Available online at www.sciencedirect.com

ScienceDirect

IFAC PapersOnLine 58-19 (2024) 1–6

Collaborative Reconfiguration of Supply Networks Based on GNN and ALC

Hai-nan Huang*, Ting Qu*, Xiao-hui Qiu*, Lin Ma, Zhong-fei Zhang***

** Guangdong International Cooperation Base of Science and Technology for GBA Smart Logistics, Jinan University, Zhuhai 519070, P.R. China. (hhn0113@outlook.com, quting@jnu.edu.cn, xhqiu95@163.com, zhangzhongfei55@stu2019.jnu.edu.cn)*

*** Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China. (mlin.ma@polyu.edu.hk)*

Abstract: With the prevalence of lean and just-in-time principles, traditional supply chains often exhibit inflexibility, leading to challenges in satisfying extensive customized orders and managing risks during disruptions. Thus, there is a need for a more flexible, resilient, and collaborative network and strategies to tackle the aforementioned challenges. In this study, we introduce a new supply network called the industry supply chain, aimed at enabling collaborative decision-making and dynamic reconfiguration. We create a graph neural network model to promptly identify sudden disturbances and devise a distributed multidisciplinary optimization model to facilitate collaborative reconfiguration. The experimental findings from an air-conditioning industry supply chain show that network reconfiguration under real-time disturbance detection reduces losses and improves operational stability.

Keywords: Supply chain, industry chain, sudden disturbance, collaborative reconfiguration, GNN, ALC.

1. INTRODUCTION

Currently, the escalating consumer demand for customization and the integration of Industry 4.0 technologies have led to a rise in customized products that consist of standard, variant, and customized parts(Shekarian & Mellat Parast, 2021). However, traditional supply chains are struggling to meet the rapidly changing demands due to their rigid network structure, challenges in sourcing suppliers for the wide variety of customized parts, lack of collaboration, and vulnerability to risks. To address these issues, there is a growing need for a more flexible, collaborative, and resilient approach to supply network and management.

Supply chains are inevitably susceptible to abrupt disturbances arising from factors such as fires, earthquakes, hurricanes, economic recessions, technological advancements, wars, and others (Shekarian & Mellat Parast, 2021), thus presenting challenges to the resilience of supply chains. Under sudden disruptions, supply chains must reconfigure their networks by considering firm, industry, and upstream and downstream factors simultaneously, presenting a challenge to supply chain collaboration. Collaboration at the firm level necessitates distributed decision-making among firms, incorporating aspects such as information utilization, firm-independent decision-making (Ivanov et al., 2018), and privacy protection (Nie et al., 2019). Moreover, at the industry level, collaboration is essential among industries providing various components, particularly in design and production, to ensure the quality and functionality of the final product. Finally, at both upstream and downstream levels, industries and firms operating at different supply stages face trade-offs concerning goals, time, and resources, highlighting the importance of coordination between these stages to achieve systemic optimization (K. Zhang et al., 2020).

The current research focus on the flexibility, collaboration, and resilience of supply networks has garnered significant attention. This study introduces a novel supply network structure, known as an industry supply chain, aimed at enhancing supply chain flexibility. To enhance supply network resilience, a graph neural network-based model for detecting supply network disturbances in real-time is proposed in this paper. Additionally, a collaborative supply network reconfiguration model, based on Augmented Lagrangian coordination (ALC), is developed in this study to achieve collaborative reconfiguration among firms, industries, and upstream and downstream partners systematically.

The article is structured as follows: Section II critically examines recent research on supply network optimization and the analysis of supply network disturbances. Section III discusses the definition, operational processes, benefits, and classifications of industry supply chain. Section IV elaborates on the principles of industry supply chain reconfiguration, encompassing the disturbance identification model and the network collaboration model. Section V presents a numerical experiment and conducts a result analysis, while Section VI offers conclusions and outlines future research directions.

2. RELATED WORKS

2.1 Supply network optimization

The purpose of supply network optimization is to identify the most efficient supply network given specific conditions by allocating resources and conducting business operations (Ivanov et al., 2017). Currently, research on optimizing supply chain networks is comprehensive, spanning various industries and sectors, including manufacturing (G. Zhang et al., 2021), services (Katoozian & Zanjani, 2022), energy (Li et al., 2019), agriculture (Mogale et al., 2018), and more.

10.1016/j.ifacol.2024.09.063

2.2 Supply network risk

Uncertainty and risk exert a substantial influence on supply networks. When facing disruption and operational risks (Shekarian & Mellat Parast, 2021), supply networks could encounter structural impairments. Scholars utilize various methodologies to develop resilient supply networks, encompassing operations optimization (Liu & Yao, 2018), simulation (Dolgui et al., 2020), optimal control (Ivanov et al., 2016), and artificial intelligence (Seify et al., 2022).

The current research findings have received widespread acclaim, but there are still areas that require further exploration. Although numerous studies have focused on supply network optimization, the majority of them only address upstream and downstream collaboration, neglecting integrated collaborative decision-making among firms, industries, and upstream and downstream entities. Existing research primarily offers specific analyses of isolated unexpected disturbances, warranting the development of a comprehensive disturbance identification and analysis method to effectively address the supply network uncertainties arising from various typical unexpected events.

3. INDUSTRY SUPPLY CHAIN

This study conceptualizes a new flexible, resilient, and collaborative supply network as an *industry supply chain*: a multi-level network formed by the integration of industry and supply chains. It relies on highly flexible and robust industry chain ecosystems to address customized demands, as depicted in Figure 1. Each industry within the industry supply chain, consisting of numerous enterprises, functions as a singular node in the network. By enhancing collaboration among firms, industries, and upstream and downstream sectors and by integrating and optimizing information, logistics, and financial flows within the industry chain, a customized supply chain is established to cater to specific demands.

The planning process involves a series of negotiations and collaborations within the industry supply chain. Initially, customization orders are received by the industry supply chain, which then negotiates with the upstream manufacturing segment to establish upstream-downstream collaborations. Subsequently, the manufacturing segment collaborates with the internal manufacturing industry to form industry collaborations. This process extends further as the manufacturing industry negotiates with internal companies to establish enterprise collaborations. In a similar fashion, the manufacturing segment engages in negotiations with the upstream first-tier supply segment to create upstream-downstream collaborations. The first-tier supply segment, in turn, negotiates with each supply industry to establish industrial collaborations, and each supply industry negotiates with its internal enterprises to form enterprise collaborations. This cycle continues into the most upstream segment. Furthermore, each related industry negotiates with the logistics industry to form industry collaborations, and the logistics industry collaborates with internal logistics enterprises to establish logistics collaborations. Ultimately, a customized, proprietary supply network is formed to meet specific needs.

The demand from downstream is passed down to enterprises through the "segment-industry-enterprise" information interaction, enabling them to identify appropriate suppliers by utilizing knowledge of industrial alliances. Conversely, the demand originating from enterprises is aggregated upwards to the industry or segment via the "enterprise-industry-segment" information exchange, thereby creating a scale effect through the consolidation of information and resources.

Traditional supply chains typically follow an upstream-downstream serial structure through firm-to-firm supply relationships. Conversely, industry supply chains exhibit a multilevel network structure, fostering industry-to-industry relationships that form a three-level collaborative network among upstream and downstream entities, inter-industry, and intra-enterprise, enhancing collaboration. Unlike the rigidity of traditional supply chains, industry supply chains establish potential supply relationships with numerous suppliers in related industries. Upon receiving customized orders, the industry supply chain promptly creates a specific supply network with potential suppliers, thereby enhancing flexibility in the supply process. Lastly, regarding network resilience, the prevailing lean thinking in supply chains tends to neglect security redundancy. In contrast, industry supply chains are

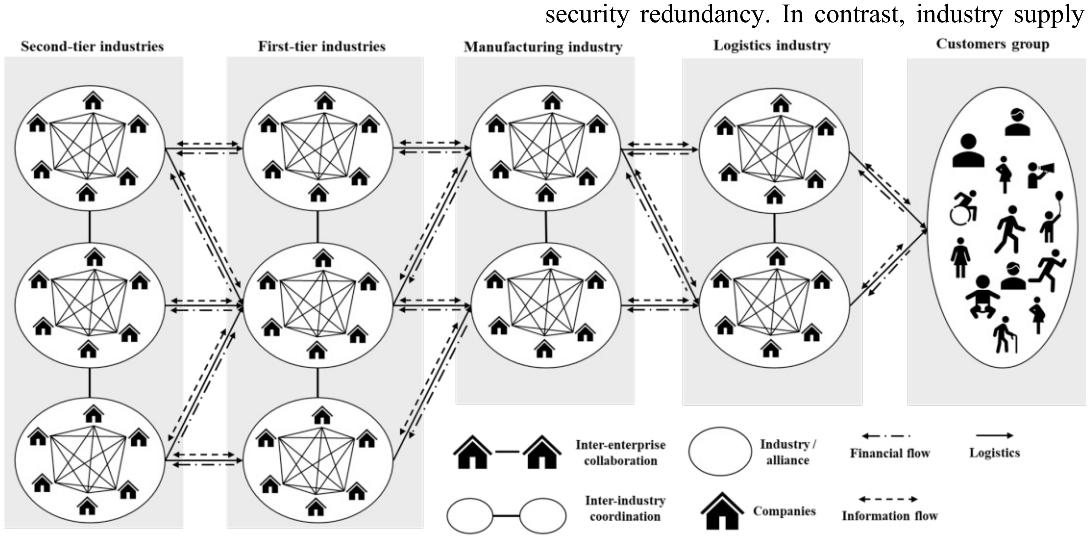

Fig. 1. Industry supply chain structure

geared towards engaging with a wide array of potential suppliers, providing a safety net in the event of supply disruptions by offering ample resources for network reconfiguration, thus enhancing network resilience.

4. MATHEMATICAL FORMULATION

This section introduces a disturbance identification model based on GNN to detect end-to-end disruptions in the supply network. The nodes identified with disturbances are then integrated into the ALC model for network reconfiguration.

4.1 DOMINANT-based disturbance identification model

DOMINANT was first proposed by Ding et al. (2019) for identifying anomalous or disturbed states of nodes on an attribute network and is one of the best current models for disturbance detection. It consists of a graph convolutional neural network (GCN) and a deep self-encoder. The GCN plays a crucial role in effectively modeling both the network's topology and node attributes for optimal node embedding learning. On the other hand, the deep self-encoder utilizes these learned embeddings to reconstruct the initial graph structure. Notably, the representation of industry supply chains as graph data lends itself well to the application of GNN. The DOMINANT framework comprises three key modules: an attribute network encoder, a structure reconstruction decoder, and an attribute reconstruction decoder.

The attribute network encoder utilizes two layers of GCN (Equations 1 and 2). The structure reconstruction decoder reconstructs the adjacency matrix (Equations 3 and 4), while the attribute reconstruction decoder regenerates the node attributes using two layers of GCN (Equation 5). Training the network involves minimizing the reconstruction errors of both structure and attributes (Equation 6). Subsequently, the disrupted score of a node is computed using Equation (7), with a higher score indicating a higher likelihood of disturbance.

$$\tilde{A} = D^{-\frac{1}{2}}(A + I)D^{-\frac{1}{2}} \tag{1}$$

$$B = ReLU\left(\tilde{A}\left(ReLU(\tilde{A}XW_1)\right)W_2\right) \tag{2}$$

$$Z = ReLU(\tilde{A}BW_3) \tag{3}$$

$$\hat{A} = sigmoid(ZZ^T) \tag{4}$$

$$\hat{X} = ReLU\left(\tilde{A}\left(ReLU(\tilde{A}BW_4)\right)W_5\right) \tag{5}$$

$$\min L = (1-\alpha)\left\|A - \hat{A}\right\|_F^2 + \alpha\left\|X - \hat{X}\right\|_F^2 \tag{6}$$

$$score(i) = (1-\alpha)\|a - \hat{a}_i\|_2^2 + \alpha\|x - \hat{x}_i\|_2^2 \tag{7}$$

Where A, X, I are adjacency matrix, node attribute matrix and unit diagonal matrix respectively. D is the diagonal matrix of $(A + I)$. The filter or feature map parameters W_i are shared for all nodes on the attributed network. The $\|\cdot\|_F$ is the Frobenius paradigm of the matrix, α is the node attribute weights in the range [0,1]

4.2 ALC-based industry supply chain reconfiguration model

This study delves into the issue of network reconfiguration within a customized order-driven industry supply chain comprising five segments: parts supply, logistics, finished product assembly, logistics, and the consumer group. Each individual firm may potentially encounter disruptions. Specifically, the industry supply chain processes R customized orders, each comprising standard, variant, and custom parts. These orders are executed through collaboration across upstream-downstream, inter-industry, and inter-firm channels. For the sake of simplification, key assumptions include: (1) single-source procurement; (2) firms making independent decisions with a focus on privacy protection; and (3) the profit-oriented nature of the industry supply chain.

Augmented Lagrangian Coordination (ALC) is a multidisciplinary optimization method (Tosserams et al., 2008) that draws on the Augmented Lagrangian method and block coordinate descent algorithm. By utilizing modern distributed computing technology, ALC integrates multidisciplinary knowledge to facilitate the distributed coordination of system components in alignment with optimization principles, ultimately realizing the optimal system-wide solution. This paper formulates the industry supply chain network reconfiguration problem as an ALC model, illustrated in Fig. 2. Initially, the DOMINANT model is utilized to monitor the status of each node in real-time; if a node is disrupted, it is removed from consideration. Subsequently, a distributed negotiation process is conducted among the upstream, downstream, inter-industry, and inter-firm, involving the transmission of coupling variables (η^i, η^{ij}) downstream and feedback of coupling variables $(\mho^i, \mho^{ij})$ upstream, continuing until reaching consensus. Ultimately, upon convergence of η^i, $\mho^i$, η^{ij}, and $\mho^{ij}$, the entire industry supply chain is optimally reconfigured.

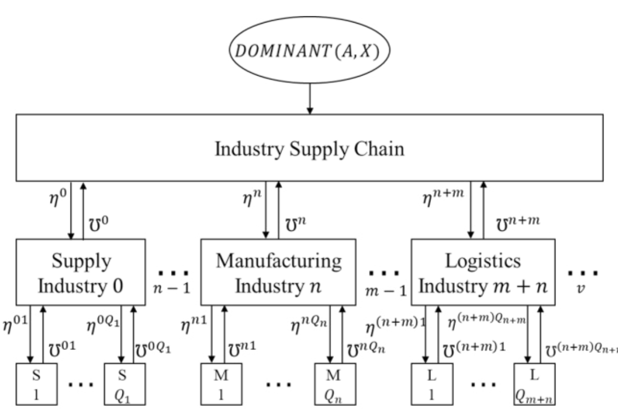

Fig. 2 Structure of the ALC reconfiguration model

In the following, we present the core part of the proposed ALC model:

Sets	
S	Set of suppliers, indexed by s.
V	Set of components/ parts, indexed by j.
M	Set of manufacturers, indexed by m.
R	Set of customized orders, indexed by r.
L	Set of logistics providers, indexed by l.
n	Number of supply industries.
m	Number of manufacturing industries.
v	Number of logistics industries.

Q_i	Maximum number of enterprises in the i industry.
Parameters	
v_u	Vector of u-th Lagrange multiplier estimates.
w_u	Vector of u-th penalty weights.
X_r	Quantity of finished products r produced.
c_{sj}	Cost of production of component j by supplier s.
ST_{sj}	Storage time of component j at supplier s.
SC_{sj}	Unit warehousing cost of part j at supplier s.
VO_j	Volume of component j.
AV_l	Capacity of the car of the logistics provider l.
k_{sj}	Discount strength of supplier s for component j.
A_{sj}	Maximum quantity of part j that can be produced by s.
B_{sj}	Whether s can produce part j, 0 if it can and 1 otherwise.
p_r	Selling price of product r.
c_r	Manufacturing cost of product r.
ST_{mr}	Storage time of product r at manufacturer m.
SC_{mr}	Unit warehousing cost of product r at manufacturer m.
k_l	Discount strength of logistician l in the range [0,1].
MO_r	Volume of product r.
a_{jr}	Whether product r contains component j.
B_{mj}	Whether m can assemble part j, 0 if so, 1 otherwise.
sd_{sm}	Distance from supplier s to manufacturer m.
md_{mr}	Distance from manufacturer m to order r.
θ_l	Transport costs per unit distance for logistician l.
ϱ_{mr}	Difficulty of transport from manufacturer m to order r.
ϱ_{sm}	Difficulty of transport from supplier s to m.
b_{sm}	Unit costs for transporting items from s to m.
o_{mr}	Unit cost of transporting items from m to order r.
Coupling variables	
$[\cdot]^{itl(h)}$	The superscripts i, t, l, h denote i industry, t firm, local level, and higher level, respectively.
z_{sjm}	Quantity of part j supplied by s to m.
p_{sjm}	Price to manufacturer m for part j supplied by s.
k_{mrl}	Quantity of r distributed by m using logistics l.
o_{mrl}	Price of transporting r produced by m by logistics l.
y_{sjml}	Quantity of part j shipped by l from s to m.
b_{sjml}	Price of transporting part$j$ from s to m by l.
Local variables	
h_{mr}	Whether product r is produced by manufacturer m.
t_{sjmr}	Whether s supplies part$j$ to m and j is belonging to r.

Manufacturer it model, $i,t \in \{n, \dots, n+m-1\}, \{1, \dots, Q_i\}$:

$$\min_{\mho^{it}=[z^{itl},p^{itl},k^{itl},o^{itl},h^{it},t^{it}]} FO^{it} + \phi^{it} \tag{8}$$

$$-FO^{it} = \sum_{r\in R}\left(X_r h_{mr}^{it}\left(P_r - c_r^{it} - ST_{mr}^{it}SC_{mr}^{it}\right)\right) - \sum_{s\in S}\sum_{j\in V} z_{sjm}^{itl}p_{sjm}^{itl} - \sum_{r\in R}\sum_{l\in L}\frac{k_{mrl}^{itl}MO_r}{AV_l}o_{mrl}^{itl} \tag{9}$$

$$\phi^{it} = \sum_{u\in c^{it}} {v_u^{it}}^T c_u^{it} + \sum_{u\in c^{it}}\left\|w_u^{it}\circ c_u^{it}\right\|_2^2 \tag{10}$$

$$c^{it} = \eta^{it} - \mho^{it} = \left[z^{ith}, p^{ith}, k^{ith}, o^{ith}\right] - \left[z^{itl}, p^{itl}, k^{itl}, o^{itl}\right] \tag{11}$$

$$z_{sjm}^{itl} = \sum_{r\in R} X_r t_{sjmr}^{it}, \forall s, j \in S, V \tag{12}$$

$$\sum_{s\in S} t_{sjmr}^{it} = h_{mr}^{it}a_{jr}, \forall j, r \in V, R \tag{13}$$

$$\sum_{r\in R} a_{jr}h_{mr}^{it}X_r \le A_{mj}^{it}, \forall j \in V \tag{14}$$

$$a_{jr}h_{mr}^{it}B_{mj}^{it} = 0, \forall j, r \in V, R \tag{15}$$

$$\sum_{l\in L} k_{mrl}^{itl} = h_{mr}^{it}X_r, \forall r \in R \tag{16}$$

Equation 9 is the manufacturer's profit function, which consists of three components: production, warehousing, and logistics. Equation 10 is the augmented Lagrangian penalty term. Equation 11 measures the consistency of the upper level. Equation 12 is the order privacy constraint. Equation 13 is the single-source sourcing constraint. Equation 14 is the volume constraint. Equation 15 is the assembly scope constraint. Equation 16 is the logistics constraint.

Supplier it model, $i,t \in \{0, \dots, n-1\}, \{1, \dots, Q_i\}$:

$$\min_{\mho^{it}=[p^{itl},z^{itl},y^{itl},b^{itl}]} FO^{it} + \phi^{it} \tag{17}$$

$$-FO^{it} = \sum_{j\in V}\sum_{m\in M}\left(\left(p_{sjm}^{itl} - c_{sj}^{it}\right)z_{sjm}^{itl} - z_{sjm}^{itl}ST_{sj}^{it}SC_{sj}^{it}\right) - \sum_{j\in V}\sum_{m\in M}\sum_{l\in L}\left\lceil\frac{y_{sjm}^{itl}VO_j^{it}}{AV_l}\right\rceil b_{sjml}^{itl} \tag{18}$$

$$\phi^{it} = \sum_{u\in c^{it}} {v_u^{it}}^T c_u^{it} + \sum_{u\in c^{it}}\left\|w_u^{it}\circ c_u^{it}\right\|_2^2 \tag{19}$$

$$c^{it} = \eta^{it} - \mho^{it} = \left[p^{ith}, z^{ith}, y^{ith}, b^{ith}\right] - \left[p^{itl}, z^{itl}, y^{itl}, b^{itl}\right] \tag{20}$$

$$p_{sjm}^{itl} = p_j\left(1 - k_{sj}^{it}\frac{z_{sjm}^{itl}}{A_{sj}^{it}}\right) + k_{sj}^{it}\frac{z_{sjm}^{itl}}{A_{sj}^{it}}\left(c_{sj}^{it} + ST_{sj}^{it}SC_{sj}^{it}\right), \forall s, j, m \in S, V, M \tag{21}$$

$$\sum_{m\in M} z_{sjm}^{itl} \le A_{sj}^{it}, \forall j \in V \tag{22}$$

$$z_{sjm}^{it}B_{sj}^{it} = 0, \forall j, m \in V, M \tag{23}$$

$$\sum_{l\in L} y_{sjm}^{itl} = z_{sjm}^{itl}, \forall j, m \in V, M \tag{24}$$

Equation 18 is the supplier's profit function, which consists of three components: production, warehousing, and logistics. Equation 19 is the augmented Lagrangian penalty term. Equation 20 measures the model's consistency at the upper level. Equation 21 is the price function for components. Equation 22 is the capacity constraint. Equation 23 is the production range constraint. Equation 24 represents the logistics constraint.

Logistics provider it model, $i,t \in \{n+m, \dots, n+m+v\}, \{1, \dots, Q_i\}$:

$$\min_{\mho^{it}=[k^{itl},o^{itl},y^{itl},b^{itl}]} -FO^{it} + \phi^{it} \tag{25}$$

$$FO^{it} = \sum_{s\in S}\sum_{j\in V}\sum_{m\in M}\left\lceil\frac{y_{sjm}^{itl}VO_j}{AV_l^{it}}\right\rceil\left(b_{sjml}^{itl} - \theta_l^{it}\varrho_{sm}SD_{sm}\right) + \sum_{m\in M}\sum_{r\in R}\left\lceil\frac{k_{mrl}^{itl}MO_r}{AV_l^{it}}\right\rceil\left(o_{mrl}^{itl} - \theta_l^{it}\varrho_{mr}MD_{mr}\right) \tag{26}$$

$$\phi^{it} = \sum_{u\in c^{it}} {v_u^{it}}^T c_u^{it} + \sum_{u\in c^{it}}\left\|w_u^{it}\circ c_u^{it}\right\|_2^2 \tag{27}$$

$$c^{it} = \eta^{it} - \mho^{it} = \left[k^{ith}, o^{ith}, y^{ith}, b^{ith}\right] - \left[k^{itl}, o^{itl}, y^{itl}, b^{itl}\right] \tag{28}$$

$$\sum_{s\in S}\sum_{j\in V}\sum_{m\in M}\left\lceil\frac{y_{sjm}^{itl}VO_j}{AV_l^{it}}\right\rceil + \sum_{m\in M}\sum_{r\in R}\left\lceil\frac{k_{mrl}^{itl}MO_r}{AV_l^{it}}\right\rceil \le E_l^{it} \tag{29}$$

$$b_{sjml}^{itl} = \theta_l^{it}\varrho_{sm}SD_{sm} + \left(b_{sm} - \theta_l^{it}\varrho_{sm}SD_{sm}\right) * \left(1 - k_l^{it}\left\lceil\frac{y_{sjm}^{itl}VO_j}{AV_l^{it}}\right\rceil\frac{1}{E_l^{it}}\right), \forall s, j, m \in S, V, M \tag{30}$$

$$o_{mrl}^{itl} = \theta_l^{it} \varrho_{mr} MD_{mr} + \left(o_{mr} - \theta_l^{it} \varrho_{mr} MD_{mr}\right) * \left(1 - k_l^{it} \left\lceil \frac{k_{mrl}^{itl} MO_r}{AV_l^{it}} \right\rceil \frac{1}{E_l^{it}}\right), \forall s, j, m \in S, V, M \tag{31}$$

Equation 26 is the logistician's profit function, which consists of the "supplier-manufacturer" and "manufacturer-customer" profits. Equation 27 is the augmented Lagrangian penalty term. Equation 28 measures the consistency of the upper-level model. Equation 29 is the vehicle quantity constraint. Equations 30–31 are the logistics price functions.

The study employed the Augmented Lagrange Multiplier Method (ALM) and Block Coordinate Descent (BCD) to coordinate and solve hierarchical models (Tosserams et al., 2008). The BCD method was specifically utilized for solving the inner loop, while ALM was applied to tackle the outer loop. This method demonstrates robust convergence capabilities for non-convex problems, thereby ensuring solution reliability.

5. EXPERIMENTAL RESULTS

The experiment was conducted in a prominent air conditioner manufacturing ecosystem in China. The air conditioner industry supply chain in this ecosystem has implemented an industrial internet platform to enhance network collaboration efficiency. Air conditioner production in this setting adheres to a discrete production model characterized by extensive customization options in terms of functions, components, appearance, and services. Specifically, this study focuses on a core industry supply chain comprising two key supply industries (compressor and motor), a single manufacturing industry, a logistics industry, and eight unique types of customized air-conditioner orders for the purpose of experimental analysis. The structure of this industry supply chain is delineated in Fig. 3:

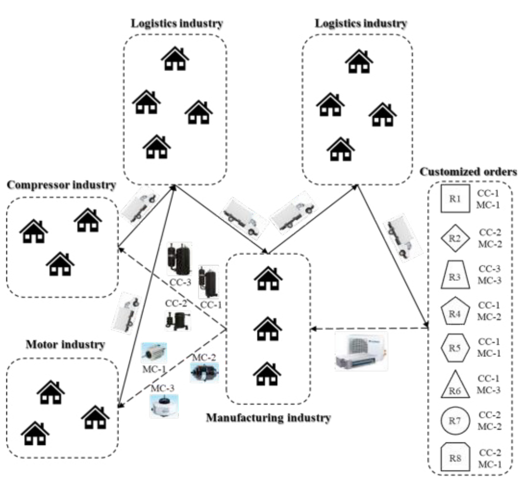

Fig. 3. Industry supply chain for core air conditioners

The study explores the efficiency of sequential network optimization (sequential optimization), and distributed synchronized network optimization (synchronized optimization) in dealing with sudden disturbances. Furthermore, it investigates the effectiveness of reconfiguration with and without the application of disturbance detection techniques (DOMINANT). Sequential optimization involves making sequential decisions for various upstream and downstream segments, while synchronized optimization is a distributed global optimization (ALC) model that simultaneously considers all upstream and downstream segments. Both methods ensure the independence and privacy of decisions in different segments.

The DOMINANT model was trained using real sudden disturbance data, including events such as fire, floods, and public health crises. Subsequently, 100 untrained sudden disturbance instances were utilized in network reconfiguration experiments, with each event potentially causing disruptions to the supply nodes. Among the 100 disturbance instances, 30 were confirmed to have an impact, of which DOMINANT successfully identified 22 disturbances, misclassified normal occurrences as disturbances in 16 cases, and correctly identified 54 normal nodes. The impact of sequential optimization and synchronized optimization during sudden disturbances is presented in Table 1.

Table 1. Performance evaluation under different programs

	Mean	Standard deviation	Min	Max
SyND	12724.7	743.5	10191.0	13151.0
SyD	12966.2	492.4	10487.0	13151.0
SeND	7757.3	721.4	4895.0	8151.0
SeD	7976.1	421.6	6079.0	8151.0

Notes: Synchronized optimization without disturbance detection (SyND); Synchronized optimization and disturbance detection (SyD); Sequential optimization without disturbance detection (SeND); Sequential optimization without disturbance detection (SeD)

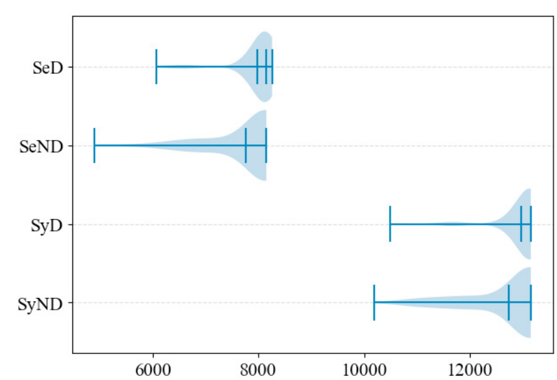

Fig.4 Violin plots of benefits under different programs

The synchronized optimization demonstrates a significant performance improvement of approximately 40% in economic benefits compared to traditional sequential optimization, regardless of the utilization of disturbance detection techniques. This indicates that the synchronized optimization approach can enhance decision-making in industry supply chains. The benefits of network reconfiguration under disturbance detection, whether employing synchronized or sequential optimization, consistently exceed those of passive execution. Analysis based on the minimum value index reveals that the benefits of network reconfiguration under disturbance detection consistently surpass those of passive execution, suggesting that disturbance detection can elevate the lower boundary of industry supply chain benefits. Fig. 4 illustrates the violin plots depicting the effects of the four programs. Notably, the violin length of network reconfiguration under disturbance detection, whether through synchronized or sequential optimization, is significantly shorter than that of passive execution. This difference underscores that the synergistic implementation of synchronized reconfiguration and disturbance detection can markedly mitigate the impact of unforeseen disturbances, maintaining the industry supply chain in a stable operational state.

6. CONCLUSIONS AND PERSPECTIVES

This study explores a novel form of supply network within the air-conditioning manufacturing sector known as the industry supply chain. It delves into the collaborative reconfiguration among firms, industries, and upstream-downstream within the industry supply chain. This paper defines and discusses the meaning, operation process, and advantages of the industry supply chain. A disturbance detection model based on DOMINANT and a distributed optimization model based on ALC are constructed to achieve dynamic reconfiguration of the network under sudden disturbance. The experimental results show that active reconfiguration under real-time disturbance detection can help reduce losses and ensure that the industry supply chain is in a stable and good operating state.

This paper presents two primary contributions. Firstly, it explores a flexible, collaborative, and resilient supply network structure (industry supply chain) designed to improve the supply and manufacturing of tailored products. Secondly, it investigates the distributed reconfiguration problem pertaining to inter-firm, inter-industry, and upstream-downstream collaboration during sudden disruptions, an issue worthy of examination.

Future research directions should focus on investigating the significant variances in structural characteristics and collaborative decision-making mechanisms among various industry supply chain types. Furthermore, this study solely addressed the network optimization problem related to order allocation, thus warranting further exploration into network optimization concerning R&D collaboration and production scheduling.

ACKNOWLEDGEMENTS

This study was funded by National Key Research and Development Program of China (2021YFB3301702); National Natural Science Foundation of China (52375498); Postgraduate Scientific Research Innovation Project of Hunan Province (QL20210217); 2019 Guangdong Special Support Talent Program – Innovation and Entrepreneurship Leading Team (China) (2019BT02S593).

REFERENCES

Ding, K., Li, J., Bhanushali, R., & Liu, H. (2019). Deep Anomaly Detection on Attributed Networks. In *Proceedings of the 2019 SIAM International Conference on Data Mining (SDM)* (pp. 594–602). Society for Industrial and Applied Mathematics.

Dolgui, A., Ivanov, D., & Rozhkov, M. (2020). Does the ripple effect influence the bullwhip effect? An integrated analysis of structural and operational dynamics in the supply chain. *International Journal of Production Research*, *58*(5), 1285–1301.

Ivanov, D., Dolgui, A., et al. (2017). Literature review on disruption recovery in the supply chain. *International Journal of Production Research*, *55*(20), 6158–6174.

Ivanov, D., Dolgui, A., et al. (2016). A dynamic model and an algorithm for short-term supply chain scheduling in the smart factory industry 4.0. *International Journal of Production Research*, *54*(2), 386–402.

Ivanov, D., Sethi, S., Dolgui, A., & Sokolov, B. (2018). A survey on control theory applications to operational systems, supply chain management, and Industry 4.0. *Annual Reviews in Control*, *46*, 134–147.

Katoozian, H., & Zanjani, M. K. (2022). Supply network design for mass personalization in Industry 4.0 era. *International Journal of Production Economics*, *244*, 108349.

Li, L., et al. (2019). Hydrogen supply chain network design: An optimization-oriented review. *Renewable and Sustainable Energy Reviews*, *103*, 342–360.

Liu, C., & Yao, J. (2018). Dynamic supply chain integration optimization in service mass customization. *Computers & Industrial Engineering*, *120*, 42–52.

Mogale, D. G., Kumar, M., Kumar, S. K., & Tiwari, M. K. (2018). Grain silo location-allocation problem with dwell time for optimization of food grain supply chain network. *Transportation Research Part E: Logistics and Transportation Review*, *111*, 40–69.

Nie, D., Qu, T., Liu, Y., et al. (2019). Improved augmented Lagrangian coordination for optimizing supply chain configuration with multiple sharing elements in industrial cluster. *Industrial Management & Data Systems*, *119*(4), 743–773.

Seify, M., Sepehri, M., Hosseinian-far, A., & Darvish, A. (2022). Fraud Detection in Supply Chain with Machine Learning. *IFAC-PapersOnLine*, *55*(10), 406–411.

Shekarian, M., & Mellat Parast, M. (2021). An Integrative approach to supply chain disruption risk and resilience management: A literature review. *International Journal of Logistics Research and Applications*, *24*(5), 427–455.

Tosserams, S., et al. (2008). Augmented Lagrangian coordination for distributed optimal design in MDO. *International Journal for Numerical Methods in Engineering*, *73*(13), 1885–1910.

Zhang, G., et al. (2021). Augmented Lagrangian coordination for energy-optimal allocation of smart manufacturing services. *Robotics and Computer-Integrated Manufacturing*, *71*, 102161.

Zhang, K., Qu, T., et al. (2020). Digital twin-based opti-state control method for a synchronized production operation system. *Robotics and Computer-Integrated Manufacturing*, *63*, 101892.