Analyzing the Manufacturing Supply Chain Performance for Urgent Item during COVID-19 Outbreak

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Abstract: As COVID-19 pandemic spreads in different regions with varying intensity, supply chains (SC) need to utilize an effective mechanism to adjust spike in both supply and demand of resources, and need techniques to detect unexpected behavior in SC at an early stage. During COVID-19 pandemic, the demand of medical supplies and essential products increases unexpectedly while the availability of recourses and raw materials decreases significantly. As such, the questions of SC and society survivability were raised. Responding to this urgent demand quickly and predicting how it will vary as the pandemic progresses is a key modeling question. In this research, we take the initiative in addressing the impact of COVID-19 disruption on manufacturing SC performance overwhelmed by the unprecedented demands of urgent items by developing a digital twin model for the manufacturing SC. In this model, we combine system dynamic simulation and artificial intelligence to dynamically monitor SC performance and predict SC reaction patterns. The simulation modeling is used to study the disruption propagation in the manufacturing SC and the efficiency of the recovery policy. Then based on this model, we develop artificial neural network models to learn from disruptions and make an online prediction of potential risks. The developed digital twin model is aimed to operate in real-time for early identification of disruptions and the respective SC reaction patterns to increase SC visibility and resilience.

Keywords: Supply Chain, COVID-19 Pandemic, Digital twin, Simulation, System Dynamics, Recovery, Artificial Neural Networks.

1. Introduction

For many decades, U.S. companies have been relying on strategic outsourcing and developing supplier relation as tools to rapidly cut costs and gain competitive advantages. The continuous pressure of cost-cutting and increasing efficiency instead of effectiveness have increased the SC vulnerability and exposure to new high-level risks such as terrorist attacks, natural disasters, geographical risks or epidemics (Kumar & Eickhoff, 2005). Low-level risks such as quality control failure, machine break-downs etc. have high probability of occurrence but low impact. High-level risks have a low probability of occurrence but have high impact and cost, which are generally difficult to be planned. The response to high-level risks requires a fast responding, dynamically adjusting methodology that will allow quick response reactions in the supply chain system. The unfathomable outbreak of COVID-19, which has damaged the lives of people and economic activity globally, represents a high impact disruption in the supply chain. The objective of this research is to demonstrate the use of digital twin model as a quick response strategy for handling any high-level risk in supply chain disruption. Unlike other disruptions risk, the COVID-19 outbreak poses one of the critical disruptions faced by SC during the last decades (Araz, Choi, Olson, & Salman, 2020). The breakdown of SC links and disruption in market demand results in delays and shortages across the SC. Evidence urges that an efficient and fast response is crucial for mitigating the fatality and economic costs to SC and society in the case of pandemics (Linton & Vakil, 2020). To the best of our knowledge, no research has examined the impact of COVID-19 outbreaks on the SCs for products with an urgent demand. This research is motivated by the significant negative impacts of COVID-19 on manufacturing SC stability and performance. The outbreak disruptions destabilize the SC operations, causing oscillations in product demand, inventory level, and production rate. Traditional SC disruption preparedness and recovery strategies are simply not sufficient for this type of disruption as they lack adaptability and reactivity to extraordinary situations (Darom et al.

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2018; Dryhurst et al. 2020). SC operational planners need to utilize the best method to adjust to spikes in both supply and demand of resources and need techniques to anticipate disruptions in demand during the pandemic. Therefore, utilizing advanced technologies has become indisputably essential because of the pandemic when many companies needed to manage risks in their supply and demand very quickly (Ivanov, Dolgui, and Sokolov 2019). Utilizing these advanced technologies to develop an intelligent control is essential for monitoring SC performance, identifying the source of vulnerabilities, and providing greater visibility across the entire chain. This intelligent control can be achieved by the adaptation of the digital twin concept in SC (Ivanov and Dolgui 2020).

Digital SC twins use advanced analytical models such as simulation and data-driven models to support the decision-making process in SC risk (Ivanov and Dolgui 2020). It represents the state of SC in real-time, with actual demand, capacity, inventory, and transportation data. For example, suppose there is a sudden drop in the number of workers due to COVID-19 at the supplier level. In that case, this disruption can be detected by an intelligent monitoring system and transferred to a simulation model in the digital twin as a disruptive event for further analysis. The output of the simulation model can be used as an input to learning algorithms to predict the impact of the disruption in real-time when actual data becomes available. SC risk managers would benefit from advanced analytical models in the digital twins for efficient monitoring and planning. However, the investigation of SC digitalization for managing disruption risk is still in its infancy. It is motivating to study how the utilization of these advanced analytical models and tools can help companies in improving their SC risk management practices and increase their competitive advantages. In this research, we address the impact of COVID-19 disruption on manufacturing SC overwhelmed by the unprecedented demand of urgent items by creating a digital SC twin model in which a system dynamics (SD) simulation and artificial neural networks (ANN) models are combined. The SD simulation model is used for analyzing the SC behavior, quantifying the impact of COVID-19 outbreaks under a set of disruptions scenarios. Using the data generated by the SD simulation, we build ANN models to learn from disruptions and the observed SC behavior. The digital SC twin model is aimed to operate in real-time using the knowledge obtained from SD and analyzed by ANN for early identification of disruptions and the respective SC reaction patterns to increase SC visibility and resilience. This model will help decision-makers of essential products to make an accurate and immediate decision in evaluating the current production plan and mitigation strategy to reduce the impacts of the pandemic before they reach critical conditions.

This paper contains five main sections. In Section 2, we briefly review some related literature with a focus on SC risk. In Section 3, we explain the methodology implemented in this research. Section 4 presents the case study and experimental results. The conclusion is presented in section 5.

2. Literature Review

2.1 Advance Analytics and Digital SC Twins:

Analytics has been recognized as a powerful tool for SC management (Kohavi, Rothleder, & Simoudis, 2002). However, advancement in modern information technology continues to deliver new opportunities for improving SC operational and strategic processes, which allow for enhanced analytics capabilities and hence improve overall performance and reduce risks. Nowadays, predictive analytics involves the use of advanced analytics methods such as simulation modeling, machine learning algorithms, and artificial intelligence to extract valuable insight from a massive amount of data that can aid the decision-making process in different fields (De Oliveira, McCormack, & Trkman, 2012; Geissbauer, Vedsø, & Schrauf, 2016; Tsai, Lai, Chao, & Vasilakos, 2015). In the context of SC risk management, advanced analytics models based on a data-driven approach have been recently utilized for improving SC resiliency and reducing disruption risk (Choi, Chan, & Yue, 2016; Choi & Lambert, 2017). Also, simulation models have been predominantly applied to problems in SC risk management (Ivanov, 2017, 2020; Schlüter, Hetterscheid, & Henke, 2019). Simulation modeling has been mostly applied for offline-strategic planning. However, the quality of a simulation model that is used to support the decision-making process when dealing with disruption risks crucially depends on the availability of up-to-date SC data because decisions often have to be taken quickly.

Today's developments in modern technologies have resulted in higher affordability of sensors, computer networks, and data collection systems, allowing for gathering lots of SC data online data such as demand data, inventory data, supplier data, and disruption data. All of this online data can be embedded into a digital SC twin where simulation and data-driven models can be integrated to improve operational planning and reduce the impact of disruptions (Ivanov and Dolgui, 2020). The concept of digital twins in SC depends on the availability of online data to design a real-time mirror of all processes along the SC. All of this wouldn't be possible without the help of modern technologies such as IoT and Big Data. These technologies have enabled more connected chains in which real-time information can be obtained. In (Li and Liu, 2019) discussed how technology Big Data leads to an opportunity for SC. They proposed a theoretical framework for data-driven SC management. Hosseini, Ivanov, & Dolgui (2019) presents the possibility of SCs in the future and mention for the first time the concept of

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digital twins in a SC. They theorized the importance and applications of digital SC twins without providing any technical details of how it can be implemented in practice. It appears that the subject of SC digitization is still in its early stages.

2.2 Simulation Modeling for SC Risk and COVID-19:

Simulation allows adding dynamic features to SC risk modeling and disease outbreaks. Dynamic SC simulation models can explore questions relating to the behavior of disrupted SC. They play an important role in modeling and quantifying the dynamics of SC systems that cannot be captured by optimization or spreadsheet modelings such as manufacturing capacity disruption with or without response policies and their impact on the SC performance. Simulation studies concerning the SC risk deal with time-dependent and gradual disruption period, periods of capacity degradation and recovery, have earned an important role in SC risk management research (Ivanov, 2017; Oliveira, Jin, Lima, Kobza, & Montevechi, 2019).

Furthermore, the complexity of the dynamic of infectious disease outbreaks such as COVID-19 dictates the use of simulation models to understand the appropriate response measures (Currie et al., 2020; Dieckmann et al., 2020). The fast outbreak of the COVID-19 pandemic has proven that models are needed quickly. This can be achieved via rapid modeling or by adjusting existing epidemiological models to simulate the dynamics of COVID-19. So far, substantial efforts have been on modeling the spread of COVID-19 (Fang, Nie, & Penny, 2020). The COVID-19 pandemic raises many more challenges that could be addressed by simulation modeling to assist decision-makers in developing the appropriate mitigation strategies. However, different decisions require different simulation models. Epidemiological simulation models are useful for predicting the number of infected individuals or for formatting the best strategies to reduce transmission, but when used alone, they will not help to reduce or manage the risk in the SC.

2.3 System Dynamics Simulation:

SD modeling was created in the 1950s by MIT professor Jay Forrester (Forrester, 1997). Drawing in his science and engineering background, Forrester sought to use the laws of electrical circuits to investigate the dynamics of economic and social systems. SD modeling is an approach for studying the dynamics of complex real-world systems (Forrester, 1997). Its main concept is that all components in a system interact through causal relationships. SD is best implemented where the purpose of the simulation is to provide a detailed examination of flow aggregation, trends, and subsystems behavior as opposed to the other simulation techniques that focus on individual flows of activity (Riedlinger and Wisniewski 2019). The reason for selecting the SD approach in this study is that SD modeling is a very effective tool for simulating feedback and capturing changes to a dynamic system over time, making it suitable for monitoring the disrupted SC continuously (Aguila and ElMaraghy, 2020). In addition, a SC has some distinctive characteristics that can well captured by SD. For example, SC consists of several stocks and flows for the resources and transformation of inputs to outputs. Furthermore, SCs normally has an inherent delay in their operations due to the nature of production and transportation. This delay can result in amplification and oscillations across the chain.

Several studies have successfully applied simulation modeling to understand SC behavior under risk (Giannakis & Louis, 2011; Ivanov, 2020; Li & Chan, 2013; Macdonald, Zobel, Melnyk, & Griffis, 2018; Petrovic, 2001; Schmitt & Singh, 2012). However, most of these studies did not use SD simulation for addressing the impact of disruption risk SC performance. Only a few studies have used SD to analyze the dynamics of SC disruption behavior under disruptions. For instance, Aguila and ElMaraghy (2020) developed a framework to investigate the applicability of SD modeling in monitoring SC behavior and evaluating the impacts of disruptions. They analyzed the effects on disruptions on different key performance indicators in multi-echelon SC. They pointed out that the impacts of disruption and the propagation of the ripple effect on the SC performance are more severe when the disruption occurs in the downstream echelons. Langroodi and Amiri (2016) used the SD approach to design a five-echelon SC and study the impact of the bullwhip effect caused by demand uncertainty and variations in price and costs. They highlighted the tradeoff between cost reduction and lead time. Huang et al. (2012) investigated the impacts of supply disruptions on two-echelon SC performance. They noticed a sudden increase in the inventory level after a disruption and observed that the length of supply disruptions contributes the most to fluctuation in inventory levels.

2.4 Artificial Neural Networks:

ANNs are algorithms inspired by the biological structure of the human brain; it mimics the ability of the brain's neural systems in a computerized way. Their approximating power comes from the parallel computing of the inputs from the given data. They can be trained in either supervised or unsupervised environments. They have a remarkable ability to handle unstable or incomplete data, which represents an essential quality regarding all uncertainties within a SC (Tsai et al., 2015; Tsai & Hung, 2016). ANNs have many types that can be categorized into two main groups, the feed-forward artificial neural network

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(FFANN) and the recurrent artificial neural networks (RANN). The FFANN has no feedback loop; information flows from one layer of neurons to the next, starting with the input layer, passing through the hidden layer for intermediate processing, and finally to the output layer. RANN has a feedback loop where data flows in both directions. The outputs are fed back to the input, so the result of RANN in a time step *t -1* affects its result later at time step *t*. FFANNs work well with static data that does not depend on past behavior of itself to predict the future. On the other hand, RANNs are suitable for modeling dynamical behaviors where past behavior of data affects the future outcomes.

In general, ANNs have been applied to several problems in SC such as customer segmentation, supplier selection, time series forecasting, order assignment, dynamic pricing, cost prediction (Alanis, Arana-Daniel, & Lopez-Franco, 2019; Min, 2010). Despite their widespread acceptance as advance decision-support tools, ANNs have seen limited application in SC risk management; only a few studies in SC risk management use ANNs can be found in (Baryannis, Validi, Dani, & Antoniou, 2019). The management of SC risks is mainly based on inaccurate and incomplete information and is surrounded by various sources of information that are not insignificant to relate. ANNs with their ability to handle unstable or incomplete data, approximation power, and pattern recognition are effective approaches for predicting and detecting changes in SC behavior under normal and risk conditions. ANN models can also be utilized to support not only decision making in SC risk management but also transforms traditional SC risk management practices of modeling SCs statically to a dynamic representation of the SC behavior adopted through learning and recognition (Baryannis et al., 2019). Unsupervised ANN models can be employed to discover patterns in SC data that may be linked to specific disruption risk. Alternatively, supervised ANN models can be trained to predict risk patterns based on preidentified example patterns.

3. Research Methodology

Managing the impact of disruptions on manufacturing SC demands a new approach that incorporates a dynamic and intelligent system to enable flexibility and responsiveness. The combination of SD simulation and ANN constitutes the full stack of technologies needed to create a model for managing disruption risk in SC. The proposed digital SC twin model is developed to operate in real-time as a monitoring and early warning system that identifies dynamic trends and detects undesired behavior of SC. This model allows SC to adjust tactics and operations for recovering from disruptions. In COVID-19, integrating this digital twin model with live stream data of outbreaks or an epidemiological model can improve SC operational and contingency planning.

Different simulation models can be integrated to study the impact of disruption outbreaks on the manufacturing SC performance (Currie et al., 2020). In this study, we use forecasts from an epidemiological model to estimate the demand for an essential item during the outbreaks of COVID-19. We use the SEIR (Susceptible – Exposed – Infectious–Recovered) model, which is one of the most popular epidemiological models for estimating the number of infected individuals and describing the dynamics of the disease outbreak. This model has been used to study the spread of COVID-19 (Fang et al., 2020). The estimated demand is continuously fed into the manufacturing SC operational model to create disruptions in demand in real-time. The reason for connecting two simulation models (SEIR and SC) is to create SC risk data similar to the ones that could come from IoT and RFID systems in the digital SC twins. The first purpose of using SD is to develop a simulation model that reflects SC behavior and the possible disruptions and mitigation strategies that could be used. The second purpose is to generate structured and clean data to support the application of ANN models. The high abstract SD model is designed to capture the dynamics of COVID-19 outbreaks and the operations of SC to generate data streams on the number of infected individuals, shipment rate, production rate, staffing level, and inventory level. The SD model produces complex time-series datasets. Due to disruptions risks, operational constraints, feedback, and delays, the changes in the SC output is not proportional to the change of the inputs.

Learning from disruptions and the observed SC behavior allows for early identification of disruptions and the respective SC reaction patterns, which can be used for real-time recovery and control. We use ANN to work as a lightweight approximator of a more resource-intensive SD model. The ANNs are trained to work online to monitor the SC environment and make the necessary predictions to help the SC system maintain its stability in disruptions using online SC feedback data from IoT and RFID. Figure 1 represents the use of ANN for monitoring and controlling SC behavior in a digital SC twin.

To provide a proof of concept, we select a Nonlinear Autoregressive model with exogenous input (NARX) to work as the kernel of the real-time monitoring engine in the digital SC twin. The NARX model is a variant of RANN that has been successfully used in time series prediction problems (Alanis et al., 2019; Gao & Er, 2005; Lin, Horne, Tino, & Giles, 1996). We use NARX to predict the dynamic changes in the inventory level of an essential item. If the predicted inventory level equals the desired level, no action is needed to adjust SC operations. However, if the predicted SC inventory level does not match the desired level, further investigation is needed to determine the root causes and adjust SC operations to stabilize the system. The NARX model is very susceptible to overfitting when the size of the training data is not large enough to generalize the error. Therefore, we use Bayesian regularization to improve the network generalizability. Bayesian regularization allows reducing the number of ineffective parameters used in the model and measuring the uncertainty in the predictions which is missing from

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the current RANN architectures (Tian & Noore, 2004). Anylogic 8 University software is used to build the SD model and MATLAB (R2020a) and to develop the NARX model.

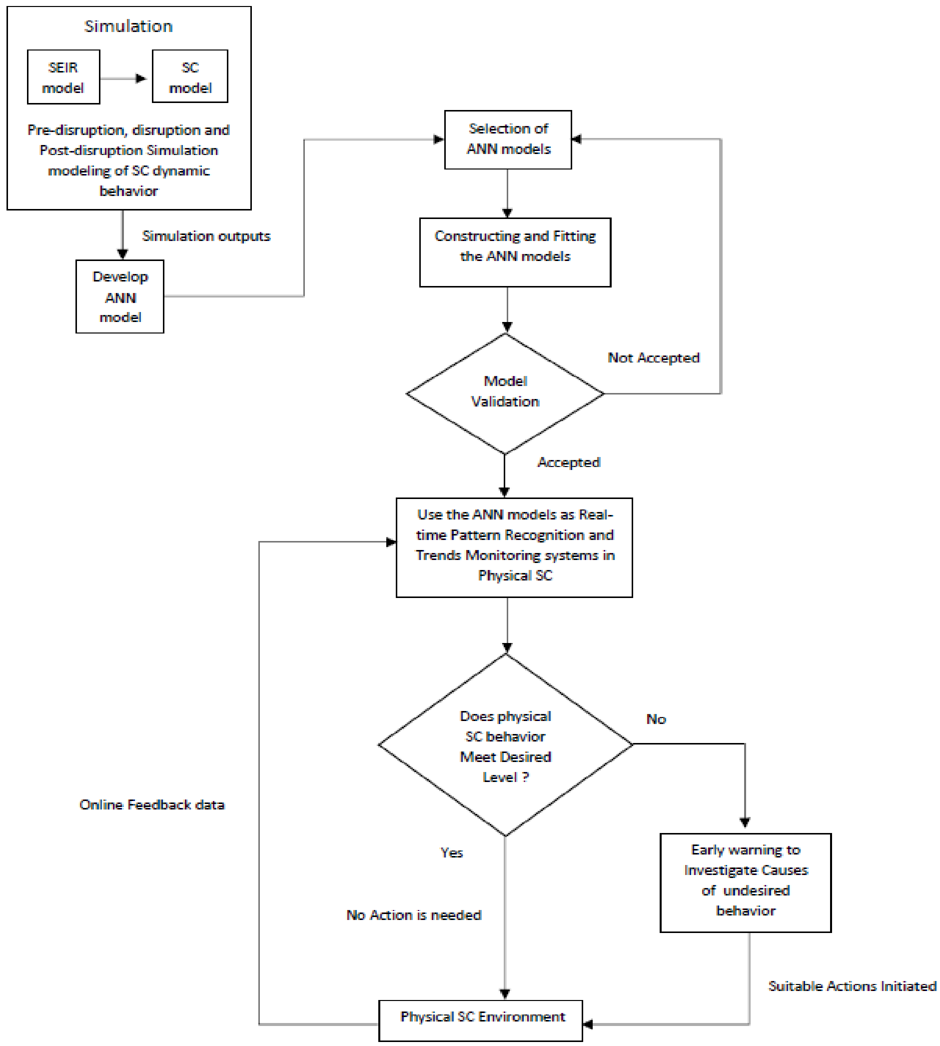

Figure 1. Monitoring and controlling SC behavior using ANNs in digital SC twins

4. Case Study

Global SC consists of cascades of companies, each receiving orders and adjusting workforce and production to meet changes in demand. Each link in global SC controls and maintains inventories of finished goods and raw materials. To understand the behavior of the global SC during the pandemic and the causes of oscillation, delays, and amplification, it is important to understand the dynamics of a single link first, that is how an individual company manages its resources and inventories to balance production/shipments with incoming orders from downstream. In this section, we use a subsystem of the manufacturing SC system developed by (Sterman, 2010) which has been validated by the author in order to test our approach. We change some parameters of this model (e.g., inventory level, order rate) and extend the model to include workforce.

This model represents a local company that manufactures and distributes medical supplies for personnel and health care providers in the Midwest. This company has built its reputation on providing products on time to its customers for many years. Product (X) makes up to 70% of company's operations. Historical data shows that the daily demand for Product X is normally distributed with a mean of 3000 and a standard deviation of 10%. The company has 100 workers with estimated

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worker productivity of 30 units/day, which is the right amount to meet the regular incoming orders from retailers. Whenever the inventory drops below the desired level; the company calls for inventory correction to gradually replenish the gap over a period of 8 weeks.

The adopted lean inventory policy is to keep three days' worth of shipments (9000 units) of product X available on hand to buffer variability in customer demand. The company continuously monitors the inventory level and relies on the adjustment of the desired inventory level for production planning and scheduling to avoid stockout. However, it allows for backorders when stockout occurs. The desired inventory level depends on the length of normal inventory coverage and the forecasting of shipments going to the distribution center. The DC aggregates the demand for all healthcare providers in nearby cities. The total number of vulnerable people in these cities are estimated to be 200,000 individuals.

The company uses information about past shipments to forecast future demand; it relies on averaging (smoothing) the shipments to detect and observe trends in data. The SC managers use the forecasted demand (average shipments rate) for adjusting both desired inventory and desired production. It takes time to correct the gap between actual inventory and desired inventory. This gap is usually corrected over a period on one month to avoid putting immediate stress on the production sector.

The company estimates the required number of workers based on the desired production. It has two main policies hiring and departures. If there are too few workers, the company hires more after some hiring delay. Similarly, if there are too many workers, the company can reduce the workforce by natural attrition or by laying off workers. Due to the company being cautious about hiring or firing workers, the gap between desired workforce and actual workforce is corrected gradually over a period of one month. Usually, the average length of stay for a worker is fifty weeks, and it takes the management around four weeks to plan for the desired workforce. The hiring rate depends on both the average departure rate and workforce adjustment (gap correction). On the other hand, the departure rate is driven by the ratio of the workforce to the normal length of stay. Typically, the more workers hired in the company, more of them are expected to leave in a given period of time as a result of employee turnover.

The company is currently facing unexpected pandemic disruptions. The company wants to analyze the effects of these disruptions on the inventory level, production rate, service level and effectiveness of the current staffing policy to ensure survivability. Based on SD outputs, NARX model is trained to capture the dynamic of the disrupted manufacturing SC behavior and make the necessary predictions to stabilize and adjust the company's operations.

4.1 Simulation model:

We connect the SEIR model to the company manufacturing SC model to create real-time demand disruption. As mentioned in the previous section, this model is used to analyze and quantify the impact of the pandemic on the SC performance and evaluate the effectiveness of the adopted response strategy.

The Classical compartmental SEIR model has four elements which are Susceptible (S), Exposed (E), Infectious (I) and Recovered (R). This epidemiological model has already been used in its original form to assess the early spread of COVID-19 in Wuhan, China (Fang, Nie, & Penny, 2020). Many infectious diseases such as HIV, SARS, and H1N1 where incubation period exists have also been modeled by SEIR technique (He, Peng, & Sun, 2020). However, since SEIR model does not have a mortality rate that reflects the COVID-19 deaths, we extend the SEIR model to include a mortality state (D) in order to estimate the number of deaths. In the extended model, the total population is $N(t) = S(t)+E(t)+I(t)+R(t)+D(t)$. It is assumed that the COVID-19 has a finite duration and, after getting infected, an individual either recovered and becomes immune or dies. The modified SEIR starts with a number of 300 infectious individuals introduced into a closed population of N= 200000 susceptible. Susceptible people have random mixing pattern with infectious ones and they become exposed to COVID-19. We assume that there is no lockdown and a normal person comes with contact with three individuals daily. The individuals who come with contact with infected people become exposed but not asymptomatic yet. After a certain period of time known as the incubation period, the exposed individuals become symptomatic and infectious. Finally, infected individuals go through illness duration before they recover or die from being exposed to COVID-19. The parameters for the modified SEIR model are adjusted based on information from existing literature. The incubation time (the period from exposure to showing symptoms) of COVID-19 ranges typically from 2-14 days (CDC, 2020) and illness duration (infectious period) of 10-20 days. We choose a moderate time of 10 and 14 days for incubation time and illness duration, respectively. The infectivity was estimated between 0.07- 0.6 (Wang et al., 2020), we select 40%. Fatality rates for COVID-19 have also varied in intensity, time, and geographic location (Ritchie, 2020) (e.g., between 6%-15% in Italy, 1-6% in US), we set the fatality rate to 4% during the whole simulation run. The set of parameters of the modified SEIR model and is represented in table 1.

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Table 1. Parameter values for modified SEIR model

Parameters	Value
Infectivity	0.4
Contact Rate	3 per day
Average Incubation Time	10 days
Average Illness duration	14 days
Total Population	200000

We connect the modified SEIR model with the manufacturing SC model to test some possible disruption scenarios that might happen during the pandemic outbreak. Figure 2 shows the complete SD model used in this study. Parameters that define the current policy and states for manufacturing SC is represented in table 2.

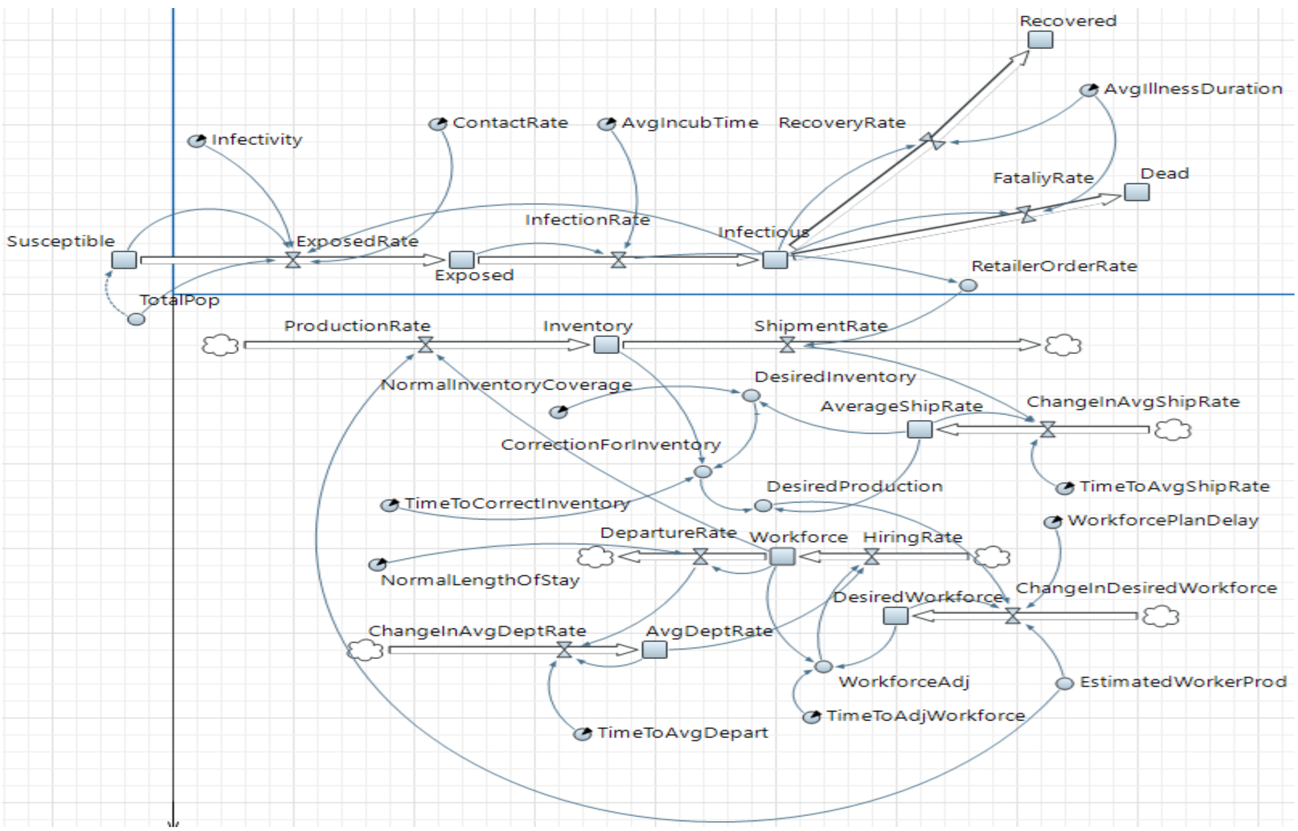

Figure 2. Complete SD model.

Table 2**.** Parameter values for manufacturing SC

Parameters	**Value**
Initial Inventory Level	9000 units
Time to Average Ship Rate	8 weeks
Initial Average Ship Rate	3000 units
Normal Inventory Coverage	3 days
Time to Correct Inventory	8 weeks
Time to Average Departure Rate	4 weeks
Initial Workforce	100 workers
Worker Productivity	30 units/day
Time to Adjust Workforce	4 weeks
Desired Workforce	100 workers
Workforce plan Delay	4 weeks
Normal Length of Stay	50 weeks
Initial Average Departure Rate	0 workers

4.2 Simulation results and analysis:

Using the proposed simulation model, we test the impact of an COVID-19 outbreak on manufacturing SC performance (i.e. inventory level, worker level, production rate and service level) under different disruptions scenarios. We ran this model for two years for all scenarios. Our scenarios are designed to address four major features of COVID-19 which differentiate them from other SC risks:

- Unexpected demand caused by the massive outbreak of an airborne virus.
- Availability of workers due to lockdowns and social distancing.
- Production suspension due to shortage in supplies.
- Waves with varying intensity due to vaccination and preventative measures.

The SC disruption can be caused by one or a combination of the above situations. In order to reduce the number of “what-if” disruption scenarios, we consider the following situations with and without risk inventory of 150000 available when inventory level drops below 100000 backorders:

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***Scenario I** : SC disruption by unexpected pandemic demand (one wave with N susceptible)*

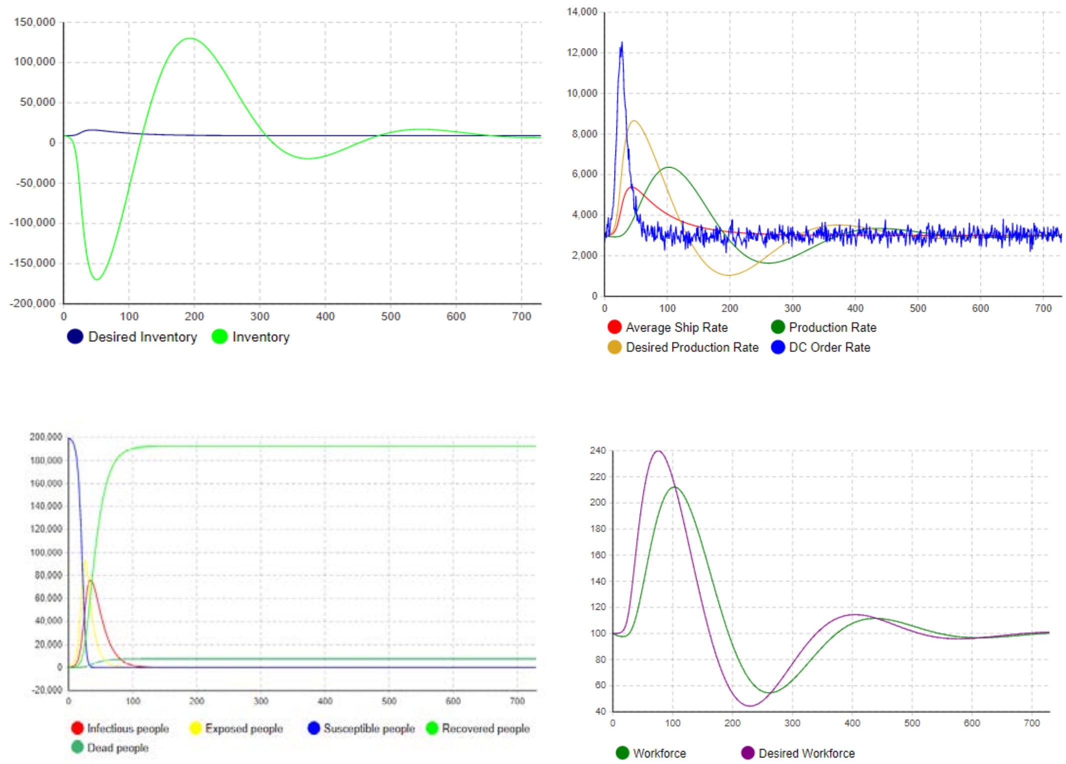

Figure 3. SC performance in Scenario I.

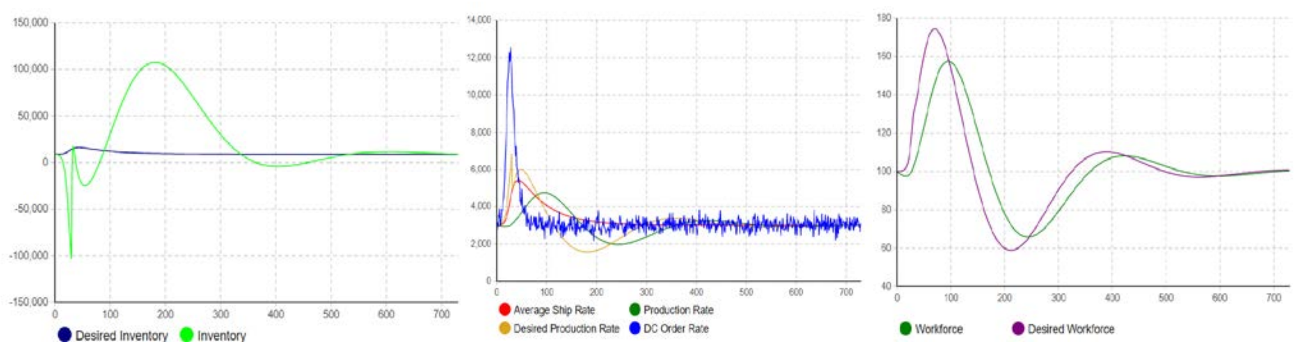

Figure 4. SC performance in Scenario I with risk inventory.

***Scenario II** : SC disruption by unexpected pandemic demand (one wave with N susceptible followed by a second wave with new 100000 susceptible)*

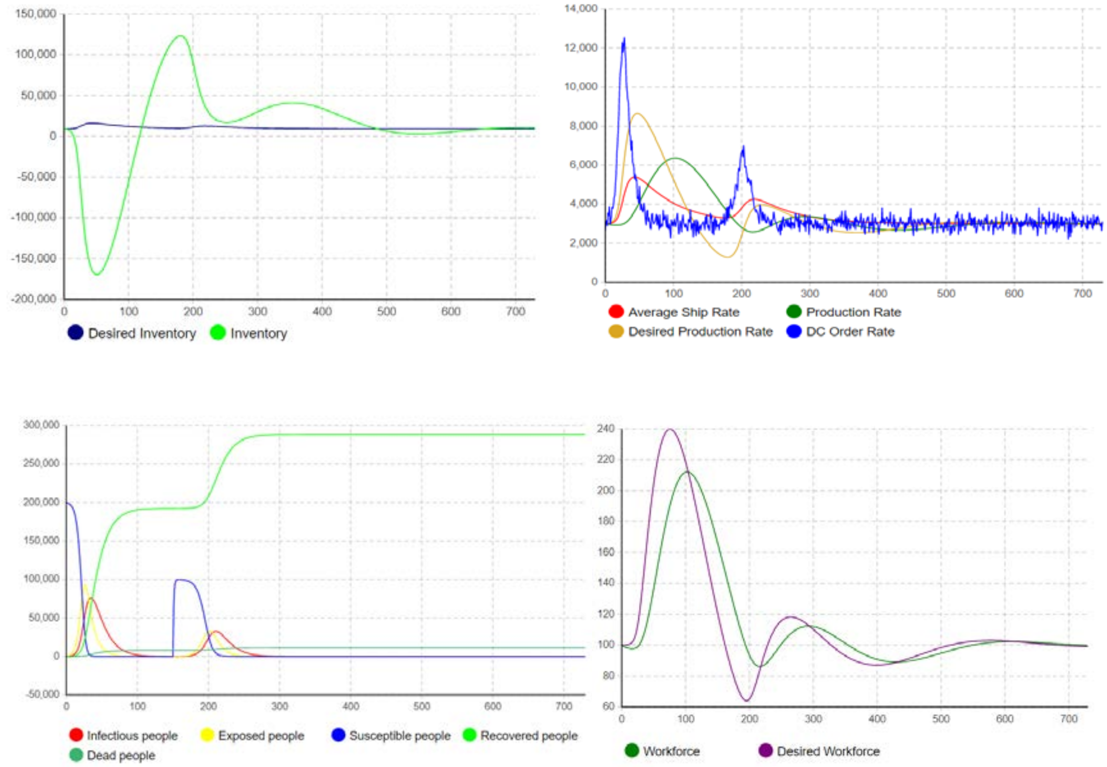

Figure 5. SC performance in Scenario II.

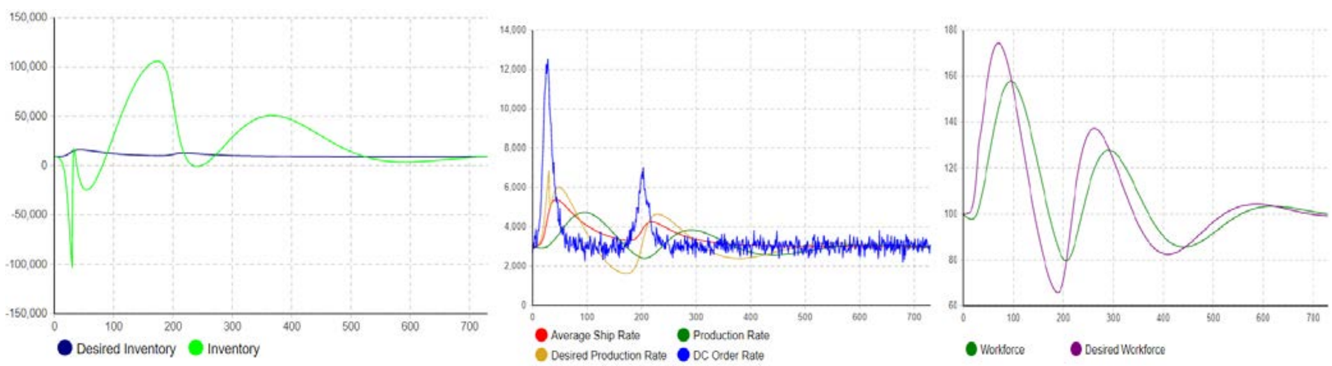

Figure 6. SC performance in Scenario II with risk inventory.

***Scenario III**: SC disruption by unexpected pandemic demand (one wave with N susceptible) and 4 months with 50% decrease in the production capacity due to a reduction in the number of workers.*

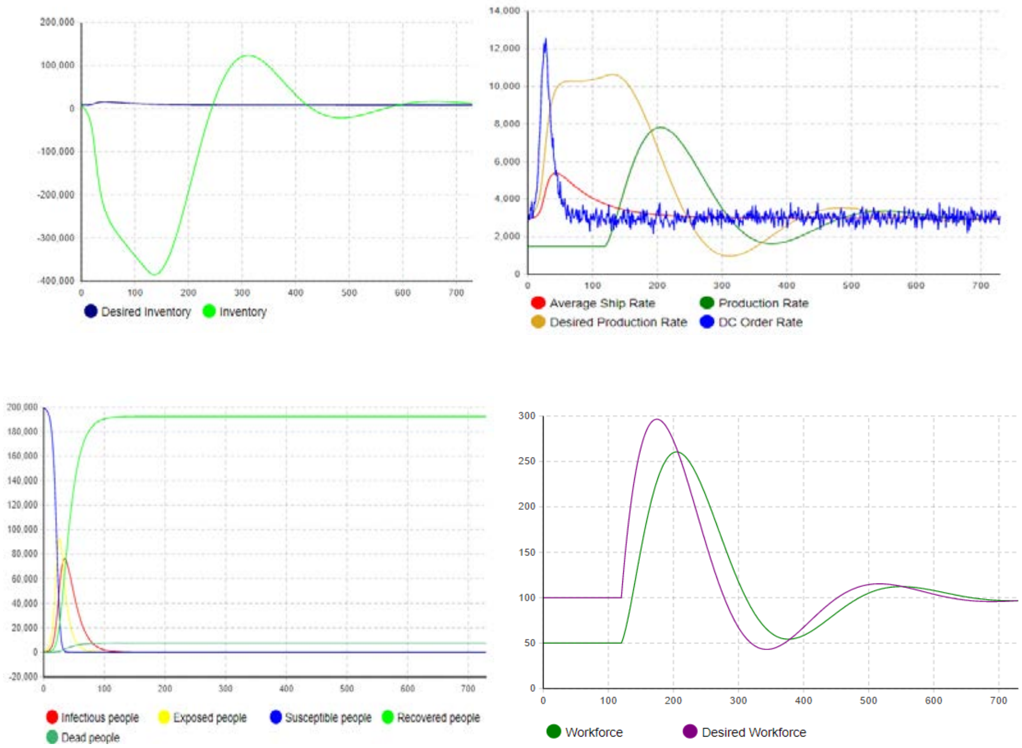

Figure 7. SC performance in Scenario III.

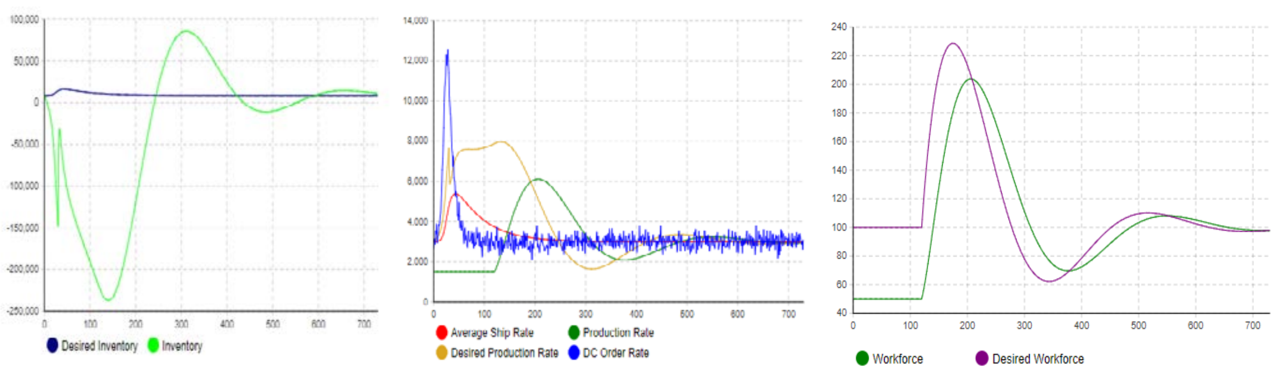

Figure 8. SC performance in Scenario III with risk inventory.

***Scenario IV**: SC disruption by unexpected pandemic demand (one wave with N susceptible) and a complete shutdown of production for 4 months due to disruption in the supply of raw materials.*

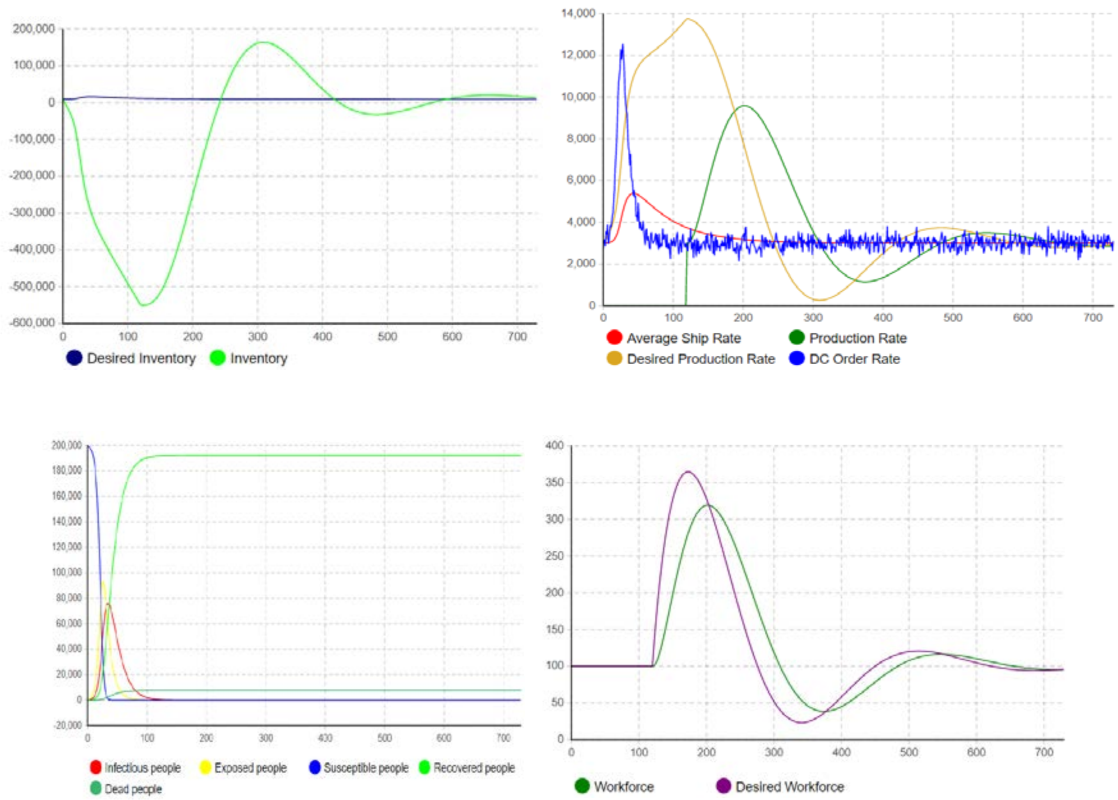

Figure 9. SC performance in Scenario IV.

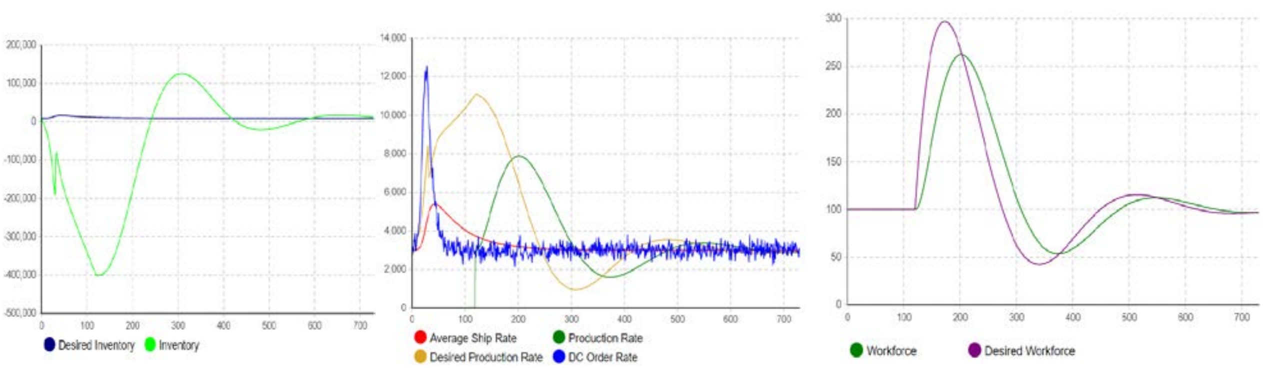

Figure 10. SC performance in Scenario IV with risk inventory.

In general, when analyzing the result in the given scenarios, we notice oscillations and distortions in the SC behavior which is expected due to the nature of disruption. The exponential growth in the number of COVID-19 cases has introduced an unexpected increase in the demand of product X, causing a continuous decline in the inventory. During the period of inventory decline, the outflow of inventory exceeds the inflow coming from production, resulting in the accumulation of backorders. The accumulation of backorders creates enormous pressure to increase production. This pressure is very clear in desired production which exceeds actual production rate in all scenarios. This disruption creates a chain of serious reactions due to the adopted policy and current state of the manufacturing SC. The management relies on the desired production when planning for workforce because production capacity is mainly constrained by number of available workers. To meet pandemic demand, the company hires more workers cautiously. Therefore, the desired workforce increases gradually in response to desired production. This delay in hiring affects production rate and then feeds back through inventory to amplify desired production, which in turn raises the desired workforce. As simulation continues, the negative feedback loop in SD system constantly corrects the imbalances by driving production rate, inventory level, and workforce toward their desired levels. As the imbalance between actual and desired levels narrows, the amplitude of fluctuations lessens, and the oscillations die out eventually.

The simulation results show both the short-term and long-term impacts of the pandemic on the manufacturing SC performance. Some of the interesting findings and insights learned from the SD model are discussed below. For instance, the production reaction appears to be proportional to the length of disruption in all scenarios. Moreover, the combination of two disruption events decreases performance. Interestingly, this does not apply to scenario II in which the overstocking results from a sudden increase in inventory after the first wave is utilized in the second one. This helps in reducing the fluctuation and recovery time. Furthermore, despite the difference between scenarios III and IV, they show similar behavior. This is because they have the same disruption duration, and the production is driven by the number of workers. Although operating with 50% capacity reduces the accumulation of backorders, it does not significantly contribute to reducing the number of stockouts (shortage) periods. Finally, having risk mitigation inventory available significantly reduces the number of workers and inventory in all cases. However, the effect of risk inventory on reducing shortage periods is not significant in scenarios III and IV due to the lengthy period of disruption. To get the most benefits from risk inventory, the amount of this emergency reserve needs to be optimized and adjusted for different situations but this beyond the scope of this study. The company should revise its lean policy; the benefits of being lean should not limit its ability to respond in a crisis such as COVID-19.

In order to compare the selected scenarios using more appropriate measures, a comparison of the observed service level is shown in Table 3. The following formula is used to compute the service level:

$$Service\ level = 1- \frac{number\ of\ stockout\ periods}{number\ of\ periods} \tag{1}$$

Table 3**.** Service level for disruption scenarios with and without Risk inventory

Scenarios	**Service Level**	**Service level with risk inventory**
I	0.65	0.87
II	0.86	0.91
III	0.49	0.51
IV	0.48	0.48

The outputs of the simulation model are used to train ANNs. For the sake of simplicity, we use the data generated by simulation from the scenario I in Figure 3 to provide a proof of concept.

4.3 Predicting inventory level time series using NARX model:

The entire dataset generated by SD model has been suitably divided into two datasets (65% for training and 35% for testing). The NARX model is used to predict future values of inventory level $y(t)$ from past values of inventory time series and past values of other time-series data $x_i(t)$. The performance of the developed prediction models is evaluated using the Root Mean Squared Error (RMSE) and Correlation Coefficient (R) statistic. For building the NARX model, MATLAB (R2020a) is used.

A network with only one hidden layer has been used while varying the corresponding number of neurons at four levels (5,10,15&20) to avoid reporting biased results. The developed models were first trained in the open-loop structure. Open-loop (series-parallel configuration) allows more efficient training than closed-loop (parallel configuration) training by providing the network with correct past inventory level $y(t)$ during the training phase to produce the correct current inventory level $y(t)$. Figure 11 shows the NARX network design and training process. The training phase is stopped if any of the following conditions occur: (1) the estimation error is below the default target (2) the model performance reaches an acceptable level; (3) it reaches the maximum number of epochs. One sample of the NARX with ten hidden neurons used in open and closed-loop structures is displayed in Figure 12.

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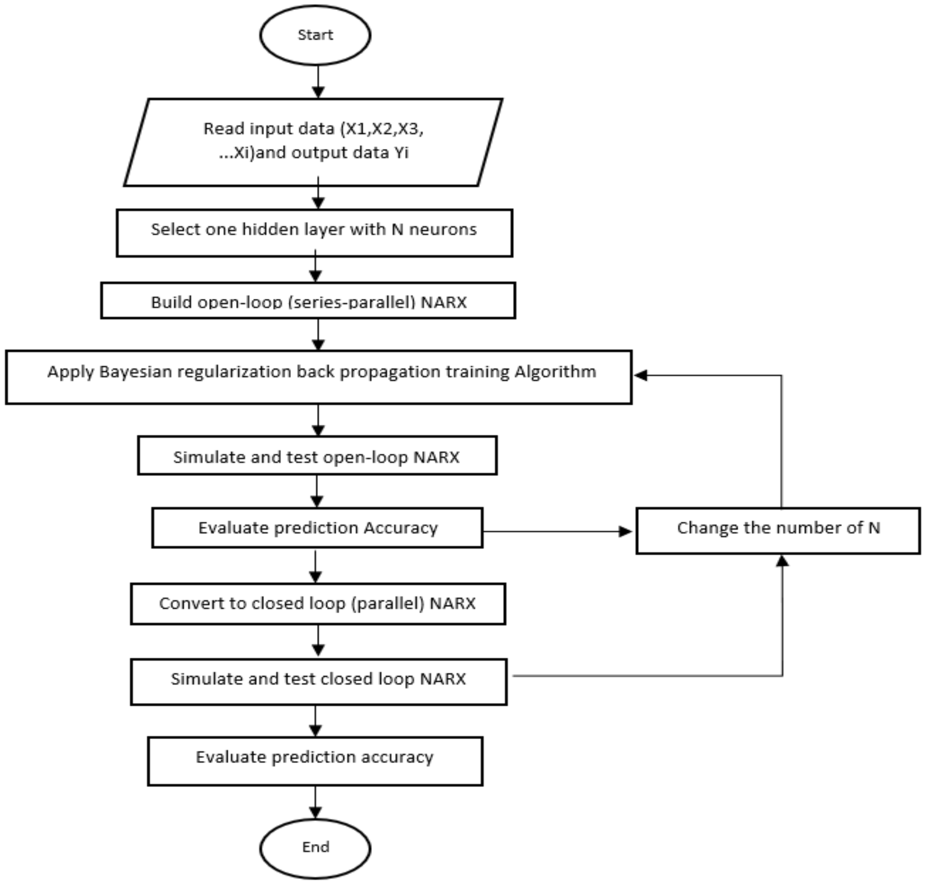

Figure 11. NARX network design and training

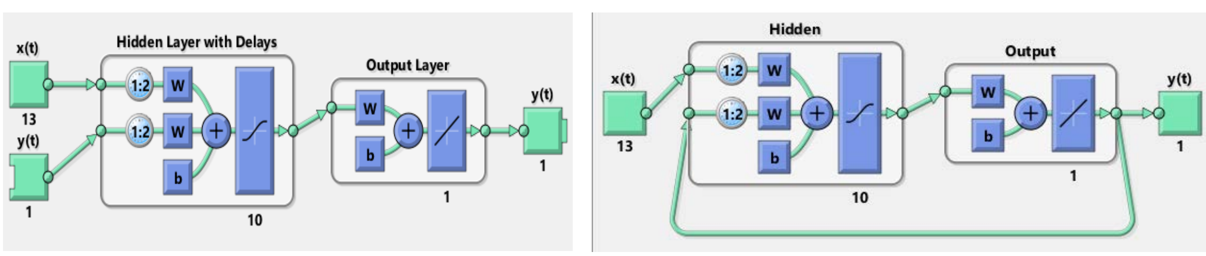

Figure 12. Series-parallel and parallel configurations for one sample of NARX

After training NARX for 100 epochs in an open-loop structure, we convert the network from an open-loop to a closed-loop structure by replacing the feedback input with a direct link from the output layer. The closed-loop configuration enables the network to perform an iterated prediction task over many time intervals. In this closed-loop structure, the network is only given the initial inventory level, and then uses its own predicted values recursively to predict new levels of inventory. Figure 13 graphically represents the closed-loop NARX's response. The degree of error expressed as the difference between predicted and actual values is also displayed in the same figure. Even though visual representation shows the goodness of fit, RMSE and R are calculated for both training and testing datasets to quantitively support the claim. Table 4 shows the result of NARX for all network configurations.

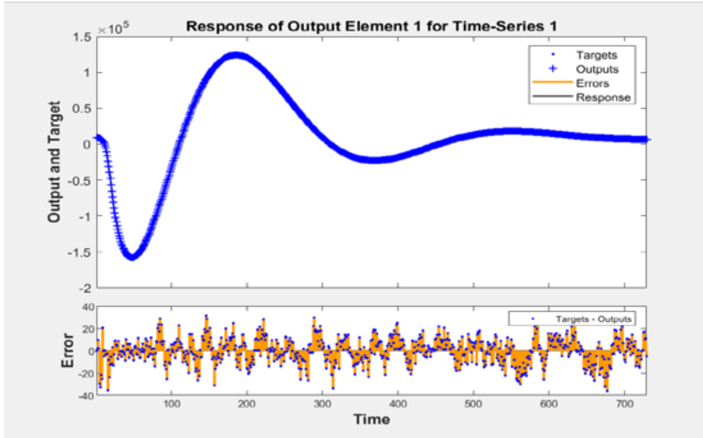

Figure 13. One Sample of Bayesian regularized closed-loop NARX performance

Table 4. RMSE & R for different network structure using two days delay

Number of neurons in the hidden layer	Training MSE	Training RMSE	Training R	Closed-loop Testing MSE	Closed-loop Testing RMSE	Closed-loop Testing R
5	85.261	9.233	0.9999	461.038	21.471	0.9892
10	81.676	9.037	0.9999	466.165	21.590	0.9871
15	78.119	8.838	0.9999	513.281	22.655	0.9801
20	78.693	8.870	0.9999	564.217	23.753	0.9799

The best prediction results are achieved with a network with five neurons in the hidden layer. Based on the obtained result, the NARX model has the potential to capture the dynamics of the manufacturing SC. This affirmation is based on the negligible RMSE values and the high R values for both training and test data for all cases. The closed-loop NARX helps the SC system to anticipate inventory deviation from defined targets dynamically and reduce action delays for feeding the system back with prediction. This can work as an early warning system at the proactive level and give the manager the ability to adjust plans and minimize the adverse effects of not having inventory available on hand in situations like the COVID-19 pandemic.

5. Conclusion

In this paper, a methodology for implementing the concept of digital SC twins to analyze and predict the impact of disruptions on the manufacturing SC of essential items is demonstrated. The digital SC twin model is aimed to operate in real-time using the knowledge obtained from SD and analyzed by ANN for early identification of disruptions and the respective SC reaction patterns to increase SC visibility and resilience. The proposed methodology takes advantage of the modeling flexibility in SD to capture complex behavior in manufacturing SC and the capability of ANN to recognize patterns for real-time monitoring and control. The analysis of SD showed both short-term and long-term impacts of the pandemic on the manufacturing SC performance under different scenarios. The effectiveness of having a risk mitigation inventory in each scenario is evaluated. The results of SD highlighted the importance of examining COVID-19 disruptions in an integrative way considering the dynamics of SEIR and manufacturing SC. The developed NARX model is used to work as a lightweight approximator of a more complex and resource-intensive simulation model. NARX model trained with Bayesian regularization showed good generalization and performance when tested on inventory time series dataset. This model can work as online controlling towers to monitor the SC environment and make the necessary predictions to help the SC system maintain its stability in disruptions using online SC feedback data from IoT and RFID.

While this study has several implications for SC risk management practices, this study also has few limitations. First, the design of the case study is not complex to address the full impact of the COVID-19 pandemic on the global SC network. Second, comparing the performance of ANNs to other machine learning algorithms would make this study more complete. In

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the future, this study can be extended by increasing the complexity of manufacturing SC network design to include more nodes at different echelons. Another possible extension is using simulation to train an AI agent to make online optimization decisions. In addition, different risk mitigation strategies such as backup supplier and redundant capacity can be considered in future extensions.

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