Multi-Scale Scenario Generation for Production Planning under Uncertainty in Global Production Networks

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Abstract

Modern production planning in Global Production Networks faces a multitude of uncertainties, ranging from short-term cost and demand fluctuations to political instabilities and large-scale disruptions. The varying types and time horizons of both uncertainties and planning parameters create the need for multi-scale scenarios that capture their different characteristics and developments across flexible time scales. This paper presents a novel scenario generation framework for deriving multi-scale scenarios along both type and time dimensions, serving as input to enhance the robustness and resilience of Global Production Networks. The scenario generation follows six consecutive steps, applying Monte-Carlo-Simulation to defined Change Drivers, Receptor Key Figures, and their interdependencies. The generated scenarios are clustered into representative scenarios using the k-means algorithm. The framework is integrated into a Decision Support System featuring an optimization module for long-term planning of Global Production Networks. An application to an industrial use case shows that the resulting network configuration is more robust than the forecast-based configuration.

Keywords: Scenario Analysis, Multi-Scale Scenarios, Global Production Network, Production Planning, Resilience, Robustness

1 Introduction

Today's companies face a multitude of planning decisions that must account for both short-term volatility and long-term, far-reaching disruptions. Recent examples from the automotive industry include technological innovations such as the transition from conventional combustion engines to electric vehicles [1], fluctuating market demand [2], shortened product life cycles [3] and increasing product variety [4]. These challenges are further intensified by unforeseeable events such as natural disasters [5] or geopolitical tensions [6]. Overall, a wide range of influencing factors complicates planning tasks in Global Production Networks (GPNs) [6]. To remain competitive in this dynamic environment, companies require proactive and forward-looking planning processes [7]. Consequently, GPNs must not only anticipate future developments but also exhibit a high capacity for adaptation and change.

Therefore, the various sources of uncertainty must be systematically considered in the planning of GPNs (R1). This includes short-, mid- and long-term uncertainties as well as different types of influencing factors, as identified in [6]. To consistently capture this heterogeneity across time horizons and types of influencing factors, multiple scales are required (R2). The uncertainties can take various forms, such as scenario-based or stochastic representations, and provide a structured basis for further analysis. Scenario analysis represents a widely used methodological approach to incorporate such uncertainties into strategic decision-making [8]. In the context of production planning, it serves as a valuable tool to account for future uncertainties in decision processes [9]. A central element of this approach is the identification of a set of representative scenarios derived from possible future developments of relevant influencing factors. These influencing factors, often referred to as Change Drivers (CDs) [9], may originate from both internal and external sources [6], making it essential to consider both to ensure holistic uncertainty consideration (R3). CDs exert pressure to change [10] and initiate change [11]. In order to react to the CDs, they must first be identified and their potential effects on production systematically derived [12]. To support this, CDs can be clustered based on shared characteristics, allowing for a more structured analysis [13]. This enables a systematic assessment of how changes impact the Production System (PS) [14]. Analogous to medicine, impacts are transmitted through receptors of the PS that are sensitive only to certain stimuli, i.e. specific CDs [15]. To systematically analyze these relationships, so-called Receptor Key Figures (RKFs) can be defined, enabling the quantification of the influence of CDs on the respective receptors. This forms the basis for developing scenario-based planning models [16].

A fundamental element of the scenario technique is the simulation of possible future scenarios by modeling different developments of the CDs. Monte-Carlo-Simulation (MCS) is a key method within stochastic scenario analysis, aiming to generate numerous potential future paths by simulating a large number of similar case studies [17]. Specifically, a MCS repeatedly performs a defined experiment in a randomized manner to generate a robust data basis based on the defined probability distributions [18]. The mathematical foundation of the MCS is the law of large numbers [19], which ensures that by running a sufficiently large number of simulations, the aggregated results converge toward a reliable representation of future outcomes [17].

While MCS enables the generation of a large number of future scenarios, this high volume also introduces significant challenges. In particular, analyzing or optimizing hundreds or even thousands of simulation runs can quickly become computationally intensive and impractical for long-term planning purposes. Moreover, the use of stochastic parameters to represent risk can complicate quantitative analysis [20], as probabilities and distribution functions are difficult to determine in a future that is not merely uncertain but largely undetermined [21]. Therefore, effective methods for scenario reduction and structuring that lead to consistent scenarios (R4), combined with traceability through graphical or schematic depictions (R5), are essential to ensure that results remain interpretable, actionable, and validatable for decision-makers. Finally, the complex environment of GPNs [6] creates the need to explicitly regard interdependencies between CDs, which most current optimization approaches lack [22] (R6).

To be practically useful, a scenario generation approach should not only enable the quantitative modeling of structured, multi-scale scenarios, but also allow direct integration into production planning tools, providing actionable input for decision-making in GPNs. Furthermore, to ensure consistency across different industrial contexts, the tool should demonstrate broad applicability and modularity, allowing adaptation to diverse production planning problems in GPNs (R7).

To address the outlined challenges, this paper introduces a novel approach that captures the inherent complexity and uncertainty of GPNs through multi-scale scenarios. To this end, a scenario generation framework is developed, which combines Receptor Theory with MCS to generate consistent scenarios. The framework enables parallel modeling of multiple heterogeneous receptors (multi-scale in type) as well as varying time intervals for both distinct and identical receptors (multi-scale in time). Graphical representations are generated for the whole scenario funnel as well as for representative scenarios and individual RKFs to guarantee transparency for decision-making. Owing to its modular structure, the proposed framework is applicable to a broad range of production planning use cases in GPNs and can be configured to specific contexts.

The structure of the paper is as follows: Section 2 reviews the related literature on uncertainty as well as scenario analysis and generation and identifies the corresponding research gap. Section 3 provides an overview of the developed scenario generation framework, which is subsequently demonstrated through a case study from the automotive industry in Section 4. Section 5 discusses the results, while Section 6 concludes the paper with a summary and an outlook on future research directions.

2 State of the Art on Scenario Consideration and Generation in Global Production Networks

2.1 Frameworks for Production Planning under Uncertainty

Uncertainty in production and supply networks has been widely addressed in literature, particularly through optimization-based frameworks. These works focus on modeling uncertain parameters such as demand, costs, or disruptions via probability distributions or scenario sets. Their objective is typically to derive robust or resilient production and network plans that remain effective under an uncertain future. [23] present a stochastic optimization model combined with an accelerated Benders decomposition algorithm to efficiently solve large-scale supply chain network design problems under multiple scenarios. Their method integrates the Sample Average Approximation to generate high-quality solutions while considering a wide range of possible future developments. [24] propose a multi-objective stochastic robust mixed-integer program for production planning in global supply chains. They build on the approach of [25] to extend traditional stochastic optimization, incorporating both expected values and their variability. [26] addresses both quantitative and qualitative uncertainties evaluating networked production sites. Quantitative uncertainties are modeled using probability distributions, while qualitative uncertainties are represented via fuzzy set theory. The uncertainty model is linked to a cost model for evaluation and MCS is applied to determine location-specific values. [27] develop an approach for robust order assignment in GPNs that explicitly addresses uncertainty arising from customer-specific product configurations, which are not known at the time of planning. This uncertainty is captured by representing possible configurations in a set of scenarios. The order assignment is then optimized such that the resulting network configuration remains robust against the worst-case workload across all scenarios. [28] introduce a resilience metric for supply chains, quantifying the expected cost increase due to potential disruptions. Disruptions are simulated by randomly selecting scenarios according to predefined probabilities, and a two-stage stochastic optimization is applied to identify cost-optimal network designs under these disruptions. [7] present a stochastic-dynamic optimization model deriving robust migration paths for GPNs using a Markov Decision Process (MDP). Uncertain cost and demand parameters are captured through CDs, whose effects are applied at discrete decision points.

While some approaches consider multiple receptors and are therefore multi-scale in type [7], [23], [24], [28], others are limited to single-scale uncertainties [27], [26]. However, none of the analyzed approaches address multi-scale scenarios that simultaneously capture both time and type dimensions in production planning. Furthermore, several approaches focus exclusively on external CDs [23], [28].

2.2 Scenario Generation Frameworks

Scenario generation frameworks in production planning aim to systematically identify and evaluate CDs, map them to production variables (e.g. through receptors), and derive scenarios that reflect potential developments in the production environment. Such approaches are often rooted in changeability and adaptability research and provide conceptual tools to link internal and external influences with decision-making. [15] introduce the receptor model, which identifies minimum requirements for production resources to increase changeability by mapping CDs to production variables, referred to as receptors. The central assumption here is that different CDs often have the same effect on the PS and thus activate the same receptor. Product or product variants, costs, time, quantity and quality are identified as receptors. [14] adds the receptor technology. In order to determine the adaptability of a factory, [29] compares adaptability enablers to adaptive objects of a factory deriving changeability of factories. Scenario management adapted to the needs of factory planning is used to transfer the scenarios created and the knowledge gained from them to planning and decision-making tasks. A detailed catalog of CDs is defined for this purpose, which leads to change requirements for the objects. [12] propose a systematic identification and evaluation of CDs, considering lead time, duration, frequency, probability of occurrence, and influence (strength, breadth, depth). This allows forecasts of CDs to support scenario creation. [30] develop a methodology for translating external influences into concrete manufacturing scenarios. Their approach adopts an extended receptor model to decompose strategic scenarios into bundles of projections directly influencing the manufacturing system. In addition, a backward analysis of the scenarios is conducted to identify underlying trends and changes to which the receptors are exposed. Finally, the findings are classified and aggregated into sub-scenarios, providing a structured basis for subsequent planning tasks.

All of the above frameworks support a wide range of production use-cases by providing a structured basis for scenario generation. However, most frameworks are not suitable for generating multi-scale scenarios in the time dimension [12], [15], [30]. Another limitation is that some approaches only take external influencing factors into account when defining scenarios [15], [30]. Finally, although they deliver structured methodologies for scenario generation, most of the frameworks do not ensure consistency of the generated scenarios [12], [15], [30].

2.3 Combined Approaches for Scenario Generation in and Planning of Global Production Networks

Combined approaches integrate stochastic influences into network design and adaptation, often by linking scenario-based analyses with optimization models such as stochastic programming or MDPs (see Section 2.1). [22] propose a multi-objective optimization model for GPNs under uncertainty. They stochastically derive future scenarios for demand and costs by defining probability distributions for discrete and continuous CDs. Continuous CDs are modeled as a Wiener Process, where for each scenario a random number for the expected trend μ and the variance σ is generated. Discrete CDs are modeled as equally distributed along the time horizon. [16] develop a method for planning changeable PSs that explicitly links scenario analysis with decision-making. They identify relevant CDs impacting the Key Performance Indicators (KPIs) of the PS. CDs are assigned an occurrence probability and a time of occurrence, exerting absolute or relative influence on the KPIs or altering their trend over time. MCS is applied to generate aggregated scenarios for each KPI, capturing the stochastic influence of the CDs. A MDP is formulated and solved in order to calculate a scaling strategy for system adaption. The resulting strategies are then analyzed to derive design guidelines for concrete changeability measures. [31] model CDs as stochastic arithmetic random walks and generate their values using MCS. In contrast to earlier approaches, these factors are not linked indirectly via uncertain parameters but exert a direct influence on the target variable. Based on multiple MCS iterations, the authors derive expected values as well as minimum and maximum outcomes of the target variable, thereby supporting decision-making in the design of GPNs. [32] propose a methodology for deriving robust network configurations from representative demand scenarios. First, numerous scenarios are generated via MCS based on the probability distribution of defined CDs and their influences on respective RKFs. These scenarios are then clustered into a reduced set of representative scenarios using the k-means algorithm. Finally, a two-stage stochastic mixed-integer linear program is applied to identify robust network configurations for the non-recourse decisions.

Most of the given approaches support the generation and planning of scenarios that are multi-scale in type and arise from both internal and external CDs [16], [21], [31]. However, some approaches do not guarantee consistency of the generated scenarios [16], [31]. While most approaches feature a clear and systematic process for scenario generation [21], [31], [32], only [32] ensure traceability for decision-makers by providing structured visual representations. Moreover, only [32] explicitly account for interdependencies between different CDs but only address single-scale scenarios in type (limited to demand) and consider solely external CDs.

2.4 Research Deficit

The reviewed approaches are evaluated using the defined criteria in Table 1. This analysis reveals several research gaps, leading to the following research questions:

1. What constitutes an effective framework for generating and managing multi-scale scenarios in GPNs?
2. How can production planning utilize and benefit from multi-scale scenarios to improve robustness and resilience?
3. How can scenario generation and planning be systematically integrated into decision-making processes while ensuring broad applicability across different production contexts?

To address these gaps, Section 3 introduces a framework for multi-scale scenario generation, embedded into a modular Decision Support System (DSS) to ensure broad applicability by adjusting the input parameters. While research questions (1) and (3) are closed by the framework itself, question (2) is addressed through an industrial use case that integrates the scenario tool with an optimization module [33].

3 Framework for Scenario Analysis in Global Production Networks

Building on the identified challenges and research gaps, this section introduces a scenario analysis framework for the configuration and management of GPNs. The framework is designed to systematically account for uncertainties of different types and time horizons by integrating receptor-based modeling with scenario generation techniques. It builds up on the work of [34], [32] and [33] and follows the scenario management approach of [35]. A key objective is to ensure universal applicability in production planning, i.e. the tool does not impose restrictions on the receptors or types of scenarios to be modeled. This flexibility and the modular structure enable its use across a wide range of decision-making contexts in GPNs.

Table 1: Comparison of relevant approaches from the state of the art

○ not fulfilled ◐ partially fulfilled ● fully fulfilled	Global Production Network (R1)	Multi –scale scenario in time and type (R2)	Internal and External Influences (R3)	Consistent scenarios (R4)	Traceability of scenarios (schematic and visual/tabular) (R5)	Interdependencies between Change Drivers (R6)	Applicability across broad range of use-cases (R7)
Frameworks for GPN Planning under Uncertainty							
Santoso et al. (2005) [22]	◐	◐	◐	Not applicable			
Mirzapour et al. (2011) [23]	◐	◐	●				
Krebs (2012) [25]	●	○	●				
Buergin et al. (2019) [26]	●	○	●				
Fattahi et al. (2020) [27]	◐	◐	◐				
Moser et al. (2021) [5]	●	◐	●				
Scenario Generation Frameworks							
Cisek et al. (2002) [15]	○	◐	◐	◐	◐	○	●
Hernández Morales (2003) [28]	○	●	●	◐	◐	○	●
Gille & Zwißler (2011) [12]	○	◐	●	◐	◐	○	●
Wonsak et al. (2021) [29]	○	◐	◐	●	◐	○	●
Combined Approaches for Scenario Generation in and Planning of GPNs							
Lanza & Moser (2014) [21]	●	◐	●	●	◐	○	◐
Staehr et al. (2020) [16]	○	◐	●	◐	○	○	◐
Schuh et al. (2022) [30]	●	◐	●	○	◐	○	◐
Brützel et al. (2025) [31]	●	○	◐	●	●	●	◐

3.1 Inputs and Scopes

To operationalize the framework, the relevant inputs and modeling scopes must first be defined. These inputs establish the descriptive model, which forms the basis for the subsequent MCS. In the following, the components of this descriptive model are introduced, followed by a definition of its scopes, i.e. the generation of single- and multi-scale scenarios.

3.1.1 Descriptive model

Probability distributions $F(\theta)$ are defined to enable stochastic modeling for MCS. The scope of this work is limited to a representative subset (triangular, normal, uniform, and Bernoulli distributions) without claiming completeness. Further distributions can be incorporated as needed.

Change Drivers

The first step is the modeling of CDs, which represent internal or external influences. Each CD $cd \in CD$ is assigned a unique identifier, a name, and a description to ensure traceability. The identifier is required later for referencing within the MCS. To capture their stochastic behavior, each CD is characterized by:

- Occurrence probability $p_{cd}^{entry} \sim F(\theta)$, determining the likelihood of occurrence $e_{cd}^{entry} \in \{0, 1\}$.
- Occurrence distribution $p_{cd}^{time} \sim F(\theta)$, specifying when the CD is expected to occur within a defined planning horizon.
- Influence time $T_{cd}^{influence} = t_{cd}^{end} - t_{cd}^{start}$, describing the time period in which the CD is active by defining its start (t_{cd}^{start}) and end time (t_{cd}^{end}).
- Frequency f_{cd}^{T}, indicating how often the CD may occur in the given time interval.

Each CD is linked to at least one receptor. A CD influences both other CDs (influenced CDs) and RKFs (influenced RKFs). This defines how the various CDs and RKFs interact.

An influence matrix $I_{cd^*,cd}$ is required to define the interdependencies of the CDs. Three types of relations are distinguished:

- Causation: one CD triggers another $I_{cd^*,cd} = 1$.
- Exclusion: the occurrence of one CD prevents another $I_{cd^*,cd} = -1$.
- Independence: no interaction between the CDs $I_{cd^*,cd} = 0$.

Note that a CD can only be either caused or excluded by other CDs, since simultaneous causation and exclusion would make a consistent value determination impossible. While the influence matrix defines how CDs interact with each other, their relevance for production planning only becomes apparent through their impact on the receptors. These receptors provide the quantitative basis for evaluating how CDs influence the PS.

Receptor Key Figures

A RKF $rkf \in RKF$ serves to quantify the influence of the CDs on production. Similar to CDs, each RKF requires a unique identifier, a name, and a description to ensure traceability. Moreover, each RKF is uniquely linked to a receptor (see e.g. [15] for possible receptors). This assignment allows systematic linking of CDs to measurable RKFs. RKFs can be of discrete or continuous type [16]. A discrete RKF takes one of two possible states (entry or non-entry value), modeled by a Bernoulli distribution Bern(p). Continuous RKFs, by contrast, are more complex as they can take a range of values [16]. Each continuous RKF is initialized with three baseline parameters defined for the entire planning horizon: an absolute initial value $V_{rkf,t}^{base,abs}$, a relative initial value $V_{rkf,t}^{base,rel}$, and an initial slope $V_{rkf,t}^{base,slope}$ [16]. In analogy, continuous RKFs are subject to an occurrence probability $p_{rkf,t}^{entry} \sim F(\theta)$. If an RKF does not occur, it takes the non-entry value (zero), whereas its absolute, relative, and slope parameters are only realized upon occurrence. Lastly, the time scale is defined by the set of timestamps $T_{rkf} \subseteq T$, which comprises all points in time at which the RKF is modeled.

Change Driver Influences

Each CD has an influence on one or more RKFs, referred to as a Change Driver Influence (CDI). For quantification, it must be defined which CD impacts which RKFs. Each CDI ($CDI_{cd,rkf}$) is unique to the pair of CD cd and RKF rkf, but can be the same for different RKFs. For continuous RKFs, three types of influences are distinguished, each modeled by a probability distribution: absolute influences $CDI_{cd,rkf}^{abs} \sim F(\theta)$, relative influences $CDI_{cd,rkf}^{rel} \sim F(\theta)$ and slope influences $CDI_{cd,rkf}^{slope} \sim F(\theta)$. The different influence types are illustrated in Figure 1.

Change Object

The RKFs are linked via the receptors to production and, more specifically, to a change object. According to [29], a change object can belong to one of the five system levels: Global/factory environment, factory area, production and logistics area, manufacturing/assembly/logistics system or

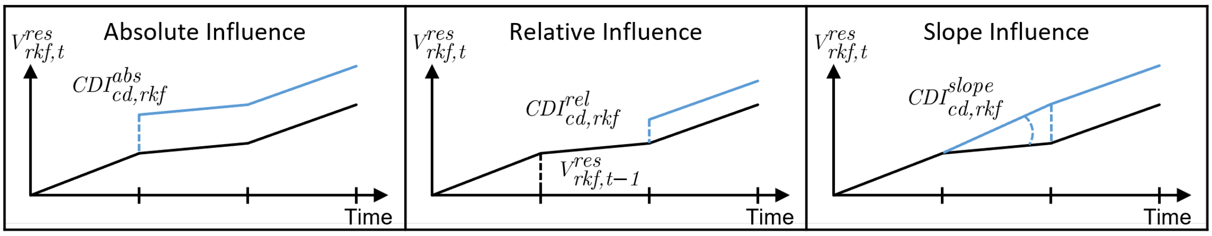


Fig. 1: Possible influence types for CDI

workstation. In the present framework, the concept of the change object is expanded to not only include the resources such as machines and workstations (i.e., operational level), but also abstract planning entities such as orders or product types (i.e., system description level). Thus, a change object can be, for example, an order or a product whose attributes are represented by RKFs. Linking change objects to RKFs establishes the connection to the underlying descriptive model.

3.1.2 Single- and Multi-Scale Scenarios

This section describes the types of scenarios that can be modeled and simulated using the proposed framework. The focus is on both single-scale and multi-scale scenarios, which allow the representation of different potential futures by accounting for various internal and external CDs. Scenario generation is designed to flexibly adapt to different change objects, and it is essential that changes to a change object can be quantified through the associated RKFs. These RKFs may be affected by external drivers (e.g., market fluctuations or political decisions) as well as internal drivers (e.g., changes in corporate strategy or technology).

Existing tools primarily support the creation of single-scale scenarios (see Section 2), simulating CDs along a single dimension, either type or time. The present approach extends this capability by introducing multi-scale scenarios, which incorporate two dimensions simultaneously (see Figure 2):

- Type Dimension: This dimension captures the type and nature of change, following [16]. It distinguishes between different types of influences (e.g., on cost, time, quantity, quality, or technology) and explicitly accounts for interactions among these influence types.
- Time Dimension: Considers developments over different time dimensions, enabling a more dynamic and realistic representation of scenarios. This allows RKFs, even of the same receptor type, to be modeled on different time scales (e.g., monthly and semi-annually).

The simultaneous consideration of these dimensions allows a deeper understanding of the possible futures and their complexity. Ensuring consistency across the resulting scenarios is crucial to produce validatable and actionable results. The proposed method of multi-scale scenario generation therefore represents a significant advancement, capturing both the complexity of real systems and the dynamic effects of CDs. These scenarios form a comprehensive basis for strategic decision-making and forward-looking analyses within DSSs.

3.2 Scenario Generation via Monte-Carlo-Simulation

The scenario generation is based on a stochastic MCS, which is carried out in six consecutive steps. This methodical application builds on the descriptive model defined in Section 3.1 and ensures coherent integration of all model elements. The steps are outlined below and illustrated in Figure 3.

Step 1: Definition and Selection of Change Drivers

The first step involves the definition and selection of the CDs that are to be included in the MCS and that have potential influence on the defined change objects. Experts compile internal and external influences and map them as CDs [16]. Various approaches can be used here, e. g., a structure can be provided by the CDs according to [6]. As there are a large number of possible

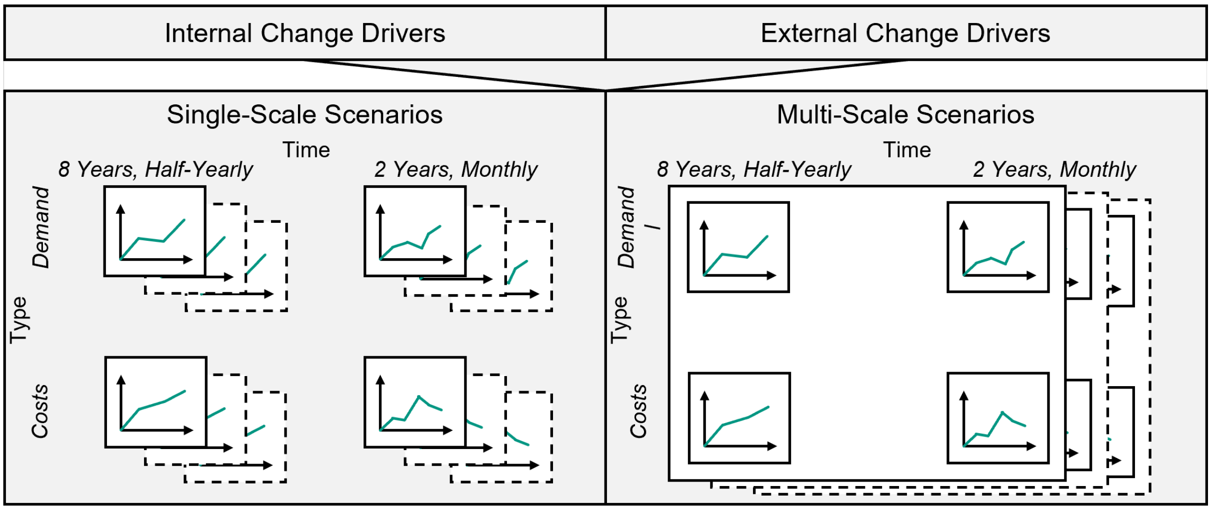


Fig. 2: Delineation of Single- and Multi-Scale Scenarios

CDs, relevant ones must first be identified. [29] and [36] provide a catalog for the selection of CDs. Furthermore, the use of receptors enable a structured selection [16]. Experienced experts and objective data sources should be consulted in order to first define CDs, including their characteristics, and then select them for a specific use case. The selection is made from the totality of all previously defined CDs. A well-founded selection, which includes the selection of CDs and their probability of occurrence and specific characteristics, guarantees the accuracy of further steps.

Step 2: Selection of Receptors and Receptor Key Figures

After defining the CDs, relevant receptors and their associated RKFs are selected. The selection depends on the specific use case and should be reduced to a necessary number in order to keep complexity manageable. Importantly, a change in the value of the RKF must have a direct influence on the PS [16]. The selection of receptors and RKFs usually results from the underlying decision models, as these specify which parameters are subject to uncertainty and therefore need to be modeled.

Step 3: Definition of Interrelationships

A crucial part of scenario generation is the definition of the interrelationships between the CDs and RKFs. The relationships among CDs themselves are defined via the influence matrix I, while the interactions between CDs and RKFs are specified through the CDIs. This step forms the structural core of the MCS, since the accuracy of the resulting scenarios directly depends on how precisely the CDIs are defined. To ensure a consistent and exact modeling of influences, the categorization of both CDs and RKFs according to the respective receptors can be applied.

Step 4: Execution of the Monte Carlo Simulation

The fourth step of scenario generation begins with the execution of the MCS. Each simulation run is assigned a unique ID for tracking purposes. The MCS utilizes the previously defined CDs, RKFs, and their interrelationships. In addition, the time horizon and time slices to be considered must be defined. These determine the representation of the RKFs and can be specified individually for each RKF. Furthermore, the number of iterations N of the MCS, as well as its time unit must be defined. Each iteration $n \in N$ defines an independent simulation run. The necessary number of iterations for a reliable result can be determined based on [37]. The MCS uses random data points from the distribution functions $F(\theta)$ to simulate the probabilities of different CDs, RKFs and CDIs as well as their characteristics.

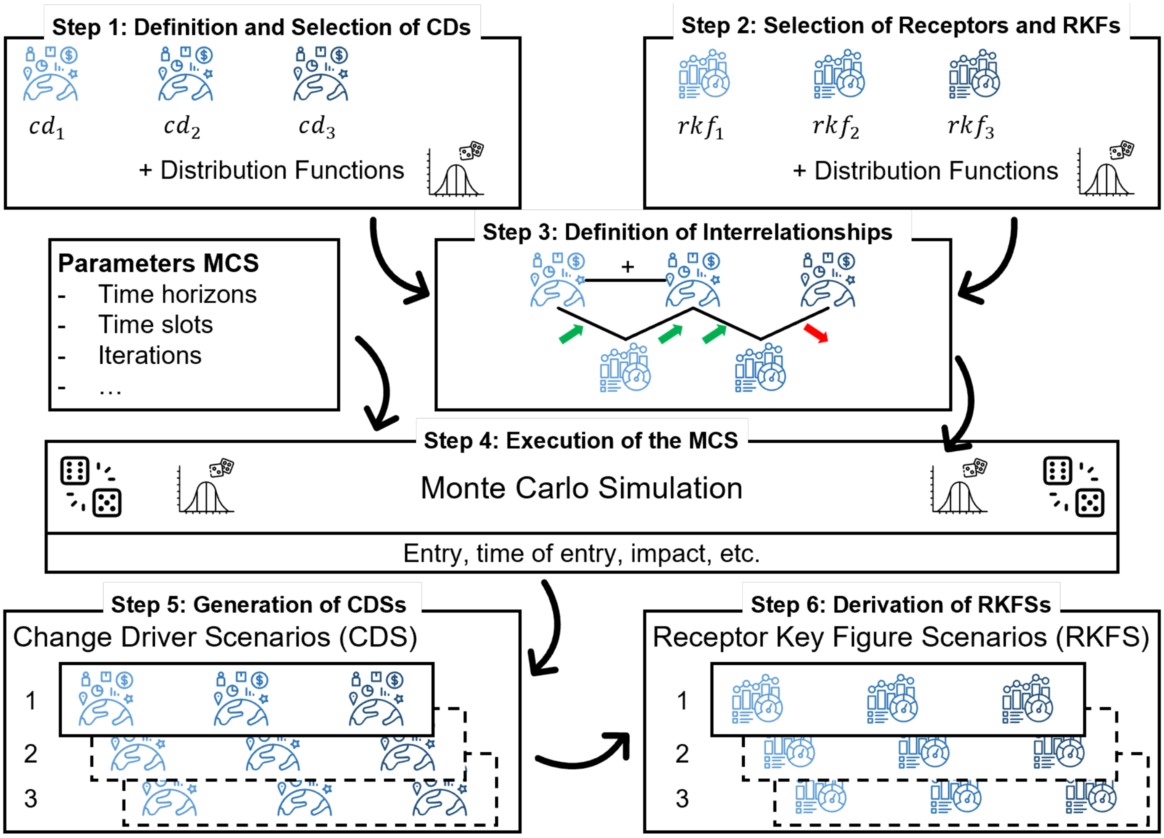


Fig. 3: Six steps of the Monte-Carlo-Simulation

Step 5: Generation of Change Driver Scenarios

The CD Scenarios (CDSs) play a central role in the scenario generation process, as they describe all possible development paths of the CDs within a simulation run n. These scenarios form the basis for constructing the RKF Scenarios (RKFSs). Taken together, all CDSs span the full spectrum of potential future developments of the CDs. A CDS specifies whether and when a CD becomes active, determined by its occurrence probability, associated distribution functions, and dependencies on other CDs. The activity status of a CD is defined as:

$$act_{cd,t} = \begin{cases} 0, & \text{if } t < t_{cd}^{\text{start}} \\ & \quad \lor\, t > t_{cd}^{\text{start}} + T_{cd}^{\text{influence}} \\ 0, & \text{if } \exists cd^* \in CD : I_{cd^*,cd} = -1 \\ & \quad \land\, act_{cd^*,t} = 1 \\ 1, & \text{if } e_{cd}^{\text{entry}} = 1 \\ & \quad \lor\, (\exists cd^* \in CD : I_{cd^*,cd} = 1 \\ & \quad \land act_{cd^*,t} = 1) \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

Here, $act_{cd,t}$ indicates whether CD cd is active at time t. The variable e_{cd}^{entry} represents the entry event of the CD, t_{cd}^{start} its start time and $T_{cd}^{influence}$ the duration of its influence. Dependencies between CDs are captured via the influence matrix I, where I_{cd} denotes the cd-th column of the matrix. A value $I_{cd^*,cd} = 1$ indicates that cd^* causes $cd, I_{cd^*,cd} = -1$ indicates exclusion and

$I_{cd^*,cd} = 0$ indicates independence. The diagonal entries $I_{cd,cd}$ are always set to 0. Each CDS is assigned a unique ID and contains the set of all relevant information: the active CDs, their respective start and end times, and their effects on the RKFs. In summary, a CDS (CDS_n) constitutes the complete input for generating the corresponding RKFSs.

Step 6: Derivation of Receptor Key Figure Scenarios

In the final step, the RKFSs are derived from the previously generated CDSs. Each RKFS ($RKFS_n$) describes the time-dependent evolution of all considered RKFs within a simulation run n. The values of the continuous RKFs result from the baseline parameters and the aggregated influences of the active CDs, as expressed in the following Equation (based on [34]):

$$\begin{gathered} V_{rkf,t}^{res} = p_{rkf,t}^{entry} * \Bigg(V_{rkf,t}^{base,abs} + \sum_{cd=1}^{CD} act_{cd,t} * \\ CDI_{cd,rkf}^{abs} + V_{rkf,t-1}^{res} * \Bigg(\prod_{cd=1}^{CD} \bigg(1 + act_{cd,t} * CDI_{cd,rkf}^{rel} * \\ V_{rkf,t}^{base,rel} \bigg) - 1 \Bigg) + V_{rkf,t-1}^{res} * ((1 + \\ V_{rkf,t}^{base,slope} \bigg) * \\ \prod_{cd=1}^{CD} \bigg(1 + act_{cd,t} * CDI_{cd,rkf}^{slope} \bigg) \Bigg) - 1 \Bigg), \\ \forall rkf \in RKF, t \in T_{rkf} \end{gathered} \tag{2}$$

The formula expresses that the value of a RKF $V_{rkf,t}^{res}$ at time t is composed of four parts: (1) its baseline absolute value, (2) additional absolute impacts from active CDs as well as (3) multiplicative relative and (4) slope-based changes caused by active CDs. The occurrence variable $p_{rkf,t}^{entry}$ ensures that a RKF only takes effect when it is realized.

The RKFSs ensure that for each RKF a value is defined at every point in time, reflecting both baseline behavior and the aggregated effects of the relevant CDs. Each RKFS is assigned a unique ID and provides the complete trajectory of all RKFs over the defined time horizon. Together, the RKFSs constitute the final output of the MCS and serve as the foundation for subsequent scenario analysis and evaluation.

3.3 Clustering to Representative Scenarios

The large number of RKFSs ($RKFS_n$) resulting from the MCS are generally described below as scenarios of the set $\overline{\Omega}$. Following the approach of [32], the number of scenarios $\overline{\Omega}$ is reduced to a manageable set of representative scenarios Ω. For this purpose, a cluster analysis is applied. Cluster analysis requires so-called features that characterize each scenario. While [32] focus only on simulated quantities and define the features time-, customer-, product- and country-specific demand, this paper extends the feature set to include further RKFs. Concrete features depend on the use case, examples can be found in the validated use case in Section 4. These properties of the scenarios, denoted as the feature vector $\overline{\Psi}_\omega$, must be taken into account during clustering.

To reduce dimensionality while maintaining essential information, a Principal Component Analysis (PCA) is applied, resulting in a reduced feature vector Ψ_ω. Clustering is then performed using the k-means algorithm. As soon as the minimization of the Euclidean distance W (see Equation 3) is achieved, the point closest to the cluster centroid C_k with feature vector Ψ_ω represents the representative scenario of this cluster. These points form the set of representative scenarios Ω.

$$W = \sum_{\omega=1}^{\overline{\Omega}} \sum_{k=1}^{K} J_{\omega,k} \| \Psi_\omega - C_k \|^2 \tag{3}$$

Here, $J_{\omega,k}$ defines whether feature vector ω belongs to cluster k ($J_{\omega,k} = 1$) or not ($J_{\omega,k} = 0$). The size of a cluster is given by the number of points in the cluster, and the relative cluster sizes correspond to the scenario probabilities $p_\omega^{Scenario}$ [32].

4 Integration and Quantification of the Results on an Industrial Case Study

The proposed framework is validated through an industrial use case of a German automotive supplier. For this purpose, the scenario generation framework is integrated into a modular DSS and adapted to the specific application context as proposed by [38].

4.1 Introduction to the Use Case

The use case focuses on the production of a vehicle safety component that is manufactured across multiple global sites operated by the industrial partner. An optimization module is employed to identify necessary tactical and strategic adjustments to the GPN, such as the opening or closure of sites and the relocation or acquisition of machinery [33]. Since future parameters are subject to uncertainty, deterministic planning is insufficient for this context, as the strategic decisions are non-recourse and must guarantee applicability to all potential future developments [33]. Specifically, the production planners identified future demand, variable costs and logistics costs as major sources of uncertainty. Consequently, the scenario generation framework is applied to simulate representative scenarios that capture a broad range of possible future developments in both the external and internal environment.

4.2 Results of the Scenario Generation

Future developments of the uncertain parameters are simulated based on the current forecasts provided by the production planners. Demand is expected to decline over the time horizon, as the product is entering a ramp-down phase. The corresponding base scenario is illustrated in Figure 4. Variable costs are assumed to increase semiannually at a constant, site-specific rate, while logistics costs are expected to rise at a constant, site-independent rate of 3.0% per year. The expected development of variable costs for Site 1 and logistics costs from Site 1 to Country 1 are exemplarily shown in Figure 5.

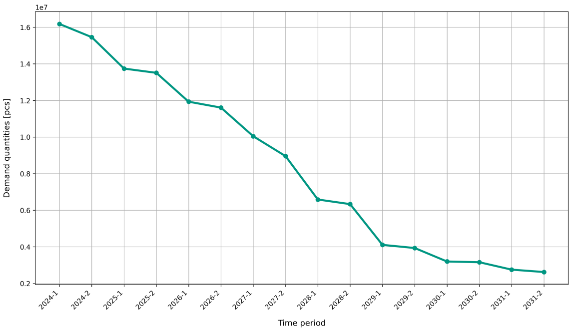


Fig. 4: Forecasted development of demand quantities

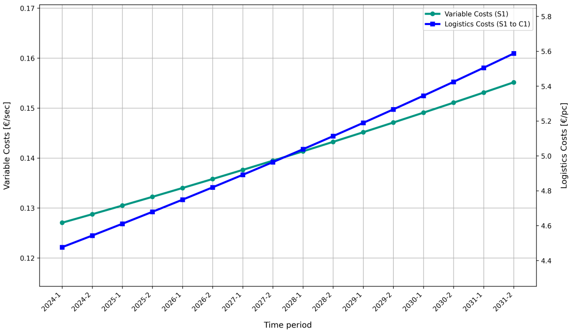


Fig. 5: Forecasted variable costs for Site 1 (S1) and logistics costs from Site 1 to Country 1 (C1)

4.2.1 Monte Carlo Simulation

In the following, the six steps of the MCS, as defined in Section 3.2, are applied to the use case.

Step 1: Definition and Selection of Change Drivers

Relevant CDs were identified in collaboration with the production planners of the industrial partner and linked to one of the two relevant receptors: Costs and Demand. The identified CDs and their respective characteristics, as defined in Section 3.1.1, are presented in Appendix Table A1.

Step 2: Selection of Receptors and Receptor Key Figures

As the GPN is subject to uncertainties in costs and demand, the two receptors Costs and Demand are defined for the MCS. The receptor Costs is divided into variable costs and logistics costs. Each production site has an individual RKF for variable costs, as these vary across sites and are influenced by different factors. Logistics costs depend on both the production and delivery locations, thus, each unique combination of production site and delivery destination constitutes an individual RKF. For the Demand receptor, each customer order is defined as a separate RKF, as order-specific characteristics such as product group, customer, and delivery country determine whether it is affected by a certain CD.

Step 3: Definition of Interrelationships

The interrelationships between CDs and RKFs are summarized in Appendix Table A2. Since no slope is defined for demand-related RKFs, they are subject only to relative and absolute influences. Conversely, cost-related RKFs are generally not subject to absolute influences, as cost developments typically evolve proportionally to their current level rather than through fixed-value shifts. Therefore, only relative influences or changes in their slope are defined. To limit the complexity of the use case, no interrelationships between CDs are modeled (corresponding to the independence type in Section 3.1).

Steps 4, 5 & 6

As steps 4, 5, and 6 are fully automated and executed by the DSS without requiring user input, except the number of iterations, they are not discussed in further detail. The number of iterations N is calculated based on the simplification of [34] of the formula from [37]:

$$N = \frac{0.25}{E^2} z^2_{\frac{(1+\gamma)}{2}} \qquad (4)$$

with the confidence interval γ, the maximal approximation error E and the functional value of the standard normal distribution z. With $E = 0.01$ and $\gamma = 0.99$ the resulting number of iterations N is calculated as $16,589$ and is rounded to $17,000$ iterations.

The resulting output of step 6, the simulated RKFSs, is illustrated in Figure 6 for total demand quantities and variable costs, and in Figure 7 for logistics costs. The rapid fluctuations in logistics costs result from the short influence durations of the CDs affecting these costs (see Appendix Table A2). In contrast to demand and variable costs, changes in logistics costs are modeled as short-term shocks rather than as sustained trends. Therefore, a joint illustration within the same figure would not be appropriate. For better comparison with the cost forecasts, variable and logistics costs are shown for the same sites as presented in Figure 4 and Figure 5.

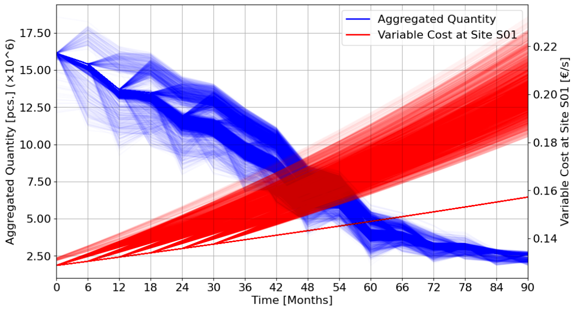


Fig. 6: Absolute Demand Quantities & Mean Variable Costs for Site 1 (all Scenarios)

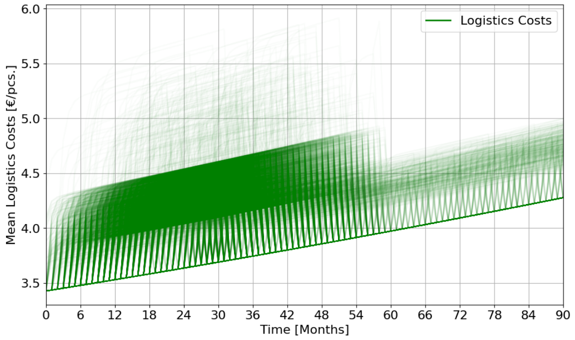


Fig. 7: Mean Logistics Costs from Site 1 to Country 1 (all Scenarios)

4.2.2 Clustering

As described in Section 3.3, the k-means algorithm is used to cluster the RKFSs generated by MCS in order to derive representative scenarios. These representative scenarios cover the key characteristics of the entire scenario funnel while remaining computationally traceable for the optimization module.

Prior to clustering, PCA is employed to reduce the dimensionality of the feature vector used for clustering. This step decreases computation time for the k-means algorithm while retaining the majority of the information contained in the original data. For the use case, an information retention level of 95% was selected.

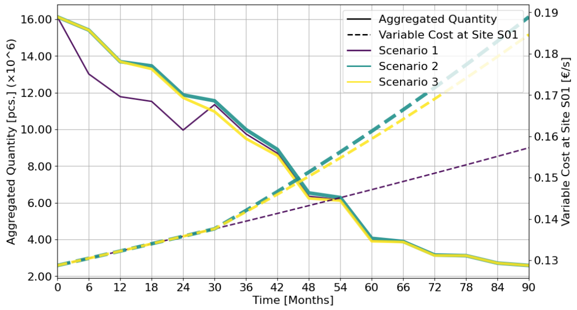


Fig. 8: Absolute Demand Quantities & Mean Variable Costs for Site 1 (representative Scenarios)

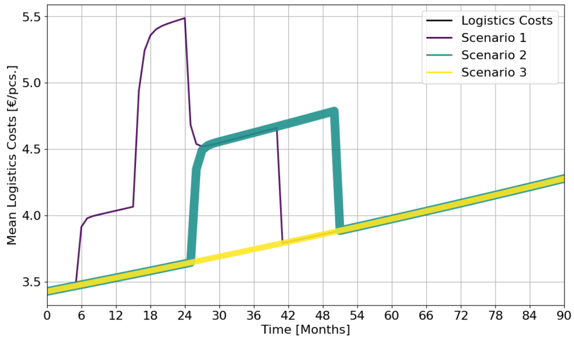


Fig. 9: Mean Logistics Costs from Site 1 to Country 1 (representative Scenarios)

The feature vector used for clustering (prior to PCA) included the following criteria, which form the basis for the respective cluster formation:

- Total demand per period
- Total demand per product group
- Total demand per country
- Mean variable costs per site
- Mean logistic costs per production site – delivery country combination

Based on the defined feature vector, the elbow method was used to determine the optimal number of clusters (k), which was found to be 3. This value was subsequently applied for the k-means clustering. The resulting clusters for demand quantities and variable costs are shown in Figure 8 and in Figure 9 for logistics costs. The scenario probabilities are 1.3% for Scenario 1 (purple), 62.1% for Scenario 2 (green), and 36.6% for Scenario 3 (yellow). The line thickness visualizes these probabilities (scaled for readability in Figure 8).

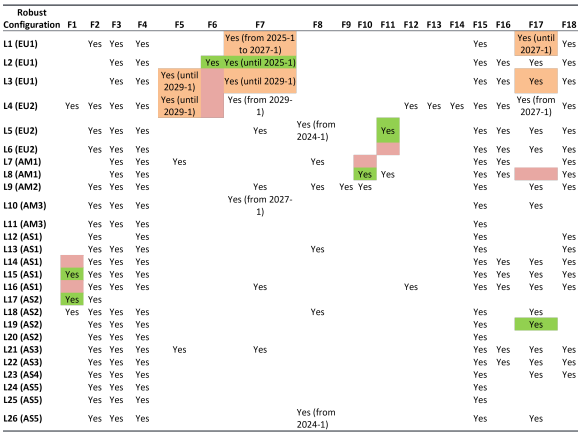
4.3 Scenario Application to Robust Global Production Network Planning

The representative scenarios serve as input for the optimization module, which applies a two-stage stochastic optimization approach to determine robust network configurations and is based on [32, 33]. In this context, strategic and tactical decision variables are defined as here-and-now decisions (i.e., decisions without recourse), while operational variables are defined as wait-and-see decisions (i.e., decisions that allow for recourse). Concretely, decisions regarding the opening or closing of sites or production lines, the purchase or relocation of machines, and the activation status of lines must be made independently of the specific scenario realization. In contrast, exact production volumes and line utilization rates can be adjusted in the short-term, once additional information about future developments becomes available. The respective production lines, their locations, and their base configurations are provided in Appendices Table A3.

In the following, the differences between the robust network configuration, derived from the simulated scenarios, and the base scenario, which represents the planners' initial estimates, are presented. Variations between the configurations result either from differences in the activation of production lines or sites, or from the purchase and reallocation of machinery, leading to altered machine configurations within the lines.

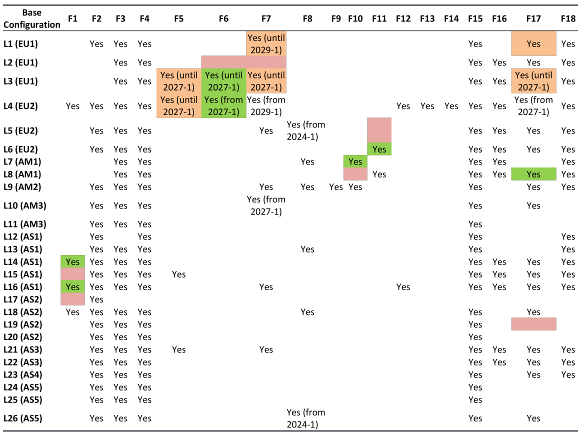
In both the robust and the base network configuration, two additional machines are purchased at site AS5 (L26) and EU2 (L5). Both configurations comprise a total of 22 machine reallocations over the entire planning horizon, which, however, show notable differences. The network configurations regarding machinery for the robust and base cases are shown in Table 2 and Table 3, respectively. To allow for clearer comparison between the two configurations, the differences are highlighted according to the following logic: machinery that is exclusively available in a given configuration is highlighted in green; machinery that is absent in the configuration but present in the other is highlighted in red; and machinery available in both configurations but differing in the period of availability is highlighted in orange.

Table 2: Line configurations for the robust solution



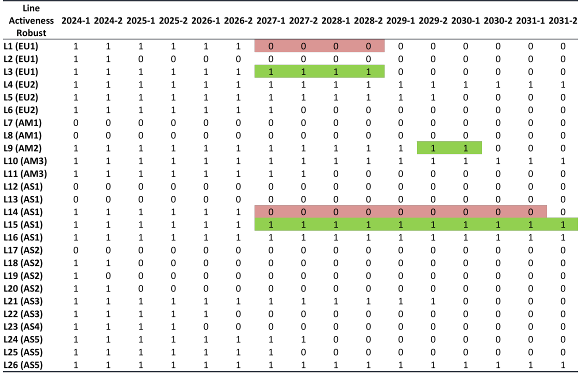
Robust Configuration	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18
L1 (EU1)		Yes	Yes	Yes			Yes (from 2025-1 to 2027-1)								Yes		Yes (until 2027-1)	Yes
L2 (EU1)			Yes	Yes		Yes	Yes (until 2025-1)								Yes	Yes	Yes	Yes
L3 (EU1)			Yes	Yes	Yes (until 2029-1)	🟥	Yes (until 2029-1)								Yes	Yes	Yes	Yes
L4 (EU2)	Yes	Yes	Yes	Yes	Yes (until 2029-1)	🟥	Yes (from 2029-1)					Yes	Yes	Yes	Yes	Yes	Yes (from 2027-1)	Yes
L5 (EU2)		Yes	Yes	Yes			Yes	Yes (from 2024-1)			Yes				Yes	Yes	Yes	Yes
L6 (EU2)		Yes	Yes	Yes							🟥				Yes	Yes	Yes	Yes
L7 (AM1)			Yes	Yes	Yes			Yes		🟥					Yes	Yes		Yes
L8 (AM1)			Yes	Yes						Yes	Yes				Yes	Yes	🟥	Yes
L9 (AM2)		Yes	Yes	Yes			Yes	Yes	Yes	Yes					Yes		Yes	Yes
L10 (AM3)		Yes	Yes	Yes			Yes (from 2027-1)								Yes		Yes	
L11 (AM3)		Yes	Yes	Yes											Yes			
L12 (AS1)		Yes		Yes											Yes			Yes
L13 (AS1)		Yes	Yes	Yes				Yes							Yes			Yes
L14 (AS1)	🟥	Yes	Yes	Yes											Yes	Yes	Yes	Yes
L15 (AS1)	Yes	Yes	Yes	Yes											Yes	Yes	Yes	Yes
L16 (AS1)	🟥	Yes	Yes	Yes			Yes					Yes			Yes	Yes	Yes	Yes
L17 (AS2)	Yes	Yes																
L18 (AS2)	Yes	Yes	Yes	Yes				Yes							Yes		Yes	
L19 (AS2)		Yes	Yes	Yes											Yes		Yes	
L20 (AS2)		Yes	Yes	Yes											Yes			
L21 (AS3)		Yes	Yes	Yes	Yes		Yes								Yes	Yes	Yes	Yes
L22 (AS3)		Yes	Yes	Yes											Yes	Yes	Yes	Yes
L23 (AS4)		Yes	Yes	Yes											Yes		Yes	Yes
L24 (AS5)		Yes	Yes	Yes											Yes			
L25 (AS5)		Yes	Yes	Yes											Yes			
L26 (AS5)		Yes	Yes	Yes				Yes (from 2024-1)							Yes		Yes	

Table 3: Line configurations for the base solution



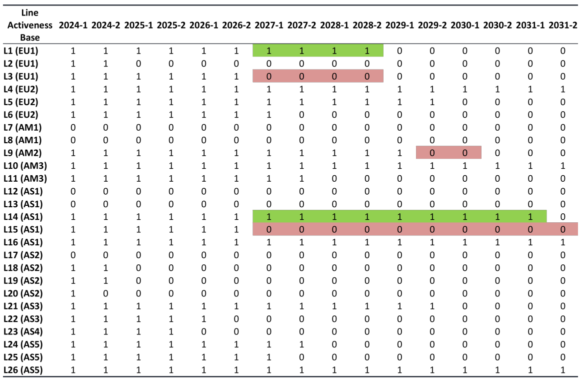
Base Configuration	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18
L1 (EU1)		Yes	Yes	Yes			Yes (until 2029-1)								Yes		Yes	Yes
L2 (EU1)			Yes	Yes		🟥	🟥								Yes	Yes	Yes	Yes
L3 (EU1)			Yes	Yes	Yes (until 2027-1)	Yes (until 2027-1)	Yes (until 2027-1)								Yes	Yes	Yes (until 2027-1)	Yes
L4 (EU2)	Yes	Yes	Yes	Yes	Yes (until 2027-1)	Yes (from 2027-1)	Yes (from 2029-1)					Yes	Yes	Yes	Yes	Yes	Yes (from 2027-1)	Yes
L5 (EU2)		Yes	Yes	Yes			Yes	Yes (from 2024-1)			🟥				Yes	Yes	Yes	Yes
L6 (EU2)		Yes	Yes	Yes							Yes				Yes	Yes	Yes	Yes
L7 (AM1)			Yes	Yes				Yes		Yes					Yes	Yes		Yes
L8 (AM1)			Yes	Yes						🟥	Yes				Yes	Yes	Yes	Yes
L9 (AM2)		Yes	Yes	Yes			Yes	Yes	Yes	Yes					Yes		Yes	Yes
L10 (AM3)		Yes	Yes	Yes			Yes (from 2027-1)								Yes		Yes	
L11 (AM3)		Yes	Yes	Yes											Yes			
L12 (AS1)		Yes		Yes											Yes			Yes
L13 (AS1)		Yes	Yes	Yes				Yes							Yes			Yes
L14 (AS1)	Yes	Yes	Yes	Yes											Yes	Yes	Yes	Yes
L15 (AS1)	🟥	Yes	Yes	Yes	Yes										Yes	Yes	Yes	Yes
L16 (AS1)	Yes	Yes	Yes	Yes			Yes					Yes			Yes	Yes	Yes	Yes
L17 (AS2)	🟥	Yes																
L18 (AS2)	Yes	Yes	Yes	Yes				Yes							Yes		Yes	
L19 (AS2)		Yes	Yes	Yes											Yes		🟥	
L20 (AS2)		Yes	Yes	Yes											Yes			
L21 (AS3)		Yes	Yes	Yes	Yes		Yes								Yes	Yes	Yes	Yes
L22 (AS3)		Yes	Yes	Yes											Yes	Yes	Yes	Yes
L23 (AS4)		Yes	Yes	Yes											Yes		Yes	Yes
L24 (AS5)		Yes	Yes	Yes											Yes			
L25 (AS5)		Yes	Yes	Yes											Yes			
L26 (AS5)		Yes	Yes	Yes				Yes (from 2024-1)							Yes		Yes	

Table 4: Line activeness for the robust solution



Line Activeness Robust	2024-1	2024-2	2025-1	2025-2	2026-1	2026-2	2027-1	2027-2	2028-1	2028-2	2029-1	2029-2	2030-1	2030-2	2031-1	2031-2
L1 (EU1)	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
L2 (EU1)	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L3 (EU1)	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
L4 (EU2)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L5 (EU2)	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
L6 (EU2)	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
L7 (AM1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L8 (AM1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L9 (AM2)	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0
L10 (AM3)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L11 (AM3)	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
L12 (AS1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L13 (AS1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L14 (AS1)	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
L15 (AS1)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L16 (AS1)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L17 (AS2)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L18 (AS2)	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L19 (AS2)	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L20 (AS2)	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L21 (AS3)	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
L22 (AS3)	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
L23 (AS4)	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
L24 (AS5)	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
L25 (AS5)	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
L26 (AS5)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 5: Line activeness for the base solution



Line Activeness Base	2024-1	2024-2	2025-1	2025-2	2026-1	2026-2	2027-1	2027-2	2028-1	2028-2	2029-1	2029-2	2030-1	2030-2	2031-1	2031-2
L1 (EU1)	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0
L2 (EU1)	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L3 (EU1)	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
L4 (EU2)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L5 (EU2)	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
L6 (EU2)	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
L7 (AM1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L8 (AM1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L9 (AM2)	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0
L10 (AM3)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L11 (AM3)	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
L12 (AS1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L13 (AS1)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L14 (AS1)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
L15 (AS1)	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0
L16 (AS1)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L17 (AS2)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L18 (AS2)	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L19 (AS2)	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L20 (AS2)	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L21 (AS3)	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
L22 (AS3)	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
L23 (AS4)	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
L24 (AS5)	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0
L25 (AS5)	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0
L26 (AS5)	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 6: Cost comparison between the base and robust configuration

Cost Differences [€]	Base Configuration	Robust Configuration
Release costs	100.00 %	102.06 %
Upgrade costs	100.00 %	100.00 %
Fix costs	100.00 %	101.13 %
Build costs	-	-
Scrap costs for lines	100.00 %	99.72 %
Line reallocation costs	-	-
Feature reallocation costs	100.00 %	99.94 %
Total costs per period	100.00 %	101.05 %

The differences in demand and cost parameters between the robust and base case also resulted in varying line activeness, as illustrated in Tables 4 and 5. The same color logic as for the machinery comparison is applied: green indicates lines active only in the respective configuration, while red marks lines that are shut down in the configuration, but active in the other.

The resulting network configurations lead to different costs for aligning and operating the GPN. Since these network configuration were derived under different demand and cost assumptions, a direct comparison of total costs would not be meaningful. Therefore, only the direct costs associated with the here-and-now decisions are compared, as they remain constant regardless of the realization of uncertain parameters. The corresponding results are presented in Table 6.

The implications of the identified differences between the robust and base network configurations are discussed in Section 5.

5 Discussion

The main advantage of the robust network configuration lies in the robustness of the here-and-now decision variables across all identified future developments of uncertain parameters. However, the degree of robustness depends on the number and diversity of simulated scenarios. In the use case, the representative scenarios included one with a significant demand decrease between 2024-1 until 2025-2, and another with a slight demand increase from 2025-2 to 2027-1. While the simulated scenarios included cases with a sharp increase in demand at the beginning of the planning horizon (Figure 6), this development was not retained in the final set of representative scenarios derived through clustering (Figure 8).

The elbow method, used to determine the optimal number of clusters for the k-means algorithm, has known limitations and may not always yield the most meaningful partitioning [39]. Alternative approaches, such as predefined cluster numbers or the application of different clustering algorithms, could improve the representativeness of the resulting scenarios. Additionally, performing multiple iterations of the DSS (i.e., simulation and optimization cycles) could help to assess the implications of a broader or more distinct (representative) scenario set. This could either be achieved by increasing the influences of the CDs on RKFs or by fixating a predefined number of clusters for the k-means algorithm.

Application of the framework within the optimization module revealed that even a slight demand increase in one representative scenario (Scenario 2) led to extended activeness of two lines to ensure feasibility. Furthermore, line L1 replaced L3, and L14 replaced L15. Since the replacements occurred within the same production sites, they can be attributed primarily to utilization and reallocation efficiency rather than to direct costs, as they are site-specific and thus constant. While purchased machinery stayed identical, differences in machine reallocations were observed. Table 2 and Table 3 show that the same machines are reallocated in the base and robust case, differing only in timing or line assignment. This suggests that no major bottlenecks were identified, and that variations result mainly from differences in line utilization/activation patterns.

Overall, the use case demonstrates that even minor configuration adjustments can improve the robustness of network design, at an additional cost of roughly 1%. The overall network configuration remained largely similar, reflecting that the simulated scenarios were closely aligned with the base case, which had already been optimized for its respective parameters. This indicates that, in the absence of extreme scenario variations, the robust optimization primarily fine-tunes line activeness and machine reallocations rather than leading to radical changes in the network layout.

6 Conclusion and Research Perspectives

In summary, this paper presents a framework for generating multi-scale scenarios (in time and type) for production planning in GPN. Scenarios are generated via a MCS executed in six steps, covering the definition of receptors, RKFs, CDs, and CDIs. The MCS outputs the CDSs, comprising the active CDs and their characteristics in each scenario (i.e. iteration of the MCS), which are then used to derive RKFSs representing the values of every RKF per scenario across all time periods. These RKFSs are subsequently clustered into representative scenarios using the k-means algorithm, which serve as input for specific use cases. The scenario generation framework is integrated into a DSS with broad applicability, as all inputs for the MCS and clustering criteria can be flexibly defined in the respective input sheets without inherent restrictions.

The DSS is applied to a specific use case from the automotive industry to validate the proposed framework. An optimization module is incorporated for long-term planning of GPNs. The receptors Costs and Demand are defined and the evolution of order volumes, variable costs and logistics costs are simulated using the scenario generation tool. While order volumes and variable costs are simulated on half-yearly slices, the volatility of logistics costs necessitates monthly modeling. Consequently, the scenario generation produces multi-scale scenarios in both time (monthly for logistics costs, half-yearly for variable costs and order volumes) and in type (Demand and Costs), which are used as input for the optimization module. The robust network configuration derived from these scenarios demonstrates that extending the activeness of two lines and adjusting line configurations ensures feasibility across all representative scenarios, increasing costs for the network configuration by approximately 1%.

The quality of the clusters generated by the k-means algorithm suggests that either the identification of the cluster number k (currently determined via the elbow method) or the clustering algorithm itself may be suboptimal. Future research could therefore focus on (a) improving the clustering module for more meaningful and intuitive clusters, and (b) enhancing transparency by visualizing the key drivers behind cluster assignments and exploring how clusters would change with different choices of k.

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Declarations

Conflict of interest. The authors declare that they have no conflict of interest.

Author Contributions. Michael Martin: Conceptualization, Methodology, Data curation, Formal analysis and investigation, Writing - original draft preparation, Software, Validation, Visualization; Yannick Gröppner: Methodology, Data curation, Formal analysis and investigation, Writing - original draft preparation investigation, Software, Validation, Visualization; Moritz Hörger: Writing - review and editing; Gisela Lanza: Funding acquisition, Resources, Supervision and Principal Investigator.

Data availability. The data sets generated during the study are not publicly available because they have not been released by the application partner.

Appendix A

Table A1: Defined Change Drivers for the use case

ID CD	Name Change Driver	Probability	Distribution Function Over Time	Influence Time
CD1	Further escalation of US tariffs	0.5	Triangular(0,12,36)	24
CD2	Escalation of the China–Taiwan conflict	0.25	Triangular(0,18,38)	48
CD3	Labor costs in Germany rising faster than expected	0.35	Uniform(0,36)	999
CD4	Declining demand for German cars	0.6	Uniform(0,96)	24
CD5	Chinese government subsidizes the production of automotive components by local companies	0.4	Triangular(12,24,48)	48
CD6	Global supply shortages due to extreme events (pandemic, environmental disaster, …)	0.15	Uniform(0,96)	18
CD7	New global regulations increasing the product's demand	0.15	Triangular(0,24,48)	36
CD8	Labor costs in Asia rising more slowly	0.25	Uniform(24,48)	999
CD9	Minimum wage in Germany increases	0.3	Triangular(0,12,36)	999

Table A2: Defined Change Driver Influences for the use case

ID CDI	ID CD	RKFs	Influence Type	Influence Distribution
CDI1	CD1	Logistics Costs to US	Relative	Uniform(0.1,0.2)
CDI2	CD1	Logistics Costs to US	Relative	Uniform(0.05,0.1)
CDI3	CD2	Logistics Costs China to EU	Relative	Uniform(0.05,0.15)
CDI4	CD2	Orders from Chinese Companies	Relative	Uniform(-0.15,-0.05)
CDI5	CD3	Variable Costs Europe	Slope	Uniform(0.03,0.05)
CDI6	CD4	Orders from German Companies	Relative	Triangular(-0.2,-0.10,-0.05)
CDI7	CD5	Orders from Chinese Companies	Relative	Uniform(0.05,0.15)
CDI8	CD5	All Orders except Chines Companies	Relative	Uniform(-0.1,-0.02)
CDI9	CD6	All Logistics Costs	Relative	Triangular(0.05,0.10,0.15)
CDI10	CD6	All Orders	Relative	Uniform(-0.25,-0.05)
CDI11	CD7	All Orders	Relative	Uniform(0.07,0.15)
CDI12	CD8	Variable Costs Asia	Slope	Uniform(-0.02,-0.05)

Table A3: Initial line configurations

Line Configuration	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15	F16	F17	F18
L1 (EU1)		Yes	Yes	Yes											Yes		Yes	Yes
L2 (EU1)	Yes		Yes	Yes	Yes	Yes	Yes								Yes	Yes	Yes	Yes
L3 (EU1)			Yes	Yes	Yes		Yes					Yes		Yes	Yes	Yes	Yes	Yes
L4 (EU2)		Yes	Yes	Yes											Yes	Yes		Yes
L5 (EU2)		Yes	Yes	Yes			Yes								Yes	Yes	Yes	Yes
L6 (EU2)		Yes	Yes	Yes			Yes								Yes	Yes	Yes	Yes
L7 (AM1)			Yes	Yes	Yes			Yes		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
L8 (AM1)			Yes	Yes						Yes	Yes				Yes	Yes	Yes	Yes
L9 (AM2)		Yes	Yes	Yes				Yes	Yes						Yes		Yes	Yes
L10 (AM3)		Yes	Yes	Yes											Yes		Yes	
L11 (AM3)		Yes	Yes	Yes											Yes			
L12 (AS1)		Yes	Yes	Yes											Yes			Yes
L13 (AS1)	Yes	Yes	Yes	Yes				Yes							Yes		Yes	Yes
L14 (AS1)		Yes	Yes	Yes											Yes	Yes	Yes	Yes
L15 (AS1)		Yes	Yes	Yes											Yes	Yes		Yes
L16 (AS1)		Yes	Yes	Yes			Yes								Yes	Yes	Yes	Yes
L17 (AS2)	Yes	Yes																
L18 (AS2)	Yes	Yes	Yes	Yes				Yes							Yes		Yes	
L19 (AS2)		Yes	Yes	Yes											Yes			
L20 (AS2)		Yes	Yes	Yes											Yes			
L21 (AS3)		Yes	Yes	Yes			Yes								Yes	Yes	Yes	Yes
L22 (AS3)		Yes	Yes	Yes											Yes	Yes	Yes	Yes
L23 (AS4)		Yes	Yes	Yes											Yes		Yes	Yes
L24 (AS5)		Yes	Yes	Yes											Yes			
L25 (AS5)		Yes		Yes											Yes			
L26 (AS5)		Yes	Yes	Yes											Yes			

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