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Digital Supply Chain Twins: System Dynamics and Artificial Neural Networks Modeling Approach for Analyzing the Impact of COVID-19 Pandemic on the Supply Chain Performance

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Abstract: As the number of COVID cases in the U.S continues to grow, the resilience of supply chains (SC) have been put to the test. SCs around the world have faced a series of shocks caused by the pandemic. Currently, there is an unprecedented increase in the demand for medical supplies. As such, the questions of SC and society survivability were raised. In this research, we address the impact of COVID-19 disruption on manufacturing SC overwhelmed by the unprecedented demands of urgent items by creating a digital SC twin 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 develop ANN models to learn from disruptions and the observed SC behavior. The developed digital SC twin model is aimed to operate in real-time using the knowledge obtained from SD and analyzed by ANNs 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, System Dynamics, 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 supply chain (SC) vulnerability and exposure to new risks such as terrorist attacks, natural disasters, geographical risks or epidemics (Kumar & Eickhoff, 2005). There are many concerns for such vulnerabilities. One of these concerns is the current unfathomable outbreak of COVID-19, which has damaged the lives of people and economic activity globally. 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 result in delays and shortages that spread 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).

The availability of medical supplies such as face masks, personal protective equipment, hand sanitizer, etc. has become essentials. 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 SC stability and performance. The outbreak disruption can destabilize the SC, causing oscillations in product demand, inventory level, and production rate. 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 aimed the pandemic when many companies needed to manage risks in their supply and demand very quickly (Ivanov, Dolgui, & Sokolov, 2019). Such an advanced 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 make use of advanced analytical models such as simulation and data-driven models to support the decision-making process in SC risk (Ivanov and Dolgui, 2020). SC risk managers would benefit from advanced analytical tools by predicting the possible impact of disruptions and SC reactions and taking advantage of real-time data for efficient contingency planning. However, the investigation of SC digitalization for managing disruption risk is still in its infancy (Ivanov and Dolgui, 2020). It is motivating to study how the utilization of these advanced analytical 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 demands of urgent items by creating a digital SC twin 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 develop ANN models to learn from disruptions and the observed SC behavior. The developed digital SC twin model is aimed to operate in real-time using the knowledge obtained from SD and analyzed by ANNs for early identification of disruptions and the respective SC reaction patterns to increase SC visibility and resilience.

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 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 the gathering of 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).

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 the case of COVID-19 dictates the use of simulation models to gain some understanding on 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. There is an urgent need to link epidemiological models with SC models to address this challenge.

2.3 System Dynamics Simulation

SD modeling was created in the 1950s by MIT professor Jay Forrester (Forrester, 1997). Drawing in his background in science and engineering, 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. The reason for selecting SD approach in this study is that SD modeling is a very effective tool for simulating feed-back and capturing changes to a dynamic system over time, which makes it suitable for monitoring the disrupted SC continuously (Aguila and ElMaraghy, 2020). This feature is not available with specific 'snapshot in time' modeling techniques such as discrete event simulation and agent-based modeling. 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.

2.3 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 (FFANN) and the recurrent artificial neural networks (RANN). The FFANN has no feed-back 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 feed-back 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 abilities to handle unstable or incomplete data, approximation power, and pattern recognition is an effective approach for predicting and detecting changes in SC behavior under both 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, ANN can be trained to predict risk patterns based on preidentified example patterns in supervised learning.

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3. Research Methodology

Different simulation models can be connected to study the impact of infectious disease on 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. The estimated demand is continuously fed into the manufacturing SC operational model to create demand disruption in real-time. The reason for connecting two simulation models is to create SC risk data similar to the ones that could come from IoT and RFID systems in the digital SC twins. We assume that the demand for the essential item or product is driven by the increase in the number of infected people. We use the SEIR (Susceptible – Exposed – Infectious– Recovered) model, which is one of the most popular epidemiological models used for estimating the number of infected individuals and describing the dynamics of the disease outbreak. This model has been frequently used to model the spreads of COVID-19 (Fang et al., 2020). In this research, we rely on SD simulation to (1) simulate and quantify the impact of the disease outbreaks on SC performance, and (2) generate structured, clean and labeled data required to support the application of ANN models in SC risk analytic. Anylogic 8 University software is used to build the SC simulation model. We use MATLAB (R2020a) to develop ANNs models.

Using the data generated by the SD simulation, we develop ANN models to learn from disruptions and the observed SC behavior. The learning component in ANN is an essential feature in digital SC twins. 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 control. The developed ANN models learn from SD simulation model to identify and detect the disruptions and changes in the behavior of different SC key parameters such as retailer demand, inventory levels, production capacity, worker availability, and shipment quantity. The ANNs are trained to work online as controlling towers for monitoring the SC environment and making the necessary predictions to help the SC system maintain its stability in disruptions using online SC feed-back data, e.g. from IoT and RFID. We use recurrent artificial neural networks (RANN) to tackle the SC time series problem.

Our modeling approach allows for better use of simulation outputs. The generated data used in ANNs models is almost free of measurement bias. This is true since every aspect of the virtual SC system is controlled, and all the recorded outputs are direct readings of SC operations, not estimates or approximated measurements. This feature can be effectively used for training, testing and fine-tuning machine learning and ANNs models because there is absolute confidence that the input data, and its labels, are not affected by measurement errors or irrelevant external factors. Moreover, instead of only relying on the SD simulation results to adjust the SC operations to achieve stability for a specific time, the use of ANN adds on the knowledge obtained from SD results. So, the decision-makers can take advantage of the ANNs parallel processing power to predict outcomes of proposed changes in SC operations and unexpected events at a very early stage so that a company would have enough time to respond and mitigate the severity of unwanted disruptions.

3.1 The use of Recurrent Artificial Neural Networks

The non-linear SD model produces a complex SC data time series. Due to operational constraints, information smoothing, feed-back, and delays, the changes in the SC output (e.g., Inventory level) is not proportional to the change of the inputs. In the case of COVID-19, predicting changes in essential items inventory can bring reliability and stability to SC, giving the managers the ability to adjust their operations accurately. 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 (achieve the desired level). In this paper, we utilize the Nonlinear Autoregressive models with exogenous input (NARX) to model SC inventory time series. This type of network 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). When predicting time series data, RANN models tend to overfit when the size of the training data set is not large enough to generalize the error. Therefore, we use the Bayesian regularization as a way to improve network generalizability of the NARX model. Bayesian regularization allows reducing the number of ineffective parameters used in the model and measuring the uncertainty in the predictions which is missing from the current RANN architectures (Tian & Noore, 2004).

4. Experiment and Results

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) to test our approach. The model is focused on the dynamic behavior of a single link in the manufacturing SC system and is composed of the following sub-models: (1) supplier-retailer sub-model, and (2) workforce sub-model. We connect the SEIR model to this manufacturing SC model to create real-time demand disruption. We also use the connected SD models to test some possible disruption scenarios that might happen during the pandemic outbreak. The implementation of SD model shows long and short terms implications of a pandemic impact on a SC system. To comply with page requirements, we show the simulation output for one scenario in which SC disruption is caused by unexpected pandemic demand only. Figure 1 shows the connected SD models and the simulation output.

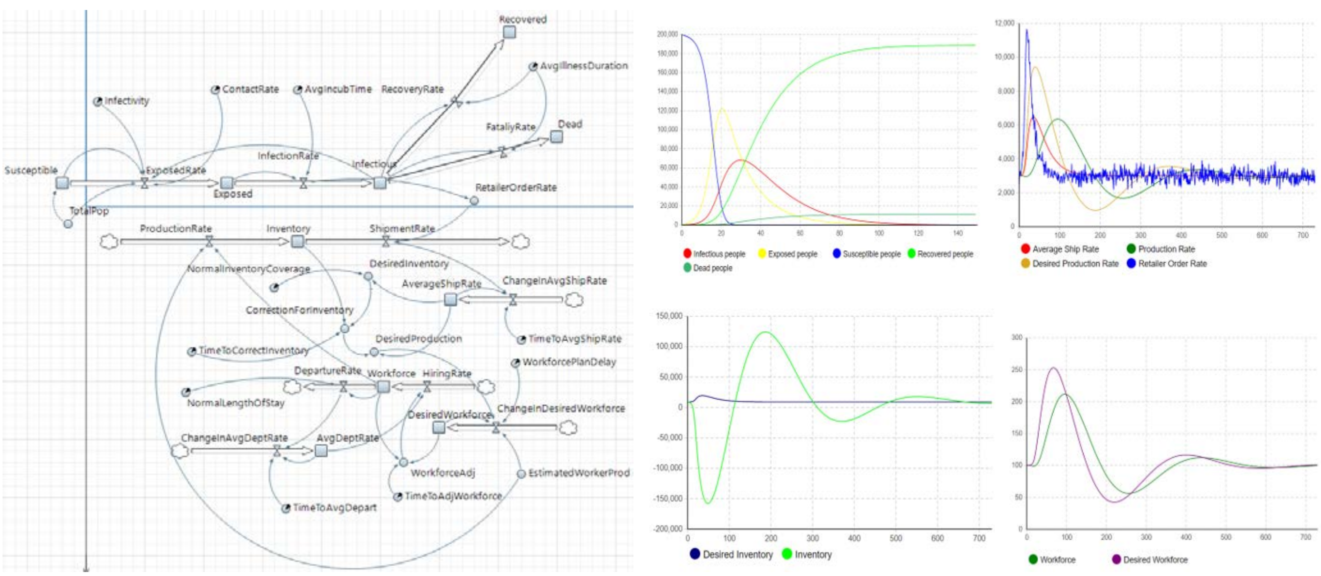

Figure 1. SD models and simulation outputs

The connected SD models can help companies in answering questions related to pandemic outbreaks such as the impact on performance, time needed to recover, and most critical scenarios of pandemic disruption. The observed service level is 67% in the demand disruption scenario. The degradation in the SC performance is critical. It takes the manufacturing SC around two years to fully recover. The SD modeling provides a disruptive method for the digital SC twin to understand, visualize, and evaluate the sequence of factors that can balance and stabilize SC operations in case of pandemic disruption. Fourteen variables in SD model are chosen to build the NARX model.

4.1 Predicting Inventory Level Time Series using the NARX model:

The entire dataset for two years has been suitably divided into two datasets (65% for training and 35% for testing).. The performance of the developed prediction models is evaluated using the Root Mean Squared Error (RMSE) and Correlation Coefficient (R) statistic.

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 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). The training phase is stopped if : (1) the estimation error is below the default target (2) the model performance reaches an acceptable level; (3) it reaches the maximum number of iterations. One sample of the NARX with ten hidden neurons used in open and closed-loop structures is displayed in Figure 2.

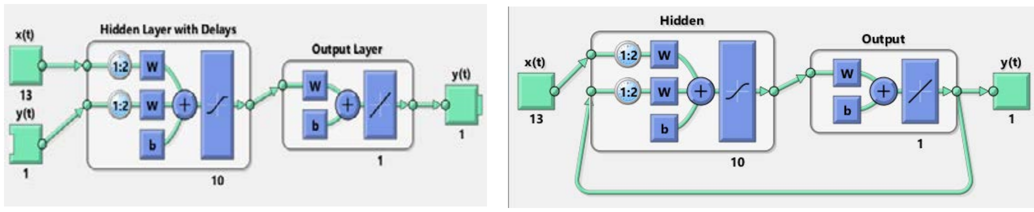

Figure 2. Series-parallel and parallel configurations for one sample of NARX

After training NARX in an open-loop structure, we converted the network from open-loop to closed-loop structure by replacing the feed-back input with a direct link from the output layer. The closed-loop configuration enables the network to perform an iterated prediction tasks over many time steps. 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 3 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 were calculated for both training and testing datasets to quantitively support the claim. Table 1 shows the result of NARX networks for all configurations.

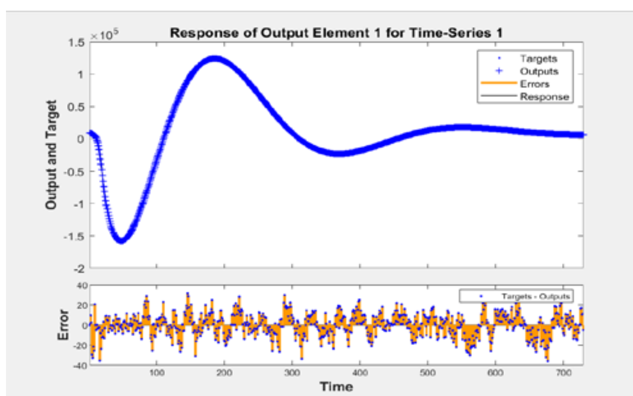

Figure 3. One Sample of Bayesian regularized closed-loop NARX performance

Table 1. 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

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The best prediction results were 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 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 would give the manager the ability to adjust plans, and therefore minimize the negative effects that come from not having inventory available on hand.

5. Conclusion

In this paper, we demonstrated a methodology for implementing the concept of digital SC twins to analyze and predict the impact of COVID-19 on SC performance. Every SC is unique and may react differently to certain risks. We examined through an SD simulation how the disruption in demand for an urgent product can affect the SC of essential supplies. The analysis of SD showed both short-term and long-term impacts of the pandemic on the manufacturing SC performance. The degradation in SC performance is significant, particularly under the pandemic outbreaks. The worst SC performance was observed under the disruption in demand and production during the pandemic duration. Such analysis can be useful for companies in developing a contingency and strategic business plans for effectively reacting to the major risk posed by COVID-19 on their SCs in the future. We developed ANN models to learn from disruptions and observed SC behavior in the SD. The gained knowledge can be applied for controlling and monitoring the SC environment in real-time to help maintain its stability.

We argued that by enabling visibility through adapting digital SC twins, situations that could result in disruptions could be identified and mitigated long before they reach critical condition. The combination of simulation and ANN creates the full stack of technologies required to build a model for SC digital twin. Integrating this virtual model with a live data stream will enable the concept of self-learning digital SC twin in Industry 4.0. The self-learning digital SC twin represents SC state for any given moment in time and allows for a visualization of SC risks, evaluation of disruption risks, and prediction of possible SC behavior. It can self-assess its own health and degeneration and further use information from advanced analytics for making smart decisions to avoid potential issues. In a self-learning digital SC twin, real-time data is continuously captured, updated and analyzed to identify or adjust the difference in planning parameters and learn what factors lead to SC failures and offers insight into the disruptions problem to support the decision-making processes. Depending on the type of and extent of the risk analysis in SC, different digital twin models can be created using the proposed methodology.

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