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Decision support system algorithms for supply chain design, planning, and stress-testing

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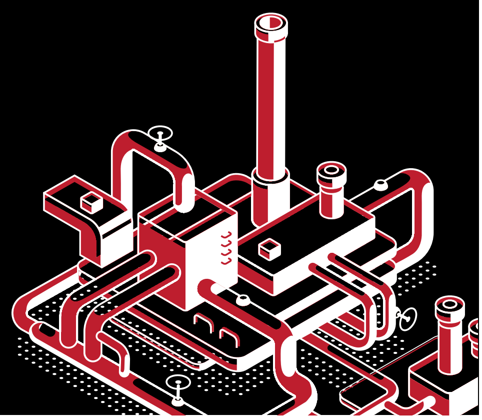

DELIVERABLE FACTSHEET

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Contributors:	Valeria Borodin, Cristina Duran, Rim-Djazia Gaouar, Aliaksandr Nekrashevich, Phu Nguyen, Anna Putintseva, Siqing Wu
Work Package Leader Responsible:	IMT
Reviewed by:	Michael Hertwig (IAO), Jalil Boudjadar (AU)

Dissemination level

☐ PU = Public

☐ CO = Confidential, only for members of the consortium

☐ RE = Restricted to a group specified by the consortium

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List of Abbreviations

AI	Artificial Intelligence
AM	Additive Manufacturing
APS	Advanced Planning and Scheduling
ATP	Available-To-Promise
CNC	Computer Numerical Control
CoC	Certificate of Conformity
CVaR	Conditional Value-at-Risk
DC	Distribution Center
DES	Discrete-Event Simulation
DP	Differential Privacy
DPA	Data Processing Agreement
DT	Digital Twin
DSS	Decision Support System
EDI	Electronic Data Interchange
FG	Finished Goods
FGI	Finished Goods Inventory
FL	Federated Learning
IoT	Internet of Things
KPI	Key Performance Indicator
MCDA	Multi-Criteria Decision Analysis
MaaS	Manufacturing-as-a-Service
ML	Machine Learning
MMFE	Martingale Model of Forecast Evolution
MoQ	Minimum Order Quantity
MoU	Memorandum of Understanding

MPS	Master Production Schedule
MTTR	Mean Time To Repair
OEE	Overall Equipment Effectiveness
OEM	Original Equipment Manufacturer
OTD	On-Time Delivery
P2P	Peer-to-Peer
PdM	Predictive Maintenance
PPM	Parts Per Million
QA	Quality Assurance
RBAC	Role-Based Access Control
S&OP	Sales & Operations Planning
SC	Supply Chain
SLA	Service Level Agreement
SMPC	Secure Multi-Party Computation
STDSM	Short-Term Demand–Supply Matching
TMS	Transportation Management System
WIP	Work-In-Process

Public summary

This deliverable introduces a Decision Support System (DSS) designed to strengthen the resilience of supply chains when facing disruptions. The DSS combines digital twin technology with advanced simulation, optimization, and data analytics, allowing organizations to anticipate risks, conduct stress tests, and adapt rapidly to unexpected events. By modeling disruption scenarios such as supplier delays, capacity reductions, or transportation breakdowns, the system enables more informed and timely decision support in a Manufacturing-as-a-Service (MaaS) context.

In addition, the deliverable details the underlying DSS algorithms for supply chain design, planning, and stress testing. It presents a set of solution approaches tailored to managing resilient supply chains under disruption in MaaS environments, together with a report that provides practical guidelines on the application of the digital twin-based DSS.

The following publications illustrate part of the work carried out within WP4 of the ACCURATE project:

1. Dmitry Ivanov (2025c). "When is the supply chain resilient? Customer and operational perspectives". In: *International Journal of Production Research*, pp. 1–16

2. Phu Nguyen and Dmitry Ivanov (2025b). "Decomposing Supply Chain Complexity: A Multilayer Network Perspective". In: *ACCURATE Publications*

3. Dmitry Ivanov (2025a). "Comparative analysis of product and network supply chain resilience". In: *International Transactions in Operational Research*

4. Dmitry Ivanov (2025b). "No risk, no fun? A bioinspired adaptation-based framework for supply chain resilience in Industry 5.0". In: *International Journal of Production Research*. DOI: https://doi.org/10.1080/00207543.2025.2496962

5. Phu Nguyen and Dmitry Ivanov (2025a). "A Two-Layer Digital Twin for Implementing Simultaneous Resilience Strategies in Electronics Manufacturing". In: *IFAC-PapersOnLine* 59.10, pp. 55–60

6. Cristian Duran-Mateluna et al. (2025b). "A Manufacturing-as-a-Service Scheduling Problem and its Tripartite Decision Perspective". In: *IFAC-PapersOnLine* 59.10, pp. 1558–1563

7. Cristian Duran-Mateluna et al. (2025a). "A Manufacturing-as-a-Service Scheduling Problem". In: *ROADEF 2025: 26ème congrès annuel de la Société Française de Recherche Opérationnelle et d'Aide à la Décision*

8. Michael Hertwig et al. (2025). "Ontology-based matchmaking and scheduling for Manufacturing as a Service". In: *Procedia CIRP* 134, pp. 372–377

9. Oscar Daniel Wilches Sarmiento, Valeria Borodin, and Alexandre Dolgui (2025). "On the end-to-end semiconductor supply chain under disruptions". In: *ROADEF 2025-26ème congrès annuel de la Société Française de Recherche Opérationnelle et d'Aide à la Décision*

10. Valeria Borodin, Vincent Fischer, et al. (2024). "Scheduling semiconductor manufacturing operations in research and development environments". In: *2024 35th Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC)*. IEEE, pp. 1–6

Chapter 1

Introduction

1.1 About this deliverable

This deliverable presents the development of a Decision Support System (DSS) for designing and managing resilient supply chains in a Manufacturing-as-a-Service (MaaS) context. The proposed DSS framework supports strategic and tactical supply chain decisions under conditions of uncertainty. It includes methodologies for modeling supply chain disruptions, evaluating resilience strategies, and optimizing performance through adaptive reconfiguration of networks. The deliverable also includes detailed guidelines for deploying and using the DSS effectively across a wide range of operational contexts, ensuring alignment with industry standards and resilience best practices.

The DSS integrates **predictive analytics, simulation, optimization,** and **digital twin technologies** to support manufacturers in coping with uncertainty and disruption while dynamically allocating procurement, production, and distribution paths after customer orders are received.

Together, these chapters provide a methodological and technological foundation for stress-testing, planning, and re-designing supply chains in MaaS environments. The deliverable reports on requirements, data collection, architectures, solution approaches, and first implementations, paving the way for advanced resilience analysis and decision support in subsequent project phases.

1.2 Structure of the document

This document is structured into five main chapters to provide both methodologies and practical implementation guidance for the supply chain resilience design while leveraging the concept of MaaS and digitalization:

- Chapter 2 introduces the conceptual framework of the digital twin–based decision support system, outlining its role within MaaS supply chain management and clarifying key concepts.
- Chapter 3 presents the core methodologies and algorithms, covering network design, planning approaches in MaaS ecosystems (including information, capacity, and material flows, as well as pricing aspects), and stress-testing models for disruption management.
- Chapter 4 provides user guidelines for the decision-support system, including data requirements, system setup, operational modes, and interpretation of results.
- Chapter 5 concludes with a synthesis of findings, managerial implications, and directions for future research.
- Appendices are provided to detail the mathematical formulations, pseudo-codes, and additional technical material supporting the main text.

1.3 Relation with other tasks and deliverables

Building on Deliverable 4.1, which introduced the simulation and optimization modeling approach for supply chain management and stress testing, Deliverable 4.2 represents a pivotal milestone at M22. It consolidates the conceptual and methodological advances into a coherent Decision-Support System (DSS) framework, thereby establishing the foundation for subsequent demonstrators and the integration of MaaS solutions, in close alignment with the activities of WP2 (ontologies and machmaking), WP3 (shop-floor level), WP5 (data spaces), and WP6 (decision-support and MaaS framework).

At the supply chain level, Deliverable 4.2 builds directly upon the outcomes of Deliverable 3.1 and Deliverable 3.2 (WP3), which address developments at the shop-floor level (see Figure 1.1).

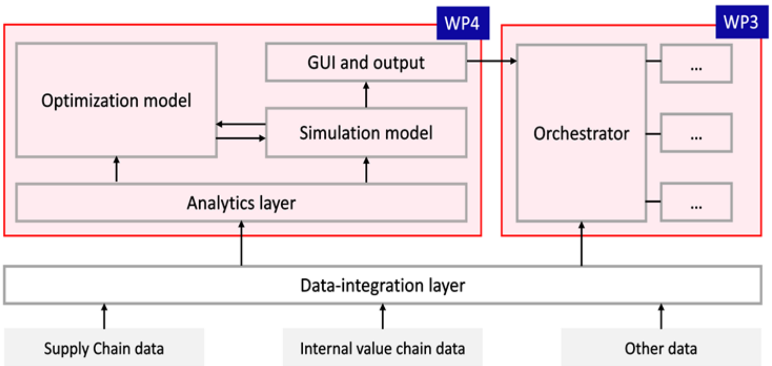


Figure 1.1: Decision-support framework: Core building blocks

Furthermore, the interrelation between the results presented in this deliverable and the use cases reported in Deliverable 7.1 is explicitly addressed, ensuring consistency and cross-fertilisation across work packages. The proposed methodologies have been systematically validated through the use cases co-designed with the ACCURATE pilots and partners in WP7. This validation process ensured not only their technical soundness but also their practical applicability in real industrial contexts. The industrial relevance and implications of these results are summarized in the dedicated box below.

Industrial implications: The case of ACCURATE pilots

By M22, several publications and dissemination actions related to the contributions of Deliverable 4.2 had been completed, thereby supporting the overall dissemination and exploitation objectives of WP8.

Chapter 2

Conceptual framework of the digital twin-based decision support system

2.1 Digital twin-based decision-support system

As highlighted in Deliverable 2.2, the *digital twin registry represents the backbone framework managing and orchestrating different models and digital twins that ensure finding the optimal Manufacturing Service or even optimizing the interaction along the value chain.* Consequently, digital twins are examined from multiple perspectives throughout the ACCURATE deliverables. **In line with the scope of the present document, our focus is placed on the algorithmic perspective.**

As illustrated in Figures 2.1-2.3, three complementary modes of interaction between simulation and optimization, each representing a progressively more advanced stage towards a simulation-based digital twin for decision support, are explicitly leveraged to design algorithms for supply chain design, planning, and stress-testing.

- **[Optimized Global System] – Optimized Simulation Settings:** (see e.g.,Chapter 3.3) In this mode, optimization is used before simulation to identify the best configuration of simulation parameters (e.g., policies, resource allocations, scheduling rules). Simulation then evaluates the system behavior under these optimized settings. The outcome is an optimized global system configuration that guides scenario analysis and policy testing. Within a DT-DSS, this corresponds to calibrating the twin with optimized baseline settings before exploring alternative scenarios.

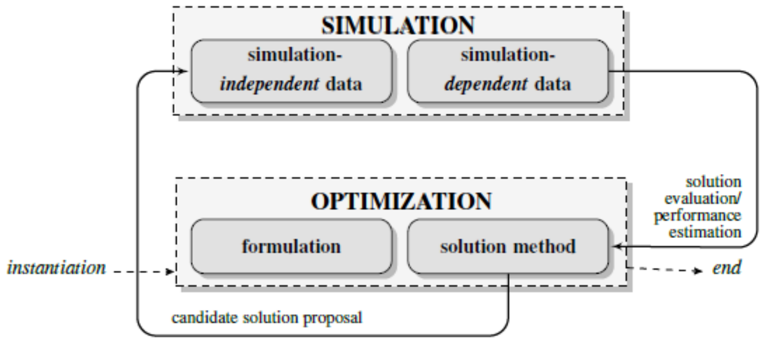


Figure 2.1: Optimized Global System: Optimized Simulation Settings (Borodin, Bourtembourg, et al. 2019)

- **[Well-informed Optimization] – Simulation for Supporting Optimization:** (see e.g., Chapter 3.3) Here, the focus shifts: simulation is embedded within the optimization loop. Candidate solutions generated by optimization are fed into simulation to assess their feasibility and performance under realistic, dynamic conditions. The feedback loop improves the quality of optimization by providing performance estimations and system responses grounded in simulation outcomes. In a DT-DSS, this enables robust decision-making by ensuring that optimization results are validated against realistic, scenario-based dynamics.

- **[Towards Digital Twin] – Simulation and Context-Based Optimization:** (see Chapter 3.2 and the developed Supply Chain Network Analysis Tool) This is the most advanced mode, where simulation and optimization operate in a continuous, context-aware loop. The system dynamically integrates real-time or near-real-time data, allowing the optimization module to adapt decision rules to evolving conditions. Simulation provides contextual performance insights, while optimization generates responses or adaptive decision rules accordingly. This corresponds to the digital twin paradigm: a living system where simulation and optimization jointly support operational and tactical decision-making under uncertainty.

The first mode provides offline support by calibrating baseline settings. The second mode enhances planning and design by ensuring that optimization solutions remain valid under dynamic, stochastic conditions. The third mode embodies the vision of a true DT: a continuously updated, simulation-driven environment that supports real-time decision support across supply chain and manufacturing contexts.

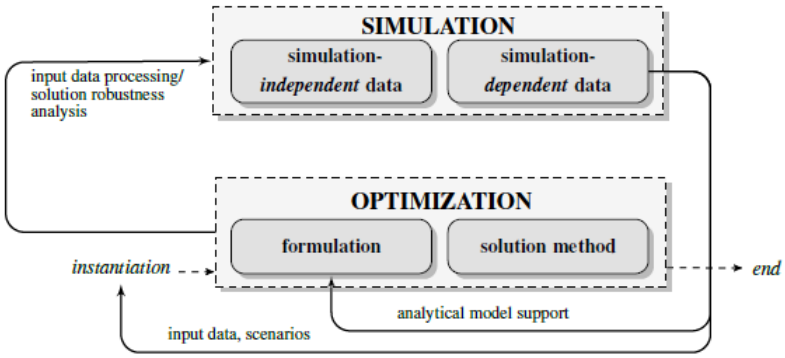


Figure 2.2: Simulation for Supporting Optimization (Borodin, Bourtembourg, et al. 2019)

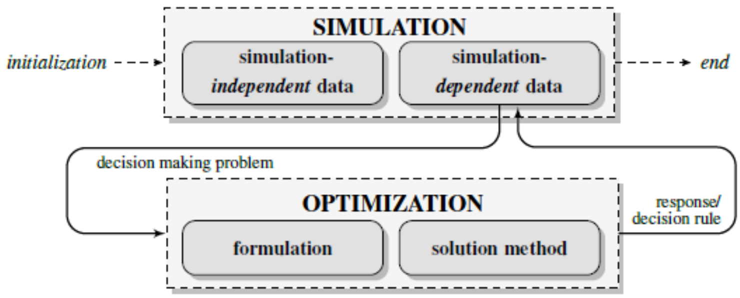


Figure 2.3: Towards Digital Twin (Borodin, Bourtembourg, et al. 2019)

Together, these modes describe an evolutionary pathway for integrating simulation and optimization into a Digital Twin-based Decision Support System (DT-based DSS), moving from static optimization, through simulation-validated optimization, towards fully dynamic, adaptive, and context-aware decision support.

2.2 Overview of decision support system in MaaS supply chain management

While effective, the classical approach to supply chain resilience has limitations, particularly in a rapidly changing global environment:

- **Slower Response Times:** Traditional methods, such as manual planning, do not offer the same speed of response as digital systems, making it harder to adjust quickly to disruptions as they unfold.

- **Increased Costs:** Buffer inventories and multiple suppliers can increase operational costs, as businesses need to maintain additional stock and manage relationships with several suppliers, often leading to inefficiencies.

- **Limited Predictive Power:** The classical approach often relies on historical data and static models, which may not fully capture the complexity of modern supply chains or anticipate emerging risks.

- **Manual Decision-Making:** The reliance on human judgment for contingency plans and communication can lead to delays and errors, particularly when dealing with complex disruptions or coordinating across multiple supply chain nodes.

Manufacturing-as-a-Service (MaaS) is an emerging, flexible, and technology-driven approach to manufacturing that integrates on-demand, decentralized, and scalable production capabilities. It allows businesses to outsource manufacturing functions to third-party providers or networks of providers that offer customizable and agile production services. MaaS is a key component in enhancing supply chain resilience by enabling companies to adapt quickly to changing demands, market conditions, and unexpected disruptions.

Unlike traditional manufacturing methods, which rely on fixed production facilities and long-term contracts, MaaS offers a more flexible and responsive model. It leverages cloud-based platforms, digital twins, and smart manufacturing technologies to optimize production and distribution processes. This approach is highly effective for mitigating risks, responding to supply chain disruptions, and maintaining operational continuity.

Based on related literature summarized in Table 2.2 and finding from other EU-related projects[3], key components of the MaaS-based manufacturing resilience strategy include:

- **On-Demand Manufacturing:** MaaS allows businesses to access manufacturing services on-demand, meaning they can scale up or down based on real-time demand without the need to invest in costly, fixed production assets. This on-demand model helps mitigate risks such as demand fluctuations, supply shortages, or production bottlenecks by enabling quick adjustments to production capacity. Companies can efficiently meet customer needs without the burden of maintaining large, in-house manufacturing infrastructures.

- **Decentralized Production Network:** A core principle of MaaS is the use of a decentralized manufacturing network where companies can select from a range of suppliers, contract manufacturers, or fabrication networks. By connecting to this network through a digital platform, businesses can access various production capabilities based on specific needs, whether it is 3D printing, injection molding, or CNC machining. The decentralization reduces reliance on a single source, thereby increasing resilience against localized disruptions like factory closures, labor shortages, or supply interruptions.

- **Real-time Monitoring:** Digital twin technology, an integral part of MaaS, enables the virtual representation of physical manufacturing assets, production lines, and processes. With real-time data collection, companies can simulate, monitor, and optimize their manufacturing processes virtually, allowing for predictive maintenance, quality assurance, and immediate adjustments to production plans. This capability enhances the flexibility of the manufacturing process, enabling quick responses to issues and optimizing production without interrupting physical operations.

- **Customization:** The MaaS approach allows businesses to offer highly customized products by enabling flexible production schedules and processes. Manufacturers in the MaaS ecosystem can quickly adapt to customer specifications and unique product requirements without lengthy setup times or large-scale changes. This ability to rapidly switch between different product configurations makes the supply chain more agile and resilient to shifts in market demand.

- **Scalability and Flexibility:** MaaS provides scalability by allowing companies to increase or decrease production levels as needed without major capital investment. This scalability is particularly useful in handling unexpected spikes in demand or supply chain disruptions. For example, during a sudden surge in demand, companies can quickly increase production by tapping into additional capacity from the MaaS network, rather than waiting for in-house resources to be expanded. This flexibility helps ensure that supply chain operations remain smooth, even under unforeseen circumstances.

- **Integration with Supply Chain Systems:** MaaS platforms typically integrate seamlessly with existing supply chain management systems, such as Enterprise Resource Planning (ERP), warehouse management systems (WMS), and Transportation Management Systems (TMS). This integration ensures that production schedules are aligned with supply chain activities, enhancing overall coordination and visibility. Real-time data sharing between manufacturers and supply chain partners also ensures that production adjustments are communicated quickly and effectively, reducing delays and bottlenecks.

- **Resource Optimization and Cost Efficiency:** By using MaaS, businesses can optimize the use of manufacturing resources such as labor, equipment, and raw materials. MaaS platforms often use data analytics to predict resource needs, minimize waste, and optimize production cycles, ultimately reducing costs. The ability to scale production and access specialized capabilities on-demand also ensures that businesses only pay for what they need, avoiding the fixed overhead costs of traditional manufacturing facilities.

- **Supply Chain Resilience Through Redundancy:** The decentralized nature of MaaS enhances supply chain resilience by providing built-in redundancy. Since companies can access a range of manufacturing services and locations, they can quickly shift production to alternative facilities or providers in the event of a disruption. For instance, if one manufacturing partner faces a production delay or shutdown, the system can automatically reroute production to another provider without significantly affecting the overall supply chain.

- **Sustainability Considerations:** MaaS can also support sustainability initiatives by enabling more efficient production processes, reducing waste, and minimizing energy consumption. With the ability to select manufacturers based on environmental performance, businesses can promote sustainable practices within their supply chains. Additionally, MaaS platforms can optimize transportation and logistics, further reducing environmental impact by minimizing unnecessary shipments and utilizing eco-friendly transportation options.

As summarized in Table 2.2, the MaaS literature spans a wide range of domains, methodologies, and contributions to operations management. Early studies (e.g.,Boccalatte et al. 2004; W. Shen et al. 2006) laid the foundations for distributed and agent-based decision-making, while more recent works have increasingly focused on explicit MaaS formulations, including bilevel and multi-objective optimization for scheduling (Chen, Feng, et al. 2024; Chen, X. Gong, et al. 2021; C. Duran-Mateluna et al. 2025), game-theoretic approaches to platform pricing (Chaudhuri et al. 2021; Chen, Feng, et al. 2024), and sector-specific applications such as additive manufacturing (see e.g., the MASTT2040 project[3]). Complementary bibliometric and conceptual reviews (Karamanli et al. 2025; E. O. Oyetunji, Abagun, and E. A. Oyetunji 2025) provide a comprehensive overview of the research landscape, highlighting the challenges of adoption.

Taken together, these studies illustrate a clear trajectory: from theoretical and agent-based explorations of distributed manufacturing towards integrated, optimization-driven models that address scheduling, coordination, and sustainability in MaaS contexts. **Deliverable 4.2 positions itself within this trajectory by extending these methodological advances into a simulation-based DT DSS framework for supply chain design, planning, and resilience assessment.**

Table 2.1: Summary of a collection of MaaS-related literature and related operations management research.

Authors (Year)	**Domain / Focus**	**Methodology**	**Contribution to Operations Management**	**Relevance to MaaS**
Karamanli et al. 2025	MaaS – Literature Review	Bibliometric and systematic review	Mapped MaaS research landscape; taxonomy of studies (theoretical, architectural, data-driven); identified gaps in scheduling and integration	Comprehensive overview of MaaS
Ege Duran and O'Sullivan 2024	Shared Manufacturing / MaaS Planning	Comparative analysis of paradigms	Defined shared manufacturing characteristics; surveyed planning & scheduling methods; highlighted need for stakeholder coordination	Focuses on shared/MaaS scheduling
Boccalatte et al. 2004	Agile Manufacturing Scheduling	Multi-agent system; Contract Net protocol	Introduced agent-based negotiation for tasks; improved just in time reactivity vs. static scheduling	Foundation for distributed decision-making in MaaS
W. Shen et al. 2006	Intelligent Manufacturing Systems	Agent-based frameworks	Showed resilience and flexibility via decentralized control; proposed holonic/heterarchical architectures	Viability of decentralized control for MaaS
Chaudhuri et al. 2021	MaaS Platform Pricing	Game-theoretic Stackelberg model	Developed optimal dynamic pricing for dual-channel supply chain; showed impact on sustainability	Explicit MaaS pricing strategy
Chen, X. Gong, et al. 2021	Real-Time Scheduling – Flow Shop	Bilevel Stackelberg optimization; Tabu search	Proposed interactive order acceptance and scheduling model; demonstrated revenue gains and responsiveness	Real-time dynamic scheduling relevant to MaaS
Chen, Feng, et al. 2024	Task–Service Matching in MaaS	Bilevel multi-objective optimization; nested algorithm	Integrated platform allocation with provider scheduling; improved global efficiency and revenue	Formal MaaS coordination model
Kang, Tan, and Zhong 2023	Cloud 3D Printing Services	Mixed integer programming, heuristic, simulation	Optimized allocation in distributed additive manufacturing; reduced lead times, improved utilization	Practical MaaS application in 3D printing
E. O. Oyetunji, Abagun, and E. A. Oyetunji 2025	Shared Manufacturing – Benefits	Conceptual classification study	Identified major benefit areas (cost, utilization, SME support); Slow adoption	Explains value proposition of MaaS adoption
ACCURATE	Shared Manufacturing, MaaS Scheduling/Pricing	Mixed integer programming, constraint programming, heuristics, metaheuristics	Tackled multi-agent scheduling with multiple objectives (tardiness vs. makespan); coordinated trade-offs effectively; pricing	MaaS scheduling and pricing

2.3 Key concepts

Manufacturing-as-a-Service

Definition 2.3.1 (Schuseil et al. 2024, the European Commission[2])**.** *MaaS represents a service-based manufacturing concept that is enabled by cloud manufacturing and managed in a centralized way for responsive, flexible, and scalable manufacturing industries.*

Supply chain management

Definition 2.3.2 (Council of Supply Chain Management Professionals (CSCMP) 2013)**.** *Supply chain management encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and logistics management. Importantly, it also involves coordination and collaboration with channel partners, including suppliers, intermediaries, third-party service providers, and customers.*

Resilience

It is worthwhile to mention that we conceptualize resilience as a multifaceted construct, with recent literature highlighting two complementary *views* of resilience (Ivanov 2024b):

- **Resilience as a Process Quality:** This aspect characterizes the inherent ability of a supply chain *"to adapt, survive, and exist"* amid changing conditions. In other words, resilience is the built-in flexibility and robustness of the system, analogous to an immune system that continuously monitors and adjusts to threats. Ivanov 2024b often compares supply chain resilience to a human immune system that can anticipate and adapt to environmental changes, enabling the organization to absorb shocks before they escalate.
- **Resilience as a Performance Outcome:** In parallel, Ivanov 2024b defines resilience in terms of measurable outcomes. Specifically, the performance deviation and recovery following a disruption. As he notes, resilience can be quantified by *"performance deviations caused by disruptions and recovery actions"*.

A supply chain's resilience can thus be evaluated by how much performance drops during a crisis and how quickly (and effectively) it bounces back to acceptable levels. By combining these views, we frame resilience both as **(i)** a capability (process quality), i.e., the readiness and adaptability of the network, **(ii)** and as a result (performance outcome), i.e., the actual stability of service levels in the face of shocks. This dual perspective is central to our contributions on supply chain dynamics.

Disruptions and disruptions

Definition 2.3.3 (Kanike 2023; Gyngyi Kovcs 2020)**.** *Disruption refers to a significant unexpected event that interrupts the normal flow or functioning of a system, such as a supply chain, causing a breakdown in processes or severe delays.*

Disruptions tend to be more abrupt, large-scale, and impactful, often requiring active management measures to restore normalcy and mitigate adverse effects. For example, supply chain disruptions can arise from sudden events, such as natural disasters, pandemics, or political crises, that halt production lines or block transportation routes, causing ripple effects throughout the entire supply chain network.

Definition 2.3.4 (Helmut Hillebrand 2020; Peters et al. 2011)**.** *Disturbance carries a broader operational connotation, referring to events or changes that interfere with the system's normal state but may not necessarily cause a complete breakdown or require immediate intervention.*

Disturbances can be smaller scale, more frequent, or gradual changes that shift system dynamics and require the system to adapt or recover over time. In operational systems, disturbances can include minor fluctuations or noise that degrade performance but might be corrected through control mechanisms without a full-scale disruption (Yang et al. 2016).

From an engineering or control systems perspective, disturbances can be continuous or stochastic inputs (such as sensor noise, environmental fluctuations) affecting system stability, whereas disruptions represent larger-scale failures or breakdowns in the system components.

In practical supply chain contexts, the distinction entails that:

- Disruptions are major events causing stoppages or failures requiring disruption management—models and strategies to recover and realign supply chain processes to resume normal operations.
- Disturbances represent perturbations or deviations from normal operations that might be manageable through routine adjustments or resilience capabilities without halting the system.

To summarize the key differences:

- *Magnitude:* Disruptions are generally more severe and impactful than disturbances.
- *Duration:* Disruptions cause immediate and often prolonged interruptions; disturbances may be transient or less impactful.
- *Management response* (or control strategies): Disruptions require active disruption management and recovery plans; disturbances may be absorbed or mitigated through system resilience or control.
- *Scope:* Disruptions often cascade through interconnected systems, causing large-scale effects; disturbances might be localized or have limited propagation.

Chapter 3

Methodologies and algorithms

3.1 Introduction

As described in Deliverable 7.1, Manufacturing-as-a-Service (MaaS) envisions a network of manufacturers openly sharing data, capacity, inventory, and even processes to meet demand flexibly.

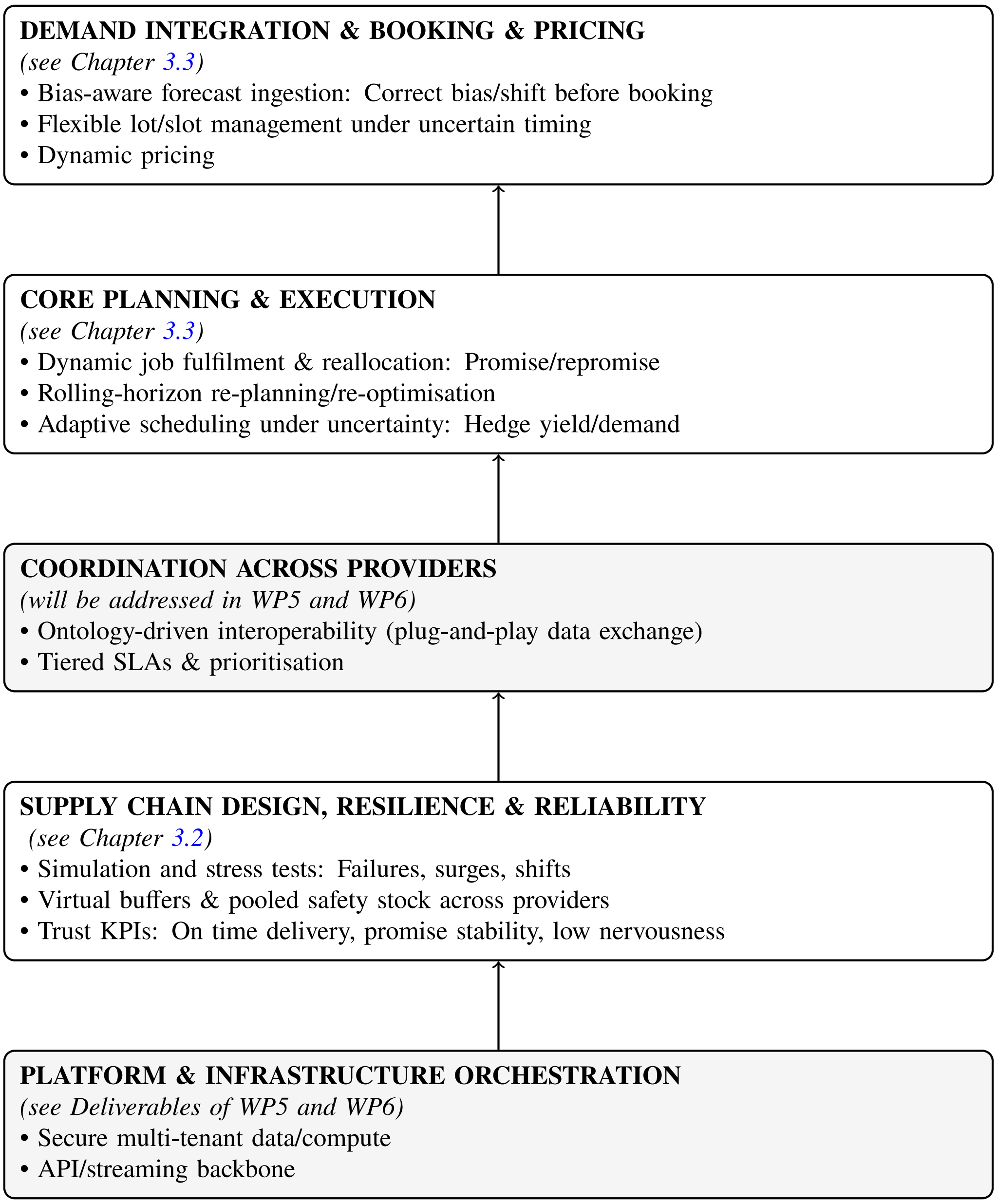


Figure 3.1: Architecture of MaaS capabilities

Achieving this vision requires careful governance structures, clear definitions of what is shared, and optimization methods to balance individual and collective goals:

- **Governance models for sharing** (ownership, trust, incentives) are addressed in Deliverables of WP5,
- **What can be shared** (data, machines, stock, planning processes, etc.): As discussed in Deliverable 7.1, a MaaS ecosystem can enable sharing of various resources and information among manufacturers, turning isolated operations into a more flexible, distributed production network. Key shareable categories include data, production capacity, inventory buffers, and even planning/execution processes.

- **Optimization challenges** will be discussed in what follows in this chapter.

Given the scope of this deliverable, we focus in what follows on the detection, prediction, and prescriptive analytics jointly with DTs and simulations enabled by the digitalization within the context of manufacturing-as-a-service.

3.2 Supply chain network design

3.2.1 Multi-echelon and multi-criteria design

Problem statement

Supply Chains (SC) operate in a volatile environment, where traditional approaches fail to ensure resilience. Organizations at large, and the ACCURATE pilots in particular, are calling for proactive disruption management as a key means to strengthen resilience and reduce vulnerabilities. A static approach, based on historical data analysis, can result in cascading failures and the bullwhip effect.

An innovative, integrated decision-making framework that enables the design of multi-echelon, resilient supply chains with increased efficiency and adaptability is crucial for both efficiency and survival. Simulation design, which enables the creation of a digital representation of a physical system, and multi-criteria decision analysis contribute to the development of such a framework through disruption anticipation and proactive decision-making analysis. A critical part of such a task is identifying the requirements for a supply chain simulation tool dedicated to supply chain design, planning, and stress-testing.

In close collaboration with the ACCURATE pilots, two approaches were distinguished:

- *Proactive management:* For proactive management, one needs to identify the critical materials and suppliers (nexus nodes identification) to increase time-to-survive when disruption occurs.

- *Reactive management:* For reactive management, the goal is to understand the impact and select the appropriate resilience strategies (decision-making support tool) to decrease time-to-recovery (Ivanov 2021). The further alignment of proactive and reactive resilience management approaches is highlighted in Chapter 3.

To integrate the decision-support model and the simulation model to develop the digital master, high interaction between the simulation and prescriptive models is required (see Figure 2.3).

Manufacturing-as-a-Service (MaaS) approach offers new opportunities to increase SC resilience and feasibility. To implement it, we propose a decision-support framework that allows for the orchestration of decentralized manufacturing resources, evaluates suitability through ontology-based matchmaking, and integrates resources into adaptive production plans. MaaS allows the creation of agile and reconfigurable networks through manufacturing capacity and volume allocation, and provides stakeholders with more planning flexibility. For MaaS implementation, organizations require a decision-making framework at both the factory level and the network level to capture the behavior of all tiers involved, enabling coordination across multi-echelon supply chain structures, where decisions are aligned across stakeholders.

Solution approaches

The proposed approach aims to evaluate how MaaS principles improve the network-wide performance in terms of resilience and network reconfiguration. Through simulation modeling of a dynamic, multi-echelon system and analyzing the insights gained from simulation runs, MaaS decision-makers have the opportunity to evaluate various recovery strategies and adopt a proactive approach to redesign the network.

For the ACCURATE project, a decision-support framework based on the concepts of digital twin and manufacturing-as-a-service is developed. The proposed framework combines a multi-echelon modeling approach, Discrete-Event Simulation (DES), and Multi-Criteria Decision Analysis (MCDA) to evaluate resilience, identify bottlenecks, critical suppliers, and areas for possible optimizations.

Multi-echelon modeling captures the structure of the supply chain across multiple stages and locations, connecting suppliers, manufacturers, distribution centers, and end customers through (Nguyen and Ivanov 2025b):

- Material, financial, and information flows across various tiers;
- Inventory policies at each node;
- Strategic interactions between tiers;
- Lead times and other target KPIs;

Multi-echelon modeling evaluates system-wide effects of disruptions or reconfigurations, helping anticipate unseen dependencies.

Discrete-event simulation models the network as a sequence of events. It is used to represent the dynamic behavior of the simulation by setting the following events to start at an exact time in the simulation:

- Production run;
- Shipment arrivals;
- Delivery/production/supply delays;
- Site closure;
- Stop of production.

DES provides a realistic view of processes under possible disruptions, tracks time-based KPIs (e.g., order fulfillment delays, queue lengths), and supports decision-making in a virtual environment.

Multi-Criteria Decision Analysis (MCDA) evaluates trade-offs between competing objectives such as costs, time, resilience, and sustainability. This helps adjust alternative strategies for decision-making based on current objectives:

- Costs versus resilience;
- Inventory versus lead time;
- Environmental impact versus delivery speed.

In the case of ACCURATE, MCDA is integrated into a decision-support framework to facilitate the comparative evaluation of alternative supply chain network designs, prioritize resilience strategies, and provide a transparent decision-making support system for users.

The solution approach aims to integrate a network-level simulation model with the MaaS approach by leveraging digital twins of the supply chain. Based on three pilot models, introduced in Deliverable 4.1, Airbus Atlantic, Tronico, and Continental, the understanding of digital simulation model template needs and characterization of the steps involved in the general pipeline creation for the ACCURATE project were identified. Each of the created instances of supply chain networks for pilots captured tiers of network, capacity range, processing logic, maintenance profile, and performance metrics for each node. Performance analysis of simulation models, both under normal operating conditions and disrupted conditions, enables the provision of necessary information for informed decision support. Simulation runs produce holistic insights into lead times, capacity utilization, and service levels, which MaaS can use to compare further states where MaaS resources are added or removed.

Supply Network Analysis Tool

In the Technical report after M18, we present the Supply Network Analysis Tool, which allows us to model and analyze the supply chain on two layers: analytical and simulation layers. For the analytical layer, the *Supply Network Analysis Tool* is developed to model the supply chain as a network. The tool aims to identify critical nodes and paths of disruption cascading. The contribution of the developed tool is twofold.

- The tool offers proactive resilience management options for implementation.
- Reducing the real-world supply chain network complexity is necessary for computationally affordable, sustainable, and user-friendly solutions. This tool is therefore helpful in simplifying the network before incorporating it into simulation models and optimization models, without losing essential details.

For the simulation layer, simulation models are developed with important supply chain policies (sourcing policies, inventory management policies). The simulation models are also helpful in estimating the resilience indicators of the service providers in matchmaking from the MaaS view. For the optimization models, we have developed two optimization models (resource allocation and the need to expedite resources).

In the continuity of Deliverable 4.1 and the Technical report after M18, let us introduce two additional key functions:

- To identify the nexus nodes (hidden critical nodes inside the network),
- To analyze the internal risk of supply chain networks.

Node-level metrics (degree centrality, betweenness centrality, eigenvector centrality, closeness centrality, etc.) describe the characteristics of the material and supplier nodes. Simulations measure the resilience performance of the network through indicators (lost sales, time-to-survive, time-to-recover, etc.). We then combine network metrics and resilience metrics into a single dataset to train the model in two steps.

The first user interface of the Supply Network Analysis Tool is illustrated in Figure 3.2. The project team has worked to advance the solution and integrated more features (generalized real-world supply chain model, generalized disruption event modelling, and interact with three levels of detail when analyzing the supply chain network level). The latest update of our solution is described in Chapter 4.

Generic simulation models: Make-To-Stock, Make-To-Order

In simulation modeling, production strategies are generally divided to Make-To-Stock and Make-To-Order. The decision support framework developed through the ACCURATE project aims to incorporate patterns for both strategies and align them with the MaaS approach.

In Make-To-Stock systems, production is driven by forecasts. The main disruption mitigation strategy is through the creation of inventory buffers. In Make-To-Order systems, production begins only after placing an order, which allows the usage of capacity flexibility and network responsiveness as disruption mitigation opportunities.

Under Make-To-Stock, a key resilience measurement is represented by safety stock. Although safety stock can be calculated in different ways, one of the approaches can be represented as given in equation (3.1):

$$SS = z \times Q_L \times \sqrt{L} \tag{3.1}$$

where SS – safety stock level, z – service level factor, Q_L – standard deviation of demand during lead time, L – lead time.

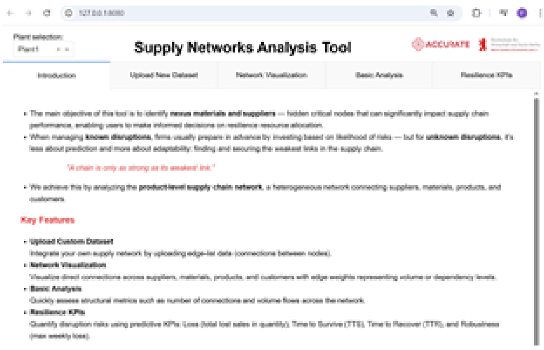
Reorder rule in this case would be represented as in equation (3.2):

$$\text{if } IP_{c,t} \leq s_c \quad \Rightarrow \quad Q_{c,t} = S_c - IP_{c,t} \tag{3.2}$$

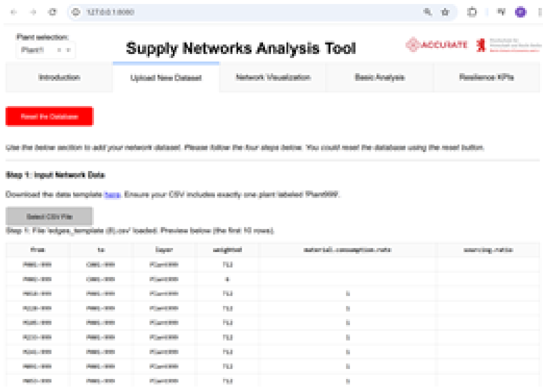
where $IP_{c,t}$ – inventory of component c: on-hand + on-order – allocated, s_c – reorder point, $Q_{c,t}$ – component order, S_c – order-up-to level.

Inventory balance would be represented as in equation (3.3):

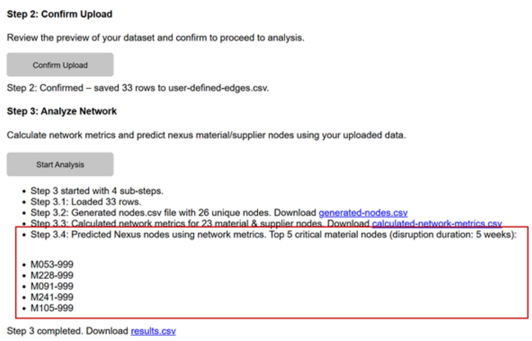
$$I_{c,t+1} = I_{c,t} + \sum_{k \in K_c} \left(Q_{ck,t-L_{ck}}\right) - r_{c,t} \tag{3.3}$$



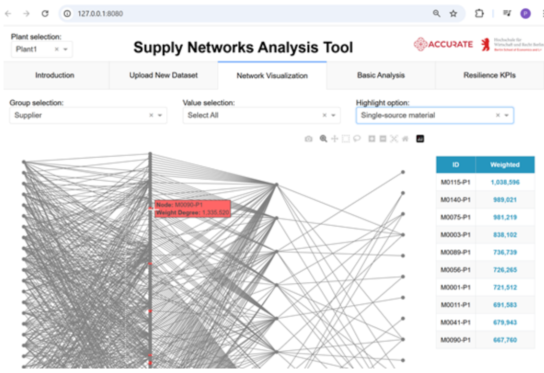
(a) Introduction view



(b) Upload network structure to predict nexus material nodes



(c) Results of nexus material node identification



(d) Visualize supply chain as a *Multipartite* network

Figure 3.2: Supply Networks Analysis Tool: *Overview and workflow*.

where $I_{c,t+1}$ – on-hand inventory of the component c in the period $t+1$, $I_{c,t}$ – on-hand inventory of the component c in the period t, $Q_{ck,t}$ – order placed at time t from supplier k of component c, $r_{c,t}$ – requirement of component c in period t.

In Make-To-Order settings, key resilience measurements would be possible capacity allocation under disruption, as in equation (3.4):

$$C(t) = C - D(t) + V \tag{3.4}$$

where C – baseline production capacity, $D(t)$ – capacity disruption at time t, V – extra volume flexibility.

Another key resilience measurement in the case of the Make-To-Order general strategy is lead time as in equation (3.5):

$$LT = \frac{Q}{C(t)} + T_{\text{setup}} \tag{3.5}$$

where Q – order size, T_{setup} – setup time.

Customer-driven release rule as in equitation (3.6):

$$Release_{p,t} = D_{p,t} + B_{p,t-1}, \qquad B_{p,t} = \max\{0, D_{p,t} - FG_{p,t}\} \tag{3.6}$$

where $Release_{p,t}$ – release quantity of product p into production, $D_{p,t}$ – external customer demand for product p in period t, $B_{p,t}$ – backlog for product p, $FG_{p,t}$ – on-hand inventory of finished good p.

Production in this case will be scheduled according to the rule in equation (3.7):

$$Prod_{p,t} = \min\{Cap_{p,t}^{shop},\ Release_{p,t+L_p^{prod}}\} \tag{3.7}$$

where $Prod_{p,t}$ – quantity of product p produced at time t, $Cap_{p,t}^{shop}$ – maximal shop-floor capacity, $Release_{p,t+L_p^{prod}}$ – release quantity of product p into production.

Industrial implications: The case of ACCURATE pilots

- Airbus Atlantic: Make-To-Stock. The system is structured to maintain inventory with safety stock and replenish inventory according to demand. A nominal finished goods warehouse regulates the demand information from the customer, so demand doesn't directly trigger production. In the event of disruption, the logic remains stock-focused: production adjusts based on whether inventories fall below predetermined thresholds, rather than directly on incoming orders.
- Tronico: Make-To-Order. The system operates in high-mix, low-volume settings, as production begins only when the system receives a product order. A customer-oriented production planning process is implemented, where a person assigns a production window as soon as a customer order is received. In this case, demand directly triggers the release of quantities, and any unmet demand results in a backlog.
- Continental: Make-To-Stock. Consistent with the automotive industry, the pilot is using a Min-Max inventory policy with demand covered from stock. This aligns with Continental's need for stable flows in a high-volume environment. The model specifies that production follows a *partial production* policy set to 100% of what the inventory policy requires, meaning production activity is entirely stock-driven.

Numerical experiments on industrial or simulated data

During the creation of pilot supply chain models, the primary data for SC modeling have been collected from Airbus Atlantic, Tronico, and Continental. Each of the analyzed supply chains has a large number of suppliers (37 from Airbus Atlantic, more than 65 from Continental, and over 600 from Tronico), which complicates the transparent understanding and management of these supply chains. Each of the companies has its own challenges, which, however, overlap with those of the others. Historical data and insights from partners, gathered during bi-weekly use case meetings, have been analyzed to collect both qualitative and quantitative data. Subsequently, we applied statistical analyses to build the supply chain network and processes.

Industrial implications: The case of ACCURATE pilots

- For Airbus Atlantic, the main task of the created simulation models is to analyze the reliability of suppliers in various conditions.
- For the Continental supply chain stress test model, the primary goal of the developed simulation model is to assess the resilience and robustness of its supply chain under various disruption scenarios. The main modeling methods involved simulating supplier shutdowns, extending delivery lead times, and introducing transportation blockages.
- For Tronico, the primary goal is to develop a two-level simulation model that encompasses both the supply chain and shop floor levels. The model includes suppliers and customers at the supply chain level, considering inventory policies and supplier search. At the shop floor level, the model includes a high-level production process, focusing on operations with bottlenecks and demonstrating an approach to solving problems related to suboptimal production performance.

Outcomes and insights

The application of multi-echelon, DES, and multi-criteria simulation approaches in industrial pilots demonstrated the capability to identify spare-nodes and provide system-wide visibility into supply chain performance under various conditions. The integration of simulation modeling with MaaS concepts enables the assessment of how flexible, decentralized manufacturing resources can mitigate disruptions and enhance agility.

The pilot models highlight that resilience requires alignment of strategic and operational decision-making. Strategic enablers include supplier diversification, robust supply chain design, and contingency planning. Operational enablers comprise flow management, tier coordination, inventory control, predictive analytics, and alternative sourcing and transport options. In combination, these measures sustain service levels during disruptions, accelerate recovery, and reinforce overall resilience.

Together, pilot models and the Supply Networks Analysis Tool create a strong foundation for MaaS integration. Having the possibility to simulate the supply chain network under normal and disrupted conditions, analyze the current network, and find that the nexus model contributes significantly to resilience improvement. Developed supply chain pilots and the Supply Network Analysis Tool aim to improve proactive, data-driven resilience planning. This provides a pathway to more agile, sustainable, and viable supply chains in increasingly volatile global environments.

Integration with MaaS

Through simulating various disruption scenarios, MaaS can access different configurations of supply/production strategies, cost, and lead-time reconfiguration. This integration of disruption scenarios with MaaS also supports strategic capacity planning. Decision-makers gain quantitative evidence on when and how to activate MaaS resources for maximum resilience, ensuring that the network remains agile and responsive. In the case of ACCURATE, data in developed supply chain instances, supported by MaaS-oriented services, includes production resources, goods, materials, and other relevant information, as explained in Deliverable 7.1. A selection of these integration options will be further developed, implemented, and demonstrated in the context of WP6 and WP7.

3.2.2 Towards dynamic network topology via Manufacturing-as-a-Service

Manufacturing-as-a-Service (MaaS) introduces new challenges for material flow optimization. Unlike vertically integrated supply chains, MaaS networks rely on distributed providers, time-slot reservations, and dynamic customer orders. This requires coordinated optimization of inbound logistics, internal production, and outbound flows.

Scope and control objects include:

- **Physical flows:** Raw materials, Work in Process (WIP), finished goods across multiple providers, by-products, excess inventory.
- **Capacity flows:** Reservable and tradable time slots, represented as virtual capacity.
- **Information flows:** Forecasts, quotes, Internet of Things (IoT) data (related to e.g., yield, failures), and Service Level Agreements (SLAs).

Table 3.1 maps the MaaS sharing landscape by resource type, clarifying what is shared, why it creates value, and how it is typically governed and controlled. For each category—ranging from information, physical capacity, and materials to logistics, orchestration processes, assurance, knowledge assets, and resilience—the table enumerates concrete sharing objects (e.g., Available-To-Promise windows, machine slots, pooled buffers), the business rationale (e.g., shorter lead times, variability pooling, improved reliability), the prevalent governance forms (centralized platforms, federated dataspaces, or bilateral agreements), and the trust/ privacy controls that make collaboration safe (role-based access, Service Level Agreements (SLAs), auditability, selective disclosure). Read left-to-right, it provides a practical checklist for designing MaaS collaborations: Identify the asset to share, define the value logic, select an appropriate coordination model, and institute proportional safeguards.

This chapter is organized to move from information flows to physical execution, showing how demand, uncertainty, and capacity interact in a MaaS setting. We begin with Chapter 3.3.1 on demand–supply matching and fulfillment, where we motivate rolling-horizon updates and introduce three building blocks—Module 1 (forecast-aware ATP and slot allocation), Module 2 (lot-sizing under uncertain timing), and Module 3 (rolling-horizon Short-Term Demand-Supply Matching)—complemented by forecast-stability metrics. We then extend the information view to *disturbance and disruption* propagation, detailing a data-driven procedure to characterize cycle-time uncertainty and related metrics and motivating its use in simulation-based digital-twin DSS.

Next, Chapter 3.3.2 turns to physical capacity, starting from an eligibility-aware unrelated-parallel-machine model and lifting it to the MaaS network level, with modeling assumptions, platform-level confirmation logic, and dynamic reallocation/freeze-fence policies.

Finally, we broaden the scope to materials (shared inventories, pooling, and allocation policies) and dynamic pricing (state-dependent quoting under capacity and due-date constraints), completing the end-to-end pipeline from signals and shocks to executable schedules and market mechanisms.

Table 3.1: MaaS sharing landscape grouped by *type of resource*

Resource type	**What gets shared?**	**Why it matters?**	**Typical governance**
Information	Rolling forecasts, ATP windows, order status, overall equipment efficiency, on-time delivery, quality certificates, traceability events, machine health snapshots	Aligns plans across firms; reduces bullwhip; enables compliance & end-to-end visibility; accelerates issue resolution	Centralized platform data hub; or federated dataspace via consortium
Physical capacity (machines, slots, skills)	Machine time, fixtures/tools, skilled operators, reservable time windows, service calendars	Scales output on demand; monetizes idle assets; shortens lead times; broadens capability access	Brokered marketplace (centralized) or federated capability directory; bilateral slot contracts
Materials (inventory & buffers)	Shared safety stock, pooled WIP buffers, decoupling stock at DB/DC, emergency spares, jointly managed raw materials	Pools variability; lowers total inventory; protects service during shocks; speeds recovery from supply delays	Consortium rules; or bilateral pooling agreement
Logistics & warehousing	Co-loading on transport lanes; shared cross-dock windows; multi-tenant DC space; return flows consolidation	Improves delivery reliability; reduces freight & handling costs; lowers emissions via consolidation	TMS marketplace (central) or federated lane/slot catalogs; carrier exchanges; neutral cross-dock operators
Processes & orchestration (planning, scheduling, dispatch)	Vertical/horizontal integration of operations management decision; allocation; ATP/repromising guardrails; cross-site routing; eligibility-based assignment; slot trading rules	Aligns mid/short-term plans; balances customer tiers; reduces nervousness; matches jobs to best-fit capabilities	Coordinator role (OEM/neutral) or market-like bidding/auctions; federated coordination with local solvers
Assurance (quality & maintenance)	Shared inspection steps/results; golden samples; defect taxonomies; calibration references; predictive-maintenance insights & playbooks	Fewer defects; faster containment; lower downtime; harmonized quality expectations across partners	Joint quality councils; federated PdM communities for similar assets
Knowledge assets (digital twins, models, ontologies)	Process & factory twins; simulation sandboxes; federated machine learning weights; shared vocabularies/ontologies; best-practice templates	Faster onboarding; consistent semantics; better what-if decisions; reusable analytics across sites	Licensed asset sharing via registries; consortium model libraries; curated ontology governance
Resilience assets (risk & continuity)	Reserve capacity; contingency routings; emergency stockpiles; crisis playbooks; mutual-aid rosters	Faster recovery; mitigates disruptions; ensures continuity of critical flows; network-level preparedness	Mutual-aid; centralized platform reserves; parametric insurance schemes

3.3 Supply chain planning in a MaaS ecosystem

3.3.1 Information flows

Demand supply matching and demand fulfillment.

In a typical production system, customers submit long-horizon demand forecasts, which are then updated on a regular basis (e.g, this is the case of Tronico and Continental), as illustrated in Figure 3.3. This leads to rolling horizon information updates (Altendorfer and Felberbauer 2023). In production planning, demand forecasts act as essential inputs that translate market expectations into tactical and operational decisions. They inform material procurement strategies and support the design of efficient production schedules, thereby linking customer demand to resource utilization within the manufacturing system.

In a MaaS network, finding a factory is overshadowed by tightly-coupled realities. Forecasts arrive biased and shift across weeks, so Available-to-Promise (ATP) must be truly dynamic, distributed across providers, and tuned to SLAs if promises are to be credible (**Module 1**). Major customers commit quantities without firm dates, pushing lot sizing to balance the cost of early stock against the risk of late backlog (**Module 2**). Machines fail, demand pivots, and previously promised orders must be re-planned in rolling fashion with stability guards to prevent schedule instability (**Module 3**). Together, these challenges define the minimum viable toolkit that turns a mere directory of factories into a trustworthy MaaS platform—one that promises well, adapts fast, shares fairly, and keeps its word.

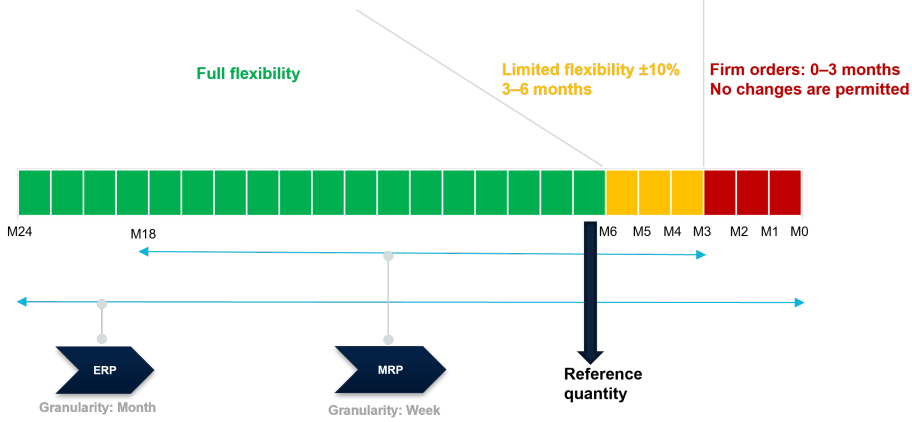


Figure 3.3: Example of period forecast updates

Module 1. Forecast-aware Available-to-Promise and Slot Allocation

Goal: Decide which orders can be promised given biased and evolving forecasts.
Features:

- Bias-corrected forecast updates: We adopt the industry-agnostic Martingale Method of Forecast Evolution (MMFE).
- Available-to-Promise (ATP) variables sized with uncertainty.
- Rolling-horizon re-promising with stability controls.

MaaS link: Ensures reliable promises across multiple providers (dynamic, distributed, tiered ATP).

Module 2. Lot-sizing under Uncertain Timing (and Quantities)

Goal. Decide production quantities and timing when customers reserve quantities but not exact slots.
Features:

- Lot sizing with stochastic demand timing (windowed arrivals), by relying on and extending state-of-the-art models, approaches, and assessment frameworks (see Appendix B).
- Trade-off: Early release $\rightarrow$ inventory cost *versus* late release $\rightarrow$ backlog risk.

MaaS link: Central to handling flexible bookings and shared inventory across providers.

Module 3. Rolling Horizon Short-Term Demand–Supply Matching (STDSM)

Goal: Reallocate and re-promise orders dynamically under changing conditions.
Features:

- MILP-based planning with decomposition into clusters of factories.
- Re-promising penalties (nervousness) and freeze fences for stability.
- Re-optimization in a rolling horizon with feedback.

MaaS link: Enables agility and dynamic orchestration of multiple factories on a shared platform.

Table 3.2: Summary of Forecast Stability Metrics

Metric	Measure	Purpose
Coefficient of Variation (CV)	Relative forecast instability	Comparing across products or lines
Mean Absolute Forecast Change (MAFC)	Absolute changes between updates	Rolling forecasts
Forecast Error Volatility (FEV)	Error consistency	If actuals are available
Forecast Instability Index (FII)	Magnitude of swings (penalizes large changes)	Detecting unstable forecasting

The algorithmic pipeline is formalized in Algorithm 1:

Algorithm 1 : Characterization and modeling of the variability of forecast fluctuations.

1: **Detect anomalies** in submitted forecasts
2: **Extract forecast stability metrics**: CV, MAFC, FEV, FII (see Table 3.2)
3: **Solve an unsupervised classification task** to identify static vs. dynamic forecast patterns
4: **Model controlled fluctuations** and integrate them explicitly into production planning decisions (see WP3) via robustness-based approaches
5: **Notify abnormal fluctuations** and **investigate MaaS mitigation strategies** (e.g., outsourcing demand peaks, reallocating to freed slots, collaborative use of partner capacity)

Industrial implications: The case of ACCURATE pilots

As highlighted in Deliverable 7.1, dedicated DSS-oriented use cases have been defined to model the variability of forecast fluctuations for Continental and Tronico. These forecasts are updated monthly. Each month, during the third week, the customer submits a 24-month rolling forecast for each item. The data is provided in Excel format, where each record corresponds to a quantity associated with a specific date and is accompanied by four status indicators.

Applicable rules:

- *Firm Orders (0–3 months):* No changes are permitted. Quantities are considered firm commitments.
- *Limited Flexibility (3–6 months):* Quantities may vary by up to ±10% relative to the forecast submitted for the previous month. From Month 6 to Month 3, a maximum deviation of ±10%

is permitted up to three times, based on the quantity forecasted at Month 6.

Notably, there are no specific constraints on the forecast value when transitioning from Month 7 to Month 6.

- *Full Flexibility (6–24 months):* No restrictions apply; forecasts are fully adjustable.

This setting illustrates the tension between **short-term rigidity** and **long-term uncertainty**, which is a recurrent challenge in industrial supply chains. By systematically analyzing these forecast dynamics, one can detect *where and when* demand variability creates mismatches with available resources, thus highlighting opportunities for Manufacturing-as-a-Service (MaaS) mechanisms. For instance:

- Peaks in demand identified through anomaly detection can be mitigated by sharing MaaS capacity.
- Stable forecast windows (0–3 months) allow advance slot-booking for MaaS partners.
- Fully flexible horizons (6–24 months) create opportunities for MaaS-based scenario exploration and collaborative planning.

Disturbances, disruptions, and their propagation.

In addition to analyzing demand forecast fluctuations and their explicit consideration, we also characterize the uncertainties affecting cycle times to investigate the value of disturbance propagation. Our focus includes known unknowns and unknown knowns (see Figure 3.4). As highlighted in Deliverable 7.1, analysis of disturbances/disruptions is done for all three pilots. This serves to better inform shop-floor decisions and estimate the current ability to absorb uncertainty.

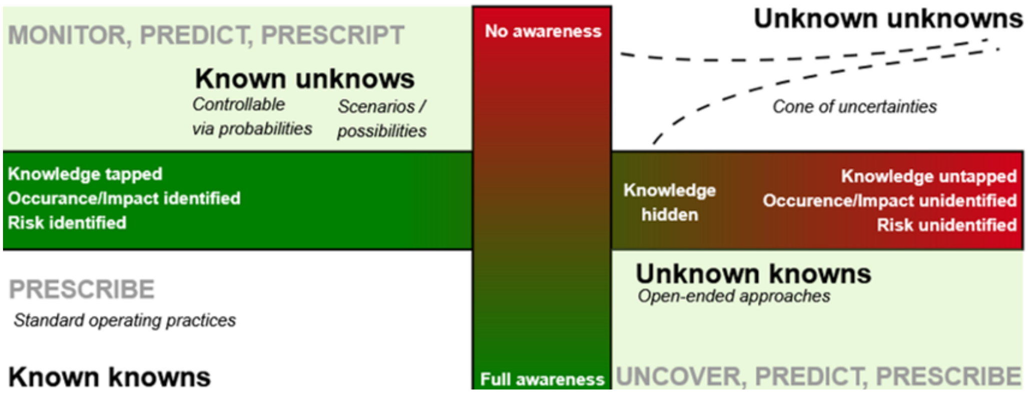


Figure 3.4: Adaptation of Rumsfeld matrix

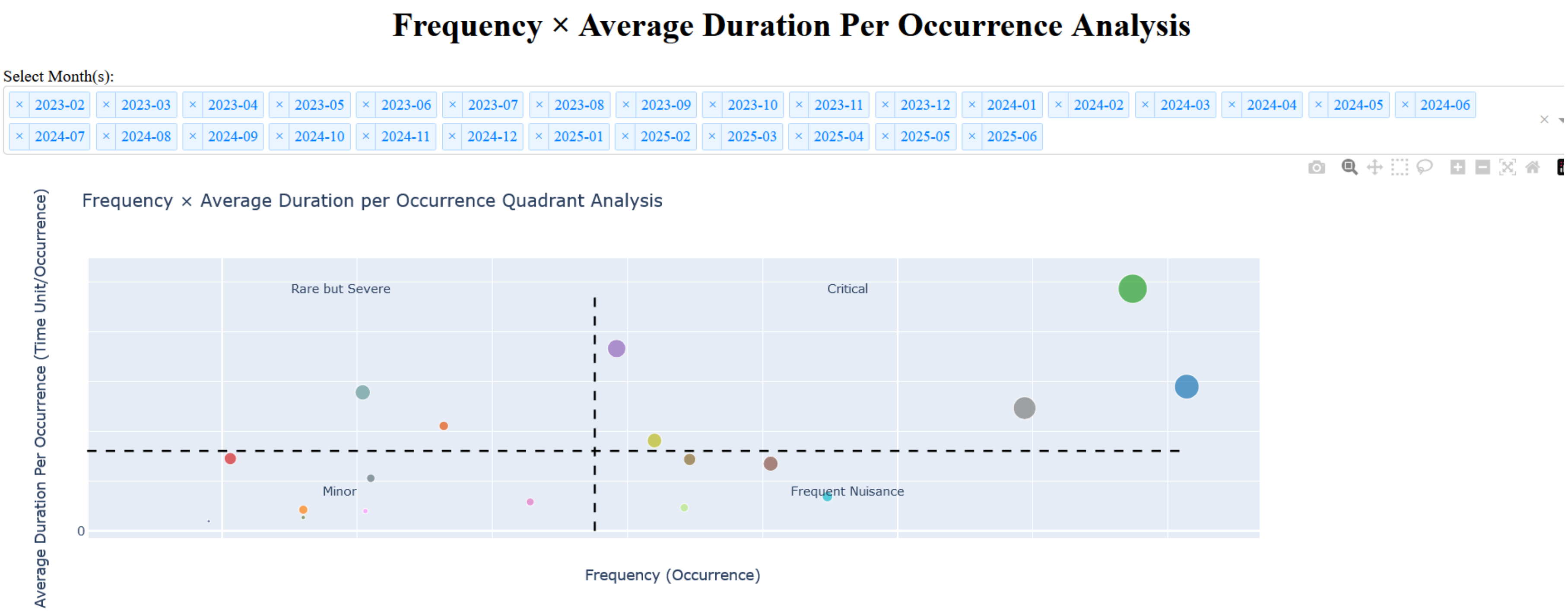


Figure 3.5: Disturbances and disruptions analysis

Consider a cloud of N points $\{o_i\}_{i=1}^{N}$ drawn independently from an unknown probability measure μ on $\mathbb{R}^p$ with compact support S corresponding to a random variable ξ. The algorithmic pipeline is formalized in Algorithm 2:

Algorithm 2 : Characterization of uncertainty at the shop-floor level.

1: **Extract the processing times/waiting times/completion times/cycle times** of operations on qualified machines, defining the routes of products,
2: **Extract the statistical summaries** (e.g., mean, standard deviations, modes).
3: **Derive the empirical probability distributions.** The main-mass, tails and shape approximation of μ can be derived from the sequence of moments associated with $\{o_i\}_{i=1}^{N}$ (see e.g., Gavriliadis and Athanassoulis 2009; Pauwels, Putinar, and Lasserre 2021).
4: **Classify performance detractors per frequency versus impact (e.g., duration)**.

Figure 3.5 illustrates an example of the uncertainty analysis, performed as described in Algorithm 2. Based on the empirical findings from pilot use-cases, the simulation models described in Section 3.2 will be enriched with real-life features to assess how MaaS capabilities can mitigate disturbances/disruptions in WP7.

3.3.2 Physical capacity

As a starting point, we considered the model proposed in (Maecker, L. Shen, and Mönch 2023) for the unrelated parallel machine scheduling problem with eligibility constraints and delivery times, aiming to minimize total weighted tardiness. The definition of their problem was motivated by a cloud-based manufacturing services provider for Printed Circuit Boards (PCB). In this context, machine customers can upload and edit their PCB designs through an online tool and place production orders. The service provider is expected to have access to a diverse network of PCB companies with varying capabilities. Building on this idea, this paper adopts a tripartite perspective of MaaS, wherein one group of users provides services, another group requests them, and a centralized MaaS framework facilitates and coordinates the exchange of these services (see Figure 3.6).

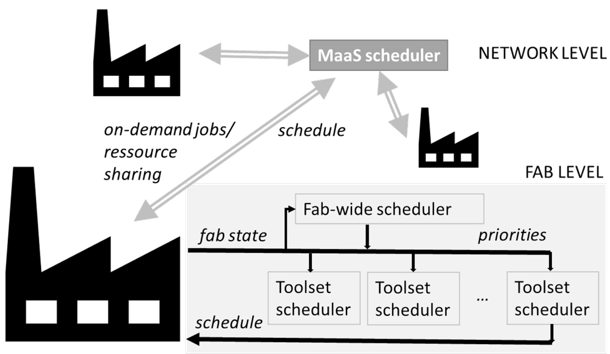


Figure 3.6: Vertical and horizontal integration of scheduling decisions: From toolset to MaaS and vice versa

Given a set of n service orders (i.e., tasks) $j \in \mathcal{J}$ and a set of m ressource providers (i.e., machines) $i \in \mathcal{M}$, the MaaS platform coordinates the assignment and sequence of tasks to the most qualified machines (see Figure 3.7). Each task j has a due date d_j, a weight w_j, a processing time p_{ij}, and a delivery time q_{ij} for each machine i. All tasks are available at time zero, each task j needs to be processed by one and only one machine without interruption, and each machine i can handle at most one task at a time. The delivery time q_{ij} occurs immediately after completing the task j on the respective machine i. Tardiness and eligibility are considered as optimization criteria.

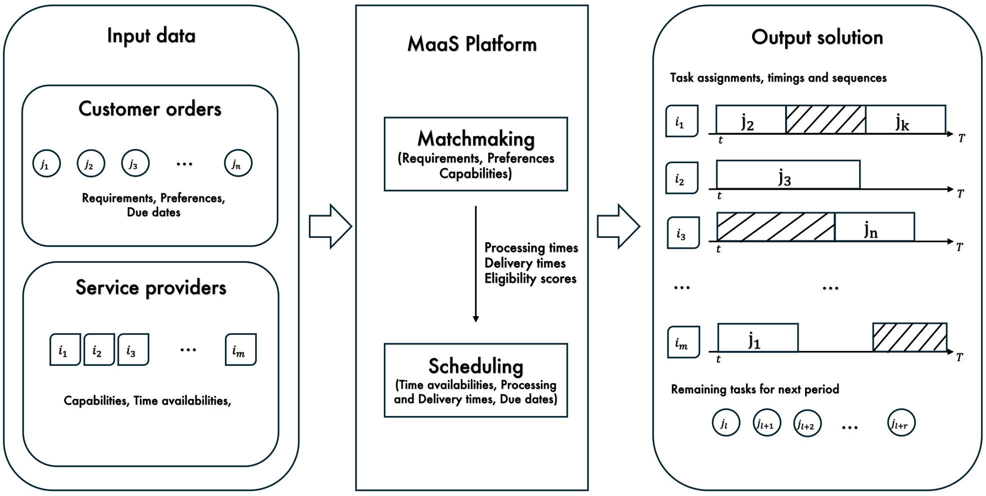


Figure 3.7: Illustration of the MaaS scheduling framework

Offline MaaS Scheduling Problem: *Assumptions*

The following assumptions are made in the formulation of the scheduling models:

1. **Task Availability:** All service orders are assumed to be available at time zero.
2. **Task dependency:** All jobs are considered as independent; no precedence constraints are included.
3. **Single-Machine Processing:** Each task is processed non-preemptively by exactly one machine; once a task starts, it runs to completion without interruption.
4. **Processing and Delivery Times:** For each task j and machine i, the processing time p_{ij} and the machine-specific delivery time q_{ij} are known and deterministic. The delivery time is assumed to occur immediately after the task is completed.
5. **Due Dates and Weights:** Each task has a predetermined due date d_j and a weight w_j that quantifies its importance, both of which are known in advance.
6. **Machine eligibility:** Although the machines may be heterogeneous in terms of processing or delivery times, it is assumed that the eligibility is evaluated during the matchmaking procedure detailed in deliverables associated with WP2.
7. **Setup Times:** If setup times exist between consecutive tasks, they are either incorporated into the processing times p_{ij}.

Appendix A provides two mathematical formulations of the core offline MaaS scheduling problem (i.e., all information about the problem is known in advance and the solution can be fully computed before execution), namely, a mixed integer programming model (see Appendix A.1) and a constraint programming model (see Appendix A.2).

MaaS Platform Framework: *Assumptions*

The MaaS context adds factors inherent to the dynamics and information flow of the platform itself, which we discuss below.

- Each job arrives at a date r_j and a deadline $\bar{d}_j$.
  - The deadline of each job is only known at time r_j, and the deadline is only known at date $\bar{d}_j$.
  - The release date corresponds to the time the client places the order, and the deadline corresponds to the date the client withdraws the order from the platform.
- Suppliers can indicate their capacities and time availability on the platform.
- At each period t, the platform provides to each supplier i a set of jobs to perform as well as the sequence of jobs to perform.

  - The platform does not necessarily schedule all available jobs.
- Once the order proposals have been made, each supplier contacts the customer to confirm the transfer or eventually reject the assignment.
  - In other words, an assignment of a job j to a suppliers s is accepted only if indicator $\bar{e}_{ij} = 1$. $\bar{e}_{ij} = 1$ is revealed to the platform only after job j has been affected to supplier j. In this case, $\bar{e}_{ij} = 0$, so job j returns to the platform and is assigned in the next period.
  - In our experiments, we consider the case where $\bar{e}_{ij} = 1$ for all supplier i and job j.
- It is considered that new suppliers or increased capacities can be dynamically incorporated.

Appendix A.3 includes an extension of the problem that considers the case where tasks arrive dynamically over time with fixed assignment (i.e., no reassignment possible) and external confirmation. In what follows, let us present several flexibility policies that enable us to further enhance the quality of MaaS solutions in online settings.

General Task Flexibility Policies

At each decision point t, the task set can be defined as:

$$\mathcal{J}_t = \mathcal{J}_t^{\text{new}} \cup \mathcal{J}_t^{\text{pending}}$$

where $\mathcal{J}_t^{\text{new}} = \{j \in \mathcal{J} \mid r_j = t\}$ are newly released tasks, and $\mathcal{J}_t^{\text{pending}}$ corresponds to a set of non-started tasks ($s_j > t$) to reassign from the previous periods of time ($r_j < t$) depending of flexibility policies.

- $\mathcal{J}_t^{\text{new}} = \{j \in \mathcal{J} \mid r_j = t\}$ are newly released tasks,
- $\mathcal{J}_t^{\text{pending}} = \{j \in \mathcal{J} \mid r_j < t,\ s_j > t,\ \delta_j = 0\}$ are tasks not yet started and not confirmed.

To allow realistic dynamic reassignments, we define several policies controlling which tasks return to $\mathcal{J}_t^{\text{pending}}$:

- **All-Rejected / Full Flexible**: All rejected tasks are considered for reassignment
  - $\mathcal{J}_t^{\text{pending}} = \{j \in \mathcal{J} \mid r_j < t,\ s_j > t,\ \delta_j = 0\}$
- **All-Unconfirmed / Semi Flexible**: All unconfirmed tasks are considered for reassignment on the same machine.
  - $\mathcal{J}_t^{\text{pending}} = \{j \in \mathcal{J} \mid r_j < t,\ s_j > t,\ \delta_j = 0\}$

Task-Specific Flexibility Policies Based on Due Dates

We introduce a task-specific flexibility policy that varies according to the due date of each task. The idea is to allow task reassignment and rescheduling within certain time windows relative to the due date, using a task-specific flexibility margin Δ_j.

Time Regions: For each task $j \in \mathcal{J}_t^{\text{pending}}$, we define three decision regions depending on the current period t:

- **Region 1: Full Flexibility (Pre-critical)**
  If $t < d_j - \Delta_j$, task j may be reassigned to any machine and fully rescheduled. We use this phase to maximize eligibility.

- **Region 2: Limited Flexibility (Critical)**
  If $d_j - \Delta_j \leq t < d_j$ and the task has not started ($s_j > t$), the machine assignment becomes fixed, but sequencing and timing on the assigned machine may still be adjusted. In this region, we aim to minimize expected tardiness.

- **Region 3: Frozen**
  If $t \geq d_j$ or if task j has already been confirmed ($\delta_j = 1$), all decisions become fixed, i.e., machine assignment, timing, and sequence are locked.

Set Definitions: At each decision epoch t, define the following subsets:

$$\mathcal{J}_t^{(1)} = \{j \in \mathcal{J}_t^{\text{pending}} \mid t < d_j - \Delta_j\}$$
$$\mathcal{J}_t^{(2)} = \{j \in \mathcal{J}_t^{\text{pending}} \mid d_j - \Delta_j \leq t < d_j \text{ and } \delta_j = 0\}$$
$$\mathcal{J}_t^{(3)} = \{j \in \mathcal{J}_t^{\text{pending}} \mid t \geq d_j \text{ or } \delta_j = 1\}$$

Flexibility Constraints:

- **Region 1:** Assignment variables y_{ij}^t remain binary and unconstrained.
- **Region 2:** Freeze assignment to the current machine:

$$y_{ij}^t = \bar{y}_{ij}, \quad \forall i \in \mathcal{M}, j \in \mathcal{J}_t^{(2)} \tag{3.8}$$

- **Region 3:** Fix start and completion times:

$$s_j = \bar{s}_j, \quad C_j = \bar{C}_j, \quad \forall j \in \mathcal{J}_t^{(3)} \tag{3.9}$$

Objective Switching: The optimization objective adapts depending on the current region of each task:

$$\min \left(\alpha \cdot \sum_{j \in \mathcal{J}_t^{(2)} \cup \mathcal{J}_t^{(3)}} w_j T_j \; - \; \beta \cdot \sum_{j \in \mathcal{J}_t^{(1)}} \sum_{i \in \mathcal{M}} e_{ij} y_{ij}^t \right) \tag{3.10}$$

where $T_j = \max(0, C_j - d_j)$ is the tardiness, e_{ij} is the eligibility score, and α, β are weighting coefficients.

Remarks:

- Δ_j can be a fixed constant or a function of task attributes, e.g., $\Delta_j = \theta(d_j - r_j)$.
- This policy enables the system to progressively adjust the schedule as the due date approaches, striking a balance between flexibility and stability.
- It can be integrated with confirmation logic and dispatching rules in the online model.

Algorithm 3 Rolling Horizon Scheduling with External Confirmation and Flexible Reassignment

Input: Simulation final horizon $T_{\max}$, task set $\mathcal{J}$ with parameters $(p_j, q_j, d_j, e_{ij}, r_j)$, machine set $\mathcal{M}$, weights w_j

Output: Scheduling decisions over time

```
Initialize confirmation flags: δ_j ← 0, ∀j ∈ J
Initialize fixed timing decisions s̄_j, C̄_j as empty
for t ← 0 to T_max do
    Define new tasks: J_t^new ← {j ∈ J | r_j = t}
    Define pending tasks: J_t^pending ← {j ∈ J | r_j < t, s_j > t, δ_j = 0}
    Define eligible tasks: J_t ← J_t^new ∪ J_t^pending
    Build the associated optimization model for period t with variables y_ij^t, z_jk, s_j, C_j, T_j
    Add constraints:
        • Assignment: Each task in J_t assigned to at most one machine
        • No reassignment for confirmed tasks (δ_j = 1)
        • Fix timing decisions (s_j, C_j) for confirmed tasks
        • Precedence, completion, and tardiness constraints
        • Optimization criteria: Minimize tardiness, maximize eligibility

    Solve the resulting optimization model
    Extract assignment decisions y_ij^t and timing decisions s_j, C_j
    Communicate proposed assignments to providers
    Receive confirmation flags δ_j from providers for tasks assigned at t
    foreach Task j with δ_j = 1 do
        Store fixed times: s̄_j ← s_j, C̄_j ← C_j
    end
    Tasks with δ_j = 0 remain in pending for next period
end
```

Table 3.3: Instance generation: *Parameters*

Parameter	Values
Processing times	$p_{ij} \sim U(1, 100)$
Delivery times	$q_{ij} \sim U(1, 30)$
Eligibility coefficients	$e_{ij} \sim U(0, 1.0)$
Due dates	$T \in \{0.4, 0.6\}$
	$R \in \{0.4, 0.6, 0.8\}$

Numerical experiments

First experimental results consider small instances with four machines and 10 tasks, based on state-of-the-art schemes. The problem parameters were generate similarly as by (Maecker, L. Shen, and Mönch 2023), in which the due dates follows the scheme of (Potts and Van Wassenhove 1982):

$$d_j \sim U\Big(\bar{p}\big(1 - T - \frac{R}{2}\big) + q^{min}, \bar{p}\big(1 - T + \frac{R}{2}\big) + q^{min}\Big),$$

where T is the tardiness factor, R is the relative range of due dates, and $\bar{p}$ and q^{min} are calculated as follows:

$$\bar{p} = \frac{1}{m} \sum_{j \in \mathcal{J}} \min_{i \in \mathcal{M}} p_{ij}, \qquad \text{and} \qquad q^{min} = \min_{i \in \mathcal{M}, j \in \mathcal{J}} q_{ij}.$$

All task weights w_j are considered equal to 1 for easier interpretation of the tardiness values, as there are no relevant considerations in this regard at this stage. All parameters are summarized in Table 3.3. 15 instance samples have been generated for each pair of parameters (T, R). In future research, we intend to develop efficient solution approaches for industrial-scale instances that consider the distributed nature of a MaaS system coordinated in a centralized way.

Industrial implications: The case of ACCURATE pilots

MaaS scheduling can be seen as a natural extension of scheduling on shop floors, as illustrated in Figure 3.6. To support distributed manufacturers in sharing and utilizing manufacturing resources, consider a MaaS framework that manages the scheduling of requested jobs on shared, unrelated parallel machines in a centralized manner. Sharing capacity could be interesting for the pilots in the following use-cases:

- **Airbus Atlantic:** Manufacturing engineering and operations must adapt tooling, layout, digital work instructions, and station balance when variants or late changes occur, while preserving throughput/quality and minimizing disruption. Aerostructure assembly is characterized by very large, complex, safety-critical structures, low production rates with high customization, reliance on skilled labor combined with targeted automation, strict certification and quality requirements, and bottlenecks in drilling/fastening and inspection. Rochefort (Airbus Atlantic) and Nola (Leonardo) are major manufacturing sites for A321 Section 14A, feeding into Saint-Nazaire for integration. The geographical spread of Section 14A production exemplifies Airbus's global aerostructure supply chain, coordinated by Airbus Atlantic as the aerostructure integrator.

- **Tronico:** Sharing capacity for the Tronico could be particularly relevant within MaaS, as electronic product lifespans are becoming increasingly shorter, while businesses today demand a growing variety of product types and greater customization options. This implies a higher quantity of production lots, smaller lot sizes, and more series changes. Instead of each electronics company investing in redundant capacity to hedge against peaks or disruptions, a MaaS platform would allow partners to access additional production slots from the ecosystem dynamically. This reduces idle time during low-demand periods while mitigating the risk of lost sales or delayed deliveries when demand suddenly increases. Furthermore, by pooling capacity across companies, the network achieves greater resilience and flexibility.

3.3.3 Materials

In traditional manufacturing, each company holds its own inventory of raw materials and finished goods. In a MaaS scenario, inventory management can become shared or centralized in several ways. Based on the insights provided by the ACCURATE pilots, the following options have been identified to be integrated in supply chain simulation models developed during the first part of the ACCURATE project

- **Common raw material stock:** If a MaaS provider serves multiple clients that use the same or similar materials, it may maintain a shared inventory of those materials to fulfill all orders. For example, a contract manufacturer might buy bulk metal or plastic resin and allocate it to different customer orders as needed. This "pooled" inventory benefits from risk pooling: the platform can buffer aggregate uncertainties with less total stock than if each client held separate safety stocks. Inventory pooling strategies have been employed in supply chain management to minimize overall inventory levels while maintaining service levels. In MaaS, shared raw inventory means the platform must decide how much common material to keep and how to allocate it to incoming jobs.

- **Extra stocks (safety stock) for variability**: While MaaS emphasizes make-to-order production (to avoid finished goods inventory), in practice, there may still be safety stocks or surplus production kept to ensure reliability. For instance, a platform might produce a few extra units of a batch in case of defects or to prepare for a possible repeat order. These extra units could potentially be offered to other clients if applicable (e.g., generic components). Managing such shared safety stock requires careful bookkeeping. The platform must track which inventory is free for allocation versus reserved.

- **Extra stocks (e.g., leftover materials or products)** can sometimes be repurposed or used in MaaS. For example, if a production run had to exceed the order quantity for quality reasons (such as a minimum batch size), the surplus might be offered to the same customer as consignment stock or even sold to another customer who can utilize it. Some platforms also create marketplaces for surplus materials or parts[1], effectively a circular economy aspect where one company's excess becomes another's supply.

3.3.4 Dynamic pricing

Although Task 4.4 ("Dynamic pricing") has experienced delays, we have developed a preliminary model that jointly optimizes dynamic pricing and supplier order placement in MaaS systems.

The literature on MaaS platform pricing is limited (Chaudhuri et al. 2021). In ACCURATE, we consider a sequential decision-making problem over a finite time horizon divided into periods $1, \dots, T$. At each period, the system state is described by two components:

- O_t: The set of orders that have been accepted but not yet scheduled,
- A_t: The set of orders that already have a production schedule.

Each order is characterized by a set of features, a price, and a demand. The relevant features depend on the specific manufacturing application. Features also specify temporal information, such as the earliest start date and the due date for completion. At the beginning of each period, a decision must be made regarding the price to post for a newly arrived order type. Based on the posted price and the demand, the system either accepts the order (in which case it is added to the list of unscheduled jobs) or rejects it. The scheduling function then determines which jobs from the list of unscheduled jobs are assigned to an available production time slot for the following period.

Figure 3.8 presents the first version of the methodological framework designed to integrate and evaluate pricing and scheduling strategies.

On the pricing side, three complementary strategies are considered:

- **Constant Price:** A constant price is assigned to each job type and remains unchanged throughout the entire planning horizon. This represents the simplest benchmark, as prices are fully independent of state or time.
- **Static Price:** Prices are fixed for each job type within a given period, but can vary across periods. The price list depends on the scheduling approach. A genetic algorithm is employed, enabling the exploration of optimized price lists.
- **Rolling Look-Ahead:** Prices are updated dynamically over time by estimating the value of future system states. Two estimation methods are applied:
  1. An approximation based on the static price,
  2. An estimation based on perfect information, representing an upper bound.
- **Fully Dynamic Pricing:** Prices depend simultaneously on the system state and the specific point in time. This can be computationally prohibitive in practice due to the extremely large solution space of the scheduling problem.

[1] see e.g., GREENCHIPS (https://greenchips.com): A web-platform that supports original equipment manufacturers and electronics manufacturing service companies in selling their excess stock globally

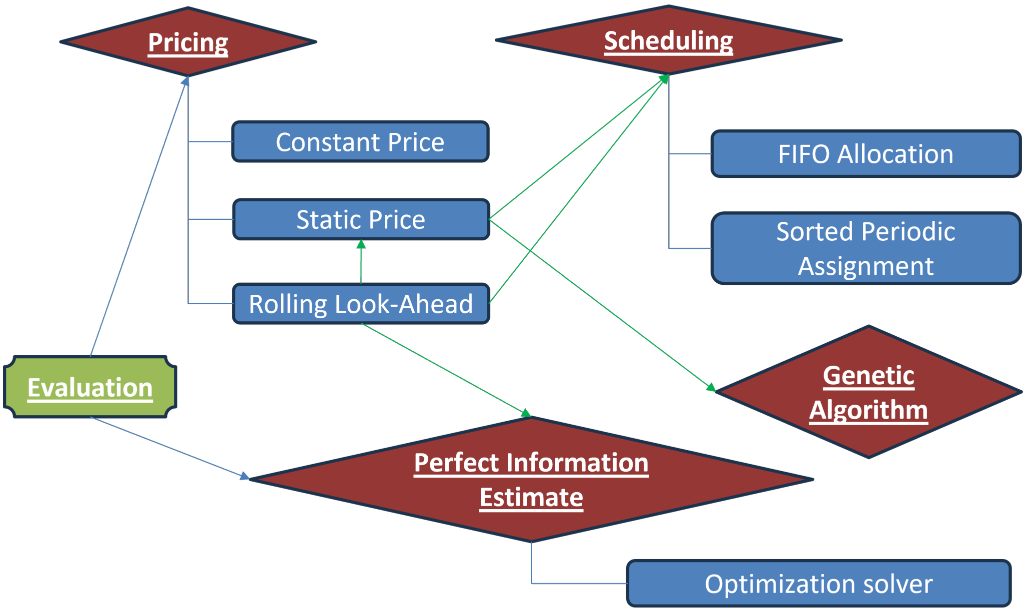


Figure 3.8: Dynamic Pricing and Scheduling: First developed framework

On the scheduling side, two baseline allocation policies are examined. The First-In-First-Out Allocation follows a simple first-come-first-served logic, while the Sorted Periodic Assignment reorders requests periodically based on predefined criteria (e.g., due dates or price levels).

The integration of these pricing and scheduling approaches leads to a set of candidate solutions, which are then benchmarked against a perfect information estimate. This reference assumes complete knowledge of future events, thus representing an upper bound on achievable performance. All strategies are subject to systematic evaluation, enabling a comparative analysis of solution quality. Preliminary numerical experiments have been conducted on small, randomly generated instances.

As an initial step, we considered the single-machine case. The work initiated in Task 4.4 of WP4 will be further improved and finalized within WP6.

3.4 Stress-test model and disruption scenarios: Conventional and MaaS-based

Disruption scenario definition and stress-testing of resilience strategies

To generate disruption scenarios for stress-testing, recent global events are employed as reference cases. The scenarios are constructed through a triangulation of historical data, partner expertise, and evidence from the scientific literature. Each scenario is parameterized in terms of:

- **Temporal duration**, and
- **Spatial scope**, with
- **Explicit impacts** defined on selected supply chain nodes and transport routes.

Table 3.4: Examples of (industry-agnostic) disruption types and their effects across pilots

Disruption type	(Industry-agnostic) Disruption	Pilots and beyond	Disruption effect
Supplier delay	Political and social instability (curfew) in the region of suppliers	Airbus Atlantic	Supplier shutdowns and longer delivery times caused a shortage of parts, late deliveries to the customer, and backlog
Supplier delay	Environmental disruptions in the region of suppliers	Airbus Atlantic	Supplier shutdowns and longer delivery times caused a shortage of parts, late deliveries to the customer, and backlog
Capacity reduction	Floods in areas surrounding Rochefort	Airbus Atlantic	Production slowdown, leading to reduced output and order delays
Supplier delay	Semiconductor crisis	Continental	Supply interruptions, backlog, dependence on specific suppliers
Supplier delay	Material shortage scenario (based on Covid-19 sequences, geopolitical risks, and social challenges)	Continental	Reduces available capacity, causing cascading order delays
Capacity reduction	Suez Canal blockage	Continental	Route shutdowns, transport bottlenecks, delays across the global network
Supplier delay	Tension in the components market (increased lead times, prices, pandemic, etc.)	Tronico	Late/missed component deliveries, production stoppages
Supplier delay	Suppliers in risk areas (natural disasters, geopolitics)	Tronico	Late/missed component deliveries, production stoppages
Capacity reduction	Breakage in the product workshop with long lead times for components	Tronico	Reduces production capacity, delays orders, and increases backlog

All developed disruption scenarios can be categorized as either *supplier delay* or *capacity reduction*. The modeling approaches for these types are illustrated in Figure 3.9, while their distribution across the supply chain is summarized in Table 3.4. As discussed in Chapter 3, the effectiveness of such stress tests depends on the ability to capture interdependencies across multiple echelons, reinforcing the role of multi-echelon modeling in disruption assessment.

Supply chain performance assessment against supplier delays and capacity reductions

Measuring resilience of simulated what-if scenarios is crucial for decision-making (A., D., and Simchi-Levi 2025). The primary KPI used in all pilot supply chains is *service level*. Service level is a percentage

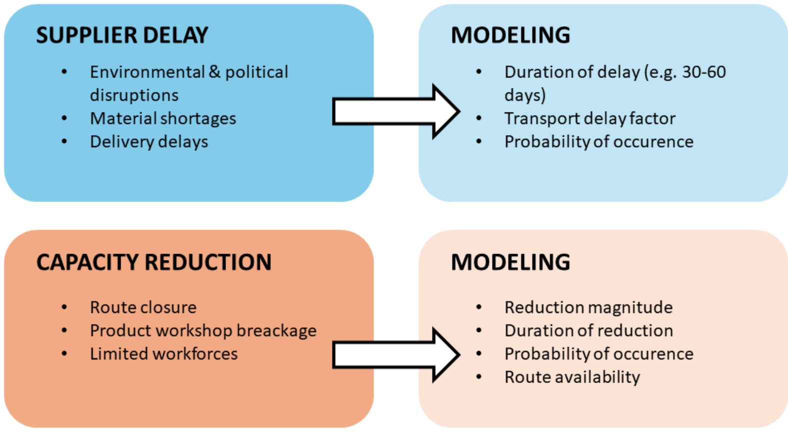


Figure 3.9: Supplier delay and capacity reduction modeling methods

of demand met on time during the simulated period, reflecting the ability of a given network to continue fulfilling customer orders. Lead time, which refers to the time between the moment an order is placed and the moment the product is delivered, is another KPI used. Time-to-recovery, which represents the time required for the network to regain its target performance after a disruption, is widely used alongside other KPIs as well (Ivanov 2025a). In the case of MaaS implementation, Time-To-Recover (TTR) for the network can be measured as in equation (3.11):

$$TTR = \frac{\sum_{n \in N} \omega(n) \times TTR(n, \text{with MaaS})}{\sum_{n \in N} \omega(n)} \tag{3.11}$$

where $\omega(n)$ is the weight of the node, proportional to how many other nodes depend on it. $TTR(n, \text{with MaaS})$ – time-to-recovery for node, when MaaS backup alternative is available.

Possible metric, which can be used for decision-making in simulation modeling with implemented MaaS principles, is backup supplier activation rule (3.12):

$$BS_{\text{active}} = \begin{cases} 1, & \text{if } L_t > L_{\text{max}} \text{ or } SL < SL_{\text{min}} \\ 0, & \text{otherwise} \end{cases} \tag{3.12}$$

where L_t – current lead time in case of disruption, L_{max} – pre-defined lead time threshold, SL – service level during disruption, SL_{min} – minimum acceptable service level.

In this case, decision-makers should consider not only lead time but also costs. One might activate a backup supplier only in case it saves more backlog cost than it costs itself, such a rule is presented in equation (3.13):

$$\Delta C_{\text{backlog}} \geq C^{\text{BS}}_{\text{setup}} + C_{\text{BS}} \times Q_{\text{BS}} \tag{3.13}$$

where $C^{\text{BS}}_{\text{setup}}$ – one-off cost to activate MaaS backup, C_{BS} – per-unit cost.

For the developed pilot supply chains, metrics and KPIs are used not only for performance evaluation but also to capture data for MaaS implementation and the results of this implementation within WP6. KPIs that access network-wide performance can provide results of MaaS implementation in specific nodes, as well as access orchestrated distributed manufacturing resources, dynamically reassigned production tasks, and integrated alternative capacities into operational plans. During simulations, these KPIs can be continuously monitored, allowing assessment of the effect of MaaS integration on resilience.

Industrial implications: The case of ACCURATE pilots

- Scenarios for stress-test are described in Deliverable 4.1. Experiments in the case of Airbus Atlantic include political instability (curfew) in the Asian region, storms in the Moluccas Straits in the Asian region, strikes of workers in Morocco, earthquakes in the Southern region of France, and floods in areas surrounding Rochefort. The disruptions included stopping suppliers and extending delivery times. Each of these stress-testing scenarios is analyzed in terms of the impact of durations of 1, 2, 3, and 4 weeks. Besides, each supplier is tested individually using two methods:
  - Supplier failure of 30-, 60-, and 90-day duration.
  - Transportation time increases by 10, 25, 50, and 100% for each of the suppliers.
- In the case of Continental, global events as the Suez Canal blockage, semiconductor crisis, and material shortage scenario are taken as baseline for stress-testing. The stress-testing scenarios included the shutdown of several suppliers and the shutdown of the route for several weeks. Each disruption scenario highlights challenges of transportation bottlenecks, supplier dependencies, and ecological impacts, all of which influence the whole network.
- Disruption scenarios for Tronico are based on cases of item obsolescence, tension in the components market, location of suppliers in risk areas (natural disasters, geopolitics), and breakage in the product workshop with long lead times for components. The work aims to develop a two-layer simulation model that integrates supply chain dynamics with shop floor operations while fostering high interaction between optimization (decision-making processes) and simulation.

Simulation-based approaches

The simulation-based approaches of disruption scenarios build on network-wide simulation models that operate under certain disrupted conditions. Each pilot supply chain mode is based on different industrial contexts and is designed as a reconfigurable simulation template.

The majority of disruption simulations are modeled using DES, which enables the modeling of various shutdowns, transportation delays, and the representation of possible cascading effects of these disruptions. This approach enables us to observe the crucial impact of the disruption effect on lead times and certain nodes (Ivanov 2025d).

The integration of MaaS concepts into the stress-testing process enables decision-makers to evaluate trade-offs among resilience, cost efficiency, and service performance. During simulation runs, various configurations of the supply chain network can be evaluated, including rerouting materials through different logistical pathways and alternative capacity usage, making it possible to define an optimal response in the event of disruptions. This enables organizations to anticipate potential disruption scenarios before they occur in real life. Through linking MaaS principles with simulation models in WP6, valuable insights for designing supply chains that are both resilient and adaptively reconfigurable in the face of unpredictable global challenges will be proposed as a service within the ACCURATE decision-support framework.

3.5 Supply chain resilience management approach

Disruption typologies

Recent global disruptions highlight the need to divide risks into various typologies. Following the Adaptation-Based view (ABW), disruptions can be classified into the following types (Ivanov 2024b):

- Operational,
- Structural, and
- Strategic.

Examples of these types and possible mitigation strategies are presented in Figure 3.10. Implementing these strategies the high-quality supplier, logistics, and production data is required. Specific data requirements are described further in Chapter 4. In the context of high-impact disruptions, MaaS enables large-scale network adaptation through the diversification of capacity sources, distributed production, and other measures.

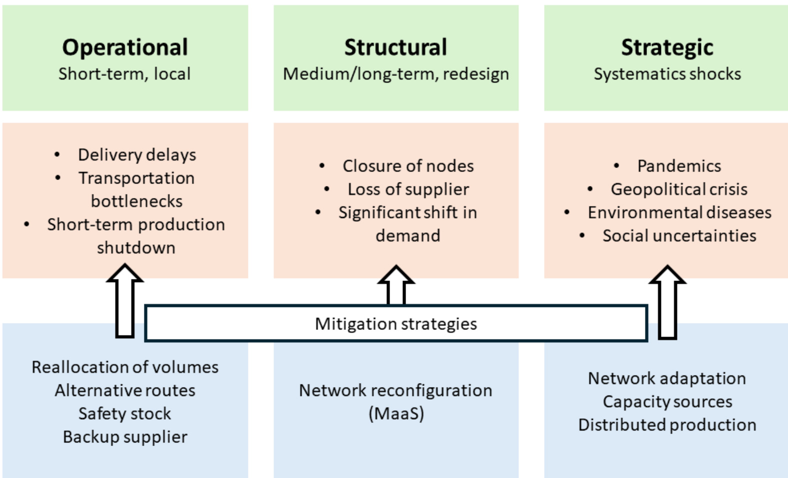


Figure 3.10: Disruption typologies

By origin, disruptions can be classified into supplier failures, production failures, transportation delays/route closure, and demand shocks (Dmitry Ivanov 2020).

- *Supplier disruptions* are represented by shutdowns, reduction of capacity, operational issues, quality problems, environmental and geopolitical risks, often affecting downstream operations. MaaS approach helps to mitigate such disruptions through switching to alternative suppliers.
- *Production disruptions* include breakdowns of equipment, production plan issues, capacity loss, process quality issues, maintenance delays or labor shortages, causing cascading effects, inventory deviations, and breakdown of the production plan.
- *Transportation delays* and/or route closures are usually represented through blockage or critical routes, strikes, vehicle or facilities damage. Effects from such disruptions include inventory shortages, production interruptions, and cascading schedule deviations.
- *Market demand shocks* are usually represented through demand collapses triggered by pandemics, regulatory changes, and market demand re-distribution. Such disruptions create an underload or an overload of the entire network capacity.

Risk propagation modeling

In complex multi-echelon networks, the effect of disruptions often propagates through interconnected tiers in non-linear and often unpredictable ways. Simulation modeling allows for capturing network interdependencies at both the network-wide and node-specific levels. This is done through mapping network dependencies between suppliers, manufacturers, distribution centers, and customers. At the same time, the rate at which an incident at one node affects downstream operations, known as the disruption spread velocity, is measured. Another method is the identification of propagation nodes, whose disruption disproportionately impacts the network. These network science approaches are especially important for distinguishing between robustness and resilience (Ivanov 2021).

In a MaaS context, risk propagation modeling provides insights into the distribution of capacity. For example, if a high-centrality node experiences a disruption, MaaS resources in adjacent tiers can be preemptively mobilized to contain the spread of delays. Simulation experiments have shown that propagation dampening can be achieved by introducing strategically located MaaS providers with the flexibility to handle multiple product types. These providers act as “shock absorbers,” reducing the severity and duration of network-wide performance drops.

Adaptive strategies and mitigation measures

Adaptive strategies and mitigation measures in case of disruptions of various origins focus on the ability of the network to respond and reconfigure without a loss of the target performance level. As explained in Chapter 3.2, these strategies can be considered as either proactive or reactive approaches. Proactive approach focuses on actions, that can be implemented in the network before the actual occurrence of a disruption, while a reactive approach is considered as post-disruption actions.

General structural flexibility of the network, which is able to reconfigure in case of disruption, is one of the great mitigation measures. The possibility of rerouting flows, redistributing volumes, and switching to alternative suppliers with minimal costs is a significant competitive advantage of the network. In this case, MaaS implementation allows for finding the best possible alternative with the least cost. One of the ways to how an exact supplier can be chosen from alternatives, is assigning weights to each supplier, as described in equation (3.14):

$$S_{(j)} = \omega_e \times \text{Eligibility}_j + \omega_r \times \text{Reliability}_j + \omega_s \times \frac{1}{T_{BS,j}} - \omega_c \times \text{Cost}_j \tag{3.14}$$

Capacity buffers, provided by parallel production lines and additional transportation volumes, as well as safety stock, can be considered another mitigation measure. In the case of parallel production lines, it is possible to reallocate production on these lines in the event of breakdowns. Dynamic reallocation of production to alternative nodes in the network in the event of a disruption also reduces recovery time in the event of a disruption. Suppliers' diversification is another adaptation strategy that requires building a robust portfolio of alternative suppliers across different regions. Such measures align with bio-inspired and cybernetic perspectives, emphasizing adaptation, redundancy, and viability as resilience-enabling mechanisms (Ivanov 2024a).

Information transparency across the network, as well as collaborative data sharing with stakeholders, allows for providing details of possible risk occurrence at an early stage. This allows us to share possible risks with stakeholders and mitigate the possible impact of the risks collaboratively. Such a collaborative approach can be supported through scenario-based planning. Running simulation-based disruption scenarios in a digital environment enables evaluating the risk in different lengths or circumstances of occurrence, allowing one to choose from several alternatives the one with the most suitable trade-off between costs and performance (Dmitry Ivanov 2020).

Recovery planning

The resilience includes not only survival abilities of the supply chain network during disruptions, but also restoring the operations to the target performance level. Recovery planning encompasses the period between the occurrence of the disruption and the network's stable post-disruption operation. One of the key metrics for recovery planning is Time-to-recovery (TTR), which measures the average time it takes to restore the network's performance to the pre-disruption level. To ensure efficient recovery planning, all actions have to be divided into short-term, medium-term, and long-term measures (see Figure 3.11). As elaborated in Chapter 4.3.3, these stress-testing principles are embedded in the DSS, enabling users to replicate disruption propagation and evaluate alternative resilience strategies.

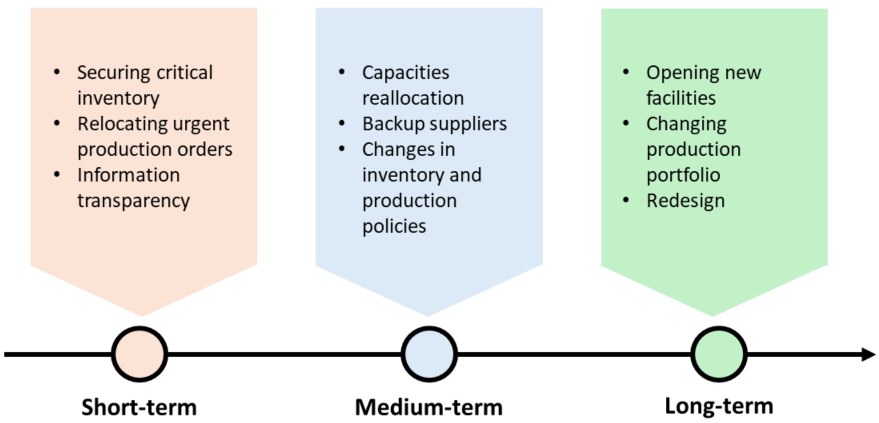


Figure 3.11: Mitigation measures

Some of these measures could be implemented as a proactive approach. For example, capacity reallocation options could be defined in advance, finding possible facilities and suppliers that can handle additional capacity. Pre-approved suppliers, logistics providers, and routes enable saving time in the event of a disruption and allow for immediate reaction without additional procurement cycles. Inventory and replenishment prioritization allows for minimizing downstream impact and service level loss. Again, the use of digital twins for testing alternative strategies in the event of disruptions allows for minimizing the negative impact on the entire network (Dmitry Ivanov 2020). This will be demonstrated in WP5 and WP6.

Through the implementation of recovery planning into the network, decision-makers can achieve better resilience and minimize negative impact. MaaS principles in this case enable the implementation of a proactive approach, allowing for immediate reaction to emerging risks and reducing the cascading effect on the entire network.

Chapter 4

DT-based DSS user guidelines

4.1 Data requirements

As explained in Deliverable 4.1, primary data requirements from industrial partners include data on inbound logistics, outbound logistics, Bill of Materials (BoM), production flow, and resources. Primary data is examined further as follows:

- **BoM data**: Products, raw materials, consumption rate.
- **Suppliers data:** The definition of suppliers, sourcing policy, analysis of the ordering processes, Minimum Order Quantity (MOQ), lead time, costs.
- **Customer data:** Demand, delivery process.
- **Production data:** Production path, bottlenecks of machines, total capacity.

To make the data suitable for further use, it must be analyzed and transformed into a DT-based DSS-applicable format.

During the transformation stage of supplier data, materials are mapped with possible sources. Analysed materials are defined in terms of single- and multiple-sourcing policies. The main idea of the sourcing policy, which is taken into account, is that in the case of multiple sources, the sourcing ratio is based on historical inbound logistics data. There is an opportunity for improvement in dynamic sourcing based on selected KPIs that can be implemented. During the transformation stage of MRP data, the flow of the ordering process is defined. The product demand is transformed into material requirements. In the material requirement stage, the data is divided into material data and material consumption data. Material requirement data is being further transformed for release. At this stage, data of supplier, lead-time, MOQ, ordering cost, holding cost, and stock-out cost are defined. During the transformation stage of customer data, synthesis demand data for simulation is developed from historical demand data. As highlighted in Chapter 3.5, without robust and well-structured data, risk propagation and resilience management approaches cannot be effectively applied.

4.2 System architecture and configuration

Recently, the architecture of digital twin support systems has evolved from isolated models to intelligent decision-support systems. Conceptual framework for digital twin implementation divides the supply chain into structural, functional, and behavioral dimensions. Structural models capture the network topology and interdependencies, functional models represent processes and resource flows, and behavioral models describe system dynamics under disruption. Together, these models form the digital foundation upon which decision-support systems can operate.

Digital twins should not be monolithic systems, but rather ecosystems of interconnected modules, including data integration platforms, simulation engines, optimization solvers, and scenario managers. Interactions between these modules, with the ability of the modules to reconfigure, allow the digital twin to remain adaptable to different industries and risk contexts.

The concept of the intelligent Digital Twin (iDT) framework introduces the integration of detection, prediction, and prescription instruments, as well as self-learning system capabilities. In the case of intelligent digital twins, decision support is provided by Artificial Intelligence (AI) and human agents to transform simulation, optimization, and stress-test results into actionable strategies. IDT contributes to proactive management and the risk of disruptions.

Architecture in this case includes three layers:

- **Physical space:** where real supply chain assets and flows operate,
- **Cyber space**, which hosts digital models, stress test engines, and risk assessment modules,
- **Collaborative decision space:** where humans and AI evaluate scenarios and develop strategies. The synergy of these modules and intelligent digital twins implementation ensures that supply chain ecosystems can achieve both structural viability and adaptive resilience under uncertainties.

During the DT development, there are several generalized stages, which are illustrated in Figure 4.1. These stages include collecting and preparing the data, inputting this data into the model, performing simulation and optimization experiments under baseline conditions, conducting stress-testing scenarios, and analyzing data obtained from the experiments. Accuracy at every stage of DT development enables the provision of accurate experimental results, allowing for the integration of results and managerial recommendations directly into the real system. As mentioned in Chapter 3, such an approach supports stress-tests integration and resilience management approaches integration.

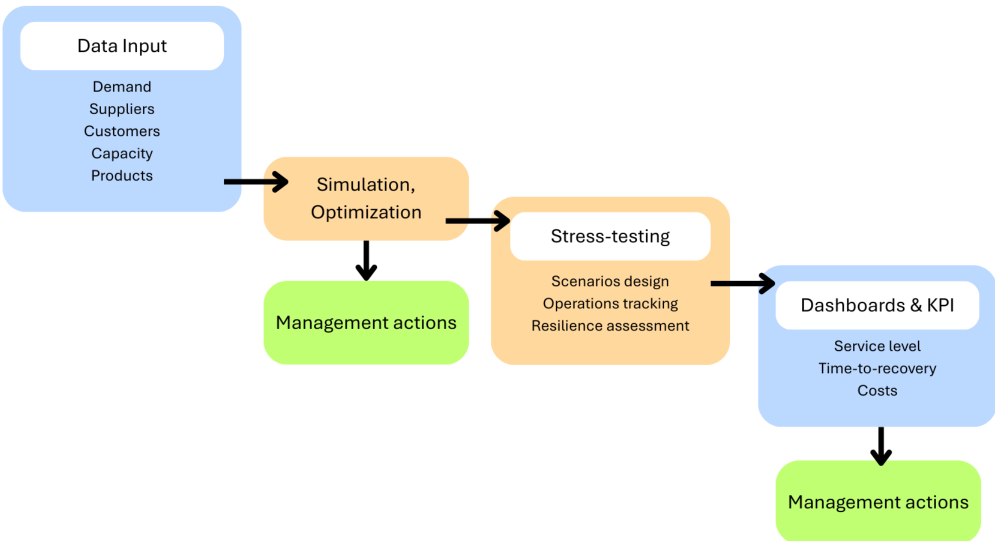


Figure 4.1: Digital Twin (DT) development path

4.3 Capabilities of the proposed decision-support system

4.3.1 Design mode: Conventional and MaaS-based

The decision support system combines structural and functional behaviours of the supply chain in combination with detection, prediction and prescription analytics and human support capabilities. This enables the DSS framework to support traditional SC planning methods and integrate them with MaaS implementation, allowing for short-, mid and long-term planning.

The comparison of conventional and MaaS-based design is illustrated in Figure 4.2.

Conventional design focuses on network configuration problems, including facility location, capacity allocation, supplier selection, and inventory policy definition. Alternatives for decision-making are the results of simulations and optimizations, which allow for balancing the trade-off between costs and KPIs.

MaaS-based design extends decision-making capabilities beyond traditional aspects and incorporates flexible production strategies and reconfigurable SC capabilities. The MaaS approach allows the use of backup suppliers, additive manufacturing providers, or logistics services, which can be dynamically reconfigured if needed. The integration of the MaaS concept into conventional design enhances resilience by facilitating the sharing, reconfiguration, and relocation of assets in response to disruptions.

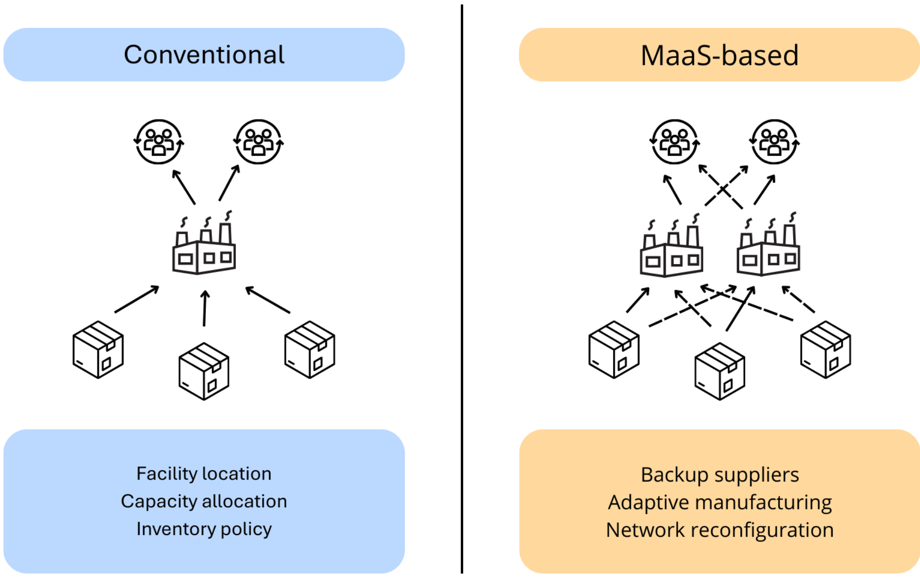


Figure 4.2: Conventional and MaaS-based design models

4.3.2 Operations management mode

At the tactical and operational levels, the DSS enables ongoing monitoring, coordination, and control of supply chain activities. This includes collecting real-time data from ERP and other systems, logistics providers, and other stakeholders in order to update the digital twin constantly. Through constant data updates, DT allows for real-time stress-testing and evaluating various strategies.

At the tactical level, the DSS supports decisions such as production planning, capacity allocation, transport routing, and inventory positioning across multiple facilities. The DSS integrates demand forecasts, supplier performance data, and logistics constraints into optimization models to propose schedules and allocations that balance cost-efficiency with service levels.

At the operational level, the DSS enables short-term control of processes. Through receiving real-time data, decision-makers can track the reaction of processes to disruptions or fluctuations of different origins. This allows managers to implement interventions such as rerouting shipments, expediting orders, or reassigning the workforce and equipment. Conducting stress-tests also helps to anticipate 'what-if' analysis to anticipate possible cascading effects on the whole supply chain.

4.3.3 Stress-testing mode

The stress testing mode of the DSS is designed to evaluate how a supply chain ecosystem performs under extreme, unexpected, or deeply uncertain conditions. Stress testing begins with the identification and modelling of disruption scenarios. These may include natural disasters, facility shutdowns, trade conflicts, or sudden demand surges. Building on the structural models of the digital twin (Ivanov, 2025), the DSS maps the network topology to identify critical nodes, dependencies, and bottlenecks. The functional models then simulate how resources and flows are constrained under disruption, while the behavioral models trace the dynamic ripple effects of failures across multiple echelons and time horizons. Key performance indicators include time to recovery (TTR), service levels (SL), costs, and other supply chain viability indicators.

Conducting stress-testing scenarios is used not only to define vulnerabilities but also to research suitable mitigation and adaptation strategies. The DSS enables the assessment of various strategies of different origins, such as supplier diversification, facility redundancy, dynamic rerouting, and inventory allocation, among others, to find a suitable trade-off between costs and resilience.

Storing information about previous disruptions and analyzing insights from previous experiences allows DSS to prepare for future challenges. DSS provides a learning capability for DT behavior in various situations. These learning capability allows building a data-based model of scenarios and responses to these scenarios, creating a memory to enhance the adaptability of the whole network. Insights, driven by these memories, enable decision-makers to develop strategies that strike a suitable balance between costs and resilience. In this sense, DT is not only a diagnostic tool but also a strategic enabler, aligning supply chain design and operations with long-term objectives.

4.4 Dashboards, managerial implications and interpretation of results

The capabilities outlined in Chapter 3 will be embedded within a Digital Resilient Supply Chain Ecosystem, as depicted in Figure 4.3 and further developed in workpackages WP5 and WP6. This ecosystem integrates data, advanced analytics, simulation, and decision-support functionalities into a coherent framework. It bridges the *cyber layer* (encompassing risk profiling, supply chain mapping, stress-testing, and marketplace functionalities) with the *physical supply chain*, while also incorporating a *dedicated human–machine* collaboration environment that provides interactive resilience dashboards for *end-users*.

Supply Chain Model, one of the main contributions of the WP4, lies in the orchestration of multi-tier supply chain mapping, risk profiling, and stress-testing digital twins within a unified environment. The outputs are directly channelled into the Decision Support System (DSS) and made accessible through end-user visualization interfaces. Within this context, ACCURATE emphasizes the importance of a proactive resilience strategy, notably through the identification of nexus nodes and critical paths, which further enables the integration of Manufacturing-as-a-Service (MaaS) principles in WP6.

4.4.1 API connection

An API has been developed to support two generalized models for simulating inventory dynamics and order generation, incorporating the capability to represent two generic categories of disruption events. The resulting model will be made available through the ACCURATE marketplace, thereby fostering reuse, interoperability, and collaboration with external developers. Furthermore, this API provides a foundation for the development of a co-simulation platform and additional solution modules to be deployed within the ACCURATE project.

The API has three main endpoints:

- **Simulation results:** Main endpoint for simulation results, as illustrated in Figure 4.4,
- **Weekly Simulation Details:** Steps of simulation calculation by week, as illustrated in Figure 4.5,

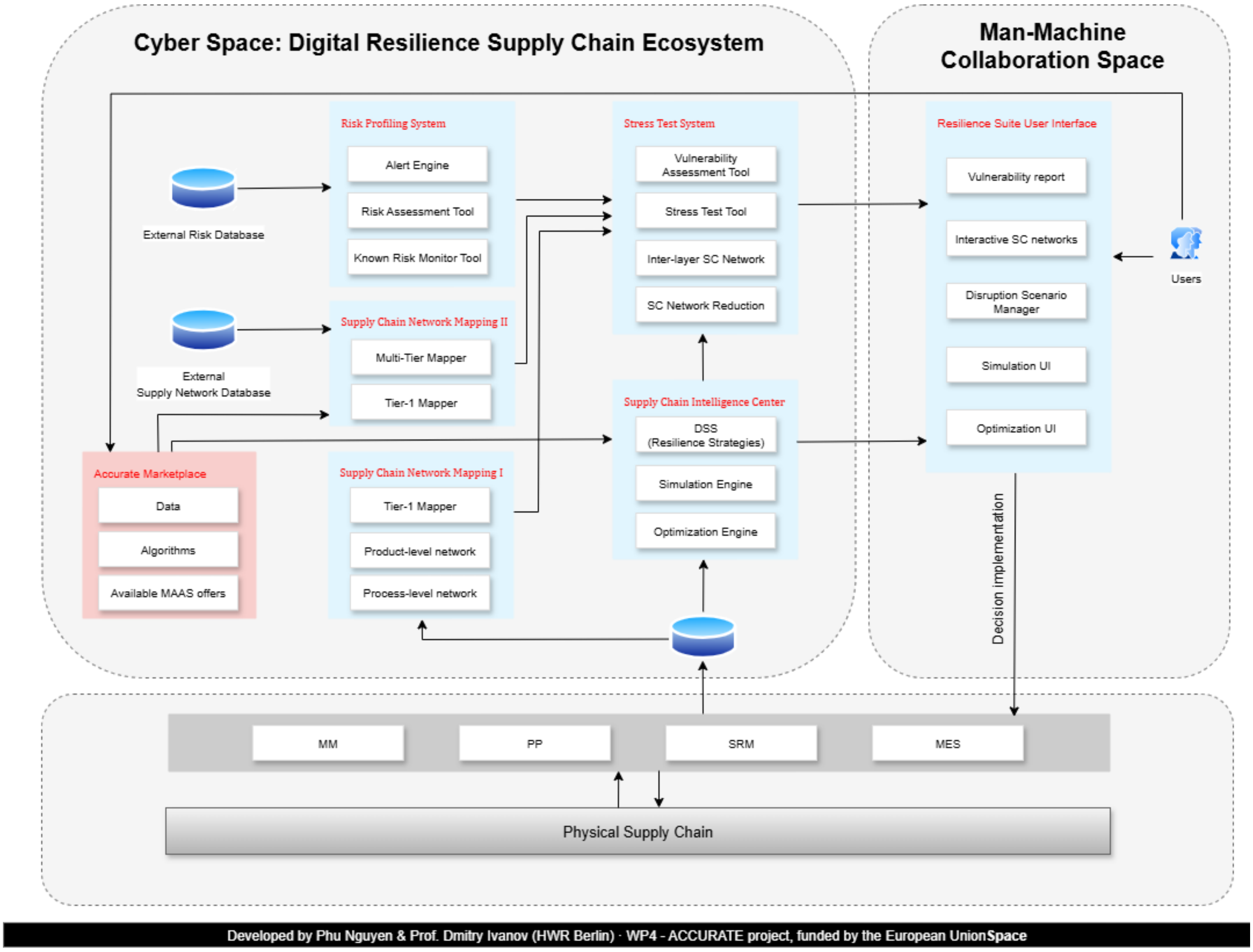


Figure 4.3: Digital Resilience Supply Chain Ecosystem

- **Material Simulation Details:** Steps of simulation calculation by material, as illustrated in Figure 4.6.

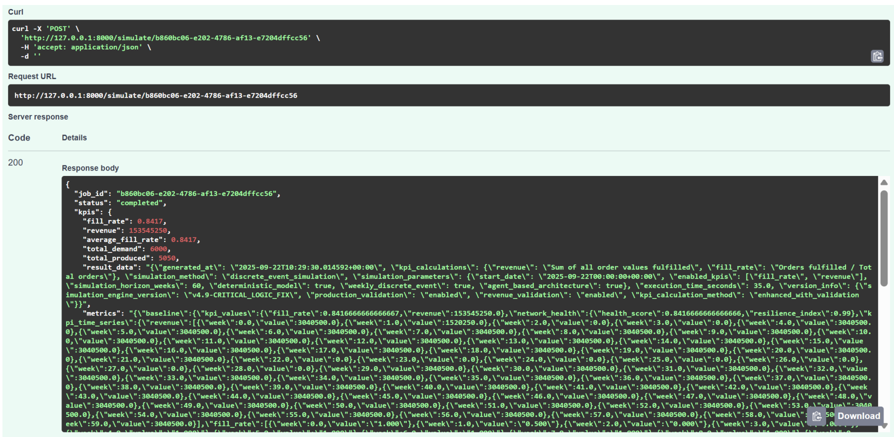


Figure 4.4: API endpoint 1: Simulation results

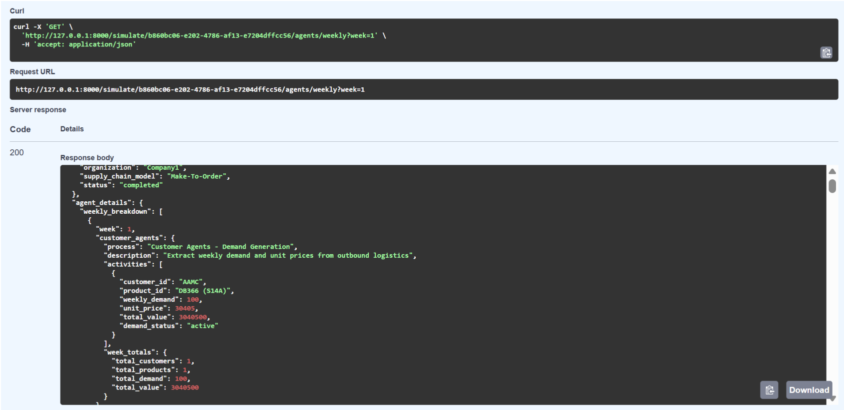


Figure 4.5: API endpoint 2: Simulation details per period of time (e.g., week)

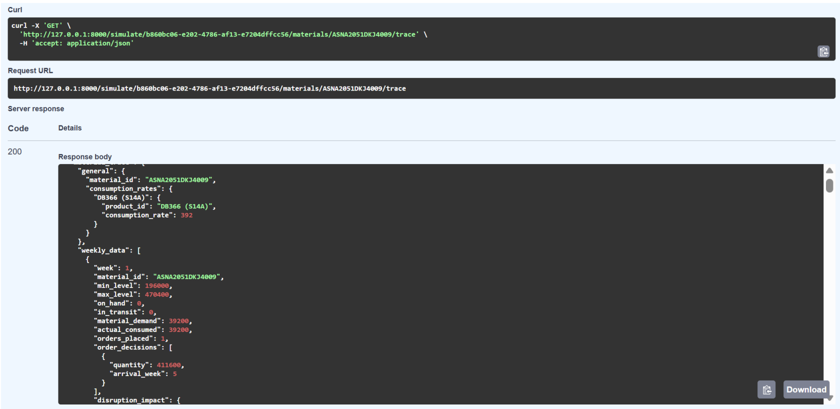


Figure 4.6: API endpoint 3: Simulation details by material

4.4.2 One-integrated supply chain resilience software

To integrate the networks of different levels of detail across the analytics layer, simulation, and the optimization layer, a dedicated software is developed in ACCURATE based on capabilities described in Chapter 3. The software analyzes *internal supply chain* data within the *product-level network* and the *process-level network*. For the deep-tier network investigation, users can acquire data from the ACCURATE marketplaces for analytics. The software enables the rapid generation of disruption scenarios during interactions with the network.

Beyond the data analysis, the designed tool is capable of simulating one or more disruption events simultaneously. The user can quickly adjust the disruption event scenario through interface without the need to generate more events, which reduces modeling efforts.

For decision support, the dashboard highlights key performance indicators, including fill rate and revenue. Fill rate is one of the most popular indicators in supply chain management. Revenue provides insights into the health of the supply chain, encompassing both financial and operational aspects. Clear visualizations and comparison features make it easier for users to interpret complex results.

The data management interface of the developed software is illustrated in Figure 4.7, which forms the foundation of these capabilities. Users can organize and monitor product- and process-level networks. It is possible to import, edit, and visualize supply chain data such as product IDs, material IDs, consumption rates, and plant names. The data management interface creates a foundation for future analysis and optimization.

The *firm-level network* is illustrated in Figure 4.8. The visualization highlights connections between suppliers and customers. Figure 4.8 illustrates the complexity of the supply chain interdependencies, where firms are positioned in different layers according to their role in the network. In the right panel,some

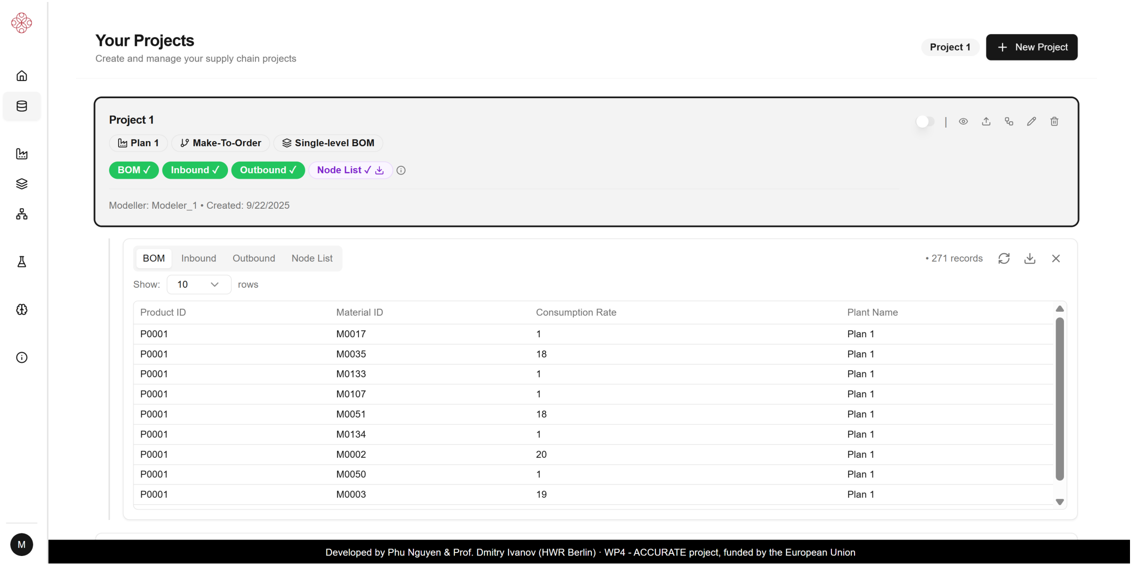


Figure 4.7: Data management

additional information about suppliers. The tool provides a 'Nexus Node Prediction' function, which allows for the identification of critical nodes within the network that may create vulnerabilities or bottlenecks.

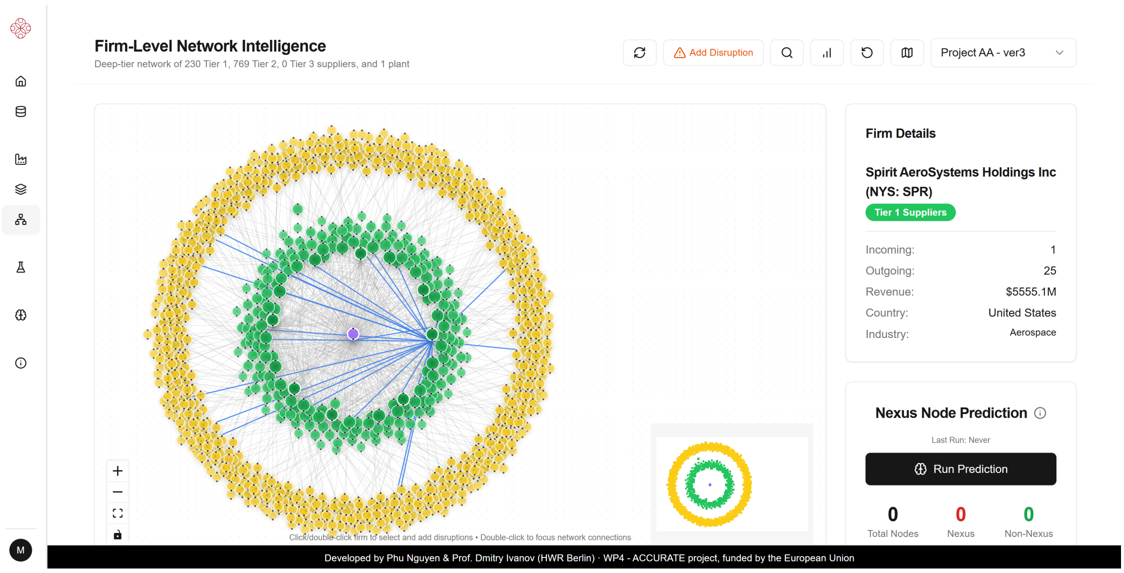


Figure 4.8: Firm-level network

The *product-level network* is illustrated in Figure 4.9. The visualization highlights the flow of materials within the supply chain. It shows flow connections between suppliers, materials, products, and customers. This view enables users to assess dependencies and identify critical materials within the network. By providing both structural and quantitative insights, the product-level network visualization facilitates informed decision-making for more effective resilience resource allocation.

A field for scenario generation is illustrated in Figure 4.10. While interacting with the network analysis, one can conveniently stress-test the network by generating a scenario with information about the target of disruption, the type of disruption, and the delay duration. Disruption types could be modeled as either capacity reduction or time delay in their general form.

The *process-level network* is illustrated in Figure 4.11. The visualization shows how customers, products, materials, and suppliers reveal dependencies across the network. Showing the links between

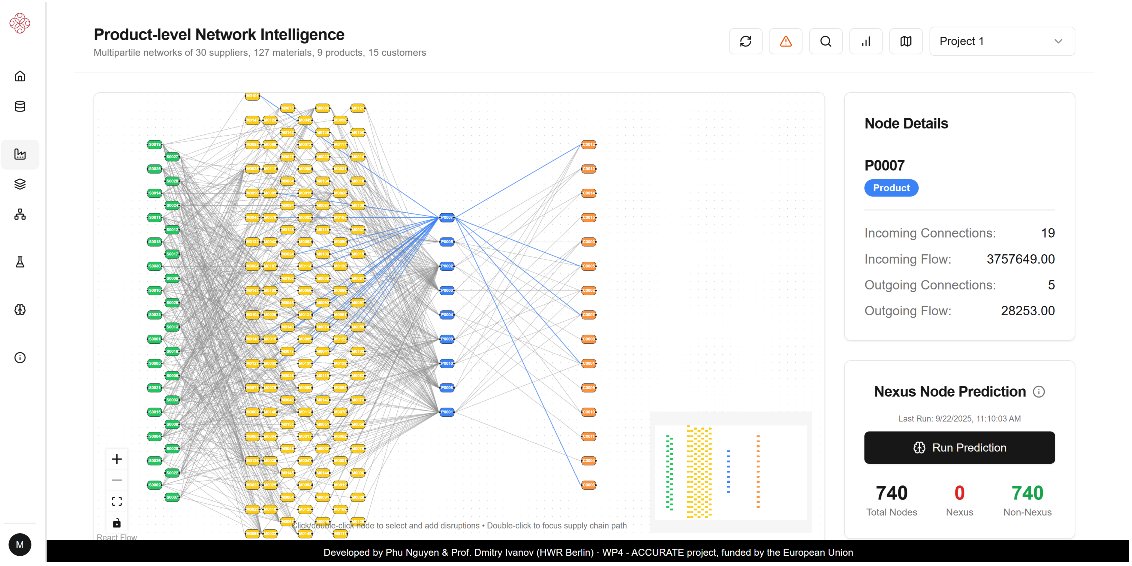


Figure 4.9: Product-level network

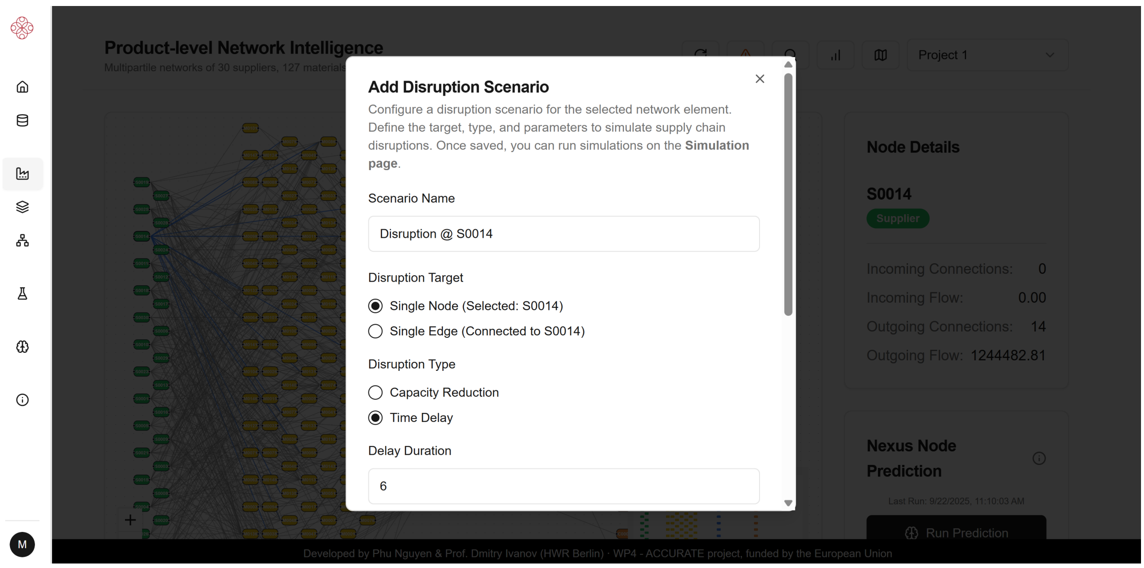


Figure 4.10: Quick Scenario Generation

clusters highlights the complexity of the interconnections, where the cascade effect from the disruptions can affect the whole supply chain. Process-level network visualization supports supply chain transparency, enabling the identification of possible bottlenecks in shop-floor operations.

The simulation center is presented in Figure 4.12. The tool enables the analysis of supply chain resilience across nodes and different scenario configurations. In the example, the scenarios of a five-week disruption at node BI and an eight-week disruption at node WAEL are modeled. Through various disruption scenarios, one can analyse the potential impact of delays and identify vulnerabilities. The tool enables proactive resilience planning and evaluation of possible mitigation strategies.

The SC resilience dashboard is illustrated in Figure 4.14. The dashboard summarizes the impact of disruptions compared to baseline scenarios. In the example, there is a decline in KPIs, specifically in fill rate and revenue. Additionally, resilience metrics, including Time-To-Survive, Time-To-Adapt, and Time-To-Recover, are provided. Through the analysis of presented metrics, the dashboard enables decision-makers to evaluate vulnerabilities, compare potential disruption scenarios, and define suitable mitigation strategies.

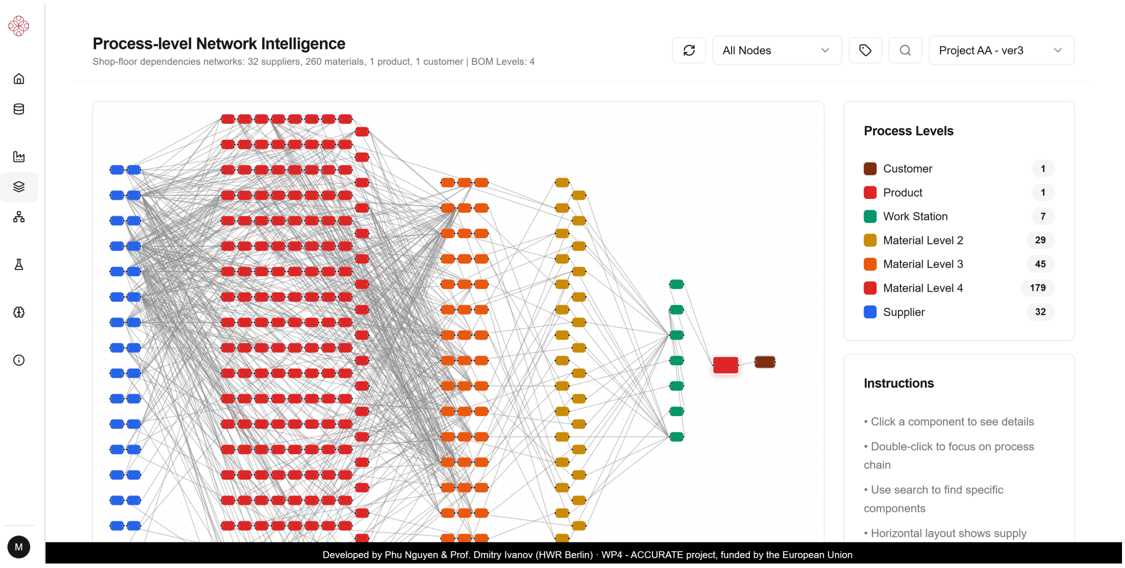


Figure 4.11: Process-level network

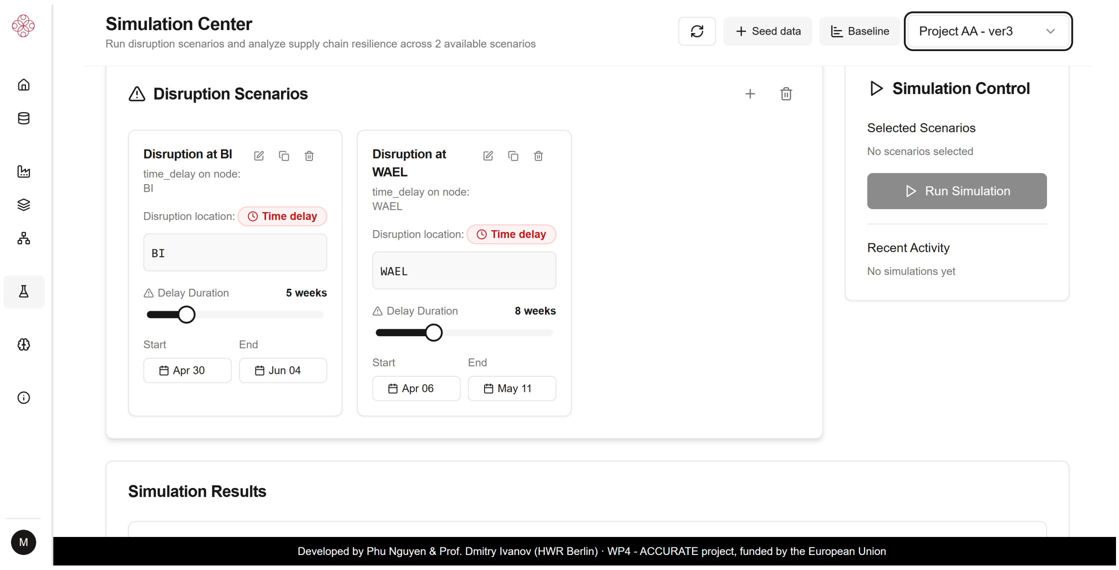


Figure 4.12: Simulation center

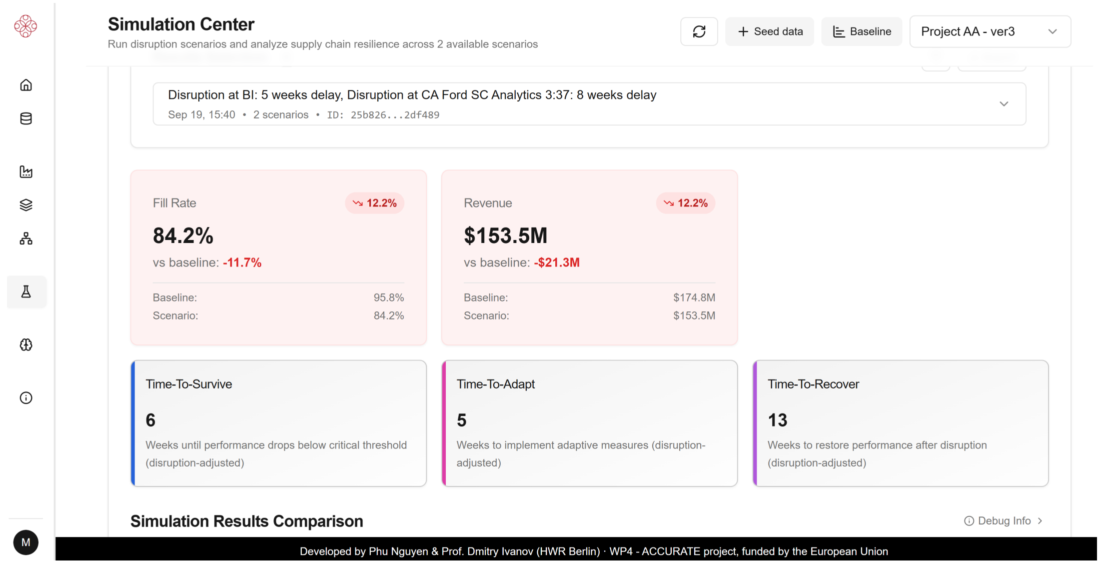


Figure 4.13: SC Resilience Dashboard (1)

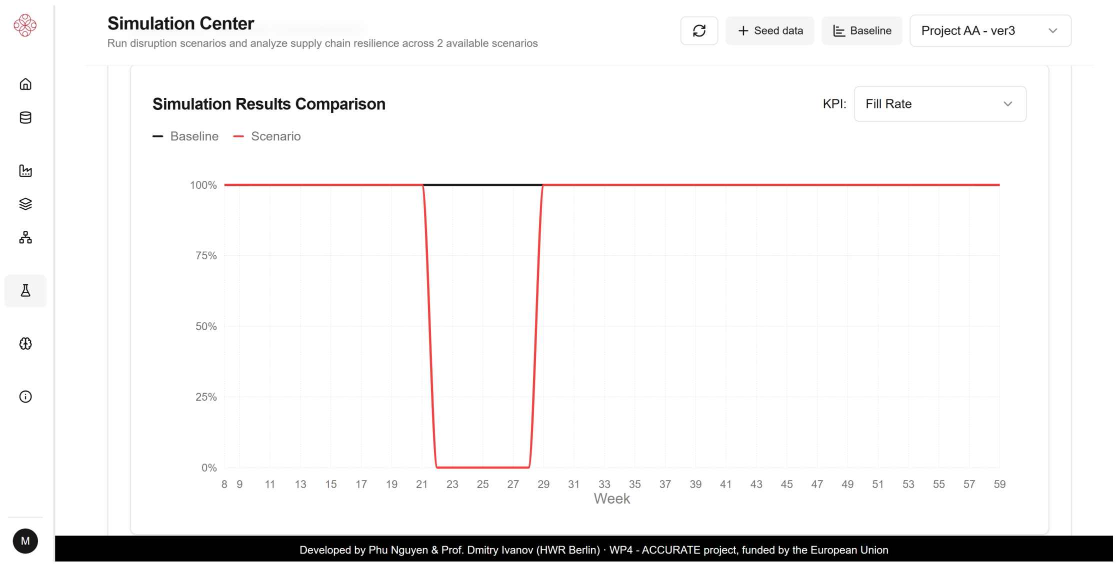


Figure 4.14: SC Resilience Dashboard (2)

Chapter 5

Conclusions and future directions

This deliverable consolidates the conceptual and methodological advances of WP4 into a coherent Digital Twin–based Decision Support System (DT-DSS) for resilient supply chain design, planning, and stress testing. The main contributions can be summarized as follows:

- **Methodological integration:** Developed a DT-based DSS architecture that combines discrete-event simulation, multi-criteria decision analysis, and optimization. This enables the modeling of multi-echelon supply chain networks, assessment of disruption propagation, and evaluation of resilience strategies under uncertainty.
- **MaaS-enabled supply chain design and planning:** Introduced decision-support models that leverage Manufacturing-as-a-Service (MaaS) principles, including decentralized resource orchestration, dynamic pricing, and flexible scheduling. These models extend conventional design frameworks by integrating backup capacity, shared inventories, and distributed decision-making.
- **Stress-testing and resilience assessment:** Implemented generalized disruption scenario modelling and simulation pipelines to quantify resilience using KPIs such as service level, lead time, time-to-survive, and time-to-recover. The methodology was validated with Airbus Atlantic, Continental, and Tronico pilots, demonstrating its applicability across diverse industrial contexts.
- **Decision-support tools and software:** Delivered **(i)** an API-based solution supporting generalized supply chain models (make-to-stock and make-to-order) and two generic disruption types, fostering interoperability and reuse, and **(ii)** a standalone integrated software embedding analytics, simulation, and dashboards into a unified resilience platform.
- **Managerial implications:** Provided guidelines for data requirements, configuration, and interpretation of results, together with interactive dashboards for nexus-node identification, disruption scenario generation, and resilience KPI monitoring. These tools support both proactive and reactive disruption management in line with industrial needs.

Overall, Deliverable 4.2 advances the state of the art by moving from fragmented optimization models to an integrated DT-DSS framework that operationalizes resilience strategies in MaaS-enabled supply chains.

Future research and development will focus on:

- Scalable heuristics and metaheuristics for large industrial instances,
- Integration of dynamic pricing mechanisms into MaaS scheduling models within WP6,
- Strengthened interoperability with WP5 (data spaces) and WP6 (MaaS decision-support framework),

- Validation through extended industrial pilots in electronics, aerospace, and automotive supply chains in WP7.

These next steps will reinforce the objectives of the ACCURATE project in terms of resilience and viability to unforeseen events (in WP6), reconfiguration and flexibility of production systems (via use-cases in WP7), digital and green transition of value chains (in WP5 and WP6), MaaS (in WP5 and WP6), ecosystem acceptance and adoption (in WP7 and WP8).

Notes

1. The BANI World, for IRSM 2022: https://www.youtube.com/watch?v=stBdyNBwfpU&ab_channel=JamaisCascio
2. Manufacturing as a Service: Technologies for customized, flexible, and decentralized production on demand: https://www.horizon-europe.gouv.fr/manufacturing-service-technologies-customised-flexible-and-dec
3. Manufacturing as a service for the EU'S twin transition until 2040 (MASTT2040): https://www.mastt2040.eu/

Appendix A

Manufacturing-as-a-Service Scheduling Problems

A.1 Bi-objective mixed-integer programming formulation

Given a set of n service orders (i.e., tasks) $j \in \mathcal{J}$ and a set of m ressource providers (i.e., machines) $i \in \mathcal{M}$, the MaaS platform coordinates the assignment and sequence of tasks to the most qualified machines. Each task j has a due date d_j, a weight w_j, a processing time p_{ij}, and a delivery time q_{ij} for each machine i. All tasks are available at time zero, each task j needs to be processed by one and only one machine without interruption, and each machine i can handle at most one task at a time. The delivery time q_{ij} occurs immediately after completing the task j on the respective machine i. The optimization criterion is the minimization of the total weighted tardiness $\sum w_j T_j$, where $T_j = \max\{C_j - d_j, 0\}$ and C_j is the completion time defined as the time by which a task reaches the customer.

$$
\begin{aligned}
\min\ & \mathcal{T} && && \text{(A.1)}\\
\max\ & \mathcal{E} && && \text{(A.2)}\\
& \sum_{i \in \mathcal{M}} y_{ij} = 1 && j \in \mathcal{J} && \text{(A.3)}\\
& s_k \geq s_j + p_{ij} - H(3 - y_{ik} - y_{ij} - z_{jk}) && i \in \mathcal{M},\ j,k \in \mathcal{J},\ j \neq k && \text{(A.4)}\\
& s_j \geq s_k + p_{ik} - H(2 - y_{ik} - y_{ij} + z_{jk}) && i \in \mathcal{M},\ j,k \in \mathcal{J},\ j \neq k && \text{(A.5)}\\
& C_j \geq s_j + (p_{ij} + q_{ij}) y_{ij} && i \in \mathcal{M},\ j \in \mathcal{J} && \text{(A.6)}\\
& T_j \geq C_j - d_j && j \in \mathcal{J} && \text{(A.7)}\\
& T_j, C_j \geq 0 && j \in \mathcal{J} && \text{(A.8)}\\
& \mathcal{T} \geq f(T_j) && && \text{(A.9)}\\
& \mathcal{E} \leq g(e_{ij}) && && \text{(A.10)}\\
& y_{ij}, z_{jk} \in \{0,1\} && i \in \mathcal{M},\ j,k \in \mathcal{J} &&
\end{aligned}
$$

The mixed-integer linear formulation includes binary assignment variables y_{ij} of task j to machine i and precedence variables z_{jk} between tasks j and k. Variables s_j denote the start time of task j. The model is formulated by expressions (A.1)- (A.10). Constraints (A.3) state that each task must be assigned to exactly one machine. Disjunctive Constraints (A.4) and (A.5) manage the precedence relationship between tasks on machines. Task completion times and tardiness values are computed according to Constraints (A.6)-(A.8). Constant H is an upper bound on task start times and can be computed by:

$$H = \max_{i \in \mathcal{M}} \left\{ \sum_{j \in \mathcal{J}} p_{ij} - \min_{j \in \mathcal{J}} p_{ij} \right\}$$

In Constraints (A.9) and (A.10), the functions $f(T_j)$ and $g(e_{ij})$ represent the tardiness (resp., eligibility) that are minimized (resp., maximized) in expression (A.1) and (A.2), respectively. Tardiness and eligibility summary measures can be different mathematical expressions of the individual delays T_j and the eligibility score e_{ij}, the main measures are presented in Table A.1.

Table A.1: Main optimization criteria

Function	Measure	Description
$f(T_j)$	$\sum_{j\in\mathcal{J}} w_j T_j$	Total Weighted Tardiness
	$T_j, \quad \forall j \in \mathcal{J}$	Maximal Tardiness
$g(e_{ij})$	$\sum_{i\in\mathcal{M}} \sum_{j\in\mathcal{J}} e_{ij} y_{ij}$	Total Eligibility
	$\sum_{i\in\mathcal{M}} e_{ij} y_{ij}, \quad \forall j \in \mathcal{J}$	Minimal Eligibility

For both objectives, measures can be considered globally or individually by task. In the former, more flexibility is allowed and a greater collaboration between the actors is considered, which is more natural in a type of MaaS platform that manages only its own equipment or a consortium of companies. In the second, it considers all tasks independently, which is more appropriate in the context of a MaaS platform with different industries and competing actors.

A.2 Constraint Programming Formulation

Another constraint programming-based formulation for the MaaS scheduling problem is proposed. In this context, interval variables are considered, which are defined as a finite domain of solutions, which, for scheduling problems, are defined directly with a value that determines the start, length, and end of the respective interval. For our problems, let x_{ij} be an optional interval variable of executing job i on machine i with duration of p_{ij}. Then, considering the problem with both objectives individually by tasks, the problem can be formulated as follows:

$$\min \quad \sum_{j\in\mathcal{J}} T_j$$

$$s.t. \quad Alternative(x_{1j}, x_{2j}, ..., x_{mj}) \qquad j \in \mathcal{J} \qquad \text{(A.11)}$$

$$noOverlap(x_{i1}, x_{i2}, ..., x_{in}) \qquad i \in \mathcal{M} \qquad \text{(A.12)}$$

$$\sum_{i\in\mathcal{M}} e_{ij} * presenceOf(x_{ij}) \geq \theta \qquad j \in \mathcal{M} \qquad \text{(A.13)}$$

$$T_j \geq endOF(x_{ij}) + presenceOf(x_{ij}) * q_{ij} - d_j \qquad j \in \mathcal{J} \qquad \text{(A.14)}$$

$$T_j \geq 0 \qquad j \in \mathcal{J} \qquad \text{(A.15)}$$

A.3 Bi-objective integer program with fixed assignment and external confirmation: Online settings

Let us now extend the offline formulation to the **online settings**, where **tasks arrive dynamically over time with release times** r_j. At each decision point t, only tasks satisfying $r_j \leq t$ are known and eligible for assignment. The platform must incrementally assign these available tasks to machines and determine their sequence, without full knowledge of future task arrivals.

We also extend the online MaaS scheduling problem by allowing **reassignment of tasks that have not yet started** and incorporate a realistic confirmation mechanism, defined as follows: After tentative assignments are made at decision time t, **the providers may confirm or reject each assigned task**. Confirmed tasks become fixed and immutable in the following periods, while rejected tasks return to the set of pending ones for future reassignment. At each decision point t, the task set is defined as:

$$\mathcal{J}_t = \mathcal{J}_t^{\text{new}} \cup \mathcal{J}_t^{\text{pending}}$$

where:

- $\mathcal{J}_t^{\text{new}} = \{j \in \mathcal{J} \mid r_j = t\}$ are newly released tasks,
- $\mathcal{J}_t^{\text{pending}} = \{j \in \mathcal{J} \mid r_j < t,\ s_j > t,\ \delta_j = 0\}$ are tasks not yet started and not confirmed.

Let us define:

- $y_{ij}^t \in \{0,1\}$: Assignment of task j to machine i at time t,
- $z_{jk} \in \{0,1\}$: Sequencing variable between tasks j and k,
- s_j, C_j, T_j: Start time, completion time, tardiness of task j,
- $e_{ij} \in [0,1]$: Indicator variable, which indicates the compatibility between machine i and task j.
- $\delta_j \in \{0,1\}$: Confirmation indicator (1 = confirmed and fixed, 0 = subject to future reassignment),
- $\bar{s}_j, \bar{C}_j$: Fixed start/completion times for confirmed tasks.

The integer programming formulation is:

$$\max\ \alpha \sum_{i\in\mathcal{M}} \sum_{j\in\mathcal{J}_t} e_{ij} - \beta \sum_{j\in\mathcal{J}} w_j^t T_j \tag{A.16}$$

$$\text{s.t.}\ \sum_{i\in\mathcal{M}} y_{ij}^t = 1 \qquad \forall j \in \mathcal{J}_t \tag{A.17}$$

$$s_k \geq s_j + p_{ij} - H(3 - y_{ik}^t - y_{ij}^t - z_{jk}) \qquad \forall i \in \mathcal{M},\ j,k \in \mathcal{J}_t,\ j \neq k \tag{A.18}$$

$$s_j \geq s_k + p_{ik} - H(2 - y_{ik}^t - y_{ij}^t + z_{jk}) \qquad \forall i \in \mathcal{M},\ j,k \in \mathcal{J}_t,\ j \neq k \tag{A.19}$$

$$C_j \geq s_j + (p_{ij} + q_{ij}) y_{ij}^t \qquad \forall i \in \mathcal{M},\ j \in \mathcal{J}_t \tag{A.20}$$

$$T_j \geq C_j - d_j \qquad \forall j \in \mathcal{J}_t \tag{A.21}$$

$$T_j, C_j \geq 0 \qquad \forall j \in \mathcal{J}_t \tag{A.22}$$

$$s_j \leq \bar{s}_j + M(1 - \delta_j) \qquad \forall j \in \mathcal{J} \tag{A.23}$$

$$s_j \geq \bar{s}_j - M(1 - \delta_j) \qquad \forall j \in \mathcal{J} \tag{A.24}$$

$$C_j \leq \bar{C}_j + M(1 - \delta_j) \qquad \forall j \in \mathcal{J} \tag{A.25}$$

$$C_j \geq \bar{C}_j - M(1 - \delta_j) \qquad \forall j \in \mathcal{J} \tag{A.26}$$

$$y_{ij}^t,\ z_{jk},\ \delta_j \in \{0,1\} \qquad \forall i \in \mathcal{M},\ j,k \in \mathcal{J} \tag{A.27}$$

where α and β are weighting coefficients.

Appendix B

Lot sizing

Table B.1: Lot sizing problem: A state-of-the-art review

References	Uncertain demand			Modeling approach				Extensions			Time horizon			Decision strategy			Sol. approach		
	T	V	T&V	P	S	F	I	Backlogging	Lost sales	Time window	finite	∞	rolling	static	dynamic	both	SP	CCP	RP
Burstein, Nevison, and Carlson 1984	✓			✓							✓								
Gioia, Fadda, and Brandimarte 2024		✓			✓				✓		✓		✓				✓		
Nevison 1985	✓			✓							✓								
Akartunalı and Dauzère-Pérès 2022	✓			✓				✓			✓								
Chotayakul and Punyangarm 2017		✓		✓							✓							✓	
Tarim and Kingsman 2004		✓		✓							✓					✓		✓	
Sereshti, Adulyasak, and Jans 2024		✓			✓			✓			✓			✓		✓	✓		
Rahmani, Hosseini, and Sahami 2025		✓			✓			✓			✓			✓		✓	✓		
Metzker et al. 2021		✓					✓	✓			✓								
Mula, Peidro, and Poler 2010		✓				✓					✓		✓						
Forel and Grunow 2023		✓		✓	✓			✓			✓		✓		✓				
H. Gong, Y. Zhang, and Z.-H. Zhang 2023		✓									✓								✓
Sox 1997			✓	✓				✓			✓			✓		✓			
ACCURATE			✓	✓	✓			✓			✓		✓			✓	✓	✓	✓

Note: T: Timing; V: Volumn; T&V: Timing & Volume; P: probabilistic formulation; S: scenario formulation; F: fuzzy logic formulation; I: interval arithmetic formulation; SP: two/multi-stage stochastic programming; CCP: chance-constrained programming; RP: robust programming; FP: fuzzy mathematical programming

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