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SIMULATED-BASED ANALYSIS OF RECOVERY ACTIONS UNDER VENDOR-MANAGED INVENTORY AMID BLACK SWAN DISRUPTIONS IN THE SEMICONDUCTOR INDUSTRY: A CASE STUDY FROM INFINEON TECHNOLOGIES AG

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ABSTRACT

The current pandemic outbreak unlike other types of events has impacted many firms' supply and demand with unprecedented consequences. The scope of these effects greatly depends on the characteristics of the industry. This research evaluates the performance of a specific implementation of vendor-managed inventory (VMI) in a case study from a semiconductor company. A multi-period, multi-echelon serial supply chain consisting of the customer VMI warehouse (facing the end demand), the supplier distribution center and the supplier manufacturing plant is studied with agent-based and discrete event simulation. The results suggest that the severity of the demand reduction plays a big role in the replenishment process of the VMI, creating a bullwhip effect which reduces the speed of recovery. The behavior of the customer in terms of the quality of the forecast and whether or not it is been inflated allows the supplier to better plan when dealing with limited capacity.

1 INTRODUCTION

The effects of the pandemic affected many Supply Chains (SC)s in different ways. Some faced supply issues due to transportation restrictions or shutdowns on their supplier's production facilities. Many companies on the other hand experienced a sharp increase in demand while simultaneously dealing with a shortage in raw material (Paul and Chowdhury 2020).

In regards with the automotive industry, auto sales plummeted as much as 80% in Europe, 70% in China and nearly 50% in the United States during the first part of the outbreak (January - April 2020) (Burkacky 2021). As Reinhard Ploss; Infineon Technologies AG Chief Executive Officer expressed, Just-in-Time practices led to orders cancellations from multiple Original Equipment Manufactures (OEMs) towards their Tier 1 suppliers (T1), responsible for example for different power train components and engine control units. Due to a reduction in consumer demand and the reaction of OEMs, T1 put on hold some of their production plants affecting their own suppliers in the process; these included semiconductor companies (Jones 2021), also refereed to as Tier 2 suppliers (T2). Such situation resulted in unbalanced inventories for two specific reasons; first, given the industry specific implementation of a continuous replenishment practice like Vendor-Managed-Inventory (VMI) which highly relies on customer's forecasts and stock reach for its production planning and second, due to the intrinsic long lead time of the semiconductor SC.

Under type of contracts like VMI, instead of placing an order, the customer pulls the required material from an inventory which the supplier must replenish and keep between certain agreed levels (Marquès et al. 2010). These levels depend on the desired reach, or number of weeks for which the current stock should maintain the average demand. A lack of pulling which no one was able to predict caused an extended pause in the replenishment processes; which led to an inventory buildup at the supplier's stocking points, increasing the risk of material scrapping and overall cash flows reductions. Customer ordering behaviour changed once again after a quick marked recovery that followed the second half of the year (LMC-Automotive 2022). High stock levels served as buffer at the beginning, allowing some flexibility during the supply allocation, but were quickly depleted due to the growing demand. The situation got worsened by additional governmental lock-downs affecting now the supply side of the network (reduced production capacity), resulting in a severe and extended chip shortage distressing particularly the automotive sector. Without enough chips, registration of new passenger cars in the European Union experienced a historic fall of 24% in 2020 and again of 2.4% in 2021, reaching a value of 9.7 million vehicles (worst performance since statistics started in 1990) (News-Wires 2022). As Plott mentiones, it wouldn't be fair to put all the blame on the shoulders of semiconductor manufacturers. Automakers cannot assume semiconductor firms to bear all this risk of the SC, especially when complex manufacturing processes distributed around the globe make it hard to adapt to drastic changes in downstream member's behavior (Miller 2021).

Recent statistics demonstrate the rise of catastrophic events over the last decade, affecting more and more organization's productivity and performance across a wide range of industries (Paul and Chowdhury 2020; Blos and Wee 2018). Unlike other SC disruptions which are normally centralized, of limited duration and affecting specific nodes of a network, pandemic disruptions are considered black swam events. They are even less frequent than other natural or man-made disasters, simultaneously or sequentially affecting the structure of one or more SCs, altering demand, distribution, production and supply (Ivanov and Das 2020). Due to the uncertainty about its development, authors like Ivanov and Das (2020) argue that management efforts should be directed in recovery strategies to increase SC resilience.

The ripple effect of such type of disruptions gets amplified in modern complex and global SCs, and the semiconductor industry perfectly fits as an example. Considering that over the last few years, more and more industries began to adopt initiatives based on VMI, including multiple semiconductor companies where the share of such practices could go beyond half of the storage locations worldwide (Marquès et al. 2010), the importance of analysing this type of collaboration practices becomes evident. The same applies from the academic perspective, not much research or cases of study have analyzed how such type of practices perform during this type of exceptional events; but it is of utmost importance to investigate what the learnings are in order to recover faster when dealing with similar future black swan disruptions.

This paper is organized as follows: Section 2 presents related literature followed by the description of the methodology in Section 3. The results of the simulation model are discussed in Section 4. Finally, the paper ends with the concluding remarks in Section 5.

2 LITERATURE REVIEW

The first part about SC resilience theory offers an overview about the main concepts and definitions. The second part refers to the definition and characteristics of VMI applied in the semiconductor industry. Finally, the usage of multi-echelon analysis and simulation as a decision support tool is addressed in the third part.

2.1 Supply Chain Resilience Theory

Supply Chain Management (SCM) refers to the coordination of multiple companies in the logistic network in order to establish an optimal strategy for the whole SC (Simchi-Levi et al. 2008, p. 2). Among the many aspects involved in SCM, Ivanov et al. (2019) highlight the importance of SC Risk Management, which deals with what the authors call "Operational" and "Disruption" Risks. Operational Risks describe expected recurrent events that appear due to inhered system uncertainties affecting the demand (quantities, frequencies) and supply (availability, lead-time). On the other hand, Disruption Risks involve exceptional events affecting mostly the SC structure. Such events, often referred to as disruptions, are by nature unanticipated and of unforeseen magnitude, natural or man made (Ivanov et al. 2019; Chowdhury et al. 2021). While analyzing existing literature in the field of risk management and Disruption Risks, Ivanov et al. (2014) and Dolgui et al. (2018) adopted the term Ripple Effect (RE) to describe the impact of severe disruptions that have structural-level consequences as well as long-term recovery periods.

In the RE context, quantitative research studies usually involve proactive and reactive measures, put in place with the common aim of increasing SC resilience (Ivanov and Dolgui 2021; Ivanov 2020). In this sense, resilience is understood as the ability of a system to withhold and restore its performance and functionality after a significant change of itself or the environment (Macdonald et al. 2018; Aven 2017). Traditional disruptions are often discrete-event oriented, with single feedback control (normal state, disruption, return to normal) and localized to a limited number of nodes (Ivanov and Dolgui 2021). COVID-19 on the other hand has been present for more than two years. Its simultaneous disruption and outbreak propagation has affected suppliers, facilities and markets (Ivanov and Dolgui 2021). A RE has therefore emerged from changes in customer behaviour across multiple industries, in addition to government mandated lockdowns which have led to the closure of plants, warehouses and logistics networks (Paul and Chowdhury 2020). By studying the resource requirements and overall sphere of influence, Chowdhury et al. (2021) state that strategies that mitigate the impact and enable a fast recovery tend to exist and overlap in the following domains: collaboration, redundancy, flexibility and visibility. A literature review conducted by Duong and Chong (2020) on SC collaboration practices in the presence of disruptions, reveal that 94,9% of the studies consider either disruptions in the supply or the demand, but not simultaneously.

2.2 Vendor Managed Inventory

Southard and Swenseth (2008) describes VMI as a collaboration practice in which the supplier has the responsibility of making replenishment decisions (timing, amounts) about the customer's inventory. The customer on the other hand, may share inventory level information as well as future forecasts or historical data about the demand, while only pulling the required material without placing any orders (Kaipia et al. 2002). Waller et al. (1999) considers reduced costs (lower customer inventory management expenses) and increased customer service levels to be the major benefit. It was concluded however, that its benefits are limited to industries with short lead time and small demand variations. Both of which are not the case of the semiconductor industry or the effects of a pandemic type disruption.

Studies on VMI performance measurement is divided into cost and non-cost oriented approaches. Non-cost based performance measurements are calculated according the the amount of violations that take place in a given time period (Stockout "SO", Understock "US" or Overstock "OS"). A violation may occur whenever the inventory is out of a minimum and maximum range (No violation "NV" zone) (Danese 2004; Sari 2007). Non-cost oriented methods seem to be more used in practice, specially in the automotive sector. Whenever the performance of a VMI stock is not at a desired level, multiple perspectives of the situation may emerge from both the customer and the supplier. From the first point of view, the other may be either replenishing too few or too much, driving the inventory to an US or an OS state. The second one may argue that the replenishment timing and quantities are fine, but that the customer is not pulling what was forecasted. In this context, a generic performance measurement algorithm was proposed by Ehm et al. (2018). Their method, other than assessing the VMI performance, allows future improvements through an algorithm that finds a responsible in case of a bad performance by means of a Root Cause Analysis (RCA), being specially designed for partners in the semiconductor industry.

2.3 Multi Echelon Inventory Analysis and Simulation

Multi Echelon Inventory Optimization (MEIO) has the objective of optimizing the inventory allocation among different SC members, achieving a required service level while reducing costs. The configuration of the network is what determines the type of SC, whether it is serial, assembly, distribution or a general SC (Vandeput 2020, p. 204).

MEIO aims to perform a global optimization, which requires the exchange of information among members of the SC, specially in regards to the inventory level at all the stocking points. The connection between VMI and MEIO is evident, as the benefits of VMI can only be achieved if the SC conducts a MEIO (Chu et al. 2015). Inventory optimization problems are usually hard to solve without the help of simulation-based techniques. The implementation of a simulation based-analysis in this research can be justified from three different perspectives. From the business point of view, the severe competition and the willingness to constantly gain a competitive advantage have pushed many firms in the semiconductor industry to conduct model-based decisions when analyzing their SCs (Dayhoff and Atherton 1987). Then, the flexibility provided by simulations as a quantitative analysis tool, which unlike some mathematical approaches, don't always require the same set of assumptions put in place in order to obtain an analytical solution, relying mostly on iterative processes (Costantino et al. 2014). Finally, the characteristics of a disruption in terms of the magnitude of the impact, the length of the duration and the frequency of occurrence are often easier to evaluate in simulation models than in direct mathematical optimization approaches (Ivanov and Rozhkov 2019).

3 METHODOLOGY

The justification in the usage of simulation for multi echelon SCs has been presented in the previous section. Likewise, so has its application in the study of the RE for networks which operate under collaboration practices put in place to increase the SC Resilience and accelerate the recovery after large scale disruptions such as the pandemic outbreak. This section introduces the methodological approach of the simulation of our research.

3.1 Simulation Paradigm

According to Grigoryev (2012), the selection of a simulation paradigm depends both on the characteristics of the problem and the required level of abstraction. Three modelling techniques are then presented: Discrete Event simulation (DES), Agent-Based (AB) and System Dynamics (SD). DES is normally used when the behaviour of the system is defined by events that occur deterministically or randomly at certain points in time, at which the system state variables change instantaneously (Banks, Carson, Nelson, and Nicol 2000, p. 14). It has been extensively used by researches in production planning and logistics transportation problems, as well as in the context of disruptions analysis (Ivanov and Rozhkov 2019). AB on the other hand, considers independent agents with internal decisions logic, interacting with each other and with the environment (Borshchev 2013, p. 57).

In the context of VMI, AB modelling allows an accurate representation of the exchange of information and goods, by creating different type of object-agents in addition to specific parties-agents with defined functions. A hybrid approach of DES and AB is then selected, due to the characterization of a disruption as a random event and the focus on multiple rule-based processes involving different type of objects, with multiple decision-makers and roles.

3.2 Model Conceptualization and Formulation

The mathematical equations governing the behaviour of the system follows a similar notation than the one presented in Vandeput (2020), (p. 109). The SC time frame consist of days d which belong to a week t. The total number of weeks considered is equal to T. If a variable is defined using $\forall d$ or $\forall t$, it should be interpreted as $\forall d \in \{1,\ldots,7\}$ or $\forall t \in \{1,\ldots,T\}$ (unless otherwise specified). A serial SC (each node has only one downstream and upstream node) consist of 3 echelons ($j=1:$ Supplier Manufacture, $j=2:$ Supplier Distribution Center (DC), $j=3:$ Customer Warehouse (WH)) with 2 stocking nodes (Supplier DC, Customer WH). If a variable is defined using $\forall j$, it should be interpreted as $\forall j \in \{1,2,3\}$ (unless otherwise specified). The Customer WH serves an immediate demand from the end-user on a daily basis ($D_{d,t}$: Demand signal D on Customer WH on day d of week t). Each echelon j in the SC experiences a deterministic and constant order lead time L^j $(weeks)$. The Customer WH stocking node $(j=3)$ follows a periodic inventory policy (R,s^3,S^3), where R is the review period, s^3 is the re-order point and S^3 is the order up-to level. The Supplier DC $(j=2)$ implements a periodic base-stock inventory policy $(R, s^2 = S^2 - 1, S^2)$. R is fixed and equal for all stocking nodes to 7 days $(1\,week)$.

The following collaboration practices are implemented in the SC:

- Regarding information Sharing (IS), at each review period R of week t, the supplier receives from the customer a forecasted weekly demand for the next N weeks ahead $(units)$: $FD_t = (fd_{t,1}\ fd_{t,2}\ \cdots\ fd_{t,N})$. For any week t when $\sum_{d=1}^{d=7} D_{d,t} > 0$, let $pe_{t,i}$ be the percentage error of the forecast provided in week t for the target week $t+i$ compared to the demand signal of the correspondent period. This situation would be referred to as the"forecast error evolution" over the time horizon N. Equation 1 presents this error.

$$pe_{t,i} = \frac{\sum_{d=1}^{d=7} D_{d,t+i} - fd_{t,i}}{\sum_{d=1}^{d=7} D_{d,t+i}} \quad \forall t, i \in \{1,\ldots,N\} \tag{1}$$

- A VMI contract is implemented in the SC, in which the supplier makes replenishment decisions for the customer in addition to production orders for its manufacturing site. This also means that the supplier has access to both the current inventory level of the customer WH and its own DC.

3.2.1 Notation and Assumptions

- $IL^j_{d,t}$ denotes the inventory level of stocking node j at day d of week t.
- $P_{d,t}$ represents the actual amount of units pulled from the Customer WH on day d of week t by the end-user. Equation 2 is limited by the available inventory at the Customer WH.

$$P_{d,t} = min\{IL^3_{d,t},\ D_{d,t}\} \quad \forall\, d,t \tag{2}$$

- $US_{d,t}$ (equation 3) is the excess demand (units short) on day d of week t, whenever the end-user can't pull the required quantity that was intended from the Customer WH. Any excess demand (units short) becomes a lost sale and is in practice not possible to estimate.

$$US_{d,t} = D_{d,t} - P_{d,t} \quad \forall\, d,t \tag{3}$$

- $WIP_{d,t}$ denotes the amount of Work in Progress (WIP) in the Supplier Manufacture at day d of week t.
- The Customer WH tends to evenly inflate their future forecast whenever they experience a shortage in a previous period. This effect depends on a factor $\gamma \in [0,\ 1]$, which increases each individual forecast contained in FD_t. Equation 4 describes this behaviour.

$$FD_t \quad \longleftarrow \quad FD_t + \left(\gamma * \frac{\sum_{d=1}^{d=7} US_{d,t-1}}{N}\right) \quad \forall\, t \tag{4}$$

- Likewise, there is no constrain in regards to the amount of material requested by the Supplier Manufacture. An order received by an echelon is instantly processed and a single product flows through the SC. There is no constraint in regards to the amount of units that can go from the Supplier DC to the Customer WH. Moreover, the lead time experienced by the Supplier Manufacture is equal to zero ($L^1 = 0$).
- Due to the characteristics of the fabrication processes, the Supplier Manufacture experiences a stochastic production yield. Since data about this characteristic is not easily accessible, a triangular distribution can be used as a good estimation to represent this uncertainty (Banks, Carson, Nelson, and Nicol 2000, p. 26): $y_t \sim triangular(minimum, maximum, peak)(\%)$
- The sum of the daily demand signal ($D_{d,t}$) over a week (i.e. the weekly demand signal) follows a normal distribution: $\left(\sum_{d=1}^{d=7} D_{d,t}\right) \sim \mathcal{N}(\mu_{DS},\ \sigma^2_{DS})$.

- The percentage error of the forecast $pe_{t,i}$ is assumed to follow a normal distribution. It is also expected to be unbiased over the period T and time horizon N, which means that for any week t and target week i: $pe_{t,i} \sim \mathcal{N}(\mu_{pe} = 0, \sigma^2_{pe})$.
- The standard deviation of the percentage error of the forecast follows a normal distribution: $\sigma_{pe} \sim \mathcal{N}(\mu_{Std}, \sigma^2_{Std})$. This takes relevance due to the relationship between $pe_{t,i}$, $fd_{t,i}$ and $D_{d,t}$ presented in equation 1.

3.2.2 Decisions and Constraints

On each review period R (every week t), the supplier decides:

- How many units (if any) should be shipped from the Supplier DC to the Customer WH, so that there is enough stock to fulfill the daily demand from the end-user while trying to remain between the minimum and maximum level.

$$re_{d,t} : \text{Amount of units shipped from the Supplier DC to the Customer WH in day } d \text{ of week } t$$

  The replenished quantity $re_{d,t}$, which depends on the available inventory on site at the Supplier DC (equation 5). At the same time due to logistics requirements, this quantity should be a multiple of a given package size pz (equation 6).

$$re_{d,t} \leq IL^2_{d,t} \quad \forall\, d,\, t \tag{5}$$

$$\frac{re_{d,t}}{pz} \in \mathbb{N}_{\geq 0} \quad \forall\, d,\, t \tag{6}$$

- How many units should enter the production at the Supplier Manufacture, considering its demand (the replenishment orders calculated) and supply, as well as the required inventory level at the Supplier DC.

$$po_{d,t} : \text{Requested amount of units sourced by the Supplier Manufacture in day } d \text{ of week } t$$

  A minimum production order $mipo$ must be also considered. Since the Supplier DC follows an $(R, s^2 = S^2 - 1, S^2)$ policy, this condition becomes relevant only when the Inventory Position (IP) at the DC ($IP^2_{d,t}$) is not below the desired level S^2. This may happen for instance if a major disruption drastically reduces the demand from the end-user. Such unforeseen event may affect the replenishment process from the Supplier DC to the Customer WH, leading to an inventory built up at the first one. If the inventory level at the DC becomes too high, the Supplier Manufacture could severely reduce the production quantities. Equation 7 describes this condition. The quantities that enter production must also consider the available bottleneck capacity cap at the Supplier Manufacture (equation 8).

$$po_{d,t} \geqslant mipo \quad \forall\, d,\, t \tag{7}$$

$$po_{d,t} \leq cap \quad \forall\, d,\, t \tag{8}$$

- $re_{d,t}$ depends on the current IP ($IP^3_{d,t}$), the re-order point and the order up-to level values of the Customer WH. Since the forecast received by the end-user changes every week, the parameters of the policy must reflect the new demand situation with the same frequency (Chu et al. 2015).

$$s^3_t : \text{Reorder point of the Customer WH in week } t$$

$$S^3_t : \text{Order up-to level for the Customer WH in week } t$$

- Similar to the calculations of s_t^3 and S_t^3, the decision on the amount of units sourced by the Supplier Manufacture $po_{d,t}$ must consider changes in the demand picture when determining the target level at the Supplier DC. Therefore, the target level must change as well accordingly.

$$S_t^2 : \text{Order up-to level for the Supplier DC in week } t$$

3.2.3 Disruption Consideration

The total period analyzed T is divided in three phases ($ph = 1$: Normal times, $ph = 2$: Disruption times, $ph = 3$: Recovery times). The forecast accuracy is affected by the pandemic disruption and the post-pandemic conditions, and consequently so is the percentage error $pe_{t,i}$. Therefore, the standard deviation of the percentage error of the forecast (σ_{pe}) depends on the phase ph in which week t is. In order to incorporate in the model the change of the customer behaviour during the disruption and post-disruption times, the same logic is applied to the distribution of the weekly demand signal, specifically to its mean and standard deviation. During Phase1, the SC works under the previously described equations in a disruption free environment. The Phase2 contains two parts with non-consecutive effects of a pandemic type disruption, affecting first the end-user behaviour (equation 9) and then the supplier's capacity (equation 10).

- Phase2a: szd weeks after the end of Phase1 and for a given amount of weeks wnd, the demand signal coming from the end-user to the Customer WH drops to zero. $ep2a$ denotes the end of Phase2a ($ep2a = ep1 + szd + wnd$). During this period, equation 2 must consider this fact.

$$D_{d,t} = 0 \quad \forall\, d,t \in \{ep1 + szd, \ldots,\ ep2a\} \tag{9}$$

- Phase2b: src weeks after the end of Phase2a and for a given amount of weeks wrc, the production capacity at the Supplier Manufacture cap is reduced by a factor $\lambda\ \in [0,\ 1]$. $ep2$ marks the end of both Phase2b and Phase2 ($ep2 = ep2a + src + wrc$). During this period, inequation 8 becomes:

$$po_{d,t} \leq\ (1 - \lambda) * cap \quad \forall\, d,t \in \{ep2a + src, \ldots,\ ep2\} \tag{10}$$

In Phase3, the Supplier Manufacture capacity has recovered. The model concept described above is implemented in Anylogic software version 8.7.10, using Rstudio 2021.09.1 for the data analysis. Figure 1 presents the adaptation of the previously described model to the case study of the semiconductor firm, where the Supply Chain Planer (SCP) determines the production quantities (po) and the Customer Logistics Managers (CLM) is involved in the replenishment quantities (re). Due to the implementation of VMI, the customer just pulls material from its WH without placing any orders.

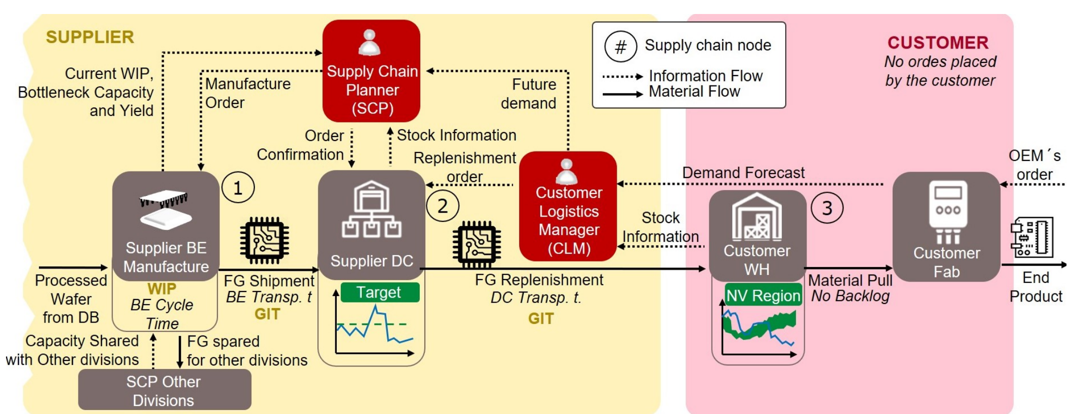


Figure 1: Model concept representation of the case study at the semiconductor company.

3.2.4 Model Output

For the development of the simulation and the study of the previously described SC, the generic performance measurement from Ehm et al. (2018) is going to be used. Three categories for the model output are identified, namely VMI-Performance-Related Metrics (with special focus on the inventory at the Customer WH), SC-Resilience-Related Metrics (considering the the RE, the bullwhip effect and the actual stock reach) and Disruption-Recovery-Related Metrics (considering the speed of the SC to restore its performance without the disruption's effects existence). 23 different key performance indicators (KPIs) are developed in total, which can be seen in table 1.

Table 1: Model output (KPIs) and categories.

KPI	Meaning	KPI	Meaning	KPI	Meaning
R1	Time to recover supplier DC from supply effect (days)	R9	Cycle service level (%)	R17	Percentage of weeks with bad performance supplier responsible (%)
R2	Time to recover supplier DC from demand effect (days)	R10	Percentage of days with no violations (%)	R18	Percentage of weeks with bad performance customer responsible (%)
R3	Time to recover supplier manufacture from supply effect (days)	R11	Forecast accuracy during normal times (%)	R19	Percentage of weeks with good performance (%)
R4	Time to recover supplier manufacture from demand effect (days)	R12	Forecast accuracy during the disruption period %)	R20	Bullwhip effect on supplier manufacture
R5	Real stock reach at customer WH (weeks)	R13	Forecast accuracy during the recovery period (%)	R21	Bullwhip effect on supplier DC
R6	Real stock reach at the supplier DC (weeks)	R14	Average weekly performance during normal times (%)	R22	Bullwhip effect on customer WH
R7	Total average difference to desired level at customer WH (%)	R15	Average weekly performance during the disruption period (%)	R23	Maximum difference to average inventory at supplier DC (%)
R8	Volume fill rate (%)	R16	Average weekly performance during the recovery period (%)		
VMI performance related		SC related		Recovery related	

4 RESULTS: CASE STUDY

The model presented in the previous section is evaluated with a 2^k factorial experimental design, using first real data from the semiconductor firm of the case study to estimate the parameters of the SC and of the random variables. After further validation, synthetic generated data is utilized. 4 Multivariate Analysis of Variance (MANOVA) procedures are conducted with the purpose of identify the relationship between the inputs (factors) and outputs (responses). There are in total 10 factors, each of them with two levels and 30 replications per simulation run. The factors' levels and their meanings are explained in table 2. The MANOVA procedures consider the factors related with the disruption on different KPIs according to the performance category. The factors which are not related to the disruption are used to construct 8 context scenarios for the SC, summarized in table 3. The results from the MANOVA procedures can be found in table 4.

Table 2: Factors levels considered for the experimental design.

Category	Factor	Description	Level 1	Level 2
Demand related	F1	Standard deviation of the random weekly demand signal during normal times (units/week)	35.000	45.000
Forecast error related	F2	Mean of the standard deviation for the random forecast percentage error (%)	0,15	0,25
Disruption related	F3	Duration of the demand effect (weeks)	4	8
	F4	Weeks between the demand and supply effect (weeks)	35	60
	F5	Duration of the supply effect (weeks)	5	9
	F6	Capacity reduction (%)	0,4	0,9
Customer related	F7	Forecast inflation factor (%)	0,1	0,8
Supplier related	F8	Available bottleneck capacity (units/week)	640.000	750.000
	F9	Demand-Supply change believe	0,25	1
	F10	Package size (units)	1.000	2.500

Table 3: Scenarios considered for the MANOVA analysis.

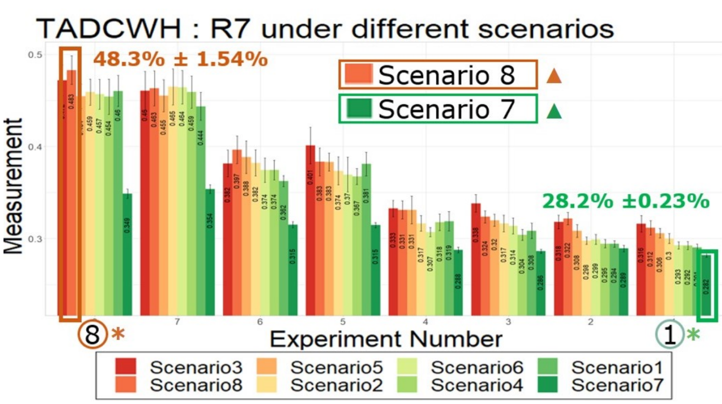
Factors	F1	F2	F7	F8	F9	F10	Description
Scenario 1	1	1	1	1	2	2	Base scenario
Scenario 2	2	1	1	1	2	2	Higher demand uncertainty
Scenario 3	1	1	1	1	1	2	Reduced believe on changes in demand
Scenario 4	1	1	1	1	2	1	Reduced package size
Scenario 5	1	2	1	1	2	2	High uncertainty in the forecast error
Scenario 6	1	1	2	1	2	2	High degree of forecast inflation
Scenario 7	1	1	1	2	2	2	More capacity available
Scenario 8	2	2	2	1	2	2	High uncertainty in demand and forecast error, forecast inflation, reduced capacity

Figure 2 demonstrates the logic behind the results analysis that took place with an individual example. The procedure concluded that the levels in F4 were not significant in regards with the total average difference to the desired level at the customer WH (R7). With only 3 factors left, $2^3 = 8$ experiments from the total output are needed (per scenario). The number of experiments are represented along the x axis. For each experiment, there are 8 context scenarios, resulting in 8 different values for the studied response per experiment. Red and green are assigned to the worst and best values. In this case, the levels in experiment 1 scenario 7 yield the best measurement, whereas the worst result are found in experiment 8 scenario 8. The numeric values of the levels can be obtained using the information in tables 2 and 3, allowing us to realize that having more available capacity is crucial when facing the effects of a pandemic outbreak in order to keep the inventory at the customer WH as close as possible to the desired levels. The results for all the responses using the previously described process are presented in table 5.

They suggest that the forecast inflation performed by the customer drastically slows down the recovery process of the SC as a whole, even though it may be beneficial for the customer node in the short term. At the same time, VMI based on reach during periods of unforeseen low demand becomes a bullwhip effect

Table 4: Results from MANOVA procedures.

MANOVA #	Responses involved	KPI's Category	Significant factors	Experiments considered
1	R7, R9, R10, R17	VMI performance related	F3, F5, F6	8
2	R12, R13, R15, R16	VMI performance related	F3, F4, F5, F6	16
3	R5, R6, R20, R21, R22, R23	SC related	F3, F4, F5, F6	16
4	R1, R2, R3, R4	Recovery related	F3, F4, F6	8



Category	Factor	Level 1	Level 2
Demand related	F1	35.000	45.000
Forecast error related	F2	0,15	0,25
Disruption related	F3	4	8
	F4	35	60
	F5	5	9
	F6	0,4	0,9
Customer related	F7	0,1	0,8
Supplier related	F8	640.000	750.000
	F9	0,25	1
	F10	1.000	2.500

Factors	F1	F2	F7	F8	F9	F10
Scenario 1	1	1	1	1	2	2
Scenario 2	2	1	1	1	2	2
Scenario 3	1	1	1	1	1	2
Scenario 4	1	1	1	1	2	1
Scenario 5	1	2	1	1	2	2
Scenario 6	1	1	2	1	2	2
Scenario 7▲	1	1	1	2	2	2
Scenario 8▲	2	2	2	1	2	2

Experiment	F3	F4	F5	F6
1*	1	2	1	1
2	2	2	1	1
3	1	2	2	1
4	2	2	2	1
5	1	2	1	2
6	2	2	1	2
7	1	2	2	2
8*	2	2	2	2

Figure 2: Example on how to read the results from the experimental design according to MANOVA procedures.

generator for the upstream members, specially in industries with long cycle times. Recovery actions which increase capacity during the supply effect of the disruption could eventually double the speed of recovery during the post-disruption period. In terms of SC related KPIs, the demand effect has a greater and long lasting impact than the supply effect. Finally, knowing the "true"demand for a VMI setting allows the supplier to improve the planning process once the demand is back.

5 CONCLUSIONS

This study contributes to the field of supply chain disruptions by first using empirical research methodologies based on a case study and experts interview, which always measure causal relationships in the system (Li et al. 2009). Through simulation modeling, our research highlights the interactions of key system parameters in a disruption phase under different scenarios. The results highlight the importance of a clear communication between the VMI partners when facing limited supply. Likewise, replenishment processes based on reach have proven to be a bullwhip effect generator factor when an unforeseen event completely stops the demand pull at the VMI WH, leading to inventories build up for the upstream member.

Table 5: Results from experimental design analyzed with MANOVA.

Variable	Best			Worst			Difference
	Value	Exp	Sce	Value	Exp	Sce	
R7	28.2	1	7	48.3	8	8	71.28%
R9	100	1,2,3,4	7,7,6-1,1-7	75.8	8	8	24.20%
R10	52.1	1,2,3,4	7	30	8	8	42.42%
R17	58.9	2,4,6,8	7	70	7	6	18.85%
R12	93.2	7,15	2	82.5	2	5	11.48%
R13	98.7	1,2,3,4,5,6,7,8	6,7	92.4	16	8	6.38%
R15	54.8	2	4	3.65	12	3	93.34%
R16	51.6	1,2,3,4	7	0.16	16	8	99.69%
R5	2.33	4,8	7	1.66	13	3	28.76%
R6	2.225	4	7	1.108	13	8	50.20%
R20	1.93	1	8	3.33	13	3	72.54%
R21	0.77	13	3	1.1	7	4	42.86%
R22	0.291	1	7	0.44	5	13	51.20%
R23	6	14	8	3	3	7	50.00%
R1	83	6	4	7	7	3	91.57%
R2	30	4	4	5	6	3	83.33%
R3	25	7	3	4	2	7	84.00%
R4	34	8	3	9	2	3	73.53%

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