Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 180 (2021) 996–1002

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Industry 4.0 and Smart Manufacturing

Developing an Artificial Intelligence Framework to Assess Shipbuilding and Repair Sub-Tier Supply Chains Risk

Rafael Diaz[a]*, Katherine Smith[b], Beatriz Acero[c], Francesco Longo[d], Antonio Padovano[e]

[a,b,c] *Old Dominion University, 5115 Hampton Boulevard Norfolk, VA 23529, United States of America*
[d,e] *University of Calabria, Via Pietro Bucci, 87036 Arcavacata, Rende CS, Italy*

Abstract

The defense shipbuilding and repair industry is a labor-intensive sector that can be characterized by low-product volumes and high investments in which a large number of shared resources, technology, suppliers, and processes asynchronously converge into large construction projects. It is mainly organized by the execution of a complex combination of sequential and overlapping stages. While entities engaged in this large-scale endeavor are often knowledgeable about their first-tier suppliers, they usually do not have insight into the lower tiers suppliers. A sizable part of any supply chain disruption is attributable to instabilities in sub-tier suppliers. This research note conceptually delineates a framework that considers the elicitation of the existing associations between suppliers and sub-tier suppliers. This framework, Shipbuilding Risk Supply Chain (Ship-RISC), offers a simulation framework to leverage real-time and data using an Industry 4.0 approach to generate descriptive and prescriptive analytics based on the execution of simulation models that support risk management assessment and decision-making.

Keywords: Type your keywords here, separated by semicolons ;

1. Introduction

The supply chain for the shipbuilding and repair industry is a non-repetitive, complex system with not only internal dependencies but also external influences from volatile political and industrial environments [1]. Usually,

* Corresponding author. Tel.: +1-757-638-4437.
E-mail address: rdiaz@odu.edu

1877-0509
10.1016/j.procs.2021.01.363

entities involved in shipbuilding and repair procurement are well-informed about the performance of first-tier suppliers. However, in most cases, they do not have the visibility of lower tiers suppliers. Disruptions and instabilities in lower levels of the supply chain will have a ripple effect and cause significant delays and cost overruns for shipbuilding projects [2]. A proficient framework that store and process historical and real-time information of suppliers and sub-tier suppliers support better understanding and managing risk throughout the shipbuilding and repair supply chain.

Grimm, Hofstetter [3] indicates that a significant number of complexities make sub-supplier management more challenging than direct supplier management. For example, a lack of contractual relationships to sub-suppliers, few opportunities to exert direct pressure on sub-suppliers, or absence of transparency concerning sub-suppliers' involvement in a focal firm's supply chains. In this sense, there is a need to need to characterize not only the disruption risk within the supplier base but also the business and operational environment in which these suppliers operate. Thus, one can predict if suppliers will be able to supply parts, components, or systems when the shipbuilding and sustainment process requires it.

The supplier base risks focus on disruptions across the availability of components, materials, and service that supports the shipbuilding process. In contrast, the business and operational environment risks concentrate on the potential industrial sector enablers and barriers caused by changes in the business environment. There is a need to focus on components of vulnerability assessments that contribute to the overall shipbuilding and sustainment process risk: 1) Upper/Lower tier supply base evaluation, 2) access to technology and industrial enablers and barriers, and 3) degree of operational stability. Focusing on assessing the interaction among these components is critical to the shipyard and participating suppliers because its misalignment has the potential to worsen costs and unnecessarily increase risk exposures due to instability caused by the extensive introduction of new technology and the volatility from the political and industrial environment[1]. These forces are exacerbated by the expected surge in the demand and commitments to reduce overhaul backlogs while exposed to unexpected emergency repairs that additionally stress the supply chain and operational performance.

With risk properly characterized and an integrated assessment, targeted investments may be prioritized to minimize vulnerability and strengthen the supply chain system resiliency. The process that leads to the proper characterization of the supply chain risk at these three strands must necessarily include consideration of the dependencies and interdependencies among critical components that support the shipbuilding and sustainment supply chain. Identification and measurement of the relationships among these critical components are confounded by several layers that include: (a) a large number of components, (b) the tier or level of the supplier, (c) the degree of systems-of-systems interconnection, (d) the external environment, (d) and nature of the dependency functions, which includes cyber-information technology, equipment, materials-goods-parts, and skilled labor-professional services.

Awareness of the business environment can help a company understand the structure of its industry and stake out a position that allows strategic investments over time while becoming a reliable source of components to the shipbuilding and maintenance process. The following sections of this research note first present a background section that positions this work within the industrial context. Then, it presents an innovative, simulation-based supplier assessment framework. It also outlines in detail how the framework is structured using a supply chain analytics perspective. A brief summary of the framework and prospective requirements, as well as future research, is subsequently presented in the conclusions.

2. Background

Overall, supply chain management refers to all parties involved, directly or indirectly, in fulfilling customer requests [4]. Diaz, Smith [1] state that in the shipbuilding supply chain environment, activities upstream include procuring material and components from numerous involved suppliers to downstream managing the deactivation of ships and submarines once they have attained their end-of-life cycle. Furthermore, these authors discuss the essential elements of a shipbuilding supply chain framework to guide an understanding of a value chain of the processes involved in the shipbuilding process.

Research in understanding the impact of sub-tier suppliers in the shipbuilding industry is scant. A few governmental reports alert the consequences of the lack of visibility of sub-tier suppliers [5, 6]. However, research that considers the impact of sub-tier suppliers has been conducted in other industries. For example, Grimm, Hofstetter [7] and Grimm, Hofstetter [3] consider sub-tier suppliers in a food supply chain. Wilhelm, Blome [8] investigated the sustainability strategies of buying firms in the food, apparel, packaging, and consumer electronics concerning second-tier suppliers and beyond.

Some authors have researched sub-supplier issues and their impact on operational performance. For example, Norrman and Jansson [9] illustrate how Ericsson, after a fire at a sub-supplier, implemented a novel approach that analyzes, assesses, and manages risk sources along the supply chain, partly by working close with suppliers and using insurance requirements as driving force. Grimm, Hofstetter [10] consider sub-supplier performance, sustainability, and compliance. Soundararajan and Brammer [11] examine sub-supplier responses to social sustainability. Awasthi, Govindan [12] study global sustainable supplier selection considering sub-supplier(s) sustainability. Kim, Park [13] examines the relationship between buyers, suppliers, and sub-suppliers and find that while buyer's effort of monitoring and information sharing to sub-suppliers improves the performance of prime suppliers, buyer's effort of knowledge sharing does not improve prime suppliers's performance. Lechler, Canzaniello [14] explore from an extended agency theory perspective on how companies can collaborate with other firms to manage suppliers and sub-suppliers effectively. Hofstetter [15] provides an overview of company challenges originating upstream in their supply chains beyond their first tier. It outlines current practices to influence organizations beyond direct suppliers. More recently, Bai and Sarkis [16] and Lechler, Canzaniello [17] analyze sustainability issues and sub-tier suppliers while Khojasteh-Ghamari and Irohara [18] approach the multi-tier supplier selection using a mathematical programming approach. Awasthi and Gold [19] provide a literature review in which is asserted that investigations of sub-supplier issues are scant from the global supplier selection perspective.

3. Framework Development

In a new digital transformation environment characterized by the extensive use of industry 4.0 tools, shipbuilding suppliers may expect to gain substantial flexibility that allows increasing operational agility that enables them to move across different profitable industrial sectors. Thus, It is critical to understand the uncertainty of the industrial sector in which each supplier operates such an industrial contextual assessment may be proficiently performed. Three important considerations for both buyers and sellers include a) the understanding of the industrial sector, and b) the capacity of the firm to switch among industries, and c) the knowledge of the degree of innovation that suppliers contribute to the operation.

The development of the conceptual model of the simulation framework proposed in this research note calls for three stages that include 1) Mapping and simulating the supply chain, 2) Developing substitution and innovation effects, and 3) Embedding artificial intelligence tools. A brief description of this development follows.

3.1. Mapping the Supply Chain

The objective of this framework strives in its capacity to clarify the cost-benefit and risk tradeoffs stemming from suppliers that provide parts and components to the shipbuilding demands. The conceptual simulation framework described in this paper brings into play Industry 4.0 tools such as machine learning to predict suppliers' risks and probabilities of disruption.

Determining suppliers' risks as well as prospective business variability is a complicated endeavor as it involves multiple dimensions that characterize the evolving nature of the relationship among components and systems affected by external and internal dynamics. With a supply chain mapped as a network composed of nodes representing suppliers and arches that represent interdependencies, one can simulate and produce relevant analytics. Thus, one can obtain predictions of the strength of the suppliers and their ability to fulfill customer requests following a similar process as Sudhahar, Veltri [20], Garvey and Pinto [21], Guariniello and DeLaurentis [22]. In other words, one can identify critical nodes, dependencies, and potential likelihoods [22] of supply chain disruptions due to the presence of weak links.

Mapping the supply chain is critical to shape and design actions that make more robust the related industrial sector analysis. This section of the framework is based on the convergence of automated analysis on Natural Language Processing (NLP) and Artificial Intelligence (AI) techniques with webscrapping to extract information about the key events and their relations. These relations are extracted by a parser and organized as a network. As the business environment is continuously changing, there is a need to monitor industrial sector conditions. Industry 4.0 tools are critical to accomplishing this goal as it enables developing and evaluating informatics tools and frameworks to collect, monitor, analyze, summarize, and visualize social media data, usually driven by specific requirements from a target application. For example, one can perform daily news screenings and determine geographic locations experiencing high levels of COVID-19 infections, and triangulate the impact of industrial partners (e.g., sub-tier) as future increases in delivery lead times. In a different context, port authorities, in concert with synchromodal logistic service providers (SLSP), may experience decreases in labor in an affected transportation mode (e.g, rail), but given the gains in the flexibility of infrastructure and assets [23] due to real-time by using real-time information of cargo and available transportation modes, they can quickly switch to alternative modes. Big data obtained in real-time is adequately processed and enables a data-driven approach to cargo and transportation mode assignments, which maximize utilization and minimize economic and environmental impact and waste [23].

3.2. Modeling Substitution and Innovation Effects

The vision of the simulation framework discussed in this paper considers the building of two modules that capture and process substitution and innovation effects through social media analytics. It includes capturing and processing structured and unstructured data formats such as text, images, audio, and video, characterized by heterogeneous and natural human language that is heavily context-dependent. The goal is that information from this module can be presented in different dashboards in which data can be streamed and visualized and presented in real-time. The devices and sources of streaming data can be factory sensors, social media sources, service usage metrics, and anything else from which time-sensitive data can be collected or transmitted. New validated metrics will be designed to monitor the evolution of industrial sectors while generating predictive analytics that provides potential outlooks for the interactions between buyers and sellers.

In the context of the supply network mapped, a Monte Carlo approach can be used to explore scenarios and simulate the effects of innovation over the supply chain. These effects propagate through arcs and nodes, and ultimately, affect shipbuilding schedules. Monte Carlo simulations enable generating stochastic samples that assist in training the network model to increase its accuracy. Empirically generated continuous or discrete probability distributions per risk dimension are drawn and connected to the network, which can be scored and assessed. Additional Monte Carlo samples are also useful in replicating innovation effects as for suppliers that have no historical data due to the degree of innovation given by the part or components to the shipbuilding process.

3.3. Artificial Neural Network (ANN) and Monte Carlo simulation

The framework proposed in this research note calls for using Artificial Neural Network (ANN) and Monte Carlo simulation to offer a capable structure that assists managers in performing an effective risk management evaluation [1]. The framework proposes this hybrid between ANN and Monte Carlo capabilities to determine and predict risks that exist among multiple relevant suppliers' attributes, e.g., delivery time, and quality. The risk probability distribution is used to generate samples through a Monte Carlo simulation, and thus, simulate the training data that is used to evaluate the overall risks of the supplier presented.

Figure 1 presents an adapted framework with ideas extended from Sanchis, Canetta [24]. Notice that some analysts and researchers might use the Monte Carlo technique to generate samples and then calculate averages in determining the overall suppliers' risks. In the framework, the Monte Carlo simulation is limited only to assess samples that will feed the neural network model as other authors have considered. The machine learning approach suggested in the framework seeks to employ ANN to approximate the real risk behavior exhibited during the evaluation process.

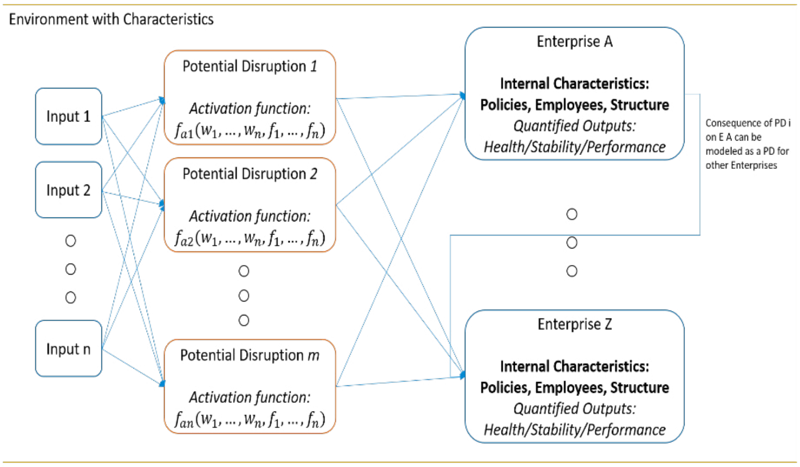

Figure 1 – Adapted Neural Network Framework

Our method extends the so-called Systems Operational Dependency Analysis (SODA)[22], which improves the Functional Dependency Network Analysis (FDNA) [21, 25]. FDNA is based on Leontief-based Input/Output model for infrastructures[26-28]. FDNA is a 2-parameters piecewise linear model of dependencies between the capabilities of complex systems. As per Guariniello and DeLaurentis [22], FDNA does not consider the influence of the internal states of a system and does not include stochasticity. It also presents limitations in modeling dependencies where the criticality may require to be absorbed rapidly and is restricted to model only substitute inputs when multiple dependencies occur simultaneously. Conversely, SODA proposes a 3-parameters piecewise linear model that enables full and partial dependency analyses. It also considers the embedding of stochasticity and dependencies that require rapid absorption. SODA has been validated by Agent-Based Model (ABM) simulations, and successfully applied the methodology to aerospace systems[22]. However, either FDNA or SODA does not consider hierarchies and the simultaneous effect of dependencies, leading to explicit hyper-vulnerability states.

Hierarchical structures and hyper-vulnerable nodes and dependencies are two critical components prevalent in complex systems [29], such as sub-tier supply chain structures that characterize the shipbuilding industry. Identifying hyper-vulnerable nodes and dependencies allow identifying hidden/latent infrastructures that are not evident to protection. An analogous application in the cybersecurity space considers protecting the operational technology (OT) related to the cyber-physical spaces (CPS) of a port supply chain. It involves a large number of sub-systems and components interacting simultaneously. In this environment, CPS consists of automatic cranes, and collaborative robots and self-driving vehicles are technologies that are entrusted with decentralized decisions. The appearance of CPSs and extensive use of OT inexorably increases operational complexity and exposure and vulnerability to cyberattacks. Cybersecurity protection of these systems requires a systemic approach to evaluate their vulnerability, cyberthreats, and countermeasures.

The final stage of building this framework calls for developing and embedding normative models that suggest solutions to managers that are not intuitive as the handling and processing of big data and complex relationships are overwhelmingly intricated to the bare human eye. More specifically, to explore additional prescriptive analytics, this framework enables assessing and suggesting suppliers' portfolio configurations that consider multiple conflicting goals that include minimizing risks, maximizing responsiveness and readiness, and minimizing objectives. As many different goals converge in this decision environment, it will be critical to anticipate priorities and a conflicting-goal matrix that allows resolving these conflicts accordingly. Analysts can adjust these priorities at any given time as the human-machine interface supports strategic decision-making.

4. Summary and Future Endeavors

Defense shipbuilding and repair firms may profit from using a real-time data-driven approach to continuously assessing the risk of supply chain disruption that steams from the flow of parts from suppliers and sub-tier suppliers. In this paper, it is proposed a framework that considers 1) a data collection of the relationships among suppliers among other dimensions, 2) the mapping and analysis of a multi-tier supplier network related to each project, and 3) the building of a simulation-based model that combines Artificial Neural Networks (ANN) and Monte Carlo Simulation. Our approach uses ANN to quantify risks per supplier, and therefore, per project while employing scenario analysis to quantify the effects of interventions to manage prospective disruptions. Monte Carlo simulation is used to obtain probabilistic behavioral data that facilitates the execution of the neural network, and therefore analysis.

Managers are expected to carefully assess these risks as each supplier might contribute to unacceptable risk levels (e.g., additional cyber risks) that may jeopardize the shipbuilding operational integrity. Risk analysts and managers are compelled to identify hidden risks that their supplier portfolio may contain. Similarly, they should be trained in the use of competent tools that analyze supplier risks, determine desired risk thresholds for their sub-tier suppliers, and suggest alternative suppliers' portfolio configurations. The use of these tools enables the anticipation of measures that renders the firm stronger as vulnerability might grow if risks are not identified and properly mitigated.

Future research endeavors include the completion of the building of a prototype that follows the conceptual model lines described in this paper and performs data extraction, industry monitoring, and simulation-based machine learning to predict risk for disruptions accurately while capable of performing prescriptive analytics.

5. Acknowledgment

This research has been partially supported by the Digital Shipbuilding Initiative - GoVirginia.org.

References

1. Diaz, R., et al., *Shipbuilding Supply Chain Framework and Digital Transformation: A Project Portfolios Risk Evaluation.* Procedia Manufacturing, 2020.
2. Diaz, R., et al., *Shipbuilding Supply Chain Framework and Digital Transformation: A Project Portfolios Risk Evaluation*, in *ISM The International Conference on Industry 4.0 and Smart Manufacturing* 2019: Italy.
3. Grimm, J.H., J.S. Hofstetter, and J. Sarkis, *Critical factors for sub-supplier management: A sustainable food supply chains perspective.* International Journal of Production Economics, 2014. **152**: p. 159-173.
4. Chopra, S. and P. Meindl, *Supply Chain Management - Strategy, Planing, and Operation*. 2010, New Jersey: Prentice Hall.
5. DoD, U., *Assessing and Strengthening the Manufacturing and Defense Industrial Base and Supply Chain Resiliency of the United States. Report to President Donald J. Trump by the Interagency Task in Fulfillment of Executive Order 13806. Office of the Under Secretary of Defense for Acquisition and Sustainment, Office of the Deputy Assistant Secretary of Defense for Industrial Policy, September 2018*. 2018.
6. Hunter, A., et al., *The Effects of Exporting on Defense Acquisition Outcomes—A Quantitative Look at FMS Contracting: Preliminary Findings.* 2019.
7. Grimm, J.H., J.S. Hofstetter, and J. Sarkis, *Understanding diffusion of corporate sustainability standards through sub-supplier management in the food supply chain.* George Perkins Marsh Institute, Worcester, 2012: p. 2012-25.
8. Wilhelm, M., et al., *Implementing sustainability in multi-tier supply chains: Strategies and contingencies in managing sub-suppliers.* International Journal of Production Economics, 2016. **182**: p. 196-212.
9. Norrman, A. and U. Jansson, *Ericsson's proactive supply chain risk management approach after a serious*

sub-supplier accident. International journal of physical distribution & logistics management, 2004.
10. Grimm, J.H., J.S. Hofstetter, and J. Sarkis, *Interrelationships amongst factors for sub-supplier corporate sustainability standards compliance: An exploratory field study.* Journal of Cleaner Production, 2018. **203**: p. 240-259.
11. Soundararajan, V. and S. Brammer, *Developing country sub-supplier responses to social sustainability requirements of intermediaries: Exploring the influence of framing on fairness perceptions and reciprocity.* Journal of Operations Management, 2018. **58**: p. 42-58.
12. Awasthi, A., K. Govindan, and S. Gold, *Multi-tier sustainable global supplier selection using a fuzzy AHP-VIKOR based approach.* International Journal of Production Economics, 2018. **195**: p. 106-117.
13. Kim, K., M. Park, and S. Ryu, *Do Buyer's Supporting Efforts For Sub-Supplier Make Prime Supplier's Performance Better?* Journal of Applied Business Research (JABR), 2017. **33**(1): p. 195-206.
14. Lechler, S., A. Canzaniello, and E. Hartmann, *Assessment sharing intra-industry strategic alliances: Effects on sustainable supplier management within multi-tier supply chains.* International Journal of Production Economics, 2019. **217**: p. 64-77.
15. Hofstetter, J.S., *Extending management upstream in supply chains beyond direct suppliers.* IEEE Engineering Management Review, 2018. **46**(1): p. 106-116.
16. Bai, C. and J. Sarkis, *Green supplier development: a review and analysis*, in *Handbook on the Sustainable Supply Chain*. 2019, Edward Elgar Publishing.
17. Lechler, S., et al., *Influence of different stakeholders on first-tier suppliers' sustainable supplier selection: insights from a multiple case study in the automotive first-tier industry.* Business Research, 2019: p. 1-30.
18. Khojasteh-Ghamari, Z. and T. Irohara, *A Decision-Making Approach for Supplier Selection in the Presence of Supply Risk.* Journal of Industrial Engineering and Management Science, 2019. **2019**(1): p. 1-14.
19. Awasthi, A. and S. Gold, *Global Sustainable Supplier Selection: A Literature Review*, in *Handbook of Research on Interdisciplinary Approaches to Decision Making for Sustainable Supply Chains*. 2020, IGI Global. p. 1-31.
20. Sudhahar, S., G.A. Veltri, and N. Cristianini, *Automated analysis of the US presidential elections using Big Data and network analysis.* Big Data & Society, 2015. **2**(1): p. 2053951715572916.
21. Garvey, P.R. and C.A. Pinto. *Introduction to functional dependency network analysis*. in *The MITRE Corporation and Old Dominion, Second International Symposium on Engineering Systems, MIT, Cambridge, Massachusetts*. 2009.
22. Guariniello, C. and D. DeLaurentis, *Supporting design via the system operational dependency analysis methodology.* Research in Engineering Design, 2017. **28**(1): p. 53-69.
23. Acero, B., R. Diaz, and R. Ungo, *Synchromodal transportation in the US: Opportunities and challenges*, in *Decision Science Institute*. 2020.
24. Sanchis, R., L. Canetta, and R. Poler, *A Conceptual Reference Framework for Enterprise Resilience Enhancement.* Sustainability, 2020. **12**(4): p. 1464.
25. Servi, L. and P.R. Garvey, *Deriving global criticality conditions from local dependencies using Functional Dependency Network Analysis (FDNA).* Systems Engineering, 2017. **20**(4): p. 297-306.
26. Haimes, Y.Y. and P. Jiang, *Leontief-based model of risk in complex interconnected infrastructures.* Journal of Infrastructure systems, 2001. **7**(1): p. 1-12.
27. Haimes, Y.Y., et al., *Inoperability input-output model for interdependent infrastructure sectors. I: Theory and methodology.* Journal of Infrastructure Systems, 2005. **11**(2): p. 67-79.
28. Haimes, Y.Y., et al., *Inoperability input-output model for interdependent infrastructure sectors. II: Case studies.* Journal of Infrastructure Systems, 2005. **11**(2): p. 80-92.
29. Wang, Y.I., J. Li, and R. Anupindi, *Risky suppliers or risky supply chains? An empirical analysis of sub-tier supply network structure on firm performance in the high-tech sector.* 2015.