Physical Internet Center

Demand-supply alignment in supply chain networks with access to hyperconnected production options

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1 Introduction

Supply chains today are complex networks with many actors such as suppliers, plants, distributors, and customers, that are often scattered around the world. Each of these supply chain networks (SCN) are interconnected as parts of global supply webs (Montreuil et. al., 2009) and as a result, their performance becomes the complex outcome of the interdependent efforts and actions of its constituent actors across the globe (Montreuil et. al., 2000).

With this complexity and continuously evolving challenges, it is inevitable to face with disruptions in information (bullwhip effect, inherent forecast errors, rapidly changing demand patterns), production (raw material, labor, machinery), or delivery (driver shortage, cargo ship problems) across the network. All these disruptions make it hard to align supply and demand through the supply chain network, and companies see themselves either ending up with huge inventories piled up at their distribution and fulfillment centers or facing sale losses. Furthermore, the recent years pervaded with effects of the COVID-19 pandemic and a global supply crisis have highlighted the ever-increasing need for demand and supply alignment.

Achieving demand-supply alignment in a real-world SCN operating in a volatile, uncertain, and disruption-prone environment requires prescriptive planning and operations management, with the ability to dynamically adapt to evolving challenges and expectations (agility). Thinking that the planning and operation of SCNs can be represented as a single comprehensive model which can be solved optimally or near optimally in such a complex, stochastic, and large-scale context may often prove counterproductive, due to its modelling and computational complexities. So is thinking that high SCN performance in such a context can be achieved by distributing the planning and operational decisions to siloed actors with disconnected models and policies.

To overcome the complexities of centrally optimizing decisions within the SCN, and misalignment induced by decentralized decision-making, we propose a Physical Internet inspired hyperconnected approach for agile and collaborative demand-supply alignment in SCNs, with the ability to leverage external options to mitigate the effects of uncertainties and disruptions. The approach fundamentally recognizes the roles and responsibilities of each actor as a node in the network as well as the inherent interdependences between the decision scopes of agents, leveraging their collective smartness, enabling their collaborative decision-making through daily updated prediction and optimization models, and developing the collective agility of SCNs. The approach aims at continually optimizing demand and supply alignment for a complex large-scale SCN subject to a highly stochastic and disruptive environment.

Overall, this paper has two key contributions. Firstly, it introduces our novel multi-agent-based approach for demand-supply alignment optimization across various functions in a multi-echelon manufacturing and distribution network and highlights its wide applicability and ability to model networks in line with the Physical Internet paradigm. Secondly, it highlights the simulation-testing capability of our proposed approach and provides an empirical analysis of the benefits of utilizing a hyperconnected network of open certified production options for a manufacturing firm facing uncertainties and constraints in a disruption-prone environment.

The paper is structured as follows. Section 2 provides an overview of related literature. Section 3 details the overall approach and key constituents. Section 4 describes our experimental setup and simulation results. Finally, Section 5 shares conclusion and avenues for further research.

2 Related Literature

Demand-supply alignment is an important measure of a SCN's capabilities to optimize integrated supply chain management. This becomes furthermore pertinent in practice where they face continuously evolving challenges, uncertainties and disruptions stemming from demand, supply, and various operational aspects of the network (Ptak and Smith, 2018; Benaben et. al., 2021). Eruguz et. al. (2015) state that multi-echelon inventory optimization for integrated supply chain management improves the overall performance in terms of customer service level and inventory costs, although they induce significant computational complexity and are unable to model the various actors of the network intricately as in the real world.

Fox et. al. (1993) described an agent-based approach for integrated supply chain management, enabling decision-making on the strategic, tactical, and operational levels. They proposed that the next generation SCNs be distributed, dynamic, intelligent, integrated, responsive, reactive, cooperative, and adaptable among others. Multi-Agent Systems (MAS) is a modelling and simulation approach influenced by the complexity paradigm and is a suitable approach for modelling real-world SCNs with multiple actors that are simultaneously acting, and continuously reacting to the actions of other actors (Dominguez et. al., 2020).

Researchers have widely used MAS to develop representative and detailed SCN models to predict and improve performance of various strategic, tactical, and operational decision-making capabilities. Montreuil et. al. (2000) originally proposed a MAS-based approach for operational planning that fundamentally recognizes the roles and responsibilities of each actor as a node in the network, and associates to each node a software agent, or a team of such agents, creating a network of software agents, with a high degree of development. Abid et. al. (2004) and Cheeseman et. al. (2005) utilized MAS framework for collaborative production planning and scheduling. Behdani et. al. (2019), Wang et. al. (2019), and Namany et. al. (2020) demonstrated resiliency improvement in critical supply networks, and provide a simulation framework for decision-makers to test various disruption scenarios and mitigation strategies.

Although MAS is a powerful tool for modelling and analyzing real-world distributed SCNs with constraints and options, there exists a gap in the existing literature in integrated supply chain management with dynamic predictive and decision-making methodologies to improve demand-supply alignment, when faced with uncertainties and disruptions. Furthermore, there is a lack of research in detailed modelling and simulation-based testing of complex SCNs with characteristics (modular containerization, collaboration, resource sharing, hyperconnected network) that enable decision makers to realize the empirical benefits of PI access and adoption.

3 Overall approach and key constituents

In this paper, we investigate the optimization of demand-supply alignment across SCNs subject to high volatility and uncertainty. We propose a collaborative and dynamic distributed-decision-making approach for end-to-end modeling, optimizing, and simulation-testing of a real-world manufacturing SCN using a Multi-Agent System (MAS) modelling approach.

We build on the approach proposed by Montreuil et. al. (2000) of recognizing the roles and responsibilities of each actor (facilities, humans, machines, software, or robots) as a node in the network, and associate to each node a software agent, or a team of such agents, creating a network of software agents. Our approach also encompasses the inherent interdependences between the decision scope of agents, and protocols for multi-agent interaction and accountability across the overall agent network. The decision-making process is facilitated with predictive and optimization models, along with smart and collaboration-enabling rule-based algorithms. The decision-making processes of the interacting agents consider their uncertainties, constraints, and options, with the goal of maximizing demand-supply alignment in their vicinity, and the overall system performance in both short and long-term horizons.

The fundamental driver towards achieving demand-supply alignment is the understanding that sales and demand are not necessarily the same. In an ideal setting where the availability of all products is maintained in the network, then sales and demand are identical. But, in practice, with the various uncertainties and constraints, it is not always feasible to maintain availability of all products. Then, demand must be estimated from sales by considering substitution, deferral, and lost sales in case of stock-out situations (Derhami and Montreuil, 2021). A dynamically estimates demand, and subsequently generates demand forecasts for each product, category, and the overall portfolio in the different geo-spatial and temporal settings and propagates them in the network of SCN actors, enabling agile decision-making.

The key planning and operational decision to achieve demand-supply alignment is agile inventory management. We utilize autonomy-based forecast-driven replenishment strategies, where the medium and long-term decisions are flexible to be updated based on forecast updates.

Autonomy denotes the ability of a SCN inventory-holding node to function seamlessly for t time units (e.g. 7 days) with r robustness (e.g. 99%), including protection relative to scenarios of interrupted supply and disrupted demand. Autonomy is computed from demand forecasts and updated daily by the to estimate the inventory replenishment required.

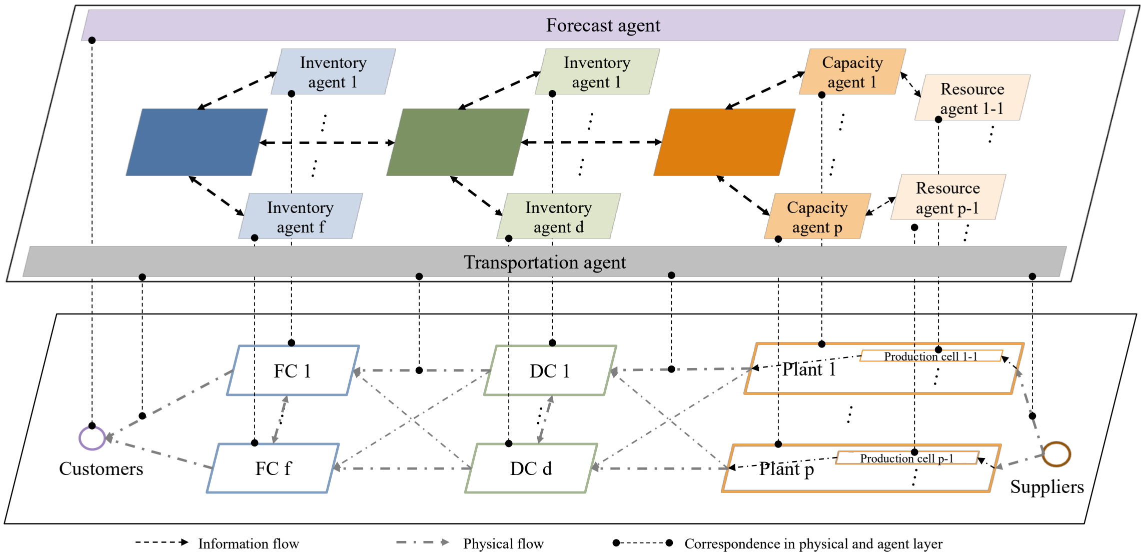
Each manufactured product has a unique bill-of-materials consisting of different components and raw materials that go through various production processes. Raw materials and other description of three primary agents in the SCN, namely and is as follows:

1. facilitates the decision-making for the agents associated to the network of FCs. It manages two primary decisions: on-demand customer order fulfillment from closest FC with inventory availability; and daily FC replenishment in modular containers from DCs by collaborating with the . FC replenishment is done by considering the unconstrained replenishment request (based on short-term autonomy at each FC) from the FC and available inventory from . The coordination enables equitable share of supply from DCs such that the minimum autonomy across FCs is maximized, while respecting full modular container constraint for all shipments as pertinent. In the case of excess inventory at any FC due to change in demand pattern, transshipments between FCs are allowed to maintain inventory balance among the FCs.

2. manages the inventory replenishments at DCs. Contrary to FC replenishment, DC replenishment is done in coordination with focusing on long-term demand forecasts to prevent potential lost-sales due to lack of inventory in case of disruptions and preparation in advance for upcoming seasonalities. The agent aims for medium-term autonomy at DCs to be able to serve FC requests. Since DC replenishment is constrained by production capacity and capabilities of the plants, it is crucial to utilize production capacity efficiently to build adequate inventory that is aligned with the forecasted demand. Aggregated weekly production capacities of the production plants are shared with the agent by capacity agents of each plant. In addition to production capacity, which directly depends on raw-material, labor, resource, and machinery availability, minimum and maximum batch sizes at plants also impacts the decision processes. DC replenishment plans are prepared by considering production, transportation, and autonomy constraints along with the objective of maximizing long-term profit under uncertainty and disruptiveness. Transshipment between distribution centers is considered as alternative sourcing option in the case of unbalanced inventory or autonomy levels between DCs due to unexpected demand realizations or disruptions in production and delivery

3. manages production planning in the plants network. The agent receives the production capacity at each plant along with the replenishment requests of DCs. The production plans are finalized with , and assigned to production plants as work-orders, after detailed examination of the production plant capacities and schedules. Since an aggregated capacity model is shared with distribution network coordinator, the requests are expected to be feasible to mostly produce on-time. In case of infeasibility, the production coordinator agent allocates the capacity to requested items in a way that minimizes the deviation from target autonomy levels at distribution centers. In addition to dedicated production plants, there are open certified production centers (OCPC) that provide contract-based production capacity and enable hyperconnected production.

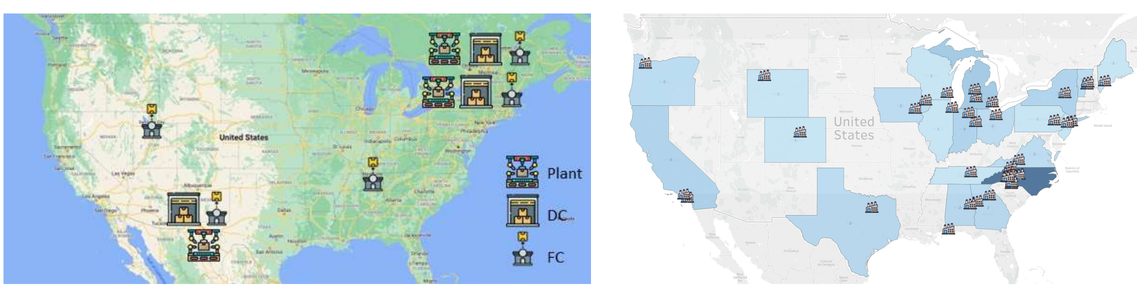
The proposed approach relies on information sensing, daily updates of predictive algorithms, optimization models and solution methodologies for each agent to its support decision-making role according to developed collaborative protocols. The approach leverages the agent network's collective smartness to enable the collaborative decision-making of each agent, and to develop the collective agility and resilience of the supply chain network. shows our multi-agent network, where the Agent layer corresponds to the physical nodes in the network and is responsible for the functional decision scope for each node in the Physical layer.



We attain informational hyperconnectivity through pertinent information access to agents based on their functional requirement, and furthermore through collaborative engagement and negotiation between agents towards collective decision making (Montreuil et. al., 2000; Montreuil et. al., 2012). The agents undertake various planning and operational decisions regarding inventory management, production planning, transportation, and order fulfillment. Physical hyperconnectivity in the system is enabled with transshipments of raw materials, intermediate and finished goods between the nodes, and access to potential production options with OCPCs through long-term contracts or spot capacity allocation (Montreuil et. al., 2012).

4 Experimental Setup and Results

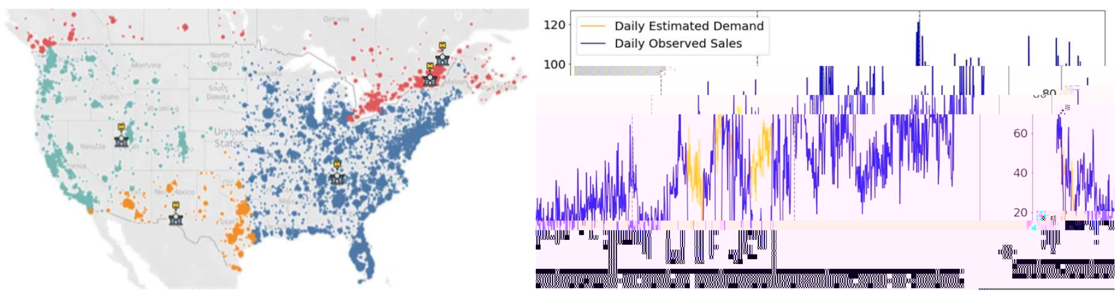
In this section, we describe the experimental setup inspired by the case of one of our industrial partners, and leverage an agent-oriented simulator to dynamically experiment the collective performance of our proposed hyperconnected approach to optimize demand-supply alignment in a complex real-world large-scale supply chain network subject to a highly stochastic and disruptive environment.



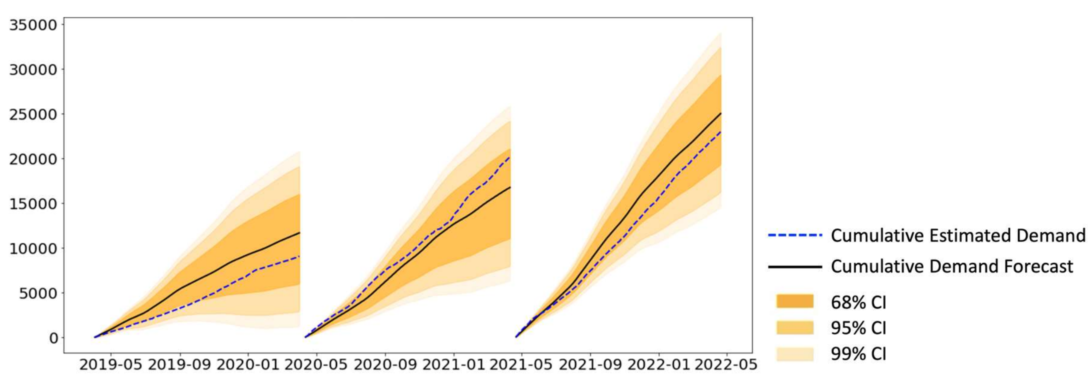
Our industry partner is a major producer of a portfolio of ready-to-assemble household furniture and serves customers in North America. Customer orders are fulfilled from five FCs, with orders being placed exclusively through e-commerce companies or the company's website, preventing backlog of orders. The FCs are replenished from three DCs, which are in turn replenished from three production plants. shows the geographical distribution of the nodes of our industry partner's SCN. In addition to the dedicated plant network, we consider the accessibility of a hyperconnected network of Open Certified Production Centers (OCPC) that provide long-term capacity allocation contracts, as shown in . All movements of raw materials to OCPC facilities and finished goods within the network are modeled to be done using modular containers, in line with the Physical Internet framework.

4.1 Demand

With the aim of highlighting the capabilities of our proposed approach in a disruptive environment, we here consider a single product that is a top-seller. shows the geographical location of customers for this product, with the color based on the closest FC. We run the agent-oriented simulation for three years: pre-disruption period (2019), COVID-19 disrupted period (2020), and post-disruption period (2021). The selected product displays a varying pattern in the three periods, with considerable stock-out durations during 2020. We begin by estimating the demand during these stock-out periods, using exponential smoothing based forecasting method (Derhami and Montreuil, 2021). shows the daily sales and estimated demand for the product in the planning horizon and observe ~10.7% lost sales.



With the estimated demand, we progress to generating demand forecasts with one-year horizon, by considering the level, trend, and various seasonalities based on historical information. We utilize the Bouchard-Montreuil (BM) method (Bouchard and Montreuil, 2009) adapted from the Holt-Winters method (Holt, 1957; Winters, 1960), which considers the various seasonalities based on calendar days and by allowing defining the seasons to be based on the similarity of patterns. Forecasts are dynamically updated daily to effectively capture the demand. illustrates the evolution of our demand forecasts, where each forecast is the cumulative demand forecast generated on a given day for the one-year horizon. Orange regions denote the confidence intervals, and the dotted line denotes the realized demand. Even though order backlog is not permitted, we highlight cumulative forecast performance as it is used by the agents for their decision-making.



4.2 Supply

We model supply with the production capacity of the plants. The plants operate for a fixed duration daily, and we estimate the daily production capacity considering historical allocation of resources to the selected product, and required capacity based on forecasts generated at the start of the planning horizon. As shown in COVID-19 pandemic impacted the SCN in late March 2020, and decreased the production capacity to zero for a month. The production capacity recovered gradually over the next months. The first month with zero capacity represents the imposed lockdowns. The following days with less than full capacity represent supplier problems, limited lockdowns, and labor shrinkage due to illness or regulations. In order to contain the complexity of this exploratory experimental setup, we assume that raw material availability is ensured in the plants, to support short-term production planning based on aggregated capacity.

Although the production shutdown was beyond the control of the decision makers, they became aware of such a possibility in the near future early on, which we will utilize as a capacity disruption signal to demonstrate the benefit of proactively reacting to disruption signals. Additionally, the OCPC facilities offer additional capacity (20%, as shown in through long-term contracts, and serve as options during normal and disrupted periods. In this paper, we assume that from the network of OCPCs, we are assured production capacity during all periods, and becomes a potential for further sensitivity analysis on the reliability of OCPCs and disruption scenarios.

4.3 Experimental parameters

We model inventory replenishment to the various nodes of SCN based on autonomy, derived from demand forecasts. The coordinator agents aim to maintain minimum 7-days autonomy at the FCs and minimum 14-days autonomy at the DCs. All shipments between nodes are modelled as stochastic random variables, with the mean estimated based on travel time between nodes based on the average truck speeds in North America.

4.4 Experiment objective

Firstly, with the aim of demonstrating the applicability of our proposed approach and the improvement in demand-supply alignment in a real-world hyperconnected SCN, we highlight the experimental capability of our approach by comparing performance metrics in the various aforementioned periods for the following four DC replenishment strategies:

1. **Myopic Lean**: The DCs maintain a myopic view, and consider only the upcoming week(s) in estimating their replenishments based on autonomy for production planning
2. **Farsighted**: The DCs maintain a farsighted view, and consider the long-term forecasts along with autonomy required to prepare in advance for upcoming seasonalities

3. **Farsighted (Signal)**: Along with maintaining a farsighted view, the DCs proactively react to a potential plant shut-down signal to mitigate the effects of the supply disruption
4. **Farsighted (Signal, OCPC)**: Along with a farsighted view and response to disruption signal, the DCs utilize the network of hyperconnected OCPC facilities when network production capacity is unable to cater to the replenishment required by DCs

Secondly, we conduct a sensitivity analysis of capacity consideration and costs of utilizing the hyperconnected OCPC facilities, on SCN performance metrics and potential benefits.

4.5 Results

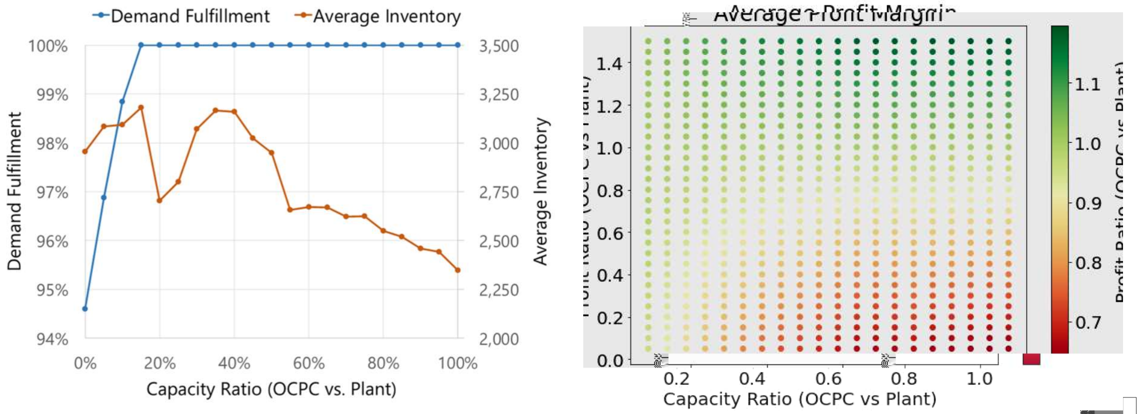
We measure demand-supply alignment performance of the DC replenishment strategies under three primary dimensions: demand fulfillment rates (lost sales), misaligned fulfillments (from further-away FCs) and average inventory levels (product availability), as shown in .

	Demand Fulfillment			Misaligned Fulfillment			Daily Average Inventory		
DC replenishment strategy	Pre	Dis	Post	Pre	Dis	Post	Pre	Dis	Post
Myopic Lean	100%	86%	76%	0%	27%	42%	1,546	522	181
Farsighted	100%	100%	82%	0%	<1%	31%	3,837	2,991	285
Farsighted (Signal)	100%	100%	89%	0%	0%	15%	3,837	4,237	789
Farsighted (Signal, OCPC)	100%	100%	98%	0%	0%	3%	3,776	3,896	1,606

The SCN is able to satisfy almost all the demand from preferred fulfillment centers during the pre-disruption period. The consequences of the supply and demand disruption are profound for the myopic lean approach where it only satisfies 86% of the demand with 27% of them fulfilled from further-away fulfillment centers. The other approaches are more resilient to disruption as they can maintain their performance close to the pre-disruption period. Post-disruption period comes with an increase in demand as can be seen in . With all approaches there is a decrease in performance dimensions, however, the benefit of maintaining a farsighted view and utilizing OCPCs on mitigating the impact of the demand disruption is evident.

Next, we investigate the impact of the degree of reliance on the hyperconnected OCPC network. illustrates the network-wide average daily inventory levels and demand fulfillment rates along with increasing OCPC production capacities for farsighted sentient approach. Here, the capacity ratio denotes the ratio of contracted capacity to the capacity at SCN's production plants. We observe that with just 15% additional contract capacity, all lost sales are eliminated.

The average daily inventory level has an overall decreasing trend with reliance on OCPCs. The fluctuation in the trend around 20% capacity ratio is a result of the sudden unforeseen demand peak in early 2021 and is a characteristic of the demand scenario considered. With a lower capacity ratio, the SCN builds inventory in preparation for the upcoming seasonalities, when it perceives it won't be able to meet autonomy in the future with the capacity available. With 20% capacity ratio, the SCN has enough capacity, so it doesn't need to produce in advance, but when faced with the demand jump, and consequently a short-lived jump in the demand forecasts, it is restricted by capacity. On the other hand, with higher capacity ratios, the SCN produces excess inventory driven by the high demand forecasts. With capacity ratios over 40%, the SCN has enough capacity to cater to the upcoming long-term demand and doesn't need to produce much in advance, hence maintaining lower average inventory levels.



Next, we conduct a sensitivity analysis on average profit margin per unit of the product with capacity ratio and profit ratio, which is a measure of the addition cost or saving from producing at OCPCs as compared to SCN's plants. shows the change in average profit margin, where value of 1 represents no change on profit margin and values larger than 1 implies increased profit margins. We observe that for lower profit ratios, i.e., when producing at OCPCs is costlier than producing at plants, the profit margin decreases with increasing capacity ratio. On the contrary, for higher profit ratios, where it is cheaper to produce at OCPCs than at plants, higher reliance on OCPCs improves the profit margin, while also decreasing average inventory levels and eliminating lost sales.

5 Conclusion

In this paper, we focus on the supply-demand alignment of a supply chain network (SCN) in a volatile, highly uncertain and disruption-prone environment. To overcome the complexities of centrally optimizing decisions within the SCN towards this goal, we propose a responsibility-oriented collaborative decision-making structure with agents that can make decisions regarding their own responsibilities, while collaborating with each other. The multi-agent system (MAS) structure we propose distributes the responsibilities to agents, and each agent has a defined set of performance criteria, required input-outputs, and protocols for communication with other agents. To prevent making infeasible or local-optimum decisions at agent-level instead of optimizing the global objectives, the impact of each agent's decisions on other agents is also incorporated into decision-making processes by using coordinator agents and allowing communication/negotiation between agents. The continuous communication (information sharing) between the agents helps to decrease the bull-whip effect (limits the disruptions in information) and allows cooperative alignment of supply and demand plans.

Daily update of demand forecasts and distributed decision-making processes enable the system to rapidly react to disruptions that have occurred or sensed. The decisions or problems that would be difficult to model and solve with all the details by using a central decision-making approach can be modelled and solved with finer granularity and higher sensitivity by agents. Furthermore, the SCN model can be tested under various disruption, helping in identifying the configurations and strategies that facilitate the desired performance, resilience, and agility.

As a future research direction to effectively navigate in the unstable supply chain context, the model needs to be equipped with sentient capabilities. This involves enabling the system to perceive, understand, and analyze the situation, and transform into a goal-oriented system that can continually define and adjust its objectives based on the dynamic circumstances. Overall, to enable agile and resilient demand-supply alignment in SCNs operating in the unstable context, we propose a goal-oriented sentient system (GOSS) that can orient itself, argue its decisions, and legitimize its actions based on dynamic targets and sentient capabilities.

References

- Abid, C.; D’Amours, S.; Montreuil, B. (2004). Collaborative order management in distributed manufacturing. Int. J. Prod. Res. 42, 283–302.
- Behdani, B., Lukszo, Z., Srinivasan, R. (2019). Agent-oriented simulation framework for handling disruptions in chemical supply chains. Comput. Chem. Eng. 122, 306–325.
- Benaben, F., Faugere, L., Montreuil, B., Lauras, M., Moradkhani, N., Cerabona, T., Gou, J., & Mu, W. (2021). Instability is the norm! A physics-based theory to navigate among risks and opportunities. Enterprise Information Systems, 16(6). https://doi.org/10.1080/17517575.2021.1878391
- Bouchard, J., and Montreuil, B. (2009). Méthode de prévision journalière de séries temporelles saisonnières, Proceeding of CIGI 2009 (8e Congrès International de Génie Industriel)
- Cheeseman, M.; Swann, P.; Hesketh, G.; Barnes, S. (2005). Adaptive manufacturing scheduling: A flexible and configurable agent-based prototype. Prod. Plan. Control 16, 479–487.
- Derhami, S., and Montreuil, B. (2021) "Estimation of potential lost sales in retail networks of high-value substitutable products." IISE Transactions: 1-28.
- Dominguez, Roberto, and Salvatore Cannella. (2020). "Insights on Multi-Agent Systems Applications for Supply Chain Management" Sustainability 12, no. 5: 1935. https://doi.org/10.3390/su12051935
- Eruguz, A. S., Sahin, E., Jemai, Z., & Dallery, Y. (2016). A comprehensive survey of guaranteed-service models for multi-echelon inventory optimization. International Journal of Production Economics, 172, 110–125. https://doi.org/10.1016/j.ijpe.2015.11.017
- Fox, Mark & Chionglo, J. & Barbuceanu, M. (1993). The Integrated Supply Chain Management Project. http://eil.utoronto.ca/wp-content/uploads/public/papers/iscm-intro.pdf
- Holt, C. C. (1957). Forecasting seasonals and trends by exponentially weighted averages (O.N.R. Memorandum No. 52). Carnegie Institute of Technology, Pittsburgh USA.
- Montreuil B., J.-M. Frayret & S. D’Amours (2000). A Strategic Framework for Networked Manufacturing, Computers for Industry, Special Issue on Computer Aided Production, vol. 42, p.299-317. https://doi.org/10.1016/S0166-3615(99)00078-0
- Montreuil, B., O. Labarthe, D. Hakimi, A. Larcher & M. Audet (2009). Supply Web Mapper, Proceedings of Industrial Engineering and Systems Management Conference (IESM), 2009-05-13/15, Montréal, Canada.
- Montreuil, B., Meller, R. D., & Ballot, E. (2012). Physical Internet Foundations. IFAC Proceedings Volumes, 45(6), 26–30. https://doi.org/10.3182/20120523-3-ro-2023.00444
- Namany, S., Govindan, R., Alfagih, L., McKay, G., Al-Ansari, T. (2020). Sustainable food security decision-making: An agent-based modelling approach. J. Clean. Prod. 255, 120296.
- Ptak, C. A., & Smith, C. (2018). Demand driven material requirements planning (Ddmrp). Industrial Press, Inc
- Wang, Z. and Zhang, J. (2019). Agent-based evaluation of humanitarian relief goods supply capability. Int. J. Disaster Risk Reduct. 36, 101105.
- Winters, P. R. (1960). Forecasting sales by exponentially weighted moving averages. Management Science, 6(3), 324–342.