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CONCURRENT BUSINESS AND DISTRIBUTION STRATEGY PLANNING USING BAYESIAN NETWORKS

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Concurrent Business and Distribution Strategy Planning Using Bayesian Networks

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Abstract:
Business and distribution strategy planning are usually carried out in a sequence. A company first devises a business plan and then a distribution strategy able to accommodate it. The separation in planning can lead to a sub-optimal decision. We propose a method of how to concurrently plan both strategies, using a Bayesian network. We present three modifications of our concurrent optimization model which are based on different optimization objectives - distribution strategy costs minimization, revenue maximization, and profit maximization. The derivation of all model modifications and the collection process of the required inputs are described in detail. The presented model is tested on a business case of the company Pilsner Urquell, a world-renowned brewery based in Pilsen, Czechia. Using the company's historical data from 01/2017 – 12/2017, we design the cost-optimum distribution strategy in the Czech market for the years 2018 - 2020. Our results are then compared with the real company development over the same period. With our model, we show that the company could have selected a more cost-effective distribution strategy in 2017.

JEL: C02, C11, C62
Keywords: Bayesian Networks, Business plan, Concurrent planning, Concurrent Optimization Model, Distribution strategy

1 Introduction

Business and distribution planning is usually carried out separately or in a sequence, despite having an enormous impact on a company's development (Zegordi and Beheshti Nia, 2009). Typically, a company first devises a business plan, and only in reaction, it develops a distribution strategy to accommodate it. The separation in planning can occur due to the senior department managers acting in their own self-interest rather than the company's as a whole (Mckinnon, 2017). However, such a practice can lead to a sub-optimal decision because the two crucial company processes are inherently dependent. Therefore, it is desirable to conduct the planning in both domains concurrently. Concurrent planning would allow firms to devise more suitable strategies, increase logistics efficiency, and reduce the overall environmental impact. In this paper, we formulate a hypothesis that business and distribution strategy planning should be conducted concurrently. We then present an optimization method to conduct planning in both domains concurrently and empirically validate it on the business case of Pilsner Urquell. The findings provided by our model suggest that the company could have adopted a long-term distribution strategy that is more cost-effective, potentially resulting in a 5.8% decrease in the distribution network operating costs. These results indicate that companies could benefit from concurrently planning their business and distribution strategies. The concurrent optimization model outlined in this study can serve as a foundation for future research in this area or be adapted to address a variety of other research questions.

In our work, we use Bayesian networks (Jensen and Nielsen, 2007; Kjaerulff and Madsen, 2013) as the underlining probabilistic model. The strength of the presented approach lies in its robustness toward the choice of business and distribution planning methods. Historically, many different approaches toward business planning have been developed which rely on past information or the expert prediction of future development, which are more prevalent (Gordon and Stover 2003, R. Huss and J. Honton 1987). Similarly, different approaches can be taken to devise distribution strategies to accommodate the business scenarios envisioned in the business plan (Mangiaracina et al., 2015). To apply the presented method, any business and distribution strategy planning methods can be utilized as long as the outputs of the business planning process are transferable to the Bayesian network framework. Furthermore, it must be possible to evaluate the business scenarios in different distribution network setups. The freedom of choice regarding the planning of the underlying processes is a significant advantage of the presented approach, which enables broad applicability to a wide range of scientific problems. The above-mentioned model features are demonstrated in a Pilsner Urquell (PU) business case study, where the Concurrent Optimization Model (COM) is applied. Furthermore, the model is used to demonstrate that long-term strategic planning is more efficient than consecutive short-term planning.

The article is structured as follows. In Section 2, we provide the background for the processes of business and distribution planning. Furthermore, we highlight the recent applications of the Bayesian networks in supply chain management-related topics. Next, we proceed to establish our notation for the Concurrent Optimization Model in Section 3. We develop the model itself, the main contribution of this article, in Section 4. The model is then implemented in Section 5 on a business case of Pilsner Urquell where we use it to plan an optimum long-term distribution strategy. We also provide reasoning on how the Covid-19 pandemic affected the results obtained from our model. The last Section 6 provides an overview and a potential for further research.

2 Literature Review

This paper is the first one to propose concurrent planning of the business and distribution strategies. To our knowledge, this problem has not been defined in any historical publication. However, the areas of business and distribution planning are broadly covered and an overview of the most important findings from these fields is provided in this chapter. Furthermore, the underlining probabilistic model of our solution, the Bayesian networks are introduced, as well as their historical and contemporary applications in supply-chain-related topics.

Every company engages in a form of business planning. A business plan can be defined as a written document that summarizes and analyzes the company and lays out concrete projections for future development (McKeever, 2011). It serves as a roadmap depicting how to reach the business goals. A business must be able to adapt to unforeseeable events to survive continually. A carefully designed business plan can be a powerful tool to help manage these external challenges. Due to the inherent unpredictability of the exact future development, firms commonly utilize some form of scenario planning. The methods most frequently debated in the literature are Trend-Impact Analysis (Gordon and Stover, 1976), Cross-Impact Analysis (Gordon and Stover, 2003) and Intuitive Logics (R. Huss and J. Honton, 1987). These approaches usually rely on expert opinion more than historical data. However, during the business planning phase, the planners often omit the limitations of their internal logistics including the distribution network.

Through a distribution network of a company, the product is transported from the company's production or storage facilities to the customer's premises. The objective of a distribution network design is to plan the most cost-efficient manner of product movement through the whole supply chain (Ambrosino and Grazia Scutellà, 2005). To stress the importance, Ballou (2001) estimated that through an efficient distribution network and effective facility management, the operation costs can be decreased by up to 15%. Customer satisfaction is also directly impacted by the quality of deliveries in terms of on-time precision and quality of delivery (Chopra, 2003). The customer experience consequently affects the number of future sales. Due to an immense amount of network alternatives, the planning process is an extraordinarily complex task requiring a methodical approach. The process can be split into three phases (Mangiaracina et al., 2015). Foremost, the scenario alternatives are generated and qualitatively assessed. This phase aims to filter out the unfeasible scenarios and obtain a short list of applicable ones. Those are evaluated in the second phase using quantitative criteria. The best alternative is hence selected based on both qualitative and quantitative criteria. The selected scenario is then perfected to the best specific configuration in the third phase (Mangiaracina et al., 2015). Distribution network design belongs to a class of optimization problems where the objective is to appoint the best route to transport goods from the origin of supply to the demand points while minimizing the costs (Ambrosino and Grazia Scutellà, 2005). The complexity of the optimization problem grows exponentially with each new parameter included in the task (Zarandi and Saghiri, 2002). Bacchetti et al. (2021) achieved an effective and computationally efficient solution to a mixed integer linear programming model for a real case of optimum distribution strategy choice. Suryawanshi and Dutta (2021) in their paper address a distribution planning problem of perishable products under disruption and demand stochasticity. They develop a mixed integer linear programming model to make strategic and operational decisions under uncertainty. They conclude that losses due to disruptions can, for example, be minimized by proactive planning, and local backups of foreign suppliers.

Bayesian networks are commonly used in various supply chain management areas, such as risk management (Garvey et al., 2015; Hosseini and Ivanov, 2020), supplier selection (Hosseini and Barker, 2016; Hosseini et al., 2019) or in the recently emerged field of predictive maintenance (Xia et al., 2022; Sahu and Palei, 2020). Garvey et al. (2015) introduced a framework to measure risk propagation in the supply network. Utilizing Bayesian networks allowed them to capture the interconnectivity of different risks and the specifics of each supply chain network. The work addresses the issue of supply chain disruptions when an adverse event can negatively impact not only a single firm but also other parts of the supply chain. Further, in the field of the supply chain, Hosseini and Barker (2016) utilize a Bayesian network to quantify the suitability of different suppliers based on various primary, environmental, and resilience criteria. In agreement with Garvey et al. (2015), the resilience criterion notably emerged as a crucial one due to the supply chain's sensitivity to disruptions. Their approach allows them to include quantitative criteria and expert evidence and comprehensively present available information. The topic of supply-side resilience specifically has been resonating recently. In their recent work, Sharma et al. (2022) developed and tested a Bayesian network-based model to help identify the crucial risk factors impacting supply chain networks. Their paper also emphasizes the versatility of their model, which can always be adjusted to reflect the most recent new information. This feature of Bayesian networks is also paramount to the method developed in this paper. Further, Hossain et al. (2019) modeled a deep-water port resilience using a Bayesian network to identify the critical factor contributing to the strategical facilities' robustness. Jeong et al. (2021) propose a risk-adaptive technology roadmap able to swiftly adapt to a complex changing environment to increase the sustainability of the technology road-mapping. In the manufacturing industry, models for maintenance planning are a common application of Bayesian networks. Jones et al. (2010) identifies and models different parameters causing a failure in the system. They apply their model to a delay-time analysis and establish a failure rate with higher accuracy than what is achieved using a simple statistical average. However, the application presented in our article is yet unexplored. Moreover, there is no mention of concurrent business and distribution planning in the literature using any other method. Importantly, the aim of our work is not to offer an alternative to the existing business or distribution strategic planning methods but a framework allowing to perform both processes concurrently.

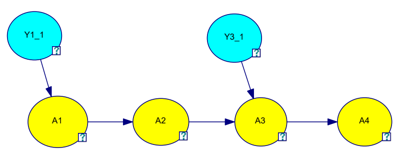
3 Notation and preliminary steps

In this article, we use the BNs as an effective tool to concurrently plan business and distribution strategies. Importantly, our method does not replace the existing approaches for business or distribution planning processes. It represents an extension allowing us to effectively combine and evaluate the information from both processes. This section describes the process of input collection for our model and establishes the variables that we use.

The preliminary step is to gather the inputs from the business and distribution planning processes. First, we describe the step of the business planning process. Although the usability of our approach is not conditioned by the use of any specific planning method, outputs from the process must be transferable to the BN. An example of our BN structure is shown in Figure 1. We work with a time outlook for n consecutive periods.

- Variable A^i, $i \in 1 \ldots n$, is the modeled company in the time period i, and its states $a^i_j, j \in 1 \ldots m^i$ are possible states the company can have in that time period. $\mathbf{A} = \{A^1, \ldots, A^n\}$ is the set of all company nodes at all time periods.
- Variables $Y^i_q, i \in \{1, \ldots, n\}, q \in \{1, \ldots, s^i\}$ represent other events influencing the company. The subscript k specifies that there are s^i parent nodes Y for a period A^i.

Figure 1: Example structure of our BN model



Now we can proceed to the collection of inputs from the distribution network planning process. The company designs a number d of feasible distribution networks $\mathbf{Z}$ which could accommodate the needs of the company $\{A^1, \ldots, A^n\}$. Symbol $Z^i_f, i \in \{1, \ldots, n\}$, $f \in \{1, \ldots, d\}$ then refers to a strategy Z_f implemented during a specific period i.

Next, we estimate several key performance indicators (KPIs) which we implement in our model. KPIs are metrics that companies track to measure their performance. Specifically, we implement revenue r, distribution network operating costs c and profit p.

- Revenue is the total amount of income generated by the sales of goods and services that a company provides. In our model, $r^i_{j,f}, i \in \{1, \dots, n\}, f \in \{1, \dots, d\}$, $j \in \{1, \dots, m^i\}$ stands for revenue in a state a^i_j while operating a distribution network Z_f. The tool selected to estimate $r^i_{j,f}$ can be chosen freely but it must be capable of doing so for every Z_f at every state a^i_j included in the BN model.
- Distribution network operating costs for a company are costs directly related to the network operations (fuel, worker wages, ...). In our model, $c^i_{j,f}, i \in \{1, \dots, n\}$, $j \in \{1, \dots, m^i\}, f \in \{1, \dots, d\}$ stands for distribution network operating costs in a state a^i_j while operating a distribution network Z_f. The tool selected to estimate $c^i_{j,f}$ can be chosen freely but it must be capable of doing so for every Z_f at every state a^i_j included in the BN model.
- We define the profit p as the difference between r and c, hence

$$p^i_{j,f} = r^i_{j,f} - c^i_{j,f}$$

.

The dependency of both r and c on a^i_j and Z_f is a logical consequence of our empirical experience and fundamental belief, that the business and distribution planning processes are dependent and should be planned concurrently.

Finally, we need to estimate the transition costs $t^i_{e,f}, i \in \{2, \dots, n\}, e, f \in \{1, \dots, d\}$. Transition costs $t^i_{e,f}$ is an additional expense a company must make between periods $i-1$ and i, when changing from a Z_e to Z_f. These costs can be, for example, associated with moving from an existing facility to a new facility. An estimate must be made for every pair due to the possibility of the following situation: $t^i_{e,f} \neq t^i_{f,e}, e, f \in \{1, \dots, d\}$.

Conditional probabilities of A^i are all obtained from the preliminary planning processes. They are as follows.

$$P(A^i|Pa(A^i)), i \in \{1, \ldots, n\}$$

3.1 Estimation of costs for every scenario using DW

To estimate the designed distribution networks across all business scenarios, we use a simulation software Distribution wizard (DW), developed by company Logio. This specialized simulation software implements an open-source engine JSprit[1] to model complex business scenarios. Effectiveness of the engine has been successfully demonstrated on a range of research activities to solve a variety of problems (Mahmoud et al., 2022). In the simulation process, DW incorporates a set of parameters allowing to realistically model a wide range of networks and to provide answers to many business questions.

JSprit uses a so called Ruin and Recreate (RAR) metaheuristic introduced by Schrimpf et al. (2000). They tested their new approach on the existing library of Vehicle Routing Problems (Dantzig and Ramser, 1959) (VRPs) and recorded overwhelmingly better results than what any other contemporary method could achieve.

Generally, the RAR principle contains three steps. First, it is necessary to define an admissible solution to the problem at hand which will obey all the predefined constraints. An admissible solution is a collection of routes (a sequence of jobs) to the given VRP. The *Ruin and Recreate* is a second step which attempts finding a better solution. The *Ruin* part selects a segment of the solution devised in the previous step and removes it from the solution. Subsequently, the removed part is recreated by the *Recreate* part as good as possible by again finding an admissible solution which obeys all the constraints. Lastly, the algorithm compares the new solution with the existing one and decides whether to preserve the previous, or keep the new solution.

[1] https://github.com/graphhopper/jsprit

4 Concurrent optimization model

In this section we present our model. First, we define a sequence of indices $\mathbf{k}_l = \{k_l^1, \ldots, k_l^n\}, k_l^{\cdot} \in \{1, \ldots, d\}$ which creates a sequence of distribution networks in time periods $\mathbf{X}_l = \{Z_{k_l^1}, \ldots, Z_{k_l^n}\}$, where each l marks a single permutation of indices[2]. The goal of our model is to find an optimum sequence of $\mathbf{X}_l$ for the whole outlook $1 \ldots n$. We propose three modifications of our model, based on three different optimization objectives.

- **Distribution strategy costs minimization**

  The customer delivery costs and the warehousing costs are minimized while keeping the defined service level. Therefore, the objective of this problem is to find a sequence of $\mathbf{X}_l$, such, that in combination with the associated $t_{e,f}^i$, the sequence yields the lowest expected total operation costs.

- **Revenue maximization**

  Revenue maximization is a common objective that many firms pursue as a priority, for example, to increase their market share. The objective of this problem is to find a sequence of $\mathbf{X}_l$, such, that in combination with the associated $t_{e,f}^i$, the sequence yields the highest expected total revenue.

- **Profit maximization**

  The objective of this problem is to find a sequence of $\mathbf{X}_l$, such, that in combination with the associated $t_{e,f}^i$, the sequence yields the highest expected total profit.

[2] There are n periods and d possible distribution network each period. Therefore, there is a total of d^n permutations.

4.1 Distribution strategy costs minimization

The first step is to obtain $\forall i \in \{1 \dots n\}$ and $\forall f \in \{1 \dots d\}$ the expected operation costs $\boldsymbol{\gamma_f^i}$. In total, there are $n * d$ estimates because we are estimating γ of every $Z_f, f \in \{1, \dots, d\}$ at every $A^i, i \in \{1, \dots, n\}$.

$$E[\gamma_f^i] = \sum_{j=1}^{m^i} c_{j,f}^i P(a_j^i | Pa(A^i)) \tag{1}$$

Using $E[\gamma_f^i]$ and $t_{e,f}^i$ we can now define the optimization problem.

$$\arg\min_l \{ \sum_{i=1}^{n} E[\gamma_{k_l^i}^i] + \sum_{i=2}^{n} t_{k_l^{(i-1)}, k_l^i}^i \} \tag{2}$$

The resulting l is such a sequence of distribution networks which yields the minimum costs.

4.2 Revenue maximization

The first step is to obtain $\forall i \in \{1, \dots, n\}$ and $\forall f \in \{1, \dots, d\}$ the expected revenue $\boldsymbol{\rho_f^i}$. In total, there are $n * d$ estimates because we are estimating ρ of every $Z_f, f \in \{1, \dots, d\}$ at every $A^i, i \in \{1, \dots, n\}$.

$$E[\rho_f^i] = \sum_{j=1}^{m^i} c_{j,f}^i P(a_j^i | Pa(A^i)) \tag{3}$$

Using $E[\rho_f^i]$ and $t_{e,f}^i$ we can now define the optimization problem.

$$\arg\max_l \{ \sum_{i=1}^{n} E[\rho_{k_l^i}^i] - \sum_{i=2}^{n} t_{k_l^{(i-1)}, k_l^i}^i \} \tag{4}$$

The resulting l is such a sequence of distribution networks which yields the maximum revenue.

4.3 Profit maximization

First step is to obtain $\forall i \in \{1, \ldots, n\}$ and $\forall f \in \{1, \ldots, d\}$ the expected total profit $\boldsymbol{\pi_f^i}$. In total, there are again $n * d$ estimates.

$$E[\pi_f^i] = \sum_{j=1}^{m^i} p_{j,f}^i P(a_j^i | Pa(A^i)) \tag{5}$$

Using $E[\pi_f^i]$ and $t_{e,f}^i$ we can now define the optimization problem.

$$\arg\max_l \{\sum_{i=1}^{n} E[\pi_{k_l^i}^i] - \sum_{i=2}^{n} t_{k_l^{(i-1)}, k_l^i}^i\} \tag{6}$$

5 Case study

5.1 Introduction

We tested the method proposed in previous sections using data and the business case of the company Pilsner Urquell. Pilsner Urquell Brewery (PU) is the largest brewery in Czechia, headquartered in Pilsen. PU has three production plants where beer and other beverages are produced. Its customers are large supermarket chains, smaller convenience stores, restaurants, and pubs. To help accommodate this vast network of clients, PU runs a network of fourteen strategically located depots in the Czech region.

PU runs its logistics at the high end of the domain standard and it achieves remarkable efficiency and results. This is possible because of their proper planning and long-term evaluations. The business task described below is one of the cases where PU wanted to analyze the situation on the market in advance and to be ready for the change when it arrives. This is necessary as all changes in logistics operations take a long time to implement. The goal is to set the optimum long-term distribution strategy in the Czech market for the years 2018 - 2020.

The case study is structured as follows. First, we provide the key facts regarding the company's operations and the business outlook. Next, we construct the BN model based on the business outlook and the historical data and simultaneously propose several feasible distribution strategies. Further, we evaluate each distribution strategy for each business scenario in terms of operation costs[3], using a specialized software created by the company Logio called Distribution wizard (DW). Consequently, using the outputs from DW and the estimated transition costs among strategies, we select the optimal distribution plan for the company for the years 2018 - 2020.

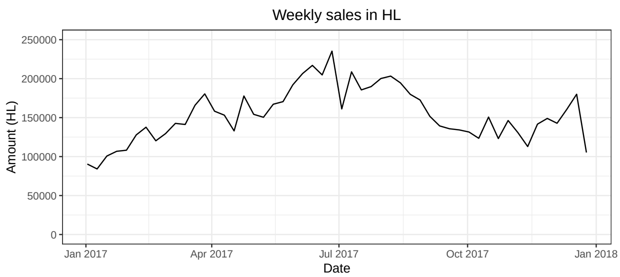
Operations description

The company's distribution network can be divided into three transportation channels:

- **Primary** - The primary channel is concerned with goods redistribution among the PU's facilities, mainly from the production plants to the depots. These shipments are almost always large amounts carried by trailers with $38t$ capacity.
- **Direct** - Through the direct channel, the product is delivered from the production plants to the distribution centers (DCs) operated by some large supermarket chains. These are always wholesale shipments carried by a trailer with $24t$ capacity. This channel is the most cost-effective because the product is transported in bulk to the customer using the most direct way.
- **Secondary** - Through the secondary channel, the product is delivered to all customers except those already delivered by the direct channel. These shipments are usually distributed using smaller trucks with $9.7t$ capacity.

[3]Prices are always listed in units, corresponding to CZK*coefficient due to a confidentiality policy of PU. Therefore, all conclusions are expressed in relative terms which remain accurate.

Figure 2: Monthly sales in HL



Source: Author's calculation based on data provided

5.2 Concurrent optimization

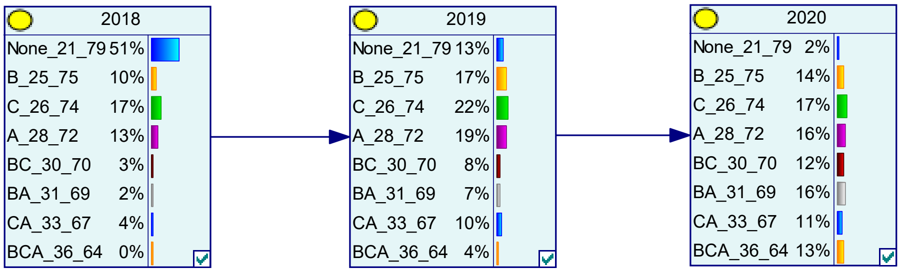
Business outlook

PU delivers its products to multiple supermarket chains. Some supermarket chains are already delivered by the direct channel in 2017. Some of the large customers prefer the direct channel as it allows them to consolidate goods and to better manage the supply of their stores. Three additional chains are signaling a possibility of a request to change to this model as well. This change would result in a transition of a portion of deliveries from the secondary and primary channels to the direct channel. Also, PU does not expect significant sales growth in the domestic market hence we assume the sales stay constant over the whole outlook.

Data

We obtained data from PU related to their distribution network operations for the full calendar year 2017. The VRP problem is very complex and the simulations require a lot of time to complete. Therefore, we select two calendar months, January and June on which the method is demonstrated. The two months is a representative sample. As can be seen in Figure 2, January is the slowest month of the year and June is when the summer peak occurs.

Figure 3: Bayesian network model



Source: Author's creation based on data provided

Bayesian network construction

Using the business outlook and the obtained data, we could proceed to the BN construction. Figure 3 shows the structure of our BN model. The model is built around the expectation that up to three customers will change to the direct way of delivery. There are three nodes $2018, 2019$, and 2020 representing the company over the three-year outlook horizon, each having eight states. The states stand for every possible scenario when none or the maximum of all three customers (A, B, C) shift their preference toward direct delivery.

The name of every state also contains the respective shares of the direct and secondary distribution channels. For example, the state BA_31_69 represents the situation when customers B and A change to the direct distribution channel, resulting in a share of direct distribution of 31% and the share of secondary 69% [4]. The probability distribution on each node in the BN is based on the company's expectations.

Possible distribution strategies

With respect to the business outlook, the company is considering closing the operations in one or two depots. Due to their location and throughput, depots in Teplice and Jihlava

[4]Primary is exempted because it is a redistribution among the PU facilities, never customer delivery

Table 1: Operating costs of different network configurations (thous. units) as estimated by DW

	No depot		Teplice		Jihlava		Both	
BS	**Jan**	**June**	**Jan**	**June**	**Jan**	**June**	**Jan**	**June**
Base	6,183	10,224	6,255	10,399	6,588	10,815	6,648	10,957
B	5,854	9,963	6,026	10,163	6,452	10,598	6,632	10,815
C	5,874	9,942	6,046	10,170	6,448	10,685	6,628	10,873
A	5,769	10,007	5,950	10,195	6,416	10,710	6,576	10,902
CB	5,789	9,713	6,002	9,924	6,516	10,486	6,721	10,710
AB	5,609	9,583	5,813	9,855	6,275	10,406	6,524	10,678
CA	5,737	9,688	5,902	10,029	6,400	10,569	6,592	10,815
CAB	5,420	9,282	5,665	9,557	6,187	10,253	6,432	10,547

were the most fitting ones to be closed. There are therefore four distinct strategies in total that the company could adopt:

- No depot closes
- Depot in Teplice closes - based on the distance, the customers get split between the nearby depots in Karlovy Vary and Mnichovo Hradiště
- Depot in Jihlava closes - the customers get split among the nearby depots in Hradec Kralove, Praha, Ceske Budejovice, and Brno
- Both depots close

Closing a depot eliminates the fix and operation costs required to run it. However, closing a depot also results in an increased distance to the affected customers which in turn increases the distribution network operation costs in other depots.

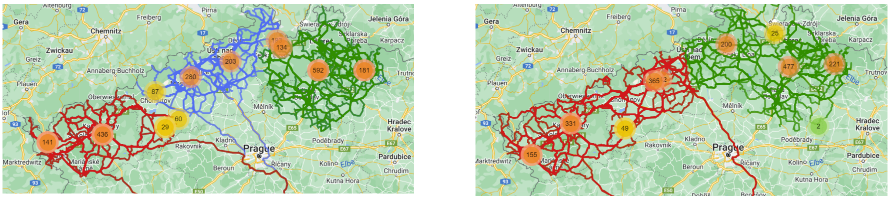
5.3 Optimum strategy selection

We have constructed the BN with our future expectation (Figure 3) and estimated the operating costs of four possible distribution strategies (Table 1) at each state in the BN.

Figure 4: Closing the Teplice depot

(a) Base setup with Teplice depot operational

(b) Alternative setup when depot in Teplice is closed



Source: Author's creation based on data provided

Before we can proceed to find the optimum sequence of distribution strategies, we need to establish the transition costs and also adjust the operations costs estimates in Table 1 for the savings achieved by closing the depots.

The transition costs are extra, one-time expenses that PU would have to make to change the network setup. We estimate the one-time cost of closing the depot in Teplice to be 350,000 units and 550,000 units in Jihlava. We assign a large penalty to the cases when a closed depot would be reopened again because, from the business perspective, it is an unrealistic development. Furthermore, PU calculated the Teplice depot operation costs for January and June to be 509,000 units and 671,000 units respectively. For the depot in Jihlava, the costs are higher at 911,000 units and 1,036,000 units. Having obtained all necessary inputs, we can apply our distribution strategy cost minimization model as described in Section 4.1. Using Formulas 1 and 2, we obtain the optimum sequence of distribution strategies for all three years.

Table 2 shows five transition paths with the lowest operation costs. For both months, the estimated optimum transition paths are identical, *Both-Both-Both*. The interpretation of this distribution plan is that PU should immediately close both depots in Teplice and in Jihlava and keep them closed for the whole outlook. Figures 4 and 5 show the situation before and after closing the depots. Although there are only minor cost differences among the top transition paths, the results clearly show that closing one or both depots would

Figure 5: Closing the Jihlava depot

(a) Base setup with Jihlava depot operational

(b) Alternative setup when depot in Jihlava is closed

Source: Author's creation based on data provided

Table 2: The top five optimum transition paths for 2018-2019-2020 by January and June, based on the projected distribution strategy operating costs (thous. units)

January		June	
Strategy	**Costs**	**Strategy**	**Costs**
Both-Both-Both	16,466	Both-Both-Both	28,288
Jihlava-Both-Both	16,856	Teplice-Both-Both	28,690
Teplice-Both-Both	16,871	Teplice-Teplice-Teplice	28,735
Teplice-Teplice-Teplice	16,876	Jihlava-Both-Both	28,786
Jihlava-Jihlava-Jihlava	17,157	Teplice-Teplice-Both	29,015

be beneficial for the company.

5.4 Comparison to the company data

We expected the company to have 0% growth over the outlook. In 2018 and 2019, PU sales grew yearly by less than 1%. Although the growth rate reached 4% in 2020, our expectation was overall reasonably accurate.

For the base scenario in our model, we estimated the operation costs to be 6,183,000 units in January and 10,224,000 units in June. PU's real costs were, on average, higher at 7,821,000 units in January and 11,783,000 units in June. The difference can be explained as a potential between the near-optimal state and reality. In the near optimum, the trucks are always fully loaded and always choose the shortest path to complete the delivery. The relative differences of 26% in January, which is off-season, and 15% in June, during the summer peak, suggest that PU operates comparably a very efficient distribution network. The potential can be mainly found in the smaller depots with smaller customer bases, for which it is much more demanding to achieve similar efficiency rates to the large depots, especially off-season.

Over 2018 - 2020, PU preserved all of their depots operational. The optimum distribution strategy selected by our model is closing both depots in Teplice and in Jihlava. As shown by our model, this strategy better corresponds with the company's persistent expectations regarding the changing preferences of the large customers. Closing these depots could have resulted in net savings of 5.5% over 2018-2020.

5.5 Impact of the Covid-19 pandemics on the company sales

By the end of 2019, Covid-19 was officially discovered in China. By the spring of 2020, Covid-19 was rapidly spreading to the majority of the world, and nearly all governments started adopting unprecedented measures of closing borders, limiting the movement of the population even within borders, and closing businesses except for essential services. The first restrictions directly affecting restaurants in Czechia came into effect on March 14[5]. Since then, the restaurants had to stay closed for 58 days, until May 11, except for takeaway orders. From May 11 until May 25, the restaurants had been allowed to reopen their outdoor areas. Afterward, restaurants could also reopen their indoor areas from May 25 until June 30, between 6 am and 23 pm. Although it was still closed at night, the customers could largely restore their social gathering habits. The reported figures from June do not seem negatively affected by the pandemic. The 5% year-to-year June sales growth that the company experienced despite the ongoing pandemics could be attributed to the release of restrictions, combined with the natural summer season and

[5] https://www.podnikatel.cz/clanky/nejvetsi-otloukanek-epidemie-hospody-byly-od-brezna-2020-zavrene-skoro-260-dnu/

the enthusiasm of customers who were recently released from unprecedented restrictions. Nevertheless, due to the reasoning above, neither January nor June sales seem to be significantly impacted by the ongoing pandemic.

However, overall data from 2020 would likely show a sales decline due to the re-adoption of major restrictions in the fall of 2020. Nevertheless, the optimum strategy selected by COM, *Both-Both-Both* would also prove robust during the pandemic. Whereas the non-essential establishments, including restaurants and pubs, remained closed for a large part of the pandemic, retail stores were preserved open. As established in the previous chapter, all restaurants and pubs are accommodated using the secondary channel. There is the highest benefit in terms of saved kilometers driven when using the regional depots (such as Teplice or Jihlava) to deliver the beer to these customers because of their number and because they place orders frequently. Therefore, when these businesses have closed, the benefit of operating the depots diminishes compared to the pre-pandemic state of affairs, and hence the *Both-Both-Both* would have been optimal for the company.

5.6 The short-term and the long-term planning comparison

In line with our second research question, we compare the short-term and the long-term optima. The hypothesis will be evaluated by comparing the long-term optimum, as selected by COM, with the sum of the costs of the strategies optimal in the short term. The optimal strategy in the long term was selected to be *Both-Both-Both*, on data from January and June as well, as depicted in Table 2. The short-term optima can be found by selecting the strategy for each year separately, including the implied transition costs in the process. The intuition behind the said approach is that the firm would only plan for one year in advance, not considering a more distant future in the planning. Therefore, a firm would select the least costly strategy for the following year at the end of each year. Using the short-term selection approach, the optimal strategy is *Teplice-Teplice-Teplice*.

The optimum is identical using the January and June data sets. In January, the total operating costs are estimated to be 16,875,000 units. Based on the June data, the result corresponds to operating costs of 28,735,000 units. Both strategies are among the top five long-term distribution strategies as depicted in Table 2. However, in both cases, they are sub-optimal. In the case of January, the strategy selected using the short-term approach, *Teplice-Teplice-Teplice*, is 2.5% more expensive than the long-term optimum *Both-Both-Both*. Using the June data, the short-term optimum is 1.5% more costly than the long-term optimum *Both-Both-Both*. Therefore, it can be concluded by averaging the results for the two peak months that the short-term optimum would be approximately 2% more expensive to operate than the long-term optimum.

6 Conclusion

Based on our empirical experience in the field, we have formulated the hypothesis that concurrent business and distribution strategy planning holds substantial potential. In this article, we presented a new method for concurrent business and distribution strategy planning using a Bayesian network. The method was described and applied to a business case of the company Pilsner Urquell. Using our method, we selected the most cost-effective distribution strategy for the company (Table 2). The company could have decreased its expected distribution network operation costs by 5.5%, had it followed the strategy selected by our model. Empirical evidence has, therefore, confirmed the validity of this hypothesis. Nevertheless, there are many unresolved issues within this field due to its complexity and multifaceted nature. One area for future research is to extend the presented model to also include inventory planning in concurrent optimization. Finally, the concurrent optimization model presented in this study offers a promising base for future research in this research area and has the potential for application on a wide range of research topics.

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