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Increasing Resilience of Supply Networks to Climate Change Induced Disruptions

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Abstract

A model is constructed to investigate the response of a supply network to disruptions due to extreme weather events, such as the 2011 flooding in Thailand that affected hard disk drive production. The supply network simplifies the complex networks seen in the real world to consist of just three business categories: manufacturers, suppliers that provide a key component to the manufacturers and retailers who sell the finished product. The suppliers, manufacturers and retailers collectively employ the same two-part mathematical rule, based on their own current inventory's level and on the recent rate of shipping to the next business category downstream, to determine how much of the good in their own inventory to manufacture/procure.

Though the model is simple, some of the behaviour is non-intuitive, including non-monotonic recovery from a severe disruption and a case seen where the time to recovery (TTR) of the manufacturer's inventory is faster when all of its production capacity is destroyed than when a portion of the production capacity is retained. We believe this model is generic enough to serve as a basis for testing the effect of climate change scenarios on measures that can improve the resilience of supply networks.

Introduction

Climate change and extreme weather affects business beyond corporate fence lines and national borders. Recent high profile events have demonstrated that extreme weather events can create widespread disruptions along global supply chains and transport networks. In 2011, floods in Thailand halted computer hard disks manufacturers and the effects cascaded along the global supply chain [Fuller, 2011]. Drought in Russia in 2010 lowered crop yields which led to restrictions in the export of agricultural products [WEF, 2013]. Climate change is expected to make some events like these more severe, as we expect some places to see more frequent and more severe heat waves and droughts, more intense storms and flooding, and higher sea levels [IPCC, 2013].

As well, global supply and transport networks are becoming more complex, interlinked and interdependent. The inherent risk profile of these systems has made them more vulnerable to disruptions created by climate change and extreme weather events. Managing supply networks under increased uncertainty argues for a comprehensive risk management approach where companies must reduce their vulnerability and build resilience [Christiansen et al., 2014].

Various disciplines have developed different understandings of the notion of resilience. Within the supply chain context some resilience concepts are based on a static view of the system structure: “the ability of a system to return to its original [or desire] state after being disrupted” [Cranfield School of Management, 2003] or “the ability to bounce back from large-scale disruptions” [Sheffi, 2008]. Others may see it as a change in system structure, including activities like increasing redundancy (e.g., hold extra inventory, maintain low capacity utilization and have many suppliers), building flexibility (e.g., adopt standardized processes and use concurrent instead of sequential processes) and changing the corporate culture (e.g., continues communication among informed employees) [Sheffi, 2005].

This paper describes the use of System Dynamics as a platform for stress testing and exploring adaptation strategies and, ultimately, of building understanding of how robust production-distribution systems can operate.

Background

An ample body of scientific literature is concerned with the future development of the earth’s climate system. In the recent Fifth Assessment Report, the IPCC uses four different possible futures of carbon dioxide (CO_2) in the atmosphere called representative concentration pathways (RCPs). The highest emission pathway results in an atmospheric CO_2 concentration reaching 936 parts per million (ppm) in 2100. Even the lowest has an atmospheric CO_2 level of 421 ppm in 2100 – still a little higher than it is today [IPCC, 2013].

This paper considers the effect these climate change projections might have on a System Dynamics model of a production-distribution system to gauge the resilience of that supply network to extreme weather induced disruptions, as well as to explore means to mitigate those disruptions.

Production-distribution systems have a long history of being investigated using System Dynamics, as well as in broader operations research. Over the past few decades, globalization and innovation have created supply chains that are becoming more complex, interconnected and interdependent. Many businesses have adopted "just-in-time" policies and similar management practices which favour quality and efficiency when operating with low inventories [Christiansen et al., 2014]. However, this also makes them more vulnerable to disruption by extreme weather and climate change. Supply networks also rely more on information flow from different a variety of stakeholders.

Consequently, a company is not only vulnerable to an extreme weather event hitting their own assets. From a manufacturer’s perspective, there are a number of possible locations that can be affected by a severe weather event: the manufacturer’s facilities itself, those parts of the supply network downstream from the manufacturer (such as the retailers or, ultimately, consumers) and those that are upstream (such as suppliers). Other elements of their supply chain that can be affected include transportation providers and communication lines [Sheffi, 2005]. Thus, for the purpose of this paper we consider three extreme weather scenarios, one affecting each of the three portions of the supply chain, to see the effect that an extreme event might have and to investigate ways to mitigate the effects of the disruption.

Various metrics have been proposed as a means to gauge the resilience of a complex system. Simchi-Levi *et al.* advocate the use of 'time to recovery' (TTR) in a recent article in Harvard Business Review [Simchi-Levi et al., 2014]. This metric considers how much time it takes for a given 'node' in a network to resume its pre-disruption level of operation. For a production-distribution system, we would ideally be concerned with comparing the cost of various disruptions to the cost of mitigating those disruptions. However, to keep our model as generic as possible, it does not explicitly account for costs at this point, and thus we are not able to use that as a metric of resilience.

However, we are able in our existing model to measure both cumulative consumer demand and the actual portion of that demand that is satisfied by the delivery of product. Thus, for this investigation we consider the 'fraction of demand met' (FODM) to be the primary measure of resilience. In a highly resilient production-distribution system, the total fraction of consumer demand that is satisfied should be very high – ideally, one – even when severe disruptions strike.

Description of the Model

The system under consideration is a simplified production-distribution network concerned with the manufacturing of external computer hard disk drives (HDDs). Suppliers provide aluminium platters, the actual rigid disks that give hard disk drives their name, to manufacturers, who produce the disk drives and then ship them to retailers. The retailers then sell HDDs directly to consumers.

For simplicity, we neglect the existence of wholesalers and distributors. Only one supplier of platters is represented explicitly, but the manufacturers have the possibility of sourcing platters from additional suppliers.

For this example, we assume that the platter supplier(s) and hard disk manufacturers are in closer proximity to each other than to the retailers or consumers, who are close to each other. This is intended to reflect the fact that, in the electronics industry, component suppliers and manufacturers are often located near each other, while retailers and consumers are often far away. Thus, we ignore delays in shipments between the supplier(s) and manufacturers and also between the retailers and the consumers, and only consider the shipping delay between the manufacturers and the retailers.

Figure 1 depicts the stock-and-flow diagram of the core of our model. Consumer demand for hard drives is exogenously controlled – it varies at rate governed by a graphical function that varies with time. For visual simplicity, some structures specific to each of our disruption scenarios have been eliminated from the Figure.

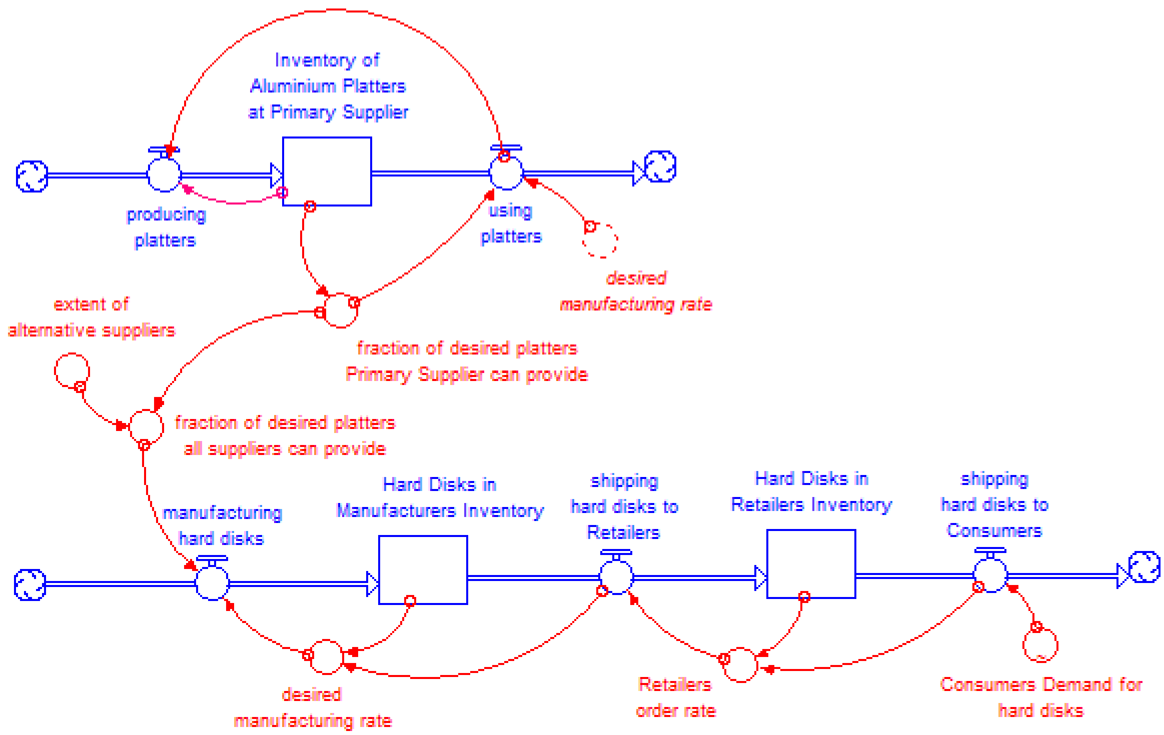

Figure 1: Stock-and-flow diagram of the hard disk drive supply network

The retailers order HDDs from the manufacturers at a rate ('Retailers order rate') that depends on the recent hard disk shipping rate ('shipping hard disks to Consumers') and the retailers' inventory level ('Hard Disks in Retailer Inventory'):

$$Retailers\ order\ rate = 0.2\ SMTH3(X,3) + 0.15(1-Y) \tag{1}$$

where X = the ratio of 'shipping hard disks to Consumers' to its initial value and Y = 'Hard Disks in Retailers Inventory'. The SMTH3() ('third-order smoothing') built-in function from STELLA is used with a smoothing time of three weeks, to help the retailers target a longer-term average of the rate of shipping hard disks to consumers, rather than the weekly ups and downs. The particular parameter values in the equation initially put the system into steady state, so that the inventory levels and shipment rates between them are constant.

This equation is intended to represent the industry aggregate rate of ordering/production, as at the micro-level, an individual business might use a radically different algorithm to decide the ordering/production rate, such as the 'security stock' approach, whereby an individual firm simply orders more of a given item whenever its level falls below a certain critical threshold [Monk, 2009].

From Equation 1 we see that the retailers' order rate goes up as the rate of shipping hard disks to consumers goes up, and goes up as the retailer's inventory of HDDs goes down. Initially, all inventories, including the retailers' inventory level, are set to '1' to make the system be in steady-state equilibrium.

The manufacturers have a 'desired manufacturing rate' and the aluminium platter supplier a rate of 'producing platters' that are both mathematically analogous to the 'Retailers order rate' equation above. For the manufacturers' 'desired manufacturing rate', X = the ratio of 'shipping to Retailers' to its initial value and Y = 'Hard Disks in Manufacturers Inventory'. For the aluminium platter supplier's 'producing platters' flow, X = the ratio of 'using platters' to its initial value and Y = 'Hard Disks in Manufacturers Inventory'.

A delay of four weeks exists in the rate for shipping hard disks to the retailers, as we assume that this is a typical value. This is incorporated into the model through the use of STELLA's DELAY() function: shipping to Retailers = DELAY(Retailers order rate, 4). Thus, the manufacturers effectively consider material in transit to be part of their inventory until the moment it arrives at the retailers, as which point it is immediately reclassified as being part of the retailers' inventory. We do this only because it is simpler than explicitly accounting for the amount of material currently in transit.

The manufacturing of hard disks depends on the availability of aluminium platters. When many suppliers are present, we assume there is never a shortage of aluminium platters, and the rate at which hard drives are actually manufactured ('manufacturing Hard Disks') always equals the manufacturers' 'desired manufacturing rate'.

If no alternative suppliers of platters are present, then the aluminium platter availability (and ultimately, the rate of manufacturing hard disks) is affected by the availability of aluminium platters at the primary supplier. When the availability of aluminium platters is above '1', there is no effect on the rate of hard disk manufacturing. However, when the aluminium platter availability is below '1', the rate of manufacturing hard disks is reduced proportionally. For simplicity this model neglects the shipping time from the platter supplier to the hard disk drive manufacturers and also the inventory of platters that the manufacturers would keep at their own facilities.

This system of equations is simulated using Euler's method with a step size of 0.1.

Now that the model is formulated and initiated in steady-state such that the suppliers', manufacturers' and retailers' inventory levels and the shipments between them are constant over time, we can examine the effect of disruptions in various extreme weather scenarios.

Scenario 1: Destruction of Supplier's Ability to Deliver Platters

First we consider a severe disruption, such as the catastrophic flood that affected Thailand in 2011, that eliminates the ability of the supplier to deliver aluminium platters to the manufacturers. Initially, the manufacturers have no alternative suppliers. At week = 10, the disaster strikes, causing the 'fraction of desired platters Primary Supplier can provide' to become 0. At week = 30, some 'fraction of desired platters all suppliers can provide' is restored (up to a value of 1) due to the sudden availability of alternative suppliers.

The figure below shows the progression of hard disks in the manufacturers' inventory. The inventory is depleted quickly when the supplier's ability to deliver aluminium platters ceases, causing the manufacturers to 'stock out' of hard drives. When the network of alternative suppliers is activated at week = 30, the manufacturers' inventory rebounds partially, then settles to an ultimate level that depends on what fraction of the desired platters the alternative suppliers are able to provide. For the case where the alternative network can supply 80% of the desired manufacturing rate, the manufacturers' inventory is able to rebound to about 2/3rds of its pre-disruption level, though actual shipments of hard drives during and after the disruption are essentially identical to when the alternative supplier network can supply 90% or 100% of the desired platters. Thus, as long as the manufacturers' extent of alternative suppliers is at least 80%, then the manufacturers' assumed initial inventory level was higher than strictly necessary to accommodate this particular disruption scenario.

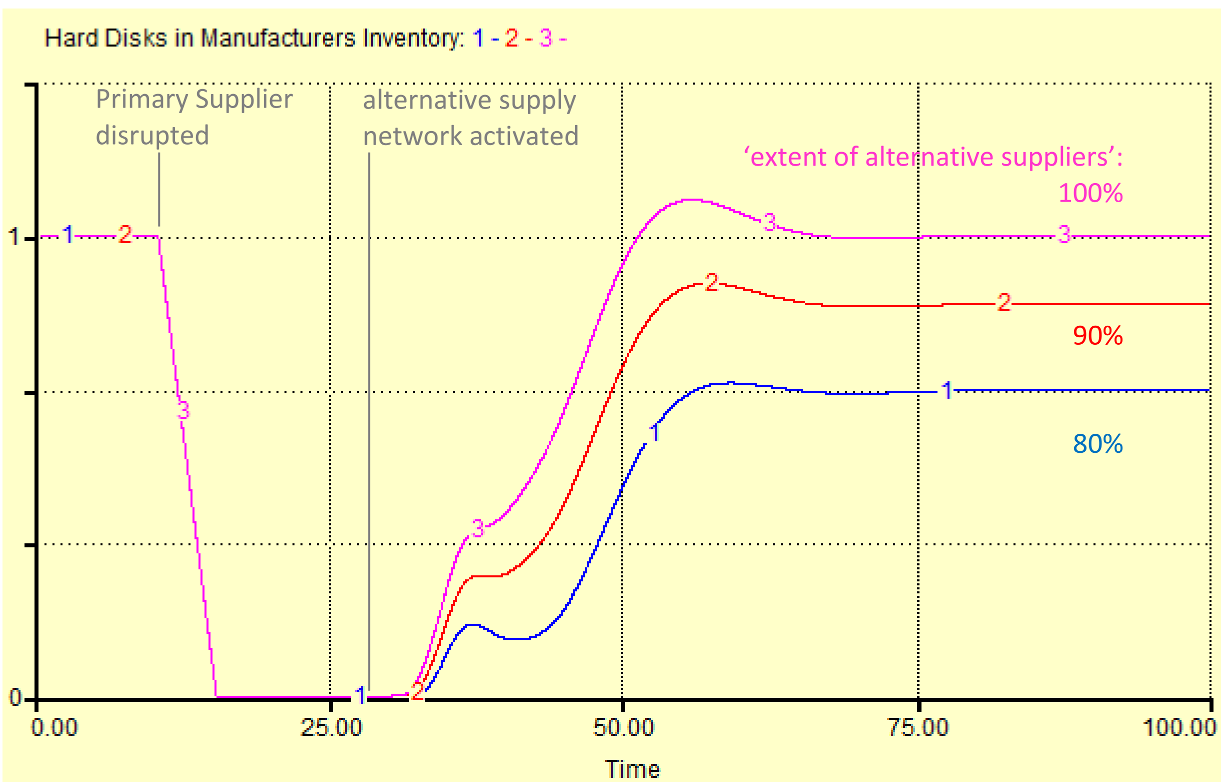

Figure 2: Manufacturers' Inventory of hard disk drives as a result of the elimination of the supplier's ability to deliver aluminium platters at week = 10 and several levels of restoration of platter supply at week = 30.

Examining the rate of inflow to the manufacturers' inventory ('manufacturing hard disks') and the outflow ('shipping to Retailers') as well as the desired rate of outflow ('Retailers order rate') shows why the behaviour patterns observed in Figure 2 are seen. These variables are illustrated in Figure 3.

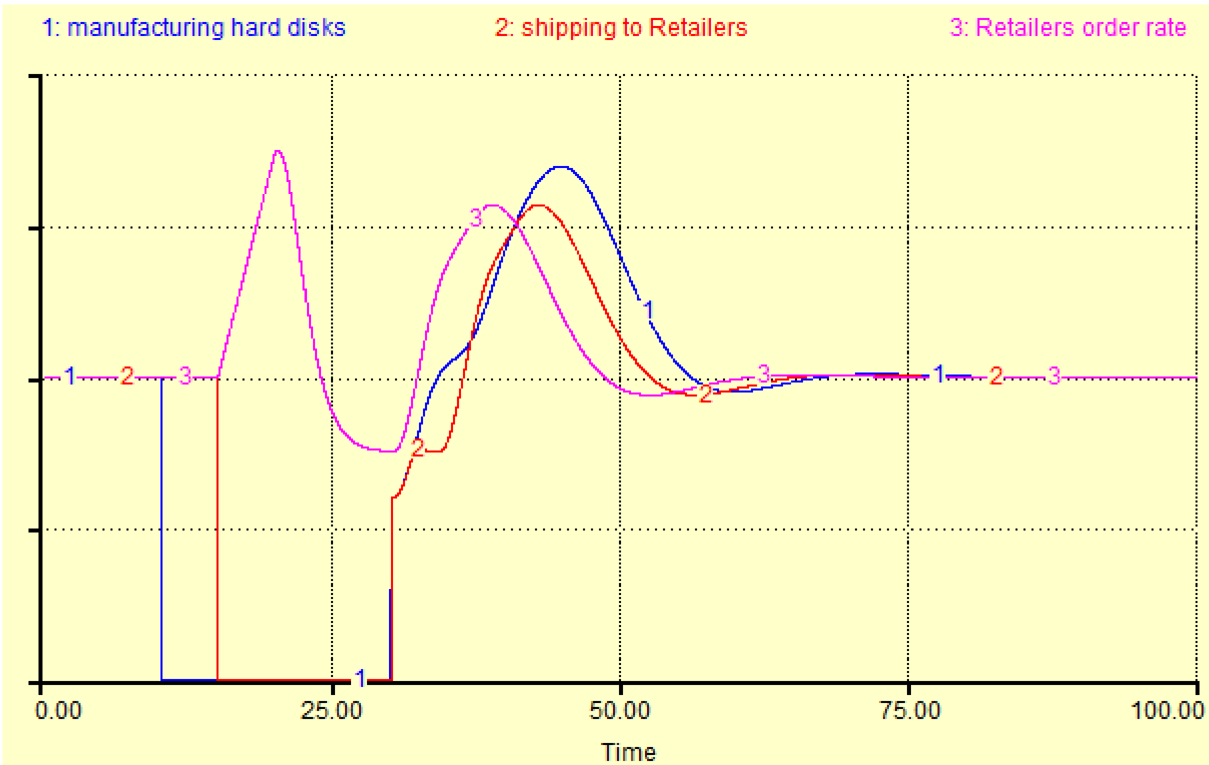

Figure 3: Three variables key to understanding changes in the manufacturers' hard disk drive inventory level. The inflow (blue line) minus the outflow (red line) determines the rate of change of the inventory. The 'shipping to Retailers' depends on a delayed value of the 'Retailers order rate', limited by available manufacturers' inventory. Case shown is for the extent of alternative suppliers being 80%.

When the disruption hits the primary supplier, the manufacturing of hard drives ceases immediately. As the inventory of HDDs is depleted, the shipping of disk drives ceases as well. The Retailers order rate varies according to Equation 1, first increasing as the retailers' inventory drops and then falling as the average rate of shipping hard disks to consumers decreases. When the network of alternative suppliers becomes available, the rate of shipping to the retailers is limited by the manufacturing rate, but later simply resumes being the 'Retailers order rate', modified by the delay.

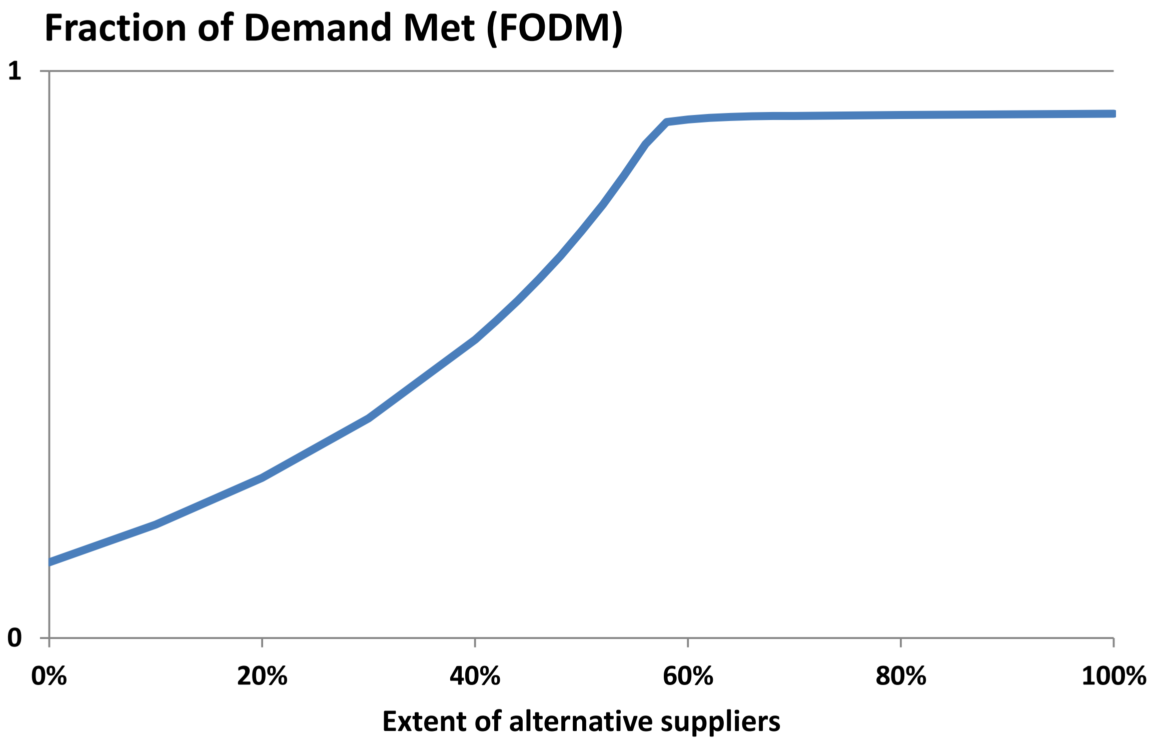

Figure 4: 'Fraction of Demand Met' (FODM) as a function of 'extent of alternative suppliers'.

Figure 4 shows the effect of the 'extent of alternative suppliers' on the 'fraction of demand met (FODM). For this scenario, values for the extent of alternative suppliers above about 0.58 do not cause the FODM to change substantially, while values below 0.58 have a strong influence on FODM.

Scenario 2: Destruction of Production Ability at Manufacturer's Facilities

In the second scenario, we consider a disruption that affects the hard disk manufacturers' production capabilities. Starting in week 10 and lasting until week 30, the manufacturers' ability to produce HDDs is reduced from the normal 0.20 units per week (compared to the normal inventory level of 1.0) to either 0.02 units (90% reduction) or 0.00 units (a 100% reduction). Unlike the previous scenario, upstream there are no alternative suppliers of aluminium platters.

Figure 5 shows the level of the manufacturers' inventory of hard disk drives when the manufacturer retains 10% of its normal production capacity during the 20-week disruption and when it loses its production capacity entirely during that period.

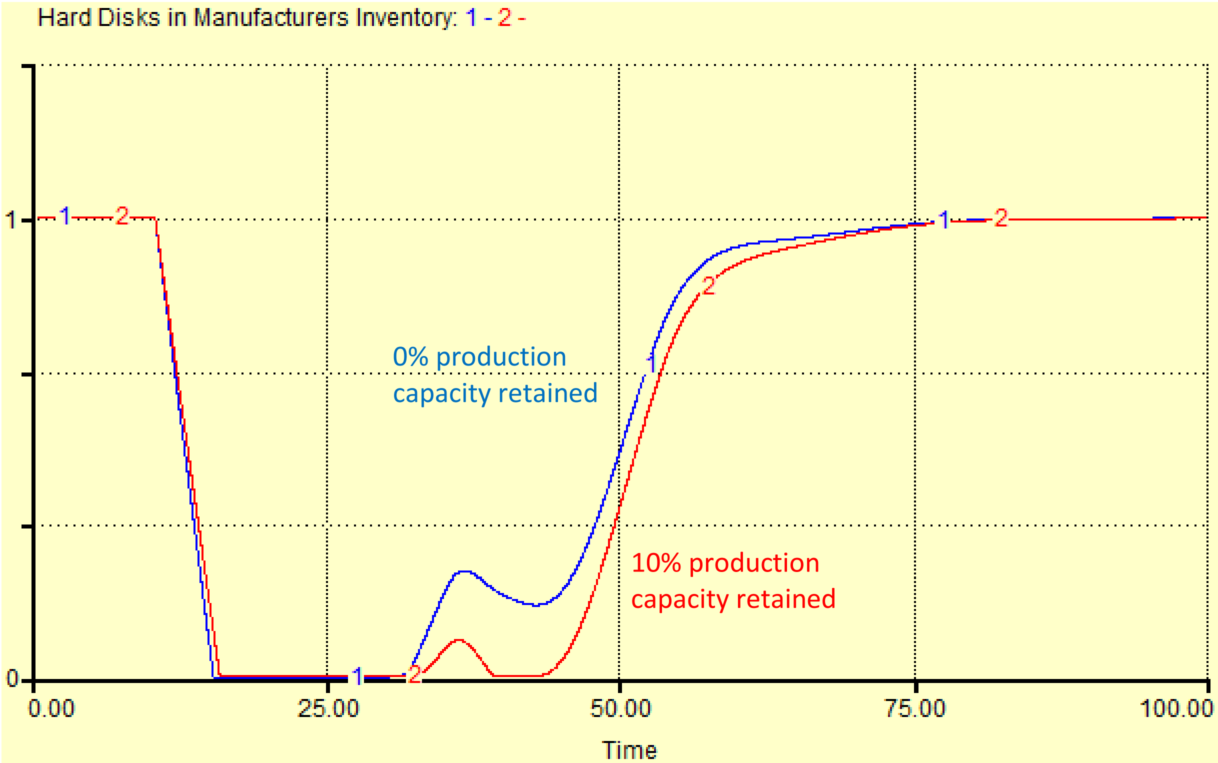

Figure 5: Manufacturers Inventory under a 20-week reduction in the manufacturer's ability to produce hard disk drives is reduced to 0% of its normal value (blue line) and to 10% of its normal value (red line). It takes longer for the manufacturer's inventory to recover its pre-disruption level when 10% of production capacity is retained, compared to 0%.

Interestingly, when the manufacturers retain 10% of their production capacity, the manufacturers' inventory level is, at all times after the disruption ends, lower than when the manufacturers lose all of their production capacity. Nevertheless, over the 100-week period the fraction of consumer demand met (FODM) is 91.3% when 10% of production capacity is retained, but only 88.7% when no production capacity is retained. For this model, any loss of half (or more) of production capacity will result in FODM being less than 1, meaning that smaller disruptions will not be noticed by the consumers.

This example shows a possible drawback of using 'time to recovery' (TTR) as a metric of system resilience, as the TTR for the manufacturers' inventory in the case of a complete loss of production capacity is less than when some production capacity is retained.

Scenario 3: A Consumer-driven Spike in Demand

Suppose that for a short period of time (for example, ten weeks starting in week 10 and ending week 20), as seen in Figure 6, consumer demand for HDDs steps up fivefold due to severe flooding that wipes out office space and computer data centers. We are primarily concerned with the fraction of consumer demand that can be met ('fraction of demand met', or FODM) during the simulation period.

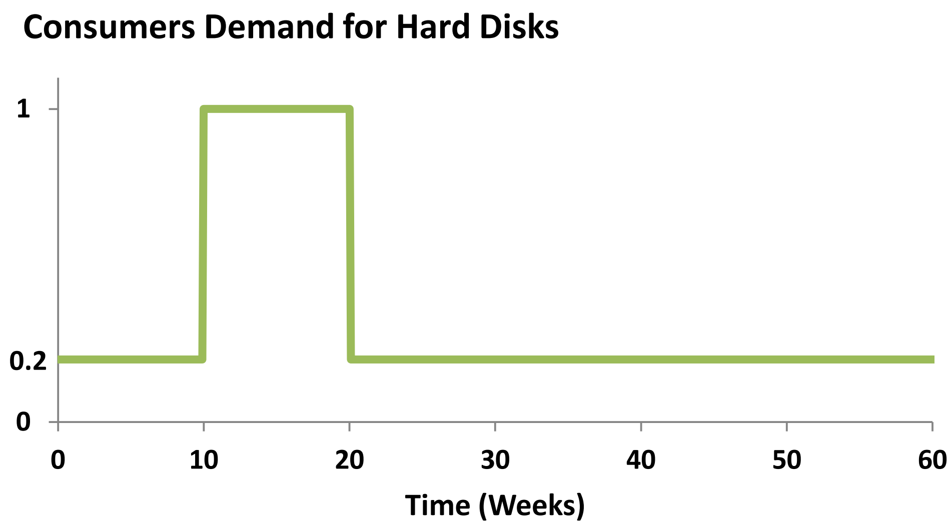

Figure 6: Consumers Demand for hard disks during Scenario 3.

Figure 7 below shows the response of the manufacturers' inventory to this 10-week fivefold spike in consumer demand. Because of the shipping delay, the manufacturers do not 'feel' the effect of the demand spike immediately. But, as the retailers' inventory is depleted and the retailers' order rate increases accordingly, the manufacturers' inventory is quickly run down. In turn, the platter supplier's inventory is depleted, which constrains the manufacturers' ability to produce disk drives at their desired rate. It is only after the demand spike ends that the supplier and, thus, manufacturers are able to rebuild their inventories to pre-disruption levels.

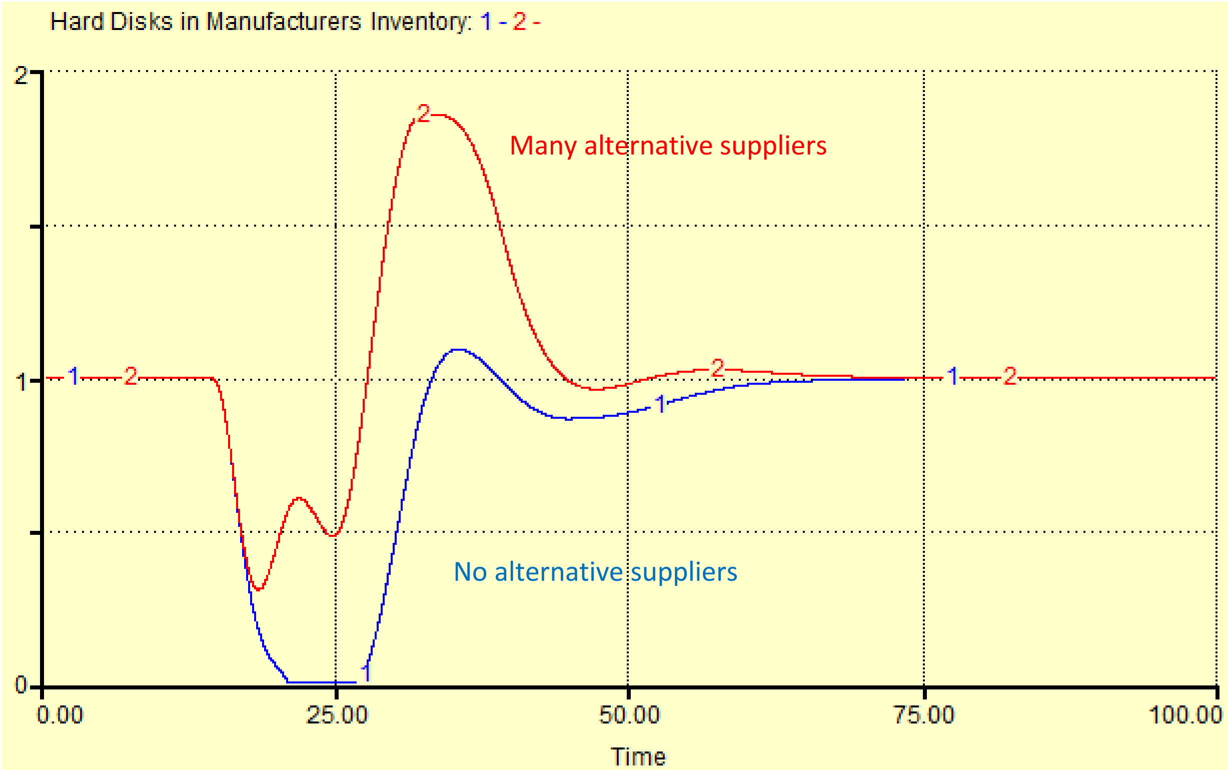

Figure 7: Manufacturers' Inventory under a 10-week spike in Consumer Demand, with alternative suppliers present (red line) and no alternative suppliers present (blue line).

However, when many alternative suppliers of platters are present, the fraction of desired platters that all suppliers collectively are able to provide is always 1. This permits the manufacturers to produce HDDs at a greatly elevated level during the demand spike. Thus, the manufacturers' inventory never 'stocks out', as it did when there were no alternative suppliers available, but when the demand spike suddenly ends, the manufacturers finds themselves with a great overstock of hard disks and a reduced rate of ordering from the retailers. The rate of manufacturing HDDs drops to zero, a complete work stoppage until the overstock of drives begins to approach normal levels again. (Without alternative suppliers present, the elevated rate of manufacturing and subsequent depressed rate are less extreme, resulting in no work stoppage.)

The case when there are ample alternative suppliers resembles a dynamic seen in aid organizations during times of crisis when a call for certain aid supplies results in a dramatic response, resulting in the organization having far more of that item than can be used in any reasonable time.

Interestingly, the fraction of demand met (FODM) for both of these cases – when alternative suppliers are present and when they are not – is the same, 89.0%. It is the retailers' inventory being depleted, not the manufacturers' inventory, that constrains shipments to consumers. And, in both cases, a 10-week spike in consumer demand causes the retailer's inventory to 'stock out' for the same duration. In each case, the simulation was run for 200 weeks, with FODM being calculated over the entire period.

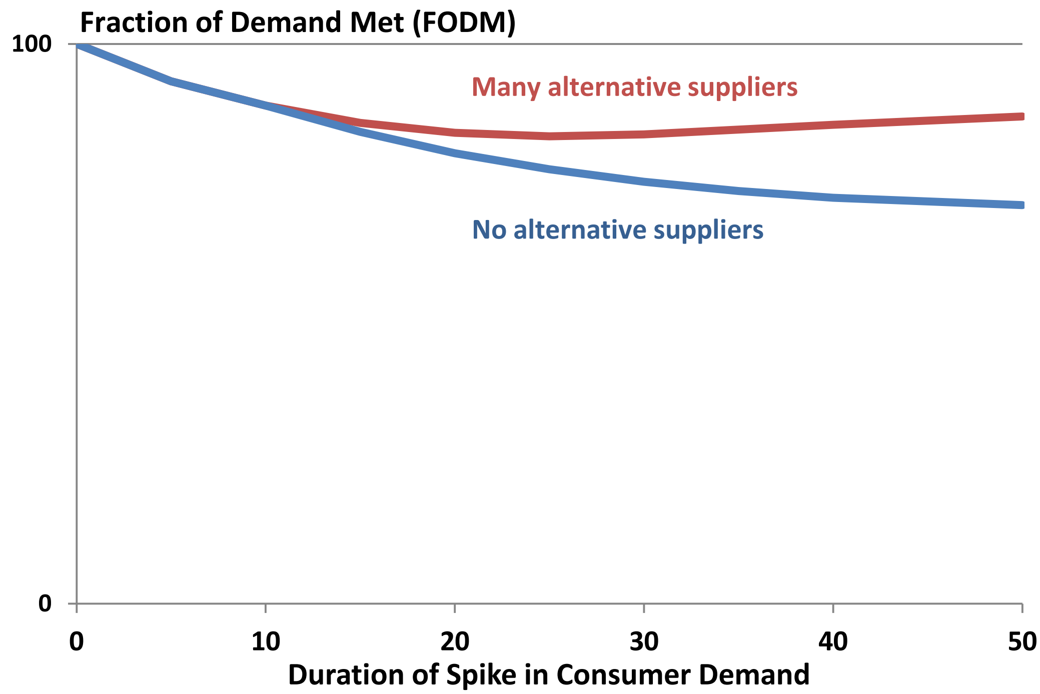

Figure 8: Fraction of demand met (FODM) as a function of duration of fivefold spike in consumer demand, for the cases when many alternative suppliers are present and when no alternative suppliers are present.

It is only spikes whose duration is longer than about 10 weeks that result in a difference in the FODM. For spikes of longer duration, having alternative suppliers increases the fraction of demand that is met, compared to not having alternative suppliers. Again though, this results in a large overstock when the demand spike ends, a higher rate of production during the crisis, and a longer work stoppage period after the crisis ends.

If at the present time, the spike in demand due to extreme weather events last approximately 10 weeks or less, then there is no benefit on FODM to cultivating a network of alternative suppliers. But Figure 8 demonstrates that when severe events become longer in duration, there is a greater need for alternative suppliers. Figures similar in concept to Figure 8 can be generated to look at event frequency and event severity, both of which might also change dramatically as the climate changes.

Conclusion

Building resilience requires a deep understanding of the dynamics of the value chain. As we saw in Scienario 1, the interactions between components of even a fairly simple supply network can generate non-intuitive behaviour patterns that are difficult to understand. In Scenario 2, the time to recovery (TTR) of the manufacturers' inventory was faster when all of its production capacity was destroyed than when 10% of the production capacity was retained. This might give us pause whenever using 'time to recovery' as a metric of resilience. In Scenario 3, the lack of alternative suppliers of a key component helped prevent the system from demonstrating the 'bust-and-boom' dynamics sometimes seen in emergency situations.

The model was developed for the example of a hard disk drive supply chain, but is potentially applicable to many manufacturing and distribution chains, or conceptually similar processes.

Fraction of demand met was used as one critical measure of a system's resilience to disruption, but future work is intended to extension of model to explicitly account for costs, both of an acute disruption but also of preparing for a disruption, as a cost-benefit analysis, particularly for the case of competing interests – such as when a disaster for one player in a system can yield a benefit for another.

Additionally, it is hoped to incorporating the 'learning effect', whereby repeated exposure to disasters and disruptions causes us to change the structure of the system – for example, the decision-making equations we use to determine ordering rates.

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Model

```
Hard_Disks_in_Manufacturers_Inventory(t) =
Hard_Disks_in_Manufacturers_Inventory(t - dt) +
(manufacturing_hard_disks - shipping_hard_disks_to_Retailers) * dt
      INIT Hard_Disks_in_Manufacturers_Inventory = 1


manufacturing_hard_disks = desired_manufacturing_rate *
fraction_of_desired_platters_all_suppliers_can_provide


shipping_hard_disks_to_Retailers = DELAY(Retailers_order_rate,4)


Hard_Disks_in_Retailers_Inventory(t) =
Hard_Disks_in_Retailers_Inventory(t - dt) +
(shipping_hard_disks_to_Retailers - shipping_hard_disks_to_Consumers) *
dt
      INIT Hard_Disks_in_Retailers_Inventory = 1


shipping_hard_disks_to_Retailers = DELAY(Retailers_order_rate,4)


shipping_hard_disks_to_Consumers = Consumers_Demand_for_hard_disks


Inventory_of_Aluminium_Platters_at_Primary_Supplier(t) =
Inventory_of_Aluminium_Platters_at_Primary_Supplier(t - dt) +
(producing_platters - using_platters) * dt
      INIT Inventory_of_Aluminium_Platters_at_Primary_Supplier = 1


producing_platters = 0.2 * (SMTH3(using_platters,3) /
INIT(using_platters)) + 0.15*(1-
Inventory_of_Aluminium_Platters_at_Primary_Supplier)


using_platters = desired_manufacturing_rate *
fraction_of_desired_platters_Primary_Supplier_can_provide
```

```
desired_manufacturing_rate = 0.2 *
(SMTH3(shipping_hard_disks_to_Retailers,3) /
INIT(shipping_hard_disks_to_Retailers)) + 0.15*(1-
Hard_Disks_in_Manufacturers_Inventory)


extent_of_alternative_suppliers = 0


fraction_of_desired_platters_all_suppliers_can_provide =
extent_of_alternative_suppliers + (1 -
extent_of_alternative_suppliers)*fraction_of_desired_platters_Primary_Su
pplier_can_provide


fraction_of_desired_platters_Primary_Supplier_can_provide =
MIN(Inventory_of_Aluminium_Platters_at_Primary_Supplier, 1)


Retailers_order_rate = 0.2 * (SMTH3(shipping_hard_disks_to_Consumers,3)
/ INIT(shipping_hard_disks_to_Consumers)) + 0.15*(1-
Hard_Disks_in_Retailers_Inventory)


Consumers_Demand_for_hard_disks = GRAPH(TIME)
      (0.00, 0.00), (15.0, 37.0), (30.0, 36.5), (45.0, 36.0), (60.0,
      36.0), (75.0, 35.5), (90.0, 33.5), (105, 33.0), (120, 32.5), (135,
      0.00), (150, 0.00)
```