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Dynamic synchromodal transport planning under uncertainty: A reinforcement learning approach

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There are many uncertain elements in transportation systems including travel times, which may vary significantly due to delays resulting from the congestion on the roads, waterways, railways or at the terminals. To tackle dynamic routing problems under uncertainty, most of the existing approaches are based on robust optimization (Abbassi et al. 2019), re-planning (Hrušovskỳ et al. 2021), or stochastic programming (Guo et al. 2021). Robust optimization hedges the solutions against worst-case realizations of the uncertain parameters and may generate unused excess capacities and stocks. Re-planning is usually used after significant delays occur, and it does not predict when and how long will the delay be. Stochastic programming relies on prior assumptions on probability distributions for the travel times or demands, and it does not account for the possible deviations from the assumed distribution (Farahani et al. 2021).

Thanks to the development of digital platforms and the rise of innovative concepts such as synchromodal transport, a transport operator can collect real-time information from the transport network (through port authorities, terminal operators and/or sensors) about uncertainties. Such information can be used to learn the pattern of uncertainties by machine learning techniques, such as Reinforcement Learning (RL). Ideally, by learning online, RL can handle the uncertainty and choose suitable actions at the right time. This study addresses the following research question: How does the transport operator learn to plan better in real-time under uncertainty in the context of synchromodal transportation? Typical uncertainties will be considered, including congestion in nodes/links and the resulting delay of vehicles.

Different from approaches that solely use RL or routing heuristics to solve vehicle routing problems (Nazari et al. 2018, James et al. 2019, SteadieSeifi et al. 2021), this study combines RL and Adaptive Large Neighborhood Search (ALNS, a routing heuristic) to make use of the strengths of both. The ALNS uses removal and insertion operators to construct routes that visit all locations. In our approach, the ALNS is used to obtain the initial solution and the RL handle the

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tricky uncertainty in real-time by replacing ALNS operators with RL operators. Solving vehicle routing problems by RL is challenging because the size of the state is very large, especially for synchromodal transport with multiple modes and transshipment (Guo et al. 2022). Benefiting from combining ALNS, the size of the state in RL can be reduced by only keeping critical factors that influence decisions. Different factors need to be kept for different types of uncertainty. For example, when a vehicle faces congestion but does not know congestion duration, the critical factor is the delay tolerance of each request, which equals to latest delivery time minus the planned delivery time. When congestion duration is larger than delay tolerance, the vehicle cannot keep serving this request and this request needs to be switched to a faster vehicle. When we consider the whole transport network, the state needs to be extended with more factors. When multiple terminals have congestions, the travel times to each congested terminal and order of congested terminals need to be added.

The dynamic synchromodal transport planning approach contains the following steps:

1. An initial solution is generated by ALNS (Zhang et al. 2021).
2. Real-time information is received for an uncertain event, e.g., congestion starts.
3. For influenced requests, RL will be used to identify which vehicle is suitable to be assigned for them. Two RL operators will be trained in two phases: (a) Removal phase. For each influenced request, RL removal operator decides whether the current vehicle is suitable to serve it or not based on the value function. (b) Insertion phase. For each removed request, the RL insertion operator decides which vehicle is used to serve the request. The RL algorithm we use is Deep Q Learning (Mnih et al. 2013).
4. Real-time information is received regarding the uncertain event, e.g., congestion dissipates. Two RL operators will receive rewards depending on whether the removal action is correct or not and whether the insertion action has the minimum cost, respectively.
5. Steps 2-4 are repeated until all requests are delivered.

Our approach initially only relies on the ALNS proposed in our previous study (Zhang et al. 2021). Over time, the RL incorporates experience from the interaction with the environment in its decision-making. When the RL operators are mature enough, they will replace ALNS operators and make decisions for requests that are influenced by uncertainty, while constraints checking is still handled by ALNS.

The European Gateway Services (EGS) network located at Rhine-Alpine corridor is selected as the real-world case to test the proposed model. Figure 1 presents the overall network of this study (Guo et al. 2020). It contains three terminals in the Port of Rotterdam and seven inland terminals in the Netherlands, Belgium, and Germany. Let's assume the congestion duration follows a normal distribution (truncated at zero to avoid negative congestion duration). The mean value and standard deviation of the normal distribution are set as 2h and 1h, respectively. Each vehicle may pass different numbers and orders of terminals. The decision for one request needs to consider not only the congestion at the current terminal but also later terminals. We assume the delay tolerance is a random value between 0h and 4h. The numbers of iterations of training and test are 100000, 10000, respectively. The training can be finished in 3 minutes and the time for the test using the trained model is less than 1 second. The results show that RL can avoid congestion in 85% cases on average. By contrast, a random operator that removes and inserts requests randomly can only avoid congestion in 49% cases.

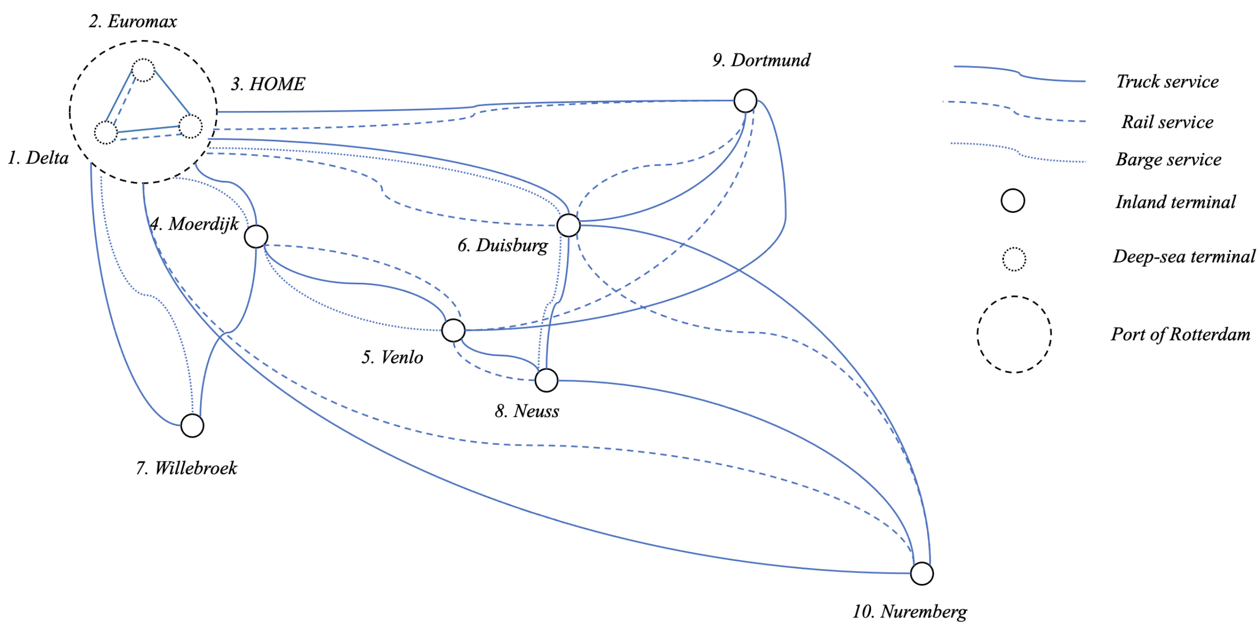

Figure 1 Transport network of EGS.

In summary, we use RL to handle uncertainty in dynamic synchromodal transport planning. The proposed model can be used by synchromodal transport operators in a digital platform, where the operator receives unexpected event information from port authorities and terminal operators.

The probability and frequency of uncertainty may change over time, how RL adapts to changing and incorporates newly gained experience in real-time will be investigated. The proposed approach will also be benchmarked against different approaches, such as stochastic programming.

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