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DYNAMIC PRICING AS A MITIGATION STRATEGY AGAINST SUPPLY NETWORK DISRUPTIONS WITH PRICE-SENSITIVE DEMAND – AN AGENT-BASED MODEL

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ABSTRACT

Supply chain disruptions can lead to immense financial losses for affected enterprises. Quantitative models which analyze the impact of disruptions and the effect of possible mitigation strategies on the overall network are needed to support the decision making process of practitioners. Therefore, we present an agent-based model of a supply network with eleven entities to analyze the benefits of dynamic pricing when confronted with material flow disruptions of different durations of two producers in the network. Our results show that dynamic pricing can reduce the financial burden of the total supply network but can also lead to strong interferences which entities are most affected by the disruption.

1 INTRODUCTION

Material flow disruptions pose a serious threat to today's supply chains as risk exposure and associated risk consequences increase, particularly as a result of stronger international cooperation and an emphasis on lean management and lean logistics (Stecke and Kumar 2009). With nearly 1,700 incidents recorded in 2017, the automotive industry, which was the most affected industry that year according to JLT's Automotive Supply Chain Disruption Report 2018, saw a 30% increase from the 1,300 incidents reported in 2016. The most common incidents were plant fires, mergers and acquisitions, hurricanes, and labor strikes. The severity of the damage is evident from the mean recovery time, which averaged 52 days for strikes, 22 days for floods, and 22 days for power outages (JLT 2018).

Due to the declining depths of added value and therefore increased, partly global, cooperation of companies, supply chains can no longer be regarded as serial entities, but rather as networks. Supply networks are highly complex and probabilistic systems with interdependent information and material flows in which the success of a network member also depends on the performance of their partners. If one or more entities suffer from serious production stops, the effects can spread across the system's connections, affecting other entities and multiplying the damage. This effect is known as the ripple effect (Ivanov 2017). In order to investigate disruptions occurring in these complex networks, simulation is particularly useful.

The academic field of supply chain risk management has attracted considerable interest over the last ten years due to the severity of the damage caused by disruptions. Intensive research has been undertaken to provide empirical research, conceptual theories on risk and risk reduction, and quantitative models for assessing risks and their impacts on the entire supply chain. The latter also integrates mitigation strategies to test their effectiveness and motivate practitioners to integrate beneficial strategies. Among the most popular mitigation strategies are backup and contingent supply as well as information sharing among partners. Even though some mitigation strategies have been studied profoundly, there are still a number of mitigation strategies that have not been considered (Bugert and Lasch 2018b).

For example, pricing strategies in supply chains with more than three entities have not yet been investigated in simulation models, except in Bugert and Lasch (2018a), who modeled responsive pricing as a reactive strategy against disruptions in a supply chain with two substitutable products and price-sensitive demand. This is rather surprising, as flexible pricing today is being facilitated by much higher data availability, information systems, more flexible pricing contracts, and e-commerce (Agatz et al. 2008). Amazon, for example, is reported to change its prices 2.5 million times a day (Mehta et al. 2018).

The main objective of this paper is to present an agent-based model of a supply network to analyze price elasticity in the presence of a significant material flow disruption and price-sensitive demand. A detailed description of the model's logic and parameters will facilitate implementation for practitioners to investigate price elasticity individually.

The rest of the paper is structured as follows. Section 2 gives a brief overview of quantitative approaches which simulate a supply chain with more than three participants and implement mitigation strategies. The outlines of the research methodology of this approach and the presentation of the corresponding research questions are presented in the third section. Section 4 presents the simulation model and discusses in detail the assumptions of the model, the model logic, and the model parameters. In section 5, the results of the simulation experiment are illustrated and the presented research questions answered. Section 6 gives a brief outlook for future research work.

2 LITERATURE REVIEW

Several simulation techniques, such as Petri-Nets (PNs), System Dynamics (SD), Discrete Event Simulation (DES), and Agent-based Modeling (ABM), are widely used to model the dynamic impact of supply chain disruptions and the effects of mitigation strategies (Wilson 2007; Wang et al. 2014; Aqlan and Lam 2016; Bugert and Lasch 2018a). In this section, we examine simulation models that concentrate on the dynamic modeling of mitigation strategies in supply chains with at least three entities. A detailed overview of supply chain disruption models can be found in Bugert and Lasch (2018a), while the ripple effect is further investigated in Dolgui et al. (2018).

Tuncel and Alpan (2010) examine the impact of mitigation strategies on a four-tier supply chain based on three disruption risks, namely quality risks, transport risks, and process risks, by using a PN. Risk mitigation is modeled conceptually as a reduced probability of occurrence. Kano et al. (2014) study the recovery phase after a disruption in a three-tier supply chain. With their PN, the authors investigate the influence on the supply chain's productivity assuming that a backup supplier is identified after a certain period of time. Zhang (2016) tests the effectiveness of information sharing by using a PN in a three-tier supply chain with two different products if stock-outs occur. The authors differentiate between five different customer behavior patterns during stock-outs.

Wilson (2007) uses an SD approach to analyze the impact of a ten-day transportation disruption at multiple locations on a five-tier supply chain. A traditional supply chain and a supply chain in which demand information is shared are compared, taking into account stock levels and service levels. Sidola et al. (2011) compare the impact of two transport disruptions on a regular and a visible four-tier supply chain, where all demand information is exchanged between supply chain partners. Performance metrics include inventory variability and the number of stock-outs of the retailer. Wang et al. (2014) consider a two-stage supply chain with one retailer and two independent suppliers, one of which is affected by a disruption. In their SD approach, the authors compare the use of a contingent supplier, who only receives orders in the event of a disruption, with a standby supplier, who maintains a certain capacity at a regular price and charges a higher price in the presence of higher demand. Li et al. (2016) explore the impact of 13 different disruption risks on the performance of a chemical supply chain with an SD model and evaluate the impact of increased transport capacity. Keilhacker and Minner (2017) examine the impact of five mitigation strategies (product substitution, recycling, increased research and development, and a mix of these strategies) to address the specific problem of supply shortages of critical earth elements due to export restrictions. Using extensive empirical data, an end-to-end supply chain model is developed, consisting of a large number of mining companies, raw material processors, manufacturers, and research laboratories. Bugert and Lasch (2018a) model a five-tier supply chain with two products in order to examine the consequences of supply chain disruptions of a different length and model the effect of responsive pricing as a mitigation strategy.

The DES model by Schmitt and Singh (2012) considers a three-tier supply chain with two suppliers, a central packaging plant, and two distribution centers with two products and predefined mitigation strategies. The model is combined with a Monte Carlo simulation to determine an aggregated distribution of the frequency and duration of disruptions per site. The authors investigate the impact of different inventory levels on the supply chain. Aqlan and Lam (2016) combine Goal Programming with a DES model to find the optimal mitigation strategies, inventory levels, and production volumes under budget constraints in a supply chain with four suppliers. Mitigation strategies are modeled by an abstract reduction of risk values. In the DES model of Ivanov (2017) a four-tier supply chain with realistic transport distances is presented. Different recovery and disruptive scenarios are examined to analyze the ripple effect. Ivanov (2018) further studies the ripple effect as well as the post-disruption periods with a DES model with four production plants and four distribution centers. The author examines the influence of the network design and mitigation strategies, such as flexible capacity and backup supply, in a real-life case study with a multitude of performance factors.

Seck et al. (2015) present an ABM approach to study the effect of different risk and recovery scenarios on the fill rate of a three-tier supply chain system with two suppliers and two sub-suppliers. The ABM model of Ledwoch et al. (2018) compares a random and scale-free network topology with a single original equipment manufacturer and 102 supplier nodes with respect to different disruption frequencies and durations. The fill rate, backlog, and inventory holding costs are considered as evaluation criteria. A random number of producing entities can perform two mitigation strategies, namely contingent rerouting by transferring orders to unimpacted suppliers and increasing buffer inventory.

Flexible sourcing (Kano et al. 2014; Wang et al. 2014; Ivanov 2018, Ledwoch et al. 2018) and information sharing (Zhang 2016; Wilson 2007; Sidola et al. 2011) are the dominant mitigation strategies modeled in simulation models regarding supply chain disruptions. Other commonly modeled strategies are increased transport or production capacities (Ivanov 2018; Li et al. 2016), buffer inventory (Schmitt and Singh 2012; Ledwoch et al. 2018), abstract mitigation by lowering the probability of risks (Aqland and Lam 2016; Tuncel and Alpan 2010), and modeling disruption recovery (Ivanov 2017; Seck et al. 2015). Apart from these strategies, only Bugert and Lasch (2018a) as well as Keilhacker and Minner (2017) model different strategies like responsive pricing, recycling, etc.

A supply network can be defined as comprising of actors, resources, and activities and their connections relating to transforming inputs into products and services (Harland and Knight 2001). There is no clear distinction between the concept of a supply chain and a supply network. We regard a supply network of having at least three tiers with more than one entity per tier. According to this definition, only the model of Ledwoch et al. (2018) and Keilhacker and Minner (2017) have a network perspective.

In theoretical contributions within the research area of supply chain risk management, a multitude of mitigation strategies are recommended, ranging from abstract strategies such as risk acceptance, risk avoidance, risk reduction, and risk transfer to a multitude of specific approaches. Rajesh et al. (2015) summarize, for example, 21 risk mitigation strategies, such as silent product rollovers, standardization, process postponement, flexible supply contracts, etc. Further publications with a summary of a multitude of mitigation strategies can be found in Aqlan and Lam (2015) and Tang (2006). As dynamic, autonomous pricing as a measure against supply chain disruptions has not yet been investigated, we propose a model that quantifies its usefulness in a supply network.

3 RESEARCH METHODOLOGY

Supply networks can be regarded as complex, dynamic systems with a multitude of stochastic influencing factors. The higher the complexity of the system, the more suitable simulation becomes compared to analytical methods. We decide to conduct a simulation experiment in order to gain a deeper understanding of the system's behavior under purposefully varying input parameters (Montgomery 2012).

Several simulation techniques with unique features and applications are available, such as System Dynamics, Petri-Nets, Agent-based Modeling, Monte-Carlo Simulation, etc. Agent-based Modeling is of particular interest for our scope of research, as it is able to represent self-organizing systems in which self-directed entities interact and influence each other (Macal and North 2014). In our model, the agents set their daily prices individually and interact with their direct partners via information and material flows.

We have checked the plausibility of our model using extreme condition tests. For this purpose, we set the lengths of the disruption to values of 0 and 50, increased demand up to 500 units and reduced it down to 100 units, set the target stocks to 20,000 units, and then checked the inventories and costs incurred.

Pre-experimental planning, the definition of research goals, the choice of factors, levels, and ranges of variables, and the selection of response variables are considered to be of importance, as they influence the choice of the experimental design (Kleijnen 2005). Our research questions (RQs) are defined as follows:

- RQ1: What are the effects of disruptions of different lengths on the entire network and on each entity if fixed prices are applied?
- RQ2: How do fluctuating prices perform compared to fixed prices if a disruption occurs?
- RQ3: How should the degree of price elasticity be chosen to optimize overall supply chain profit when demand is price-sensitive?
- RQ4: How does optimal price elasticity affect each partner's profit?

The definition of the four RQs has helped us to configure the experiment and define relevant factors which pose as input variables for the simulation experiment (Sanchez 2005). The degree of price elasticity and the customers' price-sensitivity are designated as the relevant factors which are varied in the experiment. To answer the first RQ, we will also use fixed prices, while the remaining RQs are answered by allowing the entities to set their prices individually.

In simulation studies, optimization is generally achieved by developing a response surface that represents the approximate relationships between factors and responses. Since a complete calculation of the responses of all possible factors would result in an incalculable computational effort, various designs, such as full and fractional factorial design, finer grids, space-filling designs, etc., are used to explore the response surface with reasonable effort (Sanchez 2015). We chose a uniform space-filling design where the examined factor-response signals are evenly distributed in the factorial range. Prices are defined by the agents based on historical data about their total costs and their desired yield percentage. The moving average of the total costs is apportioned to one product sold, and the profit percentage is added. The degree of price elasticity can be adjusted with the order of the moving average, which is determined to be the first factor and referred to as the price smoothing parameter. It will vary between 30 and 200 in steps of five and will be optimized by the simulation study. If the order is smaller than 30, the system becomes unstable. A normally distributed maximum price is defined for each customer up to which the customer is willing to buy. If the sales price exceeds this maximum price, the customer refuses the purchase. The mean of this maximum price is our second factor and varies between $60 and $150 in steps of five.

For a variable price selection, the system requires between 400 and 1000 days until it reaches stability. The disruption with different lengths therefore occurs at the two producers on day 1500. To ensure that the simulation runs until equilibrium is restored, the simulation runs until day 2500.

Performance variables are the total supply chain disruption costs and the disruption costs of each supply chain member. To take into account the stochastic properties of the model, each experiment iteration will be replicated 50 times, and the median of the replications' performance serves as the iteration's result.

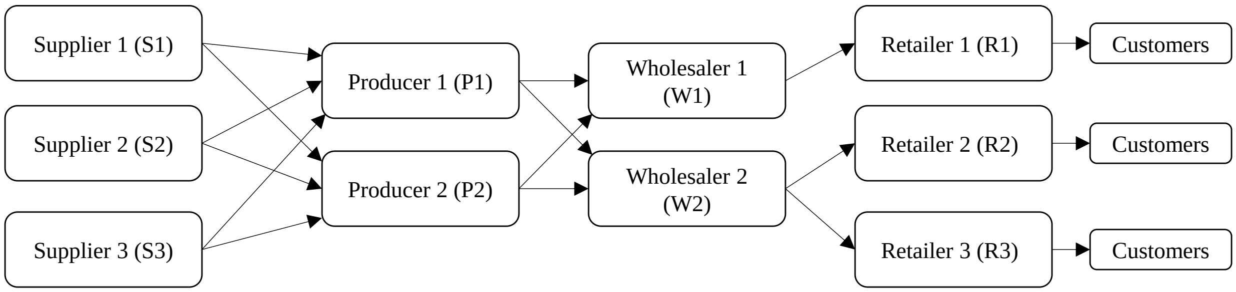

Figure 1: Supply network structure with material flow relations.

4 MODEL DESCRIPTION

4.1 Model Assumptions

The presented model consists of producing and non-producing entities in a four-tier supply network which can be seen in Figure 1. The daily number of potential customers is normally distributed. Each customer is assumed to buy a single product if the current retail price is below their maximum price expectation and the customer's waiting time limit has not been exceeded. The customer's maximum waiting time and accepted price level are stochastically modeled by a Gaussian distribution. Unmet retailer demand is considered as lost sales and is valued with opportunity costs. Upstream entities, namely the wholesaler, the producer, and the producer's supplier, are penalized with backlog costs for every piece which they are not able to dispatch directly. The backlog costs per piece are dependent on their current sales prices.

Inventory levels of producing entities are differentiated between raw material, work in progress, and finished products. The value per piece of raw material is determined by the mean purchase price, while finished products are valued by the current sales price. The value of a semi-finished good in the production process is considered to be exactly in the middle between the purchase and the sales price. Inventory levels of non-producing supply chain members are not differentiated into different categories and are valued with the mean of the purchase price and the current sales price. Holding costs per piece are incurred due to capital lock-up and warehousing costs. The inventory levels are replenished by a classical order-up-to policy. To guarantee a steady flow through the supply chain, it is assumed that the stock levels are checked daily and the order points are defined in a way that every entity orders once a day if the system is in balance. Fixed and variable order costs are tracked, and orders are immediately passed upstream.

If inventory is available upstream, the order amount is dispatched once a day and received by the downstream partner after a fixed individual transport time has passed. Transportation capacity is regarded as unlimited and fixed variable transportation costs per piece, which are paid by the sender, are considered.

Production processes require a uniformly distributed time span to occur and take place at the producer and their supplier. A given production capacity limits the amount of work in progress. Once goods are available in the inbound warehouse, production is initiated. Fixed and variable production costs are associated with the production.

The total resulting costs and the amount of sold goods are tracked daily and documented. Each entity calculates its own price so that a predetermined profit margin is achieved. The moving average of the total costs and goods sold together with the profit margin are used to calculate the current price, which is updated daily. The retailer is the only entity which uses a demand forecast for its price calculation to prevent the system from reaching an unstable state. The price elasticity can be adjusted by changing the length of the time window considered for the moving average. The shorter the time window, the more elastic the prices behave.

A major disruption occurs at both producers' facilities (P1 and P2) after the system has reached its balance. The disruptive event could be, for example, a breakdown of the IT system or the production infrastructure due to a blackout or natural causes like floodings, earthquakes, etc. During the disrupted period it is not possible for the producer to send out goods, to produce, or to order supply. Stock levels are frozen but not damaged. Goods which have already been ordered and downstream orders can be received. The profit and loss calculation still takes place each day and prices are adjusted.

4.2 Agent Organization

An agent is an autonomous, self-directed, individual entity which can function independently from other agents (Macal and North 2014). Each supply chain entity is modeled as a specific agent. All four agents have individual characteristics as well as common behavior.

Each agent is able to send out shipments to and receive orders from the downstream partners. The current prices are sent out to each downstream entity daily. Every agent calculates its sales price, compares the received orders with the inventory, and, if possible, dispatches the total required order amount. If the inventory is too low for a complete delivery, the order is partially fulfilled and will be finished once inventory is available. Each agent tracks important data such as the inventory levels, the amount of sold goods, and the backlogged order amount. After all satisfiable orders have been dispatched, the current inventory level and the expected quantity from the upstream partner are compared with the predefined target inventory level to calculate the order amount. Orders will be sent out instantly, and the expected volume from the supplier will be increased by the order amount and decreased once the shipment has arrived. The associated fixed and variable order costs are tracked. The variable order costs are dependent on the current price of the upstream partner. After the order process has been completed, the current service level is calculated and stored. The retailer calculates the service level based on the delivered order amount of this day and the total desired order amount of this day. All other entities consider the ratio of the instantly fulfilled order amount to the total desired order amount of this work day. The last daily process step of each entity is to calculate the profit. All relevant costs such as order costs, production costs, holding costs, and backlog costs are subtracted from the current revenue, and the cost and profit data are stored.

The producer and their suppliers are the only entities with a production process. The producer's supplier is placed at the upstream end of the modeled supply chain. Therefore, their supplier issues a fixed price for raw material, and the ordered material appears in the inbound warehouse of the producer's supplier after a predefined delivery time. The production process of these two entities is initiated once inbound material is available and starts after the order process has finished.

4.3 Model Parameters

The number of daily customers for R1, R2, and R3 which desire to buy a single product is modeled by a normal distribution with a mean of 250 pieces per day and standard deviation of 10 pieces per day for each entity. Customers are willing to wait a maximum of five days for their product if the retailer's inventory is empty. Holding costs, which include the physical warehousing costs and capital lockup costs, are set at 18% of a product's value per year, which results in 0.05% per day if a 360-day commercial year is considered. The backlog costs per day of the entities is determined to be 20% of each entity's current price.

Table 1: Model parameters.

	S1	S2	S3	P1	P2	W1	W2	R1	R2	R3
Minimum production time [days]	10	10	11	4	4	-	-	-	-	-
Maximum production time [days]	11	11	12	6	6	-	-	-	-	-
Production setup costs [$]	40	50	60	50	50	-	-	-	-	-
Variable production cost [$/piece]	2.75	2.5	2.2	5	5	-	-	-	-	-
Fixed order cost [$]	90	90	90	180	180	120	120	90	90	90
Target inventory [pieces]	11,000	11,000	12,000	3,000	4,000	2,000	2,000	1,500	1,500	1,500
Delivery time [days]	6	6	6	4	4	2	2	-	-	-

The variable ordering costs correspond with the current forwarded price of the upstream entity. The price of the raw material at the upstream end of the supply chain is considered to be $9 per piece for S1, $11 per piece for S2, and $12 per piece for S3. The maximum production capacity of the supplier and the producer is set at 20,000 pieces. Variable transport costs of $0.5 per piece are incurred for shipments. The yield per piece was set at 0.0% to simplify the quantification of the pure disruption costs. Remaining parameters can be found in Table 1.

5 DISCUSSION OF RESULTS

5.1 Disruption Costs with Fixed Prices

To analyze the usefulness of dynamic pricing with respect to supply network disruptions and to answer our first RQ, we have to quantify the pure disruption costs if fixed prices are assumed. In a balanced system's state, variable prices fluctuate to a small degree. The average prices over a time span of 500 days have been calculated with 25 simulation runs in order to set the fixed prices in a way that each entity's net profit stays on average at a level of $0. The prices of each entity are presented in Table 2.

Table 2: Value of fixed prices.

	S1	**S2**	**S3**	**P1**	**P2**	**W1**	**W2**	**R1**	**R2**	**R3**
Fixed prices per piece [$]	12.48	14.26	14.98	48.95	49.02	50.62	50.14	51.11	50.63	50.63

The length of the two disruptions present at P1 and P2 varies from 1 to 20 days. The results of the 50 replications for each day can be seen in the box plot diagram in Figure 2. As expected, the total disruption

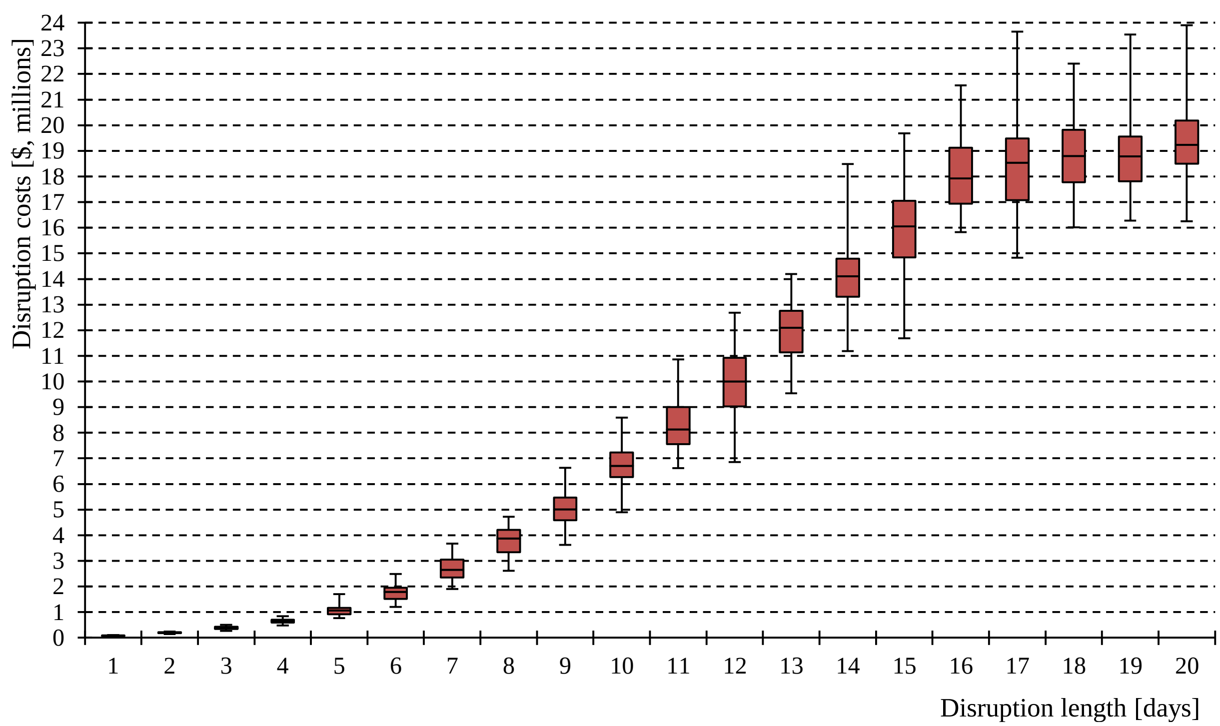

Figure 2: Box plot diagram of the total supply network disruption costs with respect to the length of the disruptions.

Table 3: Experienced disruption costs [$] by the network entities in relation to the length [days] of the disruptions.

Disruption Length	R1	R2	R3	W1	W2	P1	P2	S1	S2	S3
1						39,325	30,225	4,764	5,215	3,187
2						100,943	60,317	12,091	13,986	7,055
3						218,863	104,107	23,067	25,466	14,502
4						388,141	167,191	41,413	42,447	20,895
5						630,044	258,056	67,691	73,144	25,275
6						1,070,027	385,986	115,045	129,498	65,368
7				5,858	10,612	1,639,881	556,023	199,144	194,354	77,753
8				18,961	35,261	2,395,874	742,056	237,980	243,842	111,678
9				49,842	71,810	3,256,421	949,821	274,604	304,754	152,010
10				95,951	134,325	4,543,611	1,148,090	318,839	352,346	187,608
11				165,264	233,032	5,702,629	1,334,482	341,568	338,509	201,874
12				287,191	366,461	6,894,963	1,530,094	362,787	381,829	217,242
13				487,758	539,444	8,028,436	1,851,688	409,462	416,664	243,588
14				830,509	746,251	9,332,083	1,957,821	432,941	457,444	276,108
15				1,252,584	947,175	10,295,689	2,184,024	487,924	516,911	271,631
16	-2,031	-783	-855	1,700,434	1,238,442	11,643,362	2,281,495	497,046	480,509	278,045
17	9,865	11,392	9,930	1,746,723	1,383,057	11,868,977	2,243,312	482,756	512,976	279,350
18	23,895	24,286	22,790	1,863,052	1,406,453	11,794,960	2,364,153	472,351	540,856	307,627
19	36,284	36,792	35,721	1,852,302	1,453,479	11,663,289	2,548,034	499,887	495,009	315,129
20	49,189	49,354	48,200	1,898,342	1,607,862	11,853,249	2,571,492	504,224	527,268	300,704

costs, i.e. the sum of the disruption costs of all network entities, increase with the duration of the disruption. For a short-term disruption period of up to six days, the median of the total costs increases slowly: $80,823 (1 day), $189,480 (2 days), $369,582 (3 days), $649,688 (4 days), $1,061,379 (5 days), and $1,787,759 (6 days). Buffer and in-transit inventory can compensate for the production impairment so that the subsequent entities do not experience any stock outs and the end customer is not affected. If the supply network is interrupted for longer than 6 days and up to 16 days, the total costs of the supply network increase sharply and cause losses with a median of almost $18 million. The dispersion of total costs in the 50 replications increases in general. The buffer inventory can no longer compensate for the production impairment of P1, resulting stock outs for multiple entities in the network. For a disruption period of more than 16 days, the costs still increase but with less velocity. One reason for the slower increase can be found in the applied order policy. As soon as no inventory is available and the expected order amount rises to the complete order-up-to value, the entity stops ordering more material. Therefore, the backlog costs per day of the upstream partner remains at a constant level. Once the material is available upstream again, the backlog can be replenished more quickly to reach the condition of a stable system.

The disruption costs of each entity are presented in Table 3. With a disruption period of up to 6 days, P1, P2, S1, S2, and S3 are affected, resulting in high backlog costs and holding costs. The in transit inventory that is already heading to W1 and W2 is not affected by the disruption, so that the wholesalers' buffer inventories can still compensate for a six days disruption of P1, while the upstream suppliers S1, S2, and S3 are affected. Minor disruptions up to four days only increase the fluctuations of the incoming purchase orders for S1, S2, and S3 and thus the holding costs. Further analysis has shown that as soon as the disruption of P1 and P2 lasts longer than four days, their suppliers suffer from higher holding costs, but also from backlog costs due to the increased order backlogs of P1 and P2 after the disruption has occurred. S3 is less affected because of its higher target inventory, although its maximum production time is higher compared to the other two suppliers S1 and S2. A seven-day disruption affects W1 and W2, who suffer from a one-day stock out, since the in transit inventory is depleted and the buffer inventory is also used up. The disruption costs of W1 and W2 increase the longer the disruption lasts. A disruption period of 10 days and more leads to two multi-period stock outs for W1 and W2 with a short intermediate interval for order fulfillment. A 14-day disruption leads to multiple stock-out situations with a prolonged recovery time and high backlog costs. If the disruption of P1 and P2 is in effect for 16-day the retailer can even profit from the disruption by having less inventory but avoiding stock outs. Longer disruption periods lead to increasing losses of all retailers R1, R2, and R3. In this model, the ripple effect can clearly be seen as the disruption propagates through the network. Total disruption costs increase exponentially before the entire network is affected and a saturation phase is reached in which the costs rise more slowly. The effects of material flow disruptions spread backwards more quickly as the upstream entities immediately suffer from higher holding costs in the event of missing purchase orders. Buffer and transit inventory are effective ways to delay the consequences of a disruption, but also mitigate the negative effects if holding costs are not too high. P1, which has a target inventory of 1,000 unit less than P2, suffers far more severe consequences than P2. A 20-day disruption leads to nearly $12 million disruption costs for P1, while P2 suffers only about $2.5 million.

5.2 Disruption Costs with Dynamic Prices

This section summarizes the impact of the entities' dynamic price changes on the total disruption costs of the network and on the individual disruption costs to answer RQ2 and RQ3. Table 4 presents the percentage of total saved disruption costs (SDC) with respect to the median of the disruption costs in case of fixed prices. The simulation study determined the optimal price elasticity (E*) in relation to the average price expectancy of the customers (PE) for disruptions from 8 to 20 days in steps of two.

Table 4: Saved disruption costs (SDC) [%] with respect to the price expectancy (PE) [$] of the customers and disruption duration [days].

	8		**10**		**12**		**14**		**16**		**18**		**20**	
PE	**E***	**SDC**	**E***	**SDC**	**E***	**SDC**	**E***	**SCD**	**E***	**SDC**	**E***	**SDC**	**E***	**SDC**
60	200	24.73	200	28.18	200	29.83	200	14.00	200	31.08	200	11.76	200	10.68
65	200	40.56	200	19.54	200	30.16	200	26.03	200	40.36	200	44.33	200	44.81
70	200	78.75	200	42.31	200	14.25	200	28.39	200	22.77	200	48.02	200	13.85
75	190	96.14	200	49.87	200	19.41	200	34.78	200	11.59	200	11.04	200	8.39
80	170	99.25	200	76.65	200	32.13	200	42.23	200	2.45	200	19.57	200	62.44
85	145	100.87	200	93.02	200	51.14	200	51.02	200	4.16	200	24.92	200	46.06
90	110	100.73	180	96,95	200	73.16	200	66.57	200	9.09	200	27.19	200	11.42
95	95	101.22	165	99.43	200	90.70	200	81.14	200	13.57	200	29.93	200	35.77
100	80	101.37	150	100.58	195	99.87	200	94.87	200	19.07	200	37.32	200	24.03
105	75	102.27	135	100.53	180	99.55	195	98.68	200	25.98	200	45.41	200	27.98
110	65	102.56	120	100.01	170	100.63	185	99.32	200	34.46	200	56.49	200	36.98
115	60	102.95	110	101.32	160	100.87	170	99.58	200	48.14	200	70.47	200	47.24
120	60	103.33	100	100.87	150	101.27	165	100.68	200	62.87	200	85.46	200	60.27
125	55	103.50	95	101.23	140	101.98	155	101.62	200	77.70	200	96.56	200	75.05
130	50	103.38	90	101.95	135	101.59	145	100.98	200	90.97	200	97.86	200	89.13
135	50	104.61	85	101.86	125	102.01	135	100.27	200	96.32	190	100.82	200	96.08
140	45	104.01	80	101.24	120	101.51	130	101.84	195	98.98	185	101.19	200	99.22
145	45	102.14	75	102.05	115	101.93	125	101.09	190	99.86	175	100.95	190	99.91
150	45	103.66	75	101.87	110	101.44	120	102.50	185	98.95	170	101.74	185	101.98

Table 5: Comparison of the individual disruption costs [$] of the entities in the case of a fixed-price scenario and dynamic pricing with a price expectancy (PE) of $60, $100, and $140 with respect to the length of the disruption (DL).

E*	PE	DL	R1	R2	R3	W1	W2	P1	P2	S1	S2	S3
-	-	8				18,961	35,261	2,395,874	742,056	237,980	243,842	111,678
200	60	8	557,145	536,221	530,440	296,887	574,109	95,764	82,853	7,612	7,965	5,482
80	100	8	5,104	5,033	4,647	3,255	2,482	-35,110	-4,915	-2,180	-1,992	-1,763
45	140	8	4,821	1,182	3,555	5,617	1,177	-107,661	-16,560	-7,632	-7,622	-4,935
-	-	10				95,951	134,325	4,543,611	1,148,090	318,839	352,346	187,608
200	60	10	894,394	869,980	867,216	596,189	1,170,807	180,258	146,042	13,900	13,761	12,593
150	100	10	104,221	95,305	89,616	11,234	7,054	-3,225	3,304	-1,117	-712	-1,009
80	140	10	28,126	33,370	23,626	11,696	16,023	-171,701	-13,131	-12,670	-11,225	-5,019
-	-	12				287,191	366,461	6,894,963	1,530,094	362,787	381,927	217,242
200	60	12	1,135,561	1,111,125	1,124,436	941,144	1,864,166	358,017	240,091	26,008	25,816	21,009
195	100	12	132,107	116,054	98,233	5,340	4,177	-43,117	-1,478	-5,572	-4,188	-3,771
120	140	12	-8,681	-2,663	-16,900	1,230	1,860	-125,405	-3,069	-10,326	-7,498	-6,372
-	-	14				830,509	746,251	9,332,083	1,957,821	432,941	457,444	276,108
200	60	14	2,779,954	2,631,452	2,254,322	733,564	1,526,863	907,232	334,252	41,215	42,038	14,171
200	100	14	308,779	216,244	223,811	66,351	64,146	-67,978	2,447	-3,172	-3,210	-1,144
130	140	14	9,256	11,877	-3,446	19,201	7,142	-130,244	-16,245	-9,112	-13,371	-1,488
-	-	16	-2,031	-783	-855	1,700,434	1,238,442	11,643,362	2,281,495	497,046	480,509	278,045
200	60	16	3,464,224	2,756,522	2,733,275	587,127	1,442,141	1,547,191	327,228	49,131	52,229	16,425
200	100	16	3,137,264	3,384,475	3,213,147	1,595,445	2,999,667	192,340	86,666	-21,133	-19,205	-18,710
195	140	16	186,669	144,927	94,160	52,237	34,114	-124,189	-12,234	-9,027	-7,170	-6,886
-	-	18	23,895	24,286	22,790	1,863,052	1,406,453	11,794,960	2,364,153	472,351	540,856	307,627
200	60	18	2,521,810	1,911,553	1,761,661	2,015,688	4,922,141	2,511,203	713,628	91,423	96,699	74,442
200	100	18	2,811,022	2,862,612	2,846,011	1,318,561	2,297,081	-104,141	78,224	-20,017	-17,122	-17,076
185	140	18	90,221	97,406	84,856	-14,133	-29,297	-261,440	-31,618	-11,351	-6,841	-7,880
-	-	20	49,189	49,354	48,200	1,898,342	1,607,862	11,853,249	2,571,492	504,224	527,268	300,704
200	60	20	4,752,442	3,822,163	3,678,704	752,462	2,266,351	2,633,208	375,299	23,340	71,433	17,227
200	100	20	3,310,459	3,416,553	3,457,112	1,685,113	3,243,156	-62,449	42,160	-23,020	-25,547	-24,486
200	140	20	252,365	198,332	176,207	-9,441	-32,462	-345,220	-55,166	-11,355	-17,010	-8,499

One understandable result is that the higher the PE, the higher the SDC. The SDC can even result in over 100%, which indicates a profit generated for the total supply network. The results show that, the lower PE is, the higher E* must be chosen to achieve the best possible SDC. High values of E* are reflected in a low price elasticity. Since 200 is the upper edge of our tested optimized parameter, it is conceivable that better results can be achieved by selecting an even lower elasticity. Nevertheless, an E* of 200 still results in better SDC than the previously calculated fixed price scenario. For higher PEs, the optimal value of the price elasticity E* decreases, indicating higher price flexibility. Higher prices are chosen by the entities and not penalized by the customers. An interesting result is that the longer the disruption lasts, the less flexible prices should be chosen by the entities to achieve a high SDC. In this model, high price elasticity in the event of short-term disruptions is favorable, but depends strongly on the price expectations of the customers. Overall dynamic price changes can significantly affect the financial impact of the disruption on the total supply network.

To answer RQ4, Table 5 presents the individual disruption costs suffered by each entity of the network with a fixed price strategy and with the optimal price elasticity regarding the mean price expectations of

$60, $100, and $140. If the price expectancy is $60, the losses are mainly experienced by R1, R2, and R3, and also by W1 and W2. The producers P1 and P2 and the three suppliers can substantially reduce their suffered disruption costs compared with the application of fixed prices. If the price expectancy of the customers is $100, then the disruption costs depend on the length of the disruption. For short-term disruptions of 8 days, R1, R2, and R3 have to bear relatively small levels of disruption costs with $5,104 for R1, $5,033 for R2, and $4,647 for R3. For disruption lengths of 16 and 18 days, R2 and R3 suffer even a little bit more than in the case of a price expectancy of $60. In this model, it can be seen that, in the case of a fixed-price scenario, the disruption costs correspond strongly to the location of the disruption. The longer the disruption lasts, the more the disruption costs spread across the network, but they are at the highest at the direct location of disruption. Dynamic prices alleviate the upstream partners and the directly affected entities P1 and P2, but hurt the downstream partners. These results are interesting, since the total supply network costs can be sharply reduced, but the share of the experienced disruption costs can change extensively. If the network entities are willing to cooperate with each other, losses could be distributed equally among the network partners and the total network could profit from dynamic pricing between 2.45% and 104.61%.

6 CONCLUSION AND FUTURE RESEARCH

This approach has presented an agent-based model to quantify the financial consequences of material flow disruptions in a supply network and to analyze if dynamic price setting can reduce the negative monetary effects. By varying the disruption length, it could be seen how the disruption costs increase rapidly and how the number of impacted entities increases the longer the disruptions are in full effect. Dynamic price changes can increase the saved disruption costs up to more than 100% depending on the maximum price the customers are willing to pay and the height of the chosen price elasticity. The longer the disruptions last, the lower the price elasticity which should be chosen. In this model, dynamic prices lead to better results than fixed prices. With dynamic prices, the burden of disruption costs can shift to downstream entities while the upstream entities are alleviated.

Future research could consist of finding out how the network behaves when prices are selected cooperatively using cost information from the entire supply network. It could also be investigated to what extent different customer profiles with different price sensitivities influence the results. Real data from supply networks could be useful for further investigation. We would like to motivate researchers and practitioners to adapt the model to an individual network and incorporate further mitigation strategies into quantitative models.

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