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Development of a framework to support informed shipbuilding based on supply chain disruptions

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Abstract

In addition to stresses induced by the Covid-19 pandemic, supply chains worldwide have been growing more complex while facing a continuous onslaught of disruptions. This paper presents an analysis and extension of a graph based model for modeling and simulating the effects of such disruptions. The graph based model combines a Bayesian network approach for simulating risks with a network dependency analysis approach for simulating the propagation of disruptions through the network over time. The initial analysis provides evidence supporting extension to for using a multi-layered approach allowing for the inclusion of cyclic features in supply chain models. Initial results for individual layers and the aggregate model are presented and discussed. The paper is concluded with a discussion and recommended directions for future work.

Keywords: Supply chain; Risk and disruption analysis; Modeling and Simulation; Functional dependency analysis; Graphical models

1. Introduction

As global supply chains strive to recover from the ongoing Covid-19 pandemic, manufacturers, including those in shipbuilding, continue to face an onslaught of additional disruptions. These disruptions have included cyberattacks [1], shortages in raw material [15], and misestimation of demand [28]. All of these events are occurring at a time when the number, variety, and complexity of interconnected systems is increasing while requirements for leaner practices and implementations are decreasing [27]. This results in fewer opportunities to increase system resilience. The characteristics of this current environment have forced manufacturers to consider novel ways to counter disruptions including assessing longer term effects especially regarding larger string of events that may be composed of smaller

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individual events [17], reconsidering investments in lower supply chain tiers [7], and carefully assessing the effect of ripple effects [19].

Particularly in the shipbuilding industry which has been fraught with cost overruns and schedule delays [25], developing a more holistic model of manufacturing supply chains and component installation processes, including suppliers at the lowest tiers, can help drive investments targeted at increasing resilience [5]. In light of this problem, one approach is to design and implement a framework that allows for the quantification of risk [4]. Once risks are identified and quantified, the overall manufacturing process can be reconfigured and optimized in the interest of maximizing resilience. In particular, graphical frameworks have been proposed that combine causal methods with dependency network analysis [23].

1.1. Structure

The remainder of the paper is organized as follows. Section 2 provides background on disruptions, risk, and resilience in supply chains. Section 3 presents a comparative analysis of network dependency analysis to discrete event simulation. Section 4 introduces a multi-layer framework to incorporate cyclic features such as supply and demand. Section 5 concludes the paper and provides recommendations for future work.

2. Background

There is a significant body of previous work focused on modeling supply chains and their disruptions. Before discussing specific approaches that address the previous considerations, some general definitions will be provided. Risk in supply chains is understood as the likelihood of a disruption to impact performance [2]. Resilience is commonly understood as the ability of a supply chain, or one of its entities, to tolerate some disruption and the speed with which it is able return to normalcy [22]. This definition of resilience can be broken down into three different resilience capacities a system can demonstrate, i.e. adaptive, absorptive, and restorative [13]. Per Hosseini, *et al*, these three capacities describe the ability to absorb a disruption without taking any extraordinary action, to adapt during the occurrence of disruptive events in an attempt to prevent further disruption, and to restore normal operation after performance is lost due to disruption, respectively.

As supply chain research has recognized the importance of considering how disruptions move through supply chains, the study of the ripple, or domino, effect has become more prevalent. The ripple effect is defined as the propagation of a disruption to other entities of the supply chain [6]. When modeling the ripple effect, it is important to capture many supply chain entities while simultaneously modeling causal interactions between risks. Bayesian networks have successfully been applied to model the ripple of disruptions through complex systems such as supply chains [12] and produce quantified measures of resilience [11]. One benefit of these models is that they provide a causal representation for networks. Another is network characteristics can be learned from limited data, or subject matter expertise, incorporated in the form of priors with the opportunity for additional data to be incorporated as it becomes available increasing the accuracy of the model [18]. One problem with these approaches is that both exact and approximate algorithms for forward post-learning inference demonstrate nondeterministic polynomial-time hardness (i.e., they are NP-Hard [3]) which directly limits efforts to evaluate complex systems in real-time [10]. This shortcoming is especially restrictive as the ability to model a greater number of supply chain entities from raw material suppliers to consumers, running analysis in real time using live data, and evaluating multiple interventions to increase stability have been revealed to be increasingly important. This limitation has confined researchers to studying small or less complex supply chains while acknowledging that additional work is needed [14, 12]. Additionally, most applications of graph theory, including Bayesian networks [12], and other approaches [27], neglect the temporal component of disruption propagations. Approaches to overcome this limitation include dynamic Bayesian networks and Markov chains [14]. Of particular interest to this work is are approaches that combine a less computationally expensive approach with Bayesian networks in order to evaluate more complex models [23].

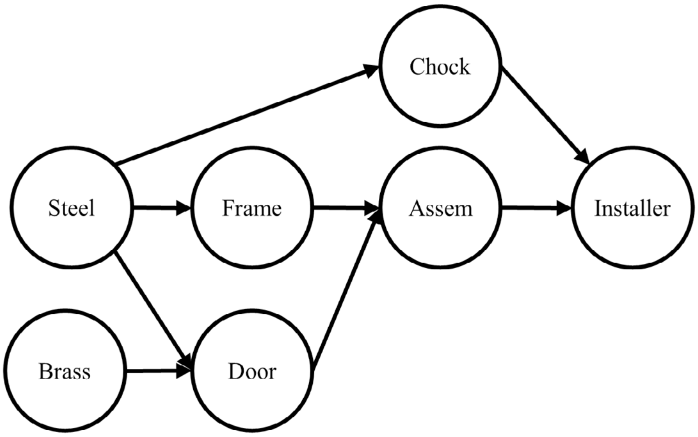


Fig. 1. Simplified network representing the supply chain for a watertight door on a ship.

3. Motivational Example

This section provides preliminary analysis to determine if network dependency analysis is sufficient to further support and inform the design and development of the current work.

3.1. Initial Example and Motivation

A theoretical supply chain for a watertight door on a Naval vessel will be used as an example throughout the remainder of this section. Watertight doors are special maritime closure devices that have specialty latches and gaskets to prevent the flow of water from one shipboard compartment to another [16]. These doors have been the subject of multiple safety alerts from the United States Coast Guard [24]. The simplified supply chain that will be used for these examples is shown in Fig. 1.

Assumptions regarding watertight door installation for this simplified supply chain are consistent with the Naval Ships' Technical Manual on Structural Closures [26]. In Figure 1, the flow of products is mapped from raw material suppliers of steel and brass to the final installation step on board a vessel. Two items are needed for the actual installation. The first are steel chocks to strengthen the cut bulkhead into which the door is installed. The second is the door assembly itself. The door assembly is composed of a frame made from steel and the door made from steel and brass.

In this example, a naval vessel supplier has recognized that installation of watertight doors is on the critical path for the overall ship construction process. In reality, the listed components can be broken down further and additional raw materials are required. However, this simplified model contains enough complexity to explain all aspects of the current methodology without needlessly including additional complexities.

3.2. Evaluation of Network Dependency Analysis

Network dependency analysis is an analytical approximation of the overall complex behavior of systems with dependencies. Discrete event simulation is a competing approach that can capture additional complexities by modeling them at a user specified level of detail. However, these higher levels of detail can drastically increase simulation run times as well as the time and level of expertise required to build a specific model. With this in mind, a study has been performed to assess whether or not sufficient detail can be captured by a network dependency analysis methodology, specifically System Operational Dependency Analysis (SODA) [9], by comparing it to a more detailed discrete event simulation model. In general, network dependency analysis methodologies characterize the output of a given node as a piecewise linear combination of the outputs of the nodes it is dependent on and an internal health value for the node.

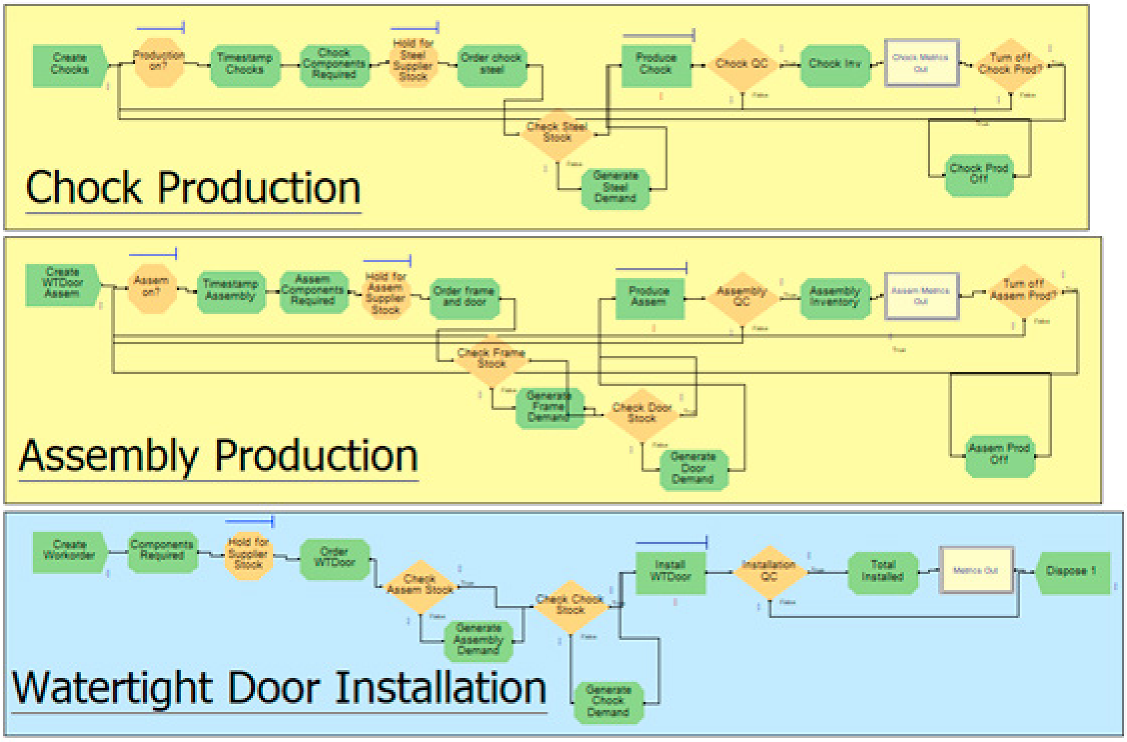


Fig. 2. Arena implementation for discrete event simulation of three-node watertight door example.

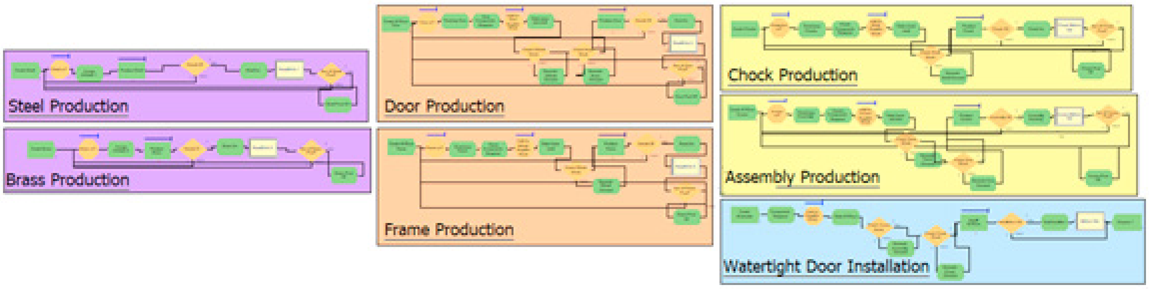
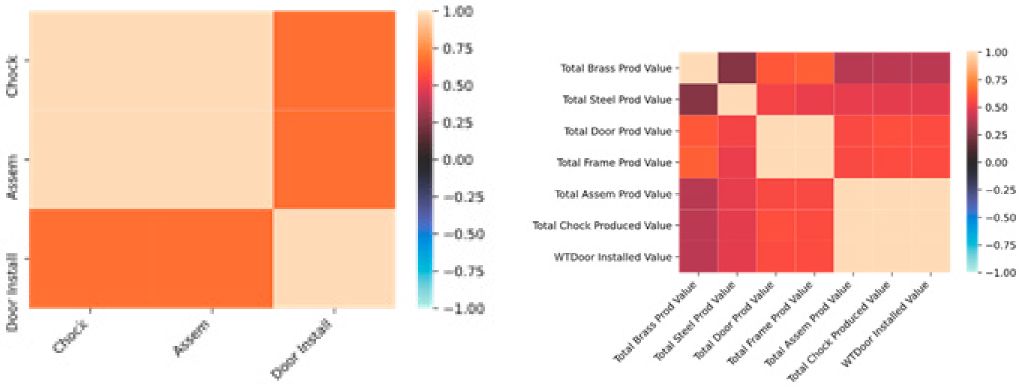


Fig. 3. Arena implementation for discrete event simulation of seven-node watertight door example.

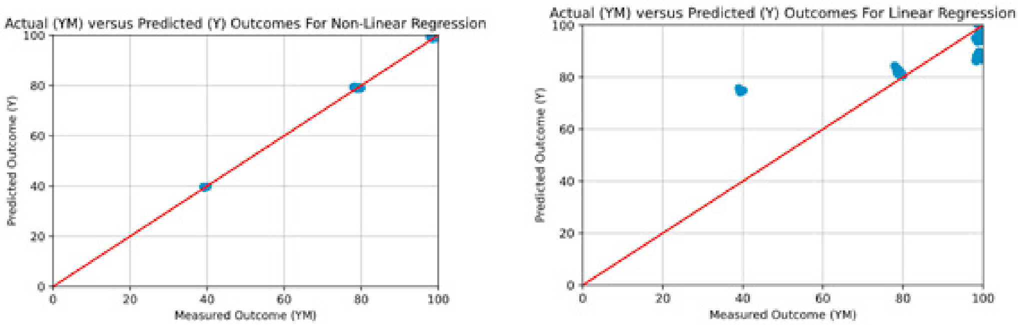
In order to assess the ability of SODA to capture the characteristics and behaviors of a supply chain model, the full seven node model (Fig. 3) and a three node submodel (Fig. 2) for the example from Fig. 1 were implemented as a discrete event simulation in Arena [21]. All suppliers were assumed to implement a (s,S) inventory policy. If current inventory was insufficient to fulfill a downstream order, the customer entity would wait for sufficient inventory to be produced. In order to implement different levels of performance, quality control nodes inspected each component produced and discarded those that were defective based on a two-way by chance decision with uniform probability.

It only requires a visual assessment to develop an initial understanding of the different in complexity between the SODA model and the discrete event simulation model. The 3 and 7 node SODA models are implemented as 43 and 91 module, or node, discrete event simulation models, respectively. Certainly, increased complexity should not have an exclusively negative connotation as implementing additional detail can enable the model to capture behavior that is closer to the real system. However in this case, the goal is to capture the overall behavior of the model while keeping the computational complexity manageable.



(a) (b)

Fig. 4. Heatmaps showing Pearson correlation coefficients for (a) 3 node and (b) 7 node simulation study.



(a) (b)

Fig. 5. Results for fitting to 3 node discrete event simulation using (a) SODA and (b) a linear model.

Before fitting the SODA model to the data generated by the discrete event simulation, it is interesting to look at heatmap plots of the correlation coefficients for the number of components produced by each node in the model. Fig. 4 shows the Pearson correlation coefficients for the correlation matrix for the (a) the 3 node model and (b) the 5 node model. It makes sense that all correlations are positive since the supply chain model forms a connected graph. It can also be seen that nodes that are in the same supply chain tier, as measured from the ship manufacturer are highly correlated.

Next, attempts were made to fit the SODA model to the simulated data generated by the discrete event model. For the 3 node model, number of chocks and assemblies produced were used as input variables while number of watertight doors installed was the corresponding output. Nonlinear regression with a user-defined loss function was used to approximate the coefficients for the SODA model. Results (Fig. 5) show the SODA model (a) is a superior model for the data when compared with a linear model (b). It is also worth mentioning that the points appear to form three clusters since the SODA model is defined as a three parameter piecewise linear model.

Finally, the SODA model was fit to the entire supply chain network. Coefficients were estimated at each tier of the supply chain. Fig. 6 shows the results of this analysis as the predicted target node productivity plotted against the values from the simulation (a-c) and the error plotted against the productivity of the input nodes (d-f). The SODA model provides a good fit between the first-tier suppliers and watertight door installer (c). However, the quality of the fit degrades when evaluating lower tier suppliers (a, b). Trends in residual plots can indicate issues with the underlying model. In the current example, the plots show heteroscedasticity which is often an indicator that an explanatory variable or other information is missing from the model.

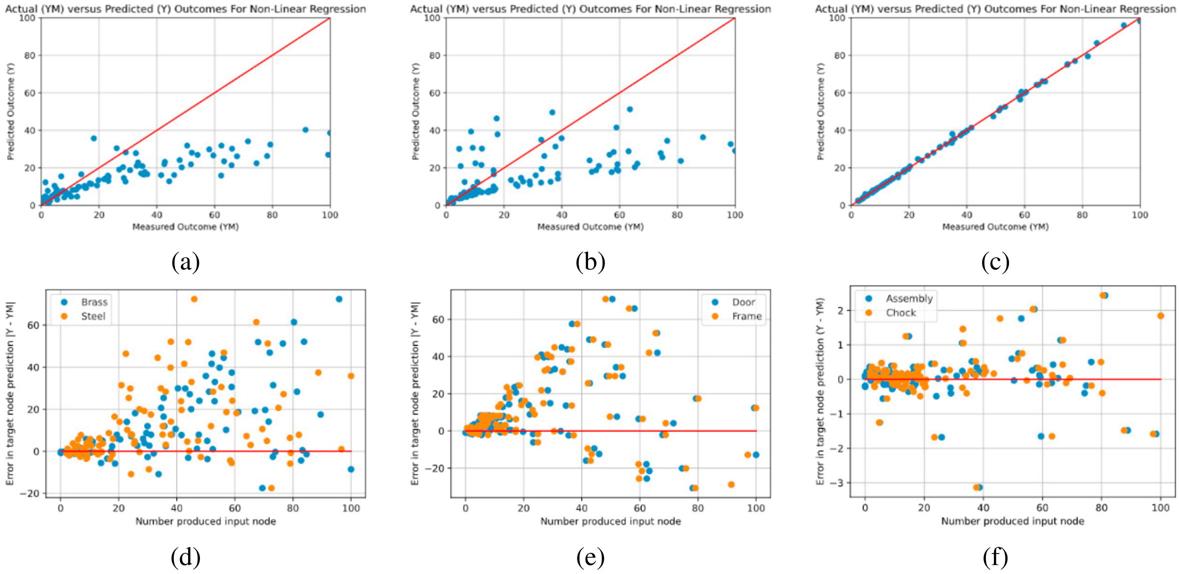


Fig. 6. Results from fitting SODA model to discrete event simulation data.

4. Multi-layered Approach

Consider introducing two layers with different topologies, namely supply and demand, as shown in Fig. 7. In general, the network structure for the dependency analysis model can change based on which outputs, or performance characteristics are considered. This, coupled with the overall sparsity of connections, means that implementing the process of calculating updated outputs is more natural to consider on a layered set of networks with each layer independently calculating the updates to one or more output parameters whose dependencies correspond to the given network structure. To simplify the explanations, it will be assumed that each output has a separate corresponding network layer. However, if the graphical structures of the corresponding network layers for two outputs are the same, these outputs can be combined into vectors and their updates can be computed simultaneously.

Consider again, the supply chain example for the installation of a watertight door. It was determined in the previous section that considering the supply chain network from only one perspective, for example available supply, inhibited the ability of the network dependency analysis model to capture the behavior of the lower tier suppliers. Now, it has been hypothesized that same supply chain network can be represented by two separate layers, i.e., supply and demand, each with their own network structure (Fig. 7). From an application perspective, this improvement allows for the consideration of two completely different perspectives, in this case a capacity-based and an information-based perspective.

The final consideration is how to handle aggregation of results into a final output that can be used to calculate the behavior of resilience over time. This methodology will assume that the specific choice of this aggregation function is application dependent. For example, in a supply chain operating under a “produce-to-order” inventory control policy, the number of items produced at a given node would be, in the best case, equal to the demand signal of the node and, in the worst case, equal to the supply capacity. Specifically, if the demand signal is s_d and the supply capacity is s_c, the output, s_o, can be calculated as:

$$s_o = \begin{cases} s_d & s_c \geq s_d \\ s_c & s_c < s_d \end{cases} = min\,(s_c, s_d) \tag{1}$$

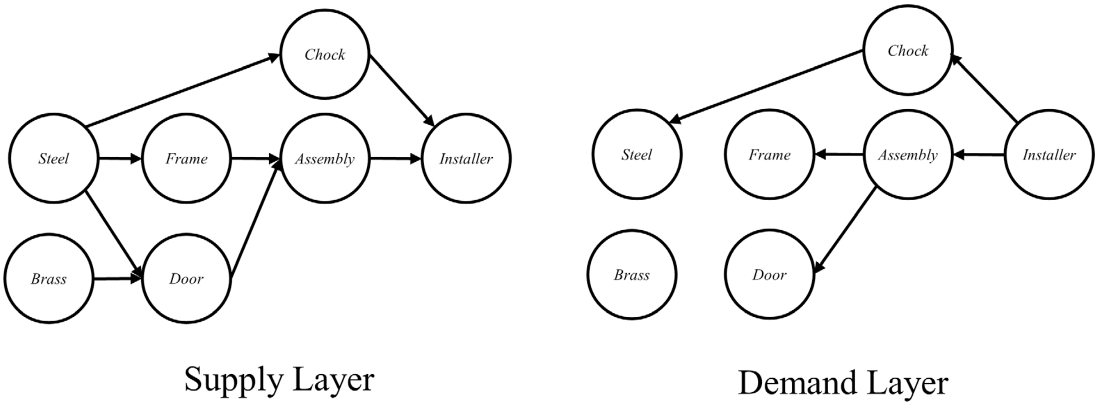


Fig. 7. Multiple network layers representing different characteristics of the watertight door supply chain.

Finally, the multi-layer model from Fig. 7 is used to produce some numerical results based on random disruptions in order to discuss aggregation methods and results. Traces of internal node health and output operability, or performance, for each layer as well as various aggregates for both layers combined.

For the simulation runs shown in Fig. 8, 9, and 10, there are several interesting observations that can be made. From the supply internal node health result (Fig. 8), steel and brass supply both experience disruptions shortly before time 2 due to an international supply chain failure effecting both steel and brass though the impact was greater on the brass supplier. Looking at the supply operability results, corresponding disruptions in the operability of the chock, frame, and door manufacturers show the ripple effect of this event through the supply chain.

For the demand results (Fig. 9), there is a disruption to installer demand shortly before time 6, but the installer's level of resilience allows the result of the recovery to be a new status quo where the overall demand is actually increased. In the demand operability plot, the assembly manufacturer's demand operability increases by nearly the same amount as the installer's operability.

Finally, looking at the aggregate plots (Fig. 10) using minimum (Eq. 1), average (Eq. 2), and maximum (Eq. 3) aggregation functions, the overall functionality of the network under different inventory assumptions is captured. Additionally, the supply and demand signals, s_c and s_d, respectively, are the operability values shown in Fig. 8b and 9b. Recall that for a "produce-to-order" inventory policy, the minimum aggregation function models the expected behavior. This relationship between aggregation function can also be linked to the decoupling point through the inventory policy [20]. It has been shown that decoupling point placement can affect performance indicators for supply chains, such as cost [8]. One example application of the results shown in Fig. 10 would be to investigate the impact of various decoupling points on the overall system performance as well as the performance of individual supply chain entities.

$$s_o = \frac{s_c + s_d}{2} \tag{2}$$

$$s_o = \begin{cases} s_c & s_c \geq s_d \\ s_d & s_c < s_d \end{cases} = max\,(s_c, s_d) \tag{3}$$

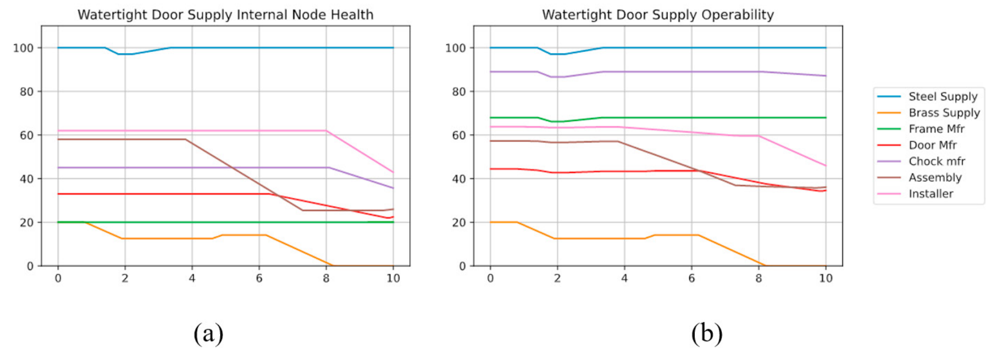


Fig. 8. (a) Internal and (b) external supply layer results for simulation run.

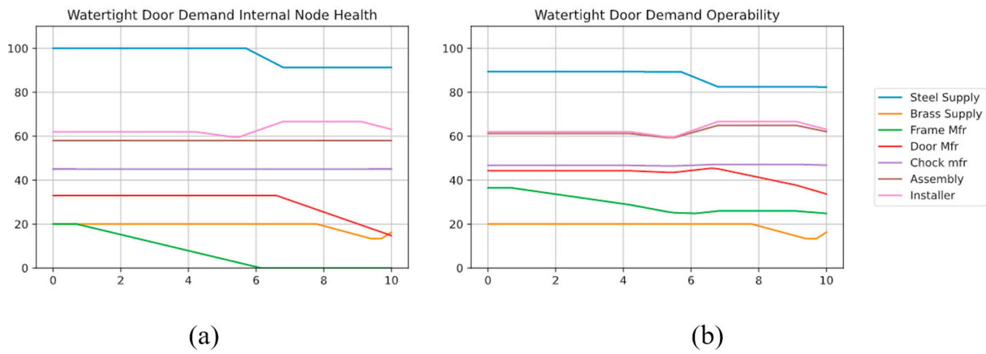


Fig. 9. (a) Internal and (b) external demand layer results for simulation run.

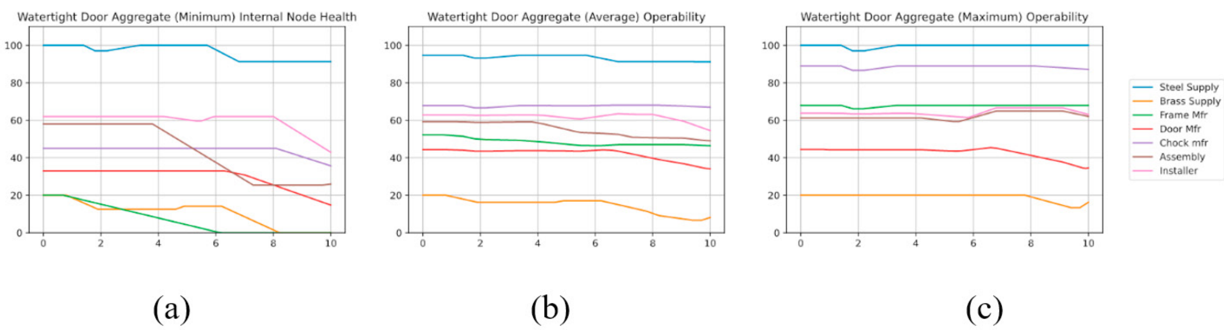


Fig. 10. Aggregated operability results using (a) minimum, (b) average, and (c) maximum aggregation functions.

5. Conclusions

Recent advances in technology and increasing globalization have increased the overall complexity of supply chains. When paired with multiple disruptions these escalations in complexity compound disturbances that are known to ripple through supply chains. Current approaches to analyzing these ripple effects are computationally complex and therefore difficult to apply to detailed supply chain models. This work has presented an analysis of a combined methodology to determine if network dependency analysis is sufficient to capture dynamic behaviors in supply chain networks. The result of this analysis indicates that a multi-layered approach with the ability to handle different topologies between layers is required. Finally, preliminary results for individual layers and the aggregated model are provided.

While the current analysis indicates that this approach is promising, there are many future promising avenues for future research. First, rather than simply reviewing results based on individual node performance, it would be interesting to analyze resilience and vulnerability for individual nodes and the network overall. Additionally, while specific discussion is supported by the results shown for individual simulation runs, future stochastic analysis will provide a better understanding of generalized network behavior.

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