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Dynamic and Stochastic Shipment Matching Problem in Multimodal Transportation

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Abstract

Multimodal transportation, as an efficient and sustainable alternative to unimodal transportation, refers to the utilization of multiple modes, the utilization of standard loading units, and flexibility in planning. The complexity of multimodal transportation at the operational level lies in being able to deal with dynamic events that are unknown before their realization. However, stochastic information on some of the events might be available from historical data. This paper proposes an anticipatory optimization approach to handle dynamic shipment requests in multimodal transportation by incorporating stochastic information of requests' origin, destination, volume, announce time, release time and due time. The experimental results show that the anticipatory approach outperforms a myopic approach in which decisions are made only based on deterministic information in reducing total costs under various scenarios of the multimodal matching system.

Hinterland transportation refers to the movement of cargo between deep-sea ports and inland terminals within specific time windows (*1*). Hinterland services mostly rely on road transportation characterized by dense networks and high flexibility in planning. The growing volumes of hinterland transportation challenge the dominance of road services, however, because of costs, congestion, and growing environmental constraints. Compared with truck transportation, barge and train transportation generate lower cost and carbon emissions but have less flexibility because of fixed schedules (*2*).

Multimodal transportation is an efficient and sustainable alternative to unimodal transportation under proper operations. It is defined as the transportation of goods by a sequence of multiple modes (e.g., road, rail, water) (*3*). The handling activities between different modes at transshipment terminals can be facilitated by using standardized loading units (i.e., containers). In addition, the flexibility offered by multimodal transportation guarantees "optimal" planning when disturbances (e.g., dynamic events) happen.

According to the decision horizon, multimodal transport planning can be divided into three groups: strategic planning in which long-term decisions (such as hub location problems) are made; tactical planning regarding medium-term decisions (such as service network design problems); and operational planning dealing with dynamicity and stochasticity that are not explicitly addressed at the tactical level (*4*). While extensive studies (*2, 5–9*) have addressed problems at the strategic and tactical level in multimodal transportation, only a few studies (*10–12*) have focused on the operational level. This paper investigates a *dynamic* and *stochastic* shipment matching (DSSM) problem in multimodal transportation at the operational level.

The advance of information and communication technologies as well as the growing amount of available historical data makes it possible to gather relevant dynamic and stochastic information for advanced shipment matching in multimodal transportation. The DSSM problem is therefore defined as the online matching of shipment requests and multimodal services with the utilization of dynamic information of newly arrived shipment requests and stochastic information of future requests. The characteristics of the problem include:

- static shipment requests which arrive in the multimodal matching system before the planning horizon;

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- real-time shipment requests which arrive dynamically over time;
- stochastic information about future requests;
- soft time windows, that is, delay in delivery is available but with a penalty;
- capacitated and time-scheduled barge and train services;
- departure-time flexible truck services with time-dependent travel times;
- transshipment operations at terminals.

The DSSM problem is dynamic since some input data (i.e., real-time shipment requests) are revealed in a dynamic fashion over a planning horizon (e.g., one week). Because of the capacity limitation of barge and train services, matching decisions made at an early stage of the planning horizon might affect the ability to make good matching decisions at a later stage. In such a dynamic problem, the probability distributions of future requests' information (including origin, destination, volume, announce time, release time and due time) are usually available. Therefore, the problem is said to be stochastic. By incorporating stochastic information into the dynamic decision-making process, decision makers might hold some barge and train capacity for future requests which are predicted to be more "important." In this way, decisions made for current requests might be suboptimal but the global performance over the planning horizon might be "optimal."

The challenge faced by dynamic and stochastic problems is known as the curse of dimensionality. This paper presents a multistage stochastic programming model to describe the DSSM problem. It develops a rolling horizon (RH) approach to handle dynamic events (e.g., real-time shipment requests). At each iteration of the RH framework a sample average approximation (SAA) method is employed to include stochastic information (e.g., the probability distribution of future requests). The combined utilization of the RH framework and the SAA method is therefore an anticipatory optimization approach (AOA). The myopic optimization approach (MOA) is defined as the utilization of the RH framework alone. Decisions made by the MOA are therefore based on deterministic information. This study compares the performance of the AOA with the MOA under various scenarios of a multimodal matching system.

The remainder of this paper is structured as follows. The next section summarizes the relevant studies in the literature. It then presents the problem description and the mathematical formulations and develops the myopic approach and the anticipatory approach. After that, it describes the instance generation and presents the experimental results. The final section provides concluding remarks and future research directions.

Literature Review

With the development of computing power, online decisions can be made incorporating dynamic and stochastic information. In the literature, dynamic and stochastic approaches have been investigated in many areas, such as vehicle routing problems (*13–16*), pickup and delivery problems (*17–21*), resource allocation problems (*22–24*), and multimodal container routing and flow control problems (*11*, *12*, *25*). However, to the best of the authors' knowledge, none of the studies in the literature investigated dynamic and stochastic models for the DSSM problem.

With regard to dynamic and stochastic vehicle routing problems, Bent and Hentenryck (*13*) proposed a multiple scenario approach to generate routing plans continuously for scenarios which include known requests and sampled future requests. Hvattum et al. (*14*) designed a multistage stochastic programming model with recourse to deal with stochastic customers. Because of the computational complexity, they developed a heuristic solution method based on sampled information and on ideas borrowed from progressive hedging. Albareda-Sambola et al. (*15*) proposed an adaptive policy which aims at estimating the best time period to serve each request within its associated time window by incorporating the probabilistic information of future customers. Ulmer et al. (*16*) proposed an offline-online approximate dynamic programming for dynamic vehicle routing with stochastic requests. Compared with vehicle routing problems, the DSSM problem investigates the "optimal" matching decisions between vehicles and requests instead of vehicle routing decisions.

In relation to dynamic and stochastic pickup and delivery problems, Cortes et al. (*17*) developed a hybrid predictive control framework that incorporates predicted information of future requests in real-time routing decisions. Ghiani et al. (*18*) described anticipatory algorithms that anticipate near-future demand through Monte Carlo sampling procedure to manage several decisions (e.g., vehicle dispatching and route rescheduling) in a unified way. Schilde et al. (*19*) investigated the benefits of incorporating stochastic information on return transport requests for a dynamic stochastic dial-a-ride problem. Lowalekar et al. (*20*) presented a multistage stochastic optimization formulation to consider potential future demand scenarios in online spatial-temporal matching of services to customers and a Benders Decomposition method to deal with large numbers of future scenarios. Agussurja et al. (*21*) proposed a Markov decision process model for a dynamic ride-sharing problem with stochastic multiperiod demands. Because of the curse of dimensionality, they employed three techniques to speed up the solution process: representative states, state space discretization, and SAA. While there are similarities, the present work differs from research on pickup and delivery problems in several ways: first, capacitated vehicles with fixed routes are considered; second, while some vehicles (e.g., trucks) have flexible departure times, others (e.g., barges and trains) follow fixed time schedules; third, transshipment operations between different vehicles are considered.

Regarding dynamic and stochastic resource allocation problems, Bilegan et al. (*22*) designed a rail freight load acceptance management system to accept or reject requests dynamically, taking into account future demand forecasting. Wang et al. (*23*) designed a booking system for barge transportation to perform accept or reject decisions for each new transport request based on expected objective function over a given time horizon. Wang et al. (*24*) developed a Markov decision process model to describe a dynamic and stochastic resource allocation problem from the viewpoint of an intermodal operator. At each decision epoch, the intermodal operator determines the booking limits on each product to be sold during the next time interval. While the resource allocation problem focuses on accepting or rejecting decisions to control the capacity of resources better, the DSSM problem investigates the "optimal" matches between vehicles and requests, and consequently the routes of requests. Furthermore, while the resource allocation problem aims to maximize profits, the DSSM problem aims to minimize costs.

In the literature, only a few articles have studied dynamic and stochastic container routing and flow control problems in multimodal transportation. Li et al. (*11*) proposed a receding horizon control approach to control and to reassign the container flows in a receding way. Van Riessen et al. (*12*) designed a decision tree to derive real-time decision rules for suitable allocation of containers to inland services. Rivera and Mes (*25*) proposed an algorithm based on approximate dynamic programming to assign newly arrived containers to either barges or trucks to achieve better performance over a planning horizon. While the container routing and flow control problems focus on the container level (i.e., integer decisions indicating the number of containers assigned to services), the DSSM problem focuses on the shipment request level (i.e., binary decisions indicating the matching between requests and services).

This paper addresses the key limitations of previous work by providing the following contributions. First, it presents a multistage stochastic optimization model to describe the DSSM problem in multimodal transportation. Second, because of the curse of dimensionality, it proposes an AOA to solve the problem under realistic instances in a reasonable time. The AOA uses a SAA method to generate sampled requests and approximate expected objective functions at each decision epoch of an RH framework. Third, numerical experiments are conducted to validate the performance of the anticipatory approach in comparison with a myopic approach.

Problem Description and Mathematical Formulations

Problem Description

We consider a platform in which a network operator receives shipment requests from shippers and receives services from carriers. Network operators can be multimodal operators, terminal operators, or alliances formed between several carriers and terminal operators. Examples of shippers include freight forwarders, drayage operators, and ocean carriers. Carriers can be barge carriers, rail operators, or truck companies.

Shippers announce shipment requests before shipments are released at deep-sea terminals, and ask to receive the matching plan before shipments' release time. Each shipment request $r \in R$ is characterized by its announce time t_r^{announce}, release time t_r^{release} at deep-sea terminal o_r, due time t_r^{due} at inland terminal d_r, and container volume u_r. Let R^0 be the set of shipment requests arriving before the planning horizon, namely, $t_r^{\text{annonuce}} = 0, r \in R^0$. Define R^t as the set of shipment requests received at time period $t = [(t-1)h, th]$, $t \in \{1, \dots, T\}$. Here, h is the length of time periods, T is the number of time periods within the planning horizon. Therefore, for request $r \in R^t$, $(t-1)h \leqslant t_r^{\text{announce}} \leqslant th$. Furthermore, request r is unknown before its announce time. However, the probability distributions $\{\pi_o, \pi_d, \pi_u, \pi_{t^{\text{announce}}}, \pi_{t^{\text{release}}}, \pi_{t^{\text{due}}}\}$ of future requests' origin, destination, volume, announce time, release time, and due time are assumed available. In addition, the only the requests considered are those accepted by network operators without the consideration of accept/reject decisions.

Carriers provide multimodal services to network operators. According to the modalities in hinterland transportation, services can be divided into three groups:

- *Barge services.* Each barge service $s \in S^{\text{barge}}$ is characterized by its departure time TD_s at origin terminal o_s, arrival time TA_s at destination terminal d_s, free capacity U_s, transport cost c_s, and carbon emissions e_s.
- *Train services.* Each train service $s \in S^{\text{train}}$ is characterized by its departure time TD_s at origin terminal o_s, arrival time TA_s at destination terminal d_s, free capacity U_s, transport cost c_s, and carbon emissions e_s.
- *Truck services.* Each truck service is viewed as a fleet of trucks which has flexible departure times and an unlimited capacity. Because of traffic

congestion at several time periods throughout a day, the travel time of truck services is time dependent (*26*). Therefore, each truck service $s \in S^{\text{truck}}$ is characterized by its origin terminal o_s, destination terminal d_s, time-dependent transit time $t_s^{\text{truck}}(\tau)$, transport cost c_s, and carbon emissions e_s. Here, τ_{rs} is the departure time of truck service s for shipment r.

A path P is defined as a combination of one or more services in sequence. The path P is feasible if the services within a combination satisfy time-spatial compatibility. Specifically, for two consecutive services s_i, s_{i+1} within path P, the destination of service s_i must be the same as the origin of service s_{i+1}; the arrival time of service s_i must be earlier than the departure time of service s_{i+1} minus loading and unloading time at transshipment terminal d_{s_i}. The set P denotes the collection of all feasible paths. A match (r, p) means shipment r will be transported by path P from its origin to its destination. A match between request $r \in R$ and path $p = [s_1, \ldots, s_l] \in P$ is feasible if it satisfies time-spatial compatibility:

- *Spatial compatibility*. The origin terminal of shipment request r should be the same as the origin of service s_1; the destination of request r should be the same as the destination of service s_l.
- *Time compatibility*. The release time of request r should be earlier than the departure time of service s_1 minus loading time at origin terminal o_r.

Let P_r be the set of all feasible paths for request r, and let c_{rp} denote the cost of matching request r with path P which consists of transport cost generated by using services, transfer cost and storage cost generated at transshipment terminals, penalty cost caused by delay in delivery (charged per container per hour), and carbon tax charged for carbon emissions of services. The objective of the multimodal matching system is to minimize the total costs for matching all the shipment requests with paths over a given planning horizon (e.g., one week). However, decisions need to be made at the end of each time period (i.e., each time stage) with dynamic information of newly received requests and stochastic information about future requests.

An illustrative example of the DSSM problem is shown in Figure 1. At time period 1 (06:00–07:00), the platform receives shipment request r_1 with 10 TEU (twenty-foot equivalent units). Path $p_1 = [s_1, s_4]$ (i.e., train-truck service combination), path $p_2 = [s_2, s_5]$ (i.e., barge-truck service combination), and path $p_3 = [s_3]$ (i.e., truck service) are all feasible for request r_1. At time period 2 (07:00–08:00), the system receives request r_2 with 8 TEU. Path $p_2 = [s_2, s_5]$ and path $p_3 = [s_3]$ are feasible for request r_2 while path $p_1 = [s_1, s_4]$ is infeasible because the departure time of s_1 (09:00) minus loading time (1 h) is earlier than the release time of request r_2 (09:00). The probability information of requests that will arrive in time period 2 and 3 is available. The platform needs to create matches for request r_1 at time stage 1 (07:00), and create matches for request r_2 at time stage 2 (08:00).

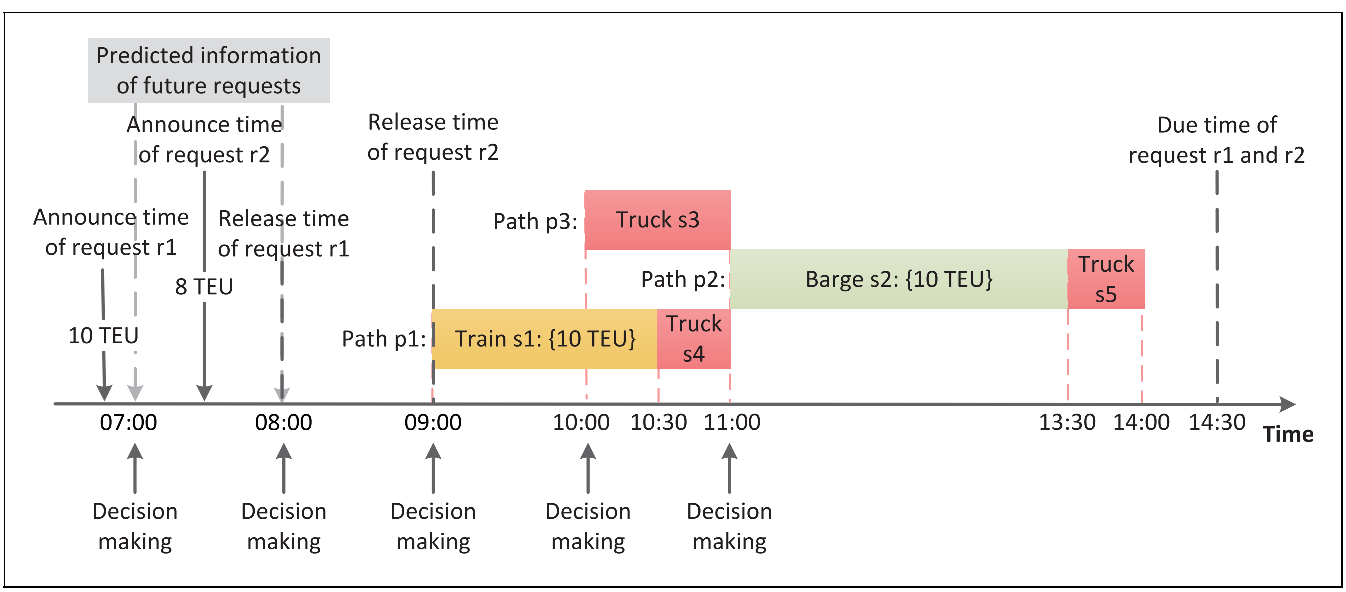

Figure 1. Illustrative example of the DSSM problem.
Note: DSSM = dynamic and stochastic shipment matching; TEU = twenty-foot equivalent units.

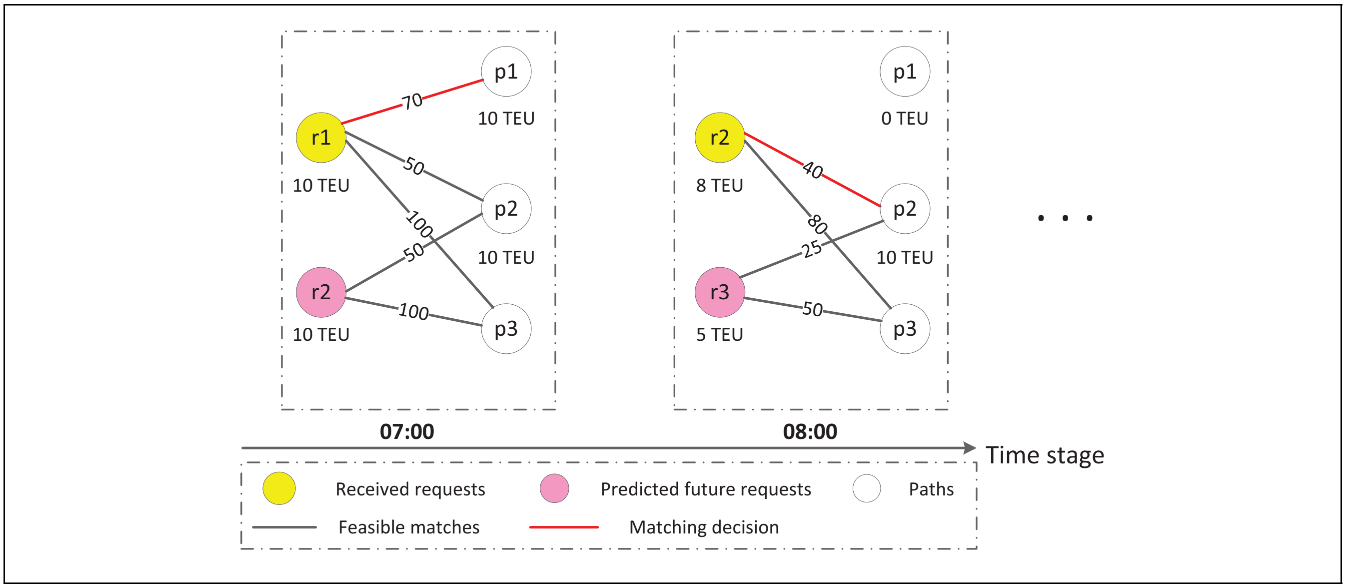

Figure 2. Illustrative example of the dynamic and stochastic shipment matching (DSSM) process.
Note: TEU = twenty-foot equivalent units.

An illustrative example of the DSSM process is shown in Figure 2. The number on the arcs means the cost of matching requests with services. At time stage 1 (07:00), the platform creates matches for current received request r_1 incorporating the information of predicted future request r_2. Path p_1 will be assigned to request r_1 instead of path p_2 since $70(r_1,p_1) + 50(r_2,p_2) < 50(r_1,p_2) + 100(r_2,p_3)$. At time stage 2, decision for request r_2 is made incorporating the information of predicted future request r_3. Here, request r_2 is assigned to path p_2, since $40(r_2,p_2) + 50(r_3,p_3) < 80(r_2,p_3) + 25(r_3,p_2)$. The total cost of matching for request r_1 and r_2 is $70 + 40 = 110$. In comparison, if only dynamic information is used for decision making (without the information of future requests), the platform will assign p_2 to request r_1 at time stage 1 (local "optimal"). Since the free capacity of path p_2 has already been assigned to request r_1, request r_2 can be only matched with path p_3 at time stage 2. Then the total cost of matching without the utilization of stochastic information is $50 + 80 = 130 > 110$.

Mathematical Formulations

The notation used in this paper is listed below. Let x_{rp}^t be a binary variable which equals 1 if shipment request $r \in R^t$ is matched with path $p \in P$, otherwise 0. Let Ω be the entire populations of requests over a planning horizon $(0, Th]$. P_{rs} is denoted as the set of feasible paths including service $s \in S^{\text{barge}} \cup S^{\text{train}}$ for shipment r, $P_{rs} = \{p | p \in P_r, s \in p\}$. The DSSM problem can be described by a multistage stochastic programming (MSP) formulation shown as follows:

$$\min_{X^0, X^1, \ldots, X^T} \sum_{r\in R^0}\sum_{p\in P_r} c_{rp}x_{rp}^0 + E_\Omega\{\sum_{r\in R^1}\sum_{p\in P_r} c_{rp}x_{rp}^1 + \ldots + \sum_{r\in R^T}\sum_{p\in P_r} c_{rp}x_{rp}^T\} \tag{1}$$

subject to

$$\sum_{p\in P_r} x_{rp}^t = 1, \quad \forall r \in R^t, t \in \{0, \ldots, T\}, \tag{2}$$

$$\sum_{r\in R^0}\sum_{p\in P_{rs}} u_r x_{rp}^0 \leqslant U_s, \quad \forall s \in S^{\text{barge}} \cup S^{\text{train}}, \tag{3}$$

$$\sum_{r\in R^t}\sum_{p\in P_{rs}} u_r x_{rp}^t \leqslant U_s - \sum_{t'\in\{0,\ldots,t-1\}}\sum_{r\in R^{t'}}\sum_{p\in P_{rs}} u_r x_{rp}^{t'}, \quad \forall s \in S^{\text{barge}} \cup S^{\text{train}}, t \in \{1, \ldots T\}, \tag{4}$$

$$x_{rp}^t \in \{0, 1\}, \quad \forall r \in R^t, p \in P, t \in \{0, \ldots T\}. \tag{5}$$

The objective of the MSP formulation is to minimize the expected total cost over the planning horizon. Constraints in Equation (2) ensure that only one path will be assigned to each shipment request. Constraints in Equations (3) and (4) ensure that the total volume of shipment requests assigned to service $s \in S^{\text{barge}} \cup S^{\text{train}}$ does not exceed its free capacity at every time stage.

The MSP is viewed as a multistage stochastic program since set R^0 is known, but sets $R^1, \ldots, R^T$ are unknown before the planning horizon. At each time stage (the end of each time period), one of the sets will become known, and R^t is the set which becomes known at time stage t. Therefore, we have the following decision process:

Sets	
R^0	Shipment requests arrived before the planning horizon
R^t	Shipment requests that are received at time period $[(t-1)h, th]$, $t \in \{1, \ldots, T\}$
$\hat{R}^t$	Active shipment requests at decision epoch t, $t \in \{1, \ldots, T\}$
$\bar{R}^t$	Active shipment requests that will be expired before decision epoch $t+1$, $t \in \{1, \ldots, T-1\}$
ω_γ^k	A sample of shipment requests received at time period $k \in \{t+1, \ldots, t+H\}$ under scenario $\gamma \in \{1, \ldots, \Gamma\}$
S	Transport services within the planning horizon, $S = S^{\text{barge}} \cup S^{\text{train}} \cup S^{\text{truck}}$
P	Feasible paths
P_r	Feasible paths for shipment request r
P_{rs}	Feasible paths for shipment request r including service s
Ω	Entire populations of shipment requests over planning horizon $(0, Th]$
Ω^t	Entire populations of shipment requests after decision epoch t
Parameters	
o_r	Origin terminal of shipment request $r \in R$
d_r	Destination terminal of shipment request $r \in R$
u_r	Container volume of shipment request $r \in R$
t_r^{announce}	Announce time of shipment request $r \in R$
t_r^{release}	Release time of shipment request $r \in R$
t_r^{due}	Due time of shipment request $r \in R$
c_{rp}	The cost of matching request r with path P
U_s	Free capacity of service $s \in S^{\text{barge}} \cup S^{\text{train}}$ at decision epoch 0
U_s^t	Free capacity of service $s \in S^{\text{barge}} \cup S^{\text{train}}$ at decision epoch t
h	The length of time periods
T	The number of time periods within a planning horizon, $t \in \{0, 1, \ldots, T\}$
E_Ω	The expected total cost over the planning horizon
E_{Ω^t}	The expected total cost after decision epoch t
Γ	The number of scenarios
H	The length of prediction horizon
Variables	
x_{rp}^t	Binary decision variable; 1 if active request $r \in \hat{R}^t$ is matched with path $p \in P$, 0 otherwise
$y_{rp}^{\gamma k}$	Binary decision variable; 1 if sampled request $r \in \omega_\gamma^k$ is matched with path $p \in P$, 0 otherwise

$$\text{decision}(X^0) \rightarrow \text{observation}(R^1) \rightarrow \text{decision}(X^1) \rightarrow \text{observation}(R^T) \rightarrow \text{decision}(X^T)$$

The objective of this study is to design the decision process in such a way that the expected value of the total cost is minimized while optimal decisions are allowed to be made at every time stage $t = \{0, 1, \ldots, T\}$. The values of the decision vector X^t, chosen at stage $t \in \{1, \ldots, T\}$, depend on the information $\xi^{[0,t]} = \{R^0, R^1, \ldots, R^t\}$ available up to time stage t, but not on the results of future observations. $U^t = [U_1^t, \ldots, U_s^t, \ldots u_{|S'|}^t], t \in \{0, \ldots, T\}$, $s \in S^{\text{barge}} \cup S^{\text{train}}$ are denoted as state variables. Here, $U_s^0 = U_s, s \in S^{\text{barge}} \cup S^{\text{train}}$. State variables are updated at each stage according to the current observation ξ^t, current decisions X^t, and current values of state variables U^t. Let Ω^t be the populations of shipment requests after time stage t. The dynamic stochastic programming (DSP) formulation of the DSSM problem at stage $t \in \{0, \ldots, T-1\}$ is presented as:

$$\textbf{P0} \quad Q_t(U^t, \xi^t, X^t) = \min_{X^t} \sum_{r \in R^t} \sum_{p \in P_r} c_{rp} x_{rp}^t + E_{\Omega^t}[Q_{t+1}(U^{t+1}, \xi^{t+1}, X^{t+1})] \tag{6}$$

subject to

$$\sum_{p \in P_r} x_{rp}^t = 1, \quad \forall r \in R^t, \tag{7}$$

$$\sum_{r \in R^t} \sum_{p \in P_{rs}} u_r x_{rp}^t \leqslant U_s^t, \quad \forall s \in S^{\text{barge}} \cup S^{\text{train}}, \tag{8}$$

$$U_s^{t+1} = U_s^t - \sum_{r \in R^t} \sum_{p \in P_{rs}} u_r x_{rp}^t, \forall s \in S^{\text{barge}} \cup S^{\text{train}}, \tag{9}$$

$$x_{rp}^t \in \{0, 1\}, \quad \forall r \in R^t, p \in P. \tag{10}$$

Constraints in Equation (7) ensure that the requests received at time period t will be matched with one feasible path. Constraints in Equation (8) ensure that the total volume of shipments assigned to service $s \in S^{\text{barge}} \cup S^{\text{train}}$

does not exceed its free capacity at time stage t. Constraints in Equation (9) denote the state transition at time stage t. The free capacity of service $s \in S^{\text{barge}} \cup S^{\text{train}}$ at time stage $t+1$ is updated by the free capacity of s at stage t and the matching decisions created at stage t.

For time stage T, all the information within the planning horizon is known, therefore,

$$Q_T(U^T, \xi^T, X^T) = \min_{X^T} \sum_{r \in R^T} \sum_{p \in P_r} c_{rp} x_{rp}^T \tag{11}$$

Optimization Approaches

In the DSP formulation presented above, it is very difficult to estimate E_{Ω^t} since the size of Ω^t might be huge even for a small instance of the DSSM problem. To address the DSSM problem with large instances, two optimization approaches are proposed: an MOA and an AOA. Both of them are based on the RH approach to handle dynamic events. The RH approach is known as an efficient periodic re-optimization approach for dynamic problems, such as crowdsourced delivery problems (*27*), ride-sharing problems (*28*), and long-haul transportation for perishable products (*29*).

MOA

This section presents an MOA in which decisions are made based on deterministic information only. The myopic approach is based on the RH framework. The multimodal matching system is therefore re-optimized at prespecified time points $\{0, h, 2h, \ldots, Th\}$. The length between two consecutive re-optimization time points is called the optimization interval, h. At each decision epoch t, decisions for all active shipment requests $\hat{R}^t$ are made. Request r is active if its announce time is earlier than th (i.e., $t_r^{\text{announce}} \leqslant th$), and its release time is later than th (i.e., $t_r^{\text{release}} \geqslant th$). However, the decision for request $r \in \hat{R}^t$ is fixed only if $t_r^{\text{release}} \leqslant (t+1)h$, namely the request will be expired before the next decision epoch. Denote $\bar{R}^t$ as the set of active requests that will be expired before decision epoch $t+1$. The network operator will inform shippers of the decisions only if a fixed match is made for them. Thus, all the fixed matches made at time stage t will have effects on the free capacity of service $s \in S^{\text{barge}} \cup S^{\text{train}}$ at time stage $t+1$.

Under the MOA, the objective is to minimize the total cost of the current-stage decisions made for active requests. The formulation of the DSSM problem at stage $t \in \{0, 1, \ldots, T\}$ is therefore changed to:

$$\mathbf{P1} \quad \min_{X^t} \sum_{r \in \hat{R}^t} \sum_{p \in P_r} c_{rp} x_{rp}^t \tag{12}$$

subject to

$$\sum_{p \in P_r} x_{rp}^t = 1, \quad \forall r \in \hat{R}^t, \tag{13}$$

$$\sum_{r \in \hat{R}^t} \sum_{p \in P_{rs}} u_r x_{rp}^t \leqslant U_s^t, \quad \forall s \in S^{\text{barge}} \cup S^{\text{train}}, \tag{14}$$

$$U_s^{t+1} = U_s^t - \sum_{r \in \bar{R}^t} \sum_{p \in P_{rs}} u_r x_{rp}^t, \quad \forall s \in S^{\text{barge}} \cup S^{\text{train}}, \tag{15}$$

$$x_{rp}^t \in \{0, 1\}, \quad \forall r \in \hat{R}^t, p \in P. \tag{16}$$

AOA

This section proposes an AOA in which decisions are made based on dynamic information and stochastic information. Specifically, the RH approach is applied to handle dynamic events. At each iteration of the RH framework, an SAA method is employed to deal with the stochastic information. Under the SAA method, E_{Ω^t} in the DSP formulation is approximated as $\Gamma^{-1} \sum_{\gamma \in \{1, \ldots, \Gamma\}}$ which comprises Γ scenarios $\{\omega_1, \omega_2, \ldots, \omega_\gamma, \ldots, \omega_\Gamma\}$, where $\omega_\gamma = \{\omega_\gamma^{t+1}, \omega_\gamma^{t+2}, \ldots, \omega_\gamma^{t+H}\}$. Let ω_γ^k be a sample of shipment requests received at time period k under scenario γ. Each scenario has the same probability Γ^{-1}. The scenarios are generated based on sampling probability distributions of future requests' origin, destination, volume, announce time, release time, and due time. In addition, $\Gamma^{-1} \sum_{\gamma \in \{1, \ldots, \Gamma\}}$ is an unbiased estimator of E_{Ω^t}, and will converge to E_{Ω^t} with probability of 1 as the sample size Γ goes to infinity and the prediction horizon $H = T$. Let $y_{rp}^{\gamma k}$ be the binary variable which equals 1 if request $r \in \omega_\gamma^k$ is matched with path $p \in P_r$, 0 otherwise. The formulation of the DSSM problem at each stage further changes to:

$$\begin{aligned} \mathbf{P2} \quad & \min_{X^t, Y^{t+1}, \ldots, Y^{t+H}} \sum_{r \in \hat{R}^t} \sum_{p \in P_r} c_{rp} x_{rp}^t \\ & + \frac{1}{\Gamma} \sum_{\gamma \in \{1, \ldots, \Gamma\}} \sum_{k \in \{t+1, \ldots, t+H\}} \sum_{r \in \omega_\gamma^k} \sum_{p \in P_r} c_{rp} y_{rp}^{\gamma k} \end{aligned} \tag{17}$$

subject to

$$\sum_{p \in P_r} x_{rp}^t = 1, \quad \forall r \in \hat{R}^t, \tag{18}$$

$$\begin{aligned} & \sum_{p \in P_r} y_{rp}^{\gamma k} = 1, \qquad \forall \gamma \in \{1, \ldots, \Gamma\}, \\ & k \in \{t+1, \ldots, t+H\}, r \in \omega_\gamma^k, \end{aligned} \tag{19}$$

$$\begin{aligned} & \sum_{r \in \hat{R}^t} \sum_{p \in P_{rs}} u_r x_{rp}^t + \sum_{k \in \{t+1, \ldots, t+H\}} \sum_{r \in \omega_\gamma^k} \sum_{p \in P_{rs}} u_r y_{rp}^{\gamma k} \leqslant U_s^t, \\ & \forall s \in S^{\text{barge}} \cup S^{\text{train}}, \gamma \in \{1, \ldots, \Gamma\}, \end{aligned} \tag{20}$$

$$U_s^{t+1} = U_s^t - \sum_{r \in \bar{R}^t} \sum_{p \in P_{rs}} u_r x_{rp}^t, \quad \forall s \in S^{\text{barge}} \cup S^{\text{train}}, \quad (21)$$

$$x_{rp}^t \in \{0, 1\}, \quad \forall r \in R^t, p \in P, \quad (22)$$

$$y_{rp}^{\gamma k} \in \{0, 1\}, \quad \forall \gamma \in \{1, \ldots, \Gamma\}, \\ k \in \{t+1, \ldots, t+H\}, r \in \omega_\gamma^k, p \in P. \quad (23)$$

The objective is to minimize the costs for active requests at time stage t and the average costs for sampled requests from time stage $t+1$ to $t+H$ under Γ scenarios. Constraints in Equations (18) and (19) ensure that one shipment will be matched with one path. Constraints in Equation (20) ensure that the total volume of shipment requests assigned to service $s \in S^{\text{barge}} \cup S^{\text{train}}$ at time stage t under all the scenarios does not exceed its free capacity at time stage t. Constraints in Equation (21) update the free capacity of service $s \in S^{\text{barge}} \cup S^{\text{train}}$ at time stage $t+1$. Here, the free capacity of barge and train services at the next time stage is only affected by the decisions for requests $\bar{R}^t$ which are active at current time stage and will be expired at the next time stage.

Numerical Experiments

This section evaluates the performance of the MOA and AOA proposed above. The approaches were implemented in MATLAB, and all experiments were executed on 3.70 GHz Intel Xeon processors with 32 GB of RAM. The optimization problems were solved with CPLEX 12.6.3.

Instances Generation

This study used a hinterland multimodal network for the numerical experiments, which includes three deep-sea terminals (i.e., node 1, 2, and 3) and seven inland terminals (i.e., node 4, 5, 6, 7, 8, 9, and 10), as shown in Figure 3. It involved one week of services including 49 barge services, 33 train services, and 34 truck services. The inland waterway and railway distances were derived from the website of European Gateway Services (https://www.europeangatewayservices.com/en) and InlandLinks (https://www.inlandlinks.eu/en), and the road distances were calculated based on Google maps. The transit cost, loading or unloading cost, storage cost, penalty cost, and carbon tax coefficients used in the experiments were derived from Li et al. (*11*), van Riessen et al. (*30*), and Qu et al. (*31*). The length of the planning horizon was set to one week for all the instances. The length of the optimization interval was set to 1 h in the MOA and the AOA. In the AOA, the size of scenarios was set to 10, and the length of the prediction horizon was set to 12 h.

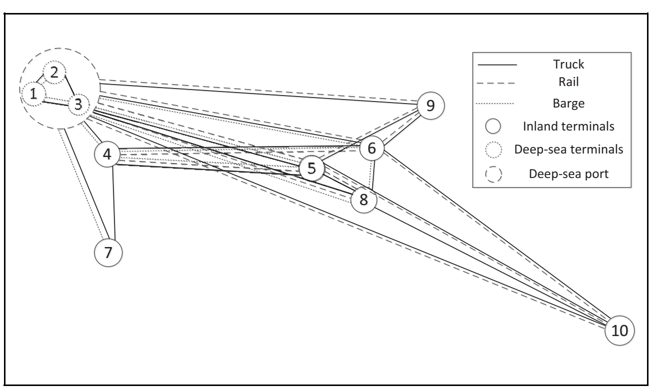

Figure 3. Topology of a hinterland multimodal network.

Several instances were generated to represent different characteristics of shipments within the given network. Each shipment is characterized by its announce time, release time, due time, OD pair, and container volume. It is assumed that:

- the origins of shipments are independent and identically distributed among $\{1, 2, 3\}$ with probabilities $\{0.66,\ 0.2,\ 0.14\}$;
- the destinations are independent and identically distributed among $\{4,\ 5,\ 6,\ 7,\ 8,\ 9,\ 10\}$ with probabilities $\{0.306,\ 0.317,\ 0.153,\ 0.076,\ 0.071,\ 0.034,\ 0.043\}$;
- the container volumes of static shipment requests are drawn independently from a uniform distribution with range [10, 30]; the container volumes of dynamic requests are drawn independently from uniform distributions with range [1, 9];
- the announce time of static requests is 0, while the frequency of dynamic requests arriving in the system belongs to Poisson distributions with mean AT^{AVE};
- the release time of static requests is drawn independently from a uniform distribution with range [1, 120]; the release time of dynamic requests is generated based on its announce time, $t_r^{\text{release}} = t_r^{\text{announce}} + \Delta T$, ΔT belongs to a uniform distribution with range [1, 6];
- the due time of shipment requests is generated based on its release time and lead time, $t_r^{\text{due}} = t_r^{\text{release}} + LD_r$, the lead time of shipments are independent and identically distributed among $\{24,\ 48,\ 72\}$ (unit: hours) with probabilities $\{0.15,\ 0.6,\ 0.25\}$.

In this paper, it is assumed that the probability distributions are available and accurate. Therefore, the same probability distributions were used to generate instances and scenarios.

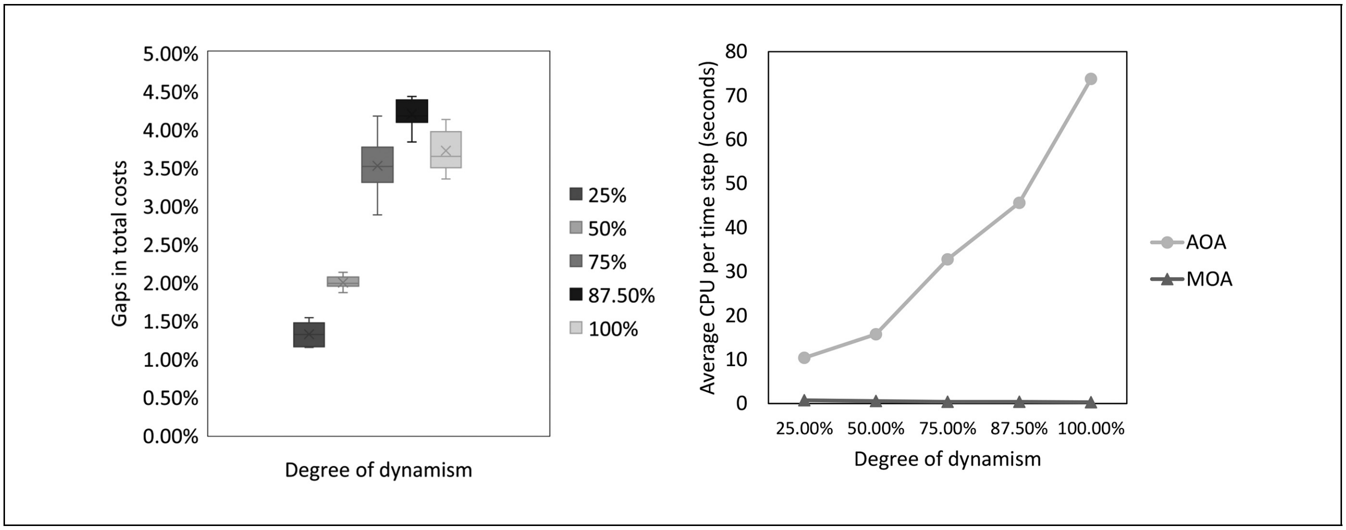

Figure 4. Comparison of the MOA and the AOA under different degrees of dynamism.
Note: AOA = anticipatory optimization approach; CPU = central processing unit; MOA = myopic optimization approach.

Comparison between the MOA and the AOA

To compare the performance of the MOA and the AOA, five groups of instances were designed with different degrees of dynamism: 25%, 50%, 75%, 87.5%, and 100%. The degree of dynamism is defined as the ratio between the number of containers from dynamic requests and the total number of containers over the planning horizon. For each group, there are 10 replications. "Gaps in total costs" were used as the performance indicator which is given by (benchmark value–objective value)/ benchmark value. Here, the total cost generated by the MOA is the benchmark value, while the total cost generated by the AOA is the objective value. Therefore, the higher the "gaps in total costs", the better the performance of the AOA. Figure 4 shows that the AOA has better performance than the MOA in all the instances in reducing total costs and the gaps between the AOA and the MOA grow with the increase of the degree of dynamism from 25% to 87.5%. Nevertheless, further increasing the degree of dynamism to 100%, the gap in total costs stays around 4%. In addition, the average computational time per time step under the AOA is within 80 s for all the instances.

To understand the differences in matching process between the MOA and the AOA, the matching results of one of the instances at every time stage were analyzed. Here, "gaps in cumulated costs" were used to represent the differences in cumulated cost at previous stages between the MOA and the AOA. The higher the "gaps in cumulated costs," the better the performance of the AOA. "Gaps in cumulated barge and train capacity utilization" were used to represent the differences in

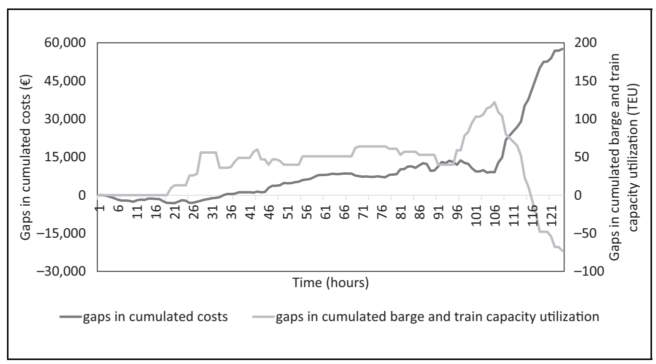

Figure 5. Differences in matching process between the MOA and the AOA.
Note: MOA = myopic optimization approach; AOA = anticipatory optimization approach.

cumulated capacity utilization of barge and train services. Figure 5 shows that in earlier stages (before time stage 36), the MOA tries to use as much barge and train capacity as possible, and the cumulated cost is lower than the AOA. However, in later stages (after time stage 104), the MOA has no barge and train capacity that can be used. In comparison, the AOA holds some capacity of barge and train services for requests arriving in later stages, the cumulated total cost over the planning horizon is lower than the MOA; the cumulated capacity utilization of barge and train services over the planning horizon is higher than the MOA. It is predictable that the longer the planning horizon, the better the performance of the AOA since it anticipates the future.

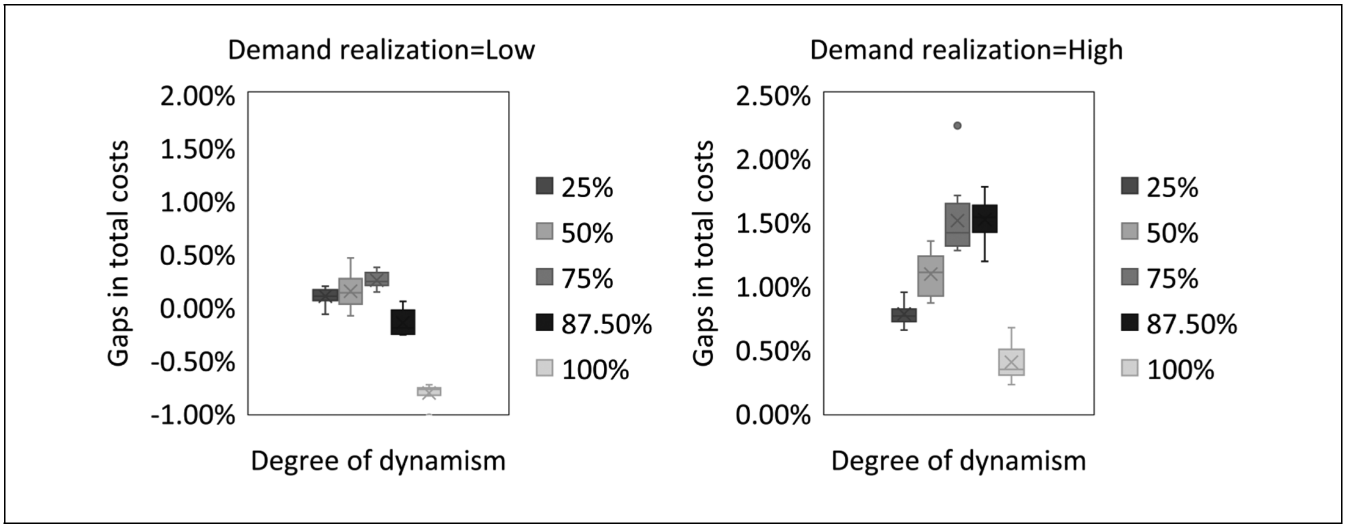

Figure 6. Performance of the AOA under prediction errors.
Note: AOA = anticipatory optimization approach.

Performance of the AOA with Imperfect Predictions

In the instances presented so far, it was assumed that the decision maker has the accurate probability distributions of future requests. Thus, the probability distributions used in sampling in the AOA are the same as the probability distributions used in generating the above instances. However, because of uncertainties in demand during special periods (e.g., high inflation rate periods, Valentine's Day, Black Friday), the demand might be lower or higher than normal periods. In this section, five groups of instances were designed with different degrees of dynamism and having lower demand realizations. The container volume of these instances is drawn independently from a uniform distribution with range [1, 3]. Another five groups of instances were designed with higher demand realizations drawn from a uniform distribution with range [7, 9]. Figure 6 shows that when realizations are lower than normal periods, the performance of the AOA is almost the same as the MOA in all the instances and even worse for instances with 100% degree of dynamism. The reason is that using the AOA, the system will hold some capacity for future requests which actually have lower demand realizations than the prediction. On the other hand, when the realizations are higher than normal periods, the AOA still has better performance than the MOA.

Conclusions and Future Research

This paper introduced a DSSM problem in multimodal transportation. The problem is dynamic since some shipment requests arrive in the system in real time. The problem is stochastic since the probability distributions of future requests are available from historical data. A MSP formulation was presented to describe the problem. Because of the curse of dimensionality, two approaches were developed: a myopic optimization approach (MOA) in which decisions are made based on deterministic information, and an anticipatory optimization approach (AOA) in which decisions are made based on incorporating dynamic and stochastic information.

These two approaches were validated on a hinterland multimodal network. The results indicate that the AOA has better performance than the MOA in reducing total costs under various scenarios of the multimodal matching system. Furthermore, the performance of the AOA was tested under imperfect prediction of the future. The results show that the AOA has no improvement when realizations are lower than normal periods as it reserves capacity for predicted future requests, but has better performance when realizations are higher than normal periods.

This paper did not present the impact of the length of optimization intervals, the length of the prediction horizon, and the size of scenarios. Future research can be carried out on these aspects. On the other hand, considering the computational complexity for instances under dynamic and stochastic scenarios, an efficient algorithm combined with parallel computing needs to be designed in the future.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: W. Guo, B. Atasoy, W. Beelaerts van Blokland, R. R. Negenborn; data collection: W. Guo; analysis and interpretation of results: W. Guo, B. Atasoy; draft manuscript preparation: W. Guo, B. Atasoy, R. R. Negenborn. All authors reviewed the results and approved the final version of the manuscript.

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