A Rule-Based Methodology for Generating and Prioritizing Feasible Reorchestration Scenarios in Manufacturing-as-a-Service

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***Abstract*—In Manufacturing-as-a-Service (MaaS) environments, disruptions such as machine breakdowns or supplier failures require rapid reorchestration of production across distributed internal and external resources. This task is challenging because recovery options must satisfy multiple operational constraints, including capacity, capability compatibility, lead time, cost, and managerial policies. While existing literature addresses service selection, optimization, simulation, and multi-criteria evaluation, the formal generation of feasible reorchestration scenarios under MaaS constraints remains insufficiently structured. This paper proposes a rule-based methodological framework for generating and prioritizing feasible reorchestration scenarios in MaaS disruption contexts. The approach combines disruption-response mapping, scenario construction rules, feasibility filtering, and multi-criteria prioritization based on operational performance indicators. A representative MaaS case study is used to validate the methodology under internal, external, and hybrid response configurations. The results show that the proposed method can systematically construct feasible recovery scenarios and transparently prioritize them according to decision-maker preferences.**

Keywords*— *Manufacturing-as-a-service, Digital enterprise, Cloud manufacturing, Servitization, Decision-support, Reorchestration

I. INTRODUCTION

Manufacturing systems increasingly operate in distributed and service-oriented environments where production capabilities can be accessed across organizational boundaries. In this context, Manufacturing-as-a-Service (MaaS) enables flexible and on-demand access to manufacturing resources through the virtualization and service-based exposure of capabilities [1], [2]. By combining internal resources with external provider capabilities, MaaS increases agility and responsiveness in production planning and execution. However, this flexibility also makes disruption management more complex. Events such as machine breakdowns, supplier failures, or capacity shortages may require rapid reorchestration of ongoing orders across internal and external resources. In such situations, decision-makers must identify recovery options that remain feasible while satisfying constraints related to capacity, capability compatibility, lead time, cost, and managerial policies. More broadly, the growing exposure of manufacturing networks to disruptions has reinforced the importance of resilience as a key operational capability [3], [4].

In MaaS disruption contexts, the challenge is not only to choose a response, but first to generate feasible recovery scenarios from internal, external, and hybrid options under multiple constraints. Reorchestration therefore becomes a configuration problem in which scenario generation, feasibility assessment, and prioritization are distinct but closely related stages. Existing research has proposed methods for service selection, disruption evaluation, and recovery planning through optimization, simulation, and decision-support approaches. However, these studies often focus on optimizing a solution or evaluating predefined alternatives. The explicit generation of feasible reorchestration scenarios under MaaS constraints remains less structured, although it is a critical step in disruption response.

This paper makes three contributions. First, it formalizes MaaS reorchestration as a structured scenario generation and prioritization problem, treating candidate recovery configurations as computable and verifiable objects rather than informal response options. Second, it proposes a rule-based method whose rules are grounded in both literature and a structured validation study conducted with industrial practitioners, ensuring that the resulting rule base reflects realistic operational constraints and priorities. The paper validates the methodology through a representative case study covering internal, external, and hybrid recovery configurations under two disruption types and two managerial policy variations, demonstrating that the approach systematically constructs feasible scenarios and ranks them transparently according to decision-maker preferences. The remainder of the paper is organized as follows. Section 2 reviews the literature, Section 3 defines the problem, Section 4 presents the methodology, Section 5 describes the case study and validation approach, Section 6 discusses the results, and Section 7 concludes the paper.

II. RELATED WORK

A. MaaS orchestration and service composition

Manufacturing-as-a-Service (MaaS) extends the principles of cloud manufacturing by enabling manufacturing capabilities to be accessed, combined, and delivered as services across distributed networks [1], [2]. In this context, service-oriented architectures and virtualization mechanisms allow production resources and capabilities to be described, discovered, and coordinated in a structured way, thereby supporting more flexible allocation and orchestration of manufacturing tasks. Early studies in cloud manufacturing and service-oriented manufacturing systems emphasized resource abstraction, service composition, and real-time coordination as key enablers of distributed production environments [5], [6].

These contributions provide the technological and conceptual basis for MaaS orchestration. However, much of this literature focuses on how services can be represented, matched, and composed in general distributed settings. Less attention is given to disruption-oriented reorchestration, where the objective is not only to select services, but to rapidly construct feasible recovery configurations under changing operational conditions and practical decision constraints. More broadly, recent work in reconfigurable manufacturing has also highlighted that the notion of configuration itself is often insufficiently formalized, which complicates both evaluation and decision support.

B. Methods for configuration selection and recovery decision support

A broad range of methods has been proposed to support decision-making in distributed manufacturing and disruption management contexts. Dynamic scheduling and allocation approaches seek to adapt production plans when conditions change, for instance by reallocating tasks or coordinating distributed resources in response to operational events [7][8], [9]. These approaches are particularly useful for handling variability and supporting responsiveness in complex environments.

In parallel, optimization-based methods have been widely used in supply chain and production network research to identify mitigation and recovery strategies under disruption [10], [11]. Such methods are valuable for analysing trade-offs and identifying high-performing solutions under formal constraints. Simulation-based approaches provide a complementary perspective by enabling the assessment of disruption impacts and recovery policies under dynamic and uncertain conditions [12], [13], [14], [15]. In addition, human-centric and interactive decision-support studies emphasize the importance of combining computational assistance with planner expertise, especially in uncertain and fast-changing environments [16] [17], [18]. Recent work on configuration selection emphasizes that candidate generation, comparison, and final choice should be treated as distinct stages rather than collapsed into a single optimization problem. It also points out that simplified combinatorial formulations may overlook uncertainty, richer operational interactions, and the role of human decision-making [19].

Taken together, these streams show that distributed manufacturing decision support has been addressed through multiple methodological lenses, including optimization, simulation, scheduling, and human-centered decision support. They provide relevant foundations for MaaS reorchestration, particularly in terms of adaptation, evaluation, and trade-off analysis.

C. Limits and research gap

Existing approaches to disruption response in distributed manufacturing typically focus on evaluating or optimizing predefined alternatives, assuming that candidate recovery configurations are already available. The explicit and structured generation of feasible reorchestration scenarios, covering internal, external, and hybrid options under MaaS-specific constraints remains less addressed. This paper proposes a rule-based methodology that fills this gap by formally separating scenario generation, feasibility filtering, and prioritization as distinct and explicit decision stages.

III. METHODOLOGY

A. Problem definition

The problem addressed in this paper is the generation and prioritization of feasible reorchestration scenarios in a Manufacturing-as-a-Service (MaaS) context following a disruption. A disruption may affect the ability of a service customer to execute an order as initially planned, for example due to machine breakdown, supplier failure, or sudden capacity loss. In response, the customer must identify alternative orchestration configurations that restore execution while respecting operational and managerial constraints. The decision context considered in this work includes four main input categories:

(i) the disruption context, which specifies the type and characteristics of the event;

(ii) the order requirements, such as quantity, due date, and cost limit;

(iii) the available resources, including internal resources and eligible MaaS providers with their capabilities and capacities; and

(iv) the operational constraints and policies, such as capability compatibility, delivery requirements, budget limits, and whether order splitting is permitted.

A reorchestration scenario is defined here as a structured candidate recovery configuration describing how the affected order is reassigned across available internal and/or external resources. In this sense, the scenario is treated as a computable and verifiable object rather than as an informal response option, so that it can support both feasibility checking and later performance assessment. Depending on the chosen response logic, a scenario may rely on internal measures only, external sourcing only, or a hybrid combination of both. Each scenario is characterized by the selected response type, the participating resources, the allocated quantities, and the associated performance attributes.

Not all generated scenarios are admissible. A scenario is considered feasible only if it satisfies all required operational constraints. These include fulfilling the required quantity, matching the necessary capabilities, respecting available capacity, complying with due-date requirements, and remaining within the acceptable cost and policy boundaries defined by the decision-maker. Based on this definition, the objective of the proposed methodology is not to directly compute a single optimal solution, but to explicitly separate three decision stages: scenario generation, feasibility filtering, and scenario prioritization. This distinction reflects an operational reality in MaaS contexts, where multiple configurations may be conceivable but only a subset is actually executable. The output of the method is therefore a ranked portfolio of admissible recovery alternatives that can support transparent decision-making in MaaS disruption contexts.

B. Overall methodology

The proposed methodology transforms a disruption context and its associated constraints into a ranked set of feasible reorchestration scenarios through four explicit stages: identifying admissible response options, generating candidate scenarios, filtering according to feasibility conditions, and prioritizing feasible alternatives. Unlike approaches that directly search for a single best configuration, the method first constructs a candidate space, then reduces it through verification rules, and finally ranks the remaining scenarios according to selected performance criteria. The overall logic is illustrated in Figure 1, starting from the disruption context, order requirements, available internal and external resources, and operational policies, the approach first identifies the admissible response families. Candidate reorchestration scenarios are then generated through explicit rules, filtered according to feasibility conditions, and finally prioritized using weighted performance criteria. The final output is a ranked portfolio of feasible recovery scenarios that supports transparent decision-making.

C. Rule-based scenario generation

The first stage of the method consists of generating candidate reorchestration scenarios through explicit decision rules. These rules link the disruption context to applicable response families and guide the construction of recovery configurations. Three main response families are considered: internal scenarios, which rely only on the service customer's own resources or recovery levers; external scenarios, which rely on MaaS providers; and hybrid scenarios, which combine internal and external responses.

Scenario generation is driven by rule-based logic. First, the disruption type determines which response families are admissible. Then, the method identifies the internal resources and external providers that are compatible with the order requirements. Candidate scenarios are constructed by combining these admissible resources according to the managerial policies defined by the user, such as whether order splitting is allowed. Each generated scenario specifies the selected response type, the participating resources, and the corresponding quantity allocation. This rule-based construction enables the method to explicitly represent recovery alternatives instead of directly returning a single selected solution. It also provides a transparent basis for explaining why a scenario has been generated and under which conditions it is applicable.

The rule-based nature of the proposed method is detailed in Table 1, which summarizes the main rule families involved in candidate generation, feasibility verification, and final prioritization. These rules structure the transformation of a disruption context into a set of admissible reorchestration scenarios by linking disruption characteristics, resource availability, allocation logic, and decision constraints. The rules were derived from a review of the disruption management literature and refined through a structured validation study conducted with industrial practitioners from the white goods manufacturing sector. The survey pursued three objectives: rating the likelihood and relevance of each disruption type, assessing the perceived applicability of each mitigation strategy, and validating the proposed links between disruptions and response families. These inputs directly shaped which rules are activated per disruption type and under which conditions, grounding the rule base in practitioner knowledge rather than theoretical assumption alone.

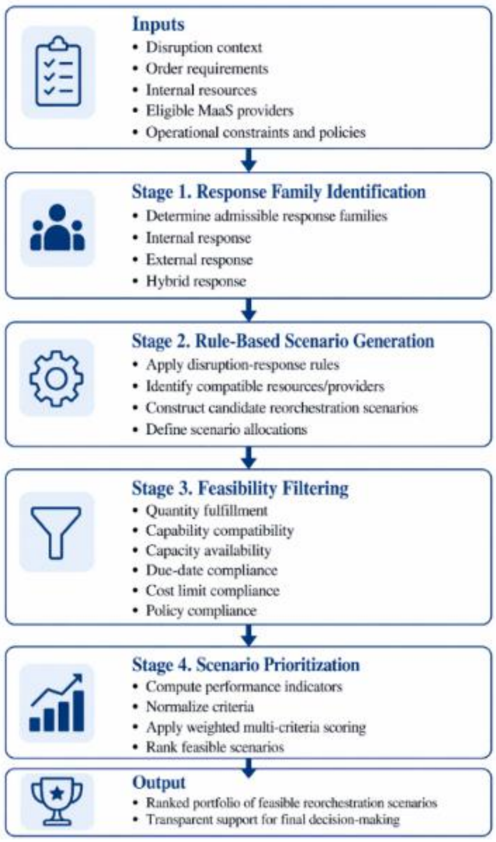

Figure 1. Framework for the rule-based generation and prioritization of feasible reorchestration scenarios under MaaS constraints [20].

Table 1. Main rule families used in the proposed methodology.

Rule family	Purpose	Example
Disruption activation	Identify affected resources and update the recovery context.	Machine breakdown reduces internal capacity and excludes scenarios relying only on the failed resource.
Response-family admissibility	Determine which response families can be used.	Supplier failure excludes scenarios using the failed supplier.
Resource eligibility	Select compatible internal	A provider is eligible only if it satisfies capability

	resources and providers.	and capacity requirements.
Scenario construction	Build candidate internal, external, and hybrid scenarios.	If both internal and external resources are available, generate all admissible response types.
Allocation and splitting	Define how demand is distributed across selected sources.	If splitting is forbidden, the full quantity must be assigned to one source.
Feasibility verification	Remove scenarios violating hard constraints.	Reject scenarios that fail quantity, capacity, due-date, cost, or policy constraints.
Prioritization	Rank feasible scenarios using weighted criteria.	Scenarios with better weighted cost, lead time, and service level are ranked higher.

D. *Feasibility filtering*

Once candidate scenarios have been generated, they are filtered according to a set of feasibility conditions. This stage ensures that only operationally admissible scenarios are retained for further evaluation. A scenario is considered feasible if it satisfies all required constraints related to quantity fulfillment, capability compatibility, capacity availability, due-date compliance, cost limits, and user-defined policies. All constraints are treated as strictly binary: a scenario that fails any single condition is removed from the candidate set entirely, regardless of how close it comes to satisfying it.

The feasibility assessment acts as a filtering mechanism between generation and prioritization. Infeasible scenarios are removed from the candidate set, while feasible ones are retained as admissible recovery alternatives. This distinction is important because it separates hard operational constraints from later performance-based comparison. As a result, scenario prioritization is only applied to configurations that are already executable under the specified MaaS conditions.

E. *Scenario prioritization*

After feasibility filtering, the remaining scenarios are prioritized using operational performance criteria. Each feasible scenario is associated with a set of indicators, such as total cost, lead time, and service level, reflecting different managerial preferences in the decision process. To support multi-criteria decision-making, each scenario is evaluated using a composite score defined as:

$$Score_i = w_c C_i^{norm} + w_t T_i^{norm} + w_s(1 - SL_i^{norm})$$

Where C_i^{norm} and T_i^{norm}re the normalized cost and lead-time values using max-value scaling, SL_i^{norm} the normalized service level (inverted so that higher service levels reduce the overall score), wc, wt, ws are the user-defined weights for cost, time, and service level, respectively with $wc + wt + ws = 1$.

IV. CASE STUDY

A. *Case study setting*

The methodology is illustrated through a representative MaaS case developed in the context of the MAASive project and informed by discussions with industrial partners. A service customer must recover the execution of a disrupted order defined by a required quantity, due date, and maximum cost using a combination of internal resources and external MaaS providers. The provider set is intentionally heterogeneous to create realistic trade-offs between cost, responsiveness, and service continuity. The main parameters are summarized in Table 2.

The available recovery resources are divided into two groups. The first group corresponds to the internal resources of the service customer, including residual capacity and optional recovery levers such as overtime. The second group corresponds to external MaaS providers, each characterized by a given capability, available capacity, lead time, and cost profile. The provider set is intentionally heterogeneous in order to create realistic trade-offs between cost, responsiveness, and service continuity.

A preliminary implementation of the proposed method was developed in Python and Streamlit for the decision-support workflow, while FlexSim was used to support execution-level performance evaluation. The implementation architecture showcased in Figure 2 . In the present paper, this implementation is considered only as an application context for the methodology rather than as the main contribution.

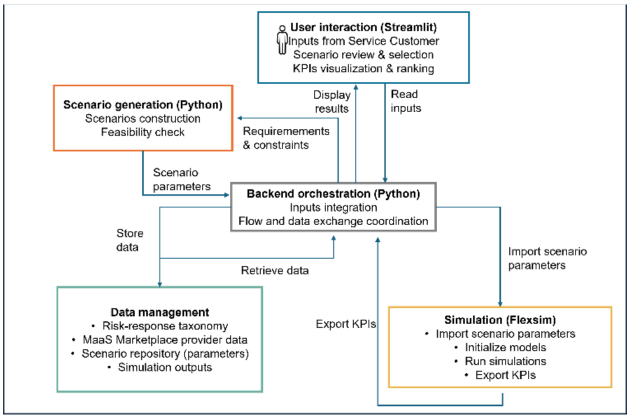

Figure 2. Implementation architecture [20]

B. *Disruption scenarios and decision assumptions*

Two representative disruption scenarios are considered in order to test the proposed methodology under distinct recovery conditions:

- **D1: Machine breakdown**, where an internal production resource becomes partially unavailable, reducing the customer's internal execution capacity;
- **D2: Supplier failure**, where an initially planned external sourcing option becomes unavailable, requiring a reallocation of the affected quantity across other internal and/or external resources.

These disruption types were selected because they activate different parts of the rule base and naturally lead to different families of recovery responses. In particular, the first disruption emphasizes internal recovery limitations and the possible need for outsourcing, while the second emphasizes the reallocation of externally sourced work.

To explore the behaviour of the methodology under different decision conditions, the case study also considers two managerial variations:
(i) **splitting policy**, with splitting either allowed or not allowed, and
(ii) **priority profile**, with either cost-oriented or service-oriented prioritization.
These assumptions make it possible to analyse not only the generation of candidate scenarios, but also the sensitivity of feasibility and prioritization results to the decision context.

Table 2. Case-study parameters and available recovery resources

Element	Capability	Capacity	Lead time	Unit cost	Notes
Order requirement	Welding	100	5 days	12,000 max	Splitting allowed / not allowed
Internal residual capacity	Welding	40	3 days	70	Reduced after breakdown
Overtime option	Welding	20	4 days	90	Optional
Provider A	Welding	60	6 days	60	Low cost, slower
Provider B	Welding	40	3 days	110	Fast, expensive
Provider C	Welding	50	4 days	85	Balanced
Provider D	Welding	20	2 days	120	Limited capacity

C. *Evaluation criteria and validation logic*

Three operational performance indicators are retained for the prioritization stage: **total cost**, representing the economic impact of the selected recovery configuration; **lead time**, representing the expected time to complete the disrupted order; and **service level**, representing the ability of the scenario to satisfy demand within the required delivery conditions. These indicators capture the main trade-offs typically faced in disruption response, namely cost efficiency, responsiveness, and service continuity.

The validation focuses on three aspects. First, it examines whether the methodology generates a structured portfolio of candidate scenarios, including internal, external, and hybrid configurations depending on the disruption and policy conditions. Second, it verifies whether the feasibility filtering stage removes scenarios that violate hard constraints such as insufficient capacity, due-date violation, excessive cost, or policy incompatibility. Third, it analyses whether the prioritization stage produces differentiated rankings depending on the selected weighting profile. The final ranking of feasible scenarios for the illustrative case is reported in Table 3.

Table 3. Final ranking of feasible reorchestration scenarios

Scenario ID	Type	Cost	Lead time	Service level	Final score	Rank
S4	Hybrid	8,700	4	0.95	0.41	2
S5	Hybrid	9,300	3	0.98	0.36	1
S6	External split	9,900	3	0.97	0.39	3

All three feasible scenarios require external providers, as internal capacity (60 units maximum with overtime) is insufficient to cover the full order. S5 ranks first by combining internal resources with Providers B and D, achieving the best lead time and service level despite higher cost. S4 is cheaper but slower, penalized by its 4-day lead time under balanced weighting. S6, fully external, ranks last due to highest cost and no internal contribution. Under D2, scenarios using the failed supplier are excluded at activation stage, reducing the feasible set. When splitting is disallowed, multi-provider scenarios are removed entirely in some cases yielding no admissible solution, a decision-relevant outcome the methodology surfaces explicitly.

V. CONCLUSION

This paper addressed disruption-oriented reorchestration in Manufacturing-as-a-Service (MaaS) environments. It proposed a methodological framework for the formal rule-based generation and prioritization of feasible reorchestration scenarios under MaaS constraints. Unlike approaches centered on directly selecting or optimizing a single response, the proposed method explicitly separates candidate scenario generation, feasibility filtering, and scenario prioritization. The case study illustrates how the approach can generate internal, external, and hybrid recovery scenarios, eliminate infeasible alternatives, and rank the feasible ones according to selected performance criteria and decision-maker preferences. The main contribution of the paper therefore lies in formalizing the intermediate decision stage between disruption occurrence and final response selection, namely the structured construction and organization of feasible reorchestration scenarios. The proposed approach has two main limitations. The case study covers a single-order, single-capability setting, leaving scalability to larger and more heterogeneous MaaS networks unassessed. No direct comparison with optimization-based approaches is provided, which limits claims about relative performance. Future work will address these points by extending validation to richer industrial settings, exploring dynamic rule refinement, and benchmarking against robust optimization techniques.

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