Optimal selection of first-tier suppliers in supply networks with disruption costs

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Abstract of the bachelor's thesis

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Abstract

Supply networks under uncertainty have gained attention in recent years. Specialized companies depend on increasingly complex supply networks for production while globalization has created large opportunities of supplier portfolio optimization. The complexity of modern supply networks and the consequences of the ongoing Covid-19 pandemic have made supply network disruptions more frequent. This has caused large economical losses globally and increasing attention to the management of supply network under uncertainty.

This thesis aims to find the optimal supplier portfolio for an illustrative supply network consisting of first-tier suppliers by risk analysis and optimization. Furthermore, this thesis discusses the strategic decisions of focusing on short-term cost-efficiency or long-term sustainability. This thesis uses a Bayesian network for risk analysis and presents an optimization model to obtain the optimal supplier portfolio. As the total costs of a supplier portfolio is minimized, the total risk of disruption and the company's business model restricts the objective function. We illustrate the method by applying it to a specialized company that requires three materials for the production. Specifically, for each material the company has three alternative suppliers with different disruption probabilities. This thesis assumes that the higher disruption probability a supplier has, the lower its costs. Because the supplier's disruption probabilities are associated with lower material costs, the optimal solution is the supplier portfolio closest to the maximum accepted risk of disruption. Furthermore, by the method of comparing estimated losses of profits with total network costs the studied company obtains a larger profit when choosing a long-term sustainable supplier portfolio rather than a short-term cost-efficient portfolio.

Keywords Supply network; uncertainty; risk analysis; disruption; optimization; disruption costs; cost-efficiency

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Abstract of the bachelor's thesis

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Sammandrag Under de senaste åren har försörjningsnätverk, som inkluderar osäkerhet, fått växande uppmärksamhet inom forskning. Specialiserade företag blir ständigt mer beroende av komplexa försörjningsnätverk samtidigt som globaliseringen skapar nya möjligheter inom leverantörsportfölj optimering. Komplexiteten inom moderna försörjningsnätverk samt konsekvenserna av den pågående Covid-19-pandemin har skapat en ökad frekvens av störningar inom försörjningsnätverk. Dessa störningar har orsakat stora ekonomiska förluster, vilket har resulterat till en växande oro inom hantering och ledning av försörjningsnätverk.
Denna avhandling siktar på att systematisk hitta den optimala leverantörsportföljen för ett illustrativt försörjningsnätverk, som enbart består av förstahandsleverantörer, genom riskanalys och optimering. Dessutom identifierar och analyserar denna avhandling ett optimalt försörjningsnätverks och dess byggstenar. Avhandlingen diskuterar också hur detta borde tas i beaktande i strategiskt beslutsfattande. I riskanalys använder denna avhandling ett Bayes nätverk varefter den optimala leverantörsportföljen definieras med hjälp av en optimeringsmodell. Modellen minimerar de totala kostnaderna, medan den totala risken för störningar samt krav för produktion begränsar den minimerade funktionen.
Vi illustrerar metoden genom att tillämpa den på ett specialiserat företag, som kräver tre olika material för företagets produktion. För varje material har företaget tre alternativa leverantörer med olika störningssannolikheter. Denna avhandling antar att ju högre störningssannolikhet en leverantör har, desto lägre blir dess kostnader. Eftersom leverantörens störningssannolikheter är förknippade med lägre kostnader, är den optimala lösningen definierad vid den maximalt accepterade risken för störningar. Med hjälp av att jämföra uppskattade förlorade vinster och totala kostnader konstaterar denna avhandling att ett långsiktigt och hållbart försörjningsnätverk är den mest lönsamma strukturer på försörjningsnätverk för det illustrerade företaget.

Nyckelord Försörjningsnätverk; osäkerhet; störning; riskanalys; optimering; störningskonstnader; kostnadseffektivitet

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1. Introduction

Uncertainties have gained increasing attention in the management of supply networks (Käki et al. 2015). Under uncertainties supply networks have risks of disruption (Vilko et al. 2015). This means that the suppliers fail to deliver ordered products required for production, potentially resulting in economic losses for a company.

According to studies, companies increasingly face challenges caused by the increasing amount of supply network disruptions (Vilko et al. 2014). Therefore, the topic of supply network uncertainties has grown importance in strategic and management decision making. Earlier, the most common strategic decision of supply network management was to minimize the costs regardless of the risks or consequences of supply network uncertainties (Käki et al. 2015). Because of the increasing number of supply network disruptions, the focus of designing a short-term cost-effective supply network has evolved into designing long-term stable and trustful supply networks (Käki et al. 2015). Furthermore, it has been found that by improving the resilience of its supply network, a company can obtain economical advantage (Vilko et al. 2014).

Supply network disruptions have become increasingly common due to many reasons. Globalization has enabled supply networks to become more globalized resulting in companies using international suppliers to find cost-effective networks (Garcia et al. 2015). Furthermore, as technology develops, companies' products are getting increasingly specialized requiring more complex supply network creating more vulnerability for the company's production (Käki et al. 2015). This creates challenges for supply network management, because a disruption can cause the whole production of a specialized product to stop.

The Covid-19 pandemic has furthermore created global challenges for supply network management (Fonsesca et al. 2020). In a study Guan et al. (2020) simulate and analyze the global Covid-19 pandemic with control measures, showing that the number of affected countries and long-lasting lockdowns are the two main factors for suppliers' disruptions. The study showed that even countries that are not directly affected suffer from large economic losses. They explain this by the supply network uncertainty caused by the lockdowns in affected countries and the increasing globalization of supply networks.

The increasingly frequent disruptions have been of concern to supply network managers and executives. According to studies, approximately 44 per cent of managers and executives expect their company's vulnerability to increase during the next five years and only 60 per cent feel confident about the management of a company when facing a supply network disruption (Käki et al. 2015). This indicates weakness in modern supply network management.

This thesis develops a systematic method to find optimal supplier portfolios for supply networks under uncertainty. The method aims to identify a company's supply network risks and calculate the corresponding probabilities. This method is developed to help managers improve a company's resilience to disruption. This thesis also analyzes whether a long-term sustainable supply network is a better strategical decision than a short-term cost-effective network.

This thesis builds a Bayesian network to identify the risks for supply network disruption. Bayesian networks are widely used probability network models that are commonly applied to identify risks and their probabilities. This thesis approaches its objective using a similar approach as Käki et al. (2015).

The second part of this thesis consists of a linear optimization problem. The optimization problem is solved by minimizing the company's total supply network costs, so that the highest level of accepted total risk of disruption is employed to constrain the decision variables. The objective function's decision variables are restricted by the requirements of the business model, which creates further implication challenges for universal applicability. The optimal supplier portfolio is determined by solving the developed optimization problem.

The third part of this thesis discusses the strategical decision between short-term cost-effectiveness and long-term sustainability. The implication possibilities to real supply network scenarios are also discussed.

This thesis illustrates the method by applying it to a simple specialized company. The illustrative company requires three materials for production and has the availability of three suppliers per material. This study focuses only on supply networks consisting of first-tier suppliers. As the materials are required for production, we assume that a disruption of at least one supplier creates a full disruption in the production in the company. Furthermore, as the three materials are different, this thesis assumes that the suppliers do not have dependencies between each other.

The other assumptions in this thesis are that (i) the demand always exceeds the supply, (ii) the supply network supports onetime delivery, and (iii) the suppliers are either fully disrupted or fully operational.

2. Earlier approaches and research

Due to the growing attention of supply networks and their uncertainties, the number of studies on supply networks has also increased (Käki et al. 2015). Systematic methods to identify and understand a company's supply network uncertainties and risks have been developed based on Bayesian networks. Also optimizing portfolios have been applied in numerous contexts. The topic and studies about supply networks under uncertainties have been approached with many different methods including simulation and risk assessment frameworks.

Käki et al. (2015) study supply networks uncertainties and supply network disruption through a three-step probabilistic risk assessment method. The PRA method is a standard model, which is commonly used in the analysis of complex systems (Käki et al. 2015). The three step PRA process begins by creating a structural model of the system. The next step consists of the identification of risks in a system and estimation their probabilities. Finally, the system's most crucial risks are identified by quantitative risk analysis. Käki et al. (2015) approach the first step of the PRA process by applying the Bayesian network to a supply network. They continue by studying the effects of dependencies as well as second-tier suppliers. They develop a method that organizations can use to identify their own risks and the company's total disruption probability. By Bayesian modeling, they find that in a company, which depend on every supplier, the probability to disruption increases as the number of suppliers increase. As management insights they conclude that complexity, supplier reliability, supplier dependency and supplier position affect supply network risk. Furthermore Käki et al. (2015) find that an increase of a specific supplier's importance causes an increase in supply network risk.

Hosseini et al. (2020) approach supply network risk by modeling a Bayesian network. Although approaching the topic with a very similar method in the beginning as Käki et al. (2015), they continue with simulating the Bayesian network to varying scenarios such as how natural disasters affect supply networks. Hosseini et al. (2020) aim to answer what creates disruptions in suppliers and how they affect downstream companies. They apply machine learning to create a systematic framework for how a Bayesian network should be used as a process. They find that a Bayesian network is suitable for supply network risk analysis, because causality and interdependencies can with low effort be captured. Furthermore, they note that with Bayesian networks, companies can better predict unforeseen disruptions caused by natural disasters, for instance.

Optimization help determine optimal solutions. Salo et al. (2022) apply multi-integer linear programming optimization to solve mixed-integer multi-stage decision problems under uncertainty. Gouglas and Marsh (2021) apply optimization to create an optimal portfolio of rapid responsive vaccines that indicates what vaccines should be invested in to create the most effective protection. They state that an optimization for optimal portfolios can be an excellent tool for decision making. However, in their scenario further data is required to define the true optimal portfolio. Bairamzadeh et al. (2018) study uncertainties in biofuel supply networks. Biofuel supply networks have many factors such as transportation, costs and production that create uncertainty to its supply network (Bairamzadeh et al. 2018). Using robust optimization to minimize costs they create an optimal supply network for biofuel.

Garcia et al (2015) study opportunities and challenges in supply network optimization. They analyze opportunities and challenges mainly through varying frameworks considering management, production, and design. Garcia et al. (2015) consider optimization being a strong tool in supply network design as technology and globalization develops. Due to the challenges caused by uncertainty and disruption, companies will have more complex networks that require more knowledge about supply network management (Garcia et al. 2015).

In addition to Bayesian networks and optimization, many alternative approaches are applied to similar studies. Carvalho et al. (2012) simulate a case study of a Portuguese automotive company to understand how mitigation strategies affect the supply network performance and how to improve its resilience to disruptions. They create two strategies (flexibility and redundancy) and design six scenarios with two control measures: lead time ratio and total costs. The simulation results allows them to redesign the supply network for the Portuguese automotive company.

Vilko et al. (2014) study supply network uncertainty from the viewpoint of risk management. They develop a framework for supply network risk management that helps understand companies' supply network risks through several uncertainty categories. The framework separates uncertainty factors into different categories such as the supply network and the external environment. They state that companies should analyze and evaluate the companies' risk of disruption to determine how much the company should invest to improve resilience of their own supply network. They also note that managers who understand the behavior of their supply network can mitigate supply network disruptions proactively and more effectively.

3. Methodology

This section presents the method used to find the optimal selection of first-tier suppliers for an illustrative company. The section describes the mathematical theory required to understand the approach and enabling businesses to apply the method to their own supply networks. The method consists of a two-step method, (i) a Bayesian network for assessing the total risk of disruption for a company and (ii) optimizing a supplier portfolio to achieve cost efficiency while maintaining resilience to disturbance. Company disruption risks found from the developed Bayesian network are used as constraints in step (ii). Vilko et al. (2014) suggest that in supply network decision making companies should determine a maximum accepted level of disruption risk. This is employed to the optimization as the main constraint when finding cost-efficiency.

This thesis illustrates the methodology through optimizing a specialized company's supply network. Figure 1 describes the company's supply network. Figure 1 illustrates the studied company's different suppliers with numbers. We denote each supplier with a letter-number combination, where the letter indicates the material in question and the number indicates the specific supplier (A.1. denotes material A and supplier 1). In this thesis the three suppliers per material have different disruption probabilities and therefore different costs. To study how much the company should invest in achieving resilience, the unit procurement costs are inversely proportional to the disruption probabilities. Note that the company has a risk for internal disruptions, which are not linked to its suppliers.

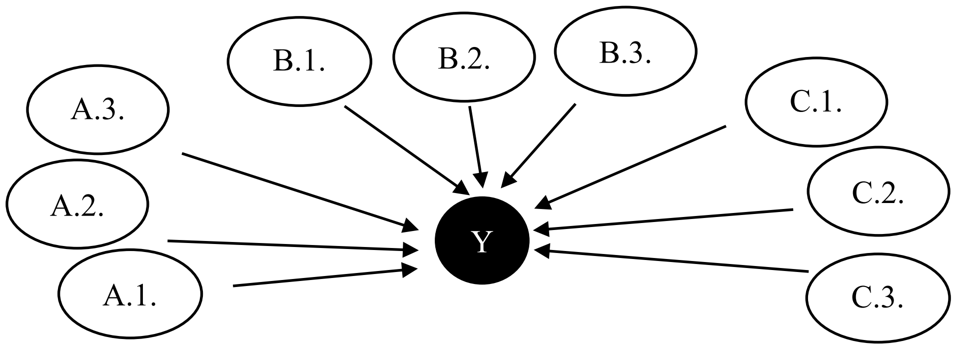

Figure 1: The company's supply network studied in this thesis

3.1 Bayesian networks

A Bayesian network is an acyclic graph modeling a joint probability distribution over a set of random variables (Friedman et al. 1997). Acyclicity means that the suppliers can cause disruption to the studied company but not the other way around. In other words, the direction of disruption moves only in the direction from upstream to downstream. As an assumption in this thesis, the company do not return any deliveries nor deliver any material to its suppliers. Thus, the property of acyclicity holds.

A Bayesian network includes nodes that are denoted with X. In the aim of this thesis the existing nodes of the supply network are the company Y and its first-tier suppliers S_k = *{1,2,…,N}*. Furthermore, nodes are categorized as child nodes and parent nodes (Käki et al. 2015). In the context of first-tier supply networks, the first-tier suppliers S_k are considered as parent nodes and the only child node is the company Y.

The state at each node can be either *disrupted* or *not disrupted*. When *disrupted*, the state of node X is x = 1 and when *not disrupted* the state is x = 0. The set space for all nodes' states is therefore simply $x \in \{1, 0\}$. The parent nodes create disruption to their corresponding child node, but the company cannot create disruption to its parent nodes. Thus, there is a function $S \rightarrow Y, Y \nrightarrow S$.

Figure 2 describes a supply network with a company Y and its five first-tier suppliers $S = \{1,2,3,4,5\}$. As Figure 2 illustrates, the states are not dependent on each other. This means that the supplier's disruptions are independent and not caused by other supplier's disruptions.

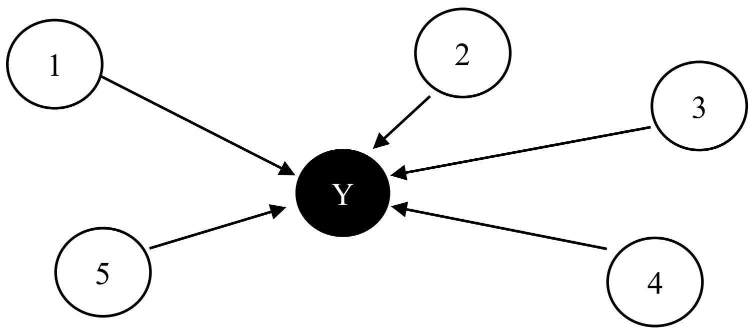

Figure 2: First-tier supply network with five suppliers

In Figure 2 the illustrated dependencies (arrows) between the suppliers and the company describes a causing of disruption in Company Y. The company can be disrupted in several ways. The company can be disrupted internally, by one supplier, by many suppliers, or by all suppliers. In an internal disruption, the company Y suffers from a disruption as a consequence of internal actions. In an external disruption, the parent nodes cause a disruption in the company Y. The Bayesian network considers every possible combination of disruptions in the network and calculates the total risk of disruption.

The conditional probability $\Pr(x = i|u = j) = \Pr(x|u)$ notes the probability of the child node x being in state i if a parent node u is in state j, with $i, j \in \{1, 0\}$. Furthermore, according to Käki et al. (2015) the sum of all conditional probabilities $\Pr(x|u)$ is

$$\sum_x \Pr(x|u) = 1\,, \forall u \tag{1}$$

The conditional probabilities are called network parameters or risk parameters (Käki et al. 2015). The number of network parameters can be found by the binary state 2^n, when the set space consists of only two states. As the number of suppliers increase linearly the number of network parameters increase exponentially, explaining the increasing supply network complexity. We express the aggregate state of all suppliers as $S = (s_1, \ldots, s_n)$, where $s_k \in \{1, 0\}$ denotes the state of supplier S_k and the state of the company Y as $y \in \{1, 0\}$. The application of Bayesian network still requires three more notations.

i. All nodes have an internal disruption probability. The internal disruption probability is denoted by a_Y for the studied company Y and by a_{S_k} for the supplier S_k.
ii. A disruption of supplier S_k does not directly cause a disruption for the company Y. The probability that the supplier S_k causes a disruption in the company Y given that the supplier S_k is disrupted is denoted by $b_{y|s_k}$. A disrupted supplier might still be able to deliver its products due to storage and therefore a disruption in a supplier does not directly lead to a disruption in the company Y.
iii. The total disruption risk for a supplier S_k is denoted by F_{S_k} and the total risk for the company Y is noted with F_Y.

The probability for all parent nodes to be in one specific combination of states is calculated by multiplying the probabilities for every individual state. The probability of one combination of all suppliers' states is therefore

$$\Pr(S = (s_1, \ldots, s_n)) = \Pr(s_1 \cap s_2 \cap \ldots \cap s_n) = \Pr(s_1) * \Pr(s_2) * \ldots * \Pr(s_n) \tag{2}$$

The probability that suppliers cause a disruption for the company is calculated as in Käki et al. (2015). We calculate it through the complement event of that the suppliers do not cause a disruption for the company. In this case, the company do not disrupt itself and the potentially disrupted suppliers do not cause a disruption to the company Y. Naturally, only the parent nodes s_k that are in state $s_k = 1$ can disrupt the child node Y and therefore the probability that the child node Y gets disrupted from its parent nodes is

$$\Pr(y = 1 | S = (s_1, \ldots, s_n)) = 1 - (1 - a_Y) * \prod_{s=1} (1 - b_{y|s})$$

(3)

To calculate the company's total risk of disruption F_Y we combine Equation 2 and Equation 3. This model is developed by Käki et al. (2015). The total risk of disruption is calculated by taking the sum of all possible combinations for the company to be disrupted. Therefore, the total risk is

$$F_c = \sum_k \Pr(y|s_k) * \Pr\,(s_k)$$

(4)

Now consider the simple supply network example described in Figure 3.

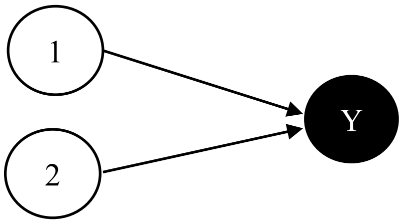

Figure 3: A company's supply network with two suppliers

In this thesis, we are interested in the company's total risk F_Y. The values a_1 and a_2 as well as b_1 and b_2 must be determined to define F_Y. These values can be approximated based on simulations or historical data (see Hossein et al. 2020). Table 1 illustrates the Bayesian network for the supply network in Figure 3 and uses Equation 2 and Equation 3 to calculate the required probabilities to then finally determine the company's F_Y.

Table 1: Bayesian network probabilities. Column 1 specifies all possible states for the parent nodes u_1 and u_2. Column 2 corresponds to Equation 2 and Column 3 corresponds to Equation 3.

$S = (s_1, s_2)$	$\Pr\,(S = (s_1, s_2)\,)$	$\Pr(y\,|\,S = (s_1, s_2))$
$s_1 = 0$, $s_2 = 1$	$(1 - a_1) * (1 - a_2)$	a_Y
$s_1 = 1$, $s_2 = 0$	$a_1 * (1 - a_2)$	$1 - (1 - a_Y) * (1 - b_{y|s_1})$
$s_2 = 0$, $s_1 = 1$	$(1 - a_1) * a_2$	$1 - (1 - a_Y) * (1 - b_{y|s_2})$
$s_1 = 1$, $s_2 = 1$	$a_1 * a_2$	$1 - (1 - a_Y) * \left(1 - b_{y|s_1}\right) * (1 - b_{y|s_2})$

The total risk for the company is calculated by multiplying the values from Column 2 and Column 3 in Table1. The total risk for the company is

$$F_Y = (1 - a_1) * (1 - a_2) * a_y +$$
$$a_1 * (1 - a_2) * [1 - (1 - a_Y) * (1 - b_{y|s_1})] +$$
$$(1 - a_1) * a_2 * [1 - (1 - a_Y) * (1 - b_{y|s_2})] +$$
$$a_1 * a_2 * [1 - (1 - a_Y) * (1 - b_{y|s_1}) * (1 - b_{y|s_2})]$$

(5)

3.2 The optimization formulation

The methodology continues by developing the optimization problem. Optimization is a approach used to support systematic decision making (Wright and Nocedal, 1999). Simply put, optimization determines the optimal solution of an objective function. The objective consists of decision variables and these decision variables are restricted through constraints (Wright and Nocedal, 1999). In this thesis, we find the optimal combination of suppliers for a company under uncertainty. The optimal supplier portfolio is found when the supply network costs are minimized subject to constraints on the total risk of disruption for a company F_Y and the required supply network structure.

The formulation of the optimization problem consists of two steps: (i) identification and modeling of the objective function containing required variables and (ii) specifying the constraints for the problem (Wright and Nocedal, 1999).

This thesis defines the total supply network costs as the sum of all the company's suppliers' costs. The suppliers' costs consist of varying factors such as management, planning transport, logistical and storage costs (Beamon, 1998). Moreover, to develop an operational optimization model that fits the requirement of the studied company, decision variables are added to the optimization problem. In this optimization problem the final optimal supplier portfolio is indicated through the decision variables. Therefore, the decision variables can only obtain two values either 0 or 1. Combining the decision variables with the supplier costs, the total cost of a company's supply networks is

$$SNK = X_1 * K_1 + X_2 * K_2 + X_3 * K_3 + X_4 * K_4 + X_5 * K_5 + X_6 * K_6 + X_7 * K_7 + X_8 * K_8 + X_9 * K_9,$$

(6)

where
$SNK =$ Total supply network costs
$K_{S_k} =$ Total costs for supplier S_k
$X_{S_k} =$ Decision variable for corresponding supplier

Without constraints, the minimization of the objective function results in an intuitive solution where all $X_{S_k} = 0$. According to the required three materials the company is required to have one supplier of each category. Therefore, the constraints of the decision variables are

$$X_1 + X_2 + X_3 = 1 \tag{7}$$

$$X_4 + X_5 + X_6 = 1 \tag{8}$$

$$X_7 + X_8 + X_9 = 1 \tag{9}$$

Furthermore, as the studied company only accepts a certain maximum level of disruption risk, the objective function is affected by the total risk of the company. The total risk of the company changes as the combination of supplier's change, assuming the companies have different disruption probabilities. Therefore, the optimization problem includes yet another constraint

$$F_Y \leq Max(F) \tag{10}$$

$F_Y =$ Total risk for disruption in a company

$Max(F) =$ Maximum accepted risk of disruption

Combining and rewriting the constraints and the objective function in general form, we obtain the final optimization problem.

Minimize

$$SNK = X_1 * K_1 + X_2 * K_2 + X_3 * K_3 + X_4 * K_4 + X_5 * K_5 + X_6 * K_6 + X_7 * K_7 + X_8 * K_8 + X_9 * K_9$$

subject to

$$F_Y \leq Max(F)$$
$$X_1 + X_2 + X_3 = 1$$
$$X_4 + X_5 + X_6 = 1$$
$$X_7 + X_8 + X_9 = 1$$
$$X_{S_k} = I_{S_k}, \qquad S_k = 1,2,\ldots,9,$$

where
I_{S_k} is the indicator function that gives the value 1 when the supplier is chosen and 0 when it is not.

This thesis solves the optimization problem mechanically. Every supplier portfolio's total risk is calculated for the Bayesian network. The costs of each possible combination are then calculated. The values are finally combined resulting in an easy-to-read table including every possible supplier combination presented by their corresponding total risk and supply costs. From this table the optimal solution is found.

4. Results

This section presents the initial parameters for the studied company and the results including the optimal supplier portfolio.

4.1 Numerical parameters

This thesis does not simulate initial parameters separately as done by Carvalho et al. (2012). From Table 2 the suppliers' initial parameters can be found. Furthermore, we see that the suppliers' disruption probabilities are inversely proportional to their corresponding costs

Table 2: Parameters.

	$a_{A.1.-A.3}$	$K_{A.1-A.3}$	$a_{B.1-B.3}$	$K_{B.1-B.3}$	$a_{C.1-C.3}$	$K_{C.1-C.3}$
$i = 1$	0.02	1500	0.02	2000	0.02	600
$i = 2$	0.05	600	0.05	800	0.05	240
$i = 3$	0.08	375	0.08	500	0.08	150

The remaining initial parameters required for the optimal supplier portfolio is presented in Table 3.

Table 3: Parameters

Max(F)	0.12
a_Y	0.05
$b_{Y\|S_k}$	0.5 for all $S_k = 1,2,\ldots,9$

4.2 Results for the Bayesian network

The company requires three different materials to its production. For each material the company can choose from three different suppliers resulting in a total of $3^3 = 27$ possible combinations. Table 4 presents all 27 different supply network combination possibilities and their corresponding risk of disruption F_Y for the company.

Table 4: Total risk of disruption for all possible combinations. Cells marked with grey indicate supplier portfolios with a total risk that exceed the maximum accepted level. $P(S_A, S_B, S_C)$ denotes the specific supplier portfolio where S_A, S_B and S_C denote the supplier for each material. Therefore, S_A, S_B and $S_C = \{1,2,3\}$

$P(S_A, S_B, S_C)$	F_Y
$P(1,1,1)$	0,0782
$P(2,1,1)$	0,0922
$P(3,1,1)$	0,1061
$P(1,2,1)$	0,0922
$P(2,2,1)$	0,1059
$P(3,2,1)$	0,1197
$P(1,3,1)$	0,1061
$P(2,3,1)$	0,1197
$P(3,3,1)$	0,1332
$P(1,1,2)$	0,0922
$P(2,1,2)$	0,1059
$P(3,1,2)$	0,1197
$P(1,2,2)$	0,1059
$P(2,2,2)$	0,1195
$P(3,2,2)$	0,1330
$P(1,3,2)$	0,1197
$P(2,3,2)$	0,1330
$P(3,3,2)$	0,1464
$P(1,1,3)$	0,1061
$P(2,1,3)$	0,1197
$P(3,1,3)$	0,1332
$P(1,2,3)$	0,1197
$P(2,2,3)$	0,1330
$P(3,2,3)$	0,1464
$P(1,3,3)$	0,1332
$P(2,3,3)$	0,1464
$P(3,3,3)$	0,1595

Table 4 shows that the total risk of disruption increases as the disruption probabilities for suppliers increase. This is intuitive as the only factor affecting the total risk is the suppliers' disruption probability and the company's internal disruption probability. The repeating values seen in the table are simply different combinations of suppliers with the same combination of supplier's probabilities for disruption. This makes sense because the three categories consist of the same disruption probability values. The increase in total risk and repeating values of Table 4 thus indicate on a functioning Bayesian network.

4.3 Optimal supplier portfolio

The combinations that exceed the Max(F)- value are rejected so that all remaining combinations are below the maximum accepted disruption level. By using our objective function with respect to its structure through Equations 5, 6 and 7 we obtain the final optimal supplier portfolio.

Table 5: The total risk for the company combined and the supply network cost. The optimal supplier portfolio $P(2,2,2)$ is the optimal supplier portfolio.

$P(S_A, S_B, S_C)$	F_Y	SNK
$P(1,1,1)$	0,0782	4100
$P(2,1,1)$	0,0922	3200
$P(3,1,1)$	0,1061	2975
$P(1,2,1)$	0,0922	2900
$P(2,2,1)$	0,1059	2000
$P(3,2,1)$	0,1197	1775
$P(1,3,1)$	0,1061	2600
$P(2,3,1)$	0,1197	1700
$P(3,3,1)$	0,1332	1475
$P(1,1,2)$	0,0922	3740
$P(2,1,2)$	0,1059	2840
$P(3,1,2)$	0,1197	2615
$P(1,2,2)$	0,1059	2540
$P(2,2,2)$	0,1195	1640
$P(3,2,2)$	0,1330	1415
$P(1,3,2)$	0,1197	2240
$P(2,3,2)$	0,1330	1340
$P(3,3,2)$	0,1464	1115
$P(1,1,3)$	0,1061	3650
$P(2,1,3)$	0,1197	2750
$P(3,1,3)$	0,1332	2525
$P(1,2,3)$	0,1197	2450
$P(2,2,3)$	0,1330	1550
$P(3,2,3)$	0,1464	1325
$P(1,3,3)$	0,1332	2150
$P(2,3,3)$	0,1464	1250
$P(3,3,3)$	0,1595	1025

Table 5 shows the final optimal supplier portfolio for the studied company. Furthermore, Table 5 shows that the increase of total risk for the company leads to a decrease of the total supply network costs. This is obtained through the assumption that a reliable supplier has higher costs than an unreliable supplier. It is intuitive that a supplier with higher costs as well as large probability of disruption would not be included in the optimal portfolio. This can also be seen in Table 5.

The company could choose more than the minimum number of suppliers. This, however, would increase the total supply network costs and would therefore not be relevant for finding the optimal supplier portfolio. Thus, the optimal supplier portfolio is P(2,2,2).

5. Discussion

This section analyzes the suggestion proposed by Vilko et al. (2014) that having a long-term sustainable supply network rather than a short-term cost-effective supply network is economically advantageous. We also discuss the applicability and real-life implications of the developed model.

5.1 Short-term cost-effectiveness versus long-term sustainability

To gain an economical advantage with a long-term sustainable supply network strategy, we compare the difference between different portfolio's expected loss of profit summed with total supply network costs. We compare the optimal supplier portfolio with every supplier portfolio with a larger disruption risk. We conclude that the long-term sustainable supply network strategy is more profitable for the company if the high-risk portfolio's sum of expected loss of profit and its corresponding supply network costs is higher than the sum for the optimal portfolio. Mathematically,

$$E(L_P) + SNK_P > E(L_o) + SNK_0 \tag{11}$$

$E(L_P) =$ Expected loss of profit for supplier portfolio with higher risk
SNK_P = Supply network costs for supplier portfolio with higher risk
$E(L_o)$ = Expected loss of profit for the optimal supplier portfolio
SNK_o = Supply network costs for the optimal supplier portfolio

The expected loss of profit caused by supplier portfolio P is denoted by $E(L_P)$ and describes the expected loss of sales for the company when operating with that specific supply portfolio. In a disruption the company is unable to continue its production, causing an internal bottleneck effect, which eventually results in loss of sales. The loss of profit L is therefore

$$L = (m - p) * w \tag{12}$$

Where *L* describes loss of profit, *m* the products selling price, *p* the production unit pride and *w* describes the number of products not produced caused by disruption. In this thesis, we study the scenario where $m = 100, p = 50\ and\ w = 1000$.

The expected loss of profit caused by the suppliers is given by

$$E(x) = \sum x * \Pr(x)$$

(13)

To determine the expected loss of profit, the disrupted probability must be estimated. These probabilities are obtained through the Bayesian network. Furthermore, in the sense of only studying the suppliers causing the disruption, the expected loss of an internal disruption must be subtracted. The expected loss of an internal disruption is

$$E(L_Y) = a_Y * L$$

(14)

As we study a company's one-time delivery, the loss of profit is constant. The expected loss of profit for the studied company is therefore

$$E(L) = \sum L * \Pr(L) - E(L_Y) = L * \sum \Pr(L) - E(L_Y)$$
$$= L * \sum \Pr(s_k) * \Pr(y|s_k) - E(L_Y) = L * F_Y - E(L_Y)$$

(15)

Table 6: A comparison between the optimal supplier portfolio (marked with grey) and the supplier portfolios with higher risk. The fifth column illustrates whether the equation holds for every high-risk portfolio.

$P(S_A, S_B, S_C)$	F_Y	SNK	E(L)	$E(L_P) + SNK_P > E(L_o) + SNK_o$
$P(2,2,2)$	0,1195	1640	5974,2	7614,2
$P(3,2,2)$	0,1330	1415	6651,5	8066,5 > 7614,2
$P(2,3,2)$	0,1330	1340	6651,5	7991,5 > 7614,2
$P(3,3,2)$	0,1464	1115	7318,4	8433,4 > 7614,2
$P(2,2,3)$	0,1330	1550	6651,5	8201,5 > 7614,2
$P(3,2,3)$	0,1464	1325	7318,4	8643,4 > 7614,2
$P(2,3,3)$	0,1464	1250	7318,4	8568,4 > 7614,2
$P(3,3,3)$	0,1595	1025	7974,0	8999,0 > 7614,2

As illustrated in Table 6 the company obtains an economical advantage when using the calculated optimal supplier portfolio. The short-term cost-effective portfolios have larger costs when expected loss of profits are considered.

Therefore, according to the methodology and analysis of this thesis, the optimal supplier portfolio when max $(F) = 0.12$ is in fact P(2, 2, 2). Thus, the strategic suggestion of a long-term sustainable supply network, as stated by Vilko et al. (2014), holds for the company.

5.2 Assessments of results

The assumptions and restrictions in mathematical models can result in an imperfect illustration of reality. This also implies to the model developed in this thesis. There are several factors that must be considered in applying the methodology to real business situations.

A real supply network rarely consists of only first-tier suppliers, especially independent first-tier suppliers. Suppliers have their own suppliers, which can disrupt the first-tier supplier's production. First-tier suppliers can also have mutual second-tier suppliers. Furthermore, a company's first-tier suppliers can be each other's suppliers, resulting in dependencies. This thesis studies a simplification of a real-life supply network, which can partly give misleading results. (For more detailed studies about complex and large networks see Käki et al. 2015)

The initial parameters in this thesis are not based on data or simulations. However, this do not affect the model as such since the model uses initial parameters in the developed optimization model. Although the initial parameters do not affect the model structure, it can be challenging to obtain reliable parameters for suppliers' disruption probabilities (Käki et al. 2015). Also, the probability value that a supplier disruption causes a company disruption $b_{y|s_k}$ can be even more challenging to assess. Moreover, the disruption probabilities may vary over time and therefore do not function as constants in the long run. Organizational and logistical changes can affect parameter values. Even unexpected disasters may affect the value of a supplier's disruption probability (Hosseini et al. 2014).

The thesis' optimization model and Bayesian network is developed uniquely for the problems faced by the company. Different industries and processes require different supply networks resulting in different structured Bayesian networks and optimization models. The models in this thesis are developed for a company that require three materials delivered by three different suppliers. Furthermore, the expected loss of profit depends on the company's operations and industries. A company does not necessarily lose all its sales when one supplier gets disrupted. For example, a retail store does not require material for production since no transformation is made. The retail supplier may experience loss of sales when facing disruption but can maintain its business by selling other suppliers' products to customers. On the other hand, vulnerable companies such as car manufacturers are extremely dependent on every supplier to successfully deliver the required components for production. In this scenario a company may lose all its sales, as illustrated in this thesis. According to Vilko et al. (2014) a company that is vulnerable for disruptions should have a lower total risk of disruption F_Y than companies with better resilience of disruption due to larger loss of profit.

This thesis only studied the scenarios when the company operates with one supplier per required material. The company could choose to order the same material from two or even all three suppliers. However, by using the model of this thesis, the total supply network's cost increases when increasing the amount of suppliers, which therefore excludes every supplier portfolio with a larger amount of suppliers than required.

6. Conclusions

This thesis has developed a method using Bayesian networks and optimization to find an optimal first-tier supplier portfolio for a company under uncertainties. The aim of this thesis is to deliver management insights on supply networks under uncertainties. Furthermore, this thesis analyzed the strategic decision of redesigning supply networks from short-term cost-effective supply networks to long-term sustainable networks. This was done by mathematically comparing differences between estimated loss of profits to differences between total supply network costs.

In recent years supply networks have become increasingly complex. Products are becoming more specialized, and globalization enables companies to build a global supply network. The strategic decision in designing supply networks does not traditionally consider uncertainties and thus better strategies might exist. As the supply networks have started to get increasingly complex, supply network disruptions have begun to occur more frequently. This has led to many problems in companies including loss of sales and productivity decrease. Managers are more concerned about the future effects of supply networks and a large percent of managers do not feel confident in their own knowledge of supply network management under uncertainties (Käki et al. 2015). This has led to a drastic increase in studies about supply networks under uncertainty.

Many studies aim to help managers understand the concept of supply networks under uncertainties by simulating alternative scenarios and getting data through control measures. Studies have also focused on the broader picture of supply network management under uncertainties with the aim of helping managers to map risks. In similar approaches as this thesis, other papers have also applied Bayesian network to identify risks mathematically. This thesis combined Bayesian network and optimization to find the optimal supplier portfolio. Furthermore, this thesis illustrated the developed model by applying it to a specialized company's supply network that operates with three different production materials. Each material can be bought from three different suppliers and each supplier have different disruption probability values. In this study, the total supplier costs are inversely proportional to the supplier's corresponding disruption probability.

Bayesian networks are widely applied acyclic probabilistic graph models that are generally applied to complex networks to identify a network's risks. In this thesis, the Bayesian network identifies risks caused by uncertain suppliers and calculates the probabilistic disruption values. The goal of applying the Bayesian network in this thesis is to calculate and compare the total risk of a company to help determine its optimal supplier portfolio. The results indicate that the total risk of a company increased as the supplier's disruption probability increased. This is intuitive as the company's risk depends only on its suppliers and we only study first-tier suppliers' impacts on a company. Further studies would aim on studying the model as second-tier suppliers are added to the supplier network and suppliers begin to have dependencies with each other. This would result in a more realistic model for examining more complex supply networks.

After identifying the company's risks, we built an optimization model that minimizes the supply network costs. In the model the calculated supply network risks restricts the objective function's decision variable with a maximum accepted disruption risk. The decision variables were also restricted according to the company's production requirements. In this study we mechanically combined every possible supplier portfolio with their corresponding costs and found the optimal solution. Further studies would aim on analyzing networks with a larger number of suppliers.

The last section of this thesis studied whether a long-term sustainable supply network can be a cost-efficient strategy. By comparing portfolios through their estimated losses of profits and costs, it was found that the optimal portfolio is in the long run more cost-efficient than the riskier portfolios with smaller costs. Further studies would aim on developing the method of finding the optimal value of most accepted risk for a company. Vilko et al. (2014) suggest that the more vulnerable a company is to disruption, the smaller the maximum level of accepted risk should be. This claim could be examined through computational analyses of more vulnerable companies with larger estimated profit losses in the face of disruptions.

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