Theodor Petřík
Institute of Economic Studies
Faculty of Social Sciences
Charles University
CZ-110 00 Prague, Czechia
theodor.petrik@fsv.cuni.cz

Martin Plajner
Institute of Information Theory and Automation
Czech Academy of Sciences
CZ-182 00 Prague, Czechia
plajner@utia.cas.cz

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FINDING AN OPTIMAL DISTRIBUTION STRATEGY PATH IN AN UNPREDICTABLE ENVIRONMENT

Abstract

Purpose: This article introduces an innovative method designed to optimize distribution strategies with respect to future uncertainty. It goes beyond the limitations of traditional scenario-based planning that often leads to suboptimal strategies due to the unpredictability of future developments and the challenge of accurately assigning probabilities to these scenarios. Consequently, the method allows selection of the most economically viable future strategy.

Methodology: Our methodology diverges from conventional approaches by refraining from making rigid assumptions about the probabilities of future scenarios. Instead, it comprehensively explores the entire allowable probability space to identify an optimal strategy that works well in possible future developments. We employed this method in the case study of a real-world company based in Czechia, where we devised three viable distribution strategies and four model development scenarios.

Results: The application of our method demonstrated its effectiveness in selecting the most advantageous strategy, as evidenced by the results of our case study. However, the applicability of the method is contingent upon the accurate definition of potential future scenarios and the evaluation of the performance of different strategies within these scenarios.

Conclusion: Our findings suggest that this approach significantly enhances strategic planning under uncertainty. Future research will seek to refine this method further by integrating causal relationships to convey additional information across different model periods, thereby improving the robustness and applicability of the strategy selection process.

Keywords: Supply chain optimization, probabilistic modelling, economic resilience, cost-benefit analysis

1. Introduction

This paper presents a robust and reliable approach to the difficult task of distribution strategy decision-making in an environment prone to significant volatility and uncertainty. Distribution strategy planning is a process that each company with a larger volume transported in their network should do. This large volume indirectly affects a company's profit and provides considerable savings even though it is inefficient. Specifically, companies categorized as medium-sized enterprises and larger[1] should already start to consider their network on a strategic long-term level. Whether it is a key topic

1 Lex-Europa

for the company depends on its segment and the efficiency of its current logistics solution. For example, based on an analysis performed by Bain and Co.[2] in the segment of consumer-packed goods, the share of distribution cost on the total revenue is 6-10%. The higher the ratio, the greater the optimization space it provides. These numbers differ in other segments but should always be critically revised and considered.

The task of distribution strategy planning itself is very complex. Distribution network design aims to plan the most cost-efficient manner of product movement through the whole supply chain (Ambrosino & Grazia Scutellà, 2005). To stress the importance, Ballou (2001) estimated that operation costs can be reduced by up to 15% through an efficient distribution network and effective facility management, making a difference between higher and lower shares in the above-mentioned analysis. Mangiaracina et al. (2015) composed a highly comprehensive review of the distribution network optimization methods in contemporary literature. However, there is a significant gap in the rigid process of handling uncertainties during planning.

From a very high level, we can divide the distribution strategy into two groups: outsourced to a partner (3PL or 4PL or other) and insourced; for a more detailed description, see e.g. Panicker et al. (2009). In the first case, there is not enough room for large distribution questions and optimization. This kind of solution fits better smaller companies than those defined above, and the current trend on the market is to regain control of the company's logistics and abandon X-PL schemes. Further, in this article, we will consider only insourced logistics solutions.[3]

When a distribution strategy is to be designed, it cannot be performed with the outlook for a small period. A distribution network is a structure that requires time to change. It consists of logistics nodes, distribution fleets, and accompanying processes; for more details, refer to Ambrosino and Grazia Scutella (2005). Logistics nodes need to be either constructed or rented. Even in the case of renting, it takes at least six months to get a logistics node fully operational. The fleet is usually leased or outsourced without losing control over the operations, and changes can be performed faster. For larger companies, the fleet agreement preparation and signing processes again demand a substantial amount of time.

These aspects create an apparent necessity to plan and optimize a distribution strategy in advance. At the same time, future effects such as market changes, new customers, drops in demand, external influences such as legislation and petrol costs, and much more, play a significant role in the process. These effects are difficult to evaluate precisely as they carry a high degree of uncertainty.

Therefore, we propose the following research question:

Given several possible development scenarios, how do we select the best long-term distribution strategy without making rigid assumptions regarding their probability?

Consequently, this article aims to propose and test a method for evaluating distribution strategies that avoids rigid assumptions about future development, thereby providing a tool for management to make informed, economically sound decisions over multi-year perspectives.

The article is structured as follows. First, we introduce the underlying model in Section 1.1, provide a literature review in Section 2, and establish the notation used in Section 3. Next, we propose a method for modeling the optimal distribution strategy and evaluating its share in the whole space of available strategies in Section 4, which is the main contribution of this article. The model is then tested in Section 5 on a business case of an electronics merchant, where we use it to plan an optimum long-term distribution strategy. Section 6 provides an overview of results and the last section concludes the whole article.

1.1 Model background

This article builds on a novel Concurrent Optimization Model (COM) (Petřík & Plajner, 2023), which allows the selection of the best long-term distribution strategy based on various development scenarios, their respective likelihoods, and the values of several potential distribution strategies. Using the COM, the authors evaluated different possible expansion strategies of a real-world company.

In the COM, the effectiveness of each strategy is measured using a key performance indicator (KPI), such as the distribution network operating costs. The COM incorporates the principles of Bayes-

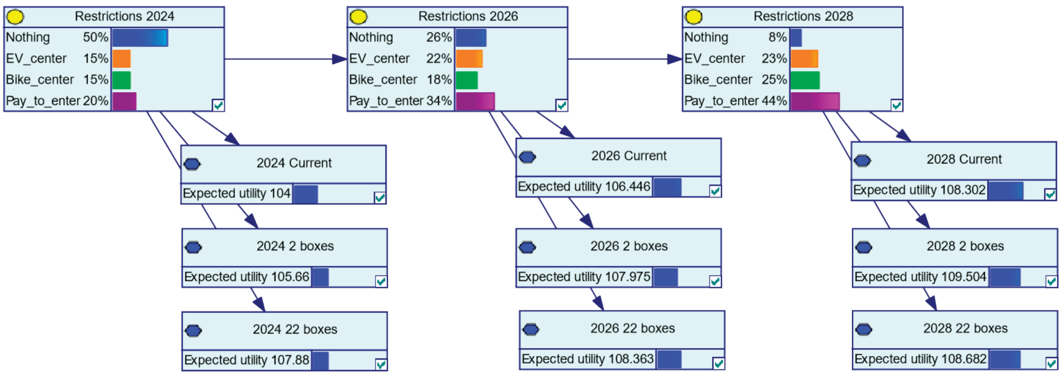
2 Bain & Co.

3 Nevertheless, specific parts of this solution can be rented or leased from 3rd parties.

ian networks (Jensen & Nielsen, 2007; Kjaerulff & Madsen, 2013) to encompass the complete system of values and beliefs. Bayesian networks are probabilistic graphical models that visually depict knowledge about a system under uncertainty. In these networks, each node represents a random variable, and each connecting arc represents a conditional probability relationship. An example structure of such a network can be seen in Figure 1. The chance nodes represent the model company each year. Each chance node has a set of states. In this particular case, there are traffic restrictions that could be adopted by the city that the company operates in. The connecting arcs between the nodes represent the conditional relationships. The variable at the beginning of an arc is called the parent of the variable at its end. A conditional relationship is specified by a conditional probability table (CPT), which specifies the probabilities of states of the child, given all states of the parent node. The three nodes dependent on each chance node in Figure 1 are called utility nodes. Their purpose is to measure the expected value of each considered distribution strategy, given the conditional probability of each scenario of the given chance node they depend on.

However, specifying precise conditional relationships usually requires a lot of work in real-world strategic planning. To address this issue, the approach described in this article assumes only limited or no knowledge of the likelihood of each modeled scenario and no knowledge of the conditional dependencies. Therefore, the model presented in this article assumes no dependent relationships between variables, and hence, we do not apply the BN framework in its entirety as Petřík and Plajner (2023) did. However, in our more general approach, we employ a similar optimization procedure to select the best option for each potential development scenario when searching through the entire probabilistic space. We subsequently measure the share of cases where each distribution strategy is optimal. A significant advantage of the method presented here lies in its ability to provide valuable insights without placing precise, potentially biased assumptions regarding future business scenario development.

Figure 1 Example of the network structure used



Source: Output from the GeNIe 3.0 academic software produced by the authors

2. *Literature review*

The presented article deals with distribution strategy planning under uncertainty, which broadly consists of distribution network design and planning. Distribution network design is not the primary focus of this article; the reader is referred to other sources, such as Chopra (2003) or Mangiaracina et al. (2015). The branch of literature related to supply chain planning under uncertainty, in line with the topic of this article, is discussed in this literature review. There are a wide range of approaches to planning and risk management in unpredictable environments of supply chains. Trend impact analysis (Gordon & Stover, 1976) and cross-impact analysis (Gordon & Stover, 2003) comprise a foundational class of scenario planning approaches, which utilize historical data and expert opinions to formulate possible future development scenarios. Both approaches were introduced mainly by the same authors and have many applications, for example, developing resilient scenarios for hospital supply chains (Nejad et al., 2021). Research in the field is ongoing, and new methods and applications are being developed; for example, the concept of VUCA (volatility, uncertainty, complexity, and ambiguity) has been explored to identify the challenges and internal barriers in realizing a resilient supply chain (Grzybowska & Tubis, 2022). Mathematical models have also been developed for recovery planning in three-tier manufacturing supply chains facing sudden disturbances (Paul et al., 2019). A common aspect of these studies is the emphasis on the need for robust planning mechanisms to navigate the complexities of modern supply chains. Bayesian networks (Jensen & Nielsen, 2007; Kjaerulff & Madsen, 2013), a class of probabilistic graphical models, have been used to deploy a probabilistic approach to risk management. Examples of specific use cases are a risk propagation model (Garvey et al., 2015), supply-side risk modeling (Sharma et al., 2022), or a resilience assessment on a deep water port (Hossain et al., 2019).

Further studies have explored predictive sales and operations planning based on statistical treatment of demand to increase a manufacturer's efficiency (Gallego-García & García-García, 2021), as well as, for example, sustainable closed-loop supply chain synergy in the forestry industry (Wang & Tian, 2022). Optimal inventory control using stochastic optimization models has also been discussed, focusing on multi-echelon supply chains with uncertain demand (Crevecoeur et al., 2019). These studies indicate the growing interest in employing probabilistic and statistical methods for planning and risk management in domains of a company's operations. Such models considering uncertainty have not been heavily utilized so far.

Despite extensive research in these areas, the specific topic of distribution strategy planning in unpredictable environments still needs to be explored. The following section presents the notation used later in our model. The main contribution of this article, our method to find an optimal distribution strategy path in an unpredictable environment, is then developed in Section 4.

3. Notation

Our model searches for the optimum long-term distribution strategy given a set of business scenarios and a set of feasible potential distribution strategies. Business scenarios can be, for example, different sales growth trajectories, shifts in consumer behavior, or a black swan event (Taleb, 2007). Distribution strategies are different configurations of the company distribution network. For the optimization procedure from the COM, they must be evaluated across all considered business scenarios. Therefore, if we, for example, consider four business scenarios and two distribution strategy setups, there must be eight estimates in total.

For clarity, we use the same basic notation (Petřík & Plajner, 2023) when appropriate.

The distribution strategy is designed for n consecutive time periods. Variable A^i, $i \in 1 \dots n$, is the modeled company in the period i and its states $a_j^i, j \in 1 \dots m^i$ are the possible business scenarios where the company can be in that period. $A = \{A^1, \dots, A^n\}$ is the set of all company nodes at all time periods. The company must then design a number d of feasible distribution networks **Z,** which could accommodate the needs of company A. Symbol $Z_f^i, i \in \{1, \dots, n\}, f \in \{1, \dots, d\}$ then refers to a strategy Z_f implemented during a specific period i.

Next, it is necessary to choose a KPI which will be used to evaluate each business scenario – a distribution network combination. We define distribution network operating costs as the one most frequently used in practice from our experience. Distribution network operating costs[4] for a company are costs related to network operations. $c_{j,f}^i, i \in \{1, \dots, n\}, j \in \{1, \dots, m^i\}, f \in \{1, \dots, d\}$ stands for distribution network operating costs in a state a_j^i while operating a distribution network Z_f. The tool to obtain all estimates c_j^i can be chosen freely, but it must be possible for every Z_f at every state a_j^i included in the model.

4. Methodology for modeling the share of cases when a distribution strategy is optimal

While facing the long-term planning task and creating a robust strategy, expectations of future development are required. This can be obtained using data and mathematical forecasting methods (such as regressions, neural networks, and the like) or experts and their opinions and educated guesses. Having worked on various distribution strategy design projects, we discovered that acquiring conditional probability tables, as described in Subsection 1.1, is challenging using either data or expert

4 The exact estimation of the distribution network operation costs is always case-specific. However, the costs usually contain fleet operating costs, warehousing costs, external pallet carrier costs, and overhead costs.

knowledge, especially with a long horizon of several years. Underlying data are usually too sparse for robust predictions, prone to unforeseen events, and expert knowledge is difficult to obtain in a precise form. The causal transitions among states between company nodes are difficult to capture and notoriously prone to misspecification. To address this difficulty, we design a process that helps experts fill their expectations into the model and calculation even though they are very imprecise. We propose to limit the possible future scenarios to a smaller area (viable options). In this area of potential future development, we estimate the percentage share when a distribution strategy is optimal. This gives strategists and planners an answer to the possibility that the selected path will be correct, which is important information in the planning process. The advantage of this approach lies in its robustness to user misperceptions about the likelihood of future development scenarios. On the other hand, even with this approach, evaluating the future distribution network scenario is necessary as it is an essential input for calculations. We use proprietary software, Distribution Wizard, which allows us to do such calculations.

The computations in the presented model are conducted separately for each company node A^i, $i \in 1...n$, from the network. Accordingly, we assume independence of different company nodes. However, the users have demonstrated a far better ability to accurately describe the probability of a_j^i by an interval than by an exact CPT. Therefore, we allow the user to restrict the probability of each state a_j^i in the network, to model their assumptions about the probability of state a_j^i.

The user-restricted probability space **P** can be defined as:

$$\boldsymbol{P} = P\left(A^i = a_j^i\right) \in \left[\overline{w_j^i}, \widehat{w_j^i}\right], i \in \{1,2,\dots,n\},$$

$$j \in \{1,2,\dots,m^i\}, \overline{w_j^i} \in [0,1], \widehat{w_j^i} \in [0,1],$$

where $\overline{w_j^i}$ and $\widehat{w_j^i}$ are the lower and the upper limit for the probability that state a_j^i can have. In the application presented in this article, we model business scenarios in which the modeled company is assumed to shift part of its wholesale from Czechia to Poland. The user-restricted probability space **P** allows us to model the situation when, for example, the scenario in mind has a probability of at least 10% and a maximum of 60% to happen in the future.

Now, let us define a subspace $\mathbf{W}_f \subseteq \mathbf{P}$, which represents all probability combinations for which a strategy $f \in \{1,\dots,d\}$ is optimal. Probabilities $p_j^i, i \in \{1,\dots,n\}, j \in \{1,\dots,m^i\}$ create the subspace W_f, where the following condition is satisfied for a given f:

$$f = \arg\min_d \left\{\sum_{j=1}^{m^i} p_j^i c_{j,d}^i\right\}. \tag{1}$$

The condition given by Equation 1 is based on the COM (Petřík & Plajner, 2023) and states that a distribution strategy Z_f yields the lowest expected distribution network operating costs at the company node A^i given the probability combination p_j^i and the costs $c_{j,d}^i$ associated to each business scenario a_j^i and each distribution strategy Z_d.

Finally, we want to estimate the size of the subspace $\boldsymbol{W_f}$. Let us first denote the size as $S \in [0,1]$, $S(W_f) = 0$ implies that the strategy is never optimal in the subspace. The size S of the strategy f is then the integral of the $(r - 1)$th order over this subspace. r is the number of states a_j^i which a company node A^i can have. One integral dimension is subtracted due to the logical restriction $\sum_j p\left(a_j^i\right) = 1$.

$$S(\boldsymbol{W_f}) = \int_{W_f}^{(r-1)} 1 dW_f \tag{2}$$

In case there are user-defined restrictions placed on the probability space **P**, $\sum_{f=1}^{d} S\left(W_f\right) \neq 1$. Therefore, the values $S\left(W_f\right)$ are normalized to

$$S'(\mathbf{W}_f) = 1 \tag{3}$$

for better interpretation. The resulting $S'(\mathbf{W}_f)$ then represents the percentage share of the cases when the strategy f is optimal in the user-restricted probability space **P**.

5. *Case study: choosing the optimal distribution strategy in an unpredictable environment*

In a case study involving a consumer electronics wholesale company[5] operating primarily in Czechia, we applied the methodology presented in Section 4 to explore the probability of three distinct

5 At the company's request, the name will remain undisclosed, as will any other fact by which it could be decisively identified. Consequently, all prices are always quoted in units corresponding to the CZK* coefficient and therefore the conclusions are expressed in relative values that remain accurate.

distribution networks being optimal under the impact of four considered scenarios of future business development. The prospective analysis extended to six years, divided into three separate time frames: 2024, 2026, and 2028. As it takes time to implement changes to the distribution network, it is reasonable to use two-year intervals. These intervals can be modified to any necessary length if needed. For this analysis, we project a steady wholesale volume relative to the outlook. The case study is structured as follows: Initially, we present the logistics operations and an overview of the modeled traffic restrictions. After that, we implement our method and examine the findings.

5.1 Description of logistics operations

The company's operations comprise two major channels and one minor channel. The first is a chain of retail electronics stores with branches in most Czech cities. The second is wholesale to a vast network of other customers. The company's last channel is an e-commerce platform, which nowadays represents only a minor portion of sales. Currently, wholesale deliveries and deliveries to the retail chain are conducted from one distribution center on the outskirts of Prague. Two main channels facilitate distribution. A network of privately operated trucks is used to deliver bulk amounts to the retail chain and to those customers whose orders are large enough. Outsourced logistics service providers are then used to deliver goods to the remaining clients. Providing shipments to these clients with 22-ton trucks is not economically viable. However, the storage and throughput capacity of the distribution centers currently in use is constantly under pressure, so part of the portfolio consisting of large consumer electronics will be moved to the new distribution center.

5.2 Business development scenarios

We modeled several business development scenarios that could significantly influence the choice of the optimal distribution strategy. In addition to the current status quo, which assumes no changes in the current state, we present three distinct scenarios.

- **Sales shift:** In this scenario, we assume that 30% of the sales, in terms of volume in m^3, nowadays conducted in retail stores would shift to e-commerce. Such a shift would reduce the overall amount transported by the fleet to the retail branches. The goods would be shipped directly to the consumers via outsourced services.
- **Wholesale shift small:** We model a wholesale shift from Czechia (-90% of the total existing sales volume in m^3) to Poland (+15,000 m^3 of the sales volume). In this scenario, the major wholesale customers in the Czech market signal the option of diverting and purchasing the goods directly from overseas manufacturers. At the same time, there are advanced negotiations with a significant online e-commerce company from the fast-emerging Polish market, which could soon become a major customer. In this scenario, most shipments to the Czech wholesale customers, whose warehouses are primarily located in the Central Bohemian Region, would stop. However, a significant amount of goods would be newly delivered to the distribution center of the Polish company situated on the outskirts of the capital, Warsaw.
- **Wholesale shift large:** We model a wholesale shift from Czechia (-90% of the total existing sales volume in m^3) to Poland (+25,000 m^3 of the sales volume). This scenario is identical to everything else except for the amount newly delivered to the Polish company.

5.3 Distribution strategies

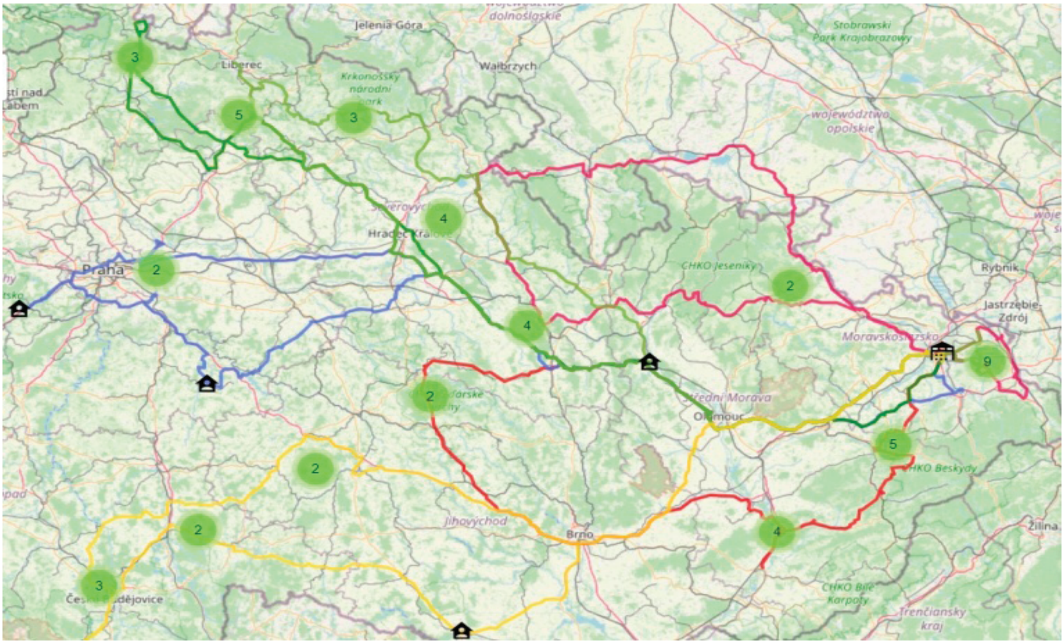
We propose three alternative strategies with different network topologies. The network topology is defined by the distribution nodes (warehouses, cross-docks) and the vehicles operating them. Each strategy corresponds to a different choice of location for the new distribution center:

- **Praha:** A new distribution center near Prague,
- **Brno:** A new distribution center near Brno,
- **Ostrava:** A new distribution center near Ostrava.

5.4 Modeling

We model one year of operations of each network as described in Subsection 5.3 under each scenario from Subsection 5.2 using actual data of historical orders provided by the company. The data includes details about precise delivery time and date, order size, the delivery channel used, and customer location addresses. To model each scenario as realistically as possible, we deployed proprietary simulation software, Distribution Wizard, from Logio, a Czech consultancy and technological company providing supply chain management services to major retailers and manufacturers worldwide since 2004. Distribution Wizard's engine[6] can solve large vehicle routing problems and integrate a wide range of parameters, enabling us to accurately model a wide range of network configurations. Next, we simulated the modeled scenarios and fine-tuned model parameters where necessary. An example of graphical output provided by DW can be seen in Figure 2. Each colored line represents a route designed by DW to deliver a given set of orders to customers on a given day. The color bears no other meaning than to visually distinguish different routes. The figure explicitly shows one of the simulations for the distribution scenario when the new distribution center is near Ostrava. The warehouse in Ostrava is represented by the synonymous pictogram on the right edge of the figure. A smaller pictogram shows customer locations. Those that are close to each another are represented by green circles, which represent their number in the area.

Figure 2 Distribution routes from the Ostrava warehouse



Source: Output from the Distribution Wizard software model done by the authors

Table 1 provides an overview of the calculated costs of each distribution strategy under each business scenario. Each figure is a combination of the expenses for one's own fleet of trucks, as estimated by DW, and the costs of outsourced pallet delivery providers. The cost of one's own fleet of trucks consists of two main parts:

- Cost per distance driven – given a specific vehicle type, the price per distance is directly related to several factors, the most influential ones are fuel consumption, maintenance, lease payment, and insurance.
- Cost per time driven – price per time is derived from the driver costs.

In our computations, we applied the cost model used by the company to estimate the distribution network operating costs as accurately as possible. In line with the non-disclosure request, the exact specifics of the cost model will remain undisclosed. Furthermore, pallet delivery costs were estimated using our knowledge of the industry standard deliv-

6 jsprit

ery prices for a given distance from the origin and the pallet weight. Since we focus on relative rather than absolute differences between the results, the final estimates were scaled for the **Praha** distribution strategy in the current state business scenario to equal 1,000,000 units. Scaling preserves the relative ratios and enhances the readability of the results for the reader.

The results suggest that building a new distribution center in Praha under the current scenario yields the lowest operating costs. Moreover, the same distribution strategy is also the most cost-efficient under the **Sales shift** scenario when we modeled a sales shift from the retail store shelves to e-commerce. Under both business scenarios, Ostrava's distribution strategy is the most expensive one. On the other hand, in the case of a wholesale shift to Poland, as modeled in the third and the fourth scenarios, **Ostrava** and **Praha** correspond to the lowest and the highest estimated costs, respectively. That is an expected outcome because the wholesale shift is much more favorable to **Ostrava** than **Praha** as it lies much closer to the Polish capital, Warsaw. The operating cost of the **Brno** strategy always lies between **Praha** and **Ostrava**.

Table 1 Comparison of the operating cost of each scenario and each strategy

Strategy	Scenario			
	Current	Sales shift	Wholesale shift small	Wholesale shift large
Praha	1,000,000	1,136,622	1,196,659	1,335,497
Brno	1,048,860	1,163,901	1,165,068	1,279,688
Ostrava	1,114,696	1,184,497	1,159,403	1,239,946

Source: Authors' computations

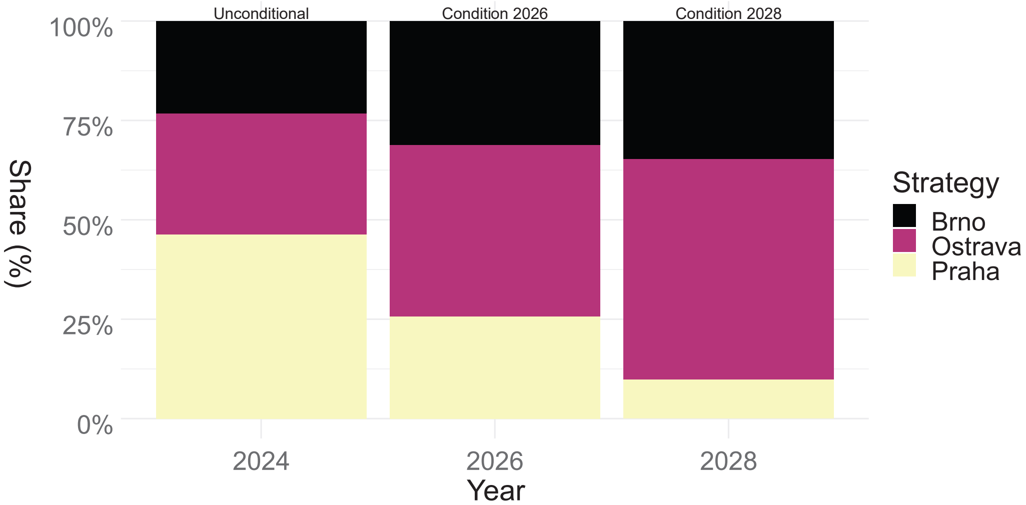
5.5 Case study results: Finding the probabilistically optimal strategy for each year

Having obtained the expected costs of each strategy under each scenario, we approached the application of the methodology presented in this paper in Section 3. In line with the proposed method, we first restrict the probability space. We limit the **Wholesale shift small** and the **Wholesale shift large**. The first restriction assumes that the probability of the **Wholesale shift small** scenario in 2026 is at least 10% and in 2028 at least 20%. The second restriction assumes that the probability of **Wholesale shift large** in 2026 is at least 5% and in 2028 at least 10%. According to condition 1, we identified the subspace for each of the three distribution strategies considered, where each strategy yields the lowest expected operating costs. The respective subspaces were approximated by discretization of the entire probability space. The tests have shown that the granularity of multiples less than or equal to 10% for each $P(a^i_j)$ quickly converges to a stable result. We have chosen a sufficient granularity of 5% to proceed with the method. Consequently, we obtained the percentage share of the cases when each given strategy is optimal. This calculation[7] was done in line with Equation 2. Finally, the shares were normalized according to Equation 3 to make the total sum equal to 1.

Figure 3 depicts the results of our model application. The stacked bars represent the shares of cases where each considered strategy is optimal in each modeled year, given the user-placed assumptions referenced in the figure caption. In 2024, the distribution strategy in Praha holds the majority share. Yet, as we explore scenarios with a higher probability of shifting wholesale operations to Poland, we observe a transition of shares from **Praha** to the strategies in **Ostrava** and **Brno**. **Ostrava** emerges as a practical alternative due to its proximity to Warsaw, making it an attractive location for a new distribution center. However, an interesting movement is seen in the shares towards the **Brno** strategy. Although the data in Table 1 suggest that placing a new warehouse in Brno is not optimal in any given scenario, this strategy still boasts the highest expected value for a considerable range of probability distributions across various scenarios. This might have been overlooked if we had relied only on traditional scenario analysis methods.

7 Since we discretized the probability space, the percentage share was not obtained by integration but by summation.

Figure 3 Shares of optimal distribution strategies each year



Condition 2026: P(Wholesale shift small), P(Wholesale shift large) > 0.05,
Condition 2028: P(Wholesale shift small), P(Wholesale shift large) > 0.10

Source: Authors' computations

The appeal of the **Brno** strategy lies in its resilience to changes across different scenarios. It might not be the best choice under any circumstance, but it is never the worst-performing one either. Hence, it embodies a safe choice. Furthermore, even when we impose user-defined probability limits on specific scenarios, as illustrated in Figure 3, the share of **Brno** changes minimally compared to **Praha** and **Ostrava** strategies. This highlights **Brno's** strategy as a steady and reliable choice. From a planning and risk management standpoint, a strategy offering the most consistent outcome can be more valuable than riskier ones, promising higher rewards. Thus, **Brno's** strategy may be compelling due to its predictability and stability.

6. Results

The method of finding the optimal distribution strategy path, as introduced in Section 4, was successfully deployed on a real company case study in Section 5. The application enabled us to identify the most fitting distribution strategy under the modeled development scenarios in three time periods. As the modeled shift to Poland becomes increasingly likely, the Ostrava strategy is probably optimal. However, Brno was found to be the most stable strategy under different development scenarios.

7. Conclusion

This article was focused on the complex topic of distribution strategy planning. First, we have described the problem and explained our motivation and connection with previous research in this area. There are some gaps in practical economic decision-making within strategic distribution network planning and current best practices. We proposed a methodology to overcome one of these problems. The key is to circumvent the problem of defining expectations about future economic conditions or potential scenarios.We replaced such expectations with probability intervals, which are much easier for users to provide. From the user's perspective, this represents a significant reduction in complexity. Furthermore, despite simplification, our method maintains a high level of information value, ensuring no loss in the quality of insights obtained. However, the presented method still assumes accurately defined and estimated development scenarios. Therefore, the proposed method is not applicable when planners cannot determine the development scenarios and assess the distribution network costs under these scenarios.

In this article, we presented a business case of a Czechia-based company looking for a potential storage location and working with many uncertainties during its decision-making process. It is a real-world example where we empirically present the usefulness and usage of the proposed method. In our example, the company can take three different potential directions. One is currently the best, and the other is the best in specific future scenarios. The last scenario is never the best-performing one when evaluating things in this straightforward way. While utilizing our method, it becomes clear that the third network is the best for over 30% of cases. It is still not the best result compared to other networks, but it shows that a methodical approach such as the one proposed helps to identify real potential. Using different probability intervals or introducing the KPI volatility in the evaluation could provide an even more strict mean variant of positive results.

We have created an approach to utilize uncertain future expectations for model-based informed management decisions. This is a crucial takeaway for distribution network planners to work with their long-term plans and uncertain events to achieve robust and reliable network designs.

What we presented in this article exhibits significant potential, and we intend to explore this field further. One of the main topics is how to introduce causal relationships between individual company states. This article removed these relationships, and we would like to introduce them back. Causal relationships add a new layer of complexity but also provide considerable potential for more complex model design, which covers more potential situations.

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