Conceptualization of a Procedural Model for Selecting Decision Support Methods in Production and Logistics

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Abstract. The complexity of modern production and logistics results in recurring decisions being made with the help of decision support methods (DSM). However, choosing an appropriate DSM is complex, especially when considering the available data. A procedural model assists practitioners in this selection by providing a structured, comprehensible, and repeatable approach. This paper proposes a procedural model that categorizes questions arising in production and logistics while supporting the selection of suitable DSMs as well as techniques for aggregating and disaggregating data.

Introduction

The processes of planning, implementation, and control within production and logistics necessitate numerous decision-making activities. These decisions vary according to factors such as time horizons and system complexity [1]. The advent of digital transformation has notably increased system complexity [2].

Given the intricate nature of decisions pertaining to complex systems, it is prudent to employ technical support for decision-making.

A variety of methods can be utilized for decision support, each with specific requirements to yield meaningful outcomes. Consequently, the selection of appropriate methods should be tailored to the specific decision support question at hand [1]. This selection process is both challenging and essential [3].

All decision support methods (DSM) are dependent on data. However, this data is often not available at an appropriate level of aggregation, being either excessively granular or overly condensed. Therefore, data aggregation, disaggregation, or in general data transformation (DT) may be necessary.

This paper presents a foundational approach to the selection and implementation of DSMs, while addressing the provision of data at suitable aggregation levels.

1 Foundations

Problem-solving typically involves addressing specific questions. The formulation of questions allows for a clear delineation of problem statements. Depending on the domain or management level, these questions can vary significantly. In the context of production and logistics, typical inquiries include evaluating changes in production capacities or planning impacts [4].

DSMs are particularly beneficial when there are conflicting objectives or when analyzing the impact of individual decisions on other decisions [5]. Three exemplary types of DSMs are outlined below:

Spreadsheet tools or simple mathematical models are frequently employed in production and logistics for efficient quick calculations that capture system dependencies [6]. Simplifications, such as static averages, are often utilized in this context.

For more complex systems involving randomness and interactions, which are critical factors in real-world scenarios, simulation can be employed [7]. However, it is essential to ensure that a question is "simulation-worthy" [4].

Not all simulation characteristics, such as temporal or stochastic elements, are necessary for every query within production and logistics domains [8].

For instance, heuristic or exact approaches may suffice for transport planning tasks [9].

To mitigate the limitations inherent in individual methods, hybrid approaches that combine multiple techniques can be advantageous, particularly during optimization tasks. Optimization strictly requires complete information availability (deterministic models). However, uncertainties are ubiquitous, leading to oversimplified representations of real systems [10]. Therefore, combining DSMs, such as simulation-based optimization, can be beneficial.

Not all DSMs require identical forms or structures of input data; hybrid applications further compound these variations by necessitating tailored adjustments across datasets beforehand. Data quality significantly influences the trustworthiness of outcomes generated by any employed method [11], with suitability, including proper granularity, playing pivotal roles. Techniques facilitating preprocessing transformations serve critical functions in adapting datasets accordingly before deployment stages, thereby enabling valid outputs to consistently emerge [12].

The interdependencies between the question under consideration, the selection of the DSM, and the available data that can be transformed underscores the need for a procedural model to ensure a structured, reproducible, and reliable approach.

2 Conceptual Approach

To address complex questions, a structured, comprehensible, and repeatable approach is essential. The specifics of the questions and the existing boundary conditions must be considered. Nonetheless, a general procedure should be provided to systematically support especially industry users. In the following, a suitable procedural model is proposed for this purpose.

2.1 Decision Process

When a decision is required in the field of production and logistics, it is associated with one or more questions (see Section 1) of varying difficulty. These questions are always addressed while considering boundary conditions such as the time horizon in question or available resources. Based on these questions and boundary conditions, a DSM is selected to facilitate an informed and comprehensible decision.

The implementation of any DSM necessitates data (see Section 1).

At this stage, various challenges may arise. Data is not available in the necessary quantity or often exists at an unsuitable level of aggregation. If the chosen DSM were applied using such data, it would lead to unreliable or even incorrect results. Therefore, the data must be adjusted according to the specific question at hand. If the data is appropriately formatted after this adjustment, or if it was already available in a suitable form, the DSM can be applied, and insights can be derived from analyzing its results. Based on these insights, decisions can then be made.

2.2 Input Variables

As outlined in Section 2.1, several input variables play a significant role both in the selection of DSM and in determining an appropriate DT. The input variables for both subprocesses exhibit similarities and are briefly described below.

The foundation for selecting both the DSM and the extent of required DT lies in the underlying question. This question defines the focus areas for answering inquiries, needed information, provides guidance on prioritizing objectives amidst conflicts, and determines the required level of detail for results, like a yes/no answer or a detailed forecast. However, the question cannot be considered in isolation; it is always tied to boundary conditions such as the available timeframe, accessible resources, and existing knowledge bases. Accordingly, the selection of DSM is always based on both the question itself and its associated boundary conditions.

To implement the chosen method successfully, data is required. The structure and level of aggregation of this data determine whether a DSM can be applied effectively. The type of data fundamentally required is defined by the question at hand. Specifically, the information needed to answer this question, dictates at what level of aggregation this data must exist. Furthermore, DSMs influence structural requirements for data as well as adjustments needed prior to application. Additionally, other boundary conditions, such as resources available for implementing various transformation techniques, must also be considered during this process.

2.3 Grouping

The selection of an appropriate DSMs and DT necessitates a comprehensive analysis of the prevailing circumstances. The complexity of potential questions and their answers vary significantly.

To streamline the DSM selection process, it is advantageous to categorize questions for example by their answer complexity and application domain while considering the associated boundary conditions.

Recommendations regarding the appropriate DSM can be derived by comparing the attributes of the questions with the requirements and strengths of individual DSMs. This process incorporates boundary conditions and their resulting groupings, thereby integrating expert knowledge.

The early selection of a DSM is crucial, as each method imposes specific requirements on the necessary data, particularly concerning data structure and aggregation levels. Boundary conditions (see Section 2.2), especially those related to the underlying question, provide key indicators for determining suitable aggregation levels for data.

Selecting an appropriate DT-method presents significant challenges for users. By creating groups, it becomes possible to select a suitable method in a simplified and comprehensible manner. These groups are established based on content-driven criteria such as data aggregation levels dictated by both questions and boundary conditions of DSMs, consideration of available data, and alignment with the requirements and potentials of various DT-methods.

2.4 Workflow

Based on the considerations outlined in Sections 2.1 to 2.3, a fundamental procedural model emerges, as illustrated in Figure 1. It becomes evident that the selection of a DSM and its corresponding DT-method based on the clients question involves a complex and multi-layered approach. This approach aims to address the underlying question at hand. The selection process is preceded by categorizing input variables (see Section 2.2) into groups (see Section 2.3), ensuring that both the uniqueness of the question and its associated boundary conditions are adequately addressed before proceeding further with implementation.

Only after this step the DSM can be implemented effectively. Following implementation and analysis of results, different scenarios may arise: The question may be fully answered; further refinement may become necessary; or entirely new questions may emerge during this iterative process. This is represented by the dashed arrow in Figure 1. The whole process can therefore be seen as iterative.

The structured workflow depicted in Figure 1 supports transparent and reproducible decision-making for selecting and implementing DSMs. This enables industry practitioners to tackle complex questions within production and logistics effectively.

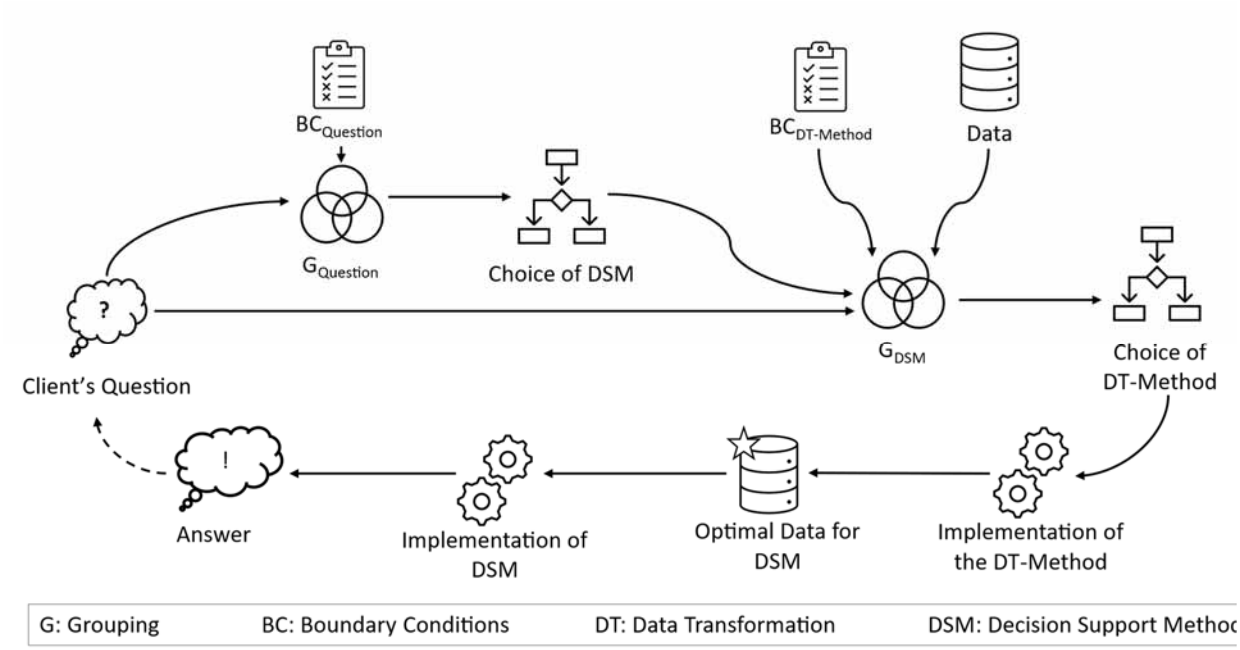

Figure 1: Schematic representation of the procedural model.

3 Outlook

The methodology delineated in Section 2 constitutes an initial framework for the development of a procedural model, thereby highlighting research imperatives that facilitate the comprehensive elaboration and practical implementation of the model.

Initially, it is imperative to analyze the questions to be addressed, classifying their complexity while taking into account boundary conditions. This classification serves as the basis for selecting an appropriate DSM. In this regard, it is also essential to collect and scrutinize the requirements of individual DSMs.

Such analysis enables the alignment of the requirements and potentials of DSMs with the demands of each specific question, thereby aiding in the selection of a suitable method. Existing methodologies for selecting DSMs in production, logistics, and related fields should be considered.

Furthermore, DT-methods must be provided to facilitate the application of selected DSMs. The requirements, strengths, and weaknesses of individual DT-methods must also be evaluated.

To implement the proposed approach in practice, it is crucial to define the individual phases, phase outcomes, and roles within the procedural model. Additionally, automated verification and validation of phase outcomes should be prioritized to enhance the credibility of the generated results and bolster trust in the reliability of this newly developed procedural model.

Publication Remark

This contribution is the revised English version of the (German) conference version published in

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