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Solution Space Management to Enable Data Farming in Strategic Network Design

Sebastian Kroeger [1,*], Marc Wegmann [1], Christoph Soellner [2] and Michael F. Zaeh [1]

[1] Institute for Machine Tools and Industrial Management, TUM School of Engineering and Design, Technical University of Munich, Bolzmannstr. 15, Garching Near Munich, 85747 Munich, Bavaria, Germany; marc.wegmann@iwb.tum.de (M.W.); michael.zaeh@iwb.tum.de (M.F.Z.)
[2] Bayerische Motoren Werke (BMW) AG, Petuelring 130, 80809 Munich, Bavaria, Germany; christoph.soellner@bmw.de
* Correspondence: sebastian.kroeger@iwb.tum.de; Tel.: +49-(89)-289-15547

Abstract: During strategic network design, not only strategic but also operational decisions must be made long before a production network is put into operation. These include determining the location and size of inventories within the production network and setting operational parameters for production lines, such as the shift model. However, the large solution space comprising a high number of highly uncertain design parameters makes these decisions challenging without decision support. Therefore, data farming offers a potential solution, as synthetic data can be generated via the execution of multiple simulation experiments spanning the solution space and then analyzed using data mining techniques to provide data-based decision support. However, data farming has not yet been applied to strategic network design due to the lack of adequate solution space management. To address this shortcoming, this paper presents a structured solution space management approach that integrates production network-specific requirements and Design of Experiment (DoE) methods. The approach enables converting the solution space in strategic network design into individual input data sets for simulation experiments, generating a comprehensive database that can be mined for data-based decision support. The applicability and validity of the comprehensive approach are ensured via a case study in the automotive industry.

Keywords: data farming; design of experiments; production networks; strategic network design; solution space management; production network simulation; value stream

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1. Introduction

During the past decades, production networks have turned out to be a successful way to secure access to markets, resources, and worldwide cost advantages, which are all necessary for enterprises to survive in global competition. The architecture of production networks, consisting of several geographically dispersed production sites and interconnected material and information flows, leads to high system complexity [1]. Within production networks, several intermediate products may be produced at different sites and then assembled into a finished product that is shipped to the customer. This linkage of the value stream of an intermediate product to the value stream of a finished product is called a comprehensive value stream. In strategic network design, network planners aim to design an efficient, comprehensive value stream [2].

However, this aim is hard to reach as production networks operate in a volatile and uncertain environment while making complex decisions in ambiguous situations. These influencing factors can be summarized as the so-called VUCA (volatility, uncertainty, complexity, and ambiguity) world [3]. The VUCA world also negatively affects the predictability of total and variant-specific demand volumes and design parameters.

Strategic network design for the production of technical products begins up to 12 years before the start of production [4]. Hence, most design parameters are subject to high volatility and uncertainty. In addition, the production network as a planning object has become increasingly complex in recent years due to the increasing number of associated plants and linkages [5]. Finally, the impact of design parameters on network performance is unknown, leading to ambiguous decision situations. To address these challenges, Kroeger and Zaeh [2] propose a data-farming-based planning approach. Data farming refers to a concept where a simulation model is used to "farm" synthetic data when real data are not available in sufficient quantity [6,7]. The synthetic data can then be used to apply data mining methods [6]. By analyzing the possible range of behavior of the simulation model, this approach leads to a comprehensive understanding of the system [8]. Moreover, the simulation experiments can cover existing uncertainty in design parameters and the solution space.

The proposed planning approach consists of three parts, as shown in Figure 1. The first part deals with solution space management and derives multiple input data sets for a value stream simulation model based on the generic solution space and an experimental design approach. The second part addresses the system behavior of the production network via a value stream simulation model and a corresponding data structure. The simulation model is required to execute all predefined simulation experiments in the experiment plan. The value stream data structure stores the simulation experiment results in a specific format to build a simulation database. Finally, the third part describes the analysis and evaluation of the simulation database based on a comprehensive digital value stream analysis using process mining [2].

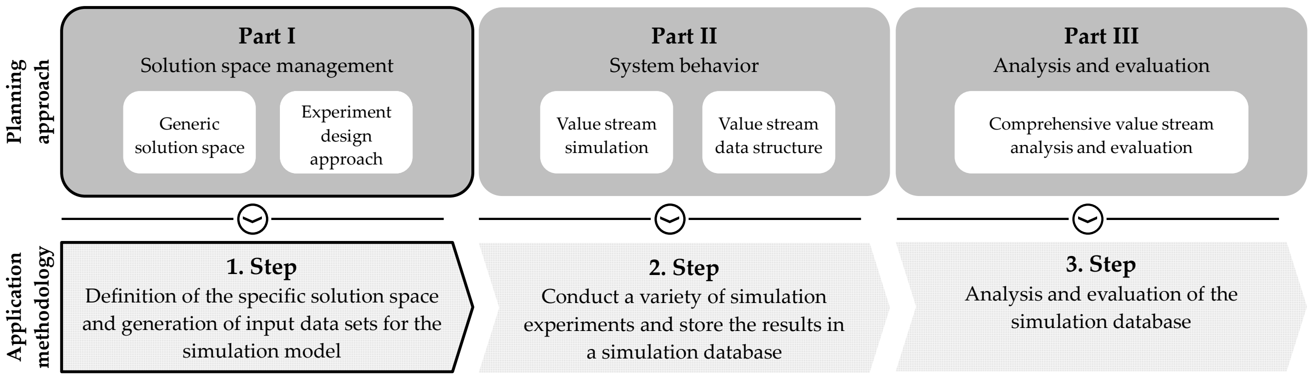

Figure 1. Data-farming-based planning approach and corresponding application methodology following [2]. This paper describes part I of the approach in detail, as the black outline indicates.

The solution space management acts as the foundation to enable the data-farming-based planning approach proposed by Kroeger and Zaeh [2], which is why this paper focuses on a detailed elaboration of Part I and the evaluation of its applicability and validity.

The remainder of this paper is structured as follows: Section 2 introduces the fundamentals needed to understand the problem statement for solution space management within the planning approach. Section 3 provides an overview of the current publications on solution space management within data farming approaches and mentions existing shortcomings. Based on this, the requirements for the developed approach are derived in Section 4. The solution space management approach is then described in Section 5, followed by an evaluation of its applicability and validity within an industrial case study of the automotive industry in Section 6. The paper concludes with a discussion of the application results and industrial implications in Section 7 and a conclusion and outlook in Section 8.

2. Fundamentals

This section introduces fundamental theories to understand the planning situation in strategic network design (Section 2.1), the data farming methodology (Section 2.2), and the basic concepts of solution space management (Section 2.3). With these fundamentals in place, the problem statement for solution space management within the planning approach by Kroeger and Zaeh [2] can be described (Section 2.4).

2.1. Strategic Production Network Design

Strategic network design addresses the two main tasks of network configuration and network coordination [9]. According to Porter [10], network configuration refers to the distribution of a company's value creation process across different locations. Network coordination deals with the timing and content of processes between different locations [10,11]. The two main tasks result in two planning levels integrated into the strategic network design [12]. Firstly, strategic structural decisions (configuration), such as decisions on plant locations and new products, are made on a strategic planning level [12]. Secondly, operational decisions, e.g., concerning the flow of goods within the network (coordination), are subject to an operational planning level within strategic network design [12]. A common approach to strategic network design presented by [12] is shown in Figure 2. This process can be linked to important interdependencies between planning decisions in strategic network design [2].

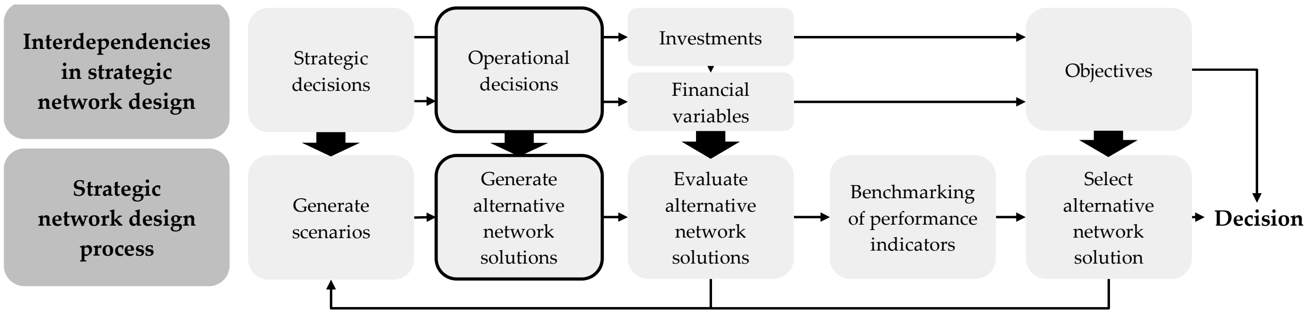

Figure 2. Generic strategic network design process and interdependencies between decisions following [2,12].

The top management makes strategic structural decisions, such as whether or not to open a new plant, to generate different manageable scenarios within the first step of the strategic network design process. These decisions set the framing conditions for network planners to create alternative network solutions for each scenario based on operational decisions such as buffer sizes for internal customer-supply relationships. Next, investments as a consequence of strategic structural decisions and other financial variables are used to evaluate all alternative solutions. Then, industry best practices are applied to benchmark each alternative solution regarding suitable performance indicators. Finally, the decision for an alternative solution can be made based on the results of the previous steps and qualitative objectives such as flexibility or customer service [12].

The data-farming-based planning approach shown in Figure 1 addresses steps two and three of the strategic network design process and assumes a set of scenarios as input data. Currently, alternative solutions are generated in the industry based on subjective and mostly unsystematic decisions by network planners. Using a data-farming-based approach opens up the solution space for alternative solutions based on operational decisions to enable systematic, objective decisions [2].

2.2. The Data Farming Approach

The data farming methodology was introduced by Brandstein and Horne [6] as a process to support decision-makers in answering questions when large numbers of alternative solutions are possible [13]. The first applications addressed warfare simulations to support NATO. The core idea of the methodology is to "farm" synthetic data through a simulation model and large experiment plans and then apply data mining methods to this data to provide decision support in problem settings when real data are unavailable. The data farming methodology is structured by a simulation-based, holistic, and iterative approach, which can be visualized by the "loop of loops" [14]. The first loop, referred to as the experiment definition loop, consists of model development and rapid scenario prototyping. The second loop, referred to as the multi-run execution loop, comprises the design of experiments, high-performance computing, as well as analysis and visualization [13]. The planning approach shown in Figure 1 is fundamentally based on the data farming methodology. Therefore, Part I, the solution space management, comprises mainly the "design of experiments", which is, according to Genath et al. [15], the most important part of the data farming methodology. Sanchez et al. [16] present different established methods for experiment design in data farming.

2.3. Solution Space Management

In product development, the solution space can be defined as the sum of all theoretically conceivable solution possibilities for a task [17]. Furthermore, the solution space can be described based on a set of degrees of freedom and their properties [18]. If the exemplary degree of freedom is the material choice for a part, then the associated properties could be alloy, steel, or magnesium. The set of properties of the degrees of freedom describes an alternative solution in the solution space [18]. Degrees of freedom differentiate between fixed and variable degrees of freedom. Fixed degrees of freedom are considered unchangeable, while variable degrees of freedom allow properties to vary within a certain range. For example, the inventory level can vary from 100 to 300 storage places [18]. To control the solution space, solution space management is necessary.

Lenders [19] developed a process model for solution space management consisting of three steps. First, solution space structuring aims at defining sub-solution spaces for each sub-problem of the main solution space [18]. In product development, the solution space is constructed based on the functions of a product. Second, solution space planning involves developing a strategy for narrowing down the solution space [18]. Third, solution space control is used to iteratively control and steer the systematic reduction of the degrees of freedom by comparing the actual state with the target state [18].

Solution space management originates from product development, but the concept has already been transferred to other domains, such as factory planning [20]. In the context of strategic network design and the planning approach shown in Figure 1, the solution space for a scenario encompasses all possible alternative network solutions. This means that fixed degrees of freedom are design parameters that are defined within a strategic structural scenario (e.g., plant locations), and variable degrees of freedom are design parameters influenced by operational decisions (e.g., inventory levels) concerning all possible combinations of design parameters.

2.4. Problem Statement

In conclusion, solution space management is an important part of the data farming methodology and equally important to the planning approach of Kroeger and Zaeh [2]. However, there are different challenges (*CH*) that can be found in the literature. First, the addressed planning subject (production network) and the planning situation (operational decisions in strategic network design) pose challenges for solution space management. Due to the complex structure of a production network, the solution space is huge (*CH1*), which is considered one of the major challenges in strategic network design [12]. Moreover, the large planning horizon in strategic network design requires dealing with the high uncertainty (*CH1*) in the available planning data while generating and evaluating alternative network solutions [4]. Another challenge arises from the need to cover the solution space as completely as possible (*CH2*) by identifying all necessary alternative network solutions within the structure and parameter variations. An equally important challenge is the need for a structured solution management process and a transparent solution path to enable a user-friendly application (*CH3*).

3. Related Work

The following sections explain related work in solution space management in the context of data farming. For that reason, Section 3.1 presents existing strategic network design approaches. Afterwards, Section 3.2 elaborates on relevant data farming applications. Then, the shortcomings of the existing approaches are derived in Section 3.3.

3.1. Strategic Network Design Approaches

There are many approaches in the scientific literature dealing with strategic network design. The approaches can be grouped into four main clusters [21–23]. First, process models such as [24,25] focus on describing the chronological sequence and purpose of decision process steps rather than identifying or evaluating alternative network solutions [22]. Second, mathematical optimization approaches such as by [26] compute an optimal network design while neglecting all process-related requirements and creating multiple alternative network solutions [21]. Third, evaluation approaches such as [27–29] focus on evaluating alternative network solutions to act as decision support [21]. Fourth, combined approaches such as [21,22,30] use process and mathematical optimization models. Therefore, these approaches generate multiple alternative network solutions within the predefined solution space [21]. As a preliminary conclusion, only evaluation and combined approaches address generating and evaluating alternative network solutions, which is necessary for solution space management. Hence, this paper describes evaluation and combined approaches in more detail.

Ude [27] presents an evaluation approach based on simulating a limited number of network configurations and evaluating the simulation results to provide a multi-criteria decision-making aid. Thereby, Ude [27] also considers uncertainty in strategic network design. Auberger et al. [29] propose a simulation-based evaluation approach with a process model. The approach evaluates a limited number of network configurations and analyzes different optimization measures to support decision-making. Merchiers [28] provides a detailed evaluation approach to various costs within production networks, separated into module, site, and network levels.

Sager [21] develops a combined approach based on the decision process and integrates a multi-criteria optimization model to generate alternative network solutions. Hochdörffer [30] suggests a five-step approach that addresses production networks' strategic, tactical, and operational planning levels. The approach provides tools for each level that are applied to an alternative network solution.

3.2. Relevant Data Farming Applications

Although the data farming methodology originates from warfare simulations [14], a recent publication by Lechler et al. [7] proves its applicability to manufacturing system simulations. The application is particularly useful in the planning phase when real data are not available. Moreover, in manufacturing, data farming leads to a comprehensive, data-based system understanding instead of focusing on predefined, specific "what-if" analyses as carried out in the past [8]. There are already several publications on the application of data farming in manufacturing.

Feldkamp et al. [31] apply data farming to a demonstrator production line. The experiment design considers quantitative factors such as buffer capacities, categorical factors such as clearance strategies, and different product mixes, resulting in approx. 102.400 simulation runs. Hunker et al. [32] apply data farming in the context of supply chains. An exemplary supply chain is analyzed using an experiment plan with 257 different experiments. Schulze et al. [33] analyze a data farming case study from vehicle assembly. For this purpose, a simulation model of a 30-station and 14-buffer assembly line was used. Moreover, the simulation model covers 50 workers and 720 different vehicle variants. The factors were separated into decision factors and disturbance factors. First, Schulze et al. [33] varied the decision factors based on a Nearly Orthogonal Latin Hypercubes (NOLH) experiment design [34], and then the disturbance factors were also varied. Schuh et al. [35] apply clustering algorithms to a simulation database that was created using the data farming methodology. Thereby, the goal is to optimize the operation status of a production system. To do so, Schuh et al. [35] compare different order control approaches in combination with a set of order prioritization rules and production volume variation. This results in 1470 simulation experiments, leading to a large simulation database for clustering analysis.

Many authors use dedicated methods (e.g., NOLH designs) to design data farming experiments. In general, the goal of these methods differs from the traditional goals of physical experimentation. For data farming, large experiment designs with good space-filling behavior are preferred over small designs [36]. Experiment design methods for data farming are not further discussed in this paper, as they are the subject of several publications, such as [16,37,38].

3.3. Shortcomings of Existing Approaches

Based on the challenges from Section 2.4, the related work can be evaluated to derive apparent shortcomings (*SH*); see Table 1. Existing strategic network design approaches mainly focus on strategic structural decisions rather than tactical and operational decisions. With respect to structural decisions, the approaches partially consider the uncertainty and the large number of design parameters, but relevant data farming applications only present use cases within production lines. Only one approach addresses a closely related application in the supply chain context. Therefore, there is a lack of solution space management for operational decisions in strategic network design (*SH1*).

Table 1. Evaluation of the related work based on the challenges (*CH1*–*CH3*).

Publications	Criteria	*CH1*	*CH2*	*CH3*
Ude [27]	*Strategic network design approaches*	◐	◐	◐
Auberger et al. [29]		●	◐	◐
Merchiers [28]		◐	○	○
Sager [21]		◐	◐	◐
Hochdörffer [30]		◐	○	○
Feldkamp et al. [31]	*Relevant data farming applications*	○	●	◐
Hunker et al. [32]		◐	●	◐
Schulze et al. [33]		○	●	◐
Schuh et al. [35]		○	◐	◐

● Predominantly fulfilled, ◐ Partially fulfilled, ○ Not fulfilled.

Moreover, strategic network design approaches either do not cover the entire solution space or reduce the solution space to a very limited number of alternative solutions. Only one strategic network design approach [21] uses a simplified solution space management process. Most relevant data farming applications use established data farming experiment design methods that properly cover the solution space. However, all data farming applications deal with a limited number and interdependencies of input planning parameters. Thus, another shortcoming arises from the need for an approach that covers the solution space of complex systems with a large number of highly interdependent design parameters (*SH2*).

Furthermore, most strategic network design approaches apply mathematical optimization models to generate an optimal alternative solution with limited transparency of the solution path. A user of an optimization algorithm cannot understand how the algorithm finds its optimal solution and thus cannot understand the interdependencies of planning parameters and resulting network performance. Moreover, relevant data farming applications only show a transparent solution path due to the limited number of input design parameters and interdependencies. In contrast, a transparent solution path and a structured process are critical to an industrial application of solution space management. This leads to another shortcoming in providing a user-friendly, industrial application-focused, well-structured, highly transparent solution space management approach (*SH3*).

4. Requirements for the Solution Space Management Approach

Based on the derived shortcomings (*SH1*–*SH3*) and the intended goal of providing input data sets for production network simulation as part of the planning approach by Kroeger and Zaeh [2], different requirements need to be addressed. Table 2 provides an overview of all relevant requirements.

Table 2. Summary of the requirements for the solution space management approach.

	Requirements
	General requirements
G-RQ1	Focus on operational decisions within the strategic network design
G-RQ2	Focus on value-stream-relevant parameters
	Methodology-based requirements
M-RQ1	Comprehensive representation of the solution space
M-RQ2	Identification of alternative solutions
	Application-based requirements
A-RQ1	Possibility to customize the approach to a problem-specific solution space
A-RQ2	Structured approach and understandable, transparent solution path
	Production-network-operations-based requirements
O-RQ1	Material flow maintenance across customer-supplier relationships
O-RQ2	Fixed demand volume for capacity planning
O-RQ3	Complete demand fulfillment of customers on a weekly basis

The requirements in Table 2 are categorized into four groups. First, general requirements (*G-RQ*) originate from the higher-level planning approach by Kroeger and Zaeh [2] by describing the addressed planning situation of operational decisions during strategic network design and the intended focus on the comprehensive value stream in production networks. Second, methodology-based requirements (*M-RQ*) emerge from the main goal of solution space management, which is to cover the entire solution space by identifying and describing alternative solutions. Third, application-based requirements (*A-RQ*) arise from the goal of industrial applicability of the solution space management approach. Therefore, the possibility of customizing the approach for different problem-specific solution spaces is necessary. Moreover, a structured approach secures industrial applicability, and an understandable, transparent solution path supports the user's acceptance of the approach's results. Fourth, production-network-operations-based requirements (*O-RQ*) emerge from the necessity to identify alternative network solutions that can be operated and simulated [21]. For each customer-supplier relationship, the inbound and outbound material flows must match. In addition, the annual demand volume of products is fixed as a restriction on the capacity dimensioning of the production network. Furthermore, another capacity-dimensioning-related restriction is set for customer demand fulfillment on a weekly basis.

5. Solution Space Management for Data Farming in Strategic Network Design

The following section builds on the requirements and describes the methodological foundation of the solution space management approach. First, an overview of the approach is presented, followed by detailed information and illustrative examples for the first step (Section 5.1) and the second step (Section 5.2) of the approach. The application of the methodology to an industrial use case is presented in Section 6.

The proposed solution management approach, shown in Figure 3, encompasses two main steps corresponding to the process model proposed by Lenders [19]; see Section 2.3. The first step (1), solution space structuring, consists of three substeps to decompose the available solution space into a solution space structure. The solution space structure can be described as a set of independent sub-solution spaces comprising multiple variable degrees of freedom. The second step (2), solution space planning, uses the solution space structure to derive alternatives for each sub-solution space based on design of experiment (DoE) approaches. Finally, the alternatives for each sub-solution space form an experiment design of alternative network solutions, which is post-processed into input data sets for simulation.

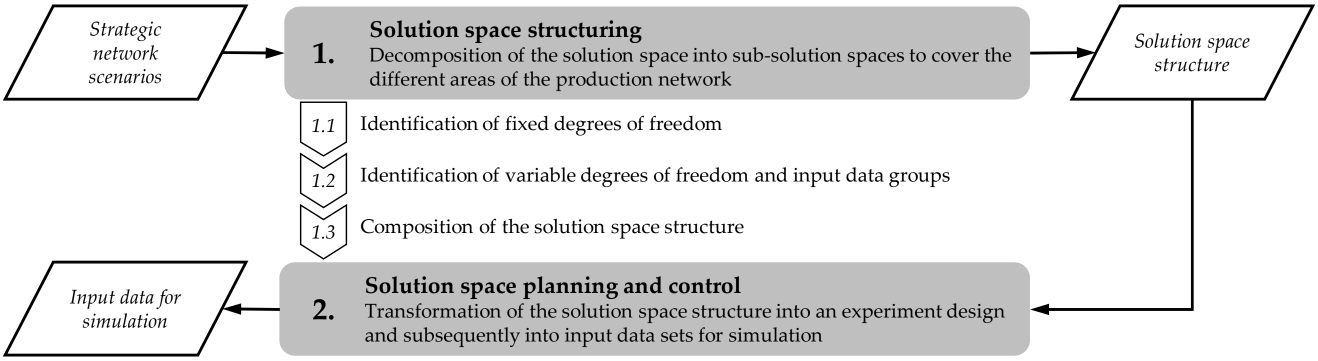

Figure 3. Overview of the solution space management approach.

5.1. Solution Space Structuring

A detailed overview of the solution space structure is shown in Figure 4. The first sub-step (1.1), identification of fixed degrees of freedom, classifies the literature-based solution space into fixed degrees of freedom, already defined by strategic network scenarios (e.g., plant locations, customer sites, and product structure), and variable degrees of freedom (e.g., number of production lines, number of warehouses, and inventory levels), defined by operational decisions. The fixed degrees of freedom set boundaries for the solution management approach, while the variable degrees of freedom can be changed by planning decisions. Several authors provide detailed descriptions of production network design parameters for the literature-based solution space [21,39–42].

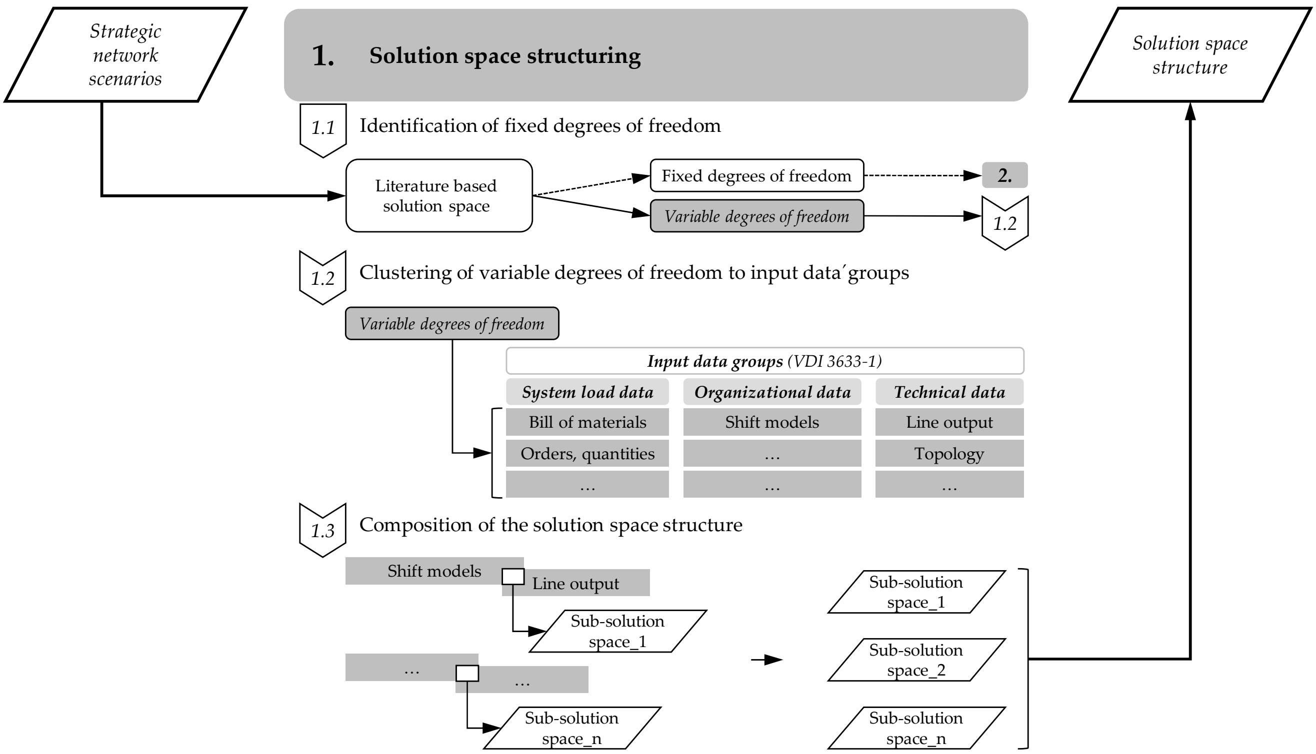

Figure 4. Detailed overview of step 1: Solution space structuring.

The second substep (1.2), clustering of variable degrees of freedom to input data groups, deals with the clustering of all variable degrees of freedom to input data groups based on VDI3633-1:2014-12 [43]. The VDI3633-1:2014-12 [43] describes organizational data (e.g., shift models), technical data (e.g., production line output, production line failures), and system load data (e.g., production orders, bills of materials) that is required to simulate any technical system, such as production networks. The solution space management approach aims to enable data farming in production networks by providing input data sets for production network simulation. Therefore, the input data sets must contain the required data according to VDI3633-1:2014-12 [43].

The third substep (1.3), composition of the solution space structure, analyzes the interdependencies between different variable degrees of freedom. The final goal is to derive a set of sub-solution spaces (solution space structure) that can be either modified independently or have clear interfaces to each other. As a simplified example, the sub-solution space to describe the production capacity is composed of the two variable degrees of freedom shift model and line output (c.f. substep 1.3 in Figure 4). This sub-solution space results from their interdependency and from the fact that the working hours (shift plan) are multiplied by the line output to calculate the production capacity.

5.2. Solution Space Planning and Control

A detailed overview of the solution space planning and control is presented in Figure 5. The main goal of this step is to transform the solution space structure into an experiment design, which is necessary to derive input data sets for simulation. Therefore, the initial solution space must be defined based on the maximum (max.) possible parameter range of all degrees of freedom, taking into account all interdependencies between degrees of freedom for each sub-solution space. In addition, the network-operations-based requirements from Table 2 are also considered at this point. Within the max. possible parameter range, DoE methods, and specific experiment design methods for data farming are applied for each sub-solution space to generate alternatives, c.f. [16]. All sub-solution space alternatives and the fixed degrees of freedom from substep 1.1 are then combined into one comprehensive experiment design, which is post-processed into input data sets for simulation. Referring to the simplified production capacity sub-solution space, the max. line output and the max. working hours are defined and divided into different levels, which act as input parameters for DoE-based parameter variation to build an experiment design.

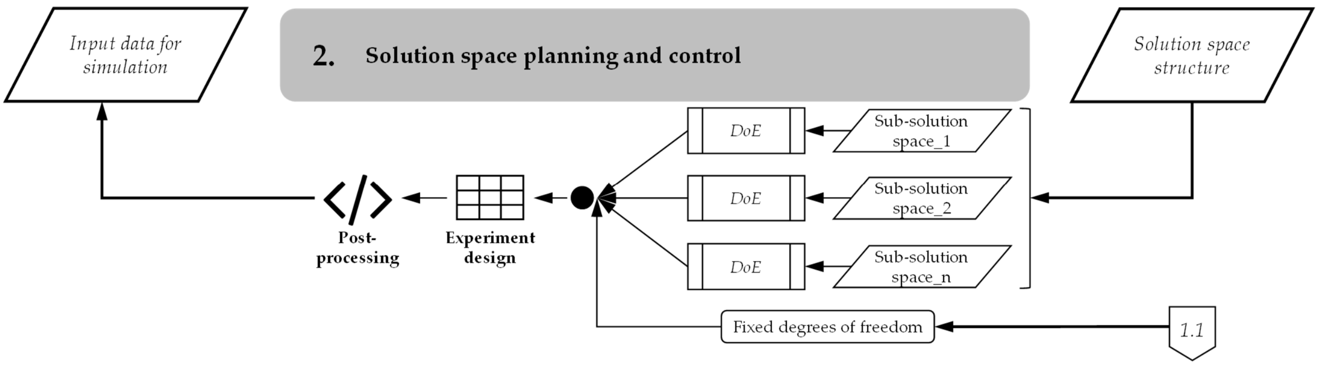

Figure 5. Detailed overview of step 2: Solution space planning and control.

Within the process model for solution space management developed by Lenders [19], solution space control is necessary for the systematic limitation of the solution space. Within the data-farming-based setting of the solution management approach, there is no need to further constrain the solution space, as no resources other than computational power are needed to simulate many experiments. Hence, the solution space control post-processes the experiment design to derive input data sets for production network simulation.

In conclusion, the developed solution space approach applies and extends the conceptual ideas of [19] to the context of operational decisions in strategic network design. Thereby, a set of input data sets for simulation can be derived that covers relevant design parameter combinations. This lays the groundwork to generate a simulation database for the data-farming-based planning approach by Kroeger and Zaeh [2].

6. Industrial Application of the Developed Approach

The following section presents the industrial application of the described solution space management approach from Section 5. First, Section 6.1 introduces the details of the application case. Then Sections 6.2 and 6.3 show the application of the two solution management approach steps according to Sections 5.1 and 5.2.

A use case was conducted at a German automotive company to evaluate the developed solution space management approach in an industrial environment. The findings are used to assess the fulfillment of the requirements presented in Section 4. All data and information presented in the following section are taken from a real use case but presented in an alienated form due to confidentiality restrictions. In particular, this applies to the characteristics of the production network, such as the number and type of products, market demand, number of sites, production line capacities, etc. Due to the alienated data base, the results presented in the following sections do not represent generally valid recommendations for action in real-life decision situations but are intended to demonstrate the applicability and validity of the developed approach.

6.1. Description of the Industrial Environment

For the presented industrial application, only one network scenario is analyzed to keep the results within the scope of this publication. A summary of the input data for the considered strategic network scenario is shown in Figure 6.

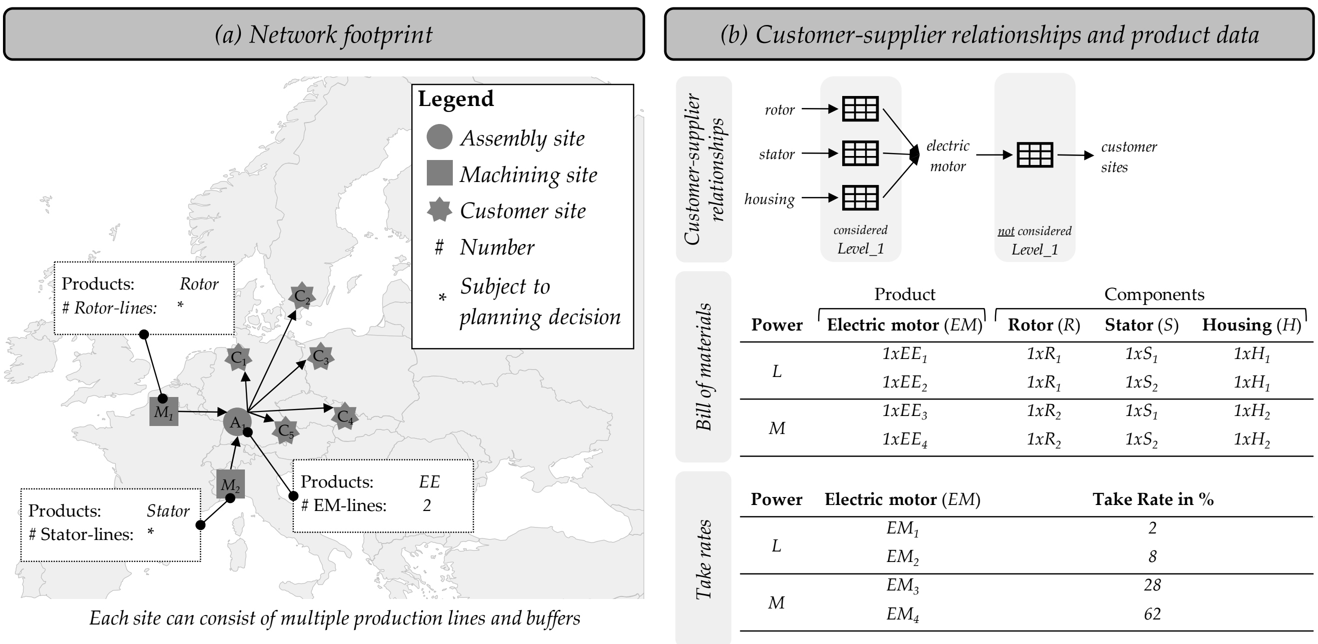

Figure 6. Summary of input data to the solution space management approach; (**a**) footprint of the production network; (**b**) customer-supplier relationships and product data.

The European network footprint with the existing machining, assembly, and customer sites, including the supply relationships, is presented in Figure 6a. Customer-supplier relationships, product data such as the bill of materials (BOM), and the take rates (share of the total demand volume) for specific product variants are shown in Figure 6b. The production network footprint can be decomposed hierarchically into a set of customer-supplier relationships on different factory levels [44,45]. The highest level of customer-supplier relationships is derived from the product structure, meaning that a *rotor*, a *stator*, and a *housing* are supplied to an assembly line to assemble an electric motor, which is subsequently supplied to a customer (*Level_1*). The next level of customer-supplier relationships exists between production lines (*Level_2*).

Moreover, the analyzed strategic scenario is also subject to a set of system constraints (*SC*) originating from the industrial environment. They are differentiated into organizational, production line, and miscellaneous constraints.

The following organizational constraints need to be obeyed:

- *SC01*: All sites operate in the same standard shift model, either 15 shifts/week or 10 shifts/week.
- *SC02*: Standard net working hours per shift vary by technology. Machining sites operate 8.0 h/shift, and assembly sites operate 7.2 h/shift.

Furthermore, the following production line constraints need to be obeyed:

- *SC03:* The number of production lines for each component (*rotor*, *stator*, *housing*) and the product (*electrical engine*) is limited to two lines.
- *SC04*: The production line behavior only considers a worst case and a realistic case for the *rotor* lines. The production line behavior for the *electrical engine*, the *stator*, and the *housing* lines is fixed.
- *SC05*: The number of production lines for the *electric motor* (two lines) and for the *housing* (two lines) is fixed.
- *SC06*: The variant flexibility of production lines is set to full flexibility (all variants) if there is only one line. If there are two lines, variant flexibility is set to one full flexibility line and one high-runner line (defined for this application as variants with a take rate > 25%).

In addition to these constraints, the following miscellaneous constraints must be obeyed:

- *SC07*: Supplier and customer production lines (*Level_2*) can be linked in either a 1:n or a 1:1 relationship. There is a decoupling buffer (warehouse) between each *Level_1* customer-supplier relationship, but only the customer-supplier relationship between *rotor*, *stator*, *housing*, and *electric motor* assembly lines is considered.
- *SC08*: The warehouses' inventory is only varied at two levels (low and high).
- *SC09*: Only two different product mix scenarios are considered ($Pmix_1$ and $Pmix_2$).

6.2. Application of Step 1: Solution Space Structuring

A summary of the results from applying *step 1* is shown in Figure 7. First, substep 1.1 derives fixed degrees of freedom from the input strategic network scenario data shown in Figure 6 and the system constraints (*SC01* to *SC09*). Next, substep 1.2 deals with the clustering of the remaining variable degrees of freedom by simulation input data types according to VDI3633-1:2014-12 [43].

All necessary input data types (organizational, technical, and system load data) are addressed. Subsequently, substep 1.3 derives a set of sub-solution spaces from grouping variable degrees of freedom into sub-decision problems. Based on the application results, the following five sub-solution spaces were derived.

- Capacity framework: This sub-solution space sets capacity-related degrees of freedom, such as the *number of production lines*, the *production line shift model*, the *max. output of the production line*, and the *production line flexibility*. For this sub-solution space, *SC01* and *SC02* are applied in terms of standard shift models and standard working hours.
- Production line behavior: This sub-solution space deals with the *production line failures* degree of freedom and is subject to *SC04* and *SC05* because only the worst and most realistic cases are considered for the production line behavior.
- Logistics information: This sub-solution space deals with the *number of warehouses*, the *warehouse inventory*, and the *number of customer-supplier-relations* degrees of freedom

and is subject to *SC08* and *SC07*, as the inventory is only varied between two categories (low and high).

- Network structure: This sub-solution space addresses the *number of production lines*, the *number of warehouses*, and the *customer-supplier-relations* degrees of freedom and is subject to *SC03*, *SC05*, and *SC07*.
- Product Mix: This sub-solution space addresses the *number of component and product variants*, the *demand for each variant*, and the *BOM* degrees of freedom and is subject to *SC09*, as only two different product mixes are considered.

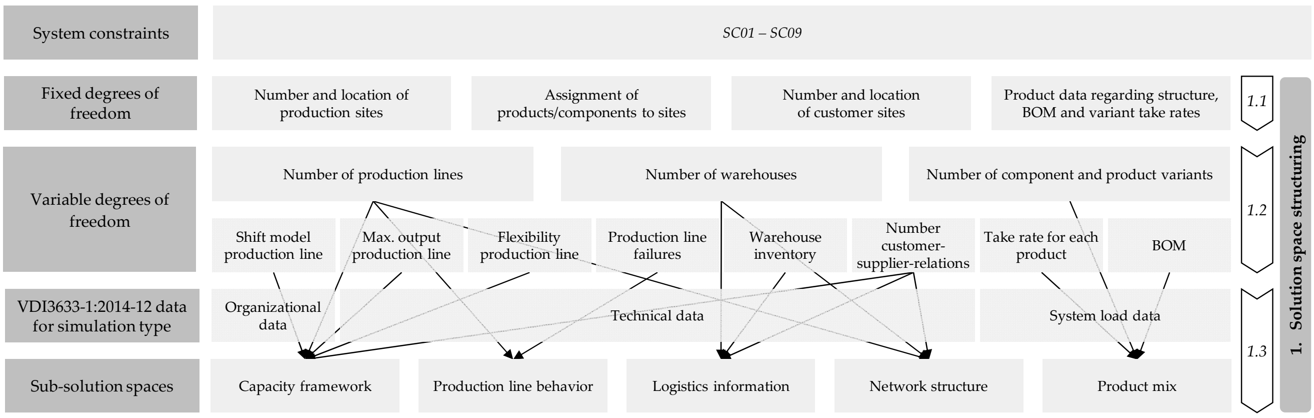

Figure 7. Application results of step 1: Solution space structuring.

In summary, the sub-solution spaces specifically address operational decisions within the strategic network design, such as inventory dimensioning, the number of production lines, and shift models.

6.3. Application of Step 2: Solution Space Planning and Control

The solution space planning and control is based on a multiplication procedure of sub-solution space alternatives to generate a comprehensive experiment design. This procedure is depicted in Figure 8.

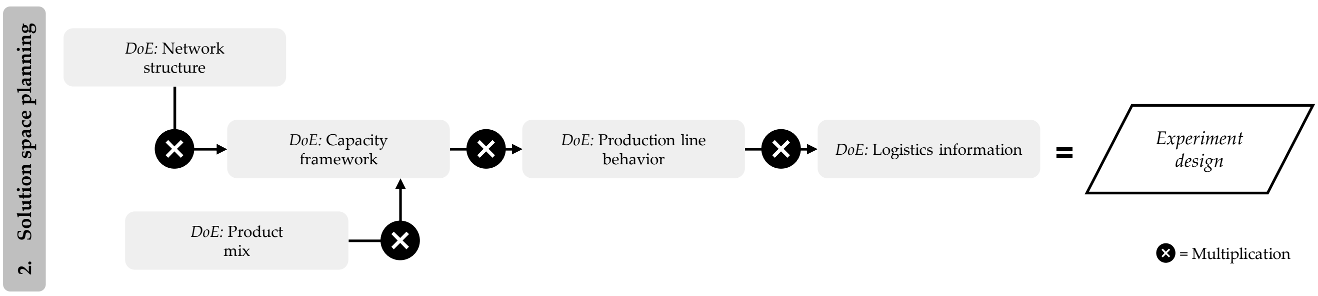

Figure 8. Multiplication procedure of sub-solution space alternatives to generate the experiment design. All solution space alternatives are constructed based on the network structure alternatives. The product mix alternatives are implicitly part of the capacity framework alternatives.

A separate DoE is required to vary the design parameters for each sub-solution space. Then, all experiment designs are crossed to generate a comprehensive experiment design. Within this procedure, some sub-solution spaces logically build on each other, as described in Figure 8. The procedure combines structural and parameter variations. Hence, a single simulation model is necessary for each network structure alternative.

The introduced levels of customer-supplier relationships can be used to derive different network structure alternatives on an operational level, as shown in Figure 9. First, the number of production lines is varied for each *Level_1* customer-supplier relationship. Then, the *Level_2* customer-supplier relationships are used to build alternative network solutions based on the decision of whether a supplier production line is linked to a customer production line in a 1:n or 1:1 manner. For this industrial application, only the number of the *rotor* and *stator* lines is varied for either one or two lines (*SC03*). The number of all other components/products production lines is preset (*SC05*, *SC01*). Moreover, there is a warehouse between the customer and the supplier for each *Level_1* customer-supplier relationship (*SC07*). In addition, all *Level_2* customer-supplier relationships are preset to be 1:n (*SC07*). This leads to four network structure alternatives being considered for industrial applications.

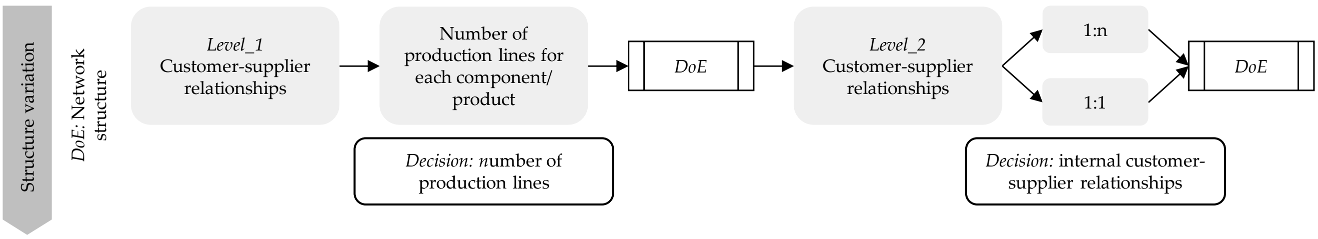

Figure 9. Procedure to derive network structure alternatives.

Next, capacity framework alternatives are generated based on the procedure depicted in Figure 10. Different planning decisions must be made for each *Level_2* (between production lines) customer-supplier relationship. The variant strategy deals with the variant flexibility of a production line, i.e., which variant can technically be produced by the production line. For the industrial application, only two options are considered: First, if only one line for a component/product exists, the variant strategy is full flexibility. Second, if there are only two lines for a component/product, the variant strategy is full flexibility for one line and high runner for the other line (*SC06*). As a result, the variant strategy does not create alternatives in this industrial application.

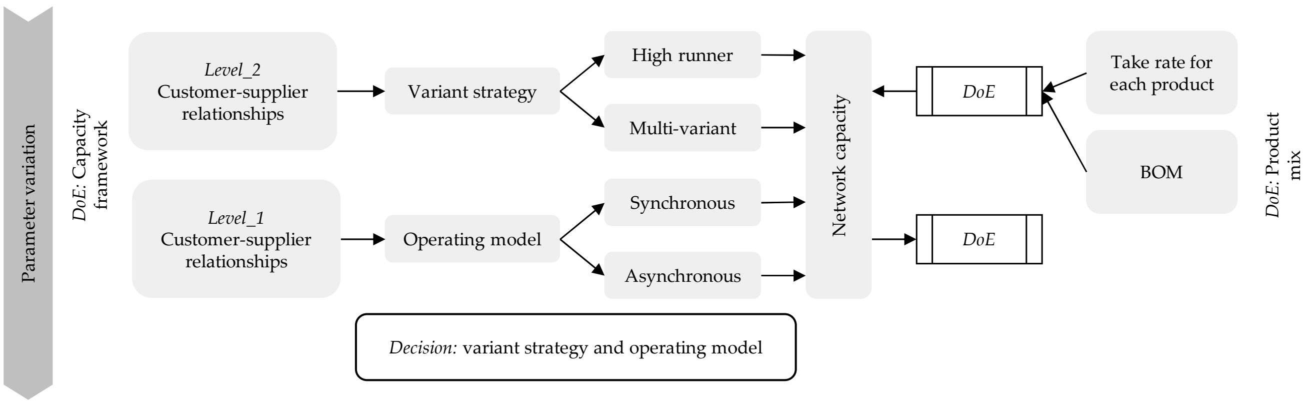

Figure 10. Procedure to derive capacity framework alternatives based on the product-mix-sub-solution space.

For each *Level_1* customer-supplier relationship, the operating model describes how a customer-supplier relationship is operated based on the degrees of freedom of *max. output production line* and *shift model*. For industrial applications, the following two operating models are considered. First, the synchronous operation of the customer and supplier production lines means that the output/demand of the lines is synchronized for a certain period of time. In this industrial application, synchronous means that both lines operate the same number of shifts per week, and the max. output of each line is potentially reduced to balance the customer line demand and the supplier line supply on a weekly basis. In contrast, asynchronous in this industrial application means that both lines operate at the max. output. On a weekly basis, this means that both lines could potentially be operated for different numbers of shifts per week. For the industrial application, only the operating model of the *Level_1* customer-supplier relationship between the *rotor*, the *stator*, the *housing*, and the *electric motor* assembly lines is considered (*SC07*). This results in two alternative operating models being considered for the industrial application.

To meet the network-operations-based requirements (*O-RQ1*–*O-RQ3*) from Table 2, the network capacity must be equal to the fixed demand volume on a weekly basis. Therefore, product mix alternatives must be included to derive capacity framework alternatives. Thus, the take rate for each product and the BOM of the product are used to generate product mix alternatives.

Capacity framework alternatives are now generated by combining the variant strategy decision alternatives, the operating model decision alternatives, and the product mix alternatives. This results in four capacity framework alternatives being considered for the industrial application. The statistical production line characteristics can be varied based on the production line failures, as shown in Figure 11a. In strategic network design, many production line characteristics are uncertain. Therefore, production line failures can be estimated based on similar existing production lines using aggregated line models, as presented in [46,47]. For this industrial application, only the production line behavior of the *rotor* lines is varied between a worst-case and a realistic case (*SC04*). Considering the different numbers of *rotor* lines for each network structure alternative, this leads to a total of eight production line behavior alternatives for this industrial application.

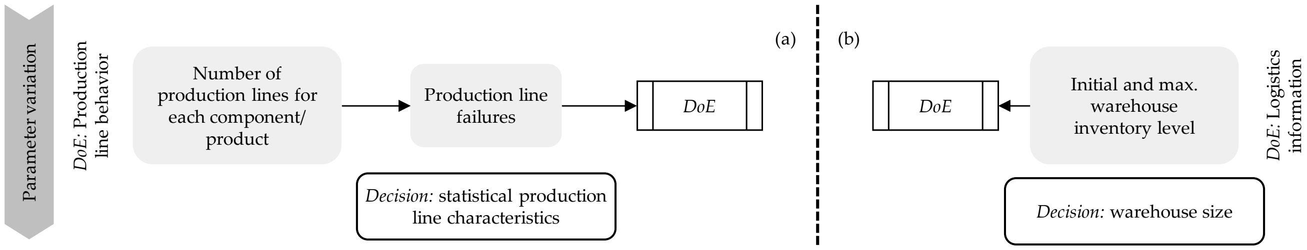

Figure 11. (**a**) Procedure to derive production line behavior alternatives; (**b**) procedure to derive logistics information alternatives.

Logistics information alternatives are generated based on the applied initial and maximum inventory levels for each warehouse; see Figure 11b. According to *SC07*, there is a warehouse in between each *Level_1* customer-supplier relationship. To create the alternatives, sampling experiment design methods such as the NOLH design [34] could also be applied. For this industrial application, three warehouses are considered within the production network (*rotor*, *stator*, and *housing*). For each warehouse, two different inventory levels are applied (*SC08*). This leads to a total of eight logistics information alternatives for this industrial application.

A summary of the number of alternative solutions for each sub-solution space is presented in Table 3. All alternative solutions are multiplied to create the final experiment design. For this industrial application, the procedure leads to 1024 alternative solutions. The final experiment design is then used to generate simulation software-specific input data sets by a post-processing Python script.

The final step of solution space control is completely different from the corresponding step in the product development context, c. f. Section 2.3. This is because there is no strict shortage of necessary resources to develop all alternative solutions. Each simulation run of the experiment design is executed, and the alternative solution is developed in a way that the simulation results can be used to evaluate the alternative solution. Thereby, the only consumed resource is computing power and data storage capacity.

Table 3. Summary of alternatives for each sub-solution space; # indicates the number of different alternatives for each sub-solution space.

Sub-Solution Space	**#**	**Description (*Applied System Constraints*)**
Network structure	4	Only the number of *rotor* and *stator* lines can either be one or two (*SC03*); all other numbers of production lines are set (*SC05* and *SC01*). All customer-supplier relationships are linked in a 1:n manner (*SC07*).
Capacity framework	4	The capacity frameworks' alternatives are built based on two different product mixes (*SC09*) and two different operating models for the relevant *Level_1* customer-supplier relationship (*SC07*). The variant flexibility is predefined for one or two lines (*SC06*).
Product mix *	2 *	Only two different product mixes are considered (*SC09*).
Production line behavior	8	The production line behavior varies only for rotor lines (*SC04*). Each rotor production line has a worst and realistic case alternative (*SC04*).
Logistics information	8	There are three warehouses considered within the production network. For each warehouse, two different inventory levels are applied (*SC08*).

* Implicitly considered within the capacity framework alternatives.

7. Discussion

Based on the industrial application of the solution space management approach, this section discusses the results and their practical implications for strategic network design. In addition, the fulfillment of the predefined requirements from Section 4 is evaluated and discussed.

7.1. Industrial Implications of the Findings

The results of the industrial application of the solution space management are structured according to the two steps of the approach, as presented in Section 5. Thus, the results and the industrial implications for step 1 are followed by the results and implications for step 2.

The industrial application of step 1, solution space structuring, has shown that all necessary input data types for simulation, according to VDI3633-1:2014-12 [43], can already be addressed during strategic network design. Furthermore, a set of sub-solution spaces can be derived for operational decisions during strategic network design, representing independent planning problems. These results suggest that simulation can be applied during strategic network design and that the large solution space can be structured into independent planning problems. Based on this, planning experts can develop alternatives for each sub-solution space, which can be combined, leading to alternative network solutions.

The industrial application of step 2, solution space planning, led to the discovery that the alternatives of each sub-solution space can be multiplied to derive an experiment design that covers the solution space. Furthermore, generating alternatives for each sub-solution space builds on different operational decisions and can be structured for each sub-solution space. The results of step 2 suggest that creating alternative solutions for strategic network design can be improved by generating alternatives for each sub-solution space, which are then multiplied for a final experiment design.

In summary, the results of the successful industrial application of solution space management in strategic network design suggest that this approach significantly supports the objective construction of alternative network solutions.

7.2. Fulfillment of the Requirements

A summary of the fulfillment of the requirements is presented in Table 4. The footer of Table 4 indicates the different levels of fulfillment (predominantly fulfilled, partly fulfilled, and predominantly not fulfilled).

Table 4. Summary of the fulfillment of requirements.

	Requirements	Fulfillment
	General requirements	
G-RQ1	Focus on operational decisions within the strategic network design	●
G-RQ2	Focus on value-stream-relevant parameters	◐
	Methodology-based requirements	
M-RQ1	Comprehensive representation of the solution space	●
M-RQ2	Identification of alternative solutions	●
	Application-based requirements	
A-RQ1	Possibility to customize the approach to a problem-specific solution space	◐
A-RQ2	Structured approach and understandable, transparent solution path	●
	Production-network-operations-based requirements	
O-RQ1	Material flow maintenance across customer-supplier-relationships	●
O-RQ2	Fixed demand volume for capacity planning	●
O-RQ3	Complete demand fulfillment of customers on a weekly basis	●

● Predominantly fulfilled, ◐ Partially fulfilled.

For the first set of general requirements, the first requirement (*G-RQ1*) is completely fulfilled. The solution space management approach inputs strategic decision design parameters and focuses on operational decision design parameters. In addition, the second requirement (*G-RQ2*) is partially fulfilled, as the addressed solution space mainly addresses the material flow side of a value stream while the information flow side is missing. The methodology-based requirements (*M-RQ1*, *M-RQ2*) are also entirely fulfilled since the set of sub-solution space comprehensively represents the solution space and alternative solutions are derived from the combination of all sub-solution spaces alternatives. The first application-based requirement (*A-RQ1*) is partially met, as only one industrial application has been carried out so far. The other requirement (*A-RQ2*) is entirely fulfilled. The solution space management is highly structured to enable the industrial application, and by multiplying the alternatives for each sub-solution space, there is a transparent, understandable solution path. The last set of requirements, the production-network-operations-based requirements (*O-RQ1*–*O-RQ4*), are all completely fulfilled. This set of requirements is mainly addressed in the derivation of alternatives for the sub-solution space capacity framework.

8. Conclusions and Outlook

Strategic network design poses several challenges, such as a large solution space comprising many highly uncertain design parameters, making the related decisions challenging without decision support. Data farming offers a potential solution, as synthetic data can be generated by running multiple simulation experiments spanning the solution space and then analyzed using data mining techniques. However, the foundation of data farming is an experiment design that spans the solution space. Therefore, solution space management is necessary to support the generation of alternative network solutions to be simulated and to create the experiment design.

This paper presents a structured solution management approach to support data-farming-based strategic network design. The presented approach transfers concepts from product development to the context of strategic network design. Therefore, two main steps are required. First, the solution space structuring step identifies fixed and variable degrees of freedom and builds sub-solution spaces that are individually addressed in the second step. The second step of solution space planning and control builds alternatives for each sub-solution space and combines all sub-solution space alternatives into a comprehensive experiment design that is processed into input data sets for simulation models. A case from the automotive industry demonstrates the industrial applicability and validity of the solution space approach and leads to several implications. It has been shown that by applying the proposed approach, it is possible to generate a set of alternative network solutions spanning the solution space. Moreover, this leads to alternative network solutions that can be processed into input data sets for simulation models.

In addition to the application results, the solution space management approach also needs to be validated as a part of the data-farming-based planning approach by Kroeger et al. [46], which will be the subject of future publications.

Several points have to be addressed in future research activities. First, applying solution space management to either a tactical or operational planning horizon could provide beneficial insights into the solution space structure of these planning problems. Second, the solution space structure could be used as an action space for a reinforcement learning algorithm to find an optimal alternative network solution with respect to the reward function. A pre-structured action space could influence the optimization time of the reinforcement algorithm. Third, until now, the application steps and the entire solution space management approach have been carried out manually. To integrate the approach into an industrial-standard network planning process, continuous digital support is required.

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References

1. Váncza, J. Production Networks. In *CIRP Encyclopedia of Production Engineering: With 85 Tables*, 2nd ed.; Chatti, S., Laperrière, L., Reinhart, G., Tolio, T., Eds.; Springer: Berlin, Germany, 2014; pp. 1377–1384. ISBN 978-3-662-53119-8.
2. Kroeger, S.; Zaeh, M.F. Towards an Efficient, Comprehensive Value Stream Planning in Production Networks. *Procedia CIRP* **2022**, *107*, 782–787. [CrossRef]
3. Mack, O.; Khare, A.; Krämer, A.; Burgartz, T. *Managing in a VUCA World*; Springer International Publishing: Cham, Switzerland, 2016; ISBN 978-3-319-16888-3.
4. Fleischmann, B.; Meyr, H.; Wagner, M. Advanced Planning. In *Supply Chain Management and Advanced Planning*; Stadtler, H., Kilger, C., Meyr, H., Eds.; Springer: Berlin/Heidelberg, Germany, 2015; pp. 71–95. ISBN 978-3-642-55308-0.
5. Lanza, G.; Ferdows, K.; Kara, S.; Mourtzis, D.; Schuh, G.; Váncza, J.; Wang, L.; Wiendahl, H.-P. Global production networks: Design and operation. *CIRP Ann.* **2019**, *68*, 823–841. [CrossRef]
6. Brandstein, A.G.; Horne, G.E. Data Farming: A Meta-technique for Research in the 21st Century. *Maneuver Warf. Sci.* **1998**, *1998*, 93–99.
7. Lechler, T.; Sjarov, M.; Franke, J. Data Farming in Production Systems—A Review on Potentials, Challenges and Exemplary Applications. *Procedia CIRP* **2021**, *96*, 230–235. [CrossRef]
8. Feldkamp, N.; Bergmann, S.; Strassburger, S. Knowledge Discovery in Manufacturing Simulations. In Proceedings of the 3rd ACM SIGSIM Conference on Principles of Advanced Discrete Simulation, London, UK, 10–12 June 2015; Taylor, S.J.E., Ed.; ACM Association for Computing Machinery: New York, NY, USA, 2015; pp. 3–12, ISBN 978-1-4503-3583-6.
9. Rudberg, M.; Olhager, J. Manufacturing networks and supply chains: An operations strategy perspective. *Omega* **2003**, *31*, 29–39. [CrossRef]
10. Porter, M.E. Changing Patterns of International Competition. *Calif. Manag. Rev.* **1986**, *28*, 9–40. [CrossRef]

11. Kaphahn, A.; Lücke, T. Koordination interner Produktionsnetzwerke. In *Produktionsplanung und-Steuerung: Grundlagen, Gestaltung und Konzepte*; Schuh, G., Ed.; Springer: Berlin, Germany, 2006; pp. 421–466, ISBN 354040306X.
12. Fleischmann, B.; Koberstein, A. Strategic Network Design. In *Supply Chain Management and Advanced Planning*; Stadtler, H., Kilger, C., Meyr, H., Eds.; Springer: Berlin/Heidelberg, Germany, 2015; pp. 107–123, ISBN 978-3-642-55308-0.
13. Horne, G.; Seichter, S. Data Farming in support of NATO operations—Methodology and proof-of-concept. In Proceedings of the IEEE 2014 Winter Simulation Conference, Savannah, GA, USA, 7–10 December 2014; pp. 2355–2363, ISBN 9781479974870.
14. Horne, G.; Åkesson, B.; Anderson, S.; Bottiger, M.; Britton, M.; Bruun, R.; Seng, C.C.; Erdoğan, O.; Ergün, İ.Y.; Geiger, A.; et al. *Data Farming in Support of NATO: Production de Données en Soutien de I'OTAN*; North Atlantic Treaty Organisation: Neuilly-sur-Seine, France, 2014; ISBN 978-92-837-0205-4.
15. Genath, J.; Bergmann, S.; Straßburger, S.; Spieckermann, S.; Stauber, S. Data Farming und Wissensentdeckung in Simulationsdaten. *Z. Wirtsch. Fabr.* **2022**, *117*, 144–150. [CrossRef]
16. Sanchez, S.M.; Sanchez, P.J.; Wan, H. Work Smarter, Not Harder: A Tutorial on Designing and Conductiong simulation Experiments. In Proceedings of the 2018 Winter Simulation Conference (WSC), Gothenburg, Gothenburg, Sweden, 9–12 December 2018; Rabe, M., Juan, A.A., Mustafee, N., Skoogh, A., Jain, S., Johansson, B., Eds.; IEEE: Piscataway, NJ, USA, 2018; pp. 237–251, ISBN 978-1-5386-6572-5.
17. Ponn, J. Systematisierung des Lösungsraums. In *Handbuch Produktentwicklung*; Lindemann, U., Ed.; Hanser: München, Germany, 2016; pp. 715–742, ISBN 9783446445819.
18. Schuh, G. *Lean Innovation*; Springer Vieweg: Berlin/Heidelberg, Germany, 2013; ISBN 3540769145.
19. Lenders, M. *Beschleunigung der Produktentwicklung Durch Lösungsraum-Management*; Apprimus-Verlag: Aachen, Germany, 2009; ISBN 978-3-940565-26-6.
20. Hilchner, R. *Typenorientiertes Lösungsraum-Management in der Fabrikplanung*; Apprimus-Verlag: Aachen, Germany, 2012; ISBN 978-3-86359-068-0.
21. Sager, B. Konfiguration Globaler Produktionsnetzwerke. Ph.D. Dissertation, Technical University of Munich, Munich, Germany, 2019.
22. Ernst, J. *Methode zur Ermittlung von Standortstrukturalternativen in Maschinenbauunternehmen*; Shaker: Darmstadt, Germany, 2012; ISBN 978-3-8440-1115-9.
23. Jacob, F. *Quantitative Optimierung Dynamischer Produktionsnetzwerke*; Shaker Verlag: Aachen, Germany, 2005; ISBN 978-3-8322-4818-5.
24. Christodoulou, P.; Fleet, D.; Phaal, R.; Probert, D.; Shi, Y.; Hanson, P. *Making the Right Things in the Right Places—A Structured Approach to Developing and Exploiting Manufacturing Footprint Strategy*; University of Cambridge, Institute for Manufacturing: Cambridge, UK, 2007; ISBN 978-1-902546-61-2.
25. Kampker, A.; Schuh, G.; Kupke, D. Production Network Design. *wt Werkstattstech. Online* **2010**, *100*, 259–263. [CrossRef]
26. Lanza, G.; Moser, R. Multi-objective optimization of global manufacturing networks taking into account multi-dimensional uncertainty. *CIRP Ann.* **2014**, *63*, 397–400. [CrossRef]
27. Ude, J. *Entscheidungsunterstützung für die Konfiguration Globaler Wertschöpfungsnetzwerke: Ein Bewertungsansatz unter Berücksichtigung Multikriterieller Zielsysteme, Dynamik und Unsicherheit*; Shaker: Aachen, Karlsruhe, 2010; ISBN 978-3-8322-9414-4.
28. Merchiers, A. *Bewertung Globaler Standortstrukturalternativen im Maschinenbau*; Apprimus Verlag: Aachen, Germany, 2008; ISBN 9783940565242.
29. Auberger, E.; Karre, H.; Wolf, M.; Preising, H.; Ramsauer, C. Configuration of manufacturing networks by a multi-objective perspective enabled by simulation and machine learning. *Procedia CIRP* **2021**, *104*, 993–998. [CrossRef]
30. Hochdörffer, J. *Integrierte Produktallokationsstrategie und Konfigurationssequenz in Globalen Produktionsnetzwerken*; Shaker Verlag: Aachen, Germany, 2018; ISBN 978-3-8440-5845-1.
31. Feldkamp, N.; Bergmann, S.; Strassburger, S.; Schulze, T. (Eds.) Knowledge Discovery and Robustness Analysis in Manufacturing Simulations. In Proceedings of the 2017 Winter Simulation Conference: WSC Turns 50: Simulation Everywhere, Las Vegas, NV, USA, 3–6 December 2017; IEEE: Piscataway, NJ, USA, 2017; ISBN 9781538634288.
32. Hunker, J.; Wuttke, A.; Scheidler, A.A.; Rabe, M. A Farming-for-Mining-Framework to Gain Knowledge in Supply Chains. In *2021 Winter Simulation Conference (WSC)*; Kim, S., Feng, B., Smith, K., Masoud, S., Zheng, Z., Szabo, C., Loper, M., Eds.; IEEE: Piscataway, NJ, USA, 2021; pp. 1–12, ISBN 9781665433129.
33. Schulze, T.; Feldkamp, N.; Bergmann, S.; Strassburger, S. Data Farming und simulationsbasierte Robustheitsanalyse für Fertigungssysteme. In Proceedings of the Tagungsband ASIM SST 2018—24. Symposium Simulationstechnik. ASIM 2018—24. Symposium Simulationstechnik, Hamburg, Germany, 4–5 October 2018; Deatcu, C., Schramm, T., Zobel, K., Eds.; ARGESIM/ASIM: Wien, Austria, 2018; pp. 243–252, ISBN 978-3-901608-12-4.
34. Hernandez, A.S.; Lucas, T.W.; Carlyle, M. Constructing nearly orthogonal latin hypercubes for any nonsaturated run-variable combination. *ACM Trans. Model. Comput. Simul.* **2012**, *22*, 1–17. [CrossRef]
35. Schuh, G.; Prote, J.P.; Hünnekes, P.; Sauermann, F. Anwendung von Verfahren des maschinellen Lernens auf Basis von Data Farming am Beispiel eines Clusteralgorithmus. In *Simulation in Produktion und Logistik 2019: Chemnitz, 18–20 September 2019*; Putz, M., Schlegel, A., Eds.; Verlag Wissenschaftliche Scripten: Auerbachl, Germany, 2019; pp. 29–37, ISBN 978-3-95735-113-5.
36. Sanchez, S.M.; Sánchez, P.J. Better Big Data via Data Farming Experiments. In *Advances in Modeling and Simulation: Seminal Research from 50 Years of Winter Simulation Conferences*; Tolk, A., Fowler, J., Shao, G., Yucesan, E., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 159–179, ISBN 978-3-319-64181-2.

37. Kleijnen, J.P.C.; Sanchez, S.M.; Lucas, T.W.; Cioppa, T.M. State-of-the-Art Review: A User's Guide to the Brave New World of Designing Simulation Experiments. *INFORMS J. Comput.* **2005**, *17*, 263–289. [CrossRef]
38. Cioppa, T.M.; Lucas, T.W. Efficient Nearly Orthogonal and Space-Filling Latin Hypercubes. *Technometrics* **2007**, *49*, 45–55. [CrossRef]
39. Neuner, C. *Konfiguration Internationaler Produktionsnetzwerke unter Berücksichtigung von Unsicherheit*; Gabler Verlag: Wiesbaden, Germany, 2009; ISBN 978-3-8349-8344-2.
40. Bundschuh, M. *Modellgestützte Strategische Planung von Produktionssystemen in der Automobilindustrie: Ein Flexibler Planungsansatz für die Fahrzeughauptmodule Motor, Fahrwerk und Antriebsstrang*; Verlag Dr. Kovac: Hamburg, Germany, 2008; ISBN 978-3-339-03794-7.
41. Jalal, A.M.; Toso, E.A.V.; Morabito, R. Integrated approaches for logistics network planning: A systematic literature review. *Int. J. Prod. Res.* **2022**, *60*, 5697–5725. [CrossRef]
42. Friemann, F. Strategische Lagerkapazitätsplanung: Ein Konzept zur Stärkeren Integration in den Strategischen Supply Chain Planungsprozess am Beispiel der Pharmazeutischen Industrie. Ph.D. Thesis, ETH Zurich, Zurich, Switzerland, 2015.
43. *ICS 03.100.10 (VDI 3633-1:2014-12)*; 3633-1: Simulation of Systems in Materials Handling, Logistics and Production; Part 1: Fundamentals. Beuth Verlag: Berlin, Germany, 2014. Available online: https://www.beuth.de/en/technical-rule/vdi-3633-blatt-1/149034959 (accessed on 27 September 2022).
44. Hopp, W.J. *Supply Chain Science*; Waveland Press: Long Grove, IL, USA, 2008; ISBN 09781577667384.
45. Wiendahl, H.-P.; ElMaraghy, H.A.; Nyhuis, P.; Zäh, M.F.; Wiendahl, H.-H.; Duffie, N.; Brieke, M. Changeable Manufacturing—Classification, Design and Operation. *CIRP Ann.* **2007**, *56*, 783–809. [CrossRef]
46. Kroeger, S.; Korder, S.; Schneider, R.; Zaeh, M.F. Sequence Scrambling in Aggregated Mixed-Model Production Line Modeling. In Proceedings of the 2022 Winter Simulation Conference (WSC): 2022 Winter Simulation Conference (WSC), Singapore, 11–14 December 2022; Feng, B., Pedrielli, Y., Shashaani, S., Song, E., Corlu, C.G., Lee, L.H., Chew, T., Roeder, T.M.K., Lendermann, P., Eds.; IEEE: Piscataway, NJ, USA, 2022; pp. 1740–1749, ISBN 978-1-6654-7661-4.
47. Pehrsson, L.; Frantzen, M.; Aslam, T.; Ng, A.H. Aggregated line modeling for simulation and optimization of manufacturing systems. In Proceedings of the 2015 Winter Simulation Conference, Huntington Beach, CA, USA, 6–9 December 2015; Yilmaz, L., Chan, W.K.V., Moon, I., Roeder, T.M.K., Macal, C., Rosetti, M., Eds.; IEEE: Piscataway, NJ, USA, 2015; pp. 3632–3643, ISBN 978-1-4673-9741-4.