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Learning Assisted Simulation-Optimization Framework for Resilient Freight Transport Corridors

Satrya Dewantara*, Bilge Atasoy†, Saiedeh Razavi §, Mahnam Saeednia‡
*Department of Transport and Planning, TU Delft, Delft, The Netherlands
muhammadsatryadewantara@student.tudelft.nl
†Department of Maritime and Transport Technology, TU Delft, Delft, The Netherlands
b.atasoy@tudelft.nl
§Department of Civil Engineering, McMaster University, Hamilton, Canada
razavi@mcmaster.ca
‡Department of Transport and Planning, TU Delft, Delft, The Netherlands
m.saeednia@tudelft.nl

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***Abstract*—The increasing volume of global freight trade, coupled with economic growth, necessitates ongoing innovation in optimizing freight operations. Over the past decade, the concept of synchromodality has been explored to encourage a modal shift from unimodal to multimodal transport. Synchromodality, with its flexibility feature, can create more resilient freight transport systems. Various models employing different techniques have been proposed to establish a resilient synchromodal framework capable of reacting to disruptions. However, there are only few studies addressing the unknown duration of disruptions. This research proposes a learning-based modular framework comprising to capture the dynamics of disruptions in multimodal transport and learn to make more effective decisions, thus addressing the challenge of limited prior knowledge about disruptions and enabling fast responses to disruptions.**

***Index Terms*—Synchromodality; Resilient freight transport; Learning-based decision support framework**

I. Introduction

Road transportation dominates inland freight movement, accounting for 77% of the EU's freight in 2020 [1]. Logistic Service Providers (LSPs) often prefer unimodal transport primarily due to its inherent reliability [2]. However, road transport introduces several externalities, including accidents, road damage, environmental harm, and congestion [3]. The Intermodal concept promotes a shift of freight transport to other modes, such as barge and train. It can offer a cheaper option for inland freight transport due to the economics of scale [2]. Despite its cost-effectiveness, the share of intermodal transport remains low due to its lack of flexibility. The concept of synchromodality aims to increase the attractiveness of intermodal transport. By having a flexibility feature within the intermodal transport, synchromodal transport provides a higher number of combined routes, thus creating added values in the trade-off between price and time to the shippers [2].

Disruptions uncertainties negatively contribute to the efficiency of conventional intermodal transport [4] and could cause a severe economic loss. Disruption with low occurrence probability but high impact such as COVID-19 increased the logistic cost by 12% globally [5]. From another spectrum where disruption occurs frequently, a study by [6] estimates $15.2 Million loss in a year due to train delays. This estimate made in 2011 will have a significantly higher value today.

This research investigates how to create a resilient intermodal freight transport system that leverages the flexibility offered by synchromodality. The resilience of a freight transport network is defined by its ability to recover from disruptions and is measured by the effort required to restore normal operations [7]. It provides a learning-based modular framework capable of capturing the disruptions generating a reaction plan. Developing the comprehensive model as mentioned above with practical solutions creates a challenge for scholars. Not only filling the gap of knowledge, the model should be practical to be implemented at the industry level, thus, shifting the freight transport paradigm away from road dependency towards more sustainable and flexible options. The modular framework utilizes optimization, simulation, and machine learning techniques allows plug-and-play possibility for connecting with different existing/under development models and is extensible, making it applicable to different eco-systems of port-inland connections, expected to improve the solution space in generating decisions to react to the disruptions.

The paper is organized as follows: Section II provides a brief literature review. In section III, the disruption profiling is explained, followed by model formulation in section IV. Finally, the preliminary results are presented in Section V.

II. Literature Review

A. Concept of Synchromodality

Synchromodality is a concept developed to address the growing freight trade and its dynamics. Its objective is to thrive in the highly competitive transportation market and meet growing customer demands by enhancing flexibility and offering more customized services [2]. This flexibility attribute enables real-time mode shifts to respond and adapt to unexpected circumstances in the uncertain and competitive market [8]. To fully leverage this flexibility, certain requirements must be met. It is suggested that Logistics Service Providers (LSPs) can make the most of this feature when shippers agree to mode-free or a-modal requests [8]. In this scenario, LSPs have the freedom to choose the mode of transport that best suits the cargo's delivery, provided it meets the customer's requirements. This flexibility is a significant departure from traditional transportation approaches, offering a responsive and adaptable solution in the face of dynamic market conditions. The flexibility allows the services to adapt and react to disruptions [9] which will be the focus of this research.

B. Dynamic Models of Synchromodal Framework

Dynamic models for synchromodal transport have been proposed in several studies. A Synchromodal Transportation Replanning (STP) for hinterland transport is developed using a mixed integer linear programming (MILP) [10]. Using a different approach, a dynamic matching problem is proposed to deal with uncertain shipment requests [11]. In this model, the shipment requests are not completely known, but rather sequentially announced using a rolling horizon approach. This approach is adopted by another model for a global shipment matching problem and improved by incorporating disruptions in the service network [12]. The reaction to disruption in these two models are reallocation planning of the containers.

Other studies propose an agent-based model to to compare the performance of unimodal, intermodal, and synchromodal for cost, time, and emissions. The model applies a synchromodal scenario by putting logic for each agent to reroute to the nearest and cheapest terminal if there is a disruption in the network, and monitor the impact on cost, time, and emission [13]. Another study proposed an agent-based framework for cooperative planning [14]. The model uses decentralized optimization with a negotiation scheme. It breaks down the problem into several sub-problems and lets the agents communicate with other agents to achieve each objective under disrupted scenarios. The model provides a sequence plan and re-plans it when exogenous events occur. A decision support system is proposed using a hybrid simulation-optimization model under synchromodal framework [15]. It employs an offline model to create the initial plan and an online model to react to the disruptions and selects one of three possible policies: wait, transshipment, or detour. The disruptions are categorized according to frequency and duration by assigning them to a random variable in the simulation. The online model will be triggered if there is a disruption occurs. The result of the study shows that the transshipment policy has the lowest share in all scenarios. This result could be a subject for future research since transshipment or mode shift plays an important role in Synchromodal. The other policy in this model is to wait, which is essentially the traditional reaction, and detour, which is practically difficult for barge and/or freight trains.

More recent studies integrate a learning approach within the synchromodal framework, such as a study by [12] that adopts the RL approach in the global shipment matching problem under dynamic and stochastic travel time settings to address the curse of dimensionality of applying dynamic programming for solving the objective following Bellman's equation. Another study using RL technique under synchromodal framework is proposed by [16]. This study builds on top of an Adaptive Large Neighborhood Search (ALNS) proposed in the study by [17] to address the service time uncertainty in synchromodal transport. Unlike the study by [12] the learning agent in this study works side by side with the ALNS model instead of replacing its role. Integration of the RL approach in the synchromodal framework, it is potentially possible to address the variation in the nature of disruptions in the network. This is considered in the study [16], in which the RL agent works together with an optimization model and a binary reward system is employed depending on whether a delay occurs due to disruptions and the taken actions. Their approach does not account for shipment volume or the length of the delay. In contrast, this research proposes a negative cost value as the reward. This method considers a higher delay penalty for higher shipment volumes, allowing the RL agent to prioritize larger shipments. Extensive disruption scenarios are incorporated for an improved learning process. The disruptions impact both demand and services, a feature that has not been extensively studies in the literature. The modular framework offers a plug and play mechanism allowing for improving/replacing/extending the modules as needed.

III. Disruption Categorization

The disruption in the freight network varies in type and impact and may require different reaction strategies either at strategic, tactical, or operational levels. It can be distinguished according to the frequency and severity, categorized into endogenous and exogenous factors [15], and come from different sources such as nature or human acts [18]. Another way to categorize the disruptions is by separating them into two spectrum as elaborated by [19]: low occurrence probability but severe impact, and high occurrence probability with low impact. The categorization of the disruptions could be useful to simplify a model while keeping the realistic behavior.

In this research, the disruption in the freight network is divided into two components encompassing disruptions on the service network (supply side) and on the requests (demand side). Each profile represents a group of similar disruptions along with the possible impact and occurrence frequency.

On the supply side, the disruption categorization has more profiles than the request disruption. Five distinct profiles are developed to represent different types of service disruptions as detailed in Table I. Each profile contains a group of disruptions with similar characteristics. The first profile is a frequent disruption that could cause a short delay on either the train or truck network. This could be caused by road congestion for trucks [13], or technical and communication problems on trains [20]. The second profile is a delay in barge service lines which, for instance, is caused by congestion in the river due to locks or high traffic [21]. The third profile, adopted from [13] is a possible delay due to more severe disruptions such as bad weather or systems maintenance. These disruptions could result in operations being halted for a

TABLE I
SERVICE DISRUPTION PROFILE

Profile	Description	Mode/ Location	Effect in the Simulation	Duration	Capacity Reduction	Occurrence per Year
1	Operational delays, road congestions	Train, Truck	Delay	1-3h	0%	30%
2	Operational delay, canal congestion	Barge	Delay	1-6h	0%	35%
3	Bad weather, labor strike, accident, systems maintenance	Train, Barge	Delay	12-48h	0%	6%
4	Terminal congestion, operational delay	Terminal	Delay	1-3h	0%	30%
5	High and low water level	Barge	Carrying capacity reduction	12-24h	20-80%	5%

TABLE II
REQUEST DISRUPTION PROFILE

Profile	Description	Location	Effect in the simulation	Delay Release	Valume Change	Occurrence per Year
6	Demand Change	Shipment	Volume change	-	-30% to + 30%	30%
7	Customs issues, main port operational delays	Shipment	Release time change	1-6h	-	30%
8	Mother vessels arrival delays	Shipment	Release time change	1-7d	-	5%

certain period. The fourth profile is a disruption in the terminal such as equipment problems or port congestion [22]. The fifth profile is a reduction on barge carrying capacity due to the fluctuation of river water level [23], [24]. The low water level restricts barges from carrying containers with their full capacity because the barges need to reduce the draft, while the high water level could limit the height of the stacked containers on the barge to prevent collisions with bridges

On the request side, three disruption profiles are considered, including two profiles of changes in container release time and a profile of alterations in shipment volume. In port-inland transportation, changes in the release time could happen due to several causes such as the late arrival of the mother vessels which can cause delays of release time up to seven days [25] or more minor issues such as customs clearance which cause delays of less than a day. Meanwhile, the volume changes could come from the shippers due to, for instance, unexpected increases in demand beyond long-term contracts. The request disruption profiles are presented in Table II.

The disruption profiles are created based on two spectrum explained by [19]. The high probability with a low severity level is represented by high occurrence per year and low value of severity (column 5 and 6) as attributed in Profile 1, Profile 2, Profile 5, Profile 6, and Profile 7. The other spectrum, the low probability with high severity disruption is attributed in Profile 3, Profile 5, and Profile 8. Each profile can only occur in certain locations. The third column in the table indicates the possible location of disruption when it occurs. It could be either in a terminal, service line, or directly on the shipment.

IV. MODEL FORMULATION

The research examines hinterland freight transportation, specifically focusing on the unidirectional flow of shipments from the main port to various inland terminals excluding the final leg of transportation from these terminals to distribution centers or warehouses. Each terminal is interconnected via dedicated service lines, which are exclusively served by one mode of transport, i.e. barges, trains, or fleets of trucks. The shipments may be transported directly or through multiple service lines, involving transfers at transshipment terminals, thus constituting a multi-modal transport network.

Real-world operations often face disruptions in both the service network and requests, manifesting as delays, capacity reductions, or changes in shipment release times. Under a synchromodal framework, the service network adapts flexibly in real-time to these disruptions. This flexibility primarily involves reallocating containers or matching them with available services, rather than altering fixed service schedules, which is typically challenging in practice.

To enable the synchromodal framework in the service network, the proposed model follows several assumptions. This study assumes the disclosure of enough information (in real time) among stakeholders to allow the central planner to re-route a shipment flexibly, assuming the necessary ICT infrastructure is available. Moreover, the modal free booking is applied to all shipments granting full authorization to the planning in reallocating the containers.

A. Simulation Module

The main objective of this simulation is to capture the dynamic nature of disruptions in the hinterland freight network representing real-world operations to create an environment for implementing a decision support system.

The inland terminals are represented by nodes located at various locations. Multiple nodes of inland terminals could be located within the main port and serve as origin points for loading shipments onto transport modes. Other nodes are scattered further in the hinterland as the transshipment terminals or destination points. These terminals are characterized by handling capacity affecting the loading or unloading time. In this simulation, several parameters are assumed infinite such as stacking yard capacity and vehicle buffer area. Violation of these parameters could result in terminal congestion and could cause a delay. Rather than creating parameters, the port congestion is modeled using random variables to represent unexpected events.

The simulation module has three main service, shipment, and disruptions processes. The service is divided into fixed and flexible schedule service. The fixed schedule follows a predetermined departure time while flexible services depend on assigned requests. The shipment and services follow parallel processes while interacting with each other. The simulation keeps track of the actual costs for transporting each shipment from its origin the its destination. The cost components consist of storage, handling, travel, and delay penalty.

During the simulation process, the disruptions are enforced according to the profiles explained earlier. The disruption on requests only applies in a small time window after a shipment is announced and before it is released. However, the disruption on the service line could occur anytime in the chain of events causing the disrupted request to wait until the disruption ends. The *always wait* policy represents the absence of synchromodal framework and potentially causes severe delays in shipment delivery.

B. Hybrid Simulation-Optimization

Under synchromodal framework, it is assumed that there is a centralized planner is responsible for generating a shipment plan at regular intervals. Thus, shipment requests are delivered according to their requirements considering various objectives such as minimizing costs, maximizing on-time delivery, or minimizing emissions. Additionally, the planning process can be triggered to create a new shipment plan in case of disruptions or new requests. This approach, known as online planning, can potentially enhance the resilience of the freight network.

The modular framework presented in this study, enables various analytical methods to plug-in, acting as a central planner. These could range from simple strategies such as first come first serve (FIFO) principal, heuristic methods or sophisticated optimization models with various objectives. The role of the optimization module, that is embedded in the simulation module, is to match requests with available services considering the time and cost parameters associated with the service lines.

Upon receiving a new request or detecting a disrupted shipment, the optimization module is triggered to initiate the planning or re-planning process. The matching decision involves assigning a service line to the shipment. In the replanning process, the new assignment replaces the original itinerary. In contrast to the *always wait* policy, this hybrid simulation-optimization model *always reassigns* affected shipments to new service lines as the disrupted location is excluded from the possible solution space.

C. Reinforcement Learning Approach

Reassigning a shipment to a different service line during a disruption can potentially improve the resilience of the freight network and is feasible within a synchromodal framework.

However, in some situations, it may be better for a shipment to wait until the disruption ends and then continue on its original itinerary. For example, if the disruption is expected to be brief or occurs at a terminal far ahead in the journey, where it is likely to be resolved before the shipment arrives. The challenge lies in the uncertainty of the disruption's duration.

To address this, a reinforcement learning technique is integrated into the model, allowing it to decide whether to wait or reassign based on the learning agent's experience. This approach enables the model to make more informed decisions, balancing the benefits of reassignment with the potential advantages of waiting.

Using a value function, the RL agent can select the best action for a given state by learning from past experiences and extensive training. Unlike supervised learning, which relies on labeled data, the RL agent is guided by a reward system that indicates the effectiveness of each action. Properly modeling the action, state, and reward system is crucial for developing an optimal RL agent.

From the perspective of a centralized planner in synchromodal transport, defining the state of the RL agent is complex. If all shipments and service attributes are considered, the state space becomes exceedingly large. However, by narrowing the perspective to a single shipment, defining the state becomes more manageable, given that each request has an independent decision-making process. In this approach, the state consists of six features: the request's current position, destination, due time, volume, type of disruption, and the current time. This framework allows decision making at the level of shipments, represented by RL sub-agents, enabling decision making based on the previous actions taken, ensuring that actions within the same request are not independent from each other.

The reward system is also implemented separately for each sub-agent. This reward is used by the RL agent to update the action value function $Q(s, a)$ for each state s and action a using the off-policy Temporal Difference Control, Q-learning technique. The total transportation cost between terminals, including transport and storage, handling, and delay costs, is used as a reward for actions. The reward calculation starts when a disruption impacts a shipment and continues until either an action resolves the issue or another disruption affects the same shipment. Since rewards are negative costs, the agent selects actions based on the value function, choosing those with values closest to zero to minimize costs.

This framework allows the RL sub-agent to make decisions based on the previous action taken, ensuring that actions

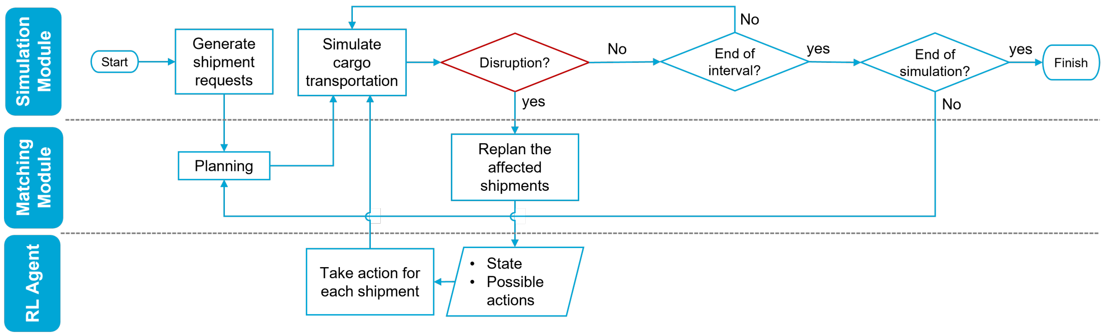

Fig. 1. Learning Assisted Hybrid Simulation-Optimization Flow

within the same request are not independent of each other. The learning technique is integrated with the existing hybrid simulation-optimization to create a comprehensive decision support system for a resilient synchromodal framework. These three modules work together by exchanging information, as illustrated in the flow diagram in Figure 1, forming a complete model of Learning-Assisted Hybrid Simulation-Optimization within the synchromodal framework.

V. Preliminary Results

To verify the model a synthetic service network, comprising 2 barge lines, 3 train lines, and 25 truck fleets with weekly recurring random departure times is considered. The network is loaded with randomly generated requests. A heuristic algorithm, following a nearest departure time rule,is constructed to act as a centralized planner and to evaluate the modular framework (implemented using *Python 3.10.6*).

The time horizon for each simulation is ten weeks. The three possible policies consisting *always wait*, *always reassign*, and *heuristic-based policy* are evaluated using the model. The *always wait* is a policy without having a replanning procedure. The *always reassign* is a policy that triggers the heuristic algorithm every time a disruption occurs and always accepts the solution. This represents a naive synchromodal framework without the RL agent. The last policy is by employing the RL agent to find the *optimal policy* using ϵ-greedy policy. To balance the exploration and exploitation [26], the ϵ value provides a small amount of probability so the RL agent occasionally chooses an action with a lower value and explores the probability of having a better reward in a longer run.

To verify the model, it runs for over 100 episodes to train the RL. In the episodic training, the RL agent applies the ϵ-greedy policy to explore and update its value function. Once training completes, the model runs again for one time with the RL agent applying a greedy policy by always choosing the best action.

Under the greedy policy, the RL agent always selects the action with the highest value. The results of the total cost of each policy are compared to see how the model performs with different policies. To ensure consistency in the verification process, a random seed of 0 is set. This means each episode encounters the same disruption occurrences, simplifying the comparison between policies. This simplification is solely for verification purposes, allowing observation of how the RL agent's performance improves despite the limited number of training episodes.

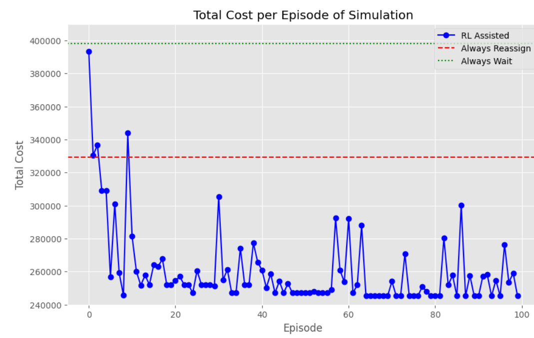

Fig. 2. RL Agent Training Result

The total costs for each training episode in Figure 2 show a decreasing pattern over episodes. The green dashed line is the total cost of *always wait* policy while the red dashed line is the total cost of *always reassign* policy. The RL agent outperforms the two other policies way before it reaches convergence. This convergence shows that the RL assisted model is matured for this specific sample case.

After going through the episodic training the learning-assisted model is evaluated again, this time using a greedy policy. This means, the model always chooses actions between wait and reassign according to the highest action value for the given states. The result obtained with greedy policy are compared against the other two policies in Figure 3.

Different policies demonstrate various performances in terms of delay and storage costs. In the sample case, the *always wait* policy results in longer waiting times at the terminal, and ultimately elevated arrival delays. Switching to the *always reassign* policy reduces delays but increases the total travel cost, due to the model choosing a longer route to avoid the disruption. Finally, the RL agent performs better by keeping the travel cost lower than *always reassign* and reducing the delay and storage costs even more, in this particular case, by having 24% lower total cost compared to *always reassign*

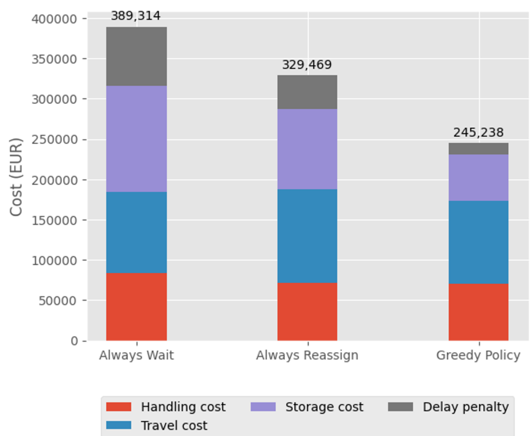

Fig. 3. Total Cost Comparison

policy.

It is important to note that the better performance of *always reassign* over *always wait* policy does not imply the superiority of one policy over the other in all cases. A different sequence of disruptions, may result in a different outcome. As for the learning-assisted model, it is expected to always perform better, or at least mimic the performance of the best policy between the other two. This result is yet to be seen and proven in the numerical experiment with a larger network and larger shipment numbers.

VI. Conclusion

This paper proposes a modular simulation-optimisation decision support tool to address the dynamic nature of demand and disruption in synchromodal transport. To address the unknown duration of disruptions in the synchromodal framework, an RL agent is integrated. Comparing three distinct policies *always wait*, *always reassign*, and an RL-assisted *greedy policy*, the model RL assisted model outperforms the other two policies by using its experience to choose the proper actions in case of a disruption occurs. The modular framework allows for extensibility to enable the plug-ins of different optimization techniques. Employing a more sophisticated optimization technique to replace the current heuristic model will provide a scalable model for a larger and more complex network. Additional future work considers a larger case with an extended disruption profile set. Furthermore, for larger problem sizes, more advanced reinforcement learning techniques, such as deep reinforcement learning can be used to handle the increased complexity and ensure scalability.

References

[1] Eurostat, "77% of inland freight transported by road in 2020," 2020.
[2] L. A. Tavasszy, B. Behdani, and R. Konings, "Intermodality and Synchromodality," *SSRN Electronic Journal*, 4 2015.
[3] G. Santos, H. Behrendt, L. Maconi, T. Shirvani, and A. Teytelboym, "Part I: Externalities and economic policies in road transport," *Research in Transportation Economics*, vol. 28, pp. 2–45, 1 2010.
[4] T. Delbart, Y. Molenbruch, K. Braekers, and A. Caris, "Uncertainty in intermodal and synchromodal transport: Review and future research directions," 4 2021.
[5] A. Rodríguez-Clare, M. Ulate, and J. P. Vasquez, "Supply Chain Disruptions, Trade Costs, and Labor Markets A framework of international trade with unemployment," tech. rep., 2023.
[6] B. W. Schlake, C. P. Barkan, and J. R. Edwards, "Train delay and economic impact of in-service failures of railroad rolling stock," *Transportation Research Record*, pp. 124–133, 12 2011.
[7] L. Chen and E. Miller-Hooks, "Resilience: An indicator of recovery capability in intermodal freight transport," *Transportation Science*, vol. 46, no. 1, pp. 109–123, 2012.
[8] B. Acero, M. J. Saenz, and D. Luzzini, "Introducing synchromodality: One missing link between transportation and supply chain management," *Journal of Supply Chain Management*, vol. 58, pp. 51–64, 1 2022.
[9] R. Giusti, D. Manerba, G. Bruno, and R. Tadei, "Synchromodal logistics: An overview of critical success factors, enabling technologies, and open research issues," *Transportation Research Part E: Logistics and Transportation Review*, vol. 129, pp. 92–110, 9 2019.
[10] W. Qu, J. Rezaei, Y. Maknoon, and L. Tavasszy, "Hinterland freight transportation replanning model under the framework of synchromodality," *Transportation Research Part E: Logistics and Transportation Review*, vol. 131, pp. 308–328, 11 2019.
[11] W. Guo, B. Atasoy, W. Beelaerts van Blokland, and R. R. Negenborn, "Dynamic and Stochastic Shipment Matching Problem in Multimodal Transportation," *Transportation Research Record*, vol. 2674, pp. 262–273, 2 2020.
[12] W. Guo, B. Atasoy, and R. R. Negenborn, "Global synchromodal shipment matching problem with dynamic and stochastic travel times: a reinforcement learning approach," *Annals of Operations Research*, 2022.
[13] T. Ambra, A. Caris, and C. Macharis, "Should I stay or should I Go? Assessing intermodal and synchromodal resilience from a decentralized perspective," *Sustainability (Switzerland)*, vol. 11, no. 6, 2019.
[14] A. Di Febbraro, N. Sacco, and M. Saeednia, "An agent-based framework for cooperative planning of intermodal freight transport chains," *Transportation Research Part C: Emerging Technologies*, vol. 64, pp. 72–85, 3 2016.
[15] M. Hrušovský, E. Demir, W. Jammernegg, and T. Van Woensel, "Real-time disruption management approach for intermodal freight transportation," *Journal of Cleaner Production*, vol. 280, 1 2021.
[16] Y. Zhang, R. R. Negenborn, and B. Atasoy, "Synchromodal freight transport re-planning under service time uncertainty: An online model-assisted reinforcement learning," *Transportation Research Part C: Emerging Technologies*, vol. 156, 11 2023.
[17] Y. Zhang, W. Guo, R. R. Negenborn, and B. Atasoy, "Synchromodal transport planning with flexible services: Mathematical model and heuristic algorithm," *Transportation Research Part C: Emerging Technologies*, vol. 140, 7 2022.
[18] X. Wang, "Optimal allocation of limited and random network resources to discrete stochastic demands for standardized cargo transportation networks," *Transportation Research Part B: Methodological*, vol. 91, pp. 310–331, 9 2016.
[19] P. Wide, L. K. Kalahasthi, and V. Roso, "Efficiency effects of information on operational disruption management in port hinterland freight transport: simulation of a Swedish dry port case," *International Journal of Logistics Research and Applications*, 2022.
[20] C. W. Palmqvist, A. Lind, and V. Ahlqvist, "How and Why Freight Trains Deviate From the Timetable: Evidence From Sweden," *IEEE Open Journal of Intelligent Transportation Systems*, vol. 3, pp. 210–221, 2022.
[21] A. Barkley and K. Mcleod, "Congestion and consolidation: An empirical study of a barge shipping merger," *Regional Science and Urban Economics*, vol. 93, 3 2022.
[22] PoR, "Barge Performance Monitor," 2024.
[23] C. van Dorsser, F. Vinke, R. Hekkenberg, and M. van Koningsveld, "The effect of low water on loading capacity of inland ships," *European Journal of Transport and Infrastructure Research*, vol. 20, no. 3, pp. 47–70, 2020.
[24] CCNR, "WATER LEVELS AND AVAILABLE VESSELS' DRAUGHT AT GAUGING STATIONS ON RHINE AND DANUBE," 2020.
[25] Statista, "Average monthly delays for late container vessel arrivals worldwide from January 2019 to July 2022," 2022.
[26] R. S. Sutton and A. G. Barto, *Reinforcement learning : an introduction*. 2018.