Ref. Ares(2025)10659566 - 03/12/2025

NARRATE

Regenerative Resilient Smart Manufacturing Networks

D4.3(a) Production Planning & Process Routing System & algorithms

2025/11/03

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Call: HORIZON-CL4-2023-TWIN-TRANSITION-01 • Topic: HORIZON-CL4-2023-TWIN-TRANSITION-01-07 • Type of action: HORIZON Research and Innovation Actions

UK Research and Innovation

UK Research and Innovation, Horizon Europe Guarantee.

Grant Agreement No.: 101138094
Topic: HORIZON-CL4-2023-TWIN-TRANSITION-01-07
Call: HORIZON-CL4-2023-TWIN-TRANSITION-01
Type of action: HORIZON-RIA

D4.3(A) PRODUCTION PLANNING & PROCESS ROUTING SYSTEM & ALGORITHMS

Work package	4
Task	3
Due date	30/11/2025
Submission date	03/12/2025
Deliverable lead	INSA
Version	2.0
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Reviewers	Frank Werner (BLU), María Ramírez (DHL)
Abstract	This deliverable presents the development of a Production Planning System designed to enhance the resilience and efficiency of Make-To-Order (MTO) manufacturing systems within Smart Manufacturing Networks (SMNs). The proposed system integrates artificial intelligence-driven methods with mathematical optimization techniques to address Master Production Scheduling (MPS) challenges under conditions of uncertainty and disruption. At the core of this work is the design of proactive and reactive resilient MPS models that incorporate Manufacturing-as-a-Service (MaaS) strategies to mitigate supply chain disruptions. To manage uncertainties related to suppliers, manufacturers, and market dynamics, the system employs stochastic programming approaches that ensure operational continuity while minimizing penalties associated with earliness, tardiness, and resource reallocation. A comprehensive Decision Support System (DSS) framework has also been developed, featuring an intelligent architecture capable of dynamically selecting optimal strategies in response to real-time conditions. The deliverable includes presenting mathematical programming approach, computational experiments validating the effectiveness of the proposed approaches, and a prototype application implementing the developed algorithms. Overall, this work advances the objectives

	of the NARRATE project by reinforcing supply chain resilience, optimizing resource utilization, and fostering a more adaptive and intelligent manufacturing ecosystem capable of effectively responding to disruptions.
Keywords	Production planning; Master Production Scheduling; Make-To-Order systems; Resilient manufacturing; Manufacturing-as-a-Service; Stochastic optimization; Decision Support Systems

Project co-funded by the European Commission in the Horizon Europe

Nature of the deliverable:	R – Document, report
Nature of the deliverable:	PU - Public

DOCUMENT REVISION HISTORY

Version	Date	Description of change	List of contributor(s)
0.1	2025/10/09	First version	INSA, AID, SERV, IPK, MUHEC, REPLY, SYN, NUN
2.0	2025/12/02	Second version	INSA, AID, SERV, IPK, MUHEC, REPLY, SYN, NUN
3.0	2025/12/03	Last revision by coordination	AID

STATEMENT ON MAINSTREAMING GENDER

The NARRATE consortium is committed to including gender and intersectionality as a transversal aspect of the project's activities. In line with EU guidelines and objectives, all partners – including the authors of this deliverable – recognise the importance of advancing gender analysis and sex-disaggregated data collection in the development of scientific research. Therefore, we commit to paying particular attention to including, monitoring, and periodically evaluating the participation of different genders in all activities developed within the project, including workshops, webinars and events but also surveys, interviews and research, in general. While applying a non-binary approach to data collection and promoting the participation of all genders in the activities, the partners will periodically reflect and inform about the limitations of their approach. Through an iterative learning process, they commit to plan and implement strategies that maximise the inclusion of more intersectional perspectives in their activities.

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How to cite this report: NARRATE (2025). D4.3(a) Production Planning & Process Routing System & algorithms (a).

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The NARRATE Consortium is the following:

Participant number	Participant organisation name	Short name	Country
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Abbreviations

AI	Artificial Intelligence
ATO	Assemble to Order
DSS	Decision Support System
DT	Digital Twin
EC	European Commission
ERP	Enterprise Resource Planning
IMC	Intelligent Manufacturing Custodian
IoT	Internet of Things
KPI	Key Performance Indicator
MaaS	Manufacturing-as-a-Service
MES	Manufacturing Execution System
MPS	Master Production Scheduling
MSx	Milestone x
MTO	Make-To-Order
MTS	Make-To-Stock
Mx	Month x
SMN	Smart Manufacturing Network
Tx.x	Task x.x
WP	Work Package

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EXECUTIVE SUMMARY

Global supply chains face unprecedented challenges due to disruptions that have exposed fundamental vulnerabilities in traditional manufacturing models. Major events such as the Fukushima nuclear disaster in 2011, the COVID-19 pandemic, and the Suez Canal blockage in 2021 caused widespread production halts, material shortages, and delivery delays that required weeks or months for recovery. These disruptions have demonstrated that conventional supply chain approaches prove inadequate when confronted with the dynamic uncertainties that characterize modern manufacturing environments.

Make-To-Order (MTO) manufacturing systems exhibit particular vulnerability to such disruptions due to their inherent operational characteristics. The NARRATE project addresses these challenges through the development of an Artificial Intelligence (AI)-driven Intelligent Manufacturing Custodian (IMC) that provides end-to-end visibility and control within Smart Manufacturing Networks (SMNs).

This deliverable, D4.3(a), presents the Production Planning System developed within Task T4.3 of Work Package 4. The system optimizes scheduling while enhancing operational efficiency, resilience, and adaptability in MTO environments. The work advances both theoretical understanding and practical implementation through the presentation of mathematical programming and prototype applications. The Production Planning Module constitutes the primary contribution to this deliverable. Advanced Master Production Scheduling (MPS) algorithms employ stochastic programming for proactive planning to mitigate disruptions. A C# Windows Forms application prototype enables real-time scheduling adjustments and integrates with Internet of Things (IoT) sensors and Digital Twins (DTs) to deliver actionable insights to production planners.

The system achieves significant operational improvements, as demonstrated through comprehensive computational experiments. The MPS algorithms reduce lost production capacity and decrease recovery time compared to traditional approaches. These improvements result from the strategic incorporation of Manufacturing-as-a-Service (MaaS) capabilities that enable dynamic replanning through alternative sourcing and external capacity utilization.

A comprehensive bibliometric analysis of 613 research papers published between 2000 and 2025 identified critical gaps in the existing literature, particularly regarding auto-adaptive Decision Support Systems (DSSs) for operational-level resilience in MTO systems. This deliverable addresses these gaps through its algorithmic developments and application prototypes, which advance the state of the art in resilient production planning.

The methodology integrates advanced optimization techniques with intelligent decision support mechanisms, validated through simulations that target key performance indicators such as reduced recovery time and minimized lost capacity. The C# application supports decision-making in pilot sectors that include furniture manufacturing, semiconductor production, and additive manufacturing through 3D printing. This work contributes directly to European Union objectives for digital transformation and green transition in manufacturing industries.

The deliverable builds upon and extends previous NARRATE outputs, including D3.3 (SMN Knowledge Model using a Neuro-symbolic Decision Support System), D4.2(a) (End-to-end AI-driven visibility model and support DSS), and D3.2 (Digital Twin design and development), to ensure comprehensive orchestration within the SMN framework.

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1. INTRODUCTION

This deliverable sets out the foundations for an intelligent, prescriptive Decision-Support System-DSS- for production planning and process routing within resilient, sustainable manufacturing networks. Focusing on Task 4.3 of Work Package 4, it outlines the contextual framework, core concepts, and baseline decision models that will inform subsequent algorithmic development and integration. As an initial report (D4.3(a)), it captures the current state of thinking, methodological choices, and early contributions that steer the path toward adaptive, threat-aware planning capabilities aligned with NARRATE's vision.

To connect these goals to the broader initiative and to the practical scope of this deliverable, the introduction proceeds in four steps. First, Background and Motivation clarify the industrial and scientific drivers—uncertainty, supply chain disruptions, and sustainability pressures—that necessitate resilient planning. Second, NARRATE Context and Objectives positions this work within the Horizon Europe–funded NARRATE initiative, explaining how regenerative, smart manufacturing networks enable self-adaptation and robustness. Third, Deliverable Scope and Objectives delineate what D4.3(a) covers now (frameworks, decision models, preliminary methods, activity planning) and what is reserved for later deliverables. Finally, Document Structure guides the reader through the organization of the report, ensuring a coherent link from context and methodology to progress and next steps.

1.1. BACKGROUND AND MOTIVATION

Traditional production planning approaches typically assume deterministic environments where capacity, demand, and supply chain parameters are known with certainty. However, real-world manufacturing faces significant uncertainties. Supply chain disruptions include supplier delays, quality issues, and logistic bottlenecks. Equipment reliability concerns encompass machine breakdowns, maintenance requirements, and performance variability. Demand volatility manifests through order cancellations, urgent rush orders, and forecast inaccuracy. Resource availability challenges involve labor shortages, material stockouts, and capacity constraints.

These uncertainties can render deterministic schedules infeasible. They force production planners into reactive firefighting mode with expensive corrective actions such as expedited shipment, overtime production, or use of premium alternative suppliers. This reactive approach leads to higher costs, lower service levels, and increased operational stress.

1.2. NARRATE CONTEXT AND OBJECTIVES

The NARRATE project aims to develop Digital Twins (DT) and AI-driven decision support tools that enhance manufacturing resilience. The project addresses the critical challenge of maintaining operational continuity in SMNs when they face disruptions, uncertainties, and rapidly changing conditions.

T4.3 will deliver an AI-enabled production planning & process routing system as extension of the neuro-symbolic DSS in T4.2 that covers the scope of the SMN ecosystem to optimize production schedules and enhance the ability of an SMN to

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incorporate & resolve disruptions from the confirmation of the order up to the delivery of the product. T4.3 will:

1. Enhance the neuro-symbolic DSS model in T3.3 to (re-)adjust production plans and/or process routings by leveraging input from T4.1 and T4.2. It will:
    - Gather historical and real-time production data, including demand forecasts, capacity utilization, and process flow data using the digital twin model of the SMN in T3.2.
    - Use machine learning algorithms to identify patterns and trends in the data.
    - Develop predictive models to forecast demand, production capacity, and resource utilization.
    - Develop a predictive analytics engine to identify potential disruptions and recommend proactive measures to mitigate risks relying on the dynamic simulation scenarios developed in T4.1.
2. To ensure comprehensive coverage, the extended DSS should incorporate the combined SMN knowledge models outlined in T4.2 and identified criteria of the impact analysis and resilience modelling.
3. Risk mitigation: using dynamic SMN segmentation by categorizing different products, customers, suppliers, and channels based on their characteristics and requirements to improve the preliminary mitigation plans in T4.1 by identifying areas that are most vulnerable to disruptions and develop final plans to mitigate those risks.
4. Intelligent algorithm development: T4.3 will develop AI-driven model to dynamically allocate resources and minimize production bottlenecks using all information from production nodes (from WP3 and T4.2) to readjust initial plans dynamically based on real-time data inputs & results from steps-1 & 2.

1.3. DELIVERABLE SCOPE AND OBJECTIVES

This deliverable presents the theoretical foundations, algorithmic developments, software implementation, and validation results for the production planning system.

Our theoretical objectives include the development of mathematical models for MPS that explicitly consider disruption scenarios. We formulate a two-stage stochastic programming framework with recourse actions. While our algorithmic objectives involve the implementation of exact solution methods, our application objectives encompass the design and development of a user-friendly DSS. We implement visualization capabilities and integrate optimization engines with intuitive interfaces. Our validation objectives include computational experiments across diverse problem instances.

1.4. DOCUMENT STRUCTURE

Section 2 establishes the overall context of the study. It discusses the complexity of production planning activities, reviews the relevant literature, identifies the main research gaps, and formulates the research questions that guide this work.

Section 3 describes the methodology, including the business understanding phase, the presentation of the mathematical programming approach, the application development process, and the strategies for integrating AI into the decision-support system.

Section 4 reports the progress and contributions of the work by presenting the user interface, the system functionalities, and the experimental validation results.

Section 5 summarizes the main achievements and reflects on their scientific and practical impact.

Section 6 outlines the next steps, with a particular focus on integration with the NARRATE platform.

2. CONTEXT AND COMPLEXITY OF PRODUCTION PLANNING

Manufacturing firms operate in complex, uncertain environments where production plans must balance cost, service levels, due-date adherence, and resource utilization under tight constraints and frequent disruptions. To manage these trade-offs, production planning is typically organized as a multi-level, sequential process spanning aggregate planning, the MPS, and detailed operations planning and scheduling.

At the top level, management sets aggregate targets for production, inventory, and labor to meet variable demand—an exercise formalized as aggregate production planning. The resulting aggregate plan provides guidance for the MPS, which translates those targets into time-phased, item-specific commitments. Master schedulers use these targets as benchmarks, yet deviations can arise due to constraints such as capacity shortages at critical work centers. Feedback from actual MPS performance is then used to adjust future aggregate plans, closing the loop between tactical execution and strategic planning.

For the MPS to be viable, it must respect resource constraints at essential operations via resource requirements planning, often referred to as rough-cut capacity planning. When infeasibilities are detected, the master schedule should be revised to reflect capacity limits, which may in turn require changes to long-term capacity plans or the aggregate plan itself. Once feasibility is confirmed, the accepted plan is released as an authorized master schedule and subsequently exploded into detailed schedules using systems such as MRP (Chung & Krajewski, 1984). The overall production planning process is illustrated in Fig. 1.

This section maps the terrain and narrows the focus from broad challenges to the specific leverage point we target. Subsection 2.1 analyzes why production planning is inherently complex (i.e., multi-objective, capacity-constrained, and disruption-prone) and highlights the implications for decision layers. Subsection 2.2 reviews the literature to position current practice and research across aggregate planning, MPS, and detailed scheduling. Subsection 2.3 then identifies the research gaps and justifies our emphasis on the MPS as a cross-environmental control point for resilience. Finally, Subsection 2.4 formalizes the problem statement and research questions that guide the remainder of the work.

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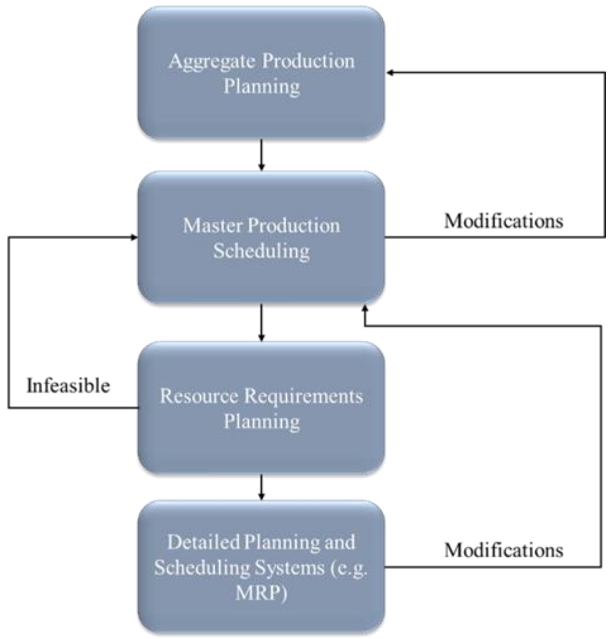

FIGURE 1 Production planning process (Chung & Krajewski, 1984)

2.1. COMPLEXITY IN PRODUCTION PLANNING ACTIVITIES

Production planning, especially at the MPS level, is one of the most complex decision-making challenges in manufacturing management. This complexity comes from the need to satisfy multiple, interrelated constraints simultaneously.

Capacity limits the number of orders that can run on production lines, the use of specific workstations or tools, and the consumption of energy and utilities. Supply chain factors include supplier capacity, lead times, reliability, and transportation limits. Product-specific constraints involve shared resources, sequence-dependent setups, quality requirements, and batch sizes. Temporal aspects add further difficulty, with due dates, seasonal variations, and maintenance schedules all influencing production.

These constraints interact dynamically and delays or disruptions in one area often cascade across the entire system. For example, a supplier delay can disrupt component availability, production sequencing, and delivery performance.

Uncertainty adds another layer of complexity. Supplier-related issues cause most supply chain disruptions, often due to quality problems, transport delays, capacity shortages, or complete shutdowns. Even with confirmed orders, demand uncertainty persists through cancellations, rush orders, or forecast errors. Equipment reliability is another major concern: machine failures and maintenance reduce effective capacity and frequently disrupt schedules.

Production planning must also balance multiple objectives: minimizing costs (labor, materials, penalties, and expedite fees), maximizing service levels (on-time delivery, responsiveness), optimizing resource use, and ensuring robustness against disruptions. Achieving this balance requires advanced DSSs capable of analyzing trade-offs and running "what-if" scenarios.

From a computational standpoint, production planning is NP-hard, even simplified cases are difficult to solve optimally. As the number of orders, resources, and constraints grows, the problem becomes exponentially harder. Moreover, planning is

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continuous: new orders, disruptions, and changing capacities require frequent re-optimization.

Finally, effective planning depends on integrating diverse data sources, including Enterprise Resource Planning (ERP) systems for orders and inventory, Manufacturing Execution System (MES) for real-time production data, supplier portals for capacity and delivery, maintenance systems for equipment status, and quality systems for defect tracking.

2.2. LITERATURE REVIEW

In the framework of production planning and control systems, the MPS is an essential component. As a high-level, time-phased plan, it specifies in detail the amount of each finished product that will be manufactured during a certain period of planning (Proud, 2012). The MPS plays a critical role in driving the entire production process, connecting the company's strategic goals with the tactical execution of operational tasks. To maximize allocation of resources, efficiently meet customer demands, and guarantee profitability, its precision and effectiveness are of the greatest significance (Thomas et al., 2008). To maximize efficiency, reduce waste, and guarantee customer satisfaction, the MPS is more than just a schedule. A thorough understanding of demand forecasts, production capacity, and supply chain dynamics are among the many elements that must be considered during its development and execution. To ensure a coordinated and effective manufacturing process, it is essential to have a well-defined MPS as the basis for all subsequent planning activities.

Due to the inherent complexity of real-world production environments, traditional MPS approaches often fail to deliver satisfactory results. Rarely, if ever, does reality conform to the idealized picture of infinite capacity and deterministic demand (Körpeoğlu, 2009). Traditional MPS systems are significantly limited in their effectiveness due to unpredictable demand patterns and supply chain disruptions (including natural catastrophes, pandemics, geopolitical instability, and supplier failures) (Serrano-Ruiz et al., 2021; Taghavi et al., 2024). Particular difficulties in MPS are caused by two key factors:

1. **Demand Uncertainty:** A major cause of instability in traditional MPS systems is inaccurate demand predictions (Atadeniz & Sridharan, 2020). There can be large gaps between anticipated and actual demand due to the inherent unpredictability of customer demand, which is worsened by variables including seasonality, economic volatility, and unexpected market events (Englberger et al., 2016). The inefficiencies in manufacturing, increased costs for keeping inventory, and missed deadlines for delivery could be the outcome of schedule modifications caused by these differences (Atadeniz & Sridharan, 2020). In Make-To-Stock (MTS) settings, production is dependent on forecasts instead of specific customer orders, which increases the effect of demand uncertainty (Amaranti et al., 2020). Several studies have looked at how inaccurate demand forecasts affect MPS performance (Ho & Ireland, 1993). So, so it is clear that we need better approaches and strategies for forecasting to lessen the impact of inaccurate predictions.
2. **Supply Chain Disruptions:** A major risk to the feasibility and responsiveness of MPS systems are disruptions in the supply chain, which include issues like supplier failures, transportation delays, and material shortages (Serrano-Ruiz et al., 2021; Taghavi et al., 2024). Any one of these disruptions, from small-scale local incidents to massive worldwide disasters, has the power to significantly impact the accessibility of

essential supplies and delay manufacturing schedules (Taghavi et al., 2024). The COVID-19 pandemic's broad impacts show that supply chains are becoming more at risk due to increasing globalization (Serrano-Ruiz et al., 2021). The resilience of an MPS system can be measured by its ability to withstand and adjust to various disruptions. Supplier diversification, effective inventory management, and backup planning are ways to lessen the impact of supply chain disruptions (Taghavi et al., 2024). There has to be MPS systems that can change with current circumstances and keep operations running even when unforeseen events happen, since supply chain resilience is becoming increasingly vital.

Several approaches used to make MPS systems more resilient are discussed in this subsection. The goal of these methods is to make the system more effective in handling unforeseen events by making it more resilient, adaptable, and able to recover from disruptions. This will allow the system to continuously meet customer demands, even when faced with uncertainty.

1. **Robust Optimization:** The goal of robust optimization methods is to develop MPS models with less sensitivity to changes in demand and lead times and other input parameters. The objective of these methods is to discover solutions that are still practical and almost optimal when the input parameters' actual values differ from their predicted values. One common component of robust optimization methods is the incorporation of uncertainty sets, which specifies the range of values that the uncertain parameters can take on. The next step is to optimize the MPS solution so that it is feasible and almost optimal across all the uncertainties. By strengthening the MPS's resilience in the face of uncertainty, this method lessens the impact of inaccurate forecasts and disruptions in the supply chain. Adjustable robust optimization and distributionally robust optimization are two examples of robust optimization methods that provide various levels of computational complexity (Englberger et al., 2016).
2. **Stochastic Programming:** When optimizing MPS, stochastic programming considers the probability of various demand scenarios by incorporating uncertainty models. Stochastic programming considers the fact that demand, lead times, and other input parameters are inherently random, as opposed to deterministic models that use a single point estimate for uncertain parameters. As a result, it is possible to create MPS solutions that either maximize the objective function's expected value or minimize the probability of unfavorable events (Englberger et al., 2016; Körpeoğlu, 2009). One popular method is two-stage stochastic programming, which entails making initial decisions and then taking recourse actions to reduce the effect of actual uncertainty (Englberger et al., 2016). To strengthen MPS resilience, this method offers a framework for incorporating proactive and reactive approaches.
3. **Supply Chain Risk Management:** Implementing steps to detect and lessen the impact of any supply chain disruptions is the core of proactive risk management in the supply chain. To achieve this goal, it may be necessary to invest in supply chain visibility tools, diversify resources, or build backup plans. Supply chain risk management makes the MPS system more resilient and less susceptible to disruptions by identifying and addressing possible problems in advance. All parties involved in the supply chain, from suppliers to manufacturers to customers, must work together closely to implement this integrated strategy (Taghavi et al., 2024). To build a strong and flexible MPS system that can handle the unknowns of the modern world, it is crucial to implement effective risk management strategies throughout the supply chain.

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As a conclusion, there is a need of advancement in developing resilient MPS strategies. The creation of MPS systems that can withstand and adapt to the uncertainties of the modern, ever-changing global environment requires the integration of optimization algorithms, advanced modeling approaches, and supply chain risk management practices.

Fig. 2 highlights the interconnectedness of key terms, forming distinct clusters that reflect dominant research themes. The most prominent cluster centers on AI and simulation (the blue cluster), linking terms such as "machine learning, "digital twin", and "simulation" to "scheduling" and "production planning." This cluster underscores the growing reliance on AI-driven tools to model dynamic production environments and optimize decision-making. For instance, DTs are depicted as critical enablers of real-time scenario testing, allowing researchers to simulate disruptions and refine scheduling strategies. A second cluster focuses on resilience and risk management (the green cluster), associating terms like "robust optimization," "stochastic programming," and "uncertainty" with challenges such as the "lot-sizing problem" and "make-to-order" systems. These linkages emphasize the integration of advanced optimization techniques to address variability in demand. A third cluster highlights traditional optimization methods (the red cluster), including "genetic algorithms" and "heuristics", which remain relevant for solving large-scale problems like "aggregate production planning."

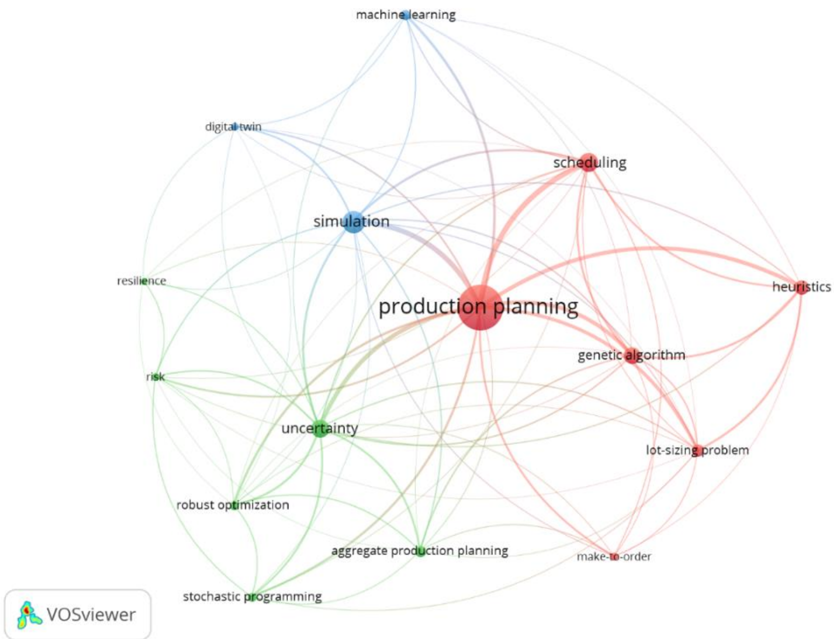

FIGURE 2 Vosviewer keyword co-occurrence network for resilient MPS

2.3. RESEARCH GAPS

Resilience research in manufacturing has largely concentrated on strategic-level levers—network redesign, multiple sourcing, capacity redundancy, and long-horizon inventory policies—while giving comparatively limited attention to operational and tactical mechanisms where disruptions are absorbed. This imbalance matters: strategic initiatives often require significant capital and long lead times, making them inaccessible or slow to effect for many firms. In contrast, short-term disturbances—supplier delays, quality spillovers, demand surges, and labor outages—accumulate to erode service levels and costs. The most immediate lever to counter these effects is the periodic readjustment of production plans. Among planning layers, the MPS occupies a pivotal position: it translates aggregate plans into time-phased, item-level commitments and propagates feasibility (or infeasibility) downstream to material planning and upstream to aggregate decisions via feedback loops.

Focusing on the MPS is also justified by its universality and leverage across different production environments. Whether in make-to-stock (MTS), assemble-to-order (ATO), or make-to-order (MTO) settings, an MPS or its functional equivalent exists to synchronize demand, capacity, and material availability over a medium-term horizon. While detailed scheduling is highly plant- and process-specific—sensitive to routing structures, dispatching rules, and equipment characteristics that vary widely across industries—the MPS layer provides a more generalizable control point. Crucially, the full spectrum of uncertainties originating from markets (demand volatility, cancellations), suppliers (lead-time variability, partial deliveries), and internal systems (availability, and changeover variability) first manifest as pressure on the MPS. Robust and adaptive MPS policies can therefore buffer, absorb, or reallocate this pressure before it cascades into costly expedited actions or chronic schedule instability.

Literature reflects this gap and opportunity. Reviews consistently note a disproportionate emphasis on network- and inventory-centric resilience strategies, with relatively scant exploration of resilient MPS design, re-planning triggers, rough-cut capacity checks under disruption, and data-driven override rules for demand and supply shocks. This leaves open questions central to NARRATE's aims: how to formalize disruption-aware MPS objectives (e.g., tardiness/earliness penalties, subcontracting and reserved supplier's costs) under heterogeneous uncertainty? How to calibrate re-planning frequency and horizons to balance nervousness against responsiveness? And how to embed capacity-feasibility checks that remain lightweight yet accurate enough for rapid re-commitment?

Addressing these gaps promises high impact: MPS decisions are common across industries, implementable without prohibitive capital expenditure, and decisive in shaping downstream feasibility and upstream resilience signals—making them the most effective focal point for operational and tactical resilience within production planning.

The theoretical gaps identified through the conducted literature review are systematically outlined as follows:

- MPS has been predominantly examined in MTS environments, with limited attention to MTO systems. Crucially, the few studies addressing MTO contexts have overlooked inherent uncertainties that are intrinsic to MTO operations. Furthermore, Fig. 3 reveals an absence of conceptual linkages between "make-to-order" frameworks and "resilience" in the literature, underscoring a critical oversight given the heightened vulnerability of MTO systems to disruptions.
- Resilience research has disproportionately emphasized strategic-level planning, with scant exploration of operational and tactical resilience mechanisms. This imbalance is problematic, as strategic resilience initiatives often entail substantial capital investments, rendering them economically prohibitive for many industries. Conversely, operational, and tactical resilience strategies target frequent, short-term disruptions that, while individually less severe, cumulatively erode system performance. Prioritizing operational resilience aligns with industrial stakeholders' pragmatic focus on mitigating recurring, manageable disruptions without incurring prohibitive costs.

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- Few studies have explicitly examined resilience within the context of MPS. This represents a significant oversight, as these domains are pivotal for maintaining production continuity amid disruptions.
- Current DSSs often utilize ML techniques for predictive tasks or stochastic methods for risk management. A pressing need exists for hybrid frameworks that synergize ML's predictive capabilities with stochastic optimization to balance accuracy and robustness and prescribe decisions.
  - There is a deficiency of research addressing two key intelligence dimensions of DSSs: knowledge-driven reasoning (e.g., integrating domain expertise with data-driven insights) and explainability (e.g., transparent algorithmic decision logic). These gaps hinder the adoption of DSSs in industrial settings, where interpretability and contextual adaptability are paramount.
  - To the best of our knowledge, no studies have investigated MaaS (a paradigm emphasizing on-demand, scalable manufacturing resources) as a resilience strategy in MPS problem. This represents a missed opportunity, as MaaS could theoretically enhance flexibility and redundancy in production networks.

Collectively, these gaps reveal a fragmented understanding of resilience in production systems, particularly at operational levels and in MTO contexts. The absence of probabilistic disruption modeling, coupled with underdeveloped hybrid DSS architectures, constrains the ability to preempt and mitigate cascading disruptions. Addressing these gaps necessitates interdisciplinary research integrating advanced analytics, prescriptive optimization, and domain-specific resilience frameworks.

2.4. RESEARCH QUESTIONS AND OBJECTIVES

Based on the identified gaps, this work pursues a single objective: How can manufacturing organizations plan an MPS under uncertainty while they consider multiple constraint types and disruption sources, rely on computationally tractable optimization methods, and embed these methods in user-friendly DSSs? The objective spans three dimensions. **Model:** a formal representation that captures problem complexity with multiple constraints, disruption classes, and explicit recourse actions. **Algorithms:** solution methods that scale to realistic instances and return results within operational time limits. **Application:** a deployable tool that planners can use effectively without advanced programming or modeling skills.

To operationalize these dimensions, the IMC serves as the central coordination and decision-routing layer of the decision support architecture. It acts as the "brain" that connects user requests with the appropriate analytical modules and ensures consistent data exchange among them. When a user submits a request—such as rescheduling after a machine breakdown or coping with a supplier delay—the IMC authenticates the user, validates the request, and retrieves relevant data (e.g., the affected line's capacity, current WIP, and pending orders) from the digital blueprints. Requests may encompass internal disruptions, external disruptions, or both; accordingly, they are routed to the production planning module (T4.3), the reconfiguration module (T4.5), or a coordinated workflow involving both, as appropriate.

The module(s) involved compute feasible alternatives (e.g., shifting orders to another period, reallocating capacity, or outsourcing to MaaS providers) and return

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candidate solutions to the IMC. The IMC performs cross-module consistency checks against material availability and operational policies, reconciles potential overlaps between alternatives, and records the resulting decision set in the system log. Finally, it formats and returns a validated, coordinated solution to the user interface, including explanatory notes on expected effects and decision rationale.

Through this workflow, the IMC enables smooth coordination across the model, algorithm, and application dimensions. It keeps decision-making consistent, traceable, and adaptive across multiple layers of the digital decision environment, effectively bridging user intent and automated reasoning under uncertainty. The overall functionality of the IMC and its interaction with the user and analytical modules is illustrated in Fig. 3.

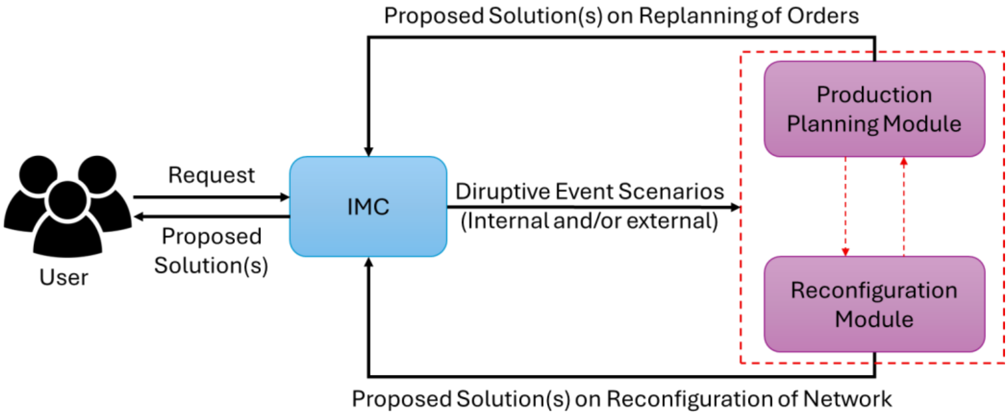

FIGURE 3 Functional structure of the IMC

We structure the investigation with four research questions:

RQ1: How can resilience-oriented strategies be systematically incorporated into operational-level decision-making frameworks to enhance adaptability during disruptions?

RQ2: How can MPS models be designed to dynamically adapt and recover swiftly when disruptions occur?

RQ3: How can the effectiveness of resilience-focused decisions be quantitatively evaluated to identify optimal strategies for maintaining system robustness and recovery?

RQ4: What approaches can be employed to enhance the intelligence and autonomy of decision-making processes, ensuring adaptive and context-aware responses to disruptions?

3. METHODOLOGY

This section describes the systematic approach we employed to address the research questions identified in Section 2.4. Our methodology encompasses four key phases: business understanding, mathematical modeling approach, application development, and AI integration.

3.1. BUSINESS UNDERSTANDING AND MODELLING

Effective production planning must match real business needs and daily work on the shop floor. We started with a clear review of the whole value chain to see how plans turn into actions at suppliers and in production. The material flow of parts and components within the manufacturing system is depicted in Fig. 4, which outlines the end-to-end progression from parts procurement to order fulfillment. The process begins with suppliers, who deliver either parts (standardized base materials) or prefabricated components to the production system. These inputs then advance to the manufacturing stage, where in-house production facilities transform supplied parts into customized components, adhering to order-specific requirements. Subsequently, all components (whether manufactured internally or sourced directly from suppliers) are routed to assemblers. At this stage, components are integrated to construct the final orders, aligning with customer order specifications. The figure highlights the interdependencies between external supply chains, internal production capabilities, and downstream assembly processes, ensuring synchronization across all stages to meet delivery commitments. We explicitly model transporters for final delivery but exclude those between suppliers and manufacturers, as suppliers retain responsibility for transporting parts/components to manufacturers. Disruptions impact suppliers, manufacturers, assemblers, or transporters, and are mitigated using a MaaS strategy comprising Supplier-as-a-Service, Manufacturer-as-a-Service, and Assembler-as-a-Service.

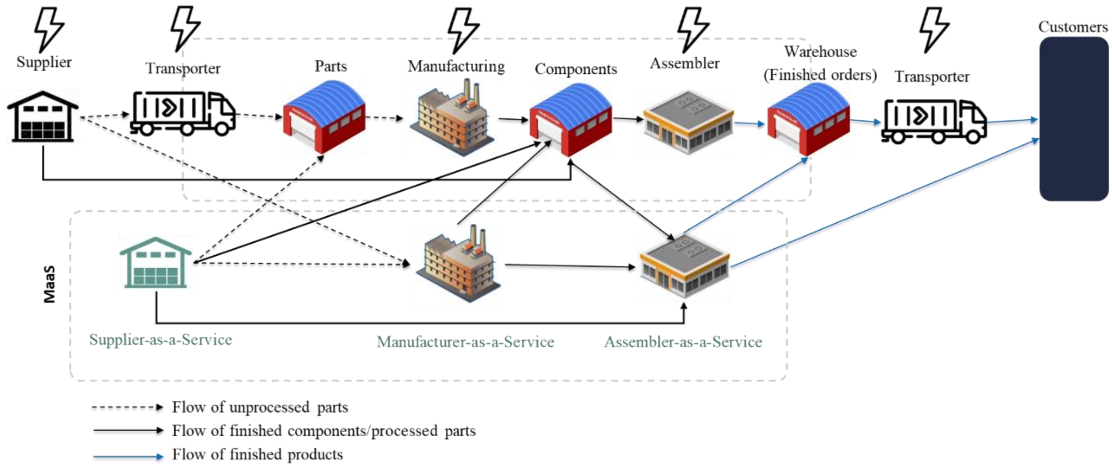

FIGURE 4 The flow of parts, components and finished orders in manufacturing process considering disruption scenarios

Central to this problem is the hierarchical structure of orders, which consist of variants, components, and parts. Variants are customer-specified configurations that define unique combinations of features within an order. These variants may individually or collectively impose constraints on the system, such as limitations tied to supplier availability or production system compatibility. In this study, these limitations caused by a variant or combination of them are called restricting characteristics. Restricting characteristics or constraints set the limits of what the plant and the supply base can deliver on time. External constraints come from outside the plant, for example a shortage of a key part, a supplier's minimum lot size, long lead time, or a transport ban. Internal constraints come from inside the plant, for example a scarce fixture, a machine with long setups that become a bottleneck, or a small team of specialists for a required test. These limits can be defined in two forms. Binary constraints say whether a needed resource exists at the right time; without the right machine, tool, or skill, the order cannot move. Capacity-based constraints set how much of a resource is available per period if total load is above the available machine hours, labor hours, or storage space, delays and backlogs follow. For example, consider a specific machine with a total available capacity of 100 units per planning period. If a particular order requires processing on this machine and consumes 4 units of its total capacity, the remaining capacity available for other orders is reduced accordingly. When the cumulative demand on the machine exceeds its capacity limit, it becomes a bottleneck, causing potential delays and scheduling conflicts. The difference between binary and capacity-based constraints can be better understood through Fig. 5.

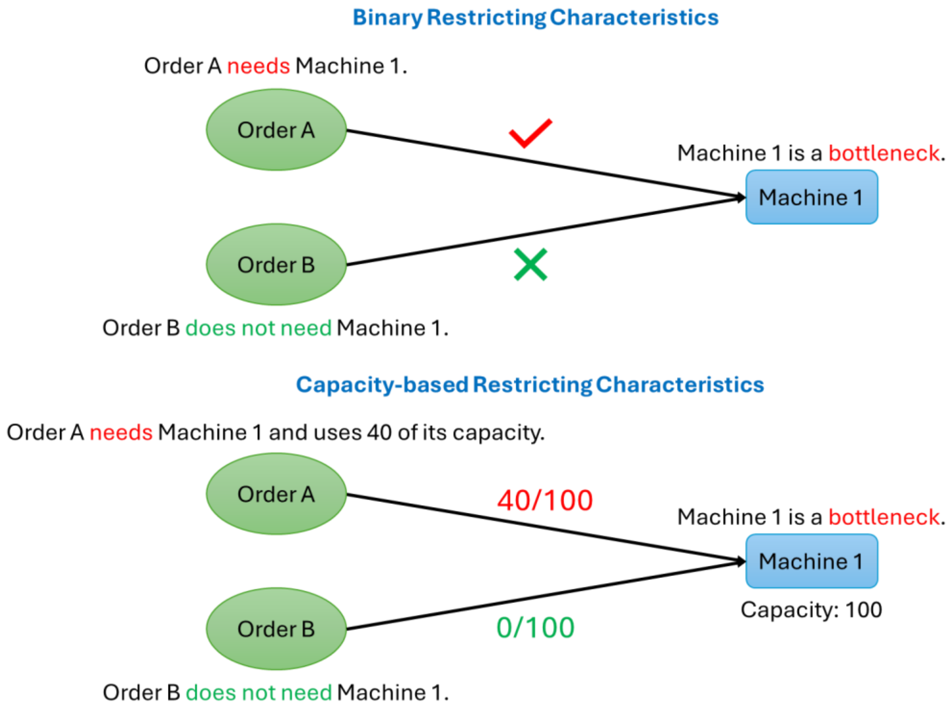

FIGURE 5 Difference between binary and capacity-based constraints

We answer these needs with a two-step flow that connects planning choices from demand to the final schedule. First comes Capacity Planning. A forecast sets demand by product family for future periods. MRP then turns that demand into time-phased component needs. The result is a supply capacity plan that sets the feasible limits for the next step. Next comes MPS in a MTO setting. MPS assigns confirmed customer orders to specific periods while it respects the internal and external limits above. MPS uses three inputs: actual order data, the supply capacity plan, and disruption data. Disruption data may be scenarios that we receive or records of events that have already happened. We therefore use two models. A proactive model uses predicted scenarios to act before a disruption. A reactive model uses realized events to respond after a disruption. Both models share the same constraints, both can move orders to other periods when needed, and both can use MaaS to cover shortfalls. Fig. 7 contrasts the proactive and reactive approaches in a clear, side-by-side view. Fig. 6 depicts the two-step flow from demand to the final schedule and clarifies how capacity planning feeds the MPS stage.

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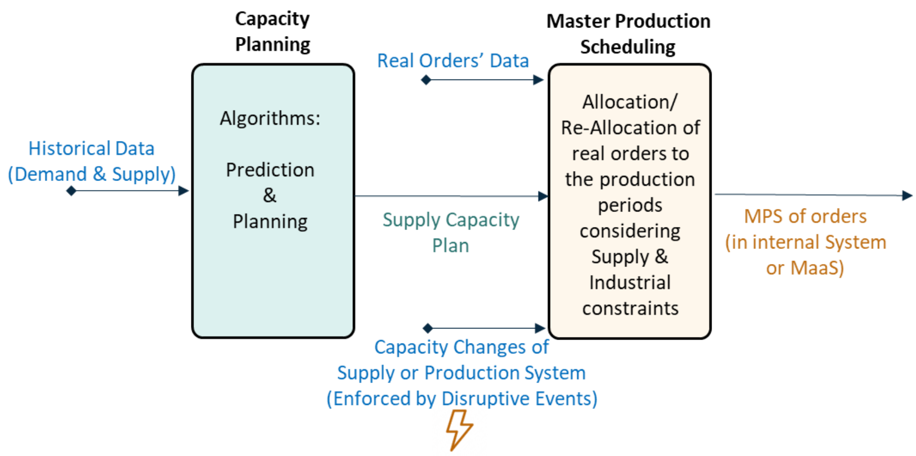

FIGURE 6 Proposed general approach for production planning

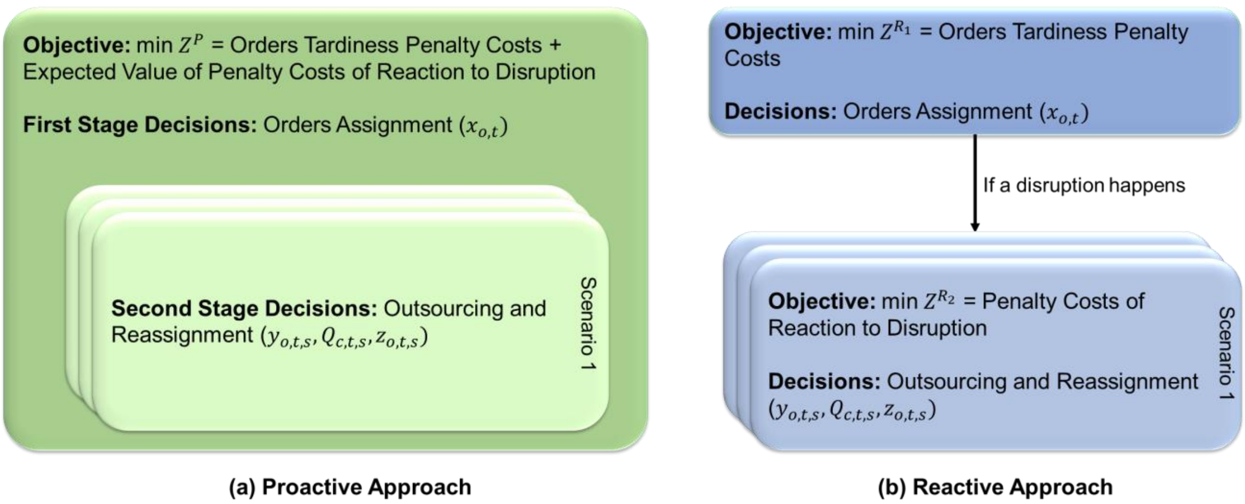

FIGURE 7 The difference between the objectives and decision variables of (a) proactive and (b) reactive approach

3.2. MATHEMATICAL MODELLING APPROACH

Mathematical models provide the foundation for optimization-based production planning. We developed comprehensive models that make key decisions while maintaining computational tractability. Mathematical programming is a branch of operations research that selects values for decision variables to maximize or minimize a stated objective subject to explicit constraints. A formulation specifies decision variables, parameters, an objective function, and a feasible region defined by equalities and inequalities; a solution is feasible if it satisfies all constraints and optimal if no other feasible solution yields a better objective value. Major classes include linear programming, mixed-integer linear programming, convex and non-convex nonlinear programming, and extensions such as stochastic and robust programs for uncertainty, as well as multi-objective variants. Solution methods range from exact algorithms (for example simplex, interior-point, branch-and-bound, branch-and-cut) to approximations and heuristics, with complexity that depends on problem structure.

Our modeling approach follows several principles. We aim for breadth to represent critical constraints and objectives relevant to real production planning. We keep tractability by formulating mixed-integer linear programs solvable by commercial solvers. The open-source solver, as well as the development of a heuristic, will be

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studied in our future work and steps. We preserve extensibility with a modular design that allows new constraints or objectives. We secure realism through validation against actual production planning scenarios. According to the formulation of the MPS model with MaaS and reserved suppliers, the notations appear in Table A1 of the appendix.

The objective is to assign orders to production periods while respecting their due dates. Assigning an order to a period before its due date generates inventory (earliness) costs, whereas assigning it to a period after its due date incurs penalty (tardiness) costs. Accordingly, the objective of the proposed mathematical model for resilient MPS is to minimize the total earliness and tardiness costs of all orders, both before and after disruptions, together with the costs of purchasing components from reserved suppliers and outsourcing orders to MaaS providers, as summarized in the equation below.

$$\begin{aligned}\min Z = {} & Earliness\ or\ Tardiness\ Penalty\ Cost\ of\ Orders\ Before\ Disruption \\ & + Probability\ of\ Disruption \\ & * (Earliness\ or\ Tardiness\ Penalty\ Cost\ of\ Orders\ After\ Disruption \\ & + Cost\ of\ Buying\ Components\ from\ Reserved\ Suppliers \\ & + Cost\ of\ Outsourcing\ Orders\ to\ MaaS\ Proividers)\end{aligned}$$

The mathematical models incorporate several key constraints. These include the capacity limits of suppliers and MaaS providers before and after disruptions, lead time constraints for components, bounds on the number of reassigned and outsourced orders, and additional constraints that govern the assignment of orders. The methodological framework and the proposed models were published in a conference paper (Belghand et al., 2025), which is provided in the Appendix.

3.3. APPLICATION DESIGN AND ARCHITECTURE

Translation of mathematical models into usable software represents a critical step. We developed the DSS for MPS as a comprehensive desktop application that embeds optimization capabilities within an intuitive user interface.

We selected development technologies based on requirements and constraints. For front-end development, we chose Windows Forms with .NET Framework for desktop UI. This platform was selected for its mature ecosystem and extensive component libraries. The standard Windows Forms controls including DataGridView were used for tabular data display and custom panels for layout organization. The interface was developed with modern flat design principles using FlatStyle controls and carefully selected color schemes. For backend development, we used C# with object-oriented design patterns to structure code into maintainable modules. For the optimization engine, we used Gurobi for commercial deployments with optimal performance.

3.4. AI INTEGRATION STRATEGY

AI techniques enhance the production planning system beyond traditional optimization by improving scenario generation, predictive analytics, and decision support. Through AI integration, planners can better anticipate disruptions, evaluate their impacts, and make more informed, proactive decisions.

The system enables users to simulate various disruption scenarios, such as supplier delays or capacity reductions, and observe their effects on production performance. By exploring these "what-if" scenarios, planners can test alternative responses and identify effective recovery strategies.

Moreover, the system provides guidance through AI-suggested thresholds for reacting to disruptions. For example, when a disruption remains within a low-impact range, it can be managed through simple replanning; at a higher threshold, reconfiguration of resources may be required; and beyond a critical point, changing suppliers becomes necessary. These thresholds help users prioritize actions and maintain resilience under uncertainty.

An AI-driven monitoring module continuously tracks supplier performance and capacity utilization. It issues alerts when potential risks are detected (for instance, when a supplier's available capacity is approaching its limit) allowing planners to act before the issue escalates.

Finally, explainable AI techniques are applied to improve transparency. Production planners need to understand the reasoning behind system recommendations. For example, the system can explain that order X is scheduled in period 5 primarily due to supplier lead time constraints, secondarily due to limited production capacity in earlier periods, and to a lesser extent because of product family restrictions. This interpretability increases trust and supports informed human oversight.

4. PROGRESS IN CONTRIBUTIONS

This section presents the main contributions of this work across two dimensions: user interface and application, and mathematical models' validation.

4.1. USER INTERFACE IMPLEMENTATION

The DSS for MPS provides a comprehensive user interface that makes sophisticated optimization accessible to production planners. This section presents key interface elements based on the actual forms we developed.

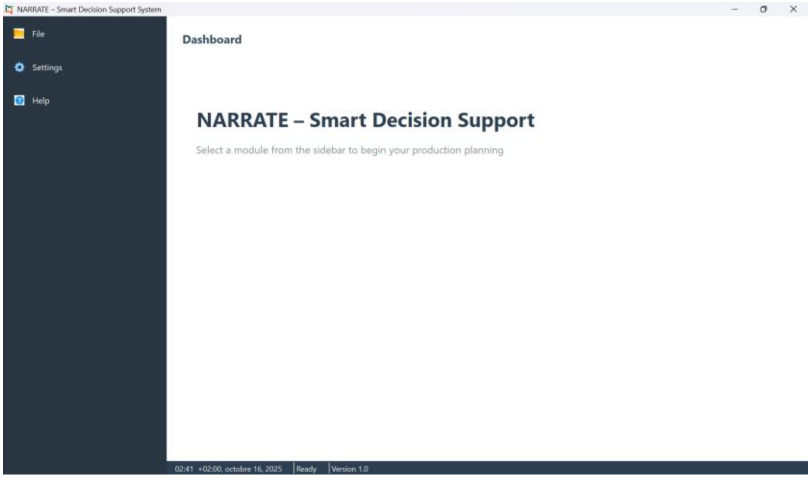

FIGURE 8 The main container form of the application

The main container form provides the application shell with sidebar navigation system. The left sidebar contains the NARRATE branding at the top. Navigation buttons are organized into logical sections, including MPS Planning and Settings. When users click a navigation button, the corresponding child form loads in the main content area. The interface provides seamless integration where all modules appear as part of a single cohesive application.

In the first step of development, we use CSV files that users import to the application but later, the application will be connected to the Blueprint Management System (BMS) developed in WP3 and directly receive the data. When the user imports data related to orders, capacities, characteristics, product families, industrial calendar, and disruption scenarios, the form containing the production schedule overview will be shown. It contains a data grid that shows the capacity, number of assigned orders, and number of characteristics used in each period. For the non-slotted orders, we have their due date, product family, and component lead time.

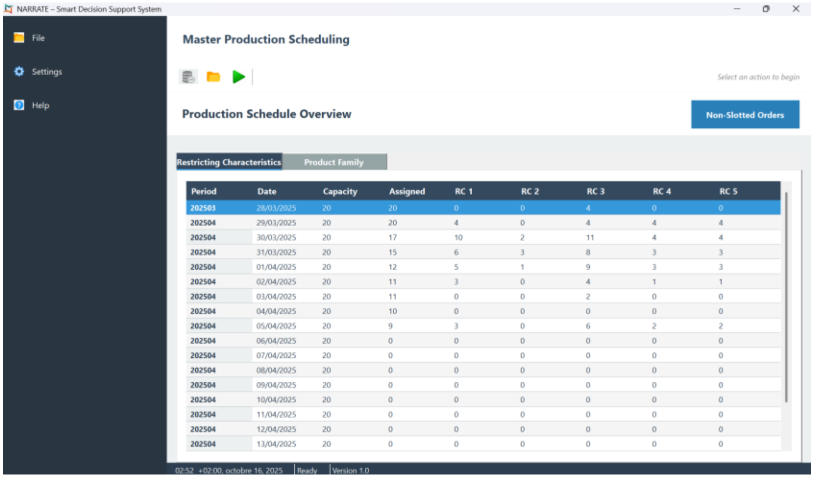

FIGURE 9 The main container form showing production schedule overview

The scenario management form is used to define and organize disruption scenarios. Each scenario is characterized by three main attributes: impact, duration, and probability. To verify the correctness of the mathematical models and validate their performance, several disruption scenarios were generated. These scenarios were inspired by data from the NARRATE pilots and focus on the most relevant uncertainties, namely disruptions affecting suppliers and the manufacturing system. A data grid lists the individual disruptions, including the affected entity, time periods, capacity reductions, and associated probabilities. Users can activate or deactivate scenarios via checkboxes, thereby controlling which scenarios are included in the optimization. In future versions, users will be able to adjust key parameters of disruption scenarios, such as the percentage of capacity loss, disruption duration, and occurrence probability, or create entirely new disruption scenarios tailored to their specific needs.

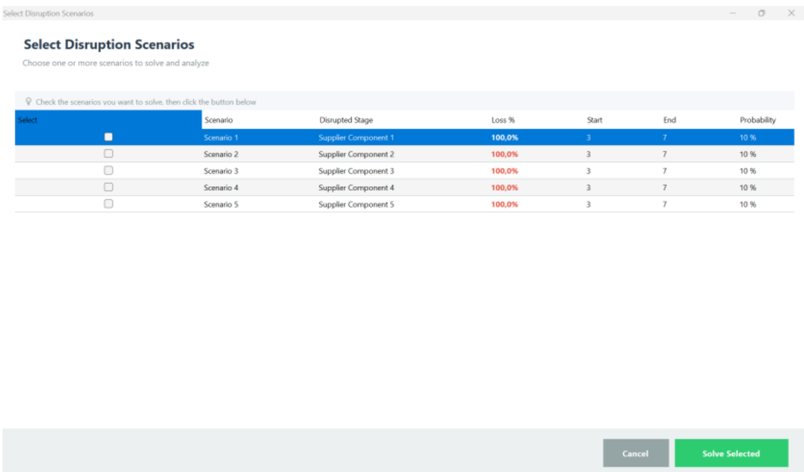

FIGURE 10 Scenario management form of the application

The results analysis form presents optimization outcomes through multiple perspectives. A summary tab displays key performance metrics including total cost, initial cost, reaction cost, lost capacity, recovery time, and number of outsourced orders in each disruption scenario. A data grid shows the capacity, number of assigned orders, and number of restricting characteristics used in each period after a disruption scenario.

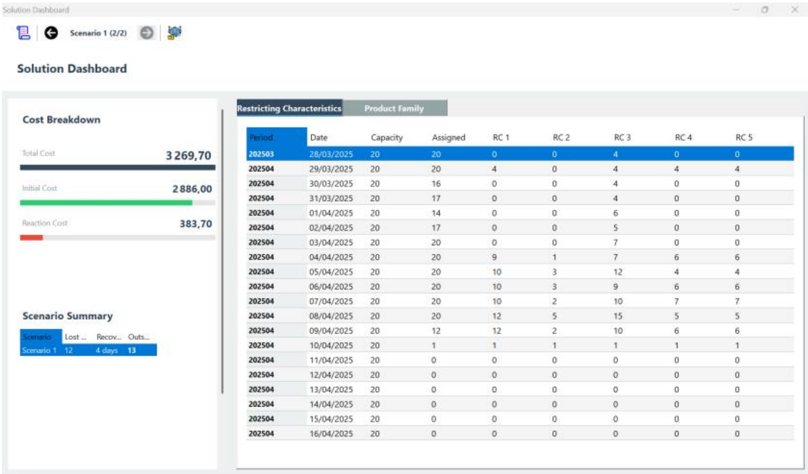

FIGURE 11 Solution analysis form of the application

4.2. MATHEMATICAL MODEL VALIDATION

In this section, numerical experiments are conducted to evaluate and compare the proactive and reactive approaches for the resilient MPS problem. Since real pilot data were not yet available at the time of testing, synthetic instances were generated based on the characteristics of the pilot datasets. In the upcoming deliverable D4.8(b), real experiments will be carried out using actual pilot data, and the developed application will be implemented and validated in these cases.

4.2.1. Instance Generation

The instances are labelled using the format Ins*-N*-S*M. For example, instance Ins12-N3-S1M indicates that it is instance number 12 and includes 3 disruption scenarios. In scenario 1, a disruption occurs affecting supplier 1. In scenario 2, the disruption impacts the manufacturing system. In scenario 3, both supplier 1 and the manufacturing system experience disruptions simultaneously. Disruptions have three critical dimensions: impact, likelihood, and duration. Table A2 provides information about these dimensions of disruptions for each instance.

4.2.2. Computational Results

All 12 instances presented in Table A2 were computed using the MIP approach for both proactive and reactive strategies. Table A3 and Table A4 show the computational results, including initial earliness/tardiness cost, disruption cost, lost capacity, recovery time, number of reassigned orders, and number of outsourced orders (MaaS) for proactive and reactive approaches, respectively. The initial earliness/tardiness cost refers to the penalty cost for orders' earliness/tardiness. The disruption cost encompasses the expected penalty cost for orders' earliness/tardiness post-disruption, the cost of purchasing components from reserved suppliers, and the cost of outsourcing orders to MaaS providers. Lost capacity represents the difference

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between the production capacity before and after the disruption, while recovery time is the duration needed to return to the initial state. Note that lost capacity and recovery time are calculated only during the disruption period.

According to the results shown in Table A3, Table A4, and Fig. 12, the initial earliness/tardiness cost of the proactive approach is equal to or higher than that of the reactive approach. This is because the reactive approach does not consider disruption risks and assigns orders optimally, resulting in a consistent initial earliness/tardiness cost across all instances. In contrast, the proactive approach considers the probabilities of disruptions when assigning orders, leading to suboptimal assignments in some cases and consequently higher initial earliness/tardiness costs. However, as illustrated in Fig. 13, the disruption costs in the proactive approach are generally lower than in the reactive approach. These two diagrams demonstrate that although the proactive approach may incur higher initial earliness/tardiness costs due to suboptimal order assignments, it effectively reduces disruption-related costs by accounting for disruption risks from the outset.

As explained in Table A2, the first five disruptions pertain to suppliers, allowing for a comparison to understand the impact of each supplier. Fig. 13 demonstrates that disruptions involving suppliers 1 and 3 have a greater impact on disruption costs compared to disruptions involving suppliers 2, 4, and 5. Consequently, ranking the suppliers based on the cost impact of disruptions, suppliers 3, 1, 5, 4, and 2 have the most to least impact, respectively.

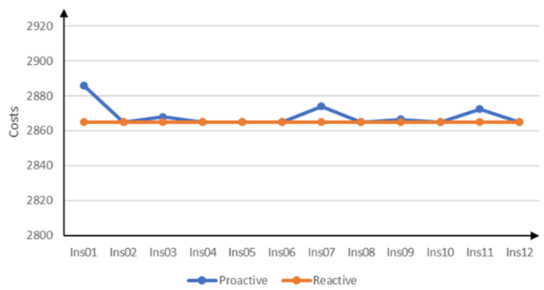

FIGURE 12 The initial earliness/tardiness costs difference between proactive and reactive approach

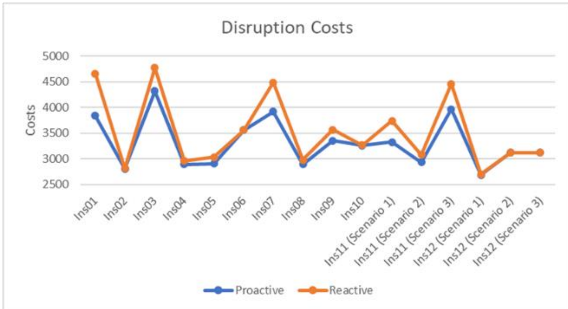

FIGURE 13 The disruption costs difference between proactive and reactive approach

As shown in Fig. 14 and Fig. 15, the lost capacity and recovery time are generally the same in both approaches. In some cases, however, the lost capacity and recovery time are lower in the proactive approach compared to the reactive approach. Differences in lost capacity and recovery time between the two approaches occur when disruptions affect the suppliers. This indicates that disruptions impacting suppliers have a greater effect on lost capacity and recovery time than those affecting the manufacturing system. Additionally, Fig. 16 shows that the number of outsourced orders is generally higher in the reactive approach compared to the proactive approach. This indicates that, due to the lack of disruption risk consideration in the reactive approach, it is necessary to employ the MaaS strategy to mitigate lost capacity, which in turn increases the overall costs.

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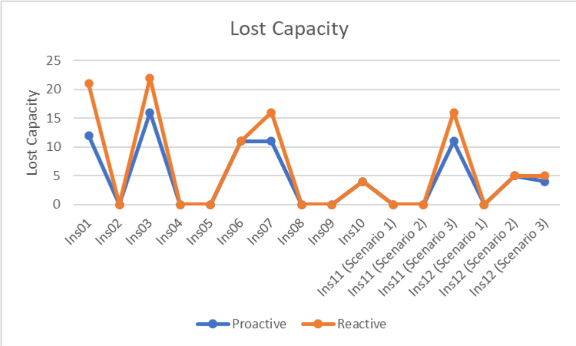

FIGURE 14 The lost capacity difference between proactive and reactive approach

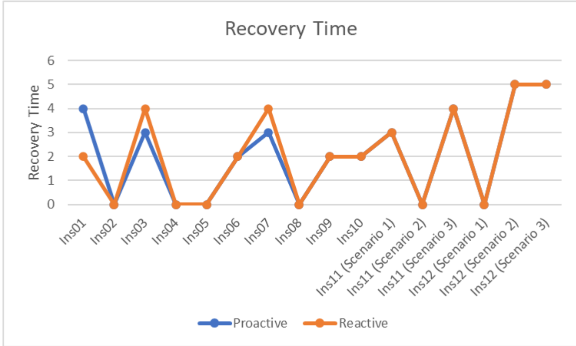

FIGURE 15 The recovery time difference between proactive and reactive approach

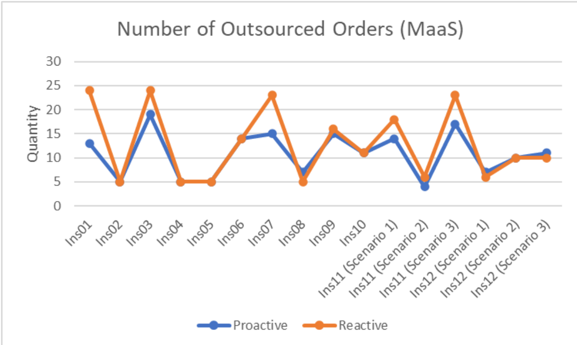

FIGURE 16 The number of outsourced orders (maas) difference between proactive and reactive approach

Based on the described figures and Table A5, it can be understood that, although the initial earliness/tardiness cost of assigning orders to periods is slightly higher in the proactive approach than in the reactive approach (due to the proactive approach not yielding the optimal schedule initially), the disruption costs are lower in the proactive approach. This is because the proactive approach considers the probability of disruptions when assigning orders. Consequently, when a disruption occurs, fewer adjustments are necessary compared to the reactive approach, resulting in lower expected orders' earliness/tardiness penalty costs. Additionally, the penalty cost for outsourced orders is lower in the proactive approach because there are fewer outsourced orders. However, the cost of supplying components from reserved suppliers is the same in both approaches. It is also evident that the number of reassigned orders has reached its limit in both approaches. Furthermore, the lost capacity in the proactive approach is less than in the reactive approach, and the recovery time is shorter in the proactive approach.

5. CONCLUSIONS

This deliverable presents a comprehensive production planning system developed within Task 4.3 of the NARRATE project. We conclude by summarizing key achievements and discussing broader impact.

5.1. SUMMARY OF KEY ACHIEVEMENTS

We accomplished the main objectives established at the project's outset. First, we developed comprehensive mathematical models for MPS under disruption

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uncertainty. Our two-stage stochastic programming framework integrates multiple constraint types including production line, supplier, and product family capacities. The framework explicitly models disruption scenarios with optimized recourse actions through MaaS and reserved suppliers.

Second, we developed DSS for MPS with an intuitive user interface. The application provides comprehensive functionality for order management, capacity configuration, scenario management, and optimization execution. The visualization tools enable users to understand and validate schedules through clear presentation of capacity utilization and performance metrics. The system will integrate seamlessly with existing enterprise systems through API and file-based data exchange.

Third, we validated system effectiveness through computational experiments. Experiments demonstrate scalability and performance across diverse problem types.

5.2. RESEARCH QUESTIONS ANSWERED

We successfully addressed all four research questions that structured our investigation. Each question focused on a critical aspect of resilient production planning under disruption.

RQ1: How can resilience-oriented strategies be systematically incorporated into operational-level decision-making frameworks to enhance adaptability during disruptions?

We demonstrated that two-stage stochastic programming provides a systematic framework for incorporating resilience into operational production planning. The approach explicitly represents multiple disruption scenarios within the optimization model rather than treating disruptions as external shocks that require reactive response. By modeling scenarios with associated probabilities, the framework captures the likelihood and magnitude of different disruption types including supplier delays, equipment failures, and capacity shortages.

The incorporation of recourse actions as decision variables ensures the framework considers resilience mechanisms during planning rather than as afterthoughts. MaaS and reserved supplier activation represent concrete resilience strategies that the model can deploy optimally based on disruption characteristics and costs. This systematic incorporation transforms resilience from an abstract concept into explicit decisions with quantified trade-offs.

RQ2: How can MPS models be designed to dynamically adapt and recover swiftly when disruptions occur?

Our model design enables dynamic adaptation and swift recovery through several mechanisms. The two-stage structure separates first-stage planning decisions from second-stage recourse decisions. This separation allows the model to maintain a base production schedule while it simultaneously prepares contingency actions for various disruption scenarios. When disruptions occur, the system activates pre-optimized recourse actions rather than searching for solutions from scratch.

The scenario-based representation allows the model to consider multiple potential scenarios simultaneously. Each scenario captures a specific disruption pattern with an optimized response. This preparedness dramatically accelerates recovery when actual disruptions match or resemble modeled scenarios. The system can immediately implement or adapt to the closest matching contingency plan rather than developing entirely new responses under time pressure.

The recourse mechanisms provide concrete adaptation pathways. MaaS activation offers external capacity when internal resources become constrained. Reserved supplier utilization provides alternative component sources when primary suppliers experience disruptions. The model optimizes these recourse decisions considering their costs and availability constraints, which ensures recovery actions are both feasible and economically justified.

RQ3: How can the effectiveness of resilience-focused decisions be quantitatively evaluated to identify optimal strategies for maintaining system robustness and recovery?

We established a comprehensive quantitative evaluation through multiple metrics and analytical approaches. Robustness indicators assess system performance across scenarios. Expected total cost provides the probability-weighted average outcome. Sensitivity to recourse costs shows trade-offs between resilience investment and service levels, which guides strategic positioning. These quantitative evaluations enable evidence-based identification of optimal resilience strategies.

RQ4: What approaches can be employed to enhance the intelligence and autonomy of decision-making processes, ensuring adaptive and context-aware responses to disruptions?

To enhance the intelligence and autonomy of decision-making processes, we integrate AI techniques that enable adaptive, context-aware, and transparent responses to disruptions. The system allows planners to simulate various disruption scenarios and analyze their potential effects on production schedules and capacity. This interactive capability supports proactive planning by helping users visualize consequences before disruptions occur.

AI-driven analytics also provide threshold-based recommendations for response strategies. The system identifies disruption severity levels and suggests corresponding actions. For instance, minor disturbances can be addressed through replanning, moderate ones may require reconfiguration, and major disruptions might necessitate supplier substitution. These adaptive thresholds guide decision-making under uncertainty and ensure consistent, data-informed responses.

Predictive monitoring modules enhance situational awareness by detecting early warning signs, such as declining supplier capacity or delayed material deliveries. When potential risks are identified, the system automatically issues alerts and recommends preemptive actions to minimize impact. This predictive layer transforms planning from a reactive to a proactive process.

Explainable AI techniques ensure that automated recommendations remain transparent and interpretable. The system provides clear justifications for its decisions, for example, specifying that an order is scheduled in a given period primarily due to supplier lead time constraints or limited capacity in earlier periods. This interpretability builds user trust and supports informed human oversight.

5.3. CONTRIBUTIONS TO NARRATE OBJECTIVES

This work directly contributes to the NARRATE project objectives by advancing intelligent, adaptive, and resilient decision-making capabilities across multiple dimensions.

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For intelligent decision-making methods (O4.3), we developed algorithms that maintain production continuity even under non-optimal or disrupted conditions. The stochastic optimization framework considers potential disruptions and plans effective recourse strategies in advance. Production planners can sustain operations despite supplier delays, equipment failures, or capacity fluctuations, ensuring continuity and stability in uncertain environments.

For advanced production planning (O4.4), the proposed two-stage framework combines optimization with scenario analysis to enable proactive, data-driven decision-making. Rather than responding reactively, organizations can simulate disruption scenarios, assess their impacts, and prepare contingency strategies before disruptions occur. This capability enhances the agility and resilience of SMNs.

For human-centered decision support (O4.5), the system integrates explainable AI and interactive visualization tools that help planners understand the reasoning behind system recommendations. Scenario simulations, threshold-based guidance, and capacity utilization charts make complex results interpretable and actionable. Planners can explore alternative responses, such as MaaS utilization, capacity reconfiguration, or supplier substitution, supported by AI-driven alerts and transparent explanations.

Finally, this work provides a foundational capability for the broader NARRATE vision of resilient and sustainable SMNs (O4.6). Production planning is a central element influencing the entire manufacturing ecosystem. By integrating stochastic optimization, predictive analytics, and explainable AI, the proposed approach shifts decision-making from reactive problem-solving to proactive resilience-building. As a result, organizations improve resource utilization, reduce waste, and strengthen their capacity to maintain performance under uncertainty.

6. NEXT STEPS

The integration of the AI-enhanced MPS-DSS into the NARRATE platform aims to transform production planning from a static optimization task into a dynamic, intelligent, and collaborative decision-making process. Within the broader NARRATE ecosystem, the MPS-DSS acts as the core engine for production scheduling and resource allocation, embedded within the IMC and its AI platform (WP4, WP6), and interacting with complementary modules for demand forecasting, DT-based simulation, supply chain monitoring, and sustainability assessment.

Technical Integration Architecture

The NARRATE platform adopts a modular architecture that enables seamless communication between different decision-support components. Each module exposes APIs for data exchange and service invocation. The MPS-DSS will integrate through this API layer, specified in the architectural design and interface definitions of T1.4 and the software module/API design activities of WP2–WP4, to both receive data inputs and send optimization outputs to other modules.

The results generated by the MPS-DSS, such as optimized production schedules, capacity utilization rates, and disruption response strategies, will be sent back to the platform. These outputs will then feed visualization dashboards and inform other decision domains, in line with the situation-awareness developed in WP3–WP4 and the platform-level implementation activities in WP6.

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Functional Integration and AI-Driven Collaboration

The integration enables a two-way interaction where AI-enhanced decision-making from the MPS-DSS informs, and is informed by, other intelligent modules within NARRATE. Through AI-driven scenario generation, users can simulate potential disruption events directly within the platform. These capabilities are consistent with the roadmap and tasks for disruption identification, scenario definition, stress testing, and evaluation defined in T2.1–T2.4 and T4.1.

For example, a planner can simulate a supplier delay, evaluate its cascading impact on production and logistic, and identify feasible recovery strategies. This capability transforms planning into a proactive and exploratory activity rather than a reactive one. The MPS-DSS also provides AI-suggested reaction thresholds that define how to respond under varying levels of disruption severity. When disruptions are minor, the system recommends simple replanning; for moderate impacts, it suggests reconfiguring production or reallocating resources; and for severe disruptions, it recommends supplier substitution. These reaction policies align with the supply chain network optimization and reconfiguration management tasks in T4.3 and T4.5.

These thresholds can be calibrated based on historical data and learned through machine learning models implemented within WP4. Once defined, they can be shared with other NARRATE components to maintain consistent response logic across the entire manufacturing network.

Explainable AI and Decision Transparency

Transparency is a central requirement for adoption in industrial environments. To support this, the MPS-DSS incorporates explainable AI techniques that clarify the reasoning behind its recommendations, in line with the transparency and explainability requirements and mechanisms described for the IMC and AI platform (WPs 4–6). When the system proposes a specific scheduling decision, users can view a breakdown of the contributing factors; for instance, that an order was scheduled in a given period primarily due to supplier lead time, secondarily due to limited production capacity, and marginally due to product-family constraints.

This interpretability allows planners to validate system logic and integrate human expertise into the final decision. Within the NARRATE platform, these explanations will be displayed through interactive visualizations and dashboards developed in T4.1, and T6.1, enabling cross-functional stakeholders, such as supply chain coordinators or production managers, to understand and validate planning outcomes.

Benefits of Integration

Integrating the AI-enhanced MPS-DSS into the NARRATE platform brings significant advantages for both operational performance and organizational resilience. The system enables predictive awareness by combining real-time data, AI-driven analytics, and optimization-based planning and the predictive/prescriptive analytics capabilities of WP4. It supports proactive management of disruptions, consistent coordination between production and supply chain functions, and greater adaptability to changing conditions.

Furthermore, this integration reinforces NARRATE's overall goal of providing an intelligent, unified decision-support ecosystem. Through shared data and coordinated analytics, the MPS-DSS contributes to global objectives such as improved manufacturing resilience, faster recovery from disruptions, higher resource efficiency, and more transparent, data-driven decision-making.

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In essence, the AI-enhanced MPS-DSS does not operate as a standalone optimization engine but as an intelligent, collaborative component of the NARRATE platform, linking predictive insights, prescriptive decisions, and human judgment to achieve a more robust and adaptive production system.

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APPENDIX

TABLE A1 TABLE OF NOTATIONS

	Sets
O	Set of orders, index $o \in O$
O_1	Subset of orders that have already assigned, $O_1 \subseteq O$
O_2	Subset of orders that are arriving, $O_2 \subseteq O, O_2 \cap O_1 = \emptyset, O_2 \cup O_1 = O$
T	Set of periods, index $t \in T$
C	Set of characteristics, index $c \in C$
F	Set of family of products, index $f \in F$
$O'_f \subseteq O$	A subset of orders that belong to family of products f; $\forall f_1, f_2 \in F, f_1 \neq f_2: \ \cup_{f \in F} O'_f = O, \ O'_{f_1} \cap O'_{f_2} = \emptyset$
S	Set of disruption scenarios, index $s \in S$
T^s	A subset of periods that are after the disruption happens, $T^s \subseteq T$
$\varphi_{c,s}$	A subset of periods from the period that the disruption happens to the period that the supplier reacts, $\varphi_{c,s} \subseteq T^s, \varphi_{c,s} = \{\tau_s, \tau_s + 1, \dots, \tau_s + RT_c - 1\}$
	Parameters
LC_t	Production line capacity in period t
$\Delta LC_{t,s}$	Change in production line capacity in period t under disruption scenario s
$FC_{f,t}$	Capacity of family product f in period t
$SC_{c,t}$	Supply capacity for characteristic c in period t
$\Delta SC_{c,t,s}$	Change in supply capacity for characteristic c in period t under disruption scenario s
$RC_{c,t}$	Reserved supplier capacity for characteristic c in period t
MSC_t	Manufacturing subcontractors' capacity in period t
D_o	Due date for order o
$b_{o,c}$	$\begin{cases} 1 & \text{if order } o \text{ requires characteristic } c \\ 0 & \text{otherwise} \end{cases}$
p^E_o	Penalty cost of earliness of order o

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p_o^L	Penalty cost of tardiness of order o
p_c^R	Penalty cost of providing unit of characteristic c from reserved supplier
p_o^M	Penalty cost of outsourcing order o to manufacturing subcontractor
LT_c	Leadtime for characteristic c provided from main supplier
$\bar{x}_{o,t}$	$\begin{cases} 1 & \text{if order } o \in O_1 \text{ is already assigned to period } t \\ 0 & \text{otherwise} \end{cases}$
U_s	Maximum orders allowed for reassigning under disruption scenario s
Pr_s	Probability of occurring disruption scenario s
τ_s	Starting period of disruption scenario s
RT_c^s	Reaction time of supplier for characteristic c
RT^m	Reaction time of manufacturing subcontractor
	Variables
$x_{o,t}$	$\begin{cases} 1 & \text{if order } o \in O_2 \text{ is assigned to period } t \\ 0 & \text{otherwise} \end{cases}$
$y_{o,t,s}$	$\begin{cases} 1 & \text{if order } o \in O \text{ is moved to period } t \in T^s \text{ under disruption scenario } s \\ 0 & \text{otherwise} \end{cases}$
E_o	Earliness of order $o \in O_2$
L_o	Tardiness of order $o \in O_2$
$E'_{o,s}$	Earliness of order o under disruption scenario S
$L'_{o,s}$	Tardiness of order o under disruption scenario S
$y'_{o,t,s}$	A binary auxiliary variable which shows the last assignment situation of order $o \in O$ after disruption scenario s ($t \in T^s$)
$Q_{c,t,s}$	Amount of characteristic c that should be bought from reserved suppliers in period $t \in T^s$ under disruption scenario s
$z_{o,t,s}$	$\begin{cases} 1 & \text{if order } o \in O \text{ is outsourced in period } t \in T^s \text{ under disruption scenario } s \\ 0 & \text{otherwise} \end{cases}$
$\theta_{o,s}$	An integer auxiliary variable which shows the difference between the period that order $o \in O$ is assigned to and the period that it is outsourced
$\theta'_{o,s}$	An integer auxiliary variable which shows the difference between the period that order $o \in O$ is assigned to and the period that it is outsourced

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$\beta_{o,s}$	A binary auxiliary variable which shows whether the order is outsourced in a different period than it was assigned

TABLE A2 INSTANCES' FEATURES

No.	Instance	Impact	Duration	Probability
1	Ins01-N1-S1	Losing all the capacity	Period 2-6	10%
2	Ins02-N1-S2	Losing all the capacity	Period 2-6	10%
3	Ins03-N1-S3	Losing all the capacity	Period 2-6	10%
4	Ins04-N1-S4	Losing all the capacity	Period 2-6	10%
5	Ins05-N1-S5	Losing all the capacity	Period 2-6	10%
6	Ins06-N1-M	Losing 25% of the capacity	Period 2-6	10%
7	Ins07-N1-S1S3	Losing all the capacity for both of the suppliers	S1: Period 2-4 S2: Period 4-6	10%
8	Ins08-N1-S2S5	Losing all the capacity for both of the suppliers	S2: Period 2-4 S5: Period 4-6	10%
9	Ins09-N1-S3S4	Losing all the capacity for both of the suppliers	S3: Period 2-3 S4: Period 3-6	10%
10	Ins10-N1-S3M	Losing 25% of the capacity for both the supplier and the manufacturer	M: Period 2-4 S3: Period 4-6	10%
11	Ins11-N3-S1S3	Losing all the capacity for both of the suppliers	S1: Period 2-4 S3: Period 4-6	S1: 10% S3: 10% Both: 2%
12	Ins12-N3-S1M	Losing 25% of the capacity for both the supplier and the manufacturer	S1: Period 2-4 M: Period 4-6	S1: 10% M: 10% Both: 2%

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TABLE A3 COMPUTATIONAL RESULTS OF SOLVING INSTANCES FOR PROACTIVE APPROACH

No.	Instance	Initial Earliness/Tardiness Cost	Disruption Cost			Lost Capacity	Recovery Time	Number of Reassigned Orders	Number of Outsourced Orders (MaaS)
			Earliness/Tardiness of orders	Reserved Suppliers Cost	MaaS Cost				
1	Ins01-N1-S1	2886	3418.5	10	407	12	4	25	13
2	Ins02-N1-S2	2865	2647.5	30	124	0	0	25	5
3	Ins03-N1-S3	2868	3333	300	683	16	3	25	19
4	Ins04-N1-S4	2865	2677.5	90	124	0	0	25	5
5	Ins05-N1-S5	2865	2703	75	124	0	0	25	5
6	Ins06-N1-M	2865	3156	0	400	11	2	25	14
7	Ins07-N1-S1S3	2874	3177	220	522	11	3	25	15
8	Ins08-N1-S2S5	2865	2662.5	60	170	0	0	25	7
9	Ins09-N1-S3S4	2866.5	2726	120	506	0	2	25	15
10	Ins10-N1-S3M	2865	2959.5	0	300	4	2	25	11
11	Scenario 1	2872.5	2823	0	501	0	3	25	14

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No.	Instance		Initial Earliness/Tardiness Cost	Disruption Cost			Lost Capacity	Recovery Time	Number of Reassigned Orders	Number of Outsourced Orders (MaaS)
				Earliness/Tardiness of orders	Reserved Suppliers Cost	MaaS Cost				
	Ins11-N3-S1S3	Scenario 2	2872.5	2707.5	130	94	0	0	25	4
		Scenario 3	2872.5	3159	220	588	11	4	25	17
12	Ins12-N3-S1M	Scenario 1	2865	2511	0	176	0	0	25	7
		Scenario 2	2865	2836.5	0	282	5	5	25	10
		Scenario 3	2865	2802.5	0	315	4	5	25	11

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TABLE A4 COMPUTATIONAL RESULTS OF SOLVING INSTANCES FOR REACTIVE APPROACH

No.	Instance	Initial Earliness/ Tardiness Cost	Disruption Cost			Lost Capacity	Recovery Time	Number of Reassigned Orders	Number of Outsourced Orders (MaaS)
			Earliness/Tardiness of orders	Reserved Suppliers Cost	MaaS Cost				
1	Ins01-N1-S1	2865	3745.5	20	891	21	2	25	24
2	Ins02-N1-S2	2865	2640	45	124	0	0	25	5
3	Ins03-N1-S3	2865	3540	300	930	22	4	25	24
4	Ins04-N1-S4	2865	2682	150	124	0	0	25	5
5	Ins05-N1-S5	2865	2803.5	100	126	0	0	25	5
6	Ins06-N1-M	2865	3157.5	0	400	11	2	25	14
7	Ins07-N1-S1S3	2865	3393	230	859	16	4	25	23
8	Ins08-N1-S2S5	2865	2733	120	124	0	0	25	5
9	Ins09-N1-S3S4	2865	2837	180	549	0	2	25	16
10	Ins10-N1-S3M	2865	2958	0	304	4	2	25	11
11	Ins11-N3-S1S3 Scenario 1	2865	3021	10	706	0	3	25	18

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		Scenario 2	2865	2744	150	183	0	0	25	6
		Scenario 3	2865	3399	209	853	16	4	25	23
12	Ins12-N3-S1M	Scenario 1	2865	2550	0	146	0	0	25	6
		Scenario 2	2865	2836.5	0	282	5	5	25	10
		Scenario 3	2865	2836.5	0	282	5	5	25	10

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TABLE A5 COMPARISON OF PROACTIVE AND REACTIVE APPROACH BASED ON THE COMPUTATIONAL RESULTS OF INS03-S1-S3

Approach	Initial Earliness / Tardiness Cost	Disruption Cost			Lost Capacity	Recovery Time	Num. of Reassigned Orders	Num. of MaaS
		Earliness / Tardiness of Orders	Reserved Suppliers Cost	MaaS Cost				
Proactive	2868	3333	300	683	16	3	25	19
Reactive	2865	3540	300	930	22	4	25	24

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Funded by the European Union under GA No 101138094. Views and opinions expressed are however those of the author(s) only and do not necessarily reflect those of the European Union. Neither the European Union nor the granting authority can be held responsible for them. • Grant Agreement No.: 101138094
Call: HORIZON-CL4-2023-TWIN-TRANSITION-01 • Topic: HORIZON-CL4-2023-TWIN-TRANSITION-01-07 • Type of action: HORIZON Research and Innovation Actions

UK Research and Innovation

UK Research and Innovation, Horizon Europe Guarantee.

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IFAC PapersOnLine 59-10 (2025) 1217–1222

Resilient Master Production Scheduling within the Context of Manufacturing-as-a-Service

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Abstract: Resiliency is the ability of a system to quickly recover from disruptions, which can lead to significant production perturbations and delays within manufacturing networks. This highlights the need to study resiliency not only at the strategic level but also at the tactical and operational levels, particularly in Make-To-Order (MTO) systems, which are inherently more susceptible to uncertainties and disruptions. As an operational level decision, Master Production Scheduling (MPS) undergoes potential disruptive events where constraints from suppliers, market demands, and production systems should be considered. In this context, Manufacturing-as-a-Service (MaaS) can be useful for mitigating supply chain risks. This research presents resilient MPS models for both proactive and reactive approaches aimed at minimizing production losses and recovery times in MTO systems, while also examining MaaS as an opportunity. By integrating empirical data with theoretical models, the results indicate that although the proactive approach incurs higher initial costs due to adjustments in the initial plan, it ultimately yields lower total costs compared to the reactive approach over the long term.

Keywords: Resiliency, Master production scheduling, Manufacturing-as-a-Service, Mathematical programming, Stochastic programming, Make-to-order production systems

1. INTRODUCTION

Resiliency refers to a system's ability to quickly recover to its initial state after a disruption. Historical events such as the Fukushima disaster in 2011, the Suez Canal blockage in 2021, and the COVID-19 pandemic illustrate how global supply chains can experience significant halts, material shortages, and delivery delays, often requiring weeks or months to return to normal (Ivanov, 2023). While resiliency has primarily been studied strategically, considering tactical and operational levels is also vital. Strategic decisions aimed at improving resiliency often involve significant costs, which may discourage industries from adopting them. Furthermore, while strategic approaches typically address long-term and exceptional disruptions, tactical and operational strategies should focus on more frequent, albeit shorter-term, disruptions. Although these shorter disruptions may have less important impacts, industrial decision-makers are keenly interested in improving the resiliency of their systems at the tactical and operational levels. Innovations in communication platforms and data sharing in particular have made it easier for manufacturers and suppliers to communicate and be informed about eventual disruptions (Gong et al., 2021). Moreover, real-time information sharing enables manufacturers to anticipate supplier disruptions related to delivery quantity or timing, which is beneficial for decision-making at the operational level.

Key characteristics of supply chain resiliency include lost production capacity and recovery time post-disruption. Two primary approaches to managing disruption risks are reactive and proactive. In the reactive approach, initial decisions are made without considering potential future disruptions, but these decisions are readjusted after a disruption occurs. In contrast, the proactive approach involves predicting potential disruptions and making initial decisions considering potential disruptions and their impacts. However, if the anticipated disruption does not occur or if a different disruption occurs, a readjustment is applied. Fig. 1 illustrates that proactive adjustments to initial plans can reduce lost capacity and recovery time compared to reactive strategies. These adjustments to initial plans can be positive or negative (the two green curves at the beginning of the timeline). Recommended proactive strategies for manufacturing supply chains include inventory storage, backup suppliers, multiple sourcing, flexibility, and MaaS. MaaS is a business model in which manufacturing processes and capabilities are provided as on-demand service. It includes the possibility of joint using of networked production infrastructures. Disruptions affect MTO systems more severely due to inherent uncertainties, making MTO disruption discussions critical.

MTO systems operate dynamically to meet specific customer demands, requiring customized production (Lu et al., 2019). MPS is essential in MTO systems for aligning operations with customer requirements, which improves efficiency and competitiveness. MPS allocates customer demand to production days/periods while accounting for manufacturing and supply limitations, creating short-term production plans. This research addresses operational-level resiliency by evaluating future disruption scenarios and resiliency criteria in MPS to minimize lost capacity and recovery time. Additionally, it explores how MaaS can enhance supply chain resiliency by recommending temporary suppliers or

Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2025.09.205