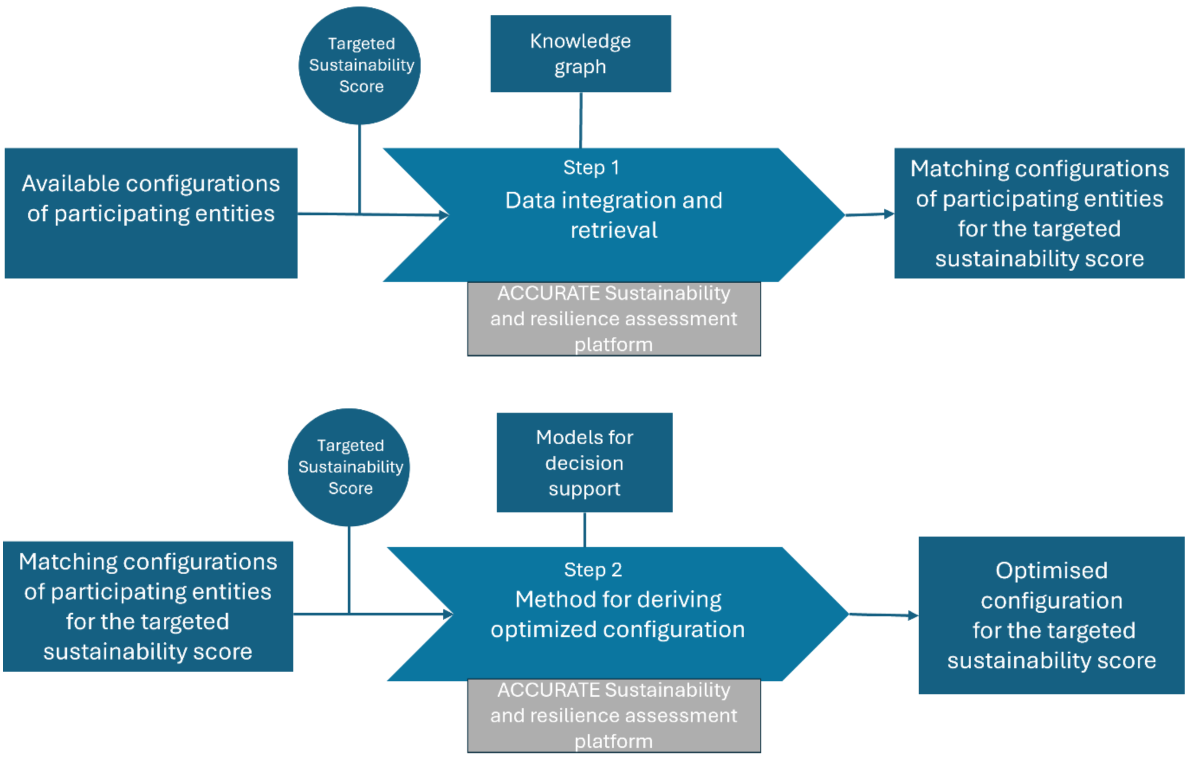

Figure 21: Proposed method for achieving circularity and sustainability in MaaS systems.

The first step is defined to address the problem of identifying right combinations of models from different stakeholders, along with their interdependencies and correlations. We propose using models and data from across the value chain as inputs to this method along with the targeted sustainability score. The expected output of this method is the matching configurations of participating entities for the targeted sustainability score (a reduced space).

Identifying the combinations of different stakeholders and their involved models, along with their interrelations and correlations, can be seen as an information integration and retrieval problem. Ontologies have been found to be very efficient in addressing information integration and retrieval problems due to their axiomatic modelling capabilities (Kasie et al., 2017). Considering the main challenge of the first step of our methodology as an information integration and retrieval problem, we propose using an ontology driven knowledge graph as an associated model to our first step. By using a knowledge graph an associated model for our first step, we anticipate that the overall effort required to develop the proposed decision support system will be reduced. Additionally, the characteristics/features of the proposed DSS as shown in Table 6 (RQ1, RQ2, RQ3, RQ4) can be completely satisfied by an ontology driven knowledge graph.
The second step is envisioned to use the output of the first step (a reduced space of the possible combinations) as its input model for deriving an optimised ecosystem configuration for the given sustainability score. We propose to use a DT based simulation and optimisation for this step. A detailed elaboration of the second step is out of scope in this work and seen as an immediate future work.

6.5 Agile Manufacturing Ecosystem Model using Ontology

6.5.1 Industrial Ontology Foundry

The next step to identifying an ontology driven knowledge graph as an associated model within the DSS, is to define the ontology model for the MaaS based agile manufacturing ecosystem. Although ontology concepts emerged in the 1980s, their application in manufacturing has been limited due to high development efforts (Hurtado & Nudler, 2012; Staab & Studer, 2013). ISO/IEC 21823-3 standard for semantic interoperability recommends reusing or referring or extending available ontologies instead of building an ontology from scratch (Sapel et al., 2024). However, many past approaches focused on creating ad hoc ontologies tailored to specific use cases, resulting in data silos applicable only to those specific scenarios (Kulvatunyou & Ameri, 2019).

Among the available, widely accepted ontologies within manufacturing domain include the initiatives such as Onto-STEP and Onto-PDM, AMLO (Kulvatunyou & Ameri, 2019; Sapel et al., 2024; Yang et al., 2023). Onto-STEP converts the aspects of STEP standard into ontology (Sapel et al., 2024). OntoPDM converts product data management aspects into ontology (Sapel et al., 2024). AMLO converts the standard AutomationML and related aspects into an ontology (Sapel et al., 2024). However, these ontologies themselves are not standardised accordingly.

The IOF (Ameri et al., 2022; Kulvatunyou & Ameri, 2019; Sapel et al., 2024) is an initiative by the OAGi[6] for developing standard ontologies applicable for the manufacturing domain. IOF uses Basic Formal Ontology (BFO): an ISO/IEC PRF 21838-2.2 standard ontology applied in several domains as a neutral top level format, as the top-level format and provides IOF core as the core ontology. A matured version of IOF core ontology is now available for public download. Additionally, provisional versions of domain specific ontologies such as supply chain management and maintenance are also available for public download[7]. The IOF envisions that various parties can extend the IOF reference ontologies to accommodate required sub-domain or application ontologies (Kulvatunyou & Ameri, 2019).

[6] https://oagi.org/
[7] https://spec.industrialontologies.org/iof/ontology

IOF core ontology covers production processes, resources, and measurement entities within a manufacturing company (Sapel et al., 2024). IOF SC management covers basic aspects needed for modelling the SC and associated entities of a manufacturing ecosystem. With these two ontologies, several basic competency questions that need to be answered in an agile manufacturing ecosystem have already been addressed by IOF ontologies (Kulvatunyou & Ameri, 2019).

Considering the coverage, an active community that supports the development, availability of ontology as files (Sapel et al., 2024), we decide to develop our ontology with the IOF. Though, similar initiative such as Ontocommons (an initiative to compile information on existing ontologies in European Union) exist, IOF is found to be most stable initiative with growing community (Sapel et al., 2024). The idea is to maximum reuse and merge IOF ontologies in addressing our research objective and extend it wherever required.

6.5.2 Proposed Ontology Model

Our initial experiments with IOF show that, several aspects and entities required for achieving our research goal are available within IOF ontologies. These include *Product*, *Processes*, *Resources* models and the relations among them in the form of PPR model (Vathoopan et al., 2021). Various aspects of supply chain, such as different stakeholders (buyer, consignee, supplier, etc.), as well as logistics related, and geography related aspects are also available.

From the perspective of the ACCURATE project, the manufacturing ecosystem itself is seen in an agile environment from a service-oriented perspective to integrate the concept of MaaS. As per ISO 59020 (Standardization, 2024c), the aspects of circularity can be applied to any levels within or out of an organisation. Redefining the main goal of ACCURATE, we arrive at: identifying the configuration(s) that yield the required sustainability score, to define a manufacturing service as the basic entity to which the aspects of circularity can be applied. Hence, the first entity to be modelled within the ontology is a manufacturing service.

There are several approaches describing the services within manufacturing domain (Cheng et al., 2017; Diedrich et al., 2022; Kulvatunyou & Ameri, 2019; Wu et al., 2015). Many studies use capability as a synonym to service, while other studies use skill as a synonym to service (Diedrich et al., 2022; Kulvatunyou & Ameri, 2019; Vathoopan et al., 2021). According to Platform Industrie4.0 (Diedrich et al., 2022), a service within the domain of manufacturing specifies the capabilities offered by a service provider to a service requester with extended description of its commercial aspects. Additionally, they distinguish the differences between service, capability and skills. We adopt the definition of a service from Platform Industrie4.0.

The main goal of MaaS is to implement manufacturing as as service in similar way to the concept of web services. From the web service domain, there was an effort to model a web service using the concept of ontology. This effort is known as OWL-S (Martin et al., 2004), and is available as a recommendation from W3C. The model of a web service as seen from OWL-S (Martin et al., 2004) is shown in Figure 22.

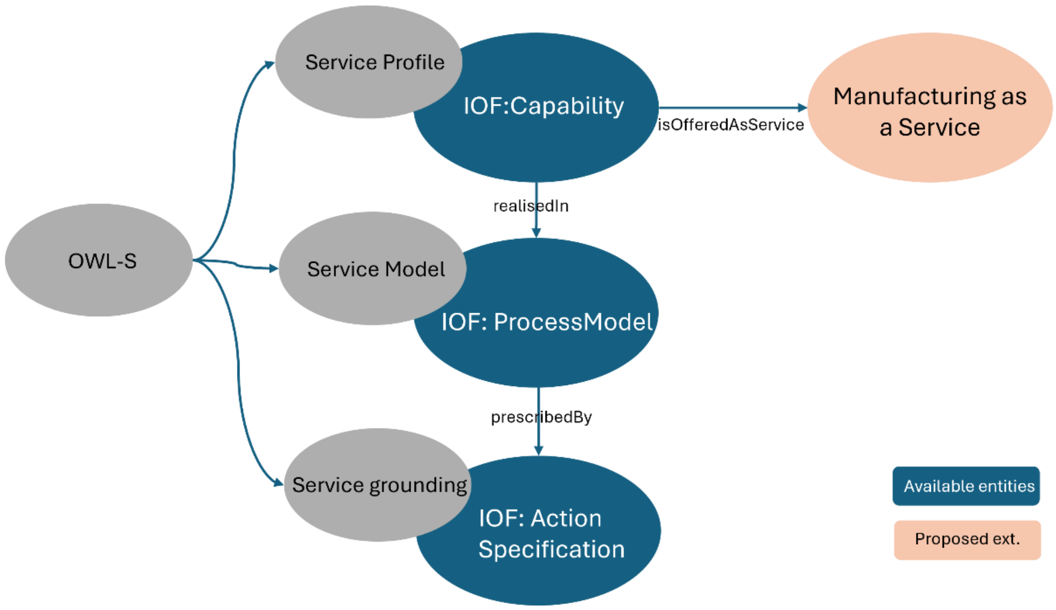

Figure 22: Mapping of the definition of MaaS from Platform Industrie4.0 to the web service model.

According to OWL-S, a service is specified using a profile, that is used to publish the service within a registry. The service profile is discoverable by someone who requests to avail a specific service. Then, there is model of the service itself, that describes the service specification and its various other aspects. Finally, the service has a grounding model, that defines how a service is implemented, for example using a specific technology (Martin et al., 2004). Mapping the definition of service from Platform Industrie4.0 to the web service model, we see the model of a MaaS using IOF.

The IOF ontology has three aspects that need to be understood for defining the model as shown in Figure 22: 1) Capability, 2) Process and 3) Action specification (Kulvatunyou & Ameri, 2019; Kulvatunyou et al., 2022). A capability is a disposition (potential) that a material entity has, which an agent is interested in realising. The capability as defined in IOF standard is realised in a process at the organisation it holds. Action specification describes what a participant shall do in a process (Kulvatunyou et al., 2022). Relying on Diedrich et al. (2022), we define a MaaS as a capability of a manufacturing/business organisation or their internal resources that are offered as a service with extended description of its commercial aspects. The model of the capability as shown in IOF ontology however, is abstract and not capable to integrate the concept of model of a MaaS (Bouzary & Frank Chen, 2018; Cheng et al., 2017; Diedrich et al., 2022; Wu et al., 2015).

After discussion with industrial partners in the ACCURATE project and analysing the approaches from literature, we rely on a registry/platform based approach for implementing the concept of MaaS. The service providers publish their MaaS within the registry and the service consumers can search for services using different requirements. On finding a match, a consumer can go for further processes such as price negotiation and contract fixing and the provider executes the service as per the contract. The first step in this approach is publishing a service within the service registry by the provider that are discoverable by a potential consumer. We consider simple services such as single machine hours, man hours, logistic service, etc. This type of service requirement can arise, for example when a machine at the company undergoes unplanned maintenance or to meet a customer requirement that cannot be fulfilled with existing machinery or available manpower. The customer requirements may include service specifications, quantity and time requirements, etc. Further the customer may also specify preferences such as geographical location, minimum time frame, and sustainability criteria.

In collaboration with our industrial partners, we defined the following competency questions to develop a MaaS model using the IOF ontology:

1. Who provides service X?
2. What is the time period during which the service available?
3. What are the available parameter range of the service provided?
4. What are the quality attributes of the provided service?
5. What is the quantity capability proposed by the service provider?
6. Is there any preconditions that need to be satisfied for availing the service?
7. What are the inputs required for availing the service?
8. What are the outputs of the service?
9. What is the geographic location of the provider?
10. What are standards assured by the provider?
11. What is the minimum time frame assured by the provider?

For answering the aforementioned competency questions, the model of capability in IOF is extended to form our proposed MaaS model as shown in Figure 23. To model the specification and attributes of a service, we propose to include the following additional entities:

- *ServiceID*: related to the MaaS model with a *hasServiceID* object attribute. The *serviceID* can refer to service classification standards such as VDI 2860, DIN 8593, etc., for unambiguous matching (Kulvatunyou & Ameri, 2019; Vathoopan et al., 2021) along with the basic description of the service.
- *Preconditions:* related to the MaaS model via *hasPrecondition* object property, *Preconditions* are proposed to include any conditions that have to be met for availing the service such as minimum quantity required.
- *Input:* related to the MaaS via *hasInput* object property. *Input* entity describes the input/s required for availing a service such as raw materials, drawings, etc and their specifications.
- *Output:* related to the MaaS via *hasOutput* object property. *Output* entity provides details of the output/s obtained as a result of executing the service and their specifications such as quantity and quality.
- *Parameters:* related to the MaaS via *hasParameter* object property. *Parameters* can be used to define the parameters of an availed service.
- *Attributes:* related to the MaaS via *hasAttributes* object property. *Attributes* can describe the quality attributes of a MaaS. To describe the time frame of the offered service we propose to include *AvailabilityInfo* entity. This entity can be related to the MaaS model via *hasAvailabilityInfo* object property. Availability information is provided to include details on when exactly the service is available for consumption.
- *RealtimeInfo:* related to the MaaS via *hasRealtimeInfo* object property. *RealtimeInfo* entity provides real time information on the execution of a realised process.

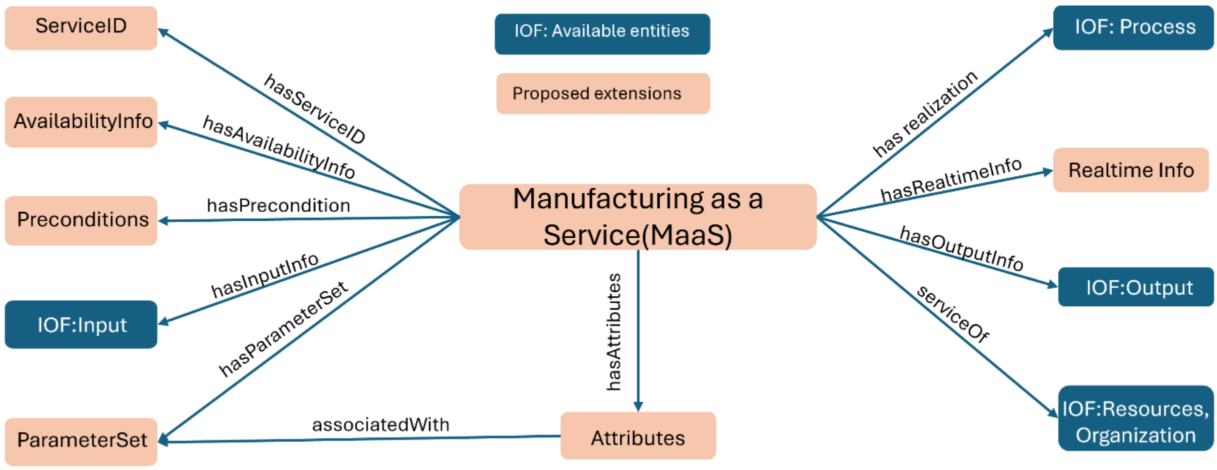

Figure 23: Proposed MaaS model in ACCURATE.

A published manufacturing service can adopt a more intricate format to encompass the entire production of a product or a specific product module. This type of a service request might include other details such as product details and associated requirements. This type of service definition is out of scope of this chapter. In IOF, a capability of published service is realised in a process. Hence, entities of the proposed MaaS model have to be mapped into the process model as well. The process model can include other details such as composition information. Further extensions, in this direction is seen as a future work.

6.6 Evaluation and Preliminary Results

To evaluate the proposed models, we take the use-case of a sample company producing Printed Circuit Board (PCB). The PCB manufacturing involves several processes such as Surface Mount Technology (SMT) Top, SMT Bottom, Automatic Visual Inspection, Depanelling, Automatic inline testing, functional testing, etc. Among these processes, Depanelling is used to separate the PCBs into modules or separate products based on the requirements. It is performed using several techniques such as Laser based cutting, manual cutting, etc. Assuming an unplanned maintenance of an in-house machine, the company needs to avail depanelling service from the MaaS providers.

A company's search criteria for a required service can be formatted as follows:

> **Requirement:** *PCB depanelling service (Curf width: 20µm, Quantity: 3000, Time frame: 4-20 days from 1 Nov 2024)*
>
> **Preferences:** *<500Km from Tolouse France, 10 days delivery, CO2_intensity < 10 kg/m, scrapRate < 5%.*

The offered service from a provider may take the form as shown in Figure 23 in this case. For implementing the matching of requested service and provided service, several approaches exist in literature (Bouzary & Frank Chen, 2018; Cheng et al., 2017; Zhang et al., 2020). Implementing a matching algorithm is out of scope of this research.

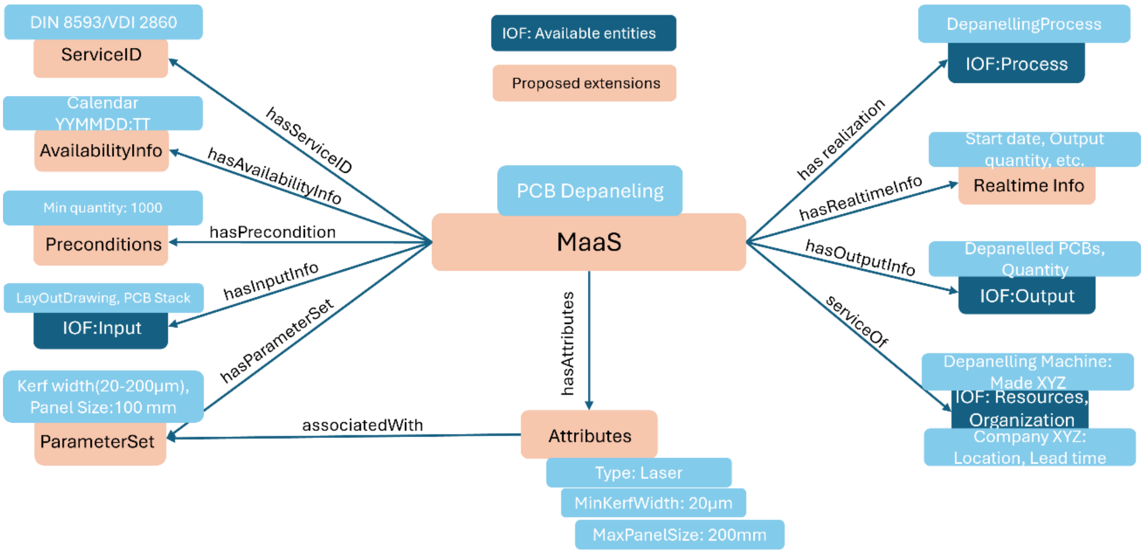

Figure 24: A sample MaaS published in the service registry.

We used Protégé editor (Yang et al., 2023) for developing our ontology. We modelled three sample MaaS with different specifications based on the model shown in Figure 24. SPARQL based query was formulated to model the requirements and preferences of the sample company. The query resulted the matching MaaS from the three available options.

6.7 Discussion and Conclusion

This chapter discusses the use of ontology-driven knowledge graphs to achieve sustainability in an agile production environment with networked MaaS. By setting a target sustainability score from the outset, the goal is to optimise the configuration of suppliers, production resources, and MaaS. This research proposes a two-step method to achieve this goal. The first step, constructing an ontology for information integration and retrieval, is elaborated upon.

As an initial contribution, after reviewing extensive literature and ontology selection criteria (Kulvatunyou & Ameri, 2019; Kulvatunyou et al., 2022; Sapel et al., 2024; Yang et al., 2023), this research identifies IOF as the preferred ontology for developing an agile manufacturing ecosystem. Anticipating the future adoption of MaaS similar to web services, this study proposes a MaaS model inspired by web services (Martin et al., 2004). It maps the state-of-the-art definitions and models of MaaS within the manufacturing domain (Cheng et al., 2017; Diedrich et al., 2022; Vathoopan et al., 2021; Wu et al., 2015). Extended entities required for modelling the proposed MaaS within IOF are introduced based on derived competency questions. The proposed model is evaluated using an example of a company searching for a specific service in the proposed service registry. Our initial experiments support the claim, as shown in (Kulvatunyou & Ameri, 2019; Kulvatunyou et al., 2022; Sapel et al., 2024), that most aspects of an agile manufacturing ecosystem can be modelled by reusing the IOF Core and Supply Chain ontologies. Further extensions required based on our MaaS model, such as composable services, are considered future work. The development of a MaaS taxonomy applicable to our use cases is identified as an immediate future task. Additionally, the development of the second step, which involves using DTs to optimise a sustainable manufacturing ecosystem, is also seen as future work.

7 Circularity, Sustainability, and Resilience Indicator Framework for a MaaS System

7.1 Data Collection for Circularity, Sustainability, and Resilience Assessment

To understand the feasibility of collecting primary data for performing circularity and sustainability assessment for MaaS providers, a two-step data collection process was setup for the pilots. The proposed methodology for circularity and sustainability assessment was explained to the pilot partners in ACCURATE, to give them an overview of the need and significance of various data to be collected from the production lines.

1. The first data collection instrument was a detailed Excel template that asked the pilot partners to: (i) assess the feasibility of data collection, and (ii) report data points on a representative production line. This template will be presented in further details in the paragraphs below.

2. The second data collection instrument refers to follow-up discussions conducted with the ACCURATE pilot partners to further understand existing challenges in data collection, and possibilities for addressing data gaps through the course of the ACCURATE project. These discussions are also presented in further details in the paragraphs below.

7.1.1 Data collection template distributed to ACCURATE pilot partners

In addition to the production line information for developing the production DES models, we distributed a data collection template to collect information required for computing circularity and sustainability indicators, linked to the developed simulation models. The pilot partners were asked to collect these data points for a representative production line (for which the simulation models will be constructed) and to report (i) historical data availability, as well as (ii) feasibility for collecting these data from the production line, e.g., using existing data collection systems or by implementing additional systems. Table 7presents the data types requested from the ACCRURATE pilot partners, along with a brief explanation of the data type and the purpose of data collection.

Table 7: Data collection template distributed to ACCURATE pilot partners for estimating the feasibility of computing circularity, sustainability and resilience indicators.

#	Category	Data Type	Brief Explanation	Purpose of data collection
01	Product	Component Mass (kg)	Mass of individual components for representative products produced in the production line based on the Bill of Materials.	Computing environment intensity of production process and mass-based CE indicators.
02	Product	Component Material Composition	Material composition for individual components for representative products produced in the production line based on the Bill of Materials.	Identifying environmental impacts from material extraction and end-of-life stages. Computing production environmental impacts based on material type.
03	Product	Component Scrap Rate (%)	Average rate of scrapped components sent for disposal.	Computing additional environmental impacts due for meeting a specific order quantity.
04	Product	Component Rework Rate (%)	Average rate of components sent for rework.	Computing additional environmental impacts due for meeting a specific order quantity.

05	Process	Average workstation utilisation rate (%)	Percentage of total production time that a workstation is active/in use.	Estimating process flexibilities needed for replanning production under disruptions.
06	Process	Workstation planned maintenance (hours)	Annual hours of planned maintenance for a individual workstations on the product line.	Estimating process flexibilities needed for replanning production under disruptions.
07	Process	Workstation unplanned shutdowns (hours)	Annual hours of unplanned shutdowns for a individual workstations on the product line.	Estimating process flexibilities needed for replanning production under disruptions.
08	Process	Workstation operator breaks (timestamp)	Duration of operator breaks planned on specific workstation.	Estimating process flexibilities needed for replanning production under disruptions.
09	Process	Workstation changeover time (hours)	In the case where multiple components can be produced in a single workstation, the time for configuring it for a new product.	Estimating process flexibilities needed for replanning production under disruptions.
10	Process	Workstation energy use (kwh)	Annual energy consumption of each workstation on a production line.	Computing environmental impacts due to energy usage.
11	Process	Workstation consumables (qty)	List specifying type and annual amount of consumables for each workstation.	Computing environmental impact due to material usage.
12	Process	Workstation emissions (qty)	List specifying type and annual amount of emissions resulting from each workstation.	Computing environmental impact from emissions to air, water, and land.
13	Human	Social impact considerations	Prioritisation of social impact categories relevant to the production system.	Estimating focal areas for social impact assessment for MaaS providers.
14	Human	Training and upskilling	Need for upskilling and training workers on specific processes on on the production line.	Estimating social impacts from changes to production and opportunities for improving well-being.

It should be noted that the data presented in Table 7 should not be considered as comprehensive data inputs for estimating for assessing the resilience, circularity, and sustainability of the MaaS provider. They represent complementary data collected, over those required for developing the DES based simulation models in WP 3 and WP 4. Furthermore, this data collection instrument served as an exploratory mechanism for opening up a conversation with pilot partners on data availability and gaps. Consequently, we did not specify rigorous data quality criteria and specifications at this stage. Finally, actual data provided by the partners is not detailed in this report due to confidentiality reasons.

7.1.2 Follow up discussions with ACCURATE pilot partners

The ACCURATE pilot partners were invited for follow-up discussions through the WP 3 meetings, as well as scheduled one-on-one meetings to better understand existing challenges with data collection and resolving data gaps. The overall goal was to reach a collective agreement on what data points could be modelled as primary data (i.e., directly collected from the production lines) and the data points that needed to be modelled from secondary sources including, commercial LCI databases, and peer-reviewed articles. Furthermore, the prioritisation of the computing specific indicators was discussed based on the realised data collection constraints.

7.1.3 Results

Results provided by the partners we analysed to understand the availability and level of aggregation of these data as shown below. It should be noted that the results shown represent the *as-is situation* across the ACCURATE pilot partners. Future work will recommend specific implementation solutions for data collection, based on the indicators selected for each UC.

Table 8: Overview of data availability and data collection changes for the individual data types.

#	Data Type	Summary
01	Component Mass (kg)	The mass of individual components was available in various technical sheets and engineering documentation. Given the complexity of collating these data, the only solution would be to make direct measurements on the production line and establish an aggressive mass-based cut-off criteria to limit the number of direct measurements to be made. It should be noted that the focus of the ACCURATE project is on the manufacturing processes, and not on the produced products themselves; estimating a PEF for a product is outside the project scope. Therefore, mass measurements are further restricted/aggregated to those required for estimating mass-intensity based indicators (e.g., ratio of total energy consumed in a manufacturing process to total mass flow).
02	Component Material Composition	Component material composition was only available in various technical sheets and material specification data sheets. Given the complexity of collating these data, and the focus of ACCURATE, the use of data is only relevant for identifying the characteristic of mass flow data (e.g., determining if a mass flow is e-waste, metal scrap, etc.).
03	Component Scrap Rate (%)	In cases where the product is electro-mechanical or electrical, the number of components was high, and several components were sourced from suppliers. Therefore, it was not possible to estimate the scrap rate for individual components. Given that production lines were multi-step processes, component scrap could be generated at different stages and in different workstations. This complexity was exacerbated when multiple products were produced (high-mix production) on a specific line. Consequently, such estimations would have to typically rely on averaged data at a product level.
04	Component Rework Rate (%)	Availability of detailed rework data was varied. In cases where the product is electro-mechanical or electrical, the number of components was high, and several components were sourced from suppliers. Therefore, while it was possible to estimate a rate for the overall product, component-level data was unavailable. In some instances, reworking was strictly limited or prohibited due to safety implications. Consequently, the computation of sustainability and circularity indicators should consider challenges in estimating these data.
05	Average workstation utilisation rate (%)	Utilisation rate data for specific machines or workstations was typically monitored periodically in terms of Overall Equipment Effectiveness (OEE). However, considering the number of workstations/machines involved, it was noted that collating such data would require significant effort. Consequently, the computation of sustainability and circularity indicators should consider challenges in estimating these data.
06	Workstation planned maintenance (hours)	Planned maintenance data for specific machines or workstations was typically documented in maintenance logs. However, considering the number of workstations/machines involved, it was noted that collating such data would require significant time and effort. Consequently, the computation of resilience indicators (e.g., in relation to reconfiguration) should estimate these data from secondary data sources or heuristic data.
07	Workstation unplanned shutdowns (hours)	Pilot partners reported that it was challenging to accurately quantify the probabilities or average mean time to failure at an individual workstation level. Resilience indicators related to production line reliability (e.g., time to failure, time to repair) would therefore have to rely on expert estimates. Furthermore, it was pointed out that in general, the operations analysed in the scope of the ACCURATE project were highly mature and unplanned failure is not a major bottleneck. Non-operation of machines due to other

		factors e.g., insufficient work-in-progress was seen as a more important consideration in terms of overall resilience.
08	Workstation operator breaks (timestamp)	Operator breaks that are scheduled are well known. The relevance of the breaks to the operation of a workstation varied significantly as some processes could operate without continuous monitoring. This variance should therefore be considered while estimating sustainability performance (i.e., if a machine is in idle state during a break) and resilience performance (e.g.,, time to detect failures, time to reconfigure the production line, etc.)
09	Workstation changeover time (hours)	The ability to estimate changeover times was a function of process complexity as well as flexibility. For example, in a highly flexible process such as automated printer circuit board assembly, that can produce multiple variants over a shift, it was challenging to estimate changeovers. In the other extreme, where a production line was dedicated towards producing a single product, they were non-existent. In other instances, e.g., where the entire line needs to be reconfigured for producing a different product, changeover times were unknown. Therefore, these data, if required for computing performance indicators, would require expert-based and/or heuristics-based values.
10	Workstation energy use (kwh)	Energy consumption data was typically collected for sustainability reporting. These data were typically available at the level of the entire factory/plant and in some specific instances at the level of individual lines. Challenges including proprietary hardware interfaces, cost of data collection, and uncertainty in data usefulness limit data collection on individual workstations or machines. Consequently, sustainability and circularity indicators requiring energy use data at the machine level would require inputs from secondary data sources (e.g., commercial LCI databases) and/or additional primary measurements.
11	Workstation consumables (qty)	Data on consumables (e.g., tools, lubricants, water) could be potentially assessed through purchasing records. However, given the consumables were shared across multiple lines and workstations, it was challenging to attribute a specific quantity of usage to a workstation without additional measurements. Consequently, sustainability and circularity indicators requiring these data would require inputs from secondary data sources (e.g., commercial LCI databases) and/or additional primary measurements.
12	Workstation emissions (qty)	Process emissions were typically solid wastes (e.g., unusable scrap) and liquids (e.g., spent fluids) that were sent for downstream processing. Aggregated data was available in some instances. Attributing a specific quantity of usage to a workstation will require significant additional effort. Consequently, sustainability and circularity indicators requiring these data would require inputs from secondary data sources (e.g., commercial LCI databases) and/or additional primary measurements.
13	Social impact considerations	A significant focus for MaaS providers was on ensuring a well-functioning and beneficial relationships with their value chains. The well-being of workers was also pointed out as important. Worker protection was seen as not relevant to the partners, due to the presence of strong worker protection regulations in their operations regions and high voluntary standards. Efforts for data sharing on social impacts are at an early stage and not fully implemented. It should be noted that given the scope of the ACCURATE project, such considerations are not expected to be dynamically linked to DT models; future efforts will investigate if relevant social impacts can be continually monitored.
14	Training and upskilling	All pilot partners reported having a mix of automated and manual processes, with the manual processes typically requiring specialised skills and extended training. Therefore, training and upskilling are seen as vital to the resilience of the business. Lack of sufficient local labour force and the extended time for training were viewed as challenges. Future efforts should investigate if it is possible to evaluate the effect of disruptions (and the consequent actions taken by a partner) on worker training and upskilling.

Based on the above results, the following recommendations are drawn for the integration of resilience, sustainability, and circularity indicators with the DES models that will be developed for the various use cases.

- CE indicators selected for assessing the pilot cases should largely be process focused and utilise aggregated material and energy flow information where possible. It will be challenging to develop and integrate indicators at a high level of granularity (e.g., at an individual workstation or component level) due to existing data availability and the significant costs of added data collection.

- Limited primary inventory data is available to compute environmental sustainability indicators. Consequently, there is a need to rely on secondary data sources, including commercial databases and peer-reviewed articles. Sufficient care should be taken to select representative process models, which require further discussions with the pilot partners. The models should be developed in a modular manner (i.e., when considering the integration of production simulation models and sustainability assessment models) to ensure secondary data can be substituted with primary data in the future, improving the accuracy of the overall assessment.

- Coupling of social sustainability indicators with the DES models, is only possible for indicator categories where a proxy can be established using direct measurement on the production line (e.g., OTD). Worker-specific indicators are to be progressively monitored, but it is potentially challenging to couple them with the DES models due to the lack of data and knowledge to establish causal relationships.

- At the production level, computation of resilience indicators needs to rely on average estimates for factors such as equipment availability, reliability, and reconfigurability. While such estimates can be readily integrated with simulation models, follow-up dialogues with the pilot partners should ensure that these results are representative of observed historical behaviour, relying on their domain expertise.

7.2 Circularity and Sustainability Indicators Workflow

To assess the circularity and sustainability in the MaaS system, a combination of indicators from the ISO 59020 standard and sustainability LCA methods will be applied. Additionally, the difference between UCs focusing on supply chain dynamics and UCs looking at production necessitates the assessment of different indicators between the two cases. The indicators were chosen based on the following criteria: together, the indicators can span a range of data types and aspects of sustainability and circularity, and there is reasonable belief that we will be able to obtain the data necessary to calculate these indicators from the simulation, the partners, or a database.

7.3 Circularity and Sustainability Indicators on the Supply Chain Level

The primary indicator recommended for sustainability on a SC level is emissions associated with transportation of materials. These emissions can be found with the knowledge of the travel path for materials, the vehicle carrying the materials, and the material weight. LCA databases, such as the ecoinvent database[8] contain information on the emissions associated with different vehicles and using the weight and distance travelled, emissions can be extrapolated from this. This indicator was chosen because it is a relatively simple sustainability indicator, and it can capture the environmental impacts of the transportation of materials under disruptions. For instance, if a critical supplier is disrupted and the company has to find an alternative source, the alternative source may have higher emissions if they use different means of travel or if products are shipped from further away. While a deeper analysis into the different materials being sourced can unveil more

[8] http://ecoinvent.org/database/

about the true sustainability of the SC, this is a task that is too complicated for the pilot partners, and to be undertaken as a part of the ACCURATE project.

A key aspect in CE is the circularity of materials, thus it is critical to look at circularity indicators as well as general sustainability indicators. Two circularity indicators were chosen to be recommended from the ACCURATE Circularity Indicator Screening Tool, to be used for SC simulations. These indicators were adapted in order to make them specially tailored to being applied on a supply chain level. The first indicator is the *SC waste factor*. Waste factor is an indicator that divides the waste generated during the production of a product by the total weight of the product, in this way, showing a proportion of waste produced to product produced (Jerome et al., 2022). The next circularity indicator is taken from the current ISO standards, *percent recycled, reused, or green materials used in productio*n. This indicator is as it seems, a proportion of recycled, reused, or green materials against the total mass of materials used (Standardization, 2024c). To adopt this indicator to work within a SC context, instead of materials used in production, it will look at percent of materials delivered to customers that are recycled, reused, or green.

7.4 Circularity and Sustainability Indicators on the Production Level

On a production level the recommended indicators measure impacts due to energy usage. Data on energy demand and the sources of energy are relatively easy to find for a singular manufacturing facility. To measure the sustainability of energy usage, WP 3 and WP 7 will look at two metrics: *average percentage of renewable energy* and *energy intensity.* The *average percentage of renewable energy* is a measurement of the proportion of energy used that comes from a renewable source. This metric is a supplemental measure from the ISO 59020 standard, meant to complement measures of material circularity (Standardization, 2024c). The other metric, *energy intensity,* is the total energy demand for a given period of time, divided by the total mass of products produced. This can be seen as generally showing the energy efficiency in the production of goods (Jerome et al., 2022).

To compliment the aforementioned sustainability indicators, four circularity indicators are recommended. These indicators cover material circularity and water circularity. In the ISO 59020 standard, aspects of circularity are split into five categories, resource inflows, resource outflows, energy, water, and economics (Standardization, 2024c). The sustainability indicators chosen for production, *percentage of renewable energy* and *energy intensity*, cover the energy category.

Resource outflow circularity is addressed using the indicator *waste factor. Waste factor* is the total waste produced during production divided by the total mass of product produced (Jerome et al., 2022). Shrinking the *waste factor* results in less waste produced during the production process. This can be reduced in many different ways whether by changing the product design, the production process, or by diverting material from being waste by reusing it. To cover the resource inflow, the metric of *average recycled content* from the ISO 59020 standard is recommended. *Average recycled content* is one of the mandatory indicators mentioned in the ISO standard on measuring and assessing circularity performance. It is the fraction of mass of a product that is produced with recycled material (Standardization, 2024c).

The final category that is within the scope of the ACCURATE project is water circularity. This will be covered using two metrics, *percent water withdrawal from circular sources* and *percent water discharged in accordance with quality requirements*. Water is an often-overlooked aspect of CE. Water withdrawn from a circular source is water that has either already been used once, so it is not considered to be virgin water, or it comes from a natural source that is renewable. Water discharged in accordance with quality requirements means that it leaves the facility and goes to either another facility to be reused or it is in a state that it can be returned directly to the environment without negative environmental impacts. This is where water is cycled back into the circular system, either through reuse in a different context, or by renewing the natural water cycle (Standardization, 2024c).

7.5 Resilience Indicators in Production Optimisation

The resilience indicators chosen to be integrated in the simulations were mainly based off of a performance curve, where a chosen performance of a system (i.e., OTD, material delivered, product produced) is plotted against time with a disruption occurring during the simulation. It is not yet decided exactly how system performance is measured for the specific UCs as further information on the DES models is needed.

Similar to circularity and sustainability indicators, resilience indicators were chosen based on, whether a simulation dealt with the SC or the production process, since different aspects of resilience are more applicable to one or the other. However, the majority of these indicators were chosen to be used with both the SC simulations and the production level simulations.

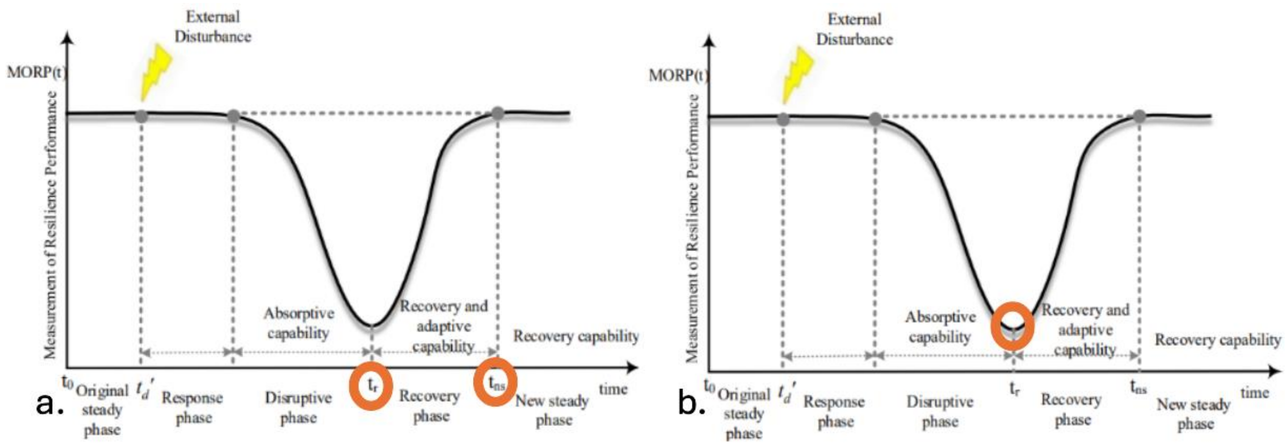

Figure 25: (a) Recovery Time and (b) Robustness adapted from Wang et al. (2022)

Figure 25 shows two performance curves with different aspects highlighted, these different aspects are used to calculate the three resilience indicators chosen to assess all user scenarios, these being *recovery time*, *robustness*, and *capacity loss*. *Recovery time*, indicated by Figure 25(a), is calculated as the time between the worst performance of a system and the time at which the system reaches a new steady state (Wang et al., 2022). This indicator quantifies how long it takes for a system to recover after a disturbance. The next resilience indicator chosen to be calculated in all scenarios is *robustness*. While *robustness* can be defined in many ways, in the scope of this work, it is defined as worst performance of a system under disruption (Wang et al., 2022) as also shown in Figure 25(b). The difference between *robustness* and *reliability* is that *robustness* assesses the resilience of a system under a large and unexpected disruption, while *reliability* focuses on a system withstanding smaller but more common disruptions (Uday & Marais, 2015). By measuring the greatest impact an event has on the overall system performance, this definition of *robustness* is sufficient to assess the ability of a system to withstand large, unexpected events.

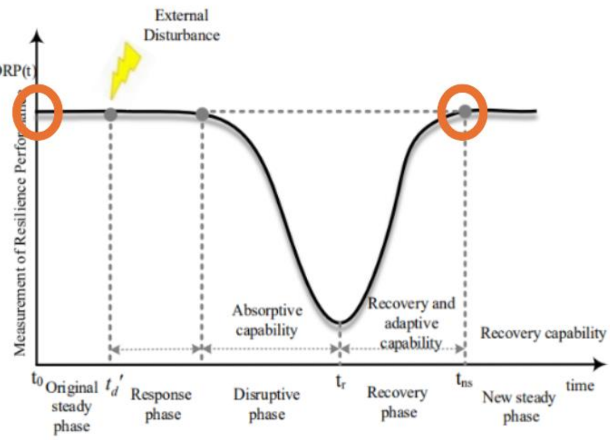

Figure 26 Capacity Loss on a Performance Curve adapted from Wang et al. (2022)

The final resilience indicator chosen for all cases is the *capacity loss*. As shown in as shown in Figure 26, *capacity loss* is the difference between the performance of the system pre-disruption and the performance of the system after it has reached a steady state after recovering. In Figure 26, there is no change in the capacity of the system, however, in other cases a full recovery is not possible, and a new system has a lower capacity that the old one. This difference would be the loss in capacity.

7.6 Resilience Indicators on the Supply Chain Level

On an SC level, the recommended resilience indicator is *time to failure*. *Time to failure* is illustrated in Figure 27, and is the difference between the time that a disruption occurred and the time that system performance begins to fail (Wang et al., 2022).

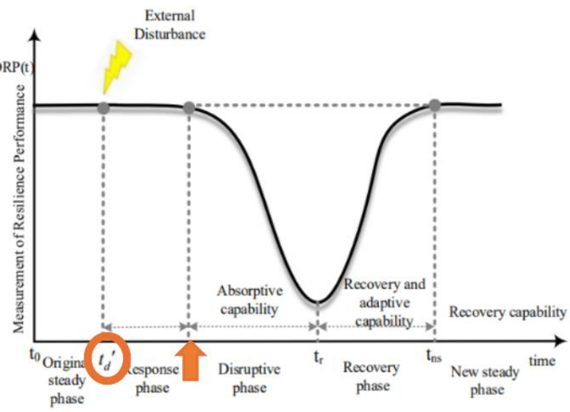

Figure 27: Time to Failure adapted from Wang et al. (2022).

Time to failure is important in assessing the SC focused aspects in ACCURATE as the pilots represent SC which are complex and the impacts of disruptions downstream of production are unknown. Thus, the time that it takes for a disruption to affect system performance will provide helpful insights into the true impacts of a disruption and the amount of time that a reconfiguration could take place.

7.7 Resilience Indicators on the Production Level

On a production level, the focus of the disruption models and DTs are focused on the product made and how disruptions in the process affect the ability of a company to deliver on time. Because of this, two additional resilience indicators were chosen to be applied to production related simulations. These indicators are *loss of performance* and *rapidity in the recovery phase*, shown in Figure 28(a) and Figure 28(b) respectively.

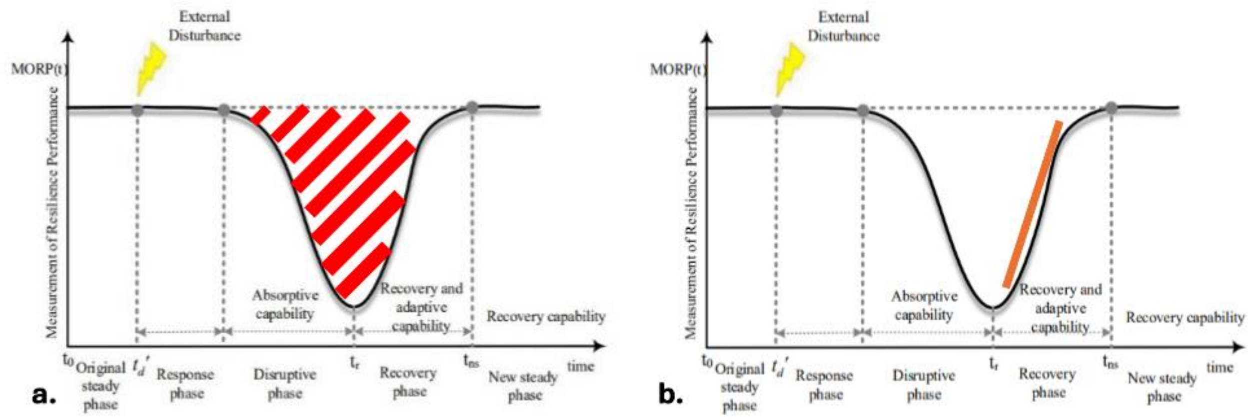

Figure 28: (a) Loss of Performance, and (b) Rapidity in the Recovery Phase, adapted from Wang et al. (2022)

Loss of performance is the total amount of lost production during the disruption period, calculated by the integral of the baseline performance minus the disrupted performance over the period of time from the beginning of performance declines to the recovery of performance to a steady state (Wang et al., 2022). This metric is important for assessing resilience on a production level, because it quantifies the total amount of production lost due to a disruption.

The other metric which was chosen to assess production level resilience *was rapidity in the recovery phase*. *Rapidity in the recovery phase* is the rate of increase in performance from the point of the worst performance to the time that a steady state is reached. It illuminates how rapid a system can recover and thus can show more dimension, combining aspects of robustness, defined as the worst performance level reached, and time to recovery (Wang et al., 2022). This metric was chosen after closely reading through the UCs for the three pilot partners in ACCURATE. These UCs were developed as a part of WP 7 during the ACCURATE project. In each UCs involving production, pilot partners stated that a rapid recovery was an important aspect to quantify.

7.8 MaaS system Use Case Workflows

In the ACCURATE project, nine distinct UCs were created as a part of WP 7. Four UCs correspond to the partner Airbus Atlantic, two to Continental, and three to Tronico. Each UC investigates important aspects of SC and production resilience based on real-world needs from the pilot partners. These UCs can be categorized into one of three categories, depending on if they pertain to the, (i) SC of a company, (ii) the production of company's products, or (iii) both. Given these three categories, appropriate circularity, sustainability, and resilience metrics are assigned to each UC category. After assigning these circularity, sustainability, and resilience metrics to the scenarios, we assessed them to see if additional metrics would be necessary in order to meet the desired outcomes for each UC (in addition to those described earlier at the SC and production levels). Out of the nine UCs, we found that six of them should have extra indicators applied to them. The following sections lay out the additional indicators to be used for each UC in addition to the circularity, sustainability, and resilience indicators listed in the previous sections of this chapter.

7.8.1 Airbus Atlantic User Scenarios

Two out of the four UCs generated for Airbus Atlantic (UC 2, UC 3) required additional indicators to assess key aspects of the disruption scenario and the production and supply chain.

UC 2 for Airbus Atlantic is titled *"SC Design and Support by Identification of Hidden Critical Suppliers/Materials*". This UC involves stress testing the SC to uncover hidden critical suppliers or materials. Along with the identified SC resilience metrics (see Section 7.6), we recommend two additional related resilience indicators, *number of critical nodes* and *proportion of critical nodes* in a system. For these metrics, network analysis is utilised, where a SC is modelled in graph form, with nodes being firms or suppliers, and edges connecting these nodes represent trade agreements and the flow of materials (Demirel, 2022). In UC 2, a critical supplier is one who's failure would result in significant impacts to the functioning of the SC. Since this user scenario uncovers previously unknown critical nodes, it is necessary to know how many of them exist and what proportion of Airbus Atlantic's SC is made up of them. An SC with a high number and proportion of critical nodes is more at risk of losing performance if one of these critical nodes are disrupted.

The other Airbus Atlantic UC that required additional indicators was UC 3, *"SC Design Recommendations for Better Absorption and Swift Adaptation"*. This UC concerns Airbus Atlantic's ability to adapt to disruptions in the SC by inventory management, supplier management, and the use of DTs. A KPI of this UC is a reduction in development lead time. In choosing additional indicators for this case, the key was to look at the ability of Airbus Atlantic to adapt and recover.

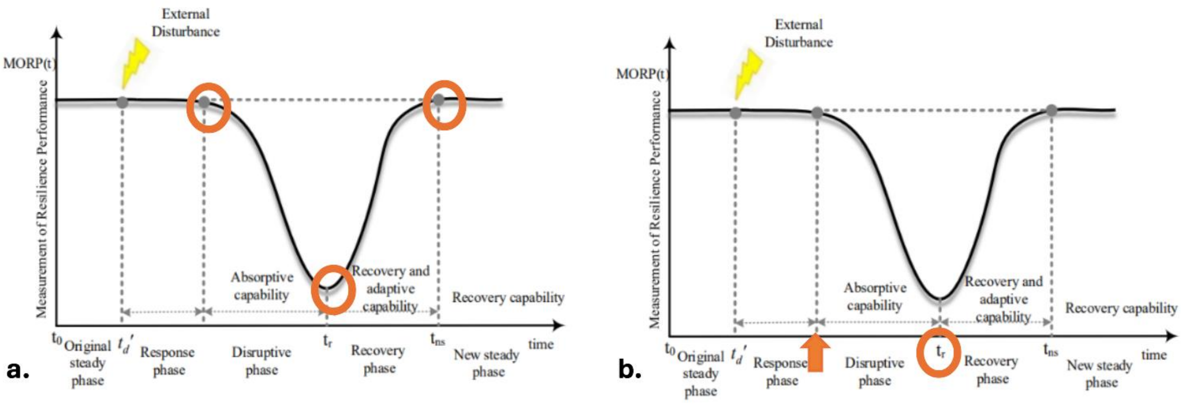

Figure 29 (a) Recoverability and (b) Disruption Time adapted from Wang et al. (2022).

Figure 29 depicts the two chosen additional metrics for UC 3, *recoverability* and *disruption time. Recoverability* is a resilience indicator which shows the ability of the system to recover from a disruption by comparing the difference between system performance before and after a disruption and the worst performance of the system. A *recoverability* of 1.0 indicates that a system can completely recover from a disruptive event and *recoverability* < 1.0 indicates that a system cannot meet pre-disruption performance. Metrics like *recoverability* and *recovery time* shed light on the recovery process a system undergoes, however, this UC is also concerned with the ability of the system to absorb a disruption. Part of this is handled by the *robustness* metric mentioned previously, however it is also important to know how long it takes the system to begin its recovery. This is where the next metric, *disruption time*, comes into play. *Disruption time* is the length of time between the beginning of system decline following a disturbance and the time when the system begins to recover, as shown in Figure 29(b).

7.8.2 Continental User Scenarios

Continental's second UC *"Production Panning Reconfiguration Under Disruption"*, aims to simulate their production lines under disruption. A key characteristic of Continental's production line mentioned in the UC is that the machinery they use have a high utilisation rate and are often used round the clock. For this reason, three extra resilience metrics are suggested that can reveal particularly vulnerable steps in the production process. These three metrics are *mean time to failure* (MTTF), *mean time between failures* (MTBF) and mean *time to repair* (MTTR). These metrics are commonly used in evaluating manufacturing (Alavian et al., 2019; Daniewski et al., 2018).

MTTF is the average life span of a machine before it breaks down. This is important information to use when scheduling maintenance. Additionally, this time can change depending on the use of a machine, for instance, running a machine for longer increments of time or at higher volumes can put it at risk for failing sooner. MTBF refers to the average time a machine can be used before experiencing a failure, this can be seen as an assessment of the reliability of a machine. Finally, MTTR refers to the average amount of time that it takes to repair a machine (Alavian et al., 2019; Daniewski et al., 2018).

7.8.3 Tronico User Scenarios

Out of the three UCs for Tronico, additional indicators are suggested for each UC to better encompass their goals. In Tronico's first UC, *"SC Optimisation for Inventory Replenishment Management",* the main issue is choosing the correct time and amount to replenish parts in their inventory. Problems which arise in replenishing stock is the unavailability of components, but on the other side, the obsolescence of components which have stayed too long in Tronico's inventory, whether through a component becoming unusable, the product becoming discontinued, or a perishable item expiring. This represents a real sustainability issue, which is why a metric termed *expiration waste* is recommended. Plainly put, this is a measurement of the total mass of waste created from components and parts becoming obsolete and unusable while held in stock. Being able to minimise this will not only have positive economic benefits, but positive environmental benefits as well.

The second UC for Tronico is *"Production Scheduling Optimisation and Shop Floor Control".* Since Tronico makes a variety of electronic components for different machines, they require flexibility and reconfigurability in their production. Because of the inherent flexibility needed to accommodate a variable production, three metrics are recommended that provide insight on the ability of a manufacturing system to reconfigure its manufacturing. The first metric *is reconfiguration time*; this is the time that it takes a production line to transition from making product '1' to product '2'. A short reconfiguration time indicates that a system can quickly adjust to the disruption of producing a new product. The second metric is the *minimum increment of conversion*. The *minimum increment of conversion* is the minimum number of machines that need to be stopped in order to change from producing product '1' to producing product '2'. The final metric is called *configuration convertibility*. This metric combines the minimum increment of conversion, the number of redundant machines and the layout of the manufacturing floor (parallel vs series configurations) in order to assess how easily it could reconfigure itself to accommodate a disruption, either the production of a new product, the breakdown of a machine, or other likely occurrences. Configuration convertibility is normalised for the number of machines on a scale from 1.0 to 10.0, 1.0 being the least able to reconfigure and 10.0 being the most flexible (Hassan et al., 2024; Maler-Speredelozzi et al., 2003).

The final Tronico UC is *"Production Planning: Batch Optimisation".* This UC seeks to choose an optimal batch size for the production of orders that Tronico has to fulfil. Currently batch sizing is manually chosen based on previous experience. These simulations will help Tronico standardise batch sizing, avoiding decreases in resource utilisation, production performance, and resilience. Currently, poorly sized batches can lead to machinery being underused or inefficiently used. In order to further investigate this, we recommend looking at the indicator *mean machine utilisation*. This is the time of machine use over the total time of production, showing how often a machine is utilised.

7.8.4 Workflow Conclusion

In conclusion, Section 7.8 recommends the use of the previous indicators in tandem with the models mentioned in Chapter 2. The following table (Table 9) outlines how the models and data collection table can be used to obtain these indicators. It should be noted that the usage of the recommended indicators relies on the ability of ACCURATE pilot partners to obtain the necessary data.

Table 9: Applicability of Resilience, Sustainability, and Circularity Indicators to the ACCURATE pilot partners and and Corresponding Data Requirements.

Indicator Type	Indicator Name	Indicator Requirements	Airbus Atlantic	Tronico	Continental
Resilience Indicators	Recovery Time	Requires a performance vs time curve, we expect to be able to get this from the DES model.	✓	✓	✓
	Robustness	Requires a performance vs time curve, we expect to be able to get this from the DES model.	✓	✓	✓
	Capacity Loss	Requires a performance vs time curve, we expect to be able to get this from the DES model.	✓	✓	✓
	Time to Failure	Requires a performance vs time curve, we expect to be able to get this from the DES model.	✓	✓	✓
	Loss in Performance	Requires a performance vs time curve, we expect to be able to get this from the DES model.	✓	✓	✓
	Rapidity in the Recovery Phase	Requires a performance vs time curve, we expect to be able to get this from the DES model.	✓	✓	✓
	Recoverability	Requires a performance vs time curve, we expect to be able to get this from the DES model.	✓		
	Disruption Time	Requires a performance vs time curve, we expect to be able to get this from the DES model.	✓		
	Reconfiguration Time	Required data on workstation changeover time (hours).		✓	
	Minimum Increment of Conversion	Requires knowledge on the layout of the manufacturing floor.		✓	
	Configuration Convertibility	Requires knowledge on the layout of the manufacturing floor.		✓	
	Mean Machine Utilisation	Requires the average workstation utilisation rate,		✓	

	Mean Time to Failure	Requires the average time until machine fails from initial purchase.			✓
	Mean Time Between Failures	Requires average time until machine fails after an initial failure.			✓
	Mean Time to Repair	Requires workstation planned maintenance (hours).			✓
Environmental Sustainability Indicators	CO_2 eq. Emissions	Requires combining primary and secondary LCI data for estimating relevant process emissions.	✓	✓	✓
	Percentage Green Energy Usage	Requires data on the location of the manufacturing facility and average energy composition (by source) of the local electricity grid.	✓	✓	✓
	Energy Intensity	Requires mass of the produced component and workstation energy use.	✓	✓	✓
Circular Economy Indicators	Supply Chain Waste Factor	Requires data on expired or scrapped parts.	✓	✓	✓
	Waste Factor	Requires data on component weight and amount of scrap produced.	✓	✓	✓
	Average Recycled Content	Requires component material composition.	✓	✓	✓
	Percent of Water from Circular Sources	Requires data on the amount of water required during manufacturing and the source of this water.	✓	✓	
	Percent Water Discharged Circular	Required data on the amount of waste water produced during manufacturing and the disposal method for this water.	✓	✓	
	Expiration Waste	Required data on the amount of expired chemicals/components in inventory sent to waste.		✓	

As previously mentioned, the special nature of sLCA indicators means that stakeholder groups and indicator categories significantly vary across the UCs. sLCA indicators are also challenging quantitatively assess based on the planned ACCURATE DT simulation models. Consequently a categorisation of these indicators is not presented in Table 9. Further work conduced in the ACCURATE project in WP 3 and WP 7 will consider the qualitative social impacts, primarily focusing on enhancing the wellbeing of workers and training and upskilling opportunities, and qualitatively assessing risks to these factors under disruptions.

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