

2015


A Simulation-Based Approach to Risk Assessment and Mitigation in Supply Chain Networks

Mamadou Seck
Old Dominion University

Ghaith Rabadi
Old Dominion University

Christian Koestler
Old Dominion University

Follow this and additional works at: https://digitalcommons.odu.edu/emse_fac_pubs

 Part of the [Industrial Engineering Commons](#), [Manufacturing Commons](#), [Operations and Supply Chain Management Commons](#), and the [Risk Analysis Commons](#)

Repository Citation

Seck, Mamadou; Rabadi, Ghaith; and Koestler, Christian, "A Simulation-Based Approach to Risk Assessment and Mitigation in Supply Chain Networks" (2015). *Engineering Management & Systems Engineering Faculty Publications*. 10.
https://digitalcommons.odu.edu/emse_fac_pubs/10

Original Publication Citation

Seck, M., Rabadi, G., & Koestler, C. (2015). A simulation-based approach to risk assessment and mitigation in supply chain networks. *Procedia Computer Science*, 61, 98-104. doi:10.1016/j.procs.2015.09.161



Complex Adaptive Systems, Publication 5
Cihan H. Dagli, Editor in Chief
Conference Organized by Missouri University of Science and Technology
2015-San Jose, CA

A Simulation-based Approach to Risk Assessment and Mitigation in Supply Chain Networks

Mamadou Seck, Ghaith Rabadi, Christian Koestler

*Department of Engineering Management and Systems Engineering, En
Old Dominion University, Norfolk, VA, 23529*

Abstract

We present in this paper a simulation-based approach to evaluate the risk associated with supply chain disruptions caused by failures in some supply chains nodes and measure the impact of such disruptions on supply chain key performance measures (KPIs) of interest. The proposed framework enables analysts and managers to repeatedly assess the risk to their supply chains based on various simulated scenarios and identify the most critical nodes whose disruption will have the highest impact on the KPIs of interest. As a result, companies can focus on the most critical supply chain assets and develop targeted mitigation plans that minimize their risk.

© 2015 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

Peer-review under responsibility of scientific committee of Missouri University of Science and Technology

Keywords: DEMO Methodology, ontological model, enterprise modeling, agents simulation

1. Introduction

Today's consumer products have reached an unprecedented level of complexity. A common product such as a smartphone is made of hundreds of parts sourced from almost as many suppliers. Furthermore, in line with the trend of globalization, businesses have become very astute in sourcing and setting up production units at the most cost-effective location, geographical distance being just one factor among many. This has stretched supply chains to the extent that a natural or geopolitical disruption can see its effects propagated thousands of kilometers away.

This situation, in conjunction with the tense competitive environment in which businesses operate, has made supply chain risk a major concern. As a result, researchers are investigating methodologies and analytical techniques to assess and mitigate risks in supply chains (Tang, 2006).

Modeling and simulation is a well suited method to assess the joint effects of structural and behavioral factors in complex systems. Simulation is thus a natural candidate technique to study the risk performance of complex supply

chains. The body of work on supply chain risk simulation is growing very fast. Various techniques have been used, including discrete event models (Schmitt, 2009), systems dynamics (Briano, 2010), Monte-Carlo approaches (Jin, Zhuang, & Liu, 2010), and agent based models (Harper, 2012), among other methods.

However, as in most modeling and simulation problems, there is a tradeoff between the level of detail in model conceptualization and the scale that the modeling approach can handle effectively. Most of the simulation approaches proposed for supply chain risk management tend to be complex and overly mired in operational details, to an extent that hinders their applicability to very large cases.

We propose an agent based conceptualization that models the supply chain at a level of abstraction which enables effective assessment of strategic risks and the development of mitigation plans.

Section 2 gives an overview of the conceptual model, introducing the entities, their parameters and the KPIs. Section 3 provides a set of simple scenarios to give some insight on the functioning of the simulation. Finally, section 4 summarizes the contribution and discusses future works.

2. An Agent Based Conceptualization of Supply Chains

A supply chain is a network designed by an organization to match supply with demand in a cost effective way while taking into account different sources variance. This network is composed of nodes which fulfil different functionalities such as production, storage, and distribution, and edges that transfer flows between the latter nodes. These flows are also of different types, including physical, informational and financial flows. While the domain of supply chain risk management is broad and may include issues as broad as fluctuating exchange rates and hedging, in this study, we are mainly interested in risks pertaining to the capability to serve the demand. We thus create a minimalist agent based conceptualization that allows us to represent the essential aspects of a supply chain and to simulate possible disruption scenarios. This section introduces the entities that have been included in the agent based model. For clarity, model entities are denoted in the text as “entity”. The attribute of an entity is denoted as “entity.attribute”.

We consider the product as it goes through the different stages of its elaboration as dictated by the bill of materials. Another consideration, maybe the most fundamental to supply chain risk, pertains to the characterization of demand. Because sourcing, producing and transporting are activities that take time, supply chain managers must have some sense of the demand days and sometimes weeks before it actually occurs. In the vast majority of markets, however, demand is not stable over time. It fluctuates based on different factors such as the strength of competition, sales and promotions, weather and seasonality, most of which are out of the manager’s control. This intrinsic variance in demand makes demand forecasting extremely difficult. The model described in this paper also represents inventory explicitly. In the remainder of this section, we discuss the model at the conceptual level by first discussion the main entities and their attributes, the behavioural functions, and finally the performance indicators.

2.1. Model Entities

- *p-reference* represents the product. It is characterized by its bill-of-materials, that is, a list of trees representing sub-components and their quantity. A *p-reference* can have more than 1 bill-of-materials, to simulate alternative recipes.
- Forecasted demand, *f-demand*, is a passive object characterized by the product reference, *p-reference*, a unique identifier for the product in need, *quantity*, denoting the quantity forecasted, and *time*, denoting the forecast window, or time at which this forecasted need will become a firm need. *f-demand.quantity* is modelled as a probability distribution to represent the observed variation in forecasted demand.
- Firm demand, *demand*, is a passive object characterized by the product reference, *p-reference*, and by the quantity demanded, *quantity*. In the simulation, *demand.quantity* is obtained by applying an error-rate to the forecasted demand. In the standard case, *error-rate* is normally distributed and centred on 0 so that the

actual demand may overshoot or undershoot the original forecast with equal probability. This central value may be pushed left (under 0) to represent organizations that tend to overestimate future needs, and vice versa for organizations that tend to underestimate future needs. The time of the firm demand is set to the current simulation time. The attribute demand.served-quantity denotes the portion of the demand.quantity that has been satisfied. This is useful for calculating fill rate key performance indicators.

- plant is the agent responsible for the production activities. It has a lead-time, which determines the length of time between the moment a production-order is placed and when this product-batch is available for pickup. It also has a capacity that sets the maximum amount that can be produced per time unit. Additionally, a plant has a failure-rate, which denotes the chance that the plant may be disrupted at a given time unit. Such an occurrence is simulated by setting the plant’s capacity to 0. Another attribute is time-to-recover, which denotes the time necessary to restore the node to 100% of its original capacity (Levi, 2014).
- stock is agent that represents inventory positions. Each stock is product specific and uses a p-reference attribute. It also has a capacity.
- production-order is a passive object characterized by a p-reference and a quantity. It is created by a plant based on a forecasted demand f-demand, by considering other factors like plant.capacity, stock.quantity, etc.
- product-batch is a passive object created by a plant after a production-order has been completed.

The edges of the network are of two types: info-link, material-link. As their names imply, an info-link is used to transfer information between nodes, such as the back-propagation of demand upstream of the network. material-link is used to transfer product-batches downstream the supply chain, from stock to plant and from plant to stock. Both links are characterized by a capacity and a delay parameters, which, combined, can be used to model the time that it takes to transfer some information or matter from one connected node to the next. If the quantity to be transferred is less than capacity, then the transfer time is delay, otherwise, the transfer time will be delay multiplied by the ratio between quantity and capacity.

2.2. Model Behavior

Here we discuss the main functions of the supply chain model. At the most abstract level, the model executes a control sequence which asks agents to perform specific tasks. As of now, the simulation model is built in the netlogo agent based simulation environment. However, the concepts used are generic and can be implemented in any similar platform. The functions are executed in the order depicted in figure 1:

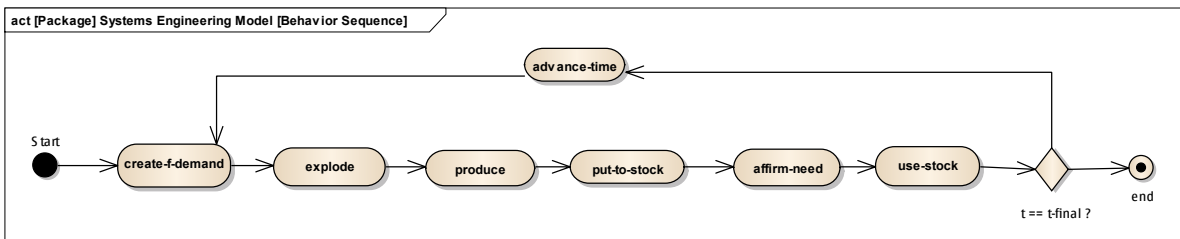


Figure 1: The sequence of function execution

- create-f-demand: This function creates a forecasted demand for the product at the simulation time $t + w$, w corresponding to the forecasting window. This forecasted demand is set based on a probability distribution, for example, a normal distribution with a mean and a standard deviation. This normal distribution is just a default, it can be changed if another distributions captures the demand variation better. If historic demand forecasts are used in the simulation, this demand can be set by picking a forecasted value from a time series.

- **explode:** This function simulates the process of MRP explosion (), whereby the gross forecasted demand is amended by the uncommitted inventory in stock and propagated through the bill-of-material. The function clones the current f-demand object for each immediate child in the bill-of-material tree and updates the time based on the lead-time necessary to create the product-batch when all components are available in stock.
- **produce:** This function is executed by plants. It ranks all forecasted needs by most imminent due date, creates a production-order, and occupies the plant for the duration set by lead-time. production-order.quantity is capped by the plant's remaining capacity.
- **put-to-stock:** Once lead-time has elapsed, the production-order type is changed into product-batch. stocks search for current product-batches and update their current quantity accordingly. The time that it takes to effect this change is delayed by the material-link's capacity and delay values.
- **affirm-need:** This function searches for f-demand objects whose time attribute is equal to the current simulation time. These objects apply the forecasting error (demand.quantity = f-demand.quantity + error) to the forecasted demand and change the object type to demand.
- **use-stock:** This function executed by stock agents searches for all demand objects whose time attribute is equal to the current simulation time and decrements stock.quantity by demand.quantity if demand.quantity is smaller or equal than stock-quantity. In this case, demand.served-quantity is set to demand.quantity. Otherwise, demand.served-quantity is set to stock.quantity and stock.quantity is reset to 0.
- **advance-time:** the simulation clock is advanced by one time unit.

2.3. Model Performance indicators

- **fill-rate:** the fill rate is calculated at each time unit by the value of the equation below, over the desired time interval:
 - $\text{sum}(\text{demand.served-quantity}) / \text{sum}(\text{demand.quantity})$
- **asset-utilization:** the utilization of plant capacity is calculated at each time unit by:
 - $\text{sum}(\text{product-batch.quantity}) / \text{sum}(\text{plant.capacity})$
- **inventory:** the current level of inventory (stock.quantity) of each stock is captured at each time unit.

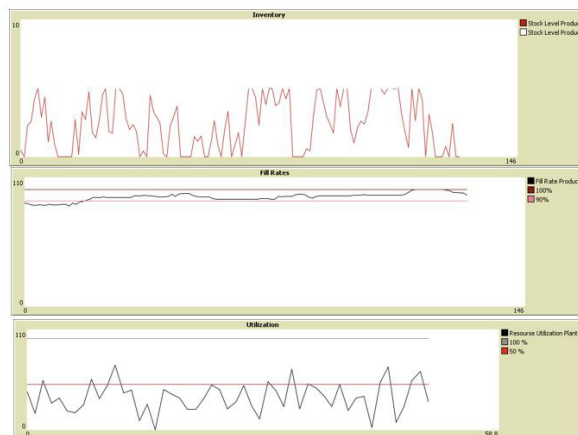


Figure 2: Performance Indicators

3. Simulation Example

Figure 3 shows the visual representation of a simple supply chain as modeled in our approach. The focal node of the supply chain is plant0, depicted as a blue square. This node supplies a product p1. This finished product is stored in stock1, depicted by a green triangle. plant0 and stock1 are connected through a material-link. To produce p1, plant0 must source a single sub-product, which is p12 or alternatively, p13. p12 is produced by plant3 and p13 by plant4. plant3 needs to source two sub-products, p121, from plant8 and p122 from plant9. To produce p13, plant4 must source p122 from plant9.

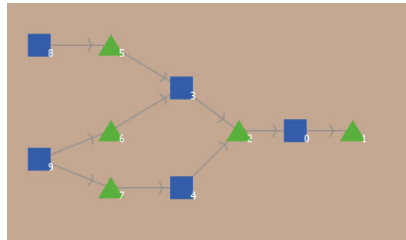


Figure 3: Supply Chain Example

Different experiments pertaining to risk may be executed with the model. To demonstrate the model's capability, we show a sequence of simple simulated scenarios: a) perfect demand forecasting, b) minor forecasting error without safety stock, c) major forecasting error with safety stock, d) propagation of upstream disruptions.

a) Perfect demand forecasting

If an organization were able to forecast demand perfectly with a time window that is larger than the cumulative lead-time across the supply chain, and with a capacity superior or equal to the demand, it would have a fill rate of 100% and no need for inventory. This scenario certainly never presents itself in reality, but it is a theoretical baseline that is useful to assess the basic functionality of the model. Figure 4 shows the output of this scenario.

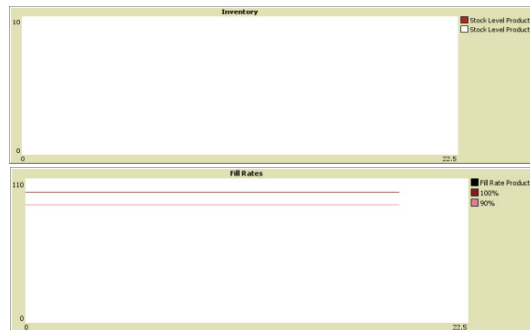


Figure 4: Scenario a) output

As theoretically expected, there is no accumulation of inventory, and a fill rate of 100%.

b) Minor forecasting error without safety stock

In this scenario, we use a forecasting error centered on 0 and a standard deviation of 15. The expected demand is set to 100 units. This means that at every instance, the actual demand may be overrated or underrated, with equal probability, by as much as 45 units. Capacity of plant0 is set to 150, and is never a constraint. Figure 5 shows the output of this scenario.

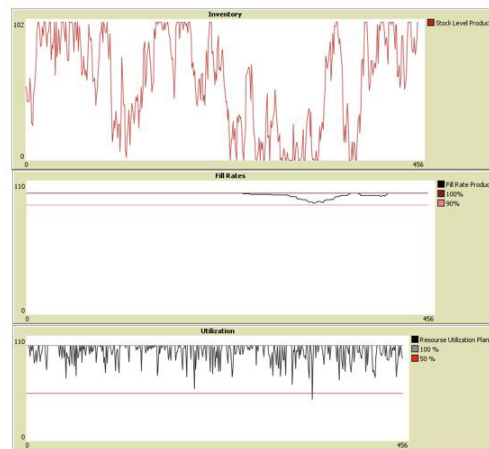


Figure 5: Scenario b) output

We can see that inventory is building up as a result successive of forecasts that exceed the actual demand in the early parts of the run. We also notice that the fill rates start to score under 100% when many successive forecasts are underestimating the actual demand. The utilization of the resources is also erratic, as a result of the variance.

c) Major forecasting error with safety stock

In this scenario, we use a forecasting error centered on 0 with a standard deviation of 33.3. The expected demand is still set to 100 units. This means that at every instance, the actual demand may be overrated or underrated by as much as 100 units in the most extreme case. We set a safety stock of 100 units. All other factors remain the same as in scenario b).

Figure 6 shows the output of this scenario. We can see that the safety stock, combined with the available extra capacity enables the supply chain to maintain a perfect fill rate. The inventory drops in some instances where successive forecasts underestimate the demand significantly, but never enough to not satisfy the immediate demand by using the safety stock.

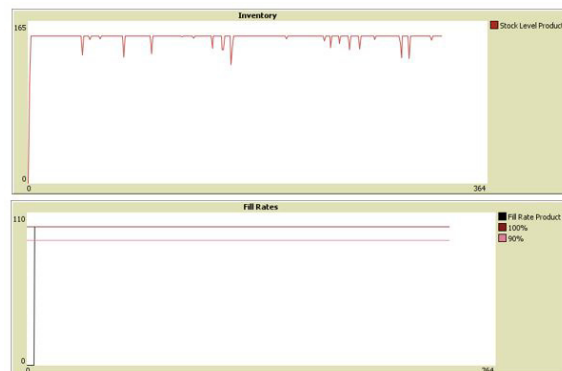


Figure 6: Scenario c) output

d) Disruption of plant9 for 10 time units

In this scenario, we set every parameter as in scenario c). At time 35, a disruption reducing capacity to 0 affects plant9. This plant has a time-to-recover of 10. The cumulative lead time from plant9 to plant0 is 5 time units. Figure 7 shows the output of scenario d).

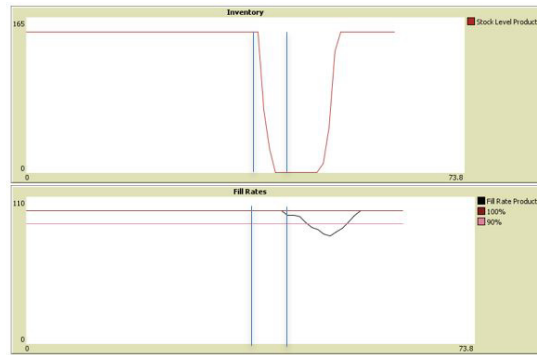


Figure 7: Scenario d) output

We can notice on Figure 7 that the disruption starts to affect the inventory of stock of five time units after it began at plant 9. When the safety stock of p1 is depleted, the fill-rate begins to drop. When production resumes in plant 9, and following the lead-time of intermediary nodes, plant 0 resumes production and rebuilds its safety stock. The fill rate subsequently returns to 100%.

These four scenarios applied to the test case have allowed us to show the functioning of the model and its capability to simulate events pertaining to supply chain risk, ranging from the minor risks associated with demand forecasting to more important risks related to suppliers undergoing major disruptions. With the help of such a simulation model, mitigation strategies such as safety stocks, dual sourcing, or even product redesign and standardization may be assessed to formulate an effective risk strategy at the supply chain level.

4. Conclusion

We have presented an agent-based approach to simulate scenarios pertaining to risk assessment and management in supply chains. The proposed conceptual model is highly abstracted and uses a limited set of essential parameters. The rationale is to make the model building simple and fast enough to be used in large, global supply chains. Furthermore, most of the operational details omitted in this conceptualization are not relevant when formulating a risk management strategy in an end-to-end supply chain spanning a large number of nodes.

Future work includes the application of this modeling framework to large scale supply chains in different industries. This will enable the identification of additional parameters, performance indicators and behavior routines to include in the model. One main limitation of the current model is that it only considers push based planning. The inclusion of demand-driven and pull approaches will certainly increase the modeling approach's applicability. Another area that we plan to explore is the coupling of the simulation framework with an optimization framework, to enable users to autonomously find the structure and parameter settings that render a supply chain most resilient.

References

1. Briano, E., Caballini, C., Giribone, P., & Revetria, R. (2010). Using system dynamics for short life cycle supply chains evaluation. In *Proceedings - Winter Simulation Conference* (pp. 1820–1832). <http://doi.org/10.1109/WSC.2010.5678887>
2. Jin, S., Zhuang, J., & Liu, Z. (2010). Monte Carlo simulation-based supply chain disruption management for wargames. In *Proceedings - Winter Simulation Conference* (pp. 2682–2693). <http://doi.org/10.1109/WSC.2010.5678964>
3. Miller, H. E., & Engemann, K. J. (2008). A Monte Carlo simulation model of supply chain risk due to natural disasters. *International Journal of Technology Policy Management*.
4. Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*. <http://doi.org/10.1016/j.ijpe.2005.12.006>
5. Harper, T. J. (2012). *Agent based modeling and simulation framework for supply chain risk management*. Air Force Institute of Technology, Wright Patterson AFB, OH, USA.
6. Schmitt, A. J., & Singh, M. Quantifying supply chain disruption risk using Monte Carlo and discrete-event simulation, *Winter Simulation Conference WSC Proceedings of the 2009* 1237–1248 (2009). <http://doi.org/10.1109/WSC.2009.5429561>
7. Simchi-Levi, D., Schmidt, W., & Wei, Y. (2014). From superstorms to factory fires: Managing unpredictable supply-chain disruptions. *Harvard Business Review*.